THE UNIVERSITY OF CHICAGO

ENTER THE PARTISAN FIRM: HOW AFFECTIVE POLARIZATION SHAPES CORPORATION AND CAREER

A DISSERTATION SUBMITTED TO
THE FACULTY OF THE DIVISION OF THE SOCIAL SCIENCES
IN CANDIDACY FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

DEPARTMENT OF SOCIOLOGY

BY
JOSHUA GARY MAUSOLF

CHICAGO, ILLINOIS
JUNE 2020

CHAPTER 1

Introduction - Overarching Questions and Frames of the Dissertation

1.1 Enter the Partisan Firm

Political partisanship dominates the headlines, especially in the wake of the 2016 presidential election and the advent of the 2020 election. Accounts of increasing divisiveness, partisanship, ideological divides, culture wars, and polarization run rampant across scientific press (Bail et al. 2018; Iyengar et al. 2019; Klein 2020; Macy et al. 2019), the news media (Cohn 2014; Douthat 2020), and studies of culture (DellaPosta, Shi, and Macy 2015), romance (Huber and Malhotra 2017), and economic behavior (McConnell et al. 2018). From dating to debates, from the office place to the Oval Office, partisanship seems ubiquitous and inescapable. Yet across the myriad media of partisan discourse exists considerable ambiguity. To glean insight in this indeterminate space of partisan division, therefore, requires specificity.

To that end, I turn my focus to examine the oft-overlooked phenomenon of political partisanship in the workplace, particularly major American corporations. From the perspective of firms alone, narratives of divisive politics exist. These include claims of politically-motivated termination (Copeland 2019; McCabe 2019), charges of political censorship or the lack thereof on social media (Confessore and Bank 2019; Timberg 2020), and the role of corporate money in politics (Bartels 2016; Domhoff 2010; Hacker and Pierson 2010; Mayer 2016). Although politics, especially partisan politics, often entangle with firms, we less often consider how partisanship in society might affect the organizational structure of firms and in turn shape the behavior of the individuals employed therein. In this dissertation, I address a series of questions such as, how has partisanship in its own right emerged in the American firm and how do partisan behaviors affect various stages of careers, such as within-firm hiring or corporate board member appointments? Fundamentally, this dissertation rests at the nexus of how dimensions of political partisanship, namely *partisan polarization*, *partisan homophily* and *affective polarization* manifest within corporate organizations, and influence the employees, leadership, and careers therein. Collectively, I argue that in recent years, political partisanship has emerged with increasing strength in the American corporation, and contributes to a systemic cycle reinforced societally, while at the same time emboldening partisanship within firms, especially affective polarization. Below, I briefly expand on the argument and high-level findings before outlining a roadmap to provide the essential definitions, background, theoretical puzzles, and literature that I engage in this dissertation.

As I will argue in this dissertation, political partisanship in its own right provides a valuable signal that can affect behavior in firms, including dimensions of individual careers. Increasingly, partisanship acts as a proxy for ideological and cultural attitudes or positions, such that allegiance to a party signals the superiority or reprehensibility of an individual's character—that is, whether an individual is *suitable* for a social situation (Iyengar and Westwood 2015; Iyengar et al. 2019). Existing research demonstrates the very social nature of informal practices in complex corporate organizations, where social and cultural fit have an established role in determining whether an individual is suitable for employment (Goldberg et al. 2016; Rivera 2012b). I will argue that such an exemplification of partisan homophily and affective polarization contributes to the activation of political partisanship within firms, thereby driving increased party sorting, such that we see increasing within-firm partisan homogeneity and increased partisan differentiation between firms of opposing parties. I will also argue that partisan processes, especially partisan homophily and affective polarization, shape careers, including initial callbacks in hiring or the appointment of incoming corporate board members. These findings underscore the salience of organizational fit alongside mechanisms of partisan homophily and affective polarization. That this transpires even when organizations have arguable performance and legal rationales to preempt partisan bias and promote diversity reaffirms the idea that political partisanship structures organizational behavior. Furthermore, such results demonstrate that the potential benefits of homogeneity and downsides of diversity are largely preferable in this age of heightened partisanship. Together, these findings suggest that the societal rise of partisanship may, in fact, not only permeate the corporation, but indeed fundamentally reshape its internal organizational structure, and that these effects will intensify in coming years. Such partisan processes may help tip the partisan balance of a firm and redefine exactly who is welcome to be hired and progress therein as a valued employee. In this way, partisanship affects not only routinized organizational behavior but, in effect, organizational strategy and the structure that follows.[1]

While this argument certainly presents a compelling narrative, to fully appreciate the research and arguments I will demonstrate in this dissertation, I must take several steps back to further unpack some core definitions, as well as the multidisciplinary background needed to set the stage and underscore the importance of partisanship. I must also fully outline the theoretical puzzles at play to not only ground the impetus for this research but also to develop the tension necessary for a satisfying conclusion to the research questions posed. In particular, we will proceed in the following order of events: First, to adequately address the question as to whether political partisanship structures behavior in firms, we must better understand the key ideas at stake. To begin, I will define and outline the relationship between political parties versus ideology. I will also establish the role of partisanship, especially partisan polarization, affective polarization, and partisan homophily. Second, I will articulate why, even without a deep theoretical anchor, we should intuitively suspect that political partisanship would be important in corporations, particularly to employees and the careers therein. Third, although such an articulation only begins to set the stage, at best, the

[1] I expand on this idea later in the main body of the introduction as well as a subsequent footnote (Chapter 1, footnote 22), and provide a deeper level of organizational theory on this concept in Appendix A. In brief, an organization's allocation of resources, including its human capital, constitutes an important dimension of its founding strategy and the structure that follows (Chandler 1962; Hannan and Freeman 1984), and thus reformulations of human capital reflect shifts in strategy and in resultant future structure and behavior (Appendix A).

scene is barren without understanding more about the way social scientists have previously conceived of the relationship between corporations, elites, and politics. While my perspective offers an alternative approach to the role of partisanship within firms, I must also address some convolution in the way politics is currently theorized, versus measured in existing organizational research. Fourth, having now established a firm grasp of key definitions and the role of partisanship in firms, I outline a pressing tension in organizational scholarship. This puzzle counterposes both theories, suggesting firms might attempt to preempt partisan discrimination and promote partisan diversity or instead embrace partisan homogeneity. Lastly, I provide a brief synopsis of the subsequent chapters. Although this is certainly some variegated terrain, I have every confidence that together, this scholarly peregrination will prove fruitful as we seek to understand the role of partisanship in the modern American firm.

1.2 The Role of Partisanship, Its Effects and Mechanisms, and the Meanings of Polarization

To answer the question of how political partisanship might act as a structuring mechanism in firms and shape the behavior or careers therein, we must first have a solid conception of political partisanship. We must also grasp the difference and relationship between party and ideology, since both concepts are critical in disambiguating the many meanings of polarization. Of these, I focus on partisan polarization, also known as party sorting, taking the particular vantage of this phenomenon as a process not a state, and from an approach rooted solely in partisan attachment. Such a perspective cleanly intersects with another process known as affective polarization as well as partisan homophily, both of which hold partisan identity at their core. Let us, therefore, begin by understanding the concept of political partisanship and political parties.

The idea of political partisanship is directly related to the concept of political parties, and more importantly, identification with a political party (Campbell et al. 1960).[2] We can trace the idea of parties to classical theories by Marx, Weber, Gramsci, and even Machiavelli (Mudge and Chen 2014). Perhaps most relevant are the Weberian and Gramscian perspectives. Whereas the Weberian perspective posited that parties existed as organizations with both class and status dimensions, the Gramscian approach emphasized the role of parties in creating "social groups... who foster class alliances" (Mudge and Chen 2014:306–9).[3] Simplifying the classical conceptualizations, the notion of parties as "social groups" appears across myriad discussions of political parties, particularly the Columbia and Michigan schools (Johnston 2006; Mudge and Chen 2014:306).[4]

The conception of political parties as a social phenomenon burgeoned in the 1960s both in sociology, with the works of Lipset (1960) expanding the Columbia School, and in political science with the social-psychological perspective of the Michigan School, notably the canonical work of Campbell et al. (1960) in *The American Voter* (Johnston 2006; Manza and Brooks 1999; Mudge and Chen 2014). Although political sociology all but relegated the analysis of parties to political science (Mudge and Chen 2014),[5] the study of parties and party identification largely stems from the work of Campbell et al.'s (1960) seminal work (Johnston 2006; Manza and Brooks 1999). As Campbell et al. (1960) argued, average citizens lacked the requisite wherewithal about political candidates and their policies to perspicaciously allocate votes on the basis of individual "class location or other social attributes," and instead relied on their socially inherited and reinforced party identifications—which are "inherited in

[2]I use the terms political identity, party identity, party identification, or the party with which an individual identifies as exchangeable terms.

[3] While an in-depth discussion of the differences between classical theorists' perspectives of political parties is beyond the scope of this section, Mudge and Chen (2014) summarize key insights of this debate in detail.

[4]For example, Mudge and Chen (2014) write, "understanding of parties as expressions of social groups—a view closely associated with Paul Lazarfeld, Seymour Martin Lipset, and their colleagues" (306), where Lazarfeld is seen as a key member of the Columbia School and Lipset extends that perspective with his *Political Man* (Johnston 2006; Lipset 1960; Manza and Brooks 1999). Johnston (2006), when discussing the canonical "Michigan school," which expanded work by the Columbia school, reiterates that "the idea of identification with a party as a social group in its own right quickly took hold after 1960" (330).

[5]The recent work of sociologist, Delia Baldassarri, among others, is a notable exception (Baldassarri and Bearman 2007; Baldassarri and Gelman 2008; Baldassarri and Goldberg 2014; Cowan and Baldassarri 2018).

childhood and reinforced in adulthood" to make judgements in casting their votes (Campbell et al. 1960; Manza and Brooks 1999:14–15). According to Campbell et al. (1960), parties are influential in many ways, including policy positions and partisan attitudes:

> Party has a profound influence across the full range of political objects to which the individual voter responds. The strength of the relationship between party identification and the dimensions of partisan attitude suggests that responses to each element of national politics are deeply affected by the individual's enduring partisan attachments. (Campbell et al. 1960:128)

The stability of American party identification is widely noted. Many scholars quote and expand upon Campbell's insight (Barber and Pope 2019; Goren, Federico, and Kittilson 2009; Johnston 2006). Goren et al. (2009) write, "party identification represents the most stable and influential political predisposition in the belief systems of ordinary citizens" (805; *c.f.* Sears 1975). Many studies reaffirm the influence of party and partisan behavior across myriad political dimensions, including voter behavior and voter choice, political perceptions, candidate evaluations, political value support, and policy attitudes, among other factors (Bartels 2000, 2002; Goren 2002; Goren et al. 2009; Green and Palmquist 1990; Layman and Carsey 2002). In essence, party identification is not determined or "constrained"—that is, bound together—by political values, but rather party identification guides the ideological development of beliefs and values (Barber and Pope 2019; Goren 2005).[6]

Clearly, from this brief examination of parties and party identification, we can see that political parties are a veritable social structure that constrains and organizes political ideology,

[6] In political science, the term *constrain* or its variations such as *constraint* or *constrained* relate to the origins and development of political attitudes, values, or beliefs (Goren 2005). For example, Poole (2005) notes that "constraint means that issues are interrelated or bundled and that ideology is fundamentally *the knowledge of what goes with what*" (12). Poole's (2005) statement follows a quote from Converse's (1964) foundational work, "The Nature of Belief Systems in Mass Publics," wherein Converse employs the term "constraint" in defining "a *belief system* as a configuration of ideas and attitudes in which the elements are bound together by some form of constraint or functional interdependence" (207). Returning to Goren's (2005) findings, political values—an ideological concept—are bound together, constrained, and determined by *party identification* rather than these ideas or systems of beliefs constraining or determining party identification. Rather, political identity exhibits remarkable stability and shapes core political value judgements (Goren 2005). See also the discussion of constraint in Baldassarri and Goldberg (2014), whose perspective on constraint focuses less on "what people believe," but rather on, "*how their beliefs are organized*" (54).

sentiments, beliefs, and behavior. Those who identify with a party—particularly its loyal adherents—are known as partisans, and their behavior to that end describes partisanship. As Green, Palmquist, and Schickler (2002), remark, "the term *partisanship* is something of a double entendre, calling to mind both partisan cheering at sports events and affiliation with political parties. Both meanings, it happens, comport with... partisan attitudes" (1).

Extending this sentiment, I will argue that political partisanship serves as a factor structuring corporate organizational forms, strategy, and political behavior. To this end, several related partisan phenomena, namely partisan polarization, affective polarization, and partisan homophily are paramount to understanding the role of party identification in shaping partisan behavior. Before unpacking these ideas, I must briefly juxtapose the theoretically disjoint but empirically related research on political ideology and political polarization, which traditionally relates to specific ideological distributions versus partisan differences.

1.2.1 The Partisan-Ideological Disconnect

While I have argued that party identification constrains ideology, what substantively do political ideology and party confer? At the most concrete level of abstraction, party identification typically falls on a scale from Democrat to Republican, with some scales including variations based on the strength of partisan attachment. Conversely, ideology often ranges from liberal to conservative with the parallel variations on strength.[7] In survey research, both party identification and ideological identity are often measured through self-identification. Furthermore, since ideology is believed to be a bound system of interdependent beliefs and attitudes—arguably constrained by party identity (Barber and Pope 2019; Goren

[7] There is a range of other possibilities: Many scales include neutral categories such as independent (party) or moderate (ideology) or simply an opt-out option such as neither (Democrat/Republican), neither (liberal/conservative), or none of the above. The American National Election Survey offers both a seven-point party identification and a three-point party identification scale. The General Social Survey follows a similar convention in their survey questionnaire for party identification and political ideology (Baldassarri and Gelman 2008; DiMaggio, Evans, and Bryson 1996; Fiorina and Abrams 2008).

2005)—ideology can be assessed by identifying positions taken on issues (Bonica 2014; Converse 1964; Poole 2005).[8]

Whereas the research demonstrates that party identification shapes ideological beliefs—that is, political views—those beliefs are not the source of party identity, but its consequence (Barber and Pope 2019; Campbell et al. 1960; Goren 2005; Johnston 2006). Presenting the distinction in this way may seem surprising to some. As some scholars note, the "liberalism/conservatism [ideological] distinction has been associated with the two major parties, the Democratic Party (more liberal) and the Republican Party (more conservative)" (Chin, Hambrick, and Treviño 2013:207). Although scholars identify a reliable—albeit general—parallel between the Democratic Party and liberal positions as well as the Republican Party and conservative stances (McCarty, Poole, and Rosenthal 2006; Poole and Rosenthal 1984, 1997), the two ideas should not be equated at the point of *measurement*. To this point, given the correlation between ideological and partisan scales and the stability of party identification (Bonica 2014; McCarty et al. 2006; Poole and Rosenthal 1984), some analysts mistakenly utilize measures of partisan political contributions as a measure of ideological giving (Chin et al. 2013; Gupta and Wowak 2017; Gupta, Briscoe, and Hambrick 2017), a point upon which I later expound.[9]

This is not to say political campaign contributions are not ideological. In fact, most contributions have an ideological component (McCarty et al. 2006). Yet, as shown by the above debate, *party identification structures ideology*, and within parties, there exists

[8]See also the prior note elaborating on quotes from Converse (1964) and Poole (2005) regarding belief systems, ideology, and constraint (Chapter 1, footnote 6).

[9]In short, we should not conflate measures of partisanship with ideology and presume they represent a valid depiction of individuals' heterogeneous ideological beliefs. This point is clear even in McCarty et al. (2006) and Poole and Rosenthal (1984). See also Bonica (2014), which discusses the variation in ideological scores within and across parties. In particular, Bonica (2014): Appendix Figures 1-2 are illustrative of the heterogeneous distribution of CFscores (ideological scores) within and between parties. More generally, this ideological heterogeneity within and between parties is well established, serving as the basis for studies in political polarization (DiMaggio et al. 1996; McCarty et al. 2006), and similarly appears as relevant in studies evaluating the relationship between individual partisan attachment and heterogeneous ideological beliefs (Baldassarri and Goldberg 2014; Hetherington 2009; Levendusky 2009; Mason 2015). See also Chapter 1, footnotes 21, 23 or the discussion in Chapter 1, section 1.3.2 and footnote 26.

significant ideological heterogeneity (Baldassarri and Goldberg 2014; Bonica 2014, 2016; McCarty et al. 2006).[10] Furthermore, although politicians may be fairly stable in their ideological positions (especially in the spatial sense), rarely change parties, or shift in their ideological extremism, the issues for which they advocate—or the ideological poles to which they gravitate—are in constant flux (Karol 2009), exacerbating partisan polarization (Baldassarri and Goldberg 2014; Hetherington 2001), and heightening partisan tension to a new climax come Election Day (Sood and Iyengar 2016).

1.2.2 Disentangling the Many Meanings of "Polarization"

The theoretical and empirical disconnect between party and ideology points to another sticking point—that of political polarization, or simply *polarization*. In many respects, this term of art is a source of considerable confusion.[11] Although colloquial definitions of polarization simply refer to acutely divided and opposed groups (Fiorina and Abrams 2008), in political

[10] For example, McCarty et al. (2006) write, "there is always substantial diversity of NOMINATE positions [ideological scores] within each party and, at times, ideological overlap between the parties" (21). In the political science literature, the NOMINATE or DW-NOMINATE scores refer to a method of measuring ideological scores, discussed in detail in Poole and Rosenthal (1997). Bonica also recognizes the extent of ideological diversity within parties (Bonica 2014, 2016), and Baldassarri and Goldberg (2014) note that issue alignment is highest among a subset termed "ideologues" versus "alternatives" or "agnostics" (45).

[11] The confusion over polarization relates, in part, to the diversity of terms for the same idea. For example, political polarization—or simply polarization—typically refers to specific distributional assumptions of political ideological beliefs, attitudes, or positions, and is occasionally called attitude polarization, ideological polarization, or issue position polarization (Baldassarri and Bearman 2007; Mason 2015; McCarty et al. 2006). The increased salience or attachment ascribed to political parties or social sorting along these lines is alternatively called partisan polarization and party sorting (Baldassarri and Goldberg 2014; Fiorina and Abrams 2008; Fiorina, Abrams, and Pope 2005). Affective polarization is a completely discrete phenomenon that relates to feelings of animosity between opposing partisans and feelings of affection between copartisans (Iyengar and Westwood 2015; Iyengar et al. 2019). Lastly, social polarization has somewhat incongruent meanings depending on the author. For example, Baldassarri and Bearman's (2007) use of social polarization is more about the alignment or divergence of issue attitudes within and between parties, versus ideologies (*c.f.* Fiorina and Abrams 2008), whereas Mason's (2015) use of social polarization is more about partisan bias and anger that can evolve between parties despite ideological agreement between them. Collectively, we can discern the idea that there can be both ideological disagreement within parties and ideological agreement between parties, but nonetheless increased sorting along party lines which is related to cross-party animus (Baldassarri and Bearman 2007; Baldassarri and Goldberg 2014; Fiorina and Abrams 2008; Mason 2015). Although a number of terms are used in the literature, my study is particularly about the pure phenomenon of partisan polarization (or party sorting) using only party attachment or expression as a process and feelings of animosity or positive affect within or across party lines (affective polarization).

science, polarization has a technical definition, which in the most robust valence, is a concept established through "spatial theory" (Lee 2015:263). As Poole and Rosenthal (1997) write, "for parties to be polarized, they must be far apart on policy issues, and the party members must be tightly clustered around the party mean" (81). Thus, polarization, in the classical sense, is a highly ideological phenomenon based on the distribution of policy preferences within parties. Clarifying the matter, Lee (2015) writes:

> Polarization in the spatial sense thus means more than increased partisan distinctiveness or division into two groups. The term does not apply if the parties are just better organized into competing "long coalitions" wrangling over control of political offices. . . Nor is polarization occurring if Democrats and Republicans merely get better organized as teams. . . polarization as understood in spatial theory refers to changes in the distribution of policy preferences within and across the parties. (Lee 2015:263)

Polarization in the spatial sense, then, is an inherently ideological phenomenon. Setting aside for a moment the finding that party identity establishes ideology, if we conversely suppose that individuals become better ideologically sorted—that is, if liberals increasingly sort into the Democratic Party and conservatives into the Republican Party—even that hypothetical process is not polarization in the strictest spatial sense (Lee 2015). Partisan sorting, while reifying party boundaries between ideological conservatives and liberals, is not sufficient to claim polarization, since liberals and conservatives—despite being better sorted—might be fixed but heterogeneous in their policy preferences (Fiorina et al. 2005; Lee 2015). The processes of everyday citizens, however, are not those of political elites. Despite ideological stability among ordinary citizens, there has been rising ideological polarization among party elites since the 1970s (McCarty et al. 2006), a fact contributing to increased *partisan* polarization of the masses (Hetherington 2001). Many of these analyses are quite complex, involving multidimensional assessments of specific policy attitudes within and between parties across time. However, measuring the strength of individual partisan or ideological attachment in surveys such as the General Social Survey (GSS) or National Election Survey (NES) is fairly straightforward, usually involving seven-point scales from strong Democrat to strong

Republican, and from extremely liberal to extremely conservative (Baldassarri and Gelman 2008; DiMaggio et al. 1996; Fiorina and Abrams 2008). As I exemplify below, partisan polarization refers to the distribution of parties and their ability to sort individuals along ideological lines (Fiorina and Abrams 2008), and affective polarization refers to a mechanism of partisan polarization characterized by animosity between parties (Iyengar et al. 2019).

1.2.3 The Importance of Partisan Polarization, Also Known as Party Sorting

Apart from traditional perspectives on polarization, a distinct but related phenomenon known as partisan polarization is also analyzed (Baldassarri and Gelman 2008; DiMaggio et al. 1996; Fiorina and Abrams 2008; Lee 2015), which can be defined as "the emergence of more internally cohesive, strongly differentiated parties," or the state that exists following such a process (Lee 2015:267). Although DiMaggio et al.'s (1996) definition of political polarization diverges from spatial theory in political science, their insight that "polarization is both a state and a process" holds under the varying conceptions of the term (693), whether we are discussing (ideological) polarization or partisan polarization. Alternatively referred to as partisan polarization or party sorting (Fiorina and Abrams 2008), partisan polarization is a process characterized by the increased attachment to a given political party among individual citizens (Baldassarri and Bearman 2007; Baldassarri and Gelman 2008; Baldassarri and Goldberg 2014). Although an individual's ideology is initially shaped by a party (Campbell et al. 1960; Goren 2005), mutable to party cues (Barber and Pope 2019; Goren et al. 2009; Macy et al. 2019), and can be affected by issue positioning of political elites (Hetherington 2001, 2009), partisan polarization or party sorting primarily conveys the strength of individual partisan attachment en masse, and its sorting function relative to individual policy positions. Individuals across the political aisle might agree on some ideological issues but nonetheless identify with opposing parties (Baldassarri and Bearman 2007; Baldassarri and Goldberg 2014; Mason 2015). They might also vehemently disagree on every conceivable issue but still identify with opposing parties. The latter case may contribute to a heightened state of partisan polarization even if true political polarization in the spatial sense is absent (Fiorina and Abrams 2008; Lee 2015), and typically, studies find increased relevance of parties despite some agreement across party lines or the lack of movement in issue polarization (Baldassarri and Goldberg 2014; DiMaggio et al. 1996; Hetherington 2001; Mason 2015). Since my study lacks data on specific ideological positions relative to partisan attachment, I focus on DiMaggio and coauthors' (1996) notion of polarization as a process (*c.f.* Fiorina and Abrams 2008), and thus characterize partisan polarization or party sorting as the existence of increasing partisan attachment, chiefly expressed as party allegiance to Democrats or Republicans. To better glean the relevance of partisan polarization over other types of political behavior, consider the following points.

First, polarization along ideological lines may not exist or be changing as much as popularly conceived (Fiorina and Abrams 2008). For example, DiMaggio et al. (1996) find little evidence of ideological polarization using survey data. Although individuals may become stronger partisans, and parties may better sort individual policy attitudes (Baldassarri and Gelman 2008; Baldassarri and Goldberg 2014; Levendusky 2009), they are not typically polarized along ideological grounds (DiMaggio et al. 1996; Fiorina and Abrams 2008; Hetherington 2009). In other words, although political elites such as congressional members may champion increasingly extreme liberal or conservative positions, and thereby clarify with which party an individual identifies (Hetherington 2001; Karol 2009), this increased partisan attachment or party sorting does not translate into individuals adopting these same extreme positions, but rather being better sorted by parties (Baldassarri and Gelman 2008; Baldassarri and Goldberg 2014). Thus, individuals might more strongly identify with the Democratic or Republican Party without becoming more liberal or conservative.[12] This ideological

[12]Even if individual ideology shifts, political polarization requires specific distributional assumptions both within and between parties (McCarty et al. 2006), ones often violated by average citizens (Baldassarri and Goldberg 2014; DiMaggio et al. 1996), and mutable to party loyalty (Barber and Pope 2019), (*c.f.* Macy et al. 2019).

heterogeneity among individuals also exists within corporate boards and across firms (Bonica 2014, 2016), and a similar degree of ideological diversity exists within political parties in Congress (Bonica 2014; McCarty et al. 2006), as well as everyday citizens (Baldassarri and Goldberg 2014; DiMaggio et al. 1996). These findings shake the popular conception of systemic polarization in politics—a misconception grounded in the semantic underpinnings of (ideological) polarization.

Second, the ideological heterogeneity possible, both within and between parties, raises an important point of partisan polarization, namely its relation to political elites and animosity between the parties. To take perhaps a well-known example, the widely reported claims of polarization in Congress, relate to increasing party sorting and non-cooperation across party lines, which has exponentially increased over the last sixty years (Andris et al. 2015). Although ideologically extreme political elites can clarify party positions and increase partisan polarization (Hetherington 2001, 2009; Karol 2009), the rise of partisanship also emerges from and facilitates increased discord between the parties, to which ideological divisions may contribute but do not necessarily cause (Iyengar and Krupenkin 2018; Iyengar and Westwood 2015; Mason 2015; Sood and Iyengar 2016). In the subsequent section, I will explicitly examine the role of this partisan animus, namely affective polarization, but for the moment, let us recognize that just as partisan attachment or party sorting can be activated by ideological extremism of political elites, so too can we witness increased feelings of partisan hostility emerging from the campaign activities of political elites (Sood and Iyengar 2016). Although partisan polarization can be generally seen in the increased relevance of political parties among everyday citizens (Baldassarri and Gelman 2008; Baldassarri and Goldberg 2014; DiMaggio et al. 1996; Fiorina and Abrams 2008; Hetherington 2001; Mason 2015), we also see party sorting, including partisan segregation, across interpersonal networks and online communities (An, Quercia, and Crowcroft 2014; Baldassarri and Bearman 2007; Bello and Rolfe 2014; Koger, Masket, and Noel 2009). Therefore, it is not simply that individuals are increasing or clarifying their party identification, but also that this phenomenon spreads beyond individuals to affect the tangible social networks and groups in which individuals associate and, more importantly, those they avoid.

1.2.4 Mechanisms of Partisan Polarization: Partisan Homophily and Affective Polarization

Although partisan polarization reflects a state of partisanship, understanding the phenomenon's emergence is also critical. Here, a number of mechanisms exist which can explain the emergence and amplification of partisan polarization. Chief among them: (1) partisan homophily and (2) affective polarization, which in some respects act as opposing micro-level levers of partisanship. Of course, beyond partisan homophily and affective polarization, we also see other potential mechanisms, including more nebulous macro phenomena such as partisan activation—as influenced by ideological polarization in elite politicians and their campaigns—as well as biased, differential media coverage whose perspective is influenced by (1) and (2) in addition to underlying corporate interests. Beyond complex political feedback loops in winner-take-all politics (Domhoff 2010; Hacker and Pierson 2010), we see additional structural, cultural, economic, demographic, and geographic explananda of variations in extant partisan identity and political ideology. Given the complexity of the landscape, I focus on two of the most ostensible mechanisms affecting individuals' partisan allegiance: Affective polarization and partisan homophily.

1.2.4.1 The Role of Affective Polarization

As previously indicated, increases in partisan polarization relate to a parallel phenomenon known as *affective polarization*. Following the idea of party sorting or *partisan polarization* is the extended concept that this party sorting differentially affects behavior and attitudes toward both copartisans and opposing party members. Denoted "affective polarization," scholars define the phenomenon as "the tendency of people identifying as Republicans or

Democrats to view opposing partisans negatively and copartisans positively" (Iyengar and Westwood 2015:691). Although affective polarization indeed reflects the dichotomy between positive feelings for copartisans and negative feelings for opposing partisans, often, it is the latter animus to which the term more often refers (Iyengar et al. 2019). For example, Iyengar et al. (2019) notes, "this phenomenon of animosity between the parties is known as affective polarization" (130).[13]

The work by Iyengar and Westwood (2015) extends research exemplifying escalating affective polarization, notably acute increases in "negative views of the out party and its supporters...since the 1980s" (Campbell et al. 1960; Green et al. 2002; Iyengar and Westwood 2015:691; Iyengar et al. 2012). Critical to this analysis, affective polarization delimits individual attitudes and behavior such that individuals not only hold animosity toward opposing party members but also view them as less intelligent (Pew Research Center 2016). In fact, the bias based on affective polarization toward political out-groups "exceeds discrimination based on race" (Iyengar and Westwood 2015:690). Critically, individuals need not uphold antipodal ideological positions—and may, in fact, agree on some points—but nonetheless find themselves virulently opposed to members of the opposite political party (Mason 2015).

And increasingly, partisan hostility rather than partisan affect motivates political participation (Iyengar and Krupenkin 2018), a fact related to the more colloquial expression of "voting for the lesser of two evils,"[14] known as anti-candidate voting (Gant and Sigelman

[13]The dichotomy between in-party and out-party feelings characterizes affective polarization (see Iyengar et al. (2019), Figure 1), however, as shown in that figure, growth of out-party animus remains the primary driver of affective polarization compared to the greater stability of in-party sentiment (Iyengar et al. 2019; Iyengar, Sood, and Lelkes 2012), (*c.f.* Iyengar and Krupenkin 2018).

[14]The exact origin of the proverb, "voting for the lesser of two evils," proves difficult to trace, for example, appearing as "voting for the 'lesser of two evils' " in (Gant and Sigelman 1985: 329) or "voting for the lesser of two evils" (Levin and Eden 1962: 55). Similarly, Downs (1957) writes, "extremist voters would be forced to vote for the one closest to them,...to select...a lesser evil before a greater" (118-9). Yet, the sentiment emerged well before Downs (1957). For example, we see among the most notable and earliest permutations of the phrase with respect to voting appear in several issues of the *American Political Science Review*, namely: (1) "the proprietors chose the lesser of two evils by either voting against the request or not voting at all" (Wright 1928: 382) and (2) "the effect was to shift the center of political gravity to the left...the benefit of

1985; Groenendyk 2012; Levin and Eden 1962: 55; Sigelman and Gant 1989), and relatedly the concepts of the alienated voter and voter abstention (Downs 1957; Levin and Eden 1962). For example, the escalation of voting driven by partisan animus as documented by Iyengar and Krupenkin (2018), prevails in the Democratic Party's consternation during the 2020 Democratic primaries to select a candidate who can best defeat Donald Trump (Bruni 2020; Frum 2020; Pfeiffer 2020).

Yet, affective polarization has ramifications beyond politics. For example, economic behavioral experiments reveal that participants bestow financial rewards on copartisans while penalizing out-party members (Carlin and Love 2013; Iyengar and Westwood 2015). Contributing to the widespread findings of affective polarization comes another point, namely, that although partisan bias may consciously afflict perceptions, it may also occur implicitly. Implicit partisan bias occurs in about 70% of Democrats and Republicans and remains more widespread than implicit racial bias (Iyengar and Westwood 2015). Partisan bias extends to behavior and decision making in a number of other contexts, including scholarship decisions, resume evaluations, and job applications (Gift and Gift 2015; Iyengar and Westwood 2015), employees' wage-floor preferences (McConnell et al. 2018), product market and purchasing behavior (McConnell et al. 2018; Panagopoulos et al. 2016), as well as family dynamics such as the growing unacceptability of one's child marrying someone of the opposing political party or the rising aversion to cross-party dialogue within families (Chen and Rohla 2018; Iyengar et al. 2012).

1.2.4.2 The Role of Partisan Homophily

Although partisan homophily is often included in the discussion of affective polarization (Iyengar et al. 2019), homophily is a state of clustering among similar others stemming from

---

the natural inclination of mankind to choose the lesser of two evils" (Holcombe 1911: 549). Of course, the general proverb of making a choice between the lesser of two evils has origins in Ancient Greece and is often attributed to Aristotle's *Nicomachean Ethics* (Speake 2008).

forces of attraction rather than repulsion (Iyengar et al. 2019; McPherson, Smith-Lovin, and Cook 2001). Following the proverbial adage, "birds of a feather flock together" (McPherson et al. 2001: 417),[15] homophily reflects the idea that contact more prevalently occurs between similar others (McPherson et al. 2001). Here, we can identify two important aspects of homophily, namely, *types* of homophily and *dimensions* of homophily, where types refer to the strength and character of the relationship between individuals and dimensions qualify the basis of similarity (McPherson et al. 2001).

For example, types often span the spectrum of relationship strength. Types include marriage, romantic partnerships, as well as close friendship at one end, and mere knowledge, loose acquaintance, or public association at the other (McPherson et al. 2001). Conversely, dimensions of homophily reflect the basis of propinquity (McPherson et al. 2001). Following the framework of (Lazarsfeld and Merton 1954), dimensions can be conceived as either *status homophily* or *value homophily*, where shared values more often than not emerge from shared status (Lazarsfeld and Merton 1954; McPherson et al. 2001). In particular, dimensions of status homophily include the expected sociodemographic and socioeconomic attributes such as race, ethnicity, sex, gender, sexual orientation, or class as well as acquired faculties like religion, educational attainment, or occupation (McPherson et al. 2001). We also find other salient political dimensions, including partisan identity (or even ideological identity) among the possible status dimensions brokering homophily (Huber and Malhotra 2017). Thus, when speaking of partisan homophily (alternatively, partisan matching), I refer to a specific subtype of the more general political homophily,[16] one of the many status dimensions of homophily

[15]This quote appears in McPherson et al. (2001), although, as noted by the authors, the actual quote has a complex lineage via (Lazarsfeld and Merton 1954) who attributed the phrase to (Burton [1651] 1927), who admits its origins predate Western thought.

[16]When reviewing the literature, a number of possible terms emerge, including partisan homophily, political homophily, partisan matching, or political matching, among others. For example, Iyengar et al. (2019) contains both the terms "political homophily" and "partisan matching," where "political homophily" extends from Huber and Malhotra's (2017) analysis of homophily on the basis of political identity, which includes both partisan and ideological identities. For specificity, I elect to use the terms partisan homophily or partisan matching when referring explicitly to homophily on partisan grounds, since terms utilizing the political descriptive could refer to (1) party or (2) ideology—as for example, the case where political polarization designates a phenomenon on ideological grounds, not political partisanship as is the case in

(Huber and Malhotra 2017; Iyengar et al. 2019; Lazarsfeld and Merton 1954; McPherson et al. 2001).

In the current literature, we have seen a number of studies evaluating partisan homophily. When considering social behavior, for example, we have witnessed a coterminous rise of increasingly distinct party member social networks (Koger et al. 2009), and increasing partisan clustering of copartisans on social media (An et al. 2014; Bello and Rolfe 2014). Such partisan homophily also translates to romantic entanglements. For example, Huber and Malhotra (2017) demonstrate the power of homophily in online dating behavior using both dimensions of ideological identity as well as partisan identity, where *partisan matching* or *partisan homophily* accounts for a significant increase in the likelihood of a messaging exchange for a given dyad (Huber and Malhotra 2017). Although political homophily in dating has not always proven salient or even observable (Klofstad, McDermott, and Hatemi 2013),[17] in the wake of the 2016 presidential election, we have seen a substantial increase in the disclosure of partisan or other political preferences in online dating profiles (Kiefer 2017), as well as evidence that mutually shared partisanship heightens perceptions of physical attraction (Nicholson et al. 2016). Similarly, about four out of five married couples uphold the same party identification, a fact "attributable primarily to mate choice based on partisan preference" (Iyengar, Konitzer, and Tedin 2018), as opposed to prior arguments that political alignment in marriage was spurious (Klofstad et al. 2013). In other words, Iyengar et al. (2018) show marital partnership to be "choice homophily" or the "the individual-level propensity to choose similar others" versus "induced homophily" (McPherson and Smith-Lovin 1987: 371). As already noted, partisan homophily in romantic relations coincides with aversion to cross-party romantic entanglements (Iyengar et al. 2012; Kiefer 2017).

partisan polarization (Fiorina and Abrams 2008). Note that this is distinct from Huber and Malhotra (2017), where political homophily captures both partisanship and ideology.

[17]Here, I use the term political homophily since Klofstad et al. (2013) evaluate homophily on the basis of political ideology (e.g., conservative-liberal). Note that this differs from Huber and Malhotra (2017) which includes both partisanship and ideology in the analysis of political homophily.

To summarize, party identification constrains ideological beliefs and policy preferences (Barber and Pope 2019; Bartels 2000, 2002; Goren 2002, 2005; Goren et al. 2009), which in combination with extreme ideological positioning by the political elite (Goren 2005; Hetherington 2001; McCarty et al. 2006), affective polarization (Iyengar and Westwood 2015; Mason 2015; Sood and Iyengar 2016), and partisan homophily (Huber and Malhotra 2017; Iyengar et al. 2018), has reified individuals' partisanship, resulting in a rising tide of partisan polarization despite fundamentally little movement in collective ideological preferences (Baldassarri and Gelman 2008; DiMaggio et al. 1996; Fiorina and Abrams 2008). Yet, the question remains as to how these socially manifested trends of partisan polarization, affective polarization, and partisan homophily permeate corporations and lead to shifts in the corporate organizational state.

1.2.5 Building an Intuitive Framework for Why Partisanship Would Matter Within Corporations

Before formally developing the competing organizational theories that might illuminate this question, or even presenting the background of how social scientists view the relation between corporations and politics, I want to first present an intuitive case for why partisanship might matter in corporations and the careers therein. At its center, this intuition builds from our earlier discussion of the difference between partisanship and ideology. Simply put, I argue that partisanship lends a stronger, more consistent, and consequential signal than ideology. To reiterate a point, although partisanship and ideology are often correlated, partisanship shapes ideological formation (Barber and Pope 2019; Goren 2005). Furthermore, within parties, there exists considerable diversity across political issues, and between parties, there may even be occasional alignment on some issues (Baldassarri and Goldberg 2014; Bonica 2014, 2016; McCarty et al. 2006). So while ideology can sow seeds of division within parties and build bridges across parties, political partisanship envelops ideological heterogeneity, resulting in a general embrace of those in the same party (partisan homophily) and an aversion to those in the opposing party (affective polarization).[18]

So, when we think of firms and the individuals therein, I suggest that partisanship, not ideology, is a far more visible, visceral signal, a fact in part motivating my exclusive measurement of party. Consider the intuitive case. Individual campaign contributions to candidates and political committees exist in the public domain. Voter registration and participation data are also readily available. Although both political contributions and voter behavior were once difficult to access, the advent of technology has put this data at our fingertips. Political contribution data is readily available from a government web application (General Services Administration: 18F 2017). Simply search for an individual and see their political contributions. Even easier, any curious individual can download a handful of available mobile apps to examine the partisanship of their contacts, including their party registration and past primary voting participation (Singer 2018). With just a few details such as name, approximate age, and state, you can look up anyone else about whom you are curious. Likewise, myriad partisan signals exist across social media such as Facebook, Instagram, or Twitter, and much of this information is publicly available. And if you happen to be connected, tools exist to help easily identify who among your network is a likely supporter of the Democratic or Republican Party, including specific partisan signals and the likely strength of their partisanship attachment (Bond and Messing 2015; Sunny He and Zong 2020). This is all to say that even with only a little information about a person, any curious individual can likely discern the partisanship of a stranger.

If the public can access this information, any employee in a corporate environment could likewise glean the partisanship of their colleagues, supervisors, and subordinates. Prospective

[18] This behavior, for instance, is at hand in the run-up to the 2020 Democratic Presidential Nomination as ideological tension builds between progressive and moderate Democratic candidates (and their followers), while at the same time calls exist to have all Democrats rally around the eventual nominee in order to defeat Donald Trump, the Republican presidential nominee (Brooks 2020; Bruni 2020; Frum 2020; Klar 2020; Pfeiffer 2020; Russonello 2020; Scher 2020; Strauss 2020).

job applicants could easily be screened. In a day and age where employers regularly screen the social media of employees and applicants, partisan signals would be apparent among many other cultural signals, even if recruiters were not explicitly searching for those qualities. Beyond determining party allegiance from digital trace data, within firms, employees send a plethora of signals in their everyday discussions and communication. Although there may be overt criticism of the majority party and even within-firm support groups for partisan minorities (Conger and Frenkel 2018; Copeland 2019; McCabe 2019), more often than not, employees at these companies repress political dissent in the workplace for fear of conflict, stigma, or even termination (Cowan and Baldassarri 2018; Goldberg et al. 2016; Iyengar and Westwood 2015).[19]

Take, for example, the workplace scenario of simply failing to feign agreement with a politically charged statement about quotidian news events. According to Cowan and Baldassarri (2018), political discourse in the workplace more often occurs when the expressed sentiment aligns with the majority party in that environment. In this scenario, failing to agree, or simply demurring with the majority sentiment could easily brand that unfortunate soul as an "ideologue"—or staunch partisan adherent of the minority party (Baldassarri and Goldberg 2014). It would likely matter little if this individual only upheld certain tenets of the minority party. Despite the ideological variation within parties (Baldassarri and Goldberg 2014; McCarty et al. 2006), the suspected support of a single issue indicative of the opposing party, confers the presumption of belonging to *that party*, and with it, the suspected allegiance to its other positions. In kind, such an individual faces ostracism *à la* affective polarization (Iyengar and Westwood 2015; Iyengar et al. 2019). And the ensuing lack of cultural fit might engender a stalled career, or even termination (Goldberg et al. 2016; King, Felin, and Whetten 2010; Stinchcombe 1965).

[19]Goldberg et al. (2016), for example, discuss the significantly higher likelihood of "involuntarily exit" if an individual lacks "cultural fit," particularly if they are "disembedded" (1204-6). Arguably, we can see examples of this in modern firms, for example, the case of a Google employee who claimed his termination was the result of being an outspoken conservative (Copeland 2019; McCabe 2019).

In sum, these aforementioned ideas reflect powerful justifications grounding why political partisanship might matter within firms. Having now fully established the background on political partisanship and having provided an initial intuition for why partisanship could shape behavior in firms, or otherwise affect the individuals and careers therein, we can now turn our attention to the next pressing task. To appreciate how partisan politics matters in firms and why this perspective matters, I must outline how social scientists have previously understood the complex relationship between corporations, elites, and politics.

1.3 Exemplifying the Empirical-Theoretic Gaps Between Organizations, Elites, and Politics

Although the above discussion may create a scenario in which the role of partisanship within corporations, particularly as it relates to careers, may seem obvious, this has not always been the case in social science research. So how have social scientists previously thought about the relationship, if any, between corporations and politics? On one hand, scholars of organizational and managerial studies have often examined organizational behavior, structure, and strategy whilst ignoring politics.[20] While I draw on a number of these theories, they are of less immediate concern. More to the point, many scholars who have examined the relationship between corporations, elites, and politics, often proceed from a vantage of the external ramifications of capitalist corporations. This often includes an assessment of the development and retention of power and resources by the corporate elite, their influence over politics, and relatedly, evaluating the pathways toward those elite careers as well as their dimensions. I seek to offer an alternative perspective, placing the role of partisanship *within* firms at its center. Although some scholars have considered the role of politics, especially political ideology in firms, such perspectives are complicated by studies that examine corporate

[20] Understandably, largely apolitical studies of organizations, including organizational behavior, structure, and strategy remains an ineffably large field. A subset therein examines organizational structure and organizational change (Chandler 1962; Downs 1967; Hannan and Freeman 1977, 1984; Stinchcombe 1965). I harness such studies later in this introduction.

behavior or career aspects without a consistent theory and measure of the political construct being evaluated.[21]

In either case, far less often do scholars theoretically and empirically document how political partisanship operates within corporate organizations. In particular, we lack adequate consideration of how party sorting—and especially its mechanisms, partisan homophily and affective polarization—manifest within organizations. We further lack consideration of how these mechanisms may affect the individual careers therein and by consequence alter organizational structure, including the state of partisan polarization, and the organizational strategy from which it ensues.[22] We might pithily restate this issue as follows. Corporations have a notable influence on society, politics, and economics (Domhoff 2010; Hacker and Pierson 2010; Mills 1956), while partisanship has an important role in politics and society (Baldassarri and Goldberg 2014; Hetherington 2001; Iyengar et al. 2019), yet we rarely witness a direct, clear, and theoretically consistent analysis of political partisanship acting

[21] A particularly problematic issue in most organizations and markets literature on this topic (*c.f.* Gupta and Wowak 2017; Gupta et al. 2017), is that these authors conflate the theoretical concept of "political ideology" with a measure of political partisanship, namely contributions to the "Democratic (Republican) party... [as reflective of] liberal (conservative) beliefs" (Gupta et al. 2017: 1019-20). Although the authors seem fully aware of political ideology, citing foundational scholars such as Poole and Rosenthal (1984) and McCarty et al. (2006), even citing a paper outlining the role of parties in constraining political ideology, values, and positions (Goren et al. 2009), they seemingly fail to contemplate why their approach is problematic. The partisanship literature shows the importance of political parties and party cues in constraining individual ideological beliefs, ideological identification, political values, or position-taking (Baldassarri and Goldberg 2014; Barber and Pope 2019; Converse 1964; Goren 2005; Goren et al. 2009), a fact that even Poole (2005) acknowledges. Making matters worse, despite using a measure of partisanship to convey the disjoint concept of political ideology, the authors also use colors and symbols of political parties, such as blue donkeys and red elephants to convey ideological differences. For sociological or economic scholars, a somewhat analogous faux-pas would be conducting a stratification analysis using a measure of income as a proxy for educational attainment. Although income and education may at times be correlated, and in fact, education often constrains individual income, the two measures should not generally serve as reciprocal proxies. I further elaborate on this idea elsewhere in the introduction as well as the conclusion.

[22] The claim that organizational structure is systematically linked to the composition of its workforce (human capital allocation), an extension of its strategy, might not at first glance be obvious. In classical theory, organizational structure follows strategy, of which human capital allocation is a component (Chandler 1962), (*c.f.* Hannan and Freeman 1984; Stinchcombe 1965). Specifically, "although strategy establishes an organization's initial structural form, that structure and its associated inertia while providing stability can also foster shifts in realized resources, such as human capital allocation, constituting a change in strategy and future structure" (Appendix A). Thus, changes in human capital allocation—of which individual partisan identity and by consequence partisan polarization are part and parcel—may reflect shifts in organizational strategy and structure, or more basically, a shift in its organizational state. I discuss this deeper level theorization at length in Appendix A .

within organizations, particularly as it relates to the individual careers within them.[23] This puzzle is not one that necessitates some grand theoretical arbitration; rather it illustrates a general theoretical myopia in the proximal scholarly traditions.

As we have seen above, political partisanship plays a significant role in society, along with a number of partisanship mechanisms, including affective polarization and partisan homophily. A societal interplay between partisanship and ideology also exists. Together, these topics receive considerable attention in political science and, to a lesser extent, consideration in sociology and economics. Curiously, this largely intradisciplinary approach to this highly interdisciplinary phenomena has resulted in some gaps in the literature. In this section, I first review the dominant social science perspectives on the relationship between corporations and politics, through which I pave the way for an alternative approach. Second, I seek to clarify the position of existing social science and organizational research that already consider politics within firms. In particular, I will disentangle robust studies that seriously measure the role of ideology in organizations from those claiming to do so, but failing in the execution. Although those robust studies primarily emphasize ideology, not partisanship, they prove a valuable foil and a useful framework for understanding the role of partisanship in organizations. First, however, we must better understand traditional perspectives of how social scientists have thought about corporations, elites, and politics.

1.3.1 The Problem with Focusing on Corporate Elites' Influence on Politics

The role of elites in corporate leadership—and more generally the study of elites—is a central topic in sociology, political science, and organizations. In this section, I would like to highlight

[23]See the prior footnote 21. Arguably, the important findings of several scholars such as Gupta et al. (2017) or Gupta and Wowak (2017), among others, reflect organizational differences in political partisanship, since by their own admission, they do not have a direct measure of political ideology, and instead use a direct measure of political partisanship, despite framing the analysis as an assessment of organizational political ideology. Although it's possible that these critiques are irrelevant, given the ideological heterogeneity within firms by scholars using robust measures of political ideology (Bonica 2016), it is possible that had such measures been used, Gupta et al. (2017) and Gupta and Wowak (2017), may not, for example, have seen the same effects.

a number of dominant perspectives with broad strokes—in particular, two perspectives: First, the perspective of corporate and elite influence, especially political influence, and second the stratification perspective which studies the development or careers of elites and the inequality created thereby. The goal here is not to provide a comprehensive overview of either perspective, but to provide context for a third perspective offered by this dissertation. In particular, rather than simply examine the external political influence of corporations or elites, or study the careers of elites apolitically, I seek to examine how political processes, chiefly political partisanship, operates *within* firms, shaping the behavior and careers therein.

A brief overview of these past perspectives will provide better context for the new perspective I introduce. I begin with the first perspective of corporate and elite influence. For example, a key concept in this broad perspective is that of a ruling class. The concept of a ruling class suggests an amalgamation of interconnected elites spread across government, corporations, and the military, and that these elites exercise power over society (Domhoff 2010; Laumann and Knoke 1987; Mills 1956; Useem 1984). Two fundamental theories—elite theory (Mills 1956) and class domination theory (Domhoff 2010)—both advance this fundamental tenet of a ruling elite.[24] While these theories highlight differences in economic control, more germane to this study is the connection of corporate elites to politics. Here, we can view politicians as rational agents eager to earn not only votes but also the favor of the politically engaged, affluent and powerful corporations, which have the financial and political capital to win elections (Dahl 1963; Downs 1957; Mayer 2016). To advance their self-interest, politicians are more likely to adopt the policy positions of the affluent, especially the top 1% (Bartels 2016; Gilens 2005, 2012; Page, Bartels, and Seawright 2013). In combination with deregulation and financialization of the economy (Hacker and Pierson 2010; Tomaskovic-Devey and Lin

[24]The chief difference between elite theory and class domination theory is that class dominance theory maintains the quiddity of Marxism by arguing that the corporate community is predominant over all other domains and controls elites within them (Domhoff 2010). While many elements of class dominance theory are useful, the totality of its perspective has numerous flaws. For example, although mobility is more rigid than once thought (Becker and Tomes 1986; Solon 1992), considerable wealth mobility still exists in America (Keister 2005), contrary to the perceived non-existent mobility argued by Domhoff (2010).

2011), some researchers have argued that we now live in a new gilded age (Bartels 2016; Frank and Cook 1995; Gilens 2012; Hacker and Pierson 2010; Keister 2014; Piketty 2014; Piketty and Saez 2006). In this new gilded age, some are concerned with the role of corporate leaders and corporations as donors or otherwise unduly influencing policy through political contributions, lobbying, and lucrative private sector careers for former politicians (Bartels 2016; Gilens 2012; Hacker and Pierson 2010; Kuttner 2010; Mayer 2016).

According to Hacker and Pierson (2010) and Domhoff (2010), divisiveness in this new gilded age exists by the design of corporate elites who sow the seeds of division among the population in order to best shield the true economic objectives of the ruling class. Necessarily, such a perspective proves contentious, and yet, at the surface, we do witness considerable ideological heterogeneity, although not ideological polarization among everyday citizens (Baldassarri and Goldberg 2014; DiMaggio et al. 1996). Nevertheless, the growing polarization among political elites contributes to increased partisan polarization of the public (Hetherington 2001; Karol 2009), a trend accelerated by corporate campaign contributions and election campaigning (Mayer 2016; Sood and Iyengar 2016). Although most individual campaign contributions are marked by partisanship and have some ideological mooring, they rarely exhibit a strategy of hedging (Bonica 2014, 2016; McCarty et al. 2006; Snyder Jr. 1990, 1992), unlike corporate political action committees (PACs), which may support both parties (Bonica 2016; Hacker and Pierson 2010; Tripathi, Ansolabehere, and Snyder 2002). This latter point, while connected to the influence of corporate elites over politics, illustrates an important caveat that I leverage. Namely, although corporate elites control corporations, which influence politics, these elites have their own unique politics, which differ from that of firms (Bonica 2016). Whereas Bonica (2016) focuses primarily on ideology, I place my emphasis on political partisanship.

On this latter point, we can cleanly transition to the second dominant perspective in the study of corporate elites, namely a largely apolitical perspective on their development and careers. Beginning with their development, beyond Domhoff's (2010) perspective of an intentionally cultivated class of ruling elites, a number of scholars have more closely examined the education of elites. Such studies revolve around the development of the ruling class through elite education (Cookson Jr. and Persell 1986; Levine 1980), including boarding schools (Baltzell 1958, 1964; Levine 1980), prestigious social clubs (Karabel 2005; Levine 1980; Useem and Karabel 1986), and exclusive social connections (Khan 2011; Useem and Karabel 1986). Among other factors, such an education is believed to not only equip the next generation of elites with the faculties to govern a corporation but is also believed to guide them toward that end (Domhoff 2010; Useem and Karabel 1986).

When we turn to that end, considerable attention is paid to corporate leadership, especially CEOs, given societal income and wealth inequality and the role of executive compensation in this equation (Bertrand 2009; Frydman and Saks 2010; Keister 2005; Piketty and Saez 2006). Popular among them are studies evaluating the role of experience, knowledge, and skills (Bertrand 2009; Frydman 2005; Murphy and Zabojnik 2004; Useem and Karabel 1986), among a number of competing theories explaining executive pay (Bertrand 2009; Bertrand and Hallock 2001; Gabaix and Landier 2008), including rent extraction (Bebchuk and Fried 2004; Bebchuk, Fried, and Walker 2002; Frydman and Saks 2010), leapfrogging (DiPrete, Eirich, and Pittinsky 2010), or interlocks (Hallock 1997; Khurana 2002). Indeed, the study of interlocks occupies considerable attention in its own right (Chu and Davis 2011, 2016; Mizruchi 1996, 2013; Murray 2017; Useem 1984). This is not to say that all studies on executive careers, action, or behavior are apolitical. As I discuss in a subsequent section, some studies consider politics, especially political ideology, in how it shapes compensation or corporate governance. Still, politics, especially political partisanship, is often not the key consideration when discussing the development of elites or their careers. As opposed to examining corporate elites' or corporations' influence on politics, or apolitically evaluating the careers of elites, I instead take an additional perspective. Here, I generalize my approach to not only consider elites but also other employees within firms. Rather than focus on the external influence of corporations on politics, I ask how partisan politics, instead, influences the careers of those within corporations.

1.3.2 Disentangling Party and Ideology in Organizational Scholarship

As already intimated, while I offer an alternative perspective of the way political partisanship might operate within corporations, particularly as it relates to shaping behavior or careers, I am far from the first scholar to consider politics within firms, especially as it relates to corporate elites. Such ideas have been discussed to varying degrees by many scholars, particularly the political profiles of executives and board members (Bonica 2016; Burris 2005; Cheng and Groysberg 2016; Chu and Davis 2016; Gupta and Wowak 2017; Stark and Vedres 2012). At the same time, a fairly predominant approach emphasizes the role of political ideology in firms. Here, some variation in the treatment of ideology versus partisanship transpires, a fact with the potential to cause confusion in situating my research.

Of these scholars, perhaps the most relevant and serious treatments is the work by Bonica (2016) in evaluating the campaign finance contributions of corporate board members and executives at Fortune 500 firms. Following the general paradigm of Bonica's major contributions, the analysis largely proceeds from a framework grounded in measuring political ideology (Bonica 2013, 2014, 2016). Nonetheless, we can glean a number of important insights and some useful framing in setting up the current debate. For example, as argued by Bonica (2016), "most corporate boards are ideologically heterogeneous" (386), which generally parallels the high degree of ideological heterogeneity in the American public (Bonica 2014; McCarty et al. 2006). Even so, although many corporate boards in Bonica's analysis fail to exhibit unilateral ideological positioning, a number of firms consist primarily of liberals or conservatives. For example, Apple is shown to only have liberals on their board while Marathon Petroleum consists of almost entirely strong conservatives (Bonica 2016: 387). Similarly, if we examine the percentage of money going to Republicans grouped by corporate board, most boards give at least half of all contribution dollars to Republicans (Bonica 2016: 388). It remains unclear, however, from these figures, the degree to which partisan sorting occurs within corporate boards. For example, we can see that at the individual level, board directors are strong partisans, but that when grouped by firm, some but not as much party sorting exists (Bonica 2016: 388). Examined in this way, we might overlook subsets of firms that are more partisan than others. Likewise, we ignore temporal changes, particularly how partisan polarization as a process may be increasing in recent years, which are likewise not captured in Bonica's (2016) data, which only goes through the 2012 and 2014 election cycles. While further analysis is needed, perhaps most utilitarian, however, remains Bonica's (2016) positing of a puzzle:

> There are two scenarios that could explain the observed within-firm heterogeneity... [the] first is that directors are selected for reasons unrelated to ideology... Alternatively, the observed heterogeneity could be by design... Companies may face pressure to correct for imbalances if its board starts to tilt too far to the left or right, not unlike pressures to correct for gender imbalances. (Bonica 2016: 390)

As argued throughout this paper, I suggest that partisanship remains an ostensible and salient factor in its own right, and following the empirical evidence of ideological heterogeneity within parties, I posit that boards, along with other firm employees, will manifest greater partisan homogeneity than might otherwise be suggested by past studies of firm ideology. I argue that more important than simply the distribution of partisans is how partisan biases affect both entry-level and corporate board hiring. Hence, when reflecting on Bonica's (2016) first point, any underlying ideological heterogeneity, especially within parties, might simply mirror the general heterogeneity of ideology in society. While I agree that board members are less likely to be selected by ideology, I argue instead that their partisanship more likely predicts their appointment, particularly when seen through the lens of affective polarization. This latter point would, therefore, suggest that board appointment would not generally follow a pattern of active partisan balancing. Furthermore, if partisan imbalances were to follow the mode of gender imbalances, those results similarly suggest an incentive to maintain partisan homogeneity rather than correct it. Chiefly, Dobbin and Jung (2011) illustrate that even though the appointment of female board members does not hinder profitability, the appointment of female board members does yield a significant, subsequent drop in firm stock value, presumably because shareholders exhibit a bias against women (Dobbin and Jung 2011). Given rampant biases against opposing partisans in American society (Iyengar et al. 2019), the appointment of board members with partisanship opposed to the partisan majority may also induce a drop in stock value.

Apart from Bonica (2016), a series of related insights provides context for the analysis of partisanship in organizations. For example, consider a related trend in the corporate board interlock literature, where political unity in campaign contributions is weakened by the decline of the inner circle (Burris 2005; Chu and Davis 2016; Useem 1984), resulting in greater partisan heterogeneity across interlocked directors but increased partisan homogeneity within corporate boards (Chu and Davis 2016). In other words, Chu and Davis's (2016) work suggests that the partisanship of a board influences the partisan contributions of fellow board members. In addition to research on the partisan or ideological distribution of board members or their networks (Bonica 2016; Burris 2005; Cheng and Groysberg 2016; Chu and Davis 2016), we also see research on how board partisanship can shape firms' proclivity to conduct business with copartisan firms (Stark and Vedres 2012), influence the compensation of executives (Gupta and Wowak 2017), and affect corporate social responsibility (Chin et al. 2013; Gupta et al. 2017) or corporate responsiveness to movements (Briscoe, Chin, and Hambrick 2014; Gupta and Briscoe 2019).[25]

As previously noted, some analyses mistakenly utilize measures of partisan political contributions—such as federal campaign finance contributions—as a measure of ideological giving (*c.f.* Chin et al. 2013; Gupta and Briscoe 2019; Gupta and Wowak 2017), even though

[25] This partisan interpretation is largely based on the measure of partisanship used in these studies, although the authors claim that they are measuring ideology using partisanship.

no measure of ideology exists in the FEC data, only those of partisanship.[26] Granted, given more advanced state-space methods of determining true ideological profiles (Bonica 2013, 2014, 2016; Poole 2005), for example by examining the recorded ideological position taking of committee candidates or inferring roll-call scores using machine learning (Bonica 2018), this objection largely dissipates with the caveat that such scores primarily reflect the ideology of political candidates not the ideology of individual contributors. Nevertheless, promoting a theory of ideology using a measure of political partisanship yields a number of caveats, especially since such an analysis makes the assumption of a general correlation of political partisanship to the highly heterogeneous ideological positions of citizens within and across parties (Baldassarri and Goldberg 2014). This assumption is even more questionable because individual contributors might lack the political wherewithal to fully deduce candidates' unique set of ideological positions, and instead contribute for a host of factors including party allegiance or alignment on only a subset of policies (Baldassarri and Goldberg 2014; Barber and Pope 2019; Campbell et al. 1960; Converse 1964; Goren 2005).

Although such critiques might prove empirically unwarranted, we currently lack evidence to the contrary, and considering the ideological diversity even in highly partisan firms—such as Apple or Marathon Petroleum—by scholars using robust continuous measures of political ideology (Bonica 2016), it is possible that had Gupta et al. (2017) and Gupta and Wowak (2017) used these measures, they might not have come to the same conclusions. Theoretically, such results could be considered largely tangential to my research as they are embedded in firm political ideology, not partisanship, even though empirically the results are highly related.

[26]Even those employing advanced ideological methods, such as Bonica (2016) are not immune to this tendency: "It displays the levels of *ideological consistency* in giving patterns of corporate elites, corporate PACs, and the general population of donors. It does so by first categorizing donors into one of ten categories based on the Republican share of major party contributions in previous election cycles and then plotting a bar chart that shows the total amounts given to Democrats and Republicans from each category" (379, emphasis added). Here, in a section entitled, "Consistency in partisan giving," Bonica claims *ideological consistency* exists because corporate elites consistently give to either the Democratic or Republican Party. Although this pattern suffices to support *partisan consistency* and may have some general consistency given ideological polarization of political elites, it does not necessarily satisfy *ideological consistency*, at least when referring to the internal, likely heterogeneous ideology of contributors. As shown by Bonica (2018), however, we might use contribution data to infer the roll-call scores for political candidates.

As such, I consider them both here and throughout the dissertation, with the reservations but the empirical understanding that they suggest that the partisanship of individuals in firms, including its leaders affects organizational behavior, which is consistent with my thesis. Herein, I build from such suppositions, which I intend to more robustly demonstrate using both theory and measures representative of partisanship.

1.4 Understanding the Interplay Between Organizations and Society

Having gained a firm grasp of where my research intersects with existing social science research, we can now turn toward better understanding the theoretical puzzle grounding the role of partisan politics within organizations. In setting up this puzzle, I seek to leverage a pivotal framework wherein we can appreciate the interplay between phenomena in society and those within organizations. Such a framework allows us to adapt theory from the organizational diversity and organizational culture literature, which I integrate with general organizational theories and our understanding of political partisanship in society, particularly forces of affective polarization and partisan homophily.

Certainly, while much has been written about corporate elites, their attributes and influence in politics, the majority of this research fails to consider how politics, especially political partisanship, might shape corporations and careers, including those of elites. To this end, we can borrow a useful framework from Davis et al. (2008), who champion increasing the integration of (1) organizations and markets research alongside (2) studies of social movements, which often fall into discrete themes. Of these, I suggest that the theme in which organizations act "as sites and carriers of social movements" proves the most salient (390-2). While my study does not focus on social movements *per se,* I do focus on the ways in which partisan processes in American society infiltrate corporate politics, and as such, Davis and coauthors' (2008) underlying insight rings true:

> Organizations are places where social life happens and, as such, can be the location of struggles over broader issues of social justice. Firms can be mechanisms for economic mobility and places in which social divides are bridged, but they can also be sites of discrimination and devices for maintaining the status quo. Thus the stakes of wider social struggles are often enacted within firms. (Davis et al. 2008:391)

Adopting this framework, firms act as sites for social life, and consequently can set the stage for partisan politics manifesting in American society. The general idea of the infiltration of the social in organizations has a considerable legacy, particularly the idea that organizations may draw upon a "common, culturally available repertoire" for situational interpretation and action (Clemens 1993: 759), or that "social forces of juxtaposition" and the "transposition" of external cultural frameworks, routines, and social networks (Powell and Sandholtz 2012: 95), including societal "pressure on existing relations," may "reconfigure models of action" and herald organizational emergence (Powell and Sandholtz 2012; Powell et al. 2005: 1134). Although corporations can theoretically serve as sites in which partisan divides are bridged, as I argue, they more often than not, act as sites where partisan divisions foment, both by reinforcing the salience of partisan homophily and by exacerbating acrimony with those across party lines via affective polarization.

Paralleling the call for the increased integration of organizational and social movements research (Davis et al. 2008), Dobbin and Sutton (1998) similarly lament the "long absence of a theory of the state in organizational analysis" (441). On one hand, we can view organizational shifts in equal opportunity employment, diversity, and anti-discrimination as responses to ambiguous federal mandates following the Civil Rights Act of 1964 (Dobbin and Sutton 1998), which they argue, reflects a "peculiar strength of America's weak state" (443). Certainly, new organizational structures cast in the paradigm of efficiency may also be viewed as a consequence of the weak state. Yet, at the same time, the Civil Rights Act of 1964 is often lauded as an exemplar of social movement legislative success and utilized in studies of movement efficacy (Andrews 2004; McAdam 1983; McAdam and Su. 2002; Olzak and Ryo

2007; Piven and Cloward 1977; Wang and Soule 2016). In this way, organizational changes following the adoption of a mobilization victory, arguably reflect a secondary ramification of social movements, or yet another example of how processes occurring in society can transcend their immediate consequence and thereafter infiltrate organizational culture, routines, and processes.

Taken together, both the perspectives of Davis et al. (2008) and Dobbin and Sutton (1998) underscore a common point found in both neoinstitutionalism (DiMaggio and Powell 1983, 1991; Meyer and Rowan 1977) and old institutionalism (Selznick 1966), which document the role that society can place on the social reproduction of processes or routines in organizations (Clemens 1993; Powell and Sandholtz 2012; Powell et al. 2005). As it relates to political partisanship, we might likewise anticipate that the external societal rise in partisanship would also manifest within organizations. This theoretical insight into how processes in society can infiltrate organizations and lead to changes therein provides an opportunity for a more formal theory of organizational change.

Although I will not fully explicate this theory here, reserving it for Appendix A, I offer a brief synopsis of my conception for changes in what I term, the organizational state. In short, this theory evolves from classic organizational theory, wherein an organization's initial structure follows its founding strategy (Chandler 1962), of which a firm's human capital allocation, including the skills of its personnel, are key elements (Chandler 1962; Hannan and Freeman 1984). Moreover, an organization's general procedures for operationalizing resources in pursuit of its organizational goals reflect another key dimension of strategy (Chandler 1962; Hannan and Freeman 1984). Although the founding organizational strategy and social systems or procedures establish a form of path dependence known as organizational reproduction or inertia (Hannan and Freeman 1984; Meyer and Rowan 1977; Stinchcombe 1965), social systems—especially informal practices such as habits, myths, routines, or repertoires (Berger and Luckmann 1966; Clemens 1993; Hannan and Freeman 1984; Meyer and Rowan 1977)—are mutable to external societal processes (Clemens 1993; Powell and Sandholtz 2012; Powell et al. 2005; Selznick 1966). A basic tenet consistent with informal organizational practice is that in order to be hired, maintain employment, or advance in an organization, individuals must "be socialized, careers molded, and power allocated to defend the value" (Stinchcombe 1965:167): that is, they must *fit* with the company (DiMaggio 1992; King et al. 2010; Schneider 1987). As I will argue, external societal processes of political partisanship, especially party sorting and affective polarization, can infiltrate informal organizational practice, resulting in a decoupling between informal and formal practice (Meyer and Rowan 1977). To the extent that such processes alter its human capital allocation, or even attributes of its personnel, constitute a shift in a key dimension of organizational strategy and consequently the structure that follows. I refer to such a shift as a change in the corporate organizational state.

1.5 Teasing Out the Organizational Incentives and Disincentives of Diversity

Given the overall lack of organizational research in political partisanship, I suggest combining empirics of political partisanship with the above theoretical framework in which we can appreciate that (1) societal processes can affect practices in firms, and (2) such changes can be interpreted as organizational change. By combining the perspective of societally induced organizational change with studies on organizational diversity and fit, I leverage an acute theoretical puzzle. To unpack this puzzle, a general approach would be to assess arguments made through the lens of diversity and organizational fit. Such a perspective, while ostensibly divorced from research on political partisanship, in some ways has a common theoretical thread. To foreshadow the discussion below at a meta-level, although theories of partisanship—especially affective polarization—appear distant from theories of organizational diversity and performance, the theoretical and empirical arguments grounding both ideas have bases in theories on homophily, intergroup contact, and social identity (Billig and Tajfel 1973; McPherson et al. 2001; Pettigrew 1998; Tajfel 1970; Tajfel and Turner 1979). When combined with our understanding of how societal phenomena, such as political partisanship, can permeate corporate culture and organizational strategy, we find a compelling case in which juxtaposed organizational theories suggesting either incentives or disincentives of partisan diversity are all the more compelling. As we shall see, the arguments vary depending upon the dimensions of diversity considered. Nonetheless, these ideas have a strong connection, not only because they share a common theoretical background to theories of affective polarization, but also because the interplay between organizational practice and society suggests that such partisan phenomena can affect organizations and the behavior therein. Without further ado, let us consider theories that suggest organizational incentives to preempt partisan bias, or instead favor partisan homogeneity.

1.5.1 Organizational Incentives to Preempt Discrimination and Promote Diversity

As suggested above, a number of potential incentives exist which suggest that organizations should preempt discrimination and promote diversity. I focus chiefly on (1) the legal and regulatory incentives for best-faith efforts, as well as (2) the potential performance benefits associated with a diverse corporate labor pool. Certainly other incentives could exist, such as the potential ramifications in public opinion or the threat of mobilization given the right igniting incident and the propulsive winds of media to fan the flames to flight (Andrews and Biggs 2006; Andrews and Caren 2010; Lipsky 1968). Yet, because my immediate interest lies in laying a founding framework to understand organizational effects of political partisanship, the mobilization facet falters. Simply put, even in the case of egregious, systemic partisan discrimination in a major corporation, although we would likely see some media kerfuffle, given the polarized state of partisan affairs, only half of the country and half of the media would care, while the rest would simply dismiss the partisan rankling as mere spin reflecting politics proceeding as usual. With this premise in mind, I discuss those mechanisms which might most realistically preempt partisan discrimination.

1.5.1.1 Legal and Regulatory Incentives to Avoid Discrimination

Commencing with the first and likely most pertinent organizational argument to prevent discrimination is that of legal and regulatory incentives. As proposed by Dobbin and Sutton (1998), firms adopt behavioral change to satisfy ambiguous government legislation, guidelines, or mandates, and thereby obviate the need for subsequent, more restrictive regulations that might have detrimental consequences to firm operations and budget. In fact, firms have developed entire diversity departments and affirmative action initiatives to this end (Dobbin and Sutton 1998), along with legal counsel replete with experts to review current literature and make suggestions to keep companies in good standing and apprised of the ambiguous and ever-shifting Equal Employment Opportunity Commission (EEOC) laws and best practices (Dobbin and Sutton 1998).

As a legal hedge, firms adopt best-faith efforts to prevent discrimination (Dobbin and Sutton 1998). We should note that, although some might liken the fervor and practice of politics to that of religion (Durkheim [1915] 1965),[27] neither political ideology nor political partisanship qualify as religion and are not otherwise included among the protected classes preventing discrimination under equal employment opportunity law (U.S. Equal Employment Opportunity Commission 2020). Nonetheless, individuals still seek litigation claiming termination for political beliefs, as prominently highlighted in the National Labor Relations Board (NLRB) case with Google (Copeland 2019; McCabe 2019),[28] even though the most prestigious firms remain far less likely to be found liable for discrimination lawsuits (McDonnell and King 2018). It therefore stands to reason that just as firms create anti-discrimination or diversity programs and adopt best-faith efforts—and even consult academic literature to

[27]Durkheim ([1915] 1965), for example, writes the following: "This is why all parties, political, economic or confessional, are careful to have periodical reunions where their members may revivify their common faith by manifesting it in common" (240).

[28]See also the National Labor Relations Board settlement agreement in the matter of Google, Case 32-CA-164766.

augment existing efforts (Dobbin and Sutton 1998)—so, too might firms anticipate party identification or political beliefs being one day added as EEOC protected classes.

Even though this *weak state* argument should incentivize firms to preempt partisan discrimination, if the prevention of partisan discrimination is not enforced or if diversity training does not emphasize this dimension, weak state arguments would languish as less than efficacious. Supposing, however, that firm counsel recognizes the legal threat and perhaps anticipates pending change to EEOC regulation on partisanship; there might still be decoupling between the advice to avoid partisan discrimination and former routines or practices that either implicitly or explicitly foster bias (Dobbin et al. 1988; Meyer and Rowan 1977; Selznick 1966; Sutton and Dobbin 1996), particularly since partisan bias so often occurs implicitly (Iyengar and Westwood 2015), thus making its eradication nettlesome. As shown by Dobbin, Kim, and Kalev (2011), corporate culture can both promote and hinder diversity, as can methods of recruitment (Reskin and McBrier 2000). Still, because discrimination lawsuits have already occurred, in part, along partisan grounds, and partisan discrimination is escalating and increasingly receiving media and academic attention (Iyengar et al. 2019), we might yet see firms attempt to curtail partisan discrimination and promote partisan diversity. Simply put, anti-discrimination initiatives, including federal compliance reviews, discrimination lawsuits, and EEOC charges can be effective (Kalev and Dobbin 2006; Kalev, Dobbin, and Kelly 2006; Skaggs 2008). Hence, legal teams at firms, in combination with human resource departments, in viewing the current partisan landscape and prior high-profile lawsuits, could very well perceive the potential threat and intercede to actively preempt partisan bias.

1.5.1.2 The Benefits of Diversity in Tenure, Job Function, and Education

Notwithstanding the suggested incentive to preclude litigation and regulation, firms might also champion partisan diversity to bolster efficiency (Dobbin and Sutton 1998). Several studies, for example, offer evidence that diversity may have positive outcomes such as creativity and innovation (DiTomaso, Post, and Parks-Yancy 2007; Dobbin and Jung 2011; Hambrick, Cho, and Chen 1996), particularly in the case of teams with functional diversity (Burt 2000). As argued by Burt (2000), "a team composed of people from diverse corporate functions spans more structural holes in the firm" (360), proffering swift access to a greater and more diverse wealth of information, and along with this advantage, the capacity for increased creativity and innovation (Ancona and Caldwell 1992; Burt 2000, 2004).[29] Similarly, some analyses demonstrate that politically heterogeneous teams may provide higher quality work (Shi et al. 2019). Given these findings, it may seem that diversity has primarily positive effects. Yet, in the case of tenure diversity, the situation proves more complex: Tenure diversity, as with many other types of diversity, may delay, challenge, or otherwise hinder communication, coordination, and thus productivity given incongruent perspectives (Ancona and Caldwell 1992; Burt 2000; Williams and O'Reilly 1998). Given a dense network structure, however, these challenges may be overcome to achieve higher productivity and reach creative and innovative solutions otherwise unavailable from a more homogenous team (Burt 2000; Reagans and Zuckerman 2001).

Bridging the collective argument that organizations should preempt discrimination and promote diversity, as argued by Dobbin and Sutton (1998), beyond efforts to avert litigation or more simply avoid overbearing regulation, organizations rebranded anti-discrimination or affirmative action efforts in the vein of promoting diversity and recouping its performance benefits as but another evolution of economic efficiency. Certainly preventing litigation and usurping the need for strict regulation fosters economic windfalls. We witness a handful of

[29] At the same time, we should note that disruptive innovation and creativity may be even higher for small teams (Wu, Wang, and Evans 2019). Note that this does not necessarily contradict Burt's argument. For example, although Burt (2000) remarks "if networks that span structural holes are social capital, there should be a positive association between performance and network size," he offers this suggestion with the caveat that increased contacts are beneficial, "as long as they do not weaken closure," and thus, the "association between performance and network size is not a powerful evidential criterion for testing between the closure and hole arguments" (Burt 2000: 374). Similarly Wu et al. (2019) primarily focus on team size versus functional diversity, but similarly find that atypical, interdisciplinary teams have benefits. Similarly, large teams lacking interdisciplinarity are rarely innovative (Wu et al. 2019).

benefits that can emerge from promoting, at least, some types of diversity. For example, functional as well as disciplinary diversity often yields positive outcomes (Burt 2000; Wu et al. 2019), and these benefits of diversity may extend to politics (Shi et al. 2019). Taken together, these facts seemingly justify assessments of employers' diversity initiatives from a perspective of honest benevolence. Yet, as I illustrate below, there are reasons for incredulity. Namely, the extolled performance gains from diversity do not always materialize. In point of fact, the performance and cultural benefits of homogeneity alongside the cost-savings of supplanting diversity's pitfalls often undermine diversity's potential benefits. In this light, we should imbue corporate championing of diversity with a healthy hint of skepticism, since, in the words of Pager and Quillian (2005), a certain duplicity undergirds "what employers say versus what they do" (Pager and Quillian 2005; Rivera 2012a).[30]

1.5.2 Organizational Incentives to Promote Homogeneity

Although we witness a number of arguments that would suggest that organizations should prize diversity and preempt discrimination, we also see potential upsides to homogeneity, value in organizational fit, and costs associated with standing out. As I will illustrate, we see both (1) rationales that bolster the argument for homogeneity while (2) appreciating a number of caveats associated with diversity that undermine efforts to promote heterogeneity.

1.5.2.1 Performance Benefits of Homogeneity and the Link to Organizational Culture

Because homogenous groups have shared perspective (Reagans and McEvily 2003), and frequently overlapping dimensions of status and value homophily (McPherson et al. 2001), we see increased voluntary communication, social support, and connectivity in such groups (Ibarra 1992, 1995; McPherson et al. 2001), as well as increased trust and improved emotional

[30] The actual quote "what employers say versus what they do" does not appear in the body of Pager and Quillian (2005) but is part of the title of that article, "Walking the Talk? What Employers Say Versus What They Do," edited above from title case for stylistic effect. Arguably duplicitous behavior also exists,

attachment (Brewer 1981; Meyerson, Weick, and Kramer 1996), the results of which bestow streamlined communication, less dysfunction, and higher performance (DiTomaso et al. 2007; Reagans and McEvily 2003). Although we might be tempted to dismiss the benefits of homogeneity as simply the upside to avoiding the downfalls of diversity (DiTomaso et al. 2007), we must come to terms with the fact that those sharing common ascriptive features or shared values inherently import external knowledge and judgements to bestow trust on those categories that would otherwise take time to develop (Brewer 1981; Meyerson et al. 1996). Although intergroup biases can at times be assuaged given common group goals and the development of positive emotions or friendship through repeated intergroup contact (Pettigrew 1998), such favorable conditions frequently go unrealized (DiTomaso et al. 2007). Even where diverse groups overcome initial bias and overcome communication challenges (Burt 2000), homogeneity—for what it lacks in potential innovation (Burt 2000, 2004; Wu et al. 2019)[31]—also affords the ability to bypass these potential pitfalls and readily proceed with the task at hand.

Even putting aside the efficiencies of relying on categorical trust and shared perspective, we likewise witness enhanced comfort and a preference to interact with individuals along idiosyncratic cultural dimensions, such as interest in leisure sports or erudite predilections (Rivera 2012b). This is especially true in high-stakes work environments involving long hours and travel, since quite frequently, colleagues might spend more time with each other than with their romantic partners or family (Rivera 2012b). Thus, having colleagues you like is not only important but is also driven by status and value homophily (McPherson et al. 2001; Rivera 2012b; Rivera and Tilcsik 2016). Such a scenario not only affords increased performance and de facto trust but also higher satisfaction and commitment (Meglino, Ravlin, and Adkins

for example, in recruiters artificial restriction of potential diversity hires to a severely limited elite pool of applicants (Rivera 2012a), or for example in the fact that diversity initiatives frequently prove ineffectual (Kalev et al. 2006).

[31]See prior note resolving Burt (2000) versus Wu et al. (2019). In either case, diverse teams (particularly diversity in functional, education, or disciplinary backgrounds) have benefits for innovation, especially for an optimally-sized team, which has diminishing returns after an upper bound of team size is reached (Wu et al. 2019).

1989), and relatedly avoids the decreased satisfaction and higher turnover associated with diverse teams (Boone et al. 2004; Elvira and Town 2001; Milliken and Martins 1996; Tsui, Egan, and O'Reilly 1991).[32] Returning to an earlier point, preference for homogeneity is not simply about streamlining communication and enhancing performance, but also about finding the comfort, trust, and solidarity born from the association with similar others. As Rivera (2012b) articulates, culture proves to be a critical factor in organizations, a point earlier highlighted by DiMaggio (1992), who even went so far as to define organizational recruitment as "cultural matching" (127), an idea that similarly harkens back to Schneider's (1987) "match of person and environment" via oppositional forces of attraction and attrition between individuals and organizations (441).[33]

Taken another way, we can view these matching processes as but another manifestation of purposive or *choice homophily* (McPherson and Smith-Lovin 1987), since the overall matching process in many respects simply necessitates that individuals align with the employer on some holistic set of overlapping status and value dimensions. Often these include rather innocuous features such as educational attainment and the hard and soft skills engendered by the right combination of human, social, and cultural capital (Becker and Tomes 1979, 1986; Coleman 1988; DiMaggio and Mohr 1985), parental cultivation (Lareau 2003, 2011), or perseverance (Duckworth et al. 2007). Yet, homophily extends beyond matching on proximally relevant job qualifications, to include matching on culture and social class (Rivera

[32] Importantly, turnover is higher for dissimilar group members, suggesting an integral impediment to any efforts striving for diversity (Milliken and Martins 1996).

[33] The concept of cultural matching in organizational contexts developed by Rivera (2012b) and echoing DiMaggio (1992), can also be seen organizationally in the general conception known as "the matching of persons to jobs" (Kalleberg and Sørensen 1979; Sørensen and Kalleberg 1981: 52), or as described by DiMaggio and Mohr's (1985) use of culture in matching marital partners. Incidentally, partisan matching is also seen in romantic partnerships (Huber and Malhotra 2017; Iyengar et al. 2018). Indeed, organizations maintain the right to delimit their membership such that individuals fundamentally align with the corporate culture, an integral part of its founding strategy and the structure that follows (Chandler 1962; King et al. 2010; Stinchcombe 1965). Yet, as seen, this idea also has industrial and organizational psychology origins from Schneider (1987), whose idea of attraction and attrition forces between similar and dissimilar individuals and organizational environments, likewise is reminiscent of the homophily argument (McPherson and Smith-Lovin 1987) and has a clear analog to the forces of attraction and repulsion found in affective polarization (Iyengar and Westwood 2015).

2012b; Rivera and Tilcsik 2016). And even while overtly favoring (or excluding) protected social classes remains prohibited under EEOC law—and there remain viable incentives for their avoidance—we still see evidence of discrimination by race (Bertrand and Mullainathan 2004; Gaddis 2015; Kang et al. 2016), gender or motherhood (Correll, Benard, and Paik 2007; England et al. 1988; Pedulla 2016; Williams 1992), and sexual orientation (Tilcsik 2011), among other ascriptive features. Admittedly, such matching could reflect a process of induced, or spurious, homophily. For example, homophily might occur incidentally, such as the result of systemic pipeline inequities (Rivera 2012a). However, as shown in a number of experiments (Bertrand and Mullainathan 2004; Gaddis 2015, 2017; Kang et al. 2016), predisposition against diversity applicants persists, regardless of whether this bias extends from traditional theories of discrimination (Quillian 2006), or rational motives to limit the downsides of diversity. This point raises another. Apart from the possible returns of a homogenous workforce, we might also expect firms to exacerbate partisan homogeneity via the simple fact that firms remain a site for the manifestation of processes occurring in society (Davis et al. 2008). The rising incidence of affective polarization, or bias against those in the opposing party, may compound in firms which prize fitting in, not only as a vector of productivity but also to avoid the socioeconomic sanctions that emerge from standing out (Dobbin and Jung 2011; Goldberg et al. 2016).[34] Even without additional layers of consideration, the situation is complex. Collectively, firms might have multiple positive motivations to value homogeneity over diversity.

[34]Within firms, there are career risks to standing out (Goldberg et al. 2016). Externally, firms that stand out, for example by appointing diversity board members, also face risks from external actor bias (Dobbin and Jung 2011). Where firms rely on business that allows individuals to freely express political thoughts, additional complexity emerges at the firm level in standing out, since the decision to allow or restrict political speech or allow campaigns to advertise invokes criticism from political elites and pundits of either party (Confessore and Bank 2019; Timberg 2020).

1.5.2.2 Outlining the Downsides of Diversity

At the same time, in assessing the organizational outcomes of diversity, we also witness a plethora of evidence suggesting that "heterogeneity on most any salient social category contributes to increased conflict, reduced communication, and lower performance," despite the aforementioned benefits, for example, in innovation (DiTomaso et al. 2007: 488; Williams and O'Reilly 1998). As previously stated, diverse teams have a higher turnover and decreased satisfaction (Boone et al. 2004; Elvira and Town 2001; Milliken and Martins 1996; Tsui et al. 1991; Walton, Murphy, and Ryan 2015), a burden brooked most acutely by minority group members (Milliken and Martins 1996). In part, minority members may face a number of pressures, including unrealistic expectations (Reskin, McBrier, and Kmec 1999; Walton et al. 2015), initial or exaggerated discrimination (Nelson, Acker, and Manis 1996; Pettigrew 1998), and communication problems (Reagans and McEvily 2003; Williams and O'Reilly 1998), especially when only a few token minority members exist (Kanter 1993). These collective issues, in turn, hasten minority members' departure (Kanter 1993; Reskin et al. 1999; Walton et al. 2015).

For teams trying to build diversity, these findings suggest that even with effective diversity training and recruitment (Dobbin et al. 2011; Kalev et al. 2006), diversity hires' tenure may prove ephemeral. Beyond wasted opportunity costs and time spent recruiting, training, and on-boarding merely transient workers, those workers' time within the firm will also generally produce multiple frictions, including increased team conflict, reduced communication, and flagging collaboration, all of which diminish team performance (DiTomaso et al. 2007; Reagans and McEvily 2003; Williams and O'Reilly 1998) . For cross-functional teams relying on swift and seamless communication, these deficits may be even greater. Of course, both positive and negative effects of diversity revolve around effective communication, teamwork, and collaboration, and as such, the magnitude of these effects is attenuated by the degree to which the organizational culture emphasizes individualism versus collectivism and collaboration (Chatman et al. 1998; Van Knippenberg, De Dreu, and Homan 2004). Collectively, however, a bevy of research finds an abundance of benefits to homogeneity and consistent detriments to diversity (DiTomaso et al. 2007; Williams and O'Reilly 1998). At the same time, as argued above, certain benefits exist for diversity, especially the prospect of increased innovation, although as argued, these trends remain more accurate for functional diversity than differences on ascriptive social features (DiTomaso et al. 2007). To this end, it appears that firms would gravitate towards partisan homogeneity over diversity. Yet, as seen, firms might alternatively deploy best-faith efforts to avoid litigation and negative press.

To reiterate the chief theoretical grounding, my research helps to address an empirical and theoretical gap in which I offer an alternative perspective to the main thrust in social science research, which often focuses on the external influence of corporations and elites on politics, or alternatively emphasizes the role of firm ideology in organizations. I take a different approach, not only seeking to evaluate the role of partisanship in its own right, but critically looking at how partisanship within firms can alter organizational structure and affect the careers therein. I offer this perspective, not just in the traditional vein of corporate leadership, but systemically throughout the firm. In this way, we can better understand how the partisanship playing a pivotal role in society might also permeate corporate culture and have a sorting effect in firms. Such a gap in understanding merges with a second puzzle. As I have illustrated, several lines of argument suggest that organizations should preempt partisan discrimination and promote diversity as a regulatory hedge, a wellspring of innovation, and as a model of efficiency. At the same time, we witness the salience of organizational fit, the productivity boons of homogeneity, and the social headwinds of partisanship in society at large. Indeed, highlighting these puzzles clarifies the theoretical mooring and motivation of this dissertation's argument. Taken together, we might ask whether organizations act as an arbiter of divisiveness or rather a site wherein partisanship is exacerbated and may, in point of fact, operate as a structuring mechanism in firms and the careers therein.

1.6 Outlining the Empirical Contributions of this Dissertation

Given the arguments which we might make on both sides, better understanding is needed to see how firms navigate the rising tide of partisan polarization in society, especially relative to affective polarization and partisan homophily, and the dynamics that these mechanisms might exercise within firms. We can then summarize these suppositions and ask, *to what degree has political partisanship emerged as a structuring mechanism in the American corporation?* Empirically, we might inquire *how exactly does partisanship determine who is hired or who is not hired within firms, and consequently shape the partisan distribution of a firm's human capital?* In this dissertation, I seek to address this central theoretical question by pursuing a multifaceted research agenda. I divide my research into three interconnected but freestanding empirical chapters. Below, I briefly describe the methods and research questions of each empirical chapter.

1.6.1 Corporate Politics: The Emergence of Partisan Polarization in Firms, 1980-2018

To frame the general hypothesis of the dissertation—that political partisanship emerges as a structuring mechanism capable of reshaping firms—presupposes the existence of party sorting between firms. Rather than take this assumption for granted, I begin the dissertation by asking: To what extent has partisan polarization emerged in the American corporation? To the extent it exists, is partisan homogeneity equal across occupations within firms, and can certain types of partisan firms emerge more strongly than others? In addressing these questions, I take a computational, historical scope, examining campaign finance records for employees at Fortune 400 firms from 1980 to 2018.

1.6.2 Office Politics: How Party Identity and Affective Polarization Alter Job Callbacks

Building from the first empirical chapter, I next turn toward experimentally testing the potential effects of partisan polarization on corporate careers. In this study, I ask: How does the party identification of a job market applicant affect the likelihood of receiving an interview callback for jobs in selective labor markets, and how might this effect vary by the applicant's prestige? I gauge prestige by the selectivity of an applicant's universities and employers, holding applicant skills and other factors constant. To address this question, I run a computationally driven field experiment in which I submit fictitious resumes and email cover letters to entry-level professional jobs, and I combine the results with external data on the partisan profile of the firm to which these applicants apply. In this way, my research will advance experimental analysis about the effects of partisanship, especially affective polarization as well as partisan homophily, for job market applicants in selective American corporations.

1.6.3 Party in the Boardroom: Affective Polarization and Corporate Board Succession

Extending the evaluation of affective polarization from the second empirical chapter, I evaluate the role of affective polarization in the decision to appoint a new board member, either as a board member succession or as an addition to the board. Whereas the second empirical chapter establishes experimental effects of partisanship for professional career entry, this chapter takes a historical approach to establishing partisan effects, especially affective polarization at the executive level. I ask: How does affective polarization influence the appointment of corporate board members, and has that effect grown more salient with the recent rise in partisan polarization?

Collectively, these three empirical dissertation chapters creatively combine historical and experimental data to elucidate how facets of partisanship, especially partisan polarization, partisan homophily, and affective polarization can act as structuring mechanisms in the American corporation. As elaborated above, I begin by establishing the emergence of partisan polarization in firms, 1980 to 2018, although the most consistent data throughout the chapters occurs most recently. After establishing partisan polarization in firms, I examine how affective polarization might manifest to shape career entry and late-stage corporate board member appointments. By conducting such a multifaceted analysis, I can triangulate a robust understanding of how political partisanship may not only permeate the American corporation, but indeed fundamentally reshape its internal organizational structure.

CHAPTER 2

Corporate Politics: The Emergence of Partisan Polarization in Firms, 1980-2018

Across the American republic, pundits, politicians, and social scientists alike have studied and speculated about the rising tide of partisan divisiveness threatening to inundate the political mooring of American society. Known as partisan polarization, and alternatively referred to as party sorting (Fiorina and Abrams 2008), the phenomenon has many definitions but often refers to the increased ability of political parties such as the Democratic and Republican parties to better sort individuals into ideological factions (Baldassarri and Gelman 2008; Fiorina and Abrams 2008; Fiorina et al. 2005; Lee 2015).[1] In the absence of ideological or policy issue measurements, however, as I will suggest, we can evaluate partisan polarization on the simple basis of whether individuals, or in this case, groups of individuals within firms, become increasingly sorted along party lines, becoming more strongly Democratic or Republican. Such a perspective is particularly compelling when we view polarization, in this case partisan polarization or party sorting, as a process not a state (DiMaggio et al. 1996; Fiorina and Abrams 2008). Evaluating the strength of partisan attachment and ability to better sort individuals into distinctive partisan factions is at the core of the party sorting or partisan polarization research and is important in its own right as a temporal process (Baldassarri and Gelman 2008; DiMaggio et al. 1996; Fiorina and Abrams 2008). As each individual's identification with a party crystalizes, that partisanship may be reified through social media (An et al. 2014; Bail et al. 2018; Bello and Rolfe 2014), and analyzed relative to public opinion and social attitudes (Baldassarri and Gelman 2008; DiMaggio et al.

[1] Note that this is a phenomenon distinct from political polarization where the ideological distribution between parties, particularly along policy positions, "must be far apart... and... tightly clustered around the party mean" (Poole and Rosenthal 1997: 81). Instead, party sorting or partisan polarization can occur even with heterogenous ideological positions and policy attitudes within and between parties (Baldassarri and Gelman 2008; Baldassarri and Goldberg 2014; Fiorina and Abrams 2008; Fiorina et al. 2005; Lee 2015).

1996). At the crux of potential ramifications to the American politic, partisan polarization relates to the rise in "affective polarization," a shifting of attitudes, particularly animosity toward or negative evaluations about those of the opposing political party, otherwise known as political "outgroups" (Iyengar and Westwood 2015: 691; Iyengar et al. 2019; Pew Research Center 2016).[2] Such biases occur implicitly and on the singular basis of party identification regardless of underlying ideology or issue positioning (Iyengar and Westwood 2015). Given the established role of social and cultural fit in determining employability in firms (Rivera 2012b; Rivera and Tilcsik 2016; Stinchcombe 1965; Sørensen and Kalleberg 1981), the rise of affective polarization suggests that political fit might also predict employability in firms and change over time. Yet, to determine this question presupposes the existence of partisan polarization, particularly increased within-firm partisan homogeneity and increased between-firm partisan distinctiveness. In this paper, I therefore ask, *to what extent has party sorting or partisan polarization emerged in the American corporation*?

Understanding the extent of partisan polarization in the American corporation has implications for the entrenchment of partisanship in American politics, a point perhaps clearer after establishing the following ideas. First, corporations increasingly fund national elections, both through corporate political action committees and secondarily by the individuals whose income and wealth originates in firms and flows to political committees (Domhoff 2010; Hacker and Pierson 2010; Mayer 2016; Page et al. 2013). Second, these campaign funds foster the election of "party elites," who have become increasingly polarized on political issues (McCarty et al. 2006), a process believed to contribute to increased partisan polarization or party sorting and affective polarization of the American voter (Hetherington 2001; Iyengar and Westwood 2015; Pew Research Center 2016). Therefore, given these points, better understanding how the corporation, a type of complex organization, may serve not only as an economic engine of partisanship—but instead might additionally act as *a socializing*

[2]Affective polarization is the most common term in scientific literature (Iyengar and Westwood 2015; Iyengar et al. 2019), but the behavior is occasionally referred to as "negative partisanship" (Klein 2020; Pew Research Center 2016).

mechanism entrenching partisanship in the American labor force and perhaps physically isolating them from opposing partisans, necessitates a new social, organizational approach toward understanding partisanship in American politics. While the effects of within-firm partisanship could be as simple as determining who a firm hires or promotes based on party allegiance, documenting such effects requires establishing the emergence and existence of *partisan polarization in the American firm*.

In this paper, I develop the idea of *partisan polarization or party sorting in the American firm*, which I will alternatively refer to as *organizational partisanship*. Organizational partisanship affords a unique perspective, whereby we can assess the idea of corporate identity or firm actorhood (Bromley and Sharkey 2017; King et al. 2010)—not as the result of official corporate documents or position-taking—but instead as the collective manifestation of corporate culture that can evolve from changes of the employees therein, including those at the executive, managerial, and lower levels.[3] In this way, we can evaluate the emergence of firms as political incubators, a phenomenon that develops relationally within firms such that the partisan firm emerges from individuals' importation or "transposition" of external cultural frameworks, routines, and social networks, especially those bearing partisanship (Clemens 1993; Davis et al. 2008; Powell and Sandholtz 2012; Powell et al. 2005). Such transposition may manifest in a variety of ways, such as self-conscious selection into or departure from firms, direct selection of those politically matching the firm's political identity, or indirect correlation of cultural attributes associated with partisan affiliation. Regardless of

[3]Here, we can think both of changes in the given fixed set of persistent employees as well as changes in the human capital allocation of firms, which as mentioned thereafter, can have roots in employees' importation of myriad external social and cultural frameworks, routines, preferences, or attitudes, among other possibilities (Clemens 1993; Davis et al. 2008; Powell and Sandholtz 2012; Powell et al. 2005). This prospect is additionally discussed in Chapter 1, and specifically relates to the idea that organizations can evolve such that organizational structure follows its strategy, of which human capital allocation and the attributes thereof are an integral component (Chandler 1962), (*c.f.* Hannan and Freeman 1984; Stinchcombe 1965). Consequently, changes in human capital allocation or attributes of this human capital, for example, from the importation of external societal frameworks (Clemens 1993; Powell and Sandholtz 2012; Powell et al. 2005), constitute a change in organizational strategy, the structure that follows, and as such, constitute a change in the organizational state. I reference this idea also in (Chapter 1, footnotes 1 and 22), and provide a deeper level of organizational theory on this concept in Appendix A.

the presentation of organizational partisanship, we can harness the idea of the firm emerging as a political actor when the composition of its members reaches a threshold of political coherence discrete from former epochs, for example, a higher degree of within-firm partisan homogeneity as opposed to past periods of relative bipartisanship.[4]

To test my theory of the emergence of organizational partisanship as defined by its employees' partisanship, I analyze the individual campaign contributions of employees at Fortune 400 companies between 1980 and 2018. Therein, I focus on two primary analytic questions, namely whether there has been an increase in partisan polarization within firms over time, and second, whether we can identify the emergence of particular firm types that exhibit strong partisan polarization. Such analysis reveals that partisan polarization has increased from 1980 to 2018, particularly since the 2012 presidential election. Such a trend occurs not only for corporate executives but for employees at all levels. Both the magnitude and directionality of these changes is unequal. Using hierarchical clustering analysis, I identify three types of emergent partisan firms, including polarized Democratic, polarized Republican, and amphibious firms, the latter of which alternate between weak Democratic and Republican states. Of these changes, the most marked changes occur in the bolstering of partisan Democratic and Republican firms.

Collectively, this study expands organizational theories of firm actorhood (Bromley and Sharkey 2017; King et al. 2010), by illustrating that beyond the emergence of new organizational structural or strategic forms (Powell and Sandholtz 2012; Powell et al. 2005), firms can have emergent partisan identities reflective of shifting partisan dynamics of the employees therein. This latter finding of increased party sorting contributes to the literature on party sorting (Baldassarri and Bearman 2007; Baldassarri and Gelman 2008; Baldassarri

[4]Note that defined this way, there could be a decoupling (*c.f.* Meyer and Rowan 1977), from the formal organizational partisanship, as defined by official corporate documents or corporate political action committees (PACs), and the informal organizational partisanship defined from partisanship of a firm's actor members, that is, its employees. Here, I am interested in firm partisanship as defined by its employees. To take an analog in political ideology, Bonica (2016) demonstrates that the ideology of a firm's board members is discrete from the ideology of its corporate PACs.

and Goldberg 2014; Fiorina and Abrams 2008), and suggests additional work exploring workplace and career effects of partisanship, particularly affective polarization (Iyengar and Westwood 2015; Iyengar et al. 2019). Empirically, the paper proves to be among the first to quantitatively and computationally assess the degree of partisanship among individuals in American corporations. Such an exercise illuminates several theoretical mediums, both in the study of partisanship as well as in underscoring how organizations can emerge as political actors through the increased salience of expressed public partisanship in the workplace.

2.1 Organizational and Individual Partisanship

2.1.1 Organizations as Political Actors and the Importance of Individuals

Understanding the emergence of organizational partisanship warrants some background on the concept of the organization as a social actor, also known as firm actorhood. Consideration of firms or organizations as performing action or existing as "actors" has increased in organizational research (Bromley and Sharkey 2017; King et al. 2010; Meyer 2010). Three important dimensions of an organization as a social actor include sovereignty, capacity for purposive action, and identity (Bromley and Sharkey 2017; King et al. 2010; Meyer and Bromley 2013), where *identity* forms the common thread bolstering the latter faculties. Quite simply, "purposive action... is guided by identity" (Bromley and Sharkey 2017: 6), and it reflects an organization's ability to perform tasks "on a scale and in a manner... unattainable by any given individual" (King et al. 2010: 298). The authority to perform these actions indicates organizational sovereignty.

The quiddity of organizational *identity* perhaps should elicit little surprise. Indeed, from an organizational vantage, a basic tenet is that in order to be hired, maintain employment, or advance in an organization, individuals must "be socialized, careers molded, and power allocated to defend the value" (Stinchcombe 1965: 167), in other words align with the company's identity as constituted by its core values (Chandler 1962; Hannan and Freeman 1977, 1984). Of course, these topics prove increasingly relevant with respect to the research question of partisanship. If an organization maintains the right to determine its members and regulate their activity (King et al. 2010: 293), as guided by their alignment with organizational identity or more generally culture (Goldberg et al. 2016; Stinchcombe 1965), such capacities manifest sovereignty, purposive action, and identity, thereby reiterating that the organization serves as a social actor. Where such identity and action is guided by politics, I additionally posit that beyond simply engaging as a social actor, the organization can also be conceived as a political actor.

What is important to recall from this discussion, is that firms can emerge as political actors not necessarily through purposive policy, but rather, when the political identity of a firm or its culture, becomes such that it informs subsequent sovereign actions curating its human capital. Throughout this process, individuals remain integral to the constitution of organizations (Meyer 2010; Meyer and Bromley 2013). As Meyer (2010) writes, "organizations... are now conceived as actors derived from their individual actor members" (Meyer 2010:2), where individuals' associations exemplify "highly participatory structures... [having] the qualities of purposive actorhood" (Brunsson and Sahlin-Andersson 2000; Meyer and Bromley 2013:377). Thus, to understand how organizations emerge as political actors, we need to better understand how their political identities can be shaped by the political identity of the individuals therein.

2.1.2 Understanding the Theoretical Basis of Individual Partisanship

To understand the political behavior of individuals, we need to first clarify individuals' modes of political understanding and action, including how they construct partisan identity versus ideology, and how allegiance to these political bases might engender behavior that regulates the manifested political identity or culture of organizations. The idea of political partisanship is directly related to the concept of political parties, and more importantly, identification with a political party (Campbell et al. 1960).[5] As Campbell et al. (1960) argued, average citizens lacked the knowledge about political candidates to allocate votes on the basis of individual "class location or other social attributes," and instead relied on their socially inherited and reinforced party identifications—which are "inherited in childhood and reinforced in adulthood" to make judgements in casting their votes (Campbell et al. 1960; Manza and Brooks 1999:14–15). According to Campbell and colleagues, parties are influential in many ways, including shaping policy positions and partisan attitudes (Campbell et al. 1960:128).

The stability of American party identification is widely noted. Many scholars quote and expand upon Campbell's insight (Goren et al. 2009; Johnston 2006). Goren et al. (2009) write that "party identification represents the most stable and influential political predisposition in the belief systems of ordinary citizens" (805). Many studies reaffirm the influence of party and partisan behavior across myriad political dimensions including voter behavior and voter choice, political perceptions, candidate evaluations, political value support, and policy attitudes, among other factors (Bartels 2000, 2002; Goren 2002; Goren et al. 2009; Green and Palmquist 1990; Layman and Carsey 2002). In essence, party identification is not determined or constrained—that is, bound together—by political values or political ideology, but rather *party identification guides the ideological development of those beliefs and values* (Barber and Pope 2019; Goren 2005; Goren et al. 2009).

2.1.3 Connecting Party Identity to Partisan Polarization

The fact that party identity shapes ideology has important implications for *partisan polarization*, which is distinguished from political polarization. Although colloquial definitions of polarization simply refer to acutely divided and opposed groups (Fiorina and Abrams 2008), in political science, polarization has a technical definition, which in the most robust valence, is a concept established through "spatial theory" (Lee 2015:263). As Poole and

[5] I use party identification or the party with which an individual identifies as exchangeable terms.

Rosenthal (1997) write, "for parties to be polarized, they must be far apart on policy issues, and the party members must be tightly clustered around the party mean" (81). Thus, polarization in the classical sense is a largely *ideological* phenomenon based on the distribution of policy preferences within parties. As opposed to political polarization, partisan polarization, alternatively referred to as party sorting, can be defined as "the emergence of more internally cohesive, strongly differentiated parties," or the state that exists following such a process (Fiorina and Abrams 2008; Lee 2015:267). Although political and partisan polarization are not equivalent, the phenomena are related. For example, despite ideological stability and diversity among ordinary citizens (DiMaggio et al. 1996), or the evidence of ideological heterogeneity within corporate boards and across firms (Bonica 2014, 2016), there has been rising ideological polarization among party elites since the 1970s (McCarty et al. 2006). This fact contributes to increased *partisan polarization* of the masses (Hetherington 2001), and in some cases, increased ideological alignment within parties (Baldassarri and Goldberg 2014; Bertrand and Kamenica 2018).[6]

The amplification of partisan polarization in America has important implications. For example, in American society, scholars argue that increased partisan polarization has had a sorting effect on individual citizens (Baldassarri and Bearman 2007; Baldassarri and Gelman 2008; Baldassarri and Goldberg 2014). We must, therefore, consider not only how partisan attitudes align within interpersonal networks but also how partisan divergence evolves in broader social networks (Baldassarri and Bearman 2007; Baldassarri and Goldberg 2014). In social networks and online communities, we see increasingly distinct networks of party members (Koger et al. 2009), and increasing partisan segregation (An et al. 2014; Bello and Rolfe 2014). Therefore, it is not simply that individuals are clarifying their party identification, but also that this phenomenon spreads beyond the individual to affect the social groups we associate with and more importantly *those we do not*.

[6] For example, Bertrand and Kamenica (2018) document that "liberals and conservatives are more different today in their social attitudes than they have ever been in the last 40 years" (38), although as Baldassarri and Goldberg (2014) note, increasing issue alignment is strongest among "ideologues" versus "alternatives" (45).

Thus, these increases in societal partisan polarization relate to a parallel phenomenon known as *affective polarization*, which scholars define as "the tendency of people identifying as Republicans or Democrats to view opposing partisans negatively and copartisans positively" (Iyengar and Westwood 2015:691). The work by Iyengar and Westwood (2015) extends research exemplifying escalating affective polarization, notably acute increases in "negative views of the out party and its supporters…since the 1980s" (Campbell et al. 1960; Green et al. 2002; Iyengar and Westwood 2015:691; Iyengar et al. 2012). Critical to this analysis, affective polarization delimits individual attitudes and behavior such that individuals not only hold animosity toward opposing party members but also view them as less intelligent (Pew Research Center 2016). In fact, the bias based on affective polarization toward political out-groups "exceeds discrimination based on race" (Iyengar and Westwood 2015:690). Given the well-known examples of racial discrimination in labor markets (Bertrand and Mullainathan 2001; Gaddis 2015; Kang et al. 2016; Pager 2003), the findings on affective polarization portend a parallel process of partisan discrimination in labor markets also exists.

This supposition is further supported by the fact that affective polarization arguably silences political dissent in the workplace for fear of conflict, stigma, or termination (Cowan and Baldassarri 2018; Goldberg et al. 2016; Iyengar and Westwood 2015).[7] Beyond partisan biases around the office, these effects extend to firm leadership, where both pay and evaluations of general competency are linked to the partisanship of executives and board members (Cheng and Groysberg 2016; Gupta and Wowak 2017). At times, board members may even avoid conducting business across party lines (Stark and Vedres 2012). Taken together, if partisanship can influence business strategy and affect the perceived suitability of executives, we might also expect that partisanship, especially affective polarization, might also influence the political composition of firm employees on a larger scale. If such a phenomenon were systemic, it

[7]Goldberg et al. (2016) for example, discuss the significantly higher likelihood of "involuntarily exit" if an individual lacks "cultural fit," particularly if they are "disembedded" (1204-6). Arguably, we can see examples of this in modern firms, for example, the case of a Google employee who claimed his termination was the result of being an outspoken conservative (Copeland 2019; McCabe 2019).

should ultimately appear in changes in the partisan composition of firm employees. As the partisan composition of firms becomes more homogenous, the partisan polarization of that firm increases.

2.1.4 The Emergence of Organizational Partisanship

Therefore, as suggested by general societal changes in partisan polarization and affective polarization, organizations themselves may evidence partisan polarization as a result of shifting partisan attachments of individuals within firms. An aggregate shift in the individual partisan attachments of firm employees, recall, constitutes the emergence of a firm as a political actor, since organizations are "derived from their individual actor members" (Meyer 2010:2), whose membership is participatory, regulated, and helps shape organizational identity (Bromley and Sharkey 2017; Brunsson and Sahlin-Andersson 2000; King et al. 2010; Meyer and Bromley 2013).

If firm actorhood or political identity can emerge from rising partisan sorting in firms as defined by the public partisan identities of its members, such a state points to the possibility of decoupling between the identity of a firm through its actor members and the firm's political identity as characterized by formal corporate measures such as public position taking, corporate lobbying, or firm-level political action committee (PAC) behavior. At the same time, the theoretical possibility of decoupling helps to highlight mechanisms whereby partisan polarization can emerge at the organizational level, particularly through related concepts of organizational routines, myths, ceremonies, and repertoires.

In many ways, the concepts of myths and ceremonies discussed by Meyer and Rowan (1977) relate to and illuminate the routinized process of institutionalization buttressing formal organizational structure. The existence of routines is substantiated by myth and ceremony—whose origins are grounded in rational efficiency which exists in theory but not practice (March and Simon 1958; Meyer and Rowan 1977).[8] Inefficiencies emerge from the inertia created, in part, from these "rationalized myths," ceremonies, routines, or habitualized actions that prevail even after they are no longer efficient (Berger and Luckmann 1966; Hannan and Freeman 1984; Meyer and Rowan 1977; Stinchcombe 1965). In fact, a second purpose of these informal structures is to account for discontinuities or "decoupling" between expressed formal structure and lines of authority, and daily enacted practice, a divide between the formal and informal structure (Meyer and Rowan 1977). Therefore, the potential political decoupling between formal organization and informal everyday members can be partly explained by the informal daily practices of the firm.

Although routines, myths, and ceremony help capture informal structure, the concept of "organizational repertoires" might also be applied (Clemens 1993). The term "organizational repertoires" refers to "the set of organizational models that are culturally or experientially available" (Clemens 1993:758). Although organizational models may refer to "examples of specific organizations" and their external actions as "governed by 'logics of appropriateness'. . . or institutional norms" (Clemens 1993:758; DiMaggio and Powell 1983; March and Olsen 1989:23–24), organizational models may also refer to the "templates for arranging relationships within an organization and sets of scripts for action" (Clemens 1993:758). It is this second definition of organizational models as templates or scripts within an organization that best reflects my application of the term to internal organizational processes. The concept of organizational repertoires also captures Hannan and Freeman's (1984) argument that as part of the institutionalization process, organizations not only have routines but "sets of routines" and a "set of rules to switch between routines" (154). In sum, such sets of routines coalesce as "organizational memory" or as Hannan and Freeman (1984) define, "an organization's repertoire of routines. . . the set of collective actions that it can do from memory" (154; *c.f.* Nelson and Winter 1982).

[8] For example, Meyer and Rowan's (1977) "rationalized myths" in organizational structures can trace their roots to economic rationality and exemplify a decoupling between formal and informal structure (343, 347).

Critically, the malleability of repertoires lends itself to transfiguration not simply from experiential histories (Berger and Luckmann 1966), but also from a "common, culturally available repertoire" for situational interpretation and action (Clemens 1993:759). In this way, the informal social structure of organizations may shift according to changing currents of societal understanding such as societal changes in partisanship or attitudes toward opposing partisan groups. If organizational repertoires are malleable to societal influence, and such organizational repertoires include hiring and promotional processes—especially the *suitability* of an individual within an organization—then the political identity of a firm and the status of firms as political actors might also shift or emerge in response to societal changes in political partisanship, such as party sorting or affective polarization.

Connecting this discussion to the broader emergence literature, we can see that "emergence is fundamentally relational," that is, new organizational forms or identities often emerge and owe a great deal to "social forces of juxtaposition," whereby intersecting social networks, ideas, culture, or repertoires recombine to result in the development of innovation such as new organizational forms, identities, or practice (Padgett and McLean 2006; Powell and Sandholtz 2012:95; Powell et al. 2005). More generally, emergence can transpire when societal, and in the case of this analysis, *political* shifts "exert pressure on existing relations and reconfigure models of action" (Powell et al. 2005:1134). Organizationally, emergence can, therefore, transpire under conditions where sociopolitical influence affects the repertoires of individual firm-actors. Since I focus on changes within specific firms, the type of emergence that occurs can be thought of as political recombination. Rather than the creation of a new firm, a firm's political identity reconfigures through the utilization of extant routines, which are influenced by the transposition of external "cognitive frameworks and moral assumptions" about their partisan identities and attitudes toward opposing versus copartisans (Iyengar and Westwood 2015; Powell and Sandholtz 2012:96). Collectively, in this paper, I advance the idea that an organization can emerge as a political actor as defined by shifts in political partisanship of its members. In so doing, I build on a number of literatures, including those in partisan polarization (Baldassarri and Bearman 2007; Baldassarri and Gelman 2008; Baldassarri and Goldberg 2014), firm actorhood (Bromley and Sharkey 2017; King et al. 2010; Meyer and Bromley 2013), and organizational emergence (Powell and Sandholtz 2012; Powell et al. 2005).

2.2 Data Sources and Preprocessing

2.2.1 Data Sources of Individual Partisanship and Occupation

Data for this project comes from the United States Federal Election Commission (FEC), a government regulatory agency that extensively documents the financial activity of elections (Federal Election Commission 2018a). Among these financial activities, Chin et al. (2013) note, "the FEC records all individual contributions of more than $200 to individual candidates; to campaign committees for federal office; to national, state, and local parties; and to political action committees (PACs)" (207). According to the FEC, "for each contribution that exceeds $200, either by itself or when added to the contributor's previous contributions made during the same calendar year, records must identify that contribution by: Amount; Date of receipt; and Contributor's full name and mailing address, occupation and employer" (Federal Election Commission 2018c).[9] And even where an individual has no prior contribution history and gives only a small donation of a few dollars, committees collect this data (Appendix B, Table B.10). Of course, given the above definition, we would not have information on individuals either contributing less than the $200 calendar-year, aggregate threshold, nor would we have data on the "dark money" that circumnavigates legally reportable contributions to political committees (Mayer 2016). Nonetheless, the FEC data proves a valuable public resource, and given the relevance of the data to myriad research questions, it has been used to various ends, including research on corporate social responsibility (Chin et al. 2013; Gupta et al. 2017),

[9] Although the FEC collects addresses, this data is not provided in the bulk downloads, therefore making the aggregation of individuals through names more challenging.

CEO pay (Gupta and Wowak 2017), or political ideology of corporations and executives (Bonica 2016), among other studies.[10] To clarify the data scope, although the FEC documents a variety of campaign finance data, I specifically focus on contributions made by individuals, not by firms or corporate political action committees. Because individuals can contribute to a firm's PAC (or any other political action committee), such individual-level contribution data is included in the analysis.

Although the mode for accessing and exploring the data varies, traditional routes include either directly downloading data from the FEC or from third-party sites such as the Center for Responsive Politics (Center for Responsive Politics 2020), (*c.f.* Bonica 2013; Chin et al. 2013). Such data, which originates from the FEC, however, may be limited in the details included, completeness, or level of aggregation. For this project, I downloaded and utilized data tables directly available from the FEC (Federal Election Commission 2018a, 2018b).[11] Structurally, the FEC data exists as a series of pipe-delimited text files for each data table-election-cycle pair. For example, there is a file for political candidates in 2012, a file for political candidates in 2014, and so forth. Other notable tables include data on individual contributions, data on the political committees to which individuals contribute, and data about where these political committees transfer funds. The resulting dataset is large by traditional social science standards. In Table 2.1, I detail the data's metadata characteristics.

[10] Although most campaign contributions have an ideological component (McCarty et al. 2006), as I previously argue, *party identification structures ideology* (Barber and Pope 2019; Goren 2005; Goren et al. 2009), and within parties there exists significant ideological heterogeneity (Bonica 2014, 2016; McCarty et al. 2006). For example, McCarty et al. (2006) write, "there is always substantial diversity of NOMINATE positions [ideological scores] within each party and, at times, ideological overlap between the parties" (21). Thus, when members of the public contribute to a political candidate or committee, it better reflects an alignment of individual and candidate partisan identity than an exact match of the individual's and the candidate's political ideology on a range of issues, in which most voters are not well versed (Campbell et al. 1960).

[11] Federal Election Commission (2018a) contains the FEC's data repository for all bulk downloads, whereas the second page Federal Election Commission (2018b) contains a more user-friendly interface with detailed documentation and data links to Federal Election Commission (2018a). Besides the bulk downloads, the FEC's page also offers various aggregations of data. In addition, FEC also has an official API, OpenFEC (General Services Administration: 18F 2017), whose documentation is available online: https://api.open.fec.gov/developers/. API refers to "Automated Programming Interface," which is a way for organizational entities to provide structured access to large databases. In testing, the FEC's API may have some issues with the results returned via the data queries.

Table 2.1: Descriptive Overview of FEC Data Tables

FEC Table Name	File Abbreviation	Total Observations (N)	Years Covered
Committees	CM	218,482	1980-2018
Candidates	CN	95,807	1980-2018
Linkages	CCL	50,775	2000-2018
Itemized Records	OTH	9,584,743	1980-2018
Contributions to Candidates	PAS2	5,122,434	1980-2018
Individual Contributions	INDIV	54,314,410	1980-2018
Operating Expenditures	OPPEXP	10,677,840	2004-2018

Source: FEC 2018a, 2018b.
Notes: The FEC has a unique pipe-delimited text file for each of the above file types for each election cycle, in the cycles they exist. The above summary metrics reflect the aggregated totals of each file type (for each election cycle) uploaded into a single SQLite table for each file type. A detailed description of each FEC table type is available at FEC 2018b. In brief: (CM): The committee master file has a single record for each registered FEC committee, which "includes federal political action committees and party committees, campaign committees for presidential, house and senate candidates, as well as groups or organizations who are spending money for or against candidates for federal office." (CN): The candidate master table "contains one record for each candidate who has either registered with the Federal Election Commission or appeared on a ballot list prepared by a state elections office." (CCL): The candidate-committee linkage file has one record for each candidate to committee linkage. (OTH): The itemized records table documents all federal transactions between registered FEC committees, including among other transactions, committee contributions, PAC contributions, and party transfers. This is the file used to recursively identify the partisanship of every itemized contribution. (PAS2): A subset of itemized records (OTH) including only contributions to candidates. (INDIV): A file recording "each contribution from an individual to a federal committee." (OPPEX): A file containing operational expenditures reported as disbursements.

2.2.2 Defining Firms and Time Periods

In this analysis, I evaluate data specific to Fortune 400 companies. Here, the term Fortune 400 refers to companies that had a rank within the top 400 of the Fortune 1000 companies in 2018 (Fortune 2018).[12] This defined the initial firm sampling frame. Each company in the Fortune 400 (as defined in 2018)[13] was queried for several years corresponding to each election cycle from 1980 to 2018. Here, the election cycle is calculated from the date of the individual contribution, where the ending two-year period defines the election cycle. For example, data in the 2016 election cycle includes contributions made in 2015 and 2016. Below, I summarize the steps I took to download, identify, and process this data.

[12]The Fortune 1000 is a list compiled by Fortune (2018). Note that this list is a superset of the list referred to as the "Fortune 500." Indeed, the list compiled by Fortune having 1000 companies, even has the designation of "Fortune 500" in its title.

[13]Although the Fortune 1000 list changes each year, there is considerable retention. For example, among the 371 companies for which I found corresponding FEC data, 202 of these companies also had data from the 1980 election cycle (Table B.2).

2.2.3 Data Preprocessing

To obtain and prepare the data, I first developed a series of *Python* and *SQL* scripts to download, extract, transform, and load the FEC data into a *SQLite* database. Such a process is often denoted a data pipeline or an ETL process (extract, transform, load), reflecting at its core the idea of data replicability, in that any scholar can replicate or update the FEC dataset used in the analysis simply by downloading and running the code repository I developed to prepare the FEC data, which I have made available online (Mausolf 2020e). I describe an overview of the ETL pipeline in Figure 2.1.

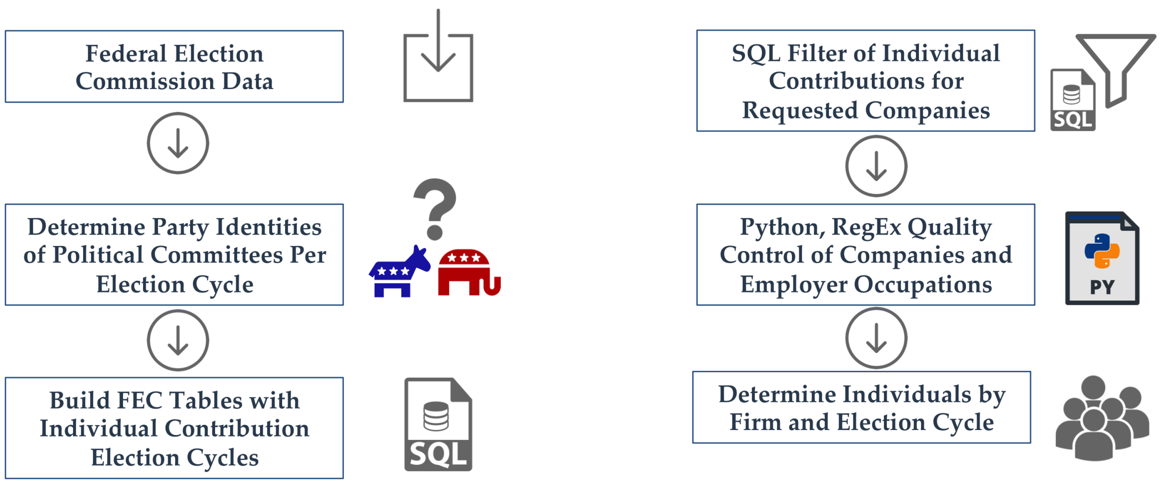


Figure 2.1: ETL Pipeline in Python and SQL

Notes: ETL (extract, transform, load) is a reproducible, code-based pipeline in database engineering. The above graphic represents major conceptual steps in that process, including downloading the data from the FEC (2018a) and building base tables, determining partisanship through a recursive algorithm (Figure 2.2), building FEC individual contribution tables linked to partisanship measures, filtering the data for requested firms, cleaning up and classifying this raw text data with regular expressions, and aggregating individual contributions to individuals by firm by election cycle.

2.2.4 Determining the Partisanship of Political Contributions

As the first stage of the ETL process, I calculate two base, correlated measures of political partisanship, which I term, the *partisan affiliation* (party id) and the *partisan score*. Although I formally define these below, the *partisan affiliation* can be thought of as the most common major party affiliation, whereas the *partisan score* is the numerical average of the major parties on a scale of -1 to 1. Thus, during the first stage of the ETL process, the partisan affiliation and partisan score are determined for each political committee in every election cycle. In each of these cycles, a recursive algorithm evaluates the partisanship of a given political committee by examining each committee's itemized contributions to other political committees. The algorithm searches each committee as illustrated in Figure 2.2.

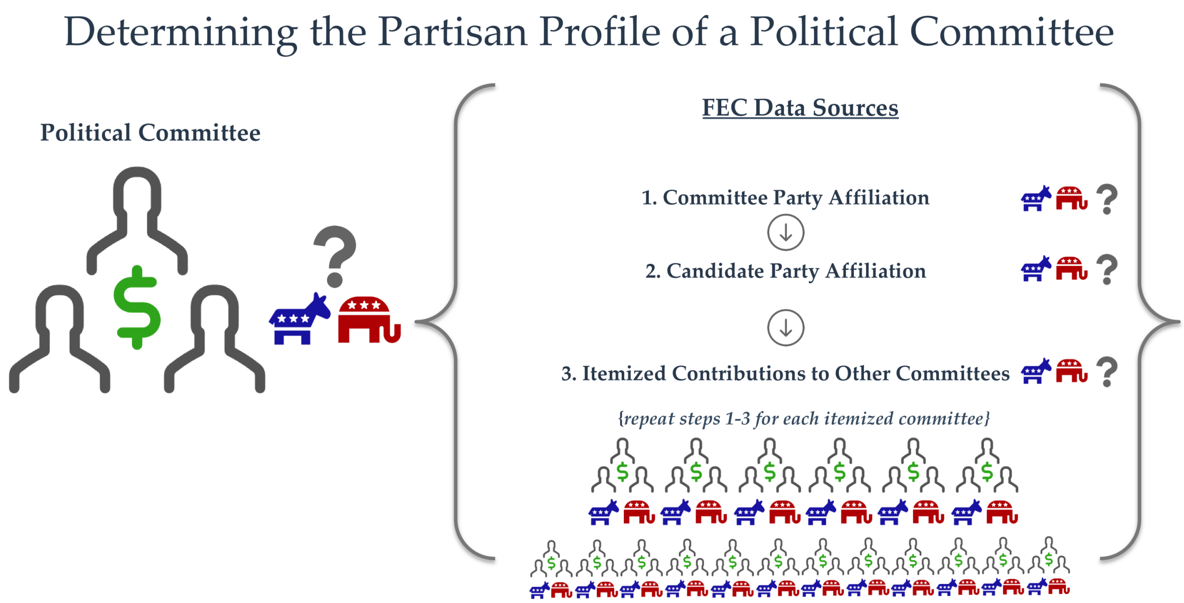


Figure 2.2: Recursive Identification of Partisanship from Itemized Contributions
Notes: This figure conceptually captures the question of determining political partisanship of an individual contribution using the recursive algorithm. For a given contribution to a political committee, that committee ID is queried in the itemized contributions table for that election cycle, resulting in a list of all committee IDs to which that committee provided a federal transfer of funds, which could include candidates or other committees. The partisanship for each committee is examined by querying committee and candidate tables, and if needed the itemized records, to a depth of two. This data is summarized and the process repeats for every political committee in every election cycle, 1980-2018.

To elaborate on the process in Figure 2.2, each political committee is (1) first checked for an available major party or major third-party affiliation.[14] If none is found, (2) the affiliated political candidate (if any) is evaluated for a valid major party. Whether a valid major party is found in steps (1) or (2), an itemized search of the committee's contributions is performed (3). In this way, the two measures, *party affiliation* and *partisan score*, can be calculated using all committee contributions. I should note that, because the algorithm is recursive,

[14]Valid major parties include the following: DEM/Democrat, IND/Independent, and REP/Republican. Major third-parties include the following: GRE/Green, LIB/Libertarian, and CON/Constitution.

the depth of recursion is limited to two levels in order to prevent an infinite loop. In this way, the most important contributions for signaling partisanship are the most immediate first-level contributions, followed by those at the second level. Accordingly, in order to give the most weight to first-level contributions, second-level itemized results are first summarized to capture the most common party affiliation. Thereafter, the collapsed first level can be evaluated to determine the most-frequent party affiliation for that political committee.[15] Lastly, the collapsed first-level parties are converted into numerical equivalencies on a -1 (DEM) to 1 (REP) scale for all major parties and major third parties. Once the numerical values are applied, the mean is computed, less null values.

Table 2.2: Example Multilevel Partisan Results of Recursive Search

		First Level Results			Second Level Results
Committee ID	Election Cycle	(1)	(2)	(3)	Steps 1-3 Results (for each UNK)
C00000000X	2008	UNK	NA	DEM, DEM, DEM, DEM, DEM, DEM, DEM, IND, DEM, UNK	UNK: {DEM, DEM, IND, REP, REP, REP, REP, REP, REP, REP}
C00000001X	2008	NA	NA	REP, REP, REP, UNK, UNK, UNK	UNK:{REP, REP, REP}, UNK:{UNK, UNK, UNK, REP, REP, REP, REP}, UNK:{DEM, IND, REP, IND, IND}

Notes: The value (NA) represents missing data as opposed to the explicitly designated unknown party (UNK). The recursive search process is typically not brief as in the examples above. For example, many committees have hundreds—if not thousands—of itemized contributions, a number of which are unknown, requiring additional itemized searches for each unknown committee.

Following the calculation of the mean using the numerical conversions for major parties and major third parties,[16] the second-level itemized contributions can be resolved to their

[15] The most frequent party affiliation is simply the party-string occurring most frequently. If two discrete, non-null parties are equally common, the result is an alphabetized concatenation of the two words. For example, either list of parties [DEM, DEM, REP, REP] or [REP, REP, DEM, DEM], would result in "DEM_REP" as the party.

[16] Major parties are assigned the following scores: DEM/Democrat: -1, IND/Independent: 0, and REP/Republican: 1. Major third parties are given scores equivalent to their closest ideological parallel for major parties as follows: GRE/Green: -1, LIB/Libertarian: 0, and CON/Constitution: 1. All other party

most-frequent party, resulting in updated first-level party affiliations. Thereafter, the most-frequent party affiliation can be determined along with the partisan score resultant of the numerical conversion's mean value. Consider the brief example seen in Table 2.2 and Table 2.3. In Table 2.2, the example political committee C00000000X has an unknown (UNK) committee party affiliation and missing or unavailable data for the candidate party affiliation. Yet, when looking through the first-level itemized contributions to other committees, we see that the committee provided itemized contributions to eight Democratic, one Independent, and one unknown committees or candidates. We would like to also know the partisanship of that remaining first-level unknown itemized contribution. Repeating the process in a second-level analysis of that unknown committee, we find that those itemized contributions went to two Democrats, one Independent, and seven Republicans, meaning that the unknown itemized contribution is overall Republican. When these affiliations are collapsed, we can now see that the committee provided contributions to eight Democrats, one Independent, and one Republican (Table 2.3). Collectively, we can see that the overall partisan affiliation of this committee is Democratic, and by converting these parties to numeric values [-1, 0, 1] from [DEM, IND, REP], we can calculate a mean partisan score of -0.70. Although this represents only a simple example, the process can indicate both the overall party affiliation best representing the political committee as well as a partisan score indicating the relative strength of that partisanship. Once the code determines the partisan affiliations and scores for each political committee and election cycle, it loads the remaining data tables for each election cycle into the OpenFEC database.

possibilities, including over eighty other valid party codes, the assorted codes for null or unknown party affiliations, and concatenated party ties, are all provided a null value rather than a [-1/1] score. To illustrate this multilevel summarization more clearly, consider the simplistic examples of two political committees' first-level and second-level itemized contributions (Table 2.3). Here, second-level contributions are the itemized contributions for each unknown (UNK) political committee that appears in the initial first-level results (Table 2.2).

Table 2.3: Example Calculated Partisan Affiliation and Score

Committee ID	Election Cycle	Collapsed Affiliations	Converted Scores	Partisan Affiliation	Partisan Score
C00000000X	2008	DEM, DEM, DEM, DEM, DEM, DEM, DEM, IND, DEM, REP	-1, -1, -1, -1, -1, -1, -1, 0, -1, 1	DEM	-0.70
C00000001X	2008	REP, REP, REP, REP, REP, IND	1, 1, 1, 1, 1, 0	REP	0.83

Notes: The two-stage summarizing implicitly weights the party affiliations of the unknown (UNK) committees such that only their summary party affiliation is considered where it can be determined as opposed to equally weighting first-level and second-level party affiliations.

2.2.5 Selecting Individual Contributions for Fortune 400 Companies

After determining the partisan affiliations and scores for every political committee in each election cycle from 1980 to 2018, my ETL pipeline joins the partisanship metrics with the individual contribution tables for each election cycle;[17] it subsequently queries and then filters data for the requested Fortune 400 companies,[18] determines an occupational hierarchy of the

[17] Information about individual contributions begins in the individual contributions table, which are uniquely identified by a sub_ID, and contain a wealth of information including the individual contributor's name, employer, occupation, contribution amount, and critically, the political committee ID, to which the contribution is given. Using this committee ID, I joined the individual contribution table with the committee master table (as well as the candidate master table), which provides the party affiliation and partisan score for each contribution. The join is performed on both the committee ID and election cycle so that every individual contribution to a committee reflects an accurate measure of that committee's partisanship during that election cycle. To avoid creating duplicate entries (known as a cross-join in SQL terms), the data is grouped by the unique contribution identifier, that is, the sub_ID. In this way, the new columns afforded by the join are simply added to the table, the number of observations (individual contributions) pre and post join are equal, and no duplicate sub_IDs exist in either table.

[18] Fortune 400 Companies are identified as a multi-step process. The first stage involves a complex SQL query using a greedy search parameter to pull contributions from the individual contribution table where either the employer or occupation column matches the name of the corporation or one of its aliases, for example Google or Alphabet. Depending on the year and contribution committee, employer or occupation information might appear separately in their expected columns or combined in one column or the other. Once greedy SQL matches are identified, they are stored in a temporary table which undergoes subsequent strict filtering that includes a variety of regular expression cleaning methods to standardize text case, remove punctuation and white space, then strictly filters the data such that it must match one of several strict criteria to offer higher confidence that the contribution is from an employee of the requested company. In addition to meeting these strict matching criteria, contributions are excluded which match common anti-aliases for the SQL query. For example, greedy searches for Apple return a variety of possibilities such as Apple Inc, or Apple Software Engineer, but also a number of invalid responses for separate companies such as Apple Bank. Lastly, I remove contributions from individuals who are explicitly not employees. For example, the occupation might state "former Goldman Sachs Associate" or "husband works for Walmart."

individual contribution,[19] and aggregates the contribution-level data to individuals by firm and election cycle. After completing the ETL pipeline, we are left with some rich descriptive data, as displayed in Table 2.4.

2.3 Analytical Framework, Analyses, and Formal Models

The analytic framework for this paper proceeds from the research questions. First, has there been an increase in partisan polarization across firms? Second, can we identify certain types of firms that emerge exhibiting a high degree of partisan homogeneity? Ostensibly, the analyses in question rely on measuring partisan polarization, particularly partisan homogeneity. Although several methods of measuring polarization exist, a common way to measure partisan polarization or party sorting is to quantify the level of partisan variation or dispersion that exists among individuals within groups, in this case firms.

2.3.1 Measuring Partisan Polarization

Partisan polarization or party sorting can be conceived on several analytic levels deserving a fair amount of nuance. In this analysis, I am particularly concerned with partisan polarization,

[19] For the purposes of this analysis, I define an identifiable individual as an employee of a corporation, regardless of rank, job title, or location, who uses the same ostensible name across individual contributions in an election cycle. In either case, by defining individuals this way, I can conceivably identify changes in individual partisanship across election cycles, for example, as an employee progresses in a company, such as a move from a manager to a director or executive. Thus, ignoring occupations or locations in delimiting individuals has benefits. To arrive at the individual-cycle aggregation or grouping process, I used regular expressions to normalize the grouping features, chiefly an individual's name (as well as the master company ID and election cycle). In particular, names were cleaned prior to this aggregation to disambiguate multiple contributions from the same individual using slightly differing permutations of a name, such as extraneous punctuation, white space, character case, middle initials, suffixes, or degrees. In this way, the analysis best represents unique individuals, however, for perhaps obvious reasons, this would combine and collapse any cases where two or more people had the same name in a company and would treat an individual who changed companies and contributed under both companies as discrete people. Because no personally identifying information that could transcend time and location is available, there is not a viable way to discount this possibility, although on the whole, this issue, I suspect, would have a minimal if any impact on the results. For example if we ignored all individuals and occupations and instead aggregated all individual contributions to the firm level, we could still detect the degree to which a firm became more politically homogenous over time.

Table 2.4: Individual Partisans at Fortune 400 Companies, 1980-2018

	1980-2018	1980-1988	1990-1998	2000-2008	2010-2018
Major Party ID					
DEM	197,062 (36)	4,458 (48)	17,191 (41)	55,553 (43)	119,860 (33)
REP	351,279 (64)	4,813 (52)	24,880 (59)	74,171 (57)	247,415 (67)
Unknown	14,132 (3)	523 (5)	1,789 (4)	4,378 (3)	7,442 (2)
Partisan Score					
minimum	-1.00	-1.00	-1.00	-1.00	-1.00
median (IQR)	0.16 (-0.52, 0.50)	0.03 (-0.24, 0.65)	0.17 (-0.29, 0.80)	0.12 (-1.00, 0.81)	0.17 (-0.14, 0.42)
mean (sd)	0.05 ± 0.68	0.09 ± 0.64	0.12 ± 0.69	-0.01 ± 0.79	0.06 ± 0.63
maximum	1.00	1.00	1.00	1.00	1.00
Unknown	3,212 (1)	170 (2)	420 (1)	888 (1)	1,734 (0)
Individual Contributions	3,863,893	17,132	81,201	321,932	3,443,628
minimum	1	1	1	1	1
median (IQR)	2.00 (1.00, 8.00)	1.00 (1.00, 2.00)	1.00 (1.00, 2.00)	1.00 (1.00, 2.00)	4.00 (1.00, 13.00)
mean (sd)	6.87 ± 14.67	1.75 ± 1.81	1.85 ± 2.43	2.40 ± 4.21	9.19 ± 17.31
maximum	3057	32	54	109	3057
Firms	336	89	158	279	334
N	562,473	9,794	43,860	134,102	374,717

Source: FEC 2018a, 2018b.
Notes: N = 562,473 (Individuals X Firm X Election Cycle) represents individual-level data aggregated from individual contributions (contribution-level data). Individual contributions detail each contribution sub_ID for all individuals in the requested firms, in each election cycle 1980-2018. Categorical data, such as party identity, reports the number for each cell, followed by a percentage: N (%). As previously noted in the data pipeline, I queried for individual contributions from employees at current Fortune 400 firms using the given company names and firm aliases and subsidiaries, wherein not all companies returned results. Additionally, companies were subsequently filtered for quality control to help ensure only members of that company are represented. As an additional control, a threshold filter of $n = 10$ was set, such that each Firm X Election Cycle must have >= 10 individuals with a known major party identity and known partisan score. For comparison, a version of the data without the threshold ($n = 10$) filter is available in the appendix. Because both Fortune 400 firms were defined in present time and because campaign contributions dramatically increase over the past few decades, we see temporal increases in both the number of contributions, the number of individuals by firm by election cycle, and the number of included firms in increasing years. In the appendix, I likewise conduct robustness checks to illustrate that we see similar trends in partisan polarization using only constant 1980 firms.

such that *within a firm*, the partisan balance gravitates toward and is clustered around a singular party identification, namely the Democratic or Republican party.

Such a state could also be characterized as *within-firm partisan homogeneity* which corresponds to *increased between-firm partisan polarization*. As a matter of definitional shorthand, when I refer to polarized Democratic or Republican firms or increased partisan polarization at the firm level, such expressions denote increased partisan homogeneity within firms such that partisanship clusters around one party pole.[20] To measure whether a firm

[20]In other words, we are not interested in the strictest sense in *within-firm partisan polarization*, a state that would be characterized by having both a bimodal distribution of strong partisans, that is both a strong Democratic and a strong Republican faction of partisans within the same firm. This state also is differentiated

has partisan homogeneity or a strong clustering around one of the partisan identities, I used a joint measure using the second, third, and fourth moments, namely, variance, skewness, and kurtosis.[21] I define this measure as follows:

$$\text{Partisan Polarization} = \Big((\ 1 - \mathrm{Var}[X]\ ) \times |\ \mathrm{Skew}[X]\ | \times\ \ln (\ \mathrm{Kurt}[X] + 10\ ) \Big) \tag{2.1}$$

As an illustration of this measure, consider the overall partisan polarization (partisan homogeneity) for two example firms in 2018, Alphabet (Google) and Marathon Petroleum. As we will subsequently see in the analysis, Alphabet can be classified as a polarized Democratic firm whereas Marathon Petroleum can be classified as a polarized Republican firm.

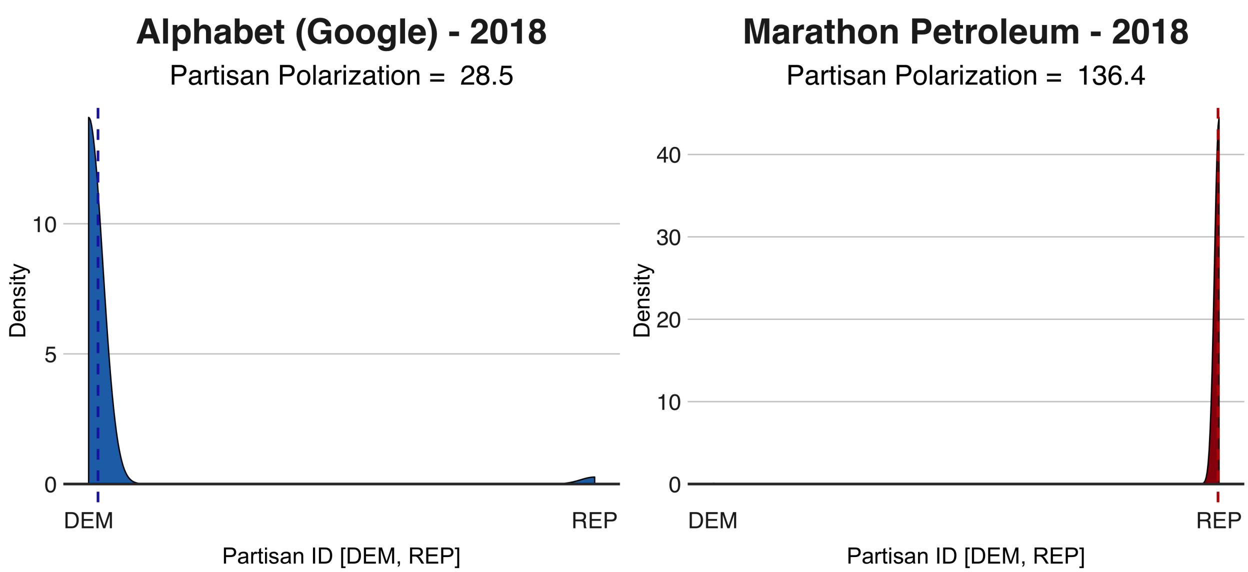


Figure 2.3: Density Distribution of Partisan Identities for Alphabet and Marathon Petroleum in 2018

Notes: Measure of partisan polarization calculated for all employees in 2018 for each company using Equation 2.1.

from a non-polarized bipartisan firm, wherein we see a highly heterogeneous mixture of weaker Democrats and Republicans.

[21] A prior version of this analysis used a simpler measure of polarization using only variance. Although not as many distributional nuances of polarization were captured, the end results were similar.

2.3.2 Within-Firm Differences or Similarities by Occupational Hierarchy

Although these two firms are illustrative of companies with a high degree of partisan polarization (within-firm partisan homogeneity), in the analysis, I take this one step further by not only considering the distribution of partisans within the entire company but also by examining similarity within firms across occupational hierarchies. In this way, we can better state whether partisan polarization is a phenomenon occurring throughout the firm versus simply an artifact of firm executives or board members. Thus, in the analysis, I calculate the partisan polarization measure (and other partisan metrics) by three levels of occupational hierarchy: Executives, which includes both proper executives as well as board members, managers inclusive of both managers and directors, and lastly, all other employees not in the first two leadership groups. Although occupational hierarchy can be determined through the FEC employer and occupation information from 2004 and onwards, election cycles 1980-2002 did not have this information. I therefore also present collective results for all employees in each election cycle 1980-2018.

2.3.3 Dynamic Time Warping Hierarchical Cluster Analysis

In this paper, I seek to illustrate the degree to which firms become more internally homogenous in their partisan expression, and similarly become more differentiated from the partisanship of firms of the opposing party. To classify firms and account for complex temporal dynamics in a variety of partisan measures captured at multiple levels of the occupational hierarchy, I combine several methods to perform what can generally be described as time series clustering. The specific method involves two processes: Dynamic time warping and hierarchical cluster analysis. Of these, hierarchical cluster analysis (HCA) is perhaps most widely known since it has been successfully applied to a number of past sociological studies of organizational emergence and organizational subsets (Laumann and Knoke 1987; Powell and Sandholtz 2012; Ruef 2000). In short, the method, as a form of unsupervised learning, typically utilizes one of two primary hierarchical clustering algorithms, namely agglomerative hierarchical clustering or divisive hierarchical clustering (Kaufman and Rousseeuw 1990; Martin Maechler and Schubert 2019; Tan and Kumar 2006). Agglomerative hierarchical clustering can proceed using two approaches alternatively referred to as agglomerative nesting (AGNES) or divisive analysis (DIANA). These approaches refer to an unsupervised learning method in which the data is either progressively merged into fewer or divided into a greater number of clusters, K, specified by the user (Kaufman and Rousseeuw 1990: 44). Although HCA algorithms have the ability to cluster data into K clusters using multivariate data across a variety of distance measures and agglomerative or divisive methods, the process does not have an inherent ability to incorporate temporal patterns. This is where dynamic time warping enters the equation. Dynamic time warping distance is a model-free dissimilarity measure which seeks to "find a mapping r between the [time] series so that a specific distance measure between the coupled observations (X_{a_i}, Y_{b_i}) is minimized" (Berndt and Clifford 1994; Montero and Vilar 2014: 5). Unlike many of the time series clustering methods outlined by Montero and Vilar (2014), dynamic time warping has the ability to take a matrix of multivariate time series. Such a feature is important to this analysis since we would like to characterize firms by their temporal patterns across multiple variable spaces. Once the dynamic time warping distance matrix is calculated, we can perform traditional hierarchical clustering analysis, which is the approach used in this study.

2.3.4 Model Evaluation

To determine the optimal method for HCA, one of the initial decisions is to specify the number of clusters, K to be used. A standard method of making this determination—known as the elbow method—is to evaluate the drop-off in additional percentage of variance explained using the total within-cluster sum of squares. Although the algorithm for calculating this metric is not amenable to a dynamic time warping distance matrix, a matrix of model features can be passed over various temporal periods. Such an analysis reveals that the HCA model gains the most information by using $K = 3$ clusters under a number of discrete temporal periods (Figure 2.4).

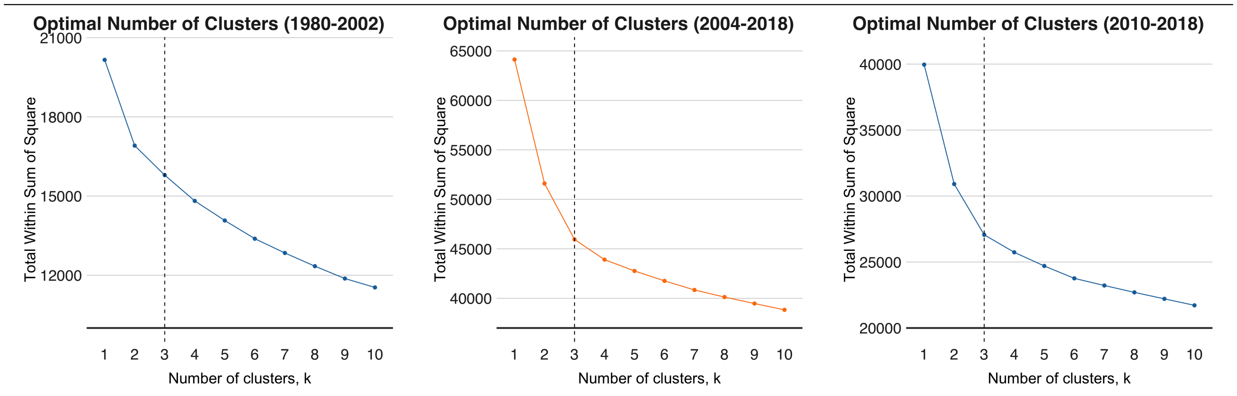


Figure 2.4: HCA Agnes Optimal Number of Clusters, 1980-2018

Notes: Optimal cluster analysis determined using the within cluster sum of squares for three HCA AGNES algorithms performed using Ward's method for individual-level firm data. The three periods evaluated include 1980-2002, 2004-2018, and 2010-2018. Each graph reveals a drop off in the additional within cluster sum of squares after K=3 clusters. AGNES in 2004-2018 has the highest total within cluster sum of squares.

Once I determined $K = 3$ optimal clusters, I tested several feature sets (multivariate time series) on which to calculate the dynamic time warping distance. For simplicity, I will refer to these time series feature sets as models, which included a variety of measures (Table 2.5). In the table, each of the listed model variables occurs by occupational hierarchy, that is, executives, managers, and others. For example, the models include a time-series of the mean-party identity of executives, of managers, and of other employees for every firm, for the years in which that data exists for that firm.

For each of these models, a dynamic time warping distance matrix was calculated, which I used to evaluate a number of possible agglomerative and divisive hierarchical clustering algorithms. Generally, the higher the resulting agglomerative or divisive coefficient, the better the model. In all cases, the AGNES model using Ward's method provided the hierarchical cluster analysis with the best coefficient (Table 2.6). Because Model 1 and Model 2 had comparable agglomerative coefficients, I selected Model 1, which utilized a greater number of partisan features.

Table 2.5: Dynamic Time Warping Model Variables, 1980-2018

Model 1 (336 x 51 x 20)	Model 2 (336 x 60 x 20)	Model 3 (336 x 30 x 20)
Mean Party ID [DEM, REP]	Mean Party ID [DEM, REP]	Mean Party ID [DEM, REP]
	Mean Party ID [DEM, OTH, REP]	Mean Party ID [DEM, OTH, REP]
Median Party ID [DEM, REP]	Median Party ID [DEM, REP]	
	Median Party ID [DEM, OTH, REP]	
Mean Partisan Score	Mean Partisan Score	Mean Partisan Score
Median Partisan Score	Median Partisan Score	Median Partisan Score
Mean Partisan Score (Mode)	Mean Partisan Score (Mode)	
Mean Partisan Score (Min)	Mean Partisan Score (Min)	
Mean Partisan Score (Max)	Mean Partisan Score (Max)	
	Total Contributions	
Variance Party ID [DEM, REP]	Variance Party ID [DEM, REP]	
Skewness Party ID [DEM, REP]	Skewness Party ID [DEM, REP]	Skewness Party ID [DEM, REP]
LN Kurtosis Party ID [DEM, REP]	LN Kurtosis Party ID [DEM, REP]	
Polarization Party ID Base	Polarization Party ID Base	Polarization Party ID Base
Polarization Party ID [0, 1] Scaled	Polarization Party ID [0, 1] Scaled	Polarization Party ID [0, 1] Scaled
Variance Partisan Score	Variance Partisan Score	
Skewness Partisan Score	Skewness Partisan Score	Skewness Partisan Score
LN Kurtosis Partisan Score	LN Kurtosis Partisan Score	
Polarization Partisan Score Base	Polarization Partisan Score Base	Polarization Partisan Score Base
Polarization Partisan Score [0, 1]	Polarization Partisan Score [0, 1]	Polarization Partisan Score [0, 1]

Notes: N = 336 firms. Each model has maximum possible dimensions of N = 336 Firms by V (model variables by occupational hierarchy) by Y = 20 Election Cycles 1980-2018. Note that each model variable occurs by occupational hierarchy collapsed to three levels such that 1980-2002, all employees are equivalent to others and 2004-2018 others only includes employees not in the executive or manager categories. Because not every firm exists in each year, the number of election cycles or dimensions of the matrix of time series varies. Therein, each univariate time series in the numeric matrix of time series matrices has varying numbers of years, depending on the election cycles in which the variable exists or the firm exists. Before dynamic time warping distance can be calculated, all variables had to be converted to numeric, and null values had to be omitted. Prior to omitting remaining null values, they were propagated using "forward" and "back" filling of features across columns. For example, if a firm was missing a statistic for managers in an election cycle that value could be carried forward from executives or backward from other employees (in the same firm). Additionally, all data was scaled (without mean-centering) prior to final omission of remaining null values.

Table 2.6: Dynamic Time Warping HCA Model Evaluation, 1980-2018

	Model Coefficient		
Model, Method	Model 1	Model 2	Model 3
AGNES, UPGMA	0.656	0.646	0.705
AGNES, WPGMA	0.703	0.688	0.753
AGNES, Single Linkage	0.622	0.608	0.707
AGNES, Complete Linkage	0.807	0.800	0.848
AGNES, Ward's Method	0.921	0.919	0.916
Diana	0.763	0.751	0.819

Source: FEC 2018a, 2018b.
Notes: N = 336 Firms. Based on data from 562,473 (Individuals X Firm X Election Cycle) for 1980-2018. This data represents individual-level data aggregated from individual contributions (contribution-level data). Companies had an inclusion threshold of $n = 10$, such that each Firm X Election Cycle must have >= 10 individuals with a known major party ID and known partisan score.

2.4 Analysis

2.4.1 Increasing Partisan Polarization Across Firms?

Returning to the core research question, I ask, *to what extent has party sorting or partisan polarization emerged in the American corporation?* As a first step of analysis, we should confider the temporal changes from 1980 to 2018. Recall, that we are interested not only in whether there has been an overall increase across all individual-level contributions within firms, but also whether we see parallel changes for discrete hierarchical levels of employment. For example, are only executives exemplifying increased party sorting, or are managers and other employees also exhibiting similar changes? Consider the aggregate changes in partisan polarization as well as the total number of individual contributors across the included Fortune 400 firms, Figure 2.5.

Examining the figure, we can see that whether we measure partisan polarization using the party affiliation or the partisan score, although there was a slight decline in within-firm partisan polarization from the 1980s through the 2000s, there have been substantial increases in partisan polarization (political homogeneity) within firms, particularly from 2012 to 2018. In part, the trend of a decline in these measures of partisanship may be explained because we are examining *within-firm* measures of dispersion, such as variance, skew, and kurtosis of partisanship. In the 1980s, not only are fewer firms in the dataset but also most firms only had a handful of individual contributors, and this was likely a self-selected and perhaps more politically homogeneous group of individuals than in later eras. For example, this might have been largely executives, although further exploration would be needed to investigate this question empirically. In either case, as the number of individuals contributing gradually increased, it appears that so, too did the political diversity, at least assuming these new contributors represent a more politically discrete group than those previously contributing. If these assumptions prove true, partisan polarization would appear to decrease because a

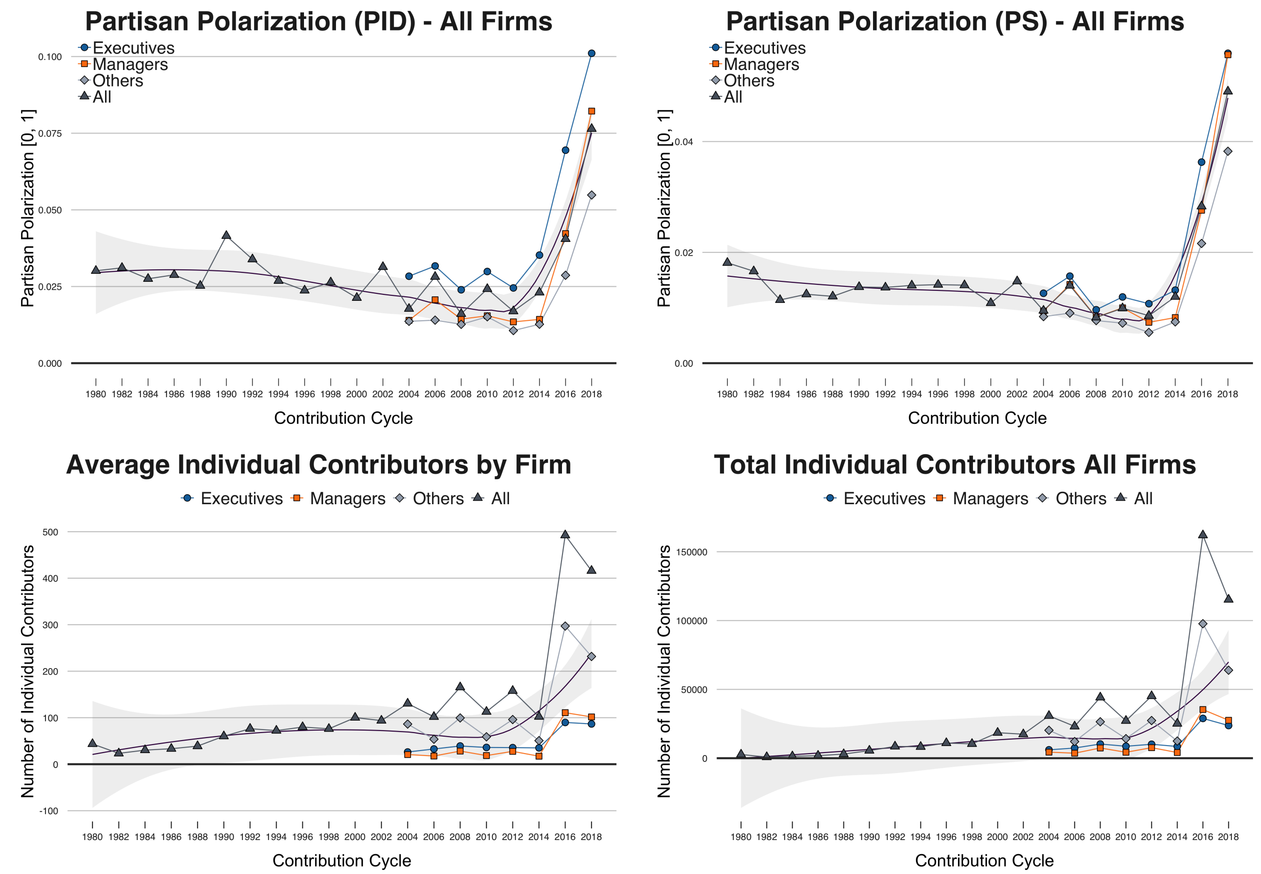


Figure 2.5: Partisan Polarization Across Fortune 400 Firms, 1980-2018

Notes: Partisan polarization calculated by election cycle and occupational hierarchy (executives, managers, others, and all employees combined) using both party identity and partisan score for all firms, 1980-2018. N=336 firms. Executives include both corporate executives (such as president, CEO, or vice president) as well as other executives and board members. Managers represents management broadly defined, including both managers and directors. The category, others, reflects firm employees not in the first two groups. All employees are the combination of these groups. Election cycles 1980-2002 did not have the occupational information needed to make this differentiation. In these figures, the raw partisan polarization scores yielded from Equation 2.1 has been rescaled to a range of [0, 1] across all years, and it should be noted that with or without the scaling, the same pattern is evident.

more diverse group of employees, not only executives, were increasingly contributing in these firms. Of course, to demonstrate this would require additional analyses beyond the current scope, which to reiterate is chiefly to document whether firms are becoming increasingly homogenous in their partisanship rather than explaining why this might occur. What is ostensible in the current data is that as the number of individual contributors continued to rise in the 2000s, the decline in partisan polarization flattened until about 2012 when, despite a continued increase in individual contributors, the manifested partisan polarization also began to increase.

This seems to be particularly true from 2014-2018, where we witness a drastic increase in the total number of individual contributors as well as the average number of individuals contributing per firm. At the same time, the partisan polarization that began between 2012 to 2014, accelerates from 2014 to 2016, a period that bore out some of the more controversial presidential politicians in recent memory. These increases illustrate that not only are a greater number of individuals than ever before expressing their partisanship, but by way of publicly expressing this partisanship with their wallets, these individuals show a greater commitment to party than their baseline state of not contributing. If individuals were randomly allocated to firms, such an activation of partisanship would not result in a marked increase in within-firm partisan homogeneity. In fact, partisan homogeneity would decline, not increase as it did post-2012. Instead, what we see is evidence that individuals within firms are becoming increasingly similar in their partisan expression, particularly after 2012, increasing thereafter through 2018.

As previously theorized, this process likely has complex mechanisms but could include increased mobility of employees to relocate or select into firms that align with their partisan identity or their ideological beliefs as structured by their partisanship. Similarly, organizations might unconsciously create partisan cultures through the actions or memorandum of executives or by the political conversations and attitudes expressed by coworkers. In some cases, those partisan opinions or attitudes might reflect derogatory sentiment towards the opposite political party. Those at odds with the political majority might remain silent rather than face ostracism or instead elect to transition to another firm better suited to their political outlook. For example, if partisan minorities were to stifle their partisan expression, voluntarily exit, or face termination, we might also see some of these same patterns demonstrated above. Such ideas have grounding in the literature, especially those on affective polarization (Cowan and Baldassarri 2018; Iyengar and Westwood 2015; Iyengar et al. 2019). To better explore some of these possibilities in subsequent analyses, for example, we could directly assess the extent to which affective polarization and partisan homophily affect hiring or corporate leadership appointments. Although these ideas are speculative, they present plausible explanations, given the evidence at hand, chiefly a decline followed by a sharp increase in partisan polarization; one that corresponds to shifts in the number of partisan contributors.

Collectively, these findings in Figure 2.5 are true of all employees on balance. While the trend exists for all employees, we can see that, in the years with discrete occupational hierarchies (2004-2018), the trend of increased party sorting also exists for executives, management, and other employees alike. Although the effects of party sorting are stronger among executives and weaker among other employees, all types of employees studied reflect this trend of increasing partisanship, on average. Rather than being simply a phenomenon affecting executives, the pattern affects all employees within the firm and suggests that over time, individual employees within these companies are becoming more politically homogenous within levels, and as suggested by the increase across all employees, they are also increasingly similar in their partisan attachments across levels. We should note several important caveats. First, early years in the temporal pattern exhibit greater variation than the average result across firms.[22] Second, partisan polarization vacillates between election cycles, particularly presidential election cycles (in which more people vote and more individuals and individual contributions exist) compared to non-presidential election cycles. Lastly, as already noted, the general decline and subsequent increase in partisan polarization is perhaps explained by the increased number of individual contributors and total contributions during this period.[23] In particular, we can view the combination or an increased number of contributors with the increased partisan polarization in society en masse to coalesce with the likely fact that even without the rise in affective polarization in recent years, individuals were already likely sorted

[22] There are several reasons for this trend. First, the Fortune 400 list, taken in 2018, necessarily shifts over time, such that only 134 of the 336 companies evaluated also had data in 1980, and of those existing in the dataset during that election cycle, only 26 had the imposed $N \geq 10$ individuals with a known major party identity and known partisan score. In part, because the graphs reflect within-firm trends averaged across multiple firms and the firms present in all years differ from firms that only have data in recent years, the increased variability in the 1980s through 2000s follows expectation.

[23] Such trends are evident in Figure 2.5, however, we can also see increased numbers of contributors by period in Table 2.4.

to some degree into firms that leaned toward the Republican or Democratic direction.[24] If such latent partisan dispositions heighten or activate following increased party sorting in society, then the increasing political polarization of political elites and their election campaigning could, in turn, amplify subsequent party sorting as an increasing number of copartisans demonstrate mutually reinforcing expressions of partisanship.[25] The dramatically increasing number of individual contributors in recent years, particularly during the 2016 election cycle, suggests that increased activation may be occurring.

2.4.2 Identifying the Emergence of Partisan Firms

Although analyzing overall trends in partisan polarization answers the first element of the research question, namely whether there has been an increase in party sorting, it does not fully address whether certain types of firms emerge as especially partisan political actors and whether these are generally Democratic or Republican firms. For that, we need to turn toward hierarchical cluster analysis, which has been previously used in the assessment of emergent organizational forms (Laumann and Knoke 1987; Powell and Sandholtz 2012; Ruef 2000). As discussed, I use a dynamic time warping distance matrix in combination with the hierarchical cluster analysis to better identify alignments in temporal partisan patterns. For emphasis, although we might arrive at similar results by simply categorizing firms in terms of overall mean partisanship and how polarized they were using a measure of partisan polarization, it would be difficult to decide exactly how to make these decisions. For example, what year would we use for each measure and which level of the occupational hierarchy should be considered for each variable, and in what year? As seen in Table 2.5, even with a small number of variables, we can have 30-60 parameters varying for up to 20 years for as many

[24]For example, see the work of increased party sorting or partisan polarization in recent years (Baldassarri and Gelman 2008; Baldassarri and Goldberg 2014), and the idea that individuals sort into firms with which they align (DiMaggio 1992; Kalleberg and Sørensen 1979; Rivera 2012b; Schneider 1987; Sørensen and Kalleberg 1981).

[25]See Hetherington (2001), Hetherington (2009), Sood and Iyengar (2016). I elaborate on the possibility of an activation hypothesis in the dissertation introduction and conclusion chapters.

as 336 firms. Dynamic time warping cluster analysis can handle such complex variations in simultaneous multivariate time series data, for example, revealing asynchronous pattern alignment, that cannot be easily deduced with a simpler method.[26] As previously shown, I utilized the dynamic time warping distance on Model 1 parameters using the AGNES, Ward's method with $K = 3$ clusters. This model provides the following cluster dendrogram.

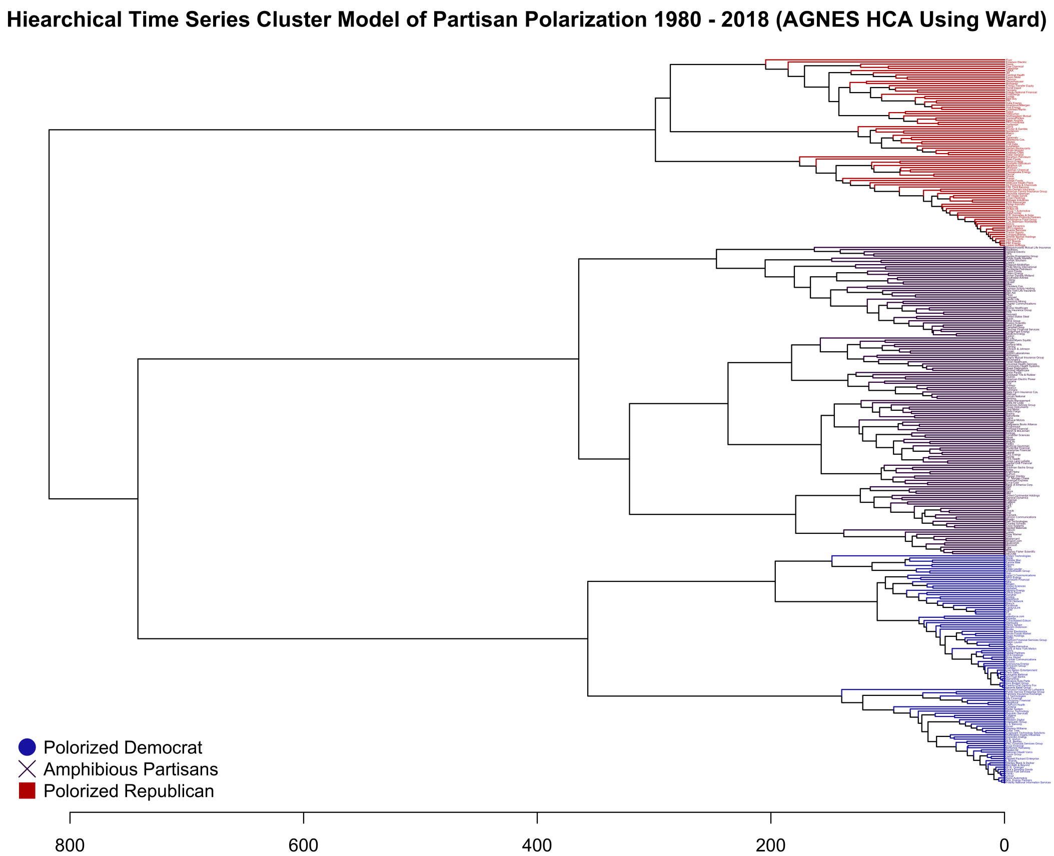


Figure 2.6: Result of Dynamic Time Warping HCA AGNES-Ward Clustering Model for Fortune 400 Companies, 1980-2018

Notes: Dynamic time warping refers to a type of time series clustering model, specifically the use of the dynamic time warping distance matrix, to which I apply the hierarchical cluster analysis (HCA) AGNES algorithm using Ward's method for individual-level firm data, 1980-2018. K=3 clusters determined the following optimal cluster analysis for various time periods. AGNES Ward's method selected, agglomerative coefficient = 0.92.

To help facilitate an understanding of the three primary clusters, I will provide a few examples to help us infer meaning from the classification. Assessing the results, I label these clusters

[26] An admittedly interesting comparison could be drawn from comparing the dynamic time warping clustering analysis with a considerably simpler manual classification using only a few variables collapsed across years and occupational categories. Such an analysis is beyond the current scope, although it should be noted that even using a simpler non-dynamic time warping hierarchical cluster analysis yields similar results, which I include in Appendix B for completeness.

as polarized Democratic, amphibious partisan, and polarized Republican firms (Figure 2.6). From Figure 2.6 we can generalize several findings about the clusters. For example, a number of the partisan Republican firms include major oil and energy companies such as Marathon Petroleum, Marathon Oil, Anadarko Petroleum, Phillips 66, or ConocoPhillips; agricultural and food companies such as Monsanto, Dean Foods, and Hormel; and major home improvement retailers or construction equipment manufacturers such as Home Depot and Caterpillar. Conversely, many of the polarized Democratic companies identified include large technology companies such as Apple, Alphabet (Google), and Amazon, as well as entertainment groups such as Disney, Netflix, or CBS, and consumer product firms like Nike or Starbucks. Meanwhile, amphibious firms represent some of the largest corporations including banks such as Goldman Sachs and J.P. Morgan Chase, automobile manufacturers such as General Motors or Ford, military providers such as Boeing, Lockheed Martin, and Northrop Grumman, and major retailers like Walmart and Walgreens. Although the exact degree of partisan polarization and the average partisanship of each company varies, as we will see, when taken on balance, the time series hierarchical clustering method appears to have identified three types of emergent firms with distinct qualities.

2.4.3 Evaluating Partisan Polarization in Democratic, Republican, and Amphibious Firms

Let us first consider changes in partisan polarization over time for the three types of organizations (Figure 2.7). Examining Figure 2.7, which illustrates changes in partisan polarization using both the party identity and partisan score measures, we can see that, similar to the overall trends across all firms, party sorting (within-firm partisan homogeneity) began to substantially increase after 2010 and 2012, particularly for polarized Republican firms. When examining the degree of partisan polarization in the identified organization types, note some general patterns that exist. First, regardless of firm type, all firms showed increases in partisan polarization from 2012 to 2018, mirroring the overarching pattern established previously. Yet, whereas the increase in party sorting does not truly crystalize in amphibious firms until after 2010-2012, polarized Democratic and Republican firms evidence a slightly higher level of partisan polarization between 2004 and 2010 compared to amphibious firms. Although a higher degree of party sorting emerges from the plots calculating polarization from the binary two-party measure versus the partisan score, both measures increase post-2012.

Focusing on Democratic firms specifically,[27] one trend that stands out in either graph is that the levels of partisan polarization, while admittedly lower on average, exemplify a higher degree of similarity across occupational levels than other types of firms. Whereas there is typically less partisan homogeneity (and a higher measure of polarization) among executives compared to other employees in Republican and amphibious firms, this is not the case in Democratic firms. In other words, the level of partisan polarization by executives in these companies is quite similar to the degree of party sorting among the average employee. By contrast, a large magnitude of difference separates the polarization of executives and other employees in amphibious firms.

This latter point deserves highlighting. Although some amphibious firms have higher levels of partisan homogeneity among executives and managers, these same firms have considerable political diversity among common employees. Consider, for example, the average employee outside firm leadership in Democratic firms who experiences less political diversity than analogous employees in amphibious firms. So while the executives in amphibious firms might have higher partisan polarization compared to executives in Democratic firms, the typical employee in a Democratic firm is more likely to work with others who hold the same partisan identity than the typical employee in an amphibious firm. In other words, in a polarized Democratic firm, an entry-level employee is more likely to share the same partisanship as firm executives. The same cannot be said for amphibious firms.

[27] Echoing a prior point, election cycles between 1980 and 1990 exhibit substantial variation, particularly for Democratic firms, many of which are technology-based and did not exist or were not in the Fortune 400 during that period.

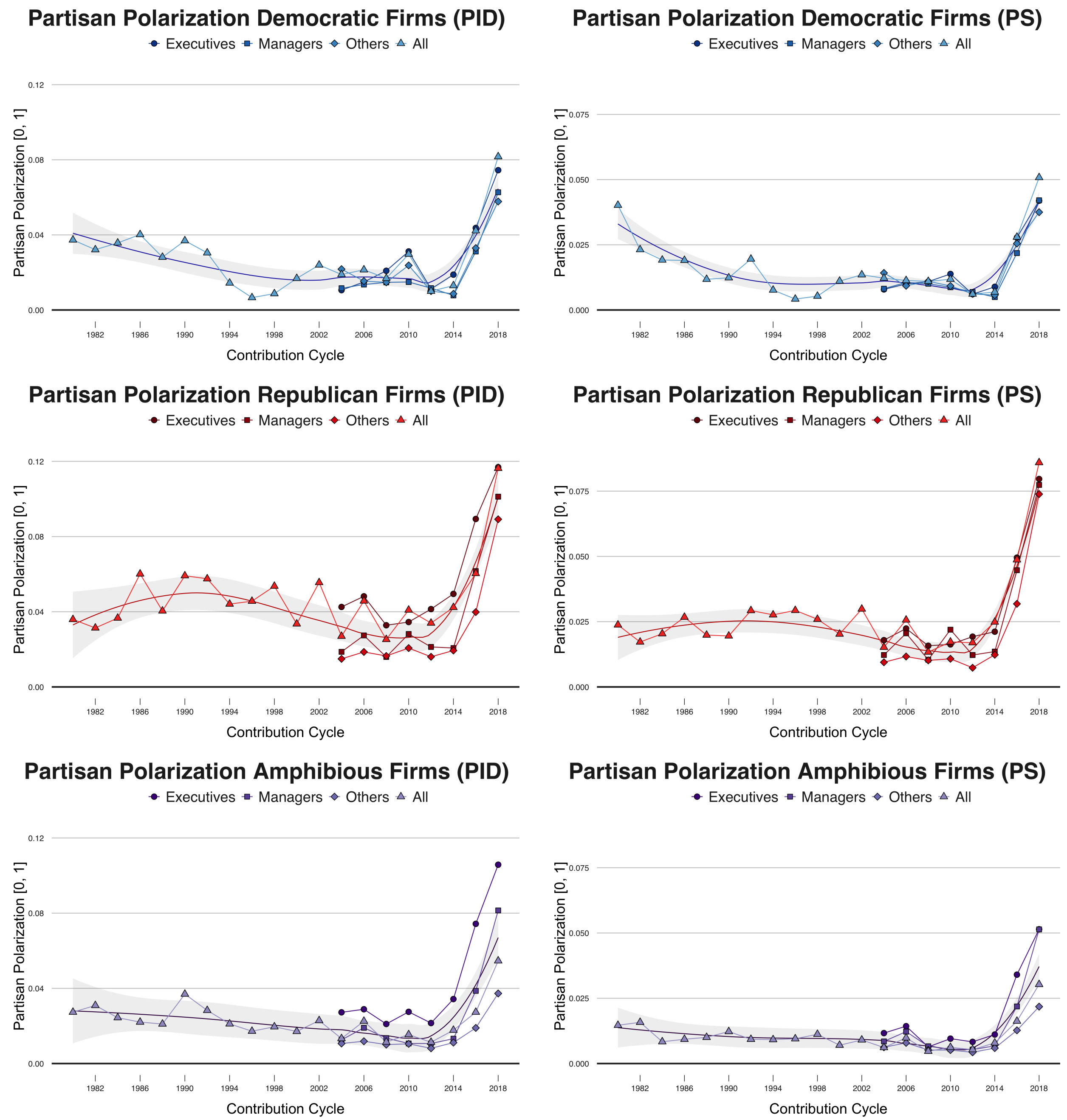


Figure 2.7: Partisan Polarization Levels (by Partisan Metric) in Identified Democratic, Amphibious, and Republican Firms

Notes: Partisan polarization calculated using *party identity* or *partisan score* for Democratic, amphibious, and Republican firms. Partisan profile classified using dynamic time warping hierarchical cluster analysis, AGNES algorithm, using Ward's method for individual-level firm data, 1980-2018. Each subplot represents one of those three identified clusters.

2.4.4 Intensifying Partisanship in Democratic, Republican, and Amphibious Firms

Yet, measures of partisan polarization in isolation do not tell the full story. We must also consider the average partisanship of these Democratic, Republican, and amphibious firms to better understand how they change over time (Figure 2.8). In particular, both polarized Democratic and Republican firms illustrate an intensification of average political partisanship across occupational hierarchies with successive election cycles. In other words, individuals within these firms are becoming stronger partisans. Employees in Democratic firms are becoming stronger Democrats while those working in polarized Republican firms are becoming stronger Republicans. These trends of intensification remain particularly acute in polarized Democratic as well as Republican firms, which demonstrate intensification of partisanship, both by mean party affiliation and mean partisan score. We can see, for example, that from 1980 to 2018, the classified Democratic firms fundamentally transform, shifting from primarily Republicans to primarily Democrats.

Whereas over 75% of individuals in these firms could be characterized as Republicans in the early 1980s, from 2016 and onward, over 60% were Democrats. Moreover, the average partisan score of individuals in these firms transformed from weak Republican to strong Democrat. To repeat a prior point, part of this phenomenon is driven by the limited number of included firms in 1980, combined with the fact that of these, an even smaller number are Democratic. Apple stands out as a preeminent example. Although Apple is presently an example of a polarized Democratic firm, in the early 1980s, we see evidence that employees contributing therein were more likely to be Republican. Combining the party transition of a small number of firms combined with the influx of many new distinctly Democratic firms, such as Tesla, Netflix, or Alphabet (Google), among others, gives the impression that this is primarily a Democratic phenomenon. Yet, considering the mean party identification in Democratic firms from 2010 to 2018, these firms showed some movement toward the Republican direction before becoming increasingly Democratic and returning to 2010 levels.

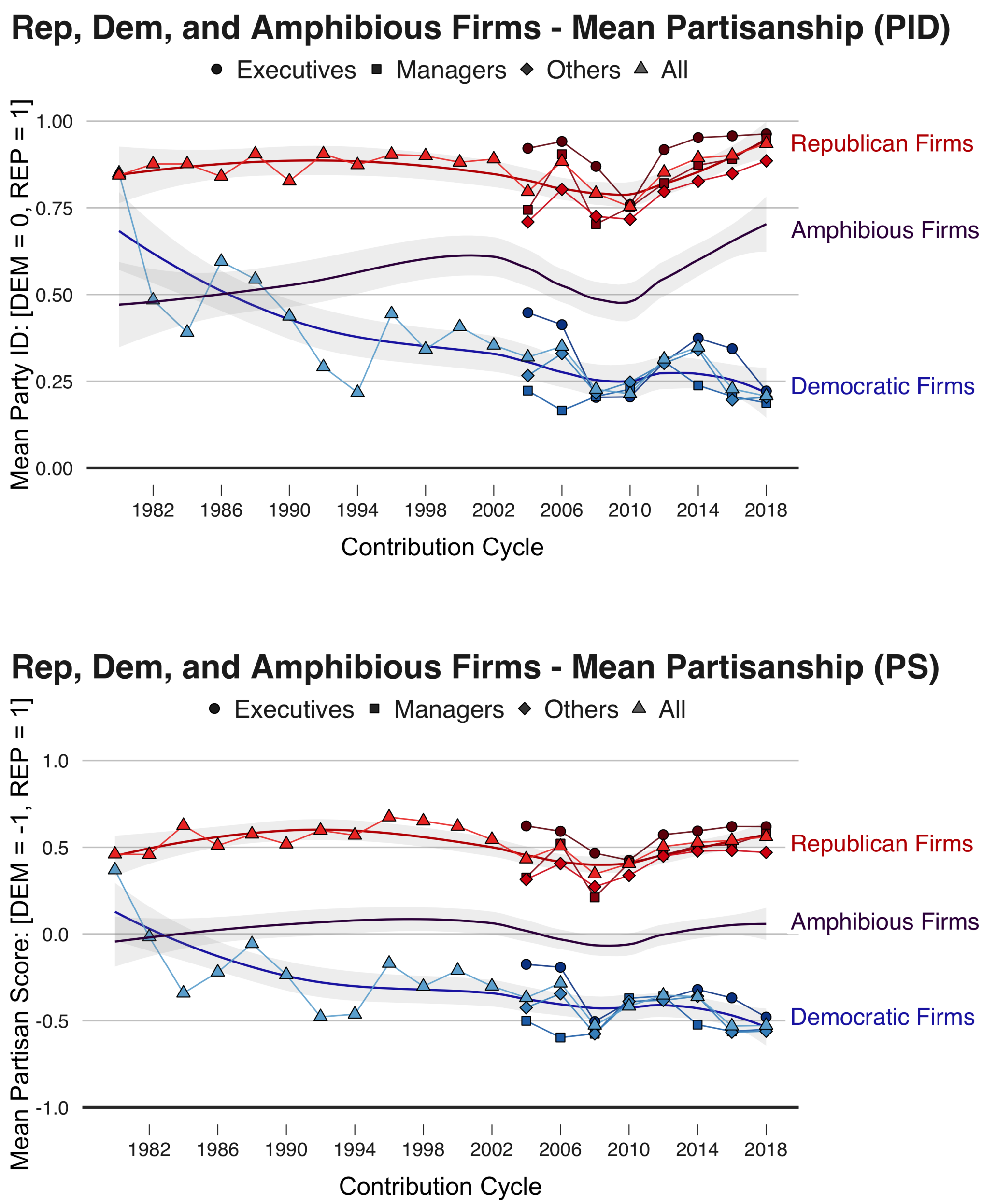


Figure 2.8: Mean Partisanship in Dynamic Time Warping AGNES-Ward (1980-2018) Democratic, Amphibious, and Republican Firms

Notes: Mean partisanship calculated using either *party identity [DEM = 0, REP = 1]* or *partisan score [DEM = -1, REP = 1]* for Democratic, amphibious, and Republican firms. Firms classified using (HCA) AGNES, Ward's method, 2004-2018, N = 336 Firms.

Echoing an earlier point, employees at all levels in these Democratic firms grew increasingly homogeneous in their partisanship. Consider in 2004 and 2006 the partisan gap between executives versus managers and other employees. By 2008, these gaps had narrowed and remained tightly correlated, particularly from 2008 to 2014, but also through the most recent presidential and midterm elections.

Offering a foil to polarized Democratic firms, polarized Republican firms also became increasingly partisan during this period. On average, these firms went from having over 50% Republicans to about 75% Republicans from 1980 to 2018. That was in contrast to the period of 2010 to 2018 in Democratic firms, wherein Democratic firms become slightly more Republican before returning to 2010 levels in 2018. In Republican firms, we see a consistent increase in Republican Party expression during this same period. A smaller subset of these firms experience even higher levels of partisan alignment. In the extreme, consider Marathon Petroleum, which in 2018 had 99.8% Republican Party identification among all measured employees. Throughout this period, the average partisan score of individuals went from primarily weak to moderate Republican and then crossed firmly into strong Republican territory in recent years. Whereas employees across levels in Democratic firms became more homogenous, a slight divide between executives and all other employees (management and others) exists in Republican firms, where executives are consistently among the strongest Republicans within those companies.

Finally, the partisanship of amphibious firms provides some important insights. Representing a large subset of firms, amphibious organizations generally leaned Republican through most years, hovering primarily around an even split between Democrats and Republicans on average. There is some evidence that this behavior is perhaps strategic and varies with presidential party leadership, particularly from 2004 and onwards. For example, in 2008 and 2010 during President Obama's first term, the majority in amphibious firms leaned towards the Democratic direction, a trend that did not fully recover in the Republican direction until the 2014-2018 election cycles. Reiterating the general partisan moderation of amphibious firms, the mean partisan score for these companies hovers around 0, which represents independents or a politically neutral position. Collectively, these findings help to validate the results of the dynamic time warping, hierarchical clustering analysis in identifying discrete types of partisan firms.

2.4.5 Linking Partisan Firms and Organizational Behavior

Although the aforementioned analyses work to establish the emergence of partisan polarization across firms—or increasing partisan homogeneity within in firms—for such analyses to reflect the idea that firms are emergent in their partisanship, at least in the collective sense that extends beyond considering firms as simply a reflection of their individual actor members, we should expect, in some sense, that these firms would also differ at the firm level in a way associated with the identified partisanship of the individual partisans therein. To help assess this possibility, I lastly consider an additional external dataset by a third party purveyor, MSCI, which documents both problematic and beneficial environmental, social, and governance (ESG) factors at the firm level for institutional investors. This dataset, known as the *MSCI ESG KLD STATS*, is a longitudinal dataset (1991-2016), which documents thoroughly researched annual scores (1 or 0) in a number of specific topic areas including positive indicators which reflect best practices for corporations as well as negative factors that firms should avoid. Of particular note, the MSCI documents diversity and labor rights factors, among other measures of corporate social responsibility.

To assess how the classified Democratic, amphibious, and Republican firms vary in their firm-level behavior, I joined the MSCI data to the clustering results by firm, summarizing the MSCI firm rankings across years. In this way, both positive and negative ranked factors accumulate over time. So how are firm behaviors associated with the dynamic time warping HCA classified clusters? Examining the correlation heatmap of significant correlations ($\alpha \leq 0.05$), we see results that mirror the expected partisan affiliations of these firms. For example, partisan polarized Democratic firms were significantly more likely to have fewer union relation concerns, and were significantly more likely to be positively ranked on their labor rights merits. In terms of firm diversity, Democratic firms were significantly correlated with having fewer total diversity concerns. As we shall see, these results offer an important contrast to the behavior manifested in polarized Republican firms.

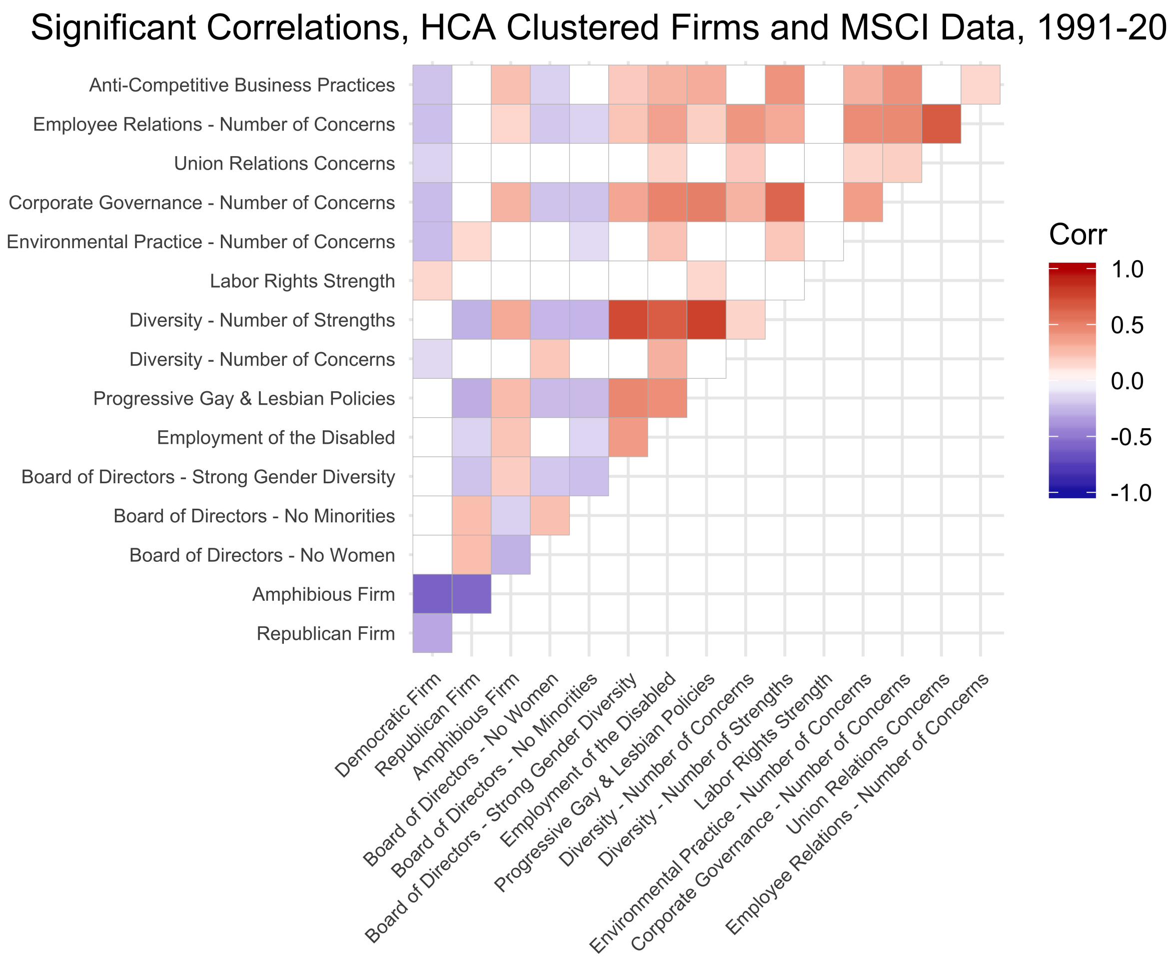


Figure 2.9: Significant Correlations of MSCI Diversity Scores and Dynamic Time Warping HCA AGNES-Ward Clusters, Fortune 400 Companies, 1991-2016

Notes: Spearman Correlations calculated for N = 320 Dynamic Time Warping HCA Clustered Firms (Model 1) that could be matched with the MSCI Data, 1991 - 2016. Variables aggregated through summation. All displayed correlations in the plot are statistically significant, $\alpha \leq 0.05$.

Switching our focus to polarized Republican firms, the diversity findings are even more stark. For instance, polarized Republican firms had a significant and strong correlation with the presence of fewer total diversity strengths, and were also less likely to have progressive gay or lesbian policies, less likely to employ the disabled, less likely to have favorable work-life benefits, and less likely to have strong gender diversity on their boards of directors. In fact, of the classified firm types, polarized Republican firms were the only ones which had significant and positive correlations to having boards of directors which both did not have any minorities and also had no women.

So how do amphibious firms fare? Although there are some issues needing attention, such as being positively associated with increased union relation concerns or a slightly higher number of diversity concerns, in most respects, amphibious firms do well on a number of the diversity metrics. For example, amphibious firms are more likely to have a higher number of diversity strengths as well as progressive gay and lesbian policies, employment for the disabled, strong work-life benefits, and strong gender diversity on their board of directors. Similarly, amphibious firms are less likely to have boards without minorities or women.

How might we adjudicate the findings for amphibious versus Democratic firms? First, there are more amphibious firms than Democratic firms, and these firms are among the oldest and most established firms in the dataset. Indeed, many of the technology firms found in the Democratic polarized firms, such as Netflix or Tesla did not exist in the 1990s, or even if they did, were not publicly traded and therefore not in the MSCI data. In combination, because the data is aggregated across years, firms that appear in more years have higher totals in both positive and negative factors, and thus have a greater potential of a significant correlation with firm classifications. In either case, the firm-level diversity, governance, and labor factors align with expectations we might have for Democratic, Republican, and amphibious firms. These results suggest that the classifications yielded using individual-level partisan data do, in fact, translate to firm-level partisan associations and organizational behavior.

2.5 Discussion

Throughout this analysis, I have sought to examine a fundamental research question: Have we seen an increase in partisan sorting within firms, such that the employees therein have become increasingly homogenous in their partisan identity? If so, do these patterns of increased party sorting uniformly exist across multiple occupational hierarchies, and have certain types of organizational forms emerged? We might also ask whether corporate politics are shifting such that the firm is emerging as a political actor as reflected by the increased partisan homogeneity and consolidated political attachments of its employees, and do such notions of firm-actorhood correlate with firm-level behavior? As I have demonstrated in the analysis, we have seen that partisan polarization has undoubtedly increased across firms in the past several decades, such that individuals within firms are increasingly alike in their partisanship and increasingly dissimilar between firms of opposing parties. Rather than a phenomenon simply affecting executives or corporate elites, party sorting has increasingly manifested across occupational hierarchies to include managers and all other types of employees. Some types of firms, however, are more affected than others.

Using dynamic time warping in combination with hierarchical cluster analysis, my study reveals three types of emergent organizational forms, namely polarized Democratic firms, polarized Republican firms, and amphibious firms that are more generally moderate and which have more partisan diversity between executives and other employees. Of these firm types, Democratic and Republican firms exemplify the strongest cases for emergence, particularly given both the homogeneity of partisan attachment across occupational levels and the transformation of these firms as increasingly strong partisan entities. As seen in the analysis, the phenomenon of increasing partisan polarization is not simply an individual-level manifestation of increasing partisanship occurring within society, but rather a condition that is systematically increasing and gravitating toward opposite partisan poles in Democratic and Republican firms, respectively. In other words, although individuals might increasingly identify with one party or another, such results would not inherently cause *firms* to appear increasingly homogenous in their partisan expression without some combination of individual sorting into firms matching their partisan disposition, and perhaps some combination of voluntary or involuntary departure or suppression of partisan minorities in firms. Rather than simply affect individuals, the partisanship that emerges among individuals in these firms translates to firm-level behavior, for example, differential institutional investor rankings on firm diversity and workforce climate.

These findings have a number of implications to the existing research. The emergence of several types of partisan polarized firms, particularly polarized Democratic firms, underscores my argument of *organizational partisanship*, or the idea that firms can emerge as political actors not only through the partisan identities and the partisan strength of its employees, but institutionally as a phenomenon associated with differential firm-level behaviors. While the mechanisms of such a phenomenon certainly deserve further attention, these results, nonetheless, have implications for the firm-actorhood literature (Bromley and Sharkey 2017; King et al. 2010; Meyer and Bromley 2013). For example, instead of harnessing the power of firm-actorhood from the perspective of position-taking in official corporate records or strategic documents (Bromley and Sharkey 2017; Meyer and Bromley 2013), which we might consider formal organizational structure, I have shown that firm-actorhood can emerge through the informal partisan representation of its employees. Recall that firm-actorhood must embody sovereignty, purposive action, and identity (King et al. 2010), where identity is the cornerstone (Bromley and Sharkey 2017; King et al. 2010) guiding purposive action, and this action is enabled by organizational sovereignty. Therefore, the actions of firms to curate and regulate the suitability, culture, and socialization of its members (Chandler 1962; Hannan and Freeman 1977; King et al. 2010; Stinchcombe 1965), whether through formal structures or informal organizational repertoires (Clemens 1993), not only exemplifies firm actorhood but also works to characterize its partisan identity and the partisan climate evident within the firm. Since these identifying qualities are partisan, and thus political, such firms may be considered political actors and evidence organizational partisanship. Methodologically, this analysis also proves fruitful in demonstrating that emergent firm classification can be identified through an analysis of firm employees, and such classifications have verifiable association with differential organizational behavior.

Building on the literature or emergent organizational forms (Padgett and McLean 2006; Powell and Sandholtz 2012; Powell et al. 2005; Ruef 2000), this work also illustrates that beyond mechanisms of reconfiguration or transposition to create new organizational forms, especially innovative and newly founded firms (Powell and Sandholtz 2012), extant firm political climates might also shift. For example, while firms might maintain existing formal structure and strategy, the transposition of external partisan attitudes or repertoires characterized by affective polarization occurring in society, could permeate the firm to activate the partisanship of those therein (Clemens 1993; Iyengar and Westwood 2015; Powell et al. 2005; Sood and Iyengar 2016). As a result, the partisanship of the labor force within firms can coalesce and strengthen. Although the current research cannot definitively uphold particular mechanisms for the emergence of organizational partisanship, for example selection hypotheses versus routinized labor market biases based in affective polarization, such studies would have presupposed the existence of a phenomenon which I have documented. Future research should attune to potential mechanisms explaining the emergence of organizational partisanship, especially affective polarization and partisan homophily.

To this end, this paper lastly builds upon a plethora of research in partisan and political polarization research. On the front of firm partisanship and polarization, my work augments scholars focused on ideological distribution of citizens and board members (Bonica 2013, 2014, 2016), taking a similar approach but examining changes specific to individual partisanship instead of ideology. My work also differs from Bonica (2016), in that I examine individual partisanship not only for executives, but also other levels of employees within firms. My work here also builds from other scholars who examine partisan polarization or party sorting (Baldassarri and Bearman 2007; Baldassarri and Gelman 2008; Baldassarri and Goldberg 2014). If we adopt the perspective of polarization as a process not a state (DiMaggio et al. 1996), then the results of increasing public expression of partisanship within firms can easily be seen in this analysis, particularly in recent years. Given the rising phenomenon of affective polarization in society (Iyengar and Westwood 2015; Iyengar et al. 2019, 2012), the increasing within-firm partisan homogeneity evidenced in this study suggests that certain firms may prove increasingly hostile toward opposing partisans. Lastly, identification of particular partisan Democratic, Republican, and amphibious firms provides further context and guidance to those evaluating differential effects of politics and partisanship for a number of organizational behaviors, such as executive pay (Gupta and Wowak 2017), corporate social responsibility (Chin et al. 2013), and business exchange (Stark and Vedres 2012). For example, I show that some of the measures of corporate social responsibility correspond to firm partisanship, an idea previously shown to associate with firm ideology (Chin et al. 2013; Gupta et al. 2017). As argued elsewhere, ideology in some of these studies, such as Gupta et al. (2017), uses the same measure of individual contributor partisanship as I did in this analysis, and in this way, my results substantiate those works, with the caveat that such scholars should advisably frame their work in terms of partisanship, not ideology. In either case, I show that partisanship throughout the firm, not just of the executives, can be associated with corporate social responsibility. Although substantial research is necessary to evaluate the complex mechanisms at play—and importantly—to document how consolidation of partisanship operates within and across firms, this paper, in helping to establish the existence and escalation of partisan polarization in Fortune 400 firms, makes a necessary first step in that direction.

CHAPTER 3

Office Politics: How Affective Polarization and Partisan Homophily Alter Hiring Decisions

In the current political climate, echoes of rising partisanship permeate popular culture, whether it's congressional gridlock, spirited debate on social media, the invitation of partisan speakers on college campuses, or even once mundane topics such as the Thanksgiving dinner or modern dating. Politics, especially partisan politics, is pervasive. Yet, we might wonder, given the fierce competition in landing a job, especially in a top company, how partisan politics affects hiring decisions and the job applications more generally. In an effort to have harmonious workplaces and perhaps avoid working with a colleague of the opposite political party, might employers simply take a pass on otherwise well-qualified applicants if they do not adhere to a firm's political culture? In this study, I investigate how the party identification of job market applicants affect the likelihood of receiving an interview callback for jobs in selective labor markets, and how might this effect vary by applicant prestige, which I gauge by the selectivity of prior universities and employers. These specific research questions inform broader theoretical questions, namely, how does affective polarization and relatedly partisan homophily affect organizational decision making, and how might it contribute to changing partisan polarization within and between firms. Although myriad experimental studies have been conducted in labor markets, few explore the processes of affective polarization specific to selective labor market entry, experimentally adjudicate selection effects on applicant party identification, or evaluate the additive benefits or congruence of applicant party identification versus ostensible qualifications. To evaluate these questions, I designed and implemented a large-scale computational resume correspondence test, utilizing experimental manipulation of applicant partisanship in resumes and cover letters. I combine this experimental data with data on firm partisanship, which affords the unique opportunity to evaluate affective polarization and partisan homophily at the firm level. These theories critically require knowledge of how the partisanship of both the applicant and the firm align or diverge. In this way, my research illuminates the role of affective polarization and partisan homophily in corporate hiring and sheds light on potential mechanisms behind rising partisan polarization in American firms.

3.1 Affective Polarization and Partisan Homophily in Selective Labor Markets

To evaluate affective polarization and partisan homophily in labor markets requires some definitional constraints. First, by selective labor markets, I refer to those not only in traditionally elite labor markets such as (1) elite professional service firms (investment banking, management consulting, and corporate law), but also other generally high profile entry-level jobs at (2) top firms in technology, quantitative finance, asset management, healthcare, and energy, among other industries. More generally, I include several job types for advanced degree applicants at a variety of companies, including those in the Fortune 1000, NASDAQ technology sector, and Russell 3000. Examining such top, as well as more generally selective firms, remains important, particularly since placement in these firms, particularly the elite ones, is seen as a gateway to top incomes and future corporate leadership (Rivera 2011, 2012a, 2012b; Useem and Karabel 1986).

Second, I seek to understand how an applicant's partisan affiliation affects hiring in selective labor markets as a process of *affective polarization*. Scholars define "affective polarization" as "the tendency of people identifying as Republicans or Democrats to view opposing partisans negatively and copartisans positively" (Iyengar and Westwood 2015:691; Iyengar et al. 2019). The work by Iyengar and Westwood (2015) extends research documenting escalating affective polarization, notably acute increases in "negative views of the out party and its supporters. . . since the 1980s" (Campbell et al. 1960; Green et al. 2002; Iyengar and Westwood 2015:691; Iyengar et al. 2019, 2012). Critical to this analysis, affective polarization delimits individual attitudes and behavior such that individuals not only hold animosity toward opposing party members but also view them as less intelligent (Iyengar and Krupenkin 2018; Iyengar and Westwood 2015; Pew Research Center 2016). In fact, the bias based on affective polarization toward political out-groups “exceeds discrimination based on race” (Iyengar and Westwood 2015:690). Given the well-known examples of racial discrimination in labor markets (Bertrand and Mullainathan 2004; Gaddis 2015; Kang et al. 2016; Pager 2003), the findings on affective polarization suggest that a parallel process of partisan discrimination in labor markets may also occur.

Specifically, we might expect effects on two dimensions. Recall that Iyengar and Westwood (2015) include both (a) negative evaluations about opposing partisans and (b) positive evaluations of copartisans under the rubric of “affective polarization,” however, the strength of these two (a) negative and (b) positive effects might vary (Iyengar and Krupenkin 2018; Iyengar et al. 2019). Indeed, the majority of studies focus on (a) negative evaluations of opposed partisans (Green et al. 2002; Iyengar and Krupenkin 2018; Iyengar and Westwood 2015; Iyengar et al. 2012; Pew Research Center 2016), going so far as to say that “this phenomenon of animosity between the parties is known as affective polarization” (Iyengar et al. 2019: 130). Thus, for convenience, I will continue to refer to (a) the negative evaluations about opposing partisans as affective polarization or partisan animus while using the term partisan homophily or partisan matching to refer to (b) positive evaluations of copartisans or those members of the same political party. In this way, we can speak more succinctly about two discrete phenomena.

Ostensibly to evaluate affective polarization (and partisan homophily) relies on an intrinsically dyadic phenomenon. We must know the party of two individuals, groups, or combinations thereof. In this case, we must know the identification of the job applicant and that of the one receiving the materials or more generally the partisanship of the company and its subunits. Without capturing both the partisanship of both the applicant and firm, we can still comment on whether generalized discrimination against one party or the other exists in the job market, an approach taken in the majority of discrimination studies in other domains.[1] Yet, understanding the degree to which the partisan backgrounds of applicant and firm match or mismatch is needed to inform the affective polarization and partisan homophily hypotheses. To this end, my work here builds on (Mausolf 2020a), which employs a method of determining the political partisanship as well as the strength of that partisanship for individuals in firms using Federal Campaign Finance (FEC) data.

3.1.1 Hypothesized Results of Affective Polarization and Partisan Homophily in the Context of Diversity

Given partisanship measures for a subset of firms, we can extend the above discussion to some provisional hypotheses. Since the bias against political out-groups "exceeds discrimination based on race" (Iyengar and Westwood 2015:690), and studies evaluating racial discrimination on job market callbacks have found significant racial effects (Bertrand and Mullainathan 2004; Gaddis 2015; Kang et al. 2016; Pager 2003), I hypothesize that fictitious applicants whose partisan identity opposes the firm to which they apply will be less likely to receive callbacks than the politically neutral, matched control, and similarly will be less likely to receive callbacks than those individuals matching the partisanship of the firm. Although I anticipate the effects of partisan homophily to be similar although from a likely weaker mechanism, I hypothesize that in general, applicants whose partisan identity matches the firm will have a slightly better chance of a callback than a matched politically neutral applicant. Across all applicants, I posit that copartisans (those with matching partisanship) will on balance receive a greater number of callbacks than opposing partisans (applicants with opposed partisanship), a hypothesis consistent with past studies of affective polarization, including

[1]For example, the typical correspondence test evaluating applicant race, ethnicity, or resume whitening does not consider or evaluate how the race or ethnicity of the individual receiving the applicant profile (or similarly firm diversity) might affect the likelihood of providing a callback for that applicant (*c.f.* Bertrand and Mullainathan 2004; Gaddis 2015; Kang et al. 2016).

evaluations of resumes (Iyengar and Westwood 2015), or the effects of an applicant matching or mismatching the partisanship of the geographic area wherein the job resides (Gift and Gift 2015). I posit that these effects will vary by the partisan polarization of the firms, such that firms exhibiting strong partisanship will be more likely to exhibit both the (a) affective polarization hypothesis and (b) partisan homophily hypothesis while firms that are either more moderate, or even bipartisan in their affiliation, may exhibit weaker, or even statistically insignificant effects for both hypotheses. In fact, for truly bipartisan firms or firms with a high degree of political diversity, these firms might even have a preference for the politically neutral applicant rather than someone with an overt signal of partisan allegiance.

This latter supposition raises an important intuition for the hypothesized effects of affective polarization and partisan homophily, in that while they may be powerful mechanisms, that very mechanism in all likelihood will work against applicant success under conditions of uncertainty or in firms manifesting partisan diversity. Where partisanship of the firm is unknown, politically neutral applicants might be more successful than the randomly assigned partisan profile. However, given other pieces of information such as (1) the partisan profile for the general population where a firm's office is located, (2) the average partisanship and partisan polarization exhibited by similar firms with known partisanship (such as energy companies versus technology firms), and (3) the average partisanship and polarization for similar jobs (such as software engineer versus financial analyst), we could likely approximate or classify the partisanship of unknown firms, using, in part, the measures along these and other features for known firms as training data. If such a classification process were reliable (using different evaluation metrics such as precision and recall), then I would anticipate that the affective polarization and partisan homophily hypotheses might also hold for firms with classified approximations of partisanship. Although I do not perform this latter method here, it remains a possibility for future studies.

3.1.2 Considering the Positive and Negative Motivations of Diversity

Relative to the overall thrust of research on affective polarization and partisan homophily, while both trends suggest that copartisans would be more likely than opposing partisans to receive a callback, we can also glean additional insight from the diversity literature. Although there is some evidence to suggest that bipartisan teams may produce higher quality work (Shi et al. 2019),[2] and that teams with functional diversity may yield greater innovation and creativity (Burt 2000, 2004; DiTomaso et al. 2007; Dobbin and Jung 2011; Hambrick et al. 1996), the vast majority of research reveals negative effects for diverse teams, particularly those with diversity on salient social dimensions, which would include partisanship (DiTomaso et al. 2007; Williams and O'Reilly 1998). Beyond averting the downsides of diversity, firms might try to capitalize on the benefits of homogeneity such as improved social connectivity, trust, and emotional attachment (Brewer 1981; Ibarra 1992, 1995; McPherson et al. 2001; Meyerson et al. 1996; Reagans and McEvily 2003). Firms might also frame these benefits of homogeneity in terms of emphasizing the importance of organizational or cultural fit, which consistently proves to be an integral feature (Goldberg et al. 2016; King et al. 2010; Rivera 2012b; Stinchcombe 1965). Although firms might arguably try to promote diversity to avoid or assuage legal sanctions, regulation, or negative press (Dobbin and Sutton 1998; Kalev and Dobbin 2006; Kalev et al. 2006; Skaggs 2008), political partisanship is not a protected class under Equal Employment Opportunity Commission guidelines (U.S. Equal Employment Opportunity Commission 2020), and even protected classes such as race, gender, or sexual orientation have not preempted ostensible discrimination (Bertrand and Mullainathan 2004; Correll et al. 2007; Gaddis 2015; Kang et al. 2016; Tilcsik 2011). Relative to the hypotheses on affective polarization and partisan homophily, therefore, most evidence in the diversity versus homogeneity and organizational fit literature substantiate the overall hypothesis that

[2] In Shi et al. (2019), for example, we see higher quality work produced by bipartisan teams in an open-source environment, namely Wikipedia editor contributions. The same dynamics may not transpire with teams in a typical corporate environment.

applicants aligning with the partisanship of the firm will receive more callbacks than applicants whose partisanship opposes that of the firm.

3.1.3 Additional Intervening Criteria for Partisan Effects: Applicant Prestige and Job Type

Beyond differences that may occur from whether the partisan direction and strength for a firm can be determined, I also anticipate that the general hypothesized effects may vary by the selectivity of firms. For example, we might wonder whether the effect of partisan homophily varies by the *selectivity of the corporation*, or more generally the job industry. Since my analysis extends beyond traditionally elite labor markets and includes other selective firms in the Fortune 1000, NASDAQ tech sector, and Russell 3000, my results, while illuminating effects for elite labor markets, will also be informative for a broader population of job applicants (*c.f.* Rivera and Tilcsik 2016).[3]

Relatedly, the study also examines how partisan homophily *varies by applicant prestige,* which I measure by the selectivity of past educational institutions and employers. Do the effects of *partisan homophily and affective polarization* outweigh the effects of applicant prestige (for example in university, degree, or skills)? In other words, it is not simply a question of whether party identification shapes selective labor market outcomes, but whether political partisanship might be an understudied effect that interacts with or outweighs human capital approaches to labor market success and failure. While the experiment does not test prestige effects within pairs, we can look across pairs to evaluate whether the effects of partisanship (affective polarization and partisan homophily) have stronger or more pronounced effects for high prestige or low prestige applicants. Before positing these effects, I need to first elaborate on why applicant prestige might matter.

[3] Broadening the scope in this way can allow for experimental manipulation of both elite labor markets and selective labor markets. As Rivera and Tilcsik (2016) note, experimental approaches to elite labor markets are challenged by the frequent method of campus recruitment by elite firms (Rivera 2011, 2012b, 2012a). This rationale was used by Rivera and Tilcsik (2016) to focus on selective but not elite law firms. Still, while recruitment for elite firms may often occur or be advertised through on-campus events, applicants, including those from elite universities can still submit resumes and applications online through employers, particularly when done at the correct time in the recruitment cycle.

Although a number of studies have examined the effects of elite credentials along with intersecting facets of college major, family socioeconomic status, human capital investment, and elite college preparatory academies (Altonji, Blom, and Meghir 2012; Barrow and Malamud 2015; Dale and Krueger 2002; Hoekstra 2009; Levine 1980; Useem and Karabel 1986), those in particular that have used correspondence tests or in-person audits have found employers prefer applicants with elite educational backgrounds, higher prestige, or markers of high social class (Gaddis 2015; Rivera 2012b; Rivera and Tilcsik 2016). In combination, these studies suggest that on balance, high prestige applicants will receive significantly more callbacks than equally skilled applicants from less selective educational and employment backgrounds. I hypothesize my experiment will similarly demonstrate that high prestige applicants with highly selective educational and employment backgrounds will receive more callbacks than equally qualified applicants from less selective backgrounds.

Using a bounded rationality approach (March and Simon 1958), employers may favor elite-credentialed applicants to minimize search costs, assuming elite universities have selected and rewarded those with the greatest ability (Rivera 2012b). Employers might also prefer elite applicants as a status symbol (Rivera 2011). Rivera (2012b) also points to a mechanism known as cultural matching, a term coined in DiMaggio (1992) and reminiscent of DiMaggio and Mohr's (1985) use of culture in matching marital partners. Given the excessively long hours (sometimes 80 or more) that employees at top firms dedicate, I suggest that once applicants are deemed to be well-qualified, employers seek to match politically (or conversely avoid working with someone of an opposed partisan identity) as well as match on other cultural attributes, looking not just for good employees but also friends (Iyengar and Westwood 2015; Rivera 2012b). This matching process depends not only on the employer but also the perspective of the potential employee such that the entire job search can be thought of as a process of matching applicants to jobs (Kalleberg and Sørensen 1979; Sørensen and Kalleberg 1981; Tilly and Tilly 1998), (*c.f.* DiMaggio 1992; Schneider 1987).

Given past findings that applicant prestige matters (Gaddis 2015; Hoekstra 2009; James et al. 1989; Rivera 2011, 2012b), we might also expect to see such effects in this analysis. That said, I hypothesize that applicant prestige may matter less for certain technology-oriented fields like data science and software engineering and matter more for business (MBA) and quantitative finance positions. This rationale generally follows from the premise that in high-intensity professions, especially elite professional service firms—such as law firms, investment banking, or consulting—only consider applicants from a select subset of super-elite, prestigious universities (Rivera 2011, 2012a, 2012b). This preference stems from viewing admission to these schools as not only a measure of merit but also as one creating a shared experience since many of the top firms' current employees also attended these schools (Rivera 2011, 2012b). As an added bonus, having a client-facing firm replete with elite-credentialed employees is also a selling point (Rivera 2011, 2012b). By contrast, highly technical jobs such as software engineering or data science often care less about where, or even whether, applicants received a degree and more about the caliber of demonstrable technical skills. At the same time, my creation of high prestige applicants is more in line with the approach taken by Gaddis (2015), which uses top universities but not necessarily only the "super-elite" top four schools evaluated in Rivera (2011).

Regardless of the job type or applicant prestige, however, we might also expect organizational variation in callback rates, especially as it relates to discrimination or bias. For example, if organizations have strong protocols discouraging discrimination, these policies may reverse or mitigate affective polarization and partisan homophily (Dobbin et al. 2011; Kalev et al. 2006; Pedulla 2016). Lastly, the degree to which partisan homophily and affective polarization matter may vary by how elite a firm is or how much time employees interact or travel in a typical week. Because more prestigious firms will have a greater number of applicants, they will be more likely to select an individual with a highly selective background on balance. With these caveats in mind, demonstrating a clear effect that affective polarization or partisan homophily matter more at one level of prestige than another will prove challenging. If enough data exists, the primary effect that may emerge across cases is that partisan matching might offer a larger benefit for applicants from less selective backgrounds, particularly if the firm exhibits strong partisan polarization. Since the hypothesized effect of applicant prestige may simply result in not enough positive responses to applicants from less selective backgrounds, however, the effects of partisan bias might only be measurable among high prestige applicants.

3.1.4 Expanding the Literature to Understand the Role of Partisanship in Hiring

Empirically, the primary questions regarding the effects of political partisanship in the hiring process as well as how applicant prestige matters have not been adequately explored in existing studies, which emphasize one of several dominant approaches. First, the majority of studies examining *elite* labor markets do not conduct experimental examinations (Rivera 2011, 2012a, 2012b). Rivera's primary work—while incredibly informative—employs qualitative rather than experimental methods to elite labor markets. Nonetheless, these studies illuminate the importance of applicant prestige, cultural matching, and intersections with diversity. In an effort to apply experimental methods, Rivera and Tilcsik (2016) study *selective* but not *elite* law firms, focusing on social class and not political partisanship.[4] Gaddis (2015) examines hiring relative to applicant prestige but does not examine elite firms specifically or evaluate political partisanship. Lastly, Iyengar and Westwood (2015) examine affective polarization based on party identity in a number of ways, including resume evaluation, but the evaluators were a random sample of adults from a survey institute and the study was unrelated to firms and actual job applications. Similarly, in studies evaluating the effect of political partisanship on job market callbacks, Gift and Gift (2015) showed that applicants

[4] As noted above, I believe there may be fruitful analyses for assessing callbacks from applications to selective firms, even if these companies also heavily participate in on-campus recruiting at elite universities. For example, top firms in management consulting (McKinsey and Company), investment banking (Goldman Sachs), hedge funds (Citadel), and technology (Google) each offers any interested prospect the opportunity to apply online. Company contacts may also be directly emailed with resumes and cover letters.

were less likely to receive a callback when their partisanship diverged from the majority party in a job locale, compared to a candidate with neutral partisanship or those aligned with the partisan majority.[5] Again, however, Gift and Gift (2015) does not evaluate these effects at the firm level or manipulate applicant prestige.

A second major approach is to examine applicant prestige. A number of scholars capture aspects of these ideas either qualitatively (Rivera 2011, 2012a, 2012b) or experimentally (Gaddis 2015; Rivera and Tilcsik 2016). Using survey or institutionally collected data, scholars have found conflicting evidence about the value and career mobility of an elite credential, especially considering the intersecting facets of college major, family socioeconomic status, human capital investment, and elite college preparatory academies (Altonji et al. 2012; Barrow and Malamud 2015; Dale and Krueger 2002; Hoekstra 2009; Levine 1980; Useem and Karabel 1986). Some of these studies evaluating applicant prestige are non-experimental and apply only to elite professional service firms Rivera (2012b). Others are experimental but only evaluate social class not educational credentials and are specific to selective law firms Rivera and Tilcsik (2016). On the basis of educational credentials alone, my study while holding skills constant, examines the effects of highly selective educational backgrounds versus less selective education (at both the graduate and undergraduate level) and captures those effects across a wide variety of jobs in the United States. The use of graduate degrees also offers a unique facet, as most studies, examine college graduates. As an additional layer of prestige, I also include highly selective versus less selective work experience.

A third and dominant dimension of experimental labor market analyses is to examine

[5]It is worth noting that some conflation of ideology and partisanship exists in Gift and Gift (2015). For example, the authors write, "three types of resume-county combinations: in-partisans (i.e., conservative resumes in Collin County and liberal resumes in Alameda County), out-partisans (i.e., liberal resumes in Collin County and conservative resumes in Alameda County), and non-partisans in both counties" (Gift and Gift 2015: 664). Despite the conflation of ideological and partisan labels, it appears what Gift and Gift (2015) tests most clearly is partisan alignment. For example, partisanship was manipulated on resumes by ascribing "Republican" or "Democratic" jobs and extracurriculars versus jobs and extracurriculars without partisan affiliation (Gift and Gift 2015: 654). Similarly, the designation of liberal/conservative counties relied on evaluating the proportion of votes given to the Obama versus McCain presidential tickets (Gift and Gift 2015: 659).

labor market discrimination by race, gender, or sexual orientation. Race is widely studied, including facets that examine discrimination on the basis of racially specific names or resume whitening (Bertrand and Mullainathan 2004; Gaddis 2015; Kang et al. 2016), racial intersections with criminal history (Pager 2003, 2007), and racial dimensions of joblessness (Pedulla 2016). Gender is likewise assessed by a number of studies, especially related to wages or motherhood penalties (Correll et al. 2007; Pedulla 2016). Sexual orientation has also been examined in audit studies (Tilcsik 2011). Given that these effects are already widely documented, my study focuses on the effects of partisanship versus applicant prestige on job market callbacks specific to white men. Future studies should compare the discovered effects for different intersections of race, gender, or social class.

Collectively, given the possible competing mechanisms, the empirical gap in the literature, and the unexplored interactions of partisanship and applicant prestige, these ideas deserve further elaboration with a thoughtful experimental design. Beyond augmenting gaps in the labor market literature, my study also contributes to a broader question that will help explain the emergence of party sorting in firms, extend the affective polarization literature to the firm level, and illuminate a debate in the organizational diversity literature.

3.2 Data and Methods

3.2.1 Experimental Method: Resume Correspondence Tests

In this analysis, I conduct a specific type of field experiment known as a *correspondence test* in order to assess callback rates for fictitious job applicants based on an experimental manipulation of applicants' political partisanship and prestige. These features are conveyed by their resumes and cover letters. Often used to examine ascriptive characteristics such as race and gender (Bertrand and Mullainathan 2004; Correll et al. 2007; Gaddis 2015; Kang et al. 2016), correspondence tests, which are alternatively referred to as "correspondence audit" studies are particularly well suited for applying to professional jobs.[6] To execute this experiment, I designed and wrote an end-to-end series of *Python* scripts which largely automate the experimental protocol, including searching for and identifying relevant jobs at a given set of companies, composing the cover letters to company representatives, making the resumes, and sending the emailed cover letters with attached resumes to respective company contacts. In the sections below, I outline additional details of the experimental design.

3.2.2 Experimental Design

In the experiment, I submit fictitious resumes and email cover letters to entry-level professional jobs for applicants completing an MBA, MS, or PhD. Specifically, I sent two email cover letters, each with a unique resume attached to a single representative at each company[7]. In this way, each firm receives a matched pair of fictitious applicants on subsequent days, where one is a treatment (partisan applicant) and the other is a control (neutral applicant).[8] This matched pair design is similar to past matched pair designs (Correll et al. 2007; Gaddis 2015;

[6]In labor market analyses, there are two principal types of field experiments: the audit study (sometimes called the "in-person audit study") and the correspondence study. Although there is some definitional looseness about these terms, the *audit study* typically refers to the use of trained actors, known as auditors, who apply or interview for jobs, whereas the *correspondence test* refers to sending fictitious resumes to job applications and measuring employer response (Bertrand and Mullainathan 2004; Pager 2003; Pager and Western 2012). For example, Pager and Western (2012) discuss Bertrand and Mullainathan (2004) among a section elaborating examples of audit studies. Here, Pager and Western (2012) mention "in-person audit studies" and "correspondence studies," without a clear delineation between the methods. Pager (2003) is clearly aware of the difference, spending considerable discussion on the matter. Adding to the confusion, Correll et al. (2007) closely mirror the exact correspondence-test method of Bertrand and Mullainathan (2004), but widely refers to their work as an audit study. Bertrand and Mullainathan (2004) explicitly differentiate their method from audit studies, spending several pages articulating the many weaknesses of the audit approach, particularly the use of trained auditors versus resumes. Pager (2003) conversely advocates the merits of audit studies over correspondence tests. More recent literature seems to adjudicate the confusion by using the terms "in-person audit" versus the terms "resume audit," "correspondence audit," and "computerized audit" to refer to traditional audit studies versus correspondence tests (Gaddis 2015; Kang et al. 2016; Pager and Western 2012). In-person audit studies have many limitations, including cost, small sample size, effective auditor matching, auditor effects, and single-blind design, among others (Bertrand and Mullainathan 2004; Heckman and Siegelman 1993; Pager 2003).

[7]To ensure no duplicates existed after the company matching process, the protocol was restricted to unique email addresses. In this way, each firm contact receives only one pair of applicants.

[8]The details of the research design are described below, and the study was preregistered prior to running the experiment (Mausolf 2020d).

Table 3.1: 2x2 Between-Subjects, Matched Pair Design

	Democrat	**Republican**
High Prestige	Democrat, Highly Selective Neutral, Highly Selective	Republican, Highly Selective Neutral, Highly Selective
Low Prestige	Democrat, Less Selective Neutral, Less Selective	Republican, Less Selective Neutral, Less Selective

Notes: Applicant prestige is primarily indicated by the *selectivity* of past educational and professional experience and to a lesser extent by the socioeconomic signal of their first name.

Pedulla 2016; Tilcsik 2011),[9] and its delivery of cover letters and resumes by email follows a standard approach adopted by many scholars (Correll et al. 2007; Gift and Gift 2015; Rivera and Tilcsik 2016; Tilcsik 2011).[10] Echoing the approach of Pedulla (2016), both the order in which a firm representative receives the treatment and control as well as the resume and cover letter version for each pair is randomized and counterbalanced.[11] Beyond the first level of experimental design of using a matched treatment-test pair of applicants, I employ a second layer of experimental design, often characterized as a 2x2 between-subjects factorial design, similar to work by Rivera and Tilcsik (2016) and Kang et al. (2016). Organizations are randomly sent one of four matched-pairs of resumes, which vary in two-dimensions. First, the partisan treatment may take one of two conditions: Democrat or Republican. Second, the matched pair may be one of two prestige backgrounds: highly selective or less selective. This results in 4 unique pairs of matched applicants as shown in Table 3.1.

[9] Gift and Gift (2015) takes the paired design one step further by sending firms a set of three resumes, one Republican, one non-partisan, and one Democratic.

[10] The method of delivering applicant pairs varies. While Tilcsik (2011) sends applications by email (599) and Correll et al. (2007) use "email, fax, or paper" (1328), Gaddis (2015) applies to jobs using a third party job search website and eliminates jobs that require application on the company's website (1459), a convention that Pedulla (2016) also follows (286). Kang et al. (2016) intended to use a matched pair design but were required to only use a single application per firm by their IRB.

[11] Both the order and design for an applicant pair are randomly and independently assigned with equal probability, resulting in counterbalanced groups. For example, the following four order/version design pairs result: $[T_A, C_B]$, $[T_B, C_A]$, $[C_A, T_B]$, $[C_B, T_A]$, for each permutation of applicant prestige level (High/Low), and treatment condition (Republican/Democrat).

Although the assignment of one of the four matched pairs is randomized, the probability of receiving a given pair is not equiprobabilistic. Instead, both the treatment conditions (Democrat or Republican) and the prestige conditions (High or Low) have the following unbalanced probabilities of selection: Democrat, Pr(0.4); Republican, Pr(0.6); Highly Prestige, Pr(0.7); and Low Prestige, Pr(0.3). The inclusion probabilities for pairs is as follows: Republican, High Prestige, Pr(0.42); Democrat, High Prestige Pr(0.28); Republican, Low Prestige, Pr(0.18); and Democrat, Low Prestige, Pr(0.12). In brief, both High Prestige, and Republican applicants are more likely. The decision to have differential assignment probabilities for the pairs follows both theoretical and empirical assumptions.

In terms of prestige, high prestige applicants are considerably more likely to receive callbacks or interviews than those with less selective academic and employment histories (Gaddis 2015; Rivera 2012b; Rivera and Tilcsik 2016). Since my primary objective is to evaluate the effects of political partisanship—and I primarily gain analytical power if the partisan or non-partisan applicant receives a callback, versus neither applicant receiving a callback—I elected to send a greater number of resumes with a higher probability of receiving a callback into the field.

Regarding unbalanced partisan conditions, my previous analysis of partisan polarization in firms (Mausolf 2020a) reveals that more firms exhibit partisan polarization in the Republican versus Democratic direction, and of those firms not exhibiting extreme partisan polarization, the majority also lean Republican. Recall that I expect there may be differential and slightly stronger effects for affective polarization (in the valence of negative bias against the opposite party) compared to partisan homophily. In other words, a political mismatch will be less likely to receive a callback than a politically neutral applicant, and this effect will be stronger than the partisan homophily effect. While dependent on the difference in effect sizes, generally, we might anticipate needing more incidences of political matches than mismatches. In this way, even though the assignment of pairs to firms is random, by providing a greater number of

Republican versus Democratic partisans in the field, I slightly increase the likelihood that there will be a partisan match between the treatment condition and the firm.

3.2.3 Experimental Delivery and Matching

Two important tensions exist in correspondence audit study designs, and these merit discussion. One tension is the use of a matched pair of applicants versus a single applicant per firm. The second tension is the method of application. Regarding the use of matched pairs versus single applicants, matched pairs afford a higher number of observations to be gathered, and thus a higher degree of statistical power than using one applicant per firm, holding the number of firms constant (Gaddis 2015). Typically, at most, a single pair of applicants will be sent to a firm, although some studies have submitted three (Gift and Gift 2015). Another important benefit from a matched pair design is the capacity to directly observe within-pair differences between the treatment and control (Gaddis 2015: 1474), which is not possible with single-applicant designs. Furthermore, matched pair designs afford the ability to draw unbiased between-pair estimates provided there are no systematic differences in the assignment of pairs to jobs or other observable characteristics conveyed through application materials (Gaddis 2015: 1459, 1474; Pager 2003: 957). Although between-pair effects can endow meaningful insights, such effects are statistically "less efficient than within-pair comparisons" (Gaddis 2015: 1459; Pager 2003: 957). Similarly, in the typical single applicant design, only between-subject effects can be evaluated, and these are less efficient than within-subject effects or the within-pair effects found in a matched pair design. As a result, most studies using a single applicant design concede some of these benefits of matched pairs and cite that a rationale for utilizing a single applicant design was the result of their institutional review board's concerns about firm time burdens or restrictions prohibiting a matched pair (Kang et al. 2016: 486; Rivera and Tilcsik 2016: 1104). Although matched-pair designs have an increased risk of detection (Gaddis 2015; Kang et al. 2016; Weichselbaumer 2015), a number of steps can be taken to help avoid discovery. One of the most basic steps includes submitting fictitious applicants at different times, often one day apart (Gaddis 2015; Pedulla 2016; Tilcsik 2011). Similarly, researchers typically vary the resume and cover letter content in a number of ways (Gaddis 2015; Pedulla 2016). I conduct similar efforts to avoid detection of the experimental pair of applicants.

The second important tension in correspondence audit studies is the delivery method, typically by email or by directly applying online. Applying online certainly has benefits, including a lower risk of detection since those applications, when applied directly to a job through a third-party, will fall in a highly populated applicant pool. The use of online applications is common (Gaddis 2015; Kang et al. 2016; Pedulla 2016).[12] Typically, however, these application-based audits have limits, chiefly that they are only permissible to the extent a third-party job board permits application directly through their website. This restriction emerges (1) ethically as an institutional review board concern (Pedulla 2016: 286); (2) methodologically as an external firm application is computationally impractical, or otherwise time-prohibitive (Gaddis 2015); or (3) methodologically as such external applications often have long and unique requirements such as transcript authentication or essay responses that preclude valid experimental manipulation (Pedulla 2016: 286; Rivera and Tilcsik 2016: 1107). Ostensibly, these three restrictions often occur in combination. Although applying directly to a third-party standardized application avoids these downsides, this strategy excludes any company requiring a direct application. Unfortunately, most major corporations' job postings only offer the option to apply directly on an external company website. Since my study specifically targets such companies, direct application is unfeasible, leaving the second approach of email submission of resumes and cover letters.

As previously mentioned, the direct submission of applicant resume and cover letters, typically by email, is commonly used in correspondence audit studies and has a number of

[12]Many scholars took the online approach. See (Gaddis 2015: 1459; Pedulla 2016: 286), who both send two applicants per firm, or (Kang et al. 2016: 488), who sent a single application.

benefits (Correll et al. 2007; Rivera and Tilcsik 2016; Tilcsik 2011; Weichselbaumer 2015). Apart from the benefits of reaching employers inaccessible through direct company-specific online applications, the method has the advantage of computational efficiency and standardization. Furthermore, greater insight can be drawn from responses gleaned via an email campaign. Quite simply, application submission to third-party job-boards results in an opaque process of uncertainty. For example, once submitted, it is unclear who eventually examines that resume. It could be a singular human resource agent, the hiring manager, or a multistage panel review. Under such uncertainty, it is impossible to match the partisan affiliation of the person or group receiving the application because their identities remain unknown. Given enough information, for example, an email method could better disentangle affective polarization and partisan homophily at the level of the application recipient versus the firm. At the same time, if only the partisanship of the firm can be determined, this latter point matters little. In either case, as mentioned above, an email campaign has multiple experimental benefits over direct application.

3.2.4 Experimental Treatment and Control of Partisanship

Experimentally, I will manipulate political affiliation with three categories (Republican, Democrat, and neutral). This can be signaled on resumes through leadership experience, such as whether an applicant was (a) president or vice president of the Young Democrats or Young Republicans or (b) president or vice president of the Student Government Association (*c.f.* Gift and Gift 2015; Iyengar and Westwood 2015). In each case, the applicant has a comparable, recognizable leadership quality justifying its existence in application materials (Tilcsik 2011), but the political identity differs from representing a Democratic, Republican, or neutral affiliation. Similar signaling of self-identity has been used by denoting extracurriculars on resumes to signal race, sexual orientation, and political party (Gift and Gift 2015; Iyengar and Westwood 2015; Kang et al. 2016; Pedulla 2016; Tilcsik 2011). In this way, the proposed experimental intervention has ecological validity grounded in past research.[13] Whereas Iyengar and Westwood (2015) signal partisanship using the aforementioned Young Republicans or Young Democrats leadership experience, Gift and Gift (2015) signals partisanship by replacing the most recent employee experience with a partisan political campaign (in addition to partisan extracurriculars). Although Gift and Gift's (2015) method provides a strong partisan signal, the specific selective labor markets I target necessitate particular, often technical, employee experiences, and thus, their employment prospects might be denigrated by simply replacing them with entry-level campaign responsibilities. In this way, partisan signaling through extracurriculars preserves partisan allegiance without altering employable skills and experience. Like both Iyengar and Westwood (2015) and Gift and Gift (2015), partisan extracurriculars are signaled on resumes, but unlike Gift and Gift (2015), I also include the partisan signal within the cover letter to enhance its effect.

Importantly, for realism, the timing and form of the partisan signal slightly vary depending on the type of applicant. For the majority of applicants (all doctoral and masters candidates except MBAs), the experimental treatment and control is applied as an undergraduate extracurricular. Conversely, MBA candidates received the treatment and control as an extracurricular in graduate school. The decision to split the timing of the partisan and control signal emerged as the appropriate course of action during pretesting and interviews with career counselors, former human resource managers, and deans of corporate relations.[14] As a result, the treatment and control for MBA applicants are reflected accordingly as either a neutral student leadership position such as the president of the "Graduate Business Association"

[13]To further substantiate the ecological validity, consider a simple search of LinkedIn. Under the search/filter by people settings, a simple people search for variations of "College Democrats," "College Republicans," "Young Democrats," and "Young Republicans," in the title or company fields reveals that hundreds of students (or former students) list the organizations on their public LinkedIn profiles as current or past positions, often associated with leadership positions therein. Even more include positions in student government.

[14]My pre-testing interviews with career counselors, former human resource managers, and deans of corporate relations agreed that for MBA applicants, it would be more plausible and realistic to include such a graduate extracurricular but not an undergraduate extracurricular given the time expanse of 4-5 years of full-time employment that occurs between undergraduate and graduate education. Conversely, for masters and doctoral applicants on a continuous educational path, the inclusion of undergraduate leadership positions makes sense in lieu of professional full-time experience.

versus a partisan leadership position in the local Young Democrats or Young Republican group (as opposed to the college-specific group for undergraduates).[15] Furthermore, as an additional method of disguising the experiment, the leadership position (either "president" or "vice president") between treatment and control is both randomized and counterbalanced and at the same time similar enough not to sway the recipient toward one applicant versus the other. Lastly, to simplify the experiment and focus on the effect of party identification, all applicants were white males matched on educational prestige, credentials, and skills.[16]

3.2.5 Determining Applicant Prestige (Selectivity) Conditions

Applicant prestige will be manipulated across two levels: high prestige applicants with experience from highly selective universities and firms and low prestige applicants from less selective universities and firms. In both cases, applicants will have majors and skills optimized for the perspective industry. Following the model of (Rivera and Tilcsik 2016), who suggested that "firms might automatically dismiss applications from students who attend…school far outside their geographic area and have no history of living in the region" (1103), I also manipulated the region of the applicants' undergraduate and graduate education to best match the region where the available job was located. At a minimum, an applicant's undergraduate degree came from an institution located in the same region as the employer.

[15] In terms of timing, MBA applicants had the most recent partisan signal, followed by software engineering masters applicants, who while having an undergraduate partisan signal, had a much more recent experience than doctoral students, whose partisan alliance in undergraduate occurred approximately six-seven years ago (given a 5-6 year PhD). Yet, although pretests suggested differential timing of the partisan signal for enhanced applicant realism, given the consensus view of entrenched partisan stability (Bartels and Jackman 2014; Campbell et al. 1960), a leadership position in a post-adulthood partisan organization, whether it occurs in college or graduate school, should serve as a reliable signal of partisan allegiance.

[16] To avoid rousing suspicion on matched pairs, the political contrast will be between the test condition (Democrat or Republican) and the control, a neutral, non-partisan category. Republicans or Democrats will be signaled as "President of College Democrats/Republicans" and the neutral category will be varied as an equivalent leadership position in student government such as "Vice President of the Student Government Association" where the selection of leadership position as president versus vice president is independently and randomly assigned and counterbalanced between treatment and control.

Where possible, applicants also attended a graduate school in that region or the next best proximal region.

3.2.5.1 Undergraduate Degrees

In terms of undergraduate education, a certain tension exists that limits implementing an extremely rigid definition of high selectivity, such as the one articulated by Rivera (2012b). If students could only attend a highly exclusive school, such as Harvard, Princeton, or Yale, high-selectivity applicants could not have a regional match to many employers, a challenge, that Rivera and Tilcsik (2016) solved by choosing selective but not elite institutions. Because I am utilizing a matched-pair design and need to present similar but not identical applicants to employers, applicants cannot have attended the same undergraduate institution. For added realism, they must each attend a graduate school at a different institution than their undergraduate degree. Yet, if there should be discrete applicants, some generous degree of regional matching, and a measure of high selectivity that allows top institutions but does not create an insurmountable status distance between highly prestigious applicants—what might that threshold be?

As I will argue, a compromise is to define a highly selective undergraduate institution as one falling within the Top-25 National Universities (both public and private) as defined by the U.S. News and World Report. With this measure, I can have the requisite minimum of three highly selective undergraduate institutions in each of the following regions: the West, the Midwest, the Northeast, the Mid-Atlantic, and the South.[17] By contrast, less selective undergraduate institutions were determined as follows. They must be public institutions,

[17]A minimum of three undergraduate institutions is required per region and selectivity level. The rationale is simple. Since the matched pair must have different undergraduate institutions and match the region, at least two institutions per region and selectivity level are warranted. However, because (A) the graduate institution must also differ from a given applicant's undergraduate alma mater and (B) top graduate programs in a field are frequently at top-25 schools (e.g. Harvard, Stanford, Chicago), a third undergraduate institution is required in order to satisfy each requirement in randomly selecting the undergraduate institution from the possibilities.

with a national ranking lower than 150 (for example, 150-200+ ranking), an acceptance rate greater than 55%, and additionally have clubs for the treatment (Democrat and Republican) and control groups (Student Government or Student Council).

3.2.5.2 Graduate Degrees

Highly selective graduate degree programs were defined as those coming from the top graduate schools for a given degree field in the country, according to the U.S. News and World Report. In all cases, preference was given to selecting programs from the Top 10 schools, although schools in the Top 15 were given consideration if it would otherwise fulfill a regional match. Schools not ranked in the Top 15 were excluded from the top highly selective graduate schools for a job applicant.[18] In cases where a regional match was unavailable, a graduate program from a proximal region was randomly selected. Conversely, less selective graduate programs were those, which had the degree in question as well as a healthy-sized department, but which were unranked, that is, had a rank of "RNP" or rank not published or were simply listed as "Unranked" from U.S. News and World Report.[19] In computer science, for example, these were schools that fell below the Top 111 departments. This also afforded the ability to provide a regional match for all less selective graduate schools.[20]

[18] The top 15 rule generally applies for statistics graduate programs as well, but the U.S. News and World Report lumps rankings for generalist statistics departments and dedicated biostatistics departments. I exclude biostatistics departments and thus use the remaining statistics departments and ordering in classifying the top 15 rule.

[19] The only exception to the "RNP" or "Unranked" rule for the U.S. News and World Report was for finding less selective statistics departments. In particular, very few statistics departments exist compared to computer science or MBAs, for example. Only a few valid RNPs existed, that is, only a few of the RNPs in statistics had healthy-sized departments with a PhD in statistics versus mathematics. In a few instances, less selective departments were selected from schools ranked approximately 70-100 by the U.S. News and World Report. To confirm their low ranking, I ensured these schools were either unranked or ranked 300-400 for statistics programs by Q.S., another educational ranking system.

[20] For MBA programs, I included two primary types of MBAs, those with an MBA focused on general management and those with an MBA concentration in finance. Regarding the MBAs with finance backgrounds, the U.S. News and World Report did not have at least two less selective (RNP/unranked) universities with a finance MBA concentration listed in the primary regions (West, Midwest, South, and Northeast). Specifically, they lacked two for the South. In this case, the U.S. News and World Report's inclusion of finance MBA programs did not seem to be complete. I found a business program that was unranked in the best business schools, namely the University of North Texas. However, although the U.S. News and World Report does not

3.2.5.3 *Internships and Work Experience*

Highly selective and less selective work experience was tailored to the types of jobs being targeted. Highly selective professional experience included summer internships at top companies in the field, as defined by the appropriate ranking lists of the most prestigious companies. Typically, these were companies with top name recognition. Less selective internship experiences included positions at smaller and unranked companies in a field. Such companies generally did not have name-brand recognition or fall on a top-ranking list. Depending on the type of position and degree, applicants would either have two summer internships or a relevant full-time position prior to graduate school and an internship during graduate school.[21] In all cases, the two prior positions were for different companies and the matched pair could have no prior companies in common. Furthermore, since top-companies were those often being applied to, applicants could not claim past work experience at the company to which they were applying.

3.2.6 Creating Applicant Identities

In addition to signaling applicant prestige using both the selectivity of education credentials and past internships, I further signal socioeconomic status and race through fictitious applicants' names. The use of names to signal race and other attributes, perhaps, has the most recognized origin in Bertrand and Mullainathan (2004), wherein the authors utilize names to signal race and evaluate socioeconomic status. A number of subsequent studies have also utilized names to signal race, and as argued by Gaddis (2017), the most common approach has been to reuse names previously employed by scholars, especially Bertrand and Mullainathan (2004) or Levitt and Dubner (2005). Gaddis (2017) specifically investigates

have the University of North Texas listed in finance programs, a search of the university's website reveals a dedicated MBA finance concentration.

[21] For example, all MBA positions had a relevant full-time position prior to graduate school and an internship during graduate school. MS candidates in computer science had an internship in both graduate school and the summer before their senior year in college.

three dimensions of names, chiefly the racial signal of first names, the socioeconomic status of first names, and the racial signal of last names. The systematic survey analysis conducted therein highlights both a wide array of first and last names strongly perceived to be white in isolation. Furthermore, the racial signal of first and last names clarifies when issued in combination (Gaddis 2017). In other words, a white first and last name combination produced a more reliable signal of whiteness than either in isolation (Gaddis 2017: 479-480). By extension, the addition of a white middle name further increases the confidence of racial signaling. Accordingly, in constructing a name for each applicant, I utilized a white first, middle, and last name from Gaddis (2017).[22] Collectively, even without further strengthening perceived whiteness through using white middle names, each of my applicants first and last name combinations will be perceived as white by over 92.4 percent of potential recipients (Gaddis 2017). I display the selected name combinations in Table 3.2.

Table 3.2: Profiles of Experimental Applicants

Profile	Prestige Level	Party	Name
P01DH	High	DEM	Graham Spencer Andersen
P02DL	Low	DEM	Brian Daniel Larsen
P03NH	High	NEU	Ryan Connor McGrath
P04NL	Low	NEU	Dustin Robert Stein
P05RH	High	REP	Matthew Zachary Hartman
P06RL	Low	REP	Cody Hunter Walsh

After creating names for each applicant, I created a unique email address for each identity. Unique emails were created using Google's Gmail service. Email addresses (alternatively Gmail login identities) created a challenge of their own, given the ubiquity of the names for each of my six identities and the prevalence of Gmail. Desired attributes of the email were as follows: the inclusion of both the first name and last name, preferably in that order. Second, I desired to preserve some semblance of professionalism by not interjecting nicknames or

[22]White first and middle names were taken from the list of first names found in Gaddis (2017), Table A1. In isolation, each first or middle name is perceived to be white: an average of 87.5% (min 74.4%, max 95.2%). Furthermore, respondents had congruent perceptions of each white first name chosen in the experiment of over "92.4 percent when given a white last name" (Gaddis 2017: 480). In isolation, each last name was perceived to be white by over 95% of respondents (Gaddis 2017: 476). Collectively, these results provide high confidence that each of my applicants' names will be perceived as white.

random number combinations into the email address. Third, since I included middle names (or middle initials) on all resumes and correspondence, I wanted to include some permutation of the middle name in each email address.[23] This increased the perceived professionalism and also lowered the likelihood that the email would already be claimed. To illustrate names, let F represent a person's first name, M represent a person's middle name, MI represent a person's middle initial, and L represent a person's last name. In almost every case, email addresses of the form $FML@gmail.com$ would be taken, and in about half of the cases, $FMIL@gmail.com$ would also be claimed.

To ensure consistency of email format, I arrived at the following combination, which worked in every case. Instead of simply including the middle initial (MI), I included a two-letter abbreviation of the middle name where the first initial comprised the consonant first letter of the middle name and the second letter comprised another consonant in the middle name, ideally the last letter, except in cases where the last letter was (a) not a consonant sound, (b) the same letter as the first letter of the last name, or (c) formed a suspicious concatenation of letters, such as 'hr.' I will represent this two-letter middle name combination as $M2$. Thus, each email address took the following form, $FM2L@gmail.com$, which are reflected as follows:

Table 3.3: Created Emails for Each Applicant Identity

Name	Email
Graham Spencer Andersen	grahamsrandersen@gmail.com
Brian Daniel Larsen	briandnlarsen@gmail.com
Ryan Connor McGrath	ryancrmcgrath@gmail.com
Dustin Robert Stein	dustinrtstein@gmail.com
Matthew Zachary Hartman	matthewzchartman@gmail.com
Cody Hunter Walsh	codyhtwalsh@gmail.com

[23]To clarify, each applicant identity has a given middle name that appears as their email identity. While every email cover letter's *FROM* field has the full name of the applicant, the name format in the email signature and resume vary between using the full middle name or only the middle initial. As mentioned elsewhere, the assignment of A/B resume cover letter versions is randomized and counterbalanced. Similarly, if a contact were to call any given applicant, the voicemail scripts for every applicant identity state their full first, middle, and last name.

Lastly, I procured a dedicated phone number for each fictitious applicant identity. Phone numbers were generated using an online service that allows unique lines in a requested U.S. area code. Like a traditional mobile number, the phones may be called and potential callers can leave a voicemail message. To add realism, each number was provided with a customized and professional voicemail greeting. Since only a matched pair would ever be sent to any given firm contact, only two unique greetings were produced (Table 3.4).

Table 3.4: Voicemail Scripts

Treatment or Control	Profile	Script
Treatment	P01DH P02DL P05RH P06RL	*Good day, you've reached the voicemail box of [FULL NAME]. Please leave your name, number, and a brief message, and I'll return your call.*
Control	P03NH P04NL	*Thank you for calling [FULL NAME]. If you leave your name and a good number to reach you, I will be happy to give you a callback shortly.*

Version A was provided as the script for the partisan identities, whereas version B was provided for the neutral control identities. The scripts were performed by two age-appropriate, midwestern, cisgender, and heteronormative males of similar build, disposition, and vocal tonality. Following the midwestern accents, treatment and control phone identities were given midwestern area codes.[24] Both selected area codes stem from areas encompassing either suburb and rural areas of major cities or large cities and the suburbs and rural areas surrounding them. In both cases, the areas codes do not signal any particular political partisanship and originate from areas with strong political diversity (containing battleground counties as well as counties going to Democrats and Republicans). Moreover, the area codes in question are not affiliated with any major research institution.[25]

[24]This approach differs slightly from Rivera and Tilcsik (2016) or Tilcsik (2011), which match applicant phone numbers to the region of the job. Although this method has its merits, because geographic regions and area codes are conflated with political partisanship, that is the experimental treatment (Gift and Gift 2015), I elected to instead control this possibility by selecting two analogous and politically ambiguous area

Table 3.5: Selected Area Codes for Applicant Identities

Treatment or Control	Profile	Area Code	Largest Cities and Counties
Treatment	P01DH P02DL P05RH P06RL	616	Michigan Grand Rapids, Holland, and Wyoming Kent and Ottawa Counties
Control	P03NH P04NL	763	Minnesota (North) Minneapolis, Anoka, and Andover Anoka, Hennepin, and Sherburne Counties

Notes: More details on the primary cities, counties, and election results can be found from the following sources: Michigan 616 Area Code Counties and Cities: (WorldAtlas 2018a); Michigan Election Results: (Politico 2016a, 2018a). Minnesota 763 Area Code Counties and Cities: (WorldAtlas 2018b); Minnesota Election Results: (Politico 2016b, 2018b).

3.2.7 Matched Pair Applicant Resumes and Cover Letter Designs

When the experimental protocol is created, the treatment (partisan applicant) versus control (neutral applicant) is randomly assigned to one of two conditions or profiles, which I will designate as a *profile* or *pair version* A or B, a fact with important properties. First, profiles A and B are delivered on different days, with one calendar day between the two delivery days. For example, the first applicants are delivered Tuesday, while the second applicants are delivered Thursday. Second, profile A and profile B differ in style and substantive content. Because a critical component of the matched pair design is that the firm recipient remains unaware of the experiment, the two resumes and cover letters must differ in a number of ways to avoid rousing suspicion, namely, style and substantive content. Third, because the assignment of treatment and control to pair version A or B is independent and random, my design avoids conflating treatment and control conditions with (1) the order in which a company receives the application or (2) the idiosyncratic differences between the resumes and cover letters, such as its style or substantive content.

codes for treatment and control. In this way, partisanship (or lack thereof) is conveyed by the experimental treatment and control on applicant materials, and not randomly conflated with the region of the job.

[25] University of Minnesota, Twin Cities is a 612 area code.

Here, I want to briefly differentiate style and substantive content from educational credentials and internship experience. Whereas undergraduate and graduate educational credentials and internship experience reflect either highly selective or less selective conditions, both the style and substantive content for each applicant resume and cover letter is designed to convey a high degree of both hard skills and soft skills. I define hard skills as demonstrable knowledge, such as programming languages, foreign languages, or quantitative method expertise among other possibilities. Soft skills include writing ability and the capacity to create a high-quality resume. Because both high and low prestige applicants use the same resume and cover letter templates, there is no measurable hard or soft skill differences between high and low prestige applicant pairs, only differences in the selectivity of institutions.

Beyond hard and soft skills, both resumes and cover letters offer similar hard attributes and softer background descriptions. I define hard attributes as elements that do not necessarily signal relevant skills but instead offer other unique individual attributes, such as an applicant's hobbies, interests, or achievements. Substantive background differences on resumes, which are also referenced in cover letters, include specific thesis titles and the descriptions of past work experience. Note that these descriptions, while linked to job types (such as data science), are independent of the exact internships and academic institutions.

Importantly, although both the cover letters and resumes have unique albeit equally high quality expressions of suitability and interest in the position, the structural formatting of the cover letters, resumes, and names in both materials differ to avoid suspicion. Cover letters have a number of differences, particularly in the length and number of paragraphs.[26] Resumes

[26]Structurally, profile A and profile B cover letters vary. One of the most noticeable structural differences is the overall length and paragraph structure. Whereas profile A is approximately 290 words distributed over four paragraphs, profile B is approximately 225 words spread over three paragraphs. The exact length difference varies depending on the particular job type applied for as well as the randomly selected educational and employment institutions for that applicant. Another structural difference in the cover letters is the contact information. Whereas profile A includes both a phone number and email in the signature, profile B only includes the phone number. Either candidate can still be contacted by email since the contact need only hit reply in both cases.

differ in the titles of sections and order and format they appear,[27] the spacing and format of resume headers,[28] the description of theses,[29] and the layout of content in sections.[30]

Lastly, the name format,[31] and phone number format,[32] differ in both materials. Furthermore, stylistic differences refer to changes in the measurable cover letter and resume

[27]Regarding resume structure, there are a number of differences. Profile A has the following sections, ordered as follows: "Education," "Skills," "Professional Experience," "Leadership, Awards, and Honors," and "Additional Information." Profile B presents different wording for these sections and alternates the order of appearance: "Education," "Work Experience," "Honors, Awards, and Accomplishments," "Technical Skills," and "Supplemental Qualifications." Some variation around the titles of sections exists depending on resume type and the content therein. For instance, in MBA resumes, we have (A) "Leadership, Honors, and Distinctions" versus (B) "Awards, Accomplishments, and Affiliations." While profile A has left-justified section headers, profile B uses center-justified header sections. To subtly differentiate the final section, profile B does not include hobbies or interests, whereas profile A has these attributes. In MBA resume types, profile B includes a summary statement, which is omitted in profile A. The exact formatting of A and B versions for each job type is available online (Mausolf 2020f), and an example of A and B versions is listed in Appendix C.

[28]Whereas profile A uses a single line header for contact information, profile B uses a multi-line header. Profile A simply lists the address, phone number, and email separated by a pipe: |. Profile B includes the "Address:" across two lines, "Phone:" (single line), and "Email:" (single line).

[29]Profile A includes the thesis title (set off using a bullet point) and then a list of "Keywords" with another bullet point. Profile B sets off the thesis description with a bullet point, followed by the title, and keywords in form, "a thesis which develops and applies keyword1, keyword2, and keyword3." For MBA resumes, which do not have a thesis, a similar convention exists in differentially describing the MBA focus and concentrations.

[30]The layout of profile A and profile B differ. For sections noting years or time-periods (education, experience, honors), profile A lists dates in a left-justified column and content in a subsequent left-justified column. Profile B conversely lists content in a left-justified column and uses a subsequent right-justified column for dates. In other words, dates are on the left side of the page for profile A and on the right side of the page for profile B. In profile A, non-date sections (skills and additional information) have a descriptive (such as programming or languages) in the same left-justified date column. Substantive content falls into a subsequent left-justified column. By contrast, profile B rejects this formatting and instead uses two equal-width columns in each of the non-date sections, each containing bullet points. As with other differences, slight variations exist in the MBA resumes.

[31]As a method of further differentiation, I alter the name structure presented in the resume and emails. While all emails' *FROM* field (what appears in the inbox) list the full name of the applicant, the name format in the email signature, resume, and resume filename differ for profile A and profile B. While profile A utilizes the full first, middle, and last name in all materials, profile B utilizes the first name, middle initial, and last name for the email signature, resume, and resume filename.

[32]Profile A uses the common XXX.XXX.XXXX format for phone numbers in the email cover letter and resume. Profile B uses the format (XXX) XXX-XXXX. All cases leave out the international country code (+1). Pretesting interviews suggested the inclusion of a country code might suggest to employers that the applicant had an international background. Since all applicants are applying from U.S. universities to U.S. offices, not including the country code should not lead to confusion for employer contacts and also not confuse employers by possibly signaling the applicant has an international background.

design, such as the fonts employed for the resumes,[33] cover letters,[34] and email signatures;[35] bullet choice icons used for the resumes,[36] cover letter salutations and closings,[37] and email subject lines[38]. In order to provide further context, I have included a hypothetical example of profile A and profile B resume and cover letter for the treatment and control pair P03NH and P05RH applying to a fictitious *data science* job (Appendix C).[39] To reiterate a point above, although one pair version of a resume could randomly be more successful than the other, by independently randomizing and counterbalancing the experimental treatment to pair versions, this should not compromise the experimental validity in aggregate. Lastly, a number of other differences not enumerated or noted here also exist. The exact templates for each A/B version of resumes and cover letters for every job type exist on Github for reference (Mausolf 2020f).

---

[33]For example, the resume for profile A uses the default LaTex font, computer modern roman (a serif font), whereas profile B uses the sans-serif Helvetica. This change has several additional stylistic ramifications. For example, LaTex supports a typography convention known as *textsc* or small caps, which can be used to emphasize certain attributes. This format is supported for computer modern roman but not Helvetica.

[34]In the HTML versions of the email cover letters, profile A uses the serif font Garamond whereas profile B uses a sans-serif Helvetica. In the email signatures, profile A uses Garamond in addition to Copperplate, where the latter font achieves the boldface effect for the school. Conversely, profile B uses Helvetica exclusively. Whereas profile A uses a smaller font for the applicant title and contact information, profile B uses the same font size throughout. Lastly, whereas profile A uses a justified spacing, profile B uses a standard non-justified spacing and a left page alignment.

[35]An additional stylistic difference between the matched pairs is in the color used for the graduate school name in each email signature. Profile A has some stylistic flourishes in the colors, namely the school has the *rgb* color of the graduate school the applicant attends and the hyperlinks for the phone and email are a shade of blue $rgb(17, 131, 204)$. Conversely, profile B lacks these color flourishes, and is instead, a consistent shade of black $rgb(0, 0, 0)$ throughout.

[36]Different bullet points are utilized between resume styles. Whereas profile A uses *diamond* bullet points, profile B uses *circ* bullet points.

[37]Whereas profile A uses an informal salutation of "Hi Firstname," profile B uses the more formal "Dear Firstname Lastname:" as a salutation. Whereas profile A uses "All the best," followed by the applicant's first name (and then the full email signature) as an email closing, profile B uses "Sincerely," and only the full signature to close the email.

[38]For most cases, the format of profile A subject line takes the form "{JOB TITLE} Opening - {COMPANY}" whereas profile B uses the subject line "Position | {JOB TITLE}." Thus, the primary differences occur in the word to convey a job (Position versus Opening), the placement of that word, and the use of a hyphen "-" versus a pipe "|" if it exists. Lastly, most profile A versions include the company name. Exceptions occur when the name of the company is included in the job title. For example, a job title might be "Economist/Statistician - Amazon Search" and in such a case, the subject line becomes "Economist/Statistician - Amazon Search Opening" not "Economist/Statistician - Amazon Search Opening - Amazon."

[39]The included resumes and cover letters in Appendix C are fictitious in that the job being applied to as well as the contact name were generated for the purpose of pretesting, and the account emailed was one of the master email accounts created for this study.

3.2.8 Identifying Firms and Contacts

As with any job search, an initial step is often to identify companies with potential jobs and then search those companies for relevant job openings based on job titles and associated keywords. To maximize prospects, a job applicant would likely target jobs with the best-perceived match to their background. The experimental job search I executed involved a similar albeit computational approach.

First, I identified high profile companies that were likely to have numerous jobs, particularly for the primary job fields of interest: data science, statistics, quantitative finance, software engineering, project management (MBA), financial analysis and planning (MBA), or business analytics (MBA). These job fields are of particular interest as being high-demand job fields with excellent compensation and can be found at a large number of firms. Unlike other top-paying jobs, such as management consulting, there are many more firms hiring for these positions and such positions have openings year-round rather than a highly specific recruitment season. To search for these jobs, I examined top companies, sourced from several ranking lists (Table 3.6).

Table 3.6: Company Lists to Search for Jobs

List	Companies
Fortune 1000	1,000
Institutional Investor Hedge Fund 100	100
Vault Consulting Top 50	50
Vault Best Boutique Consulting Firms	25
Vault Banking 50	50
Vault Accounting 50	50
Vault Law 100	100
Forbes The Cloud 100	100
CNBC Disruptor 50	50
Business Insider Top Valued Private Tech	25
NASDAQ Tech Companies	629
Glassdoor Top 100 (Large)	100
Glassdoor Top 50 (Medium and Small)	50
Russell 3000 Index	3,000
Total Deduplicated Companies	4,209

In most cases, these sources did not have a downloadable list, and so I wrote elementary Pythonic web-scrapers to collect this information as a CSV datafile. The CSVs from each source were appended, cleaned, deduplicated, and pre-processed for use in a more advanced series of web-scraping scripts, which searched for a number of full-time jobs for each company on a job aggregator,[40] and identified the best matching and most recent job of the possible choices.[41] Ideal jobs were then matched to an external database of relevant firm contacts.[42] These curated job opportunities with firm contact points were passed to the experimental protocol file, which was used in the computational deployment of the experiment, described in the following section.

[40]I wrote a web-scraper to search a popular job aggregator. Job types were rank-ordered such that if multiple ideal job matches were found at a firm and were posted within the same period, the job type with the highest rank was selected. The web-scraping script searched for ideal matching jobs for each job type using a series of targeted queries, and the search was performed at different levels of posting recency, such as 14 days or 30 days. Where multiple ideal jobs were found at different levels of recency, the most recent ideal job was selected. Web-scraping of ideal jobs from the aggregator was supplemented with manual job search queries on another popular professional social networking site. This was necessary, as not all companies had listed jobs on the primary aggregator searched with the web-scraper.

[41]During the search process, each company was searched for every one of the seven possible job types, each with their associated keywords and backup keys. For example, at technology firms, data science and software engineering were the top job types, respectively. Similarly, different types of firms were searched for the two primary types of MBA positions at different ranks. For MBA programs, I included two primary types of MBAs, those with an MBA focused on general management and those with an MBA concentration in finance. An examination of the supplementary code reveals a third 'mba_analyst' type. These applicants have an identical background to MBAs in general management and exist simply to apply to more generalized business analyst positions, which are less specific in the appropriate background. That is, in some cases, an MBA is preferred while in others, an MBA might be a disadvantage over an undergraduate depending on the firm's salary expenditure. Thus, such job types were applied to only in cases where the foregoing more specific job types did not exist. In other words, mba_analyst positions represented the lowest rank job type, selected only if no other jobs were found for the other six job types.

[42]A firm contact is no single type of representative and varies by firm. To the extent the possibility of multiple firm contacts existed, I strived to select ones who had positions using permutations of "Recruiter" or "Talent Acquisition." Interviews with former human resource officers and career counselors suggested that those in recruiting or talent acquisition would make the most sense as the first option of firm contact. Not only is this their daily job but also these individuals would receive more emails regarding current job opportunities than the average human resource manager or generalist. It should be noted that only full-time corporate recruiters or talent acquisition specialists were selected, not temporary "contract" workers who only exist on a temporary basis. Typically, HR managers reflected a secondary option where no recruiters existed. In terms of seniority, I elected to optimize contacts at the manager and other (non-managerial) levels, using higher positions, such as directors, only where no relevant lower-ranked human resources (recruiter, talent acquisition, or general HR) personal existed and no obvious hiring manager could be found. In some cases, no HR contacts existed. In such a case, I would select a plausible hiring manager. For example, if the job being applied for were a software engineer, I would select an engineering manager as a firm contact if no human resource options existed.

3.2.9 Computational Deployment of the Experiment

The computational deployment of the experiment is one of the more complex elements of this study. Pragmatically, the experiment is deployed using a custom Python module that I developed for this project (Mausolf 2020f). This repository contains dozens of Python scripts and several thousand lines of code. The basic computational process falls into a number of stages described in Table 3.7.

Since many of the substantive details of these steps have already been described in prior sections, I will focus most of the effort on the actual deployment of the experiment. Once provided an experimental protocol, the experiment can be run with a single command line prompt: *python experiment.py*. The immediate action after this running this command is the random assignment of the full experimental selection that matches job applicant backgrounds to undergraduate and graduate schools as well as internships based on their prestige level, job type, and region of the job's location (step 3). Once created, the code divides match version A and B applicants into two files to be executed with a one day gap in between calendar days (Tuesday and Thursday). For each of those applicants, two versions of an email are drafted and embedded in a single email, both an HTML version (which are how most emails appear) and a plain text version that will be readable to employer contacts who might have HTML disabled. Also attached to that email is a PDF version of the resume. Both the resume and cover letter are customized to the company, contact point, job type, education, and work experience using the details assigned in step 3. That email and attachment are then sent, concluding step 4. The actual time to deploy this process is relatively swift. For example, in testing, a batch of 1500 version (A) resumes/cover letters were created and sent in 89.57 minutes. The remaining 1500 version (B) resumes and cover letters took an additional 86.71 minutes to deploy following the specified time delay. In this manner, the delivery time would vary roughly an hour and a half between delivery days. It is important to note that online SMTP email services, as used in this experiment, supposedly have a rate

Table 3.7: Computational Process

Stage	Overview	Tasks
1	Pre-Experimental Processing	A: Web-scraping currently available jobs for specified companies, job types, and keywords B: Filter and identify ideal jobs using detailed criteria C: Collect business contacts for companies with jobs D: Fuzzy match company jobs and company contacts
2	Create Experimental Protocol	A: Load external jobs data, contacts data, and region data B: Randomly assign matched pair prestige states C: Randomly assign match pair versions (order/style/substance) D: Randomly assign treatments (Democrat / Republican) and control (neutral) to pair E: Match assignments to applicant profiles (names, emails, phone, login credentials) F: Log full experimental protocol details G: Save consolidated protocol (only needed columns) to run
3	Assign Applicant Backgrounds Using Protocol	[All steps, random selection without replacement] A: Select graduate school for each matched pair using region, job type, and prestige B: Select undergraduate school for each matched pair using experimental treatment/control condition, prestige, region, and graduate school C: Select internship for each matched pair using job type, prestige, and company being applied to
4	Deploy Experiment	[For each applicant] A: Write a cover letter using match pair version (A/B) template for given job type using all applicant information (e.g. name, email, phone, education, internships, treatment/control, among others factors) B: Compile both HTML and plain text versions of the above cover letter C: Create HTML/plain text email signatures using the above D: Modify the LaTex A/B resume template using the above information and compile a PDF version E: Write an email to each contact using the cover letter and signature (HTML/plain text) F: Attach the compiled resume for the applicant and send the email (Group A occurs Tuesday; Group B occurs Thursday)

limit of 500 emails per account over a rolling 24-hour period. Testing revealed this limit to be approximately 1100 per email account (1099, 1101, and 1099 in three tests). Depending on the number of jobs per account, the overall experimental protocol could hypothetically need to be divided into several batches in order to avoid surpassing the practical email limit. This is particularly true for the most common email account associated with the high prestige, politically neutral control. However, multiple batches were not necessary.

Although creating the code necessary to run this experiment is time-consuming, a greater degree of precision and reproducibility is garnered using the computational approach. After the experiment is run, a log exists capturing all the details, including those generated in steps 3 and 4. Because the code is scalable, the only elements necessary to, for instance, apply to 2000 jobs instead of 1000 jobs, is simply an expanded array of companies with jobs for one of the job types that this experiment targets. Of course, increasing the size also varies with the temporal fluctuations of firms' day-to-day available job openings as well as having an available contact point for a given firm.

3.2.10 Post-Experiment Data Preparation

In this study, I specifically evaluate how the alignment of a job applicant's political partisanship with that of the firm affects the likelihood of receiving a callback for a given job. To perform this analysis first requires defining a callback, among other types of response options, categorizing and cleaning responses, and determining the partisanship of firms.

3.2.10.1 Defining Callbacks, Other Responses, and Bounces

Following the precedent of other scholars, I define a callback as either an email or phone response (or combination thereof) to a given applicant indicating the desire to coordinate a subsequent preliminary interview or phone screen. Thus, simple responses, such as requests for additional information or requirements that the applicant first applies online, were coded as a reply but not a callback and thus excluded from the callback analyses. Besides the two main types of response (callback or reply), applicants might also receive additional reply types, such as an automated email or out of office reply. When evaluating the response, it is important to note that applicants might receive multiple rapid-fire replies before it was possible to notify them that the applicant was no longer interested, following IRB guidelines. For instance, a recruiter might initially reply asking if the applicant had already applied online, and shortly thereafter send another email and perhaps a call saying regardless, they would like to keep the ball rolling and set up an interview. Relatedly, automatic replies were sometimes, but not always, followed by another response (sometimes weeks later) asking to set up an interview. In this way, the ultimate outcomes (callback, other reply, non-response) were determined by manual review for each response. In determining the overall response, I set the result for that applicant as equal to the highest-level response. For example, if they received an automatic reply, a reply asking if they already applied online, followed by a callback to set up an interview, the overall outcome was designated as a callback.

Of course, since the experimental protocol described above relies upon sending emails to a firm contact, the success of the application depends first on the email reaching a valid, firm contact. Necessarily, the automated process resulted in a number of delivery issues, among them, bounces and invalid contacts. Since firm contact email addresses were sourced from a subscription dataset, even though such emails claimed to be recently validated, some were no longer valid in practice. Furthermore, emails could bounce or fail to be delivered due to corporate spam filters, which preempted delivery attempts. At times, rather than directly bounce, an automated response would indicate that the employee no longer worked at the company, which would be coded as a bounce. After the first wave of applications was deployed, I determined which set of firms had one or more bounce or other related errors for the applicant pair. In these cases, I generated a new experimental protocol given a new contact at each firm in question and deployed a second wave of the experiment.

3.2.10.2 *Categorizing Experimental Outcomes*

After deploying both waves of the experiment, I waited at least one month before coding the final experimental outcomes for each applicant,[43] which relied on a combination of manual coding and categorization of the email responses with computational adjudication of determining the applicant associated with a given reply, bounce, or error. To illustrate a challenge of this method not often discussed, we have the determination of which result belonged to a given applicant profile (and related randomized factors) in the experimental protocol. While it might seem that we could simply determine this information from the sender profile (and email), employer contact email, and experimental wave, this was not always true. In the case of a callback or reply, a frequent occurrence was some behind-the-scenes communication on the firm side, such that often the person replying had received the applicant's resume and cover letter from the person initially emailed or some series of preceding individuals. Often, the initial firm contact was not copied and the email history not included, making alignment with the result challenging, at least using an automated computational approach. This was particularly true in the case of voicemail replies. Similarly, the initial contact would frequently respond where the received email was some alternate variation of the original sent email. For example, an email might be sent to *first.last@corp.com* whereas the response might come from *last.f@division.corp.com*. Bounces followed similar challenges, such as automated Gmail explananda denoting reasons for the bounce, which often included a version of the firm's domain in the details of the explanation. Computational coding of these thousands of outcomes highly facilitated the process, which I supplemented with a manual review and completion of cases not resolvable through automated processes. Similarly, automatically transcribed phone replies necessitated manual review to determine the company replying to the given applicant.

[43] The first wave of the experiment began on Tuesday 4/2/2019 and Thursday 4/4/2019, while the second wave of the experiment began on Tuesday 4/23/2019 and Thursday 4/25/2019. The final results of the email and phone replies were not conducted until after a month had elapsed since the last resumes were sent on 4/25/2019, which concluded on 5/28/2019.

3.2.10.3 Determining Firm Partisanship for Applicants

Of course, as previously stated, to properly analyze affective polarization and partisan homophily requires some knowledge of not only the partisanship of the fictitious applicant but also that of the firm. To calculate firm-side partisanship, I utilize the corporate politics data from Mausolf (2020a), which originated from the Federal Election Commission (Federal Election Commission 2018a).[44] For brevity, I refer to this as the FEC-CP data. In particular, I utilize company-level data on the mean party identity in a firm for a given election cycle (2008-2018), which I averaged to generate an overall partisan identity for the firm. Yet, this data contains only a subset of Fortune 500 firms, specifically, 334 firms for the period in question (Mausolf 2020a). Furthermore, a number of these firms either did not have a relevant job opening or valid email contact. For example, no firm contact could be identified or the firm had errors during the experiment. In total, I determined the political partisanship of 134 applicant-pairs using the FEC-CP data (Mausolf 2020a). I supplemented the FEC-CP data by determining the political partisanship of additional firms using data from OpenSecrets.org (Center for Responsive Politics 2020), specifically the search feature which enables a curious user to search for a firm and determine its partisan leaning by examining the overall contribution amounts given by individuals in a firm to each political party. Although an API exists for OpenSecrets, there did not appear to be an API feature to extract this type of information, and given the idiosyncratic locations and interactiveness of the data, writing a viable web-scraper would have proven more cumbersome than performing a manual search for a subset of 195 additional applicant-pairs, wherein I prioritized determining the partisanship for firms providing callbacks, bringing the total number of cases for which I had FEC and experimental data to 329 applicant-pairs or 658 applicants.

[44] In particular, I utilize data grouped by firm (thus ignoring occupational hierarchy) for election cycles 2008-2018, which captures a firm's most recent partisanship using the mean party identity [DEM, REP] (Mausolf 2020a). Because the mean is calculated across years and substantially more individuals contributed in 2016 and 2018, the mean is even more weighted toward recent partisanship.

3.2.11 Methods of Analysis

After deploying both waves of the experiment, categorizing the results, and determining the partisanship of firms, we have the following descriptive statistics of the data (Table 3.8). As shown in Table 3.8, I attempted to send 3,856 total applications, and of these, 2,670 matched pairs were received by firm contacts. Of the received applicants, I was able to determine the firm's political partisanship for 658 matched applicants. In my analysis, I primarily focus on the results for these applicants, which uniquely afford the opportunity to evaluate affective polarization and partisan homophily hypotheses. Before reviewing these results, briefly consider the overall results for each of these three groups (Table 3.8).

Following the experiment, I conduct several types of analyses. At the most basic level, I provide a series of descriptive statistics and bivariate statistics, such as bar-plots with confidence intervals and t-tests. I provide this basic descriptive analysis first for all overall applicants in the scenario of unknown partisanship about the firms being applied to. This follows the standard approach in most of the correspondence-audit literature when evaluating biases based on applications. For example, studies on racial bias in job applications using resumes typically focus on variations in the callback response by applicant features (Bertrand and Mullainathan 2004; Gaddis 2015), without considering, for example, how the level of extant firm diversity might influence the decision to give minority applicants a callback.

Yet, beyond the comparison for the overall state of partisan biases in job market callbacks, I provide analysis for the subset of applicants where we can determine the partisanship of the firm and thus evaluate the degree to which affective polarization and partisan homophily affect callback outcomes. Here, I offer similar bivariate statistics, such as bar-plots with confidence intervals and t-tests to compare differences between the outcomes of partisan mismatching or matching compared to neutral applicants, how this varies by the partisanship of the firm. Following the work in similar analyses, I also provide a number of formal models to substantiate the bivariate results.

Table 3.8: Descriptive Statistics of Experimental Job Applicants

	Sent Applicants	Received Applicants	Matched Applicants
Total Job Applicants			
Sent Applicants	3856	2670	658
Received Applicants	2,710 (70.28%)	2,670 (100.00%)	658 (100.00%)
Failed Applicants	1,146 (29.72%)	0 (0.00%)	0 (0.00%)
Application Results			
Received Callback	139 (3.60%)	139 (5.21%)	69 (10.49%)
Received Other Reply	442 (11.46%)	441 (16.52%)	108 (16.41%)
Received Any Response	581 (15.07%)	580 (21.72%)	177 (26.90%)
Applicant Profiles			
P01DH	540 (14.00%)	372 (13.93%)	73 (11.09%)
P02DL	236 (6.12%)	166 (6.22%)	43 (6.53%)
P03NH	1,369 (35.50%)	934 (34.98%)	222 (33.74%)
P04NL	559 (14.50%)	401 (15.02%)	107 (16.26%)
P05RH	829 (21.50%)	562 (21.05%)	149 (22.64%)
P06RL	323 (8.38%)	235 (8.80%)	64 (9.73%)
Applicant Partisanship			
Republican	1,152 (29.88%)	797 (29.85%)	213 (32.37%)
Neutral	1,928 (50.00%)	1,335 (50.00%)	329 (50.00%)
Democrat	776 (20.12%)	538 (20.15%)	116 (17.63%)
Applicant Prestige			
High Prestige	2,738 (71.01%)	1,868 (69.96%)	444 (67.48%)
Lower Prestige	1,118 (28.99%)	802 (30.04%)	214 (32.52%)
Job Type			
Data Science	1,048 (27.18%)	732 (27.42%)	310 (47.11%)
Quantitative Finance	30 (0.78%)	26 (0.97%)	14 (2.13%)
Statistics	28 (0.73%)	26 (0.97%)	2 (0.30%)
Computer Science	1,014 (26.30%)	686 (25.69%)	160 (24.32%)
MBA - Analyst	206 (5.34%)	162 (6.07%)	16 (2.43%)
MBA - Finance	680 (17.63%)	470 (17.60%)	66 (10.03%)
MBA - Project Management	850 (22.04%)	568 (21.27%)	90 (13.68%)
Job Region			
Northeast	854 (22.15%)	606 (22.70%)	162 (24.62%)
Mid-Atlantic	176 (4.56%)	126 (4.72%)	38 (5.78%)
Midwest	774 (20.07%)	510 (19.10%)	140 (21.28%)
South	980 (25.41%)	654 (24.49%)	168 (25.53%)
West	1,072 (27.80%)	774 (28.99%)	150 (22.80%)
Experiment Stats			
Firm Contacts	1928	1335	329
Unique Firms	1626	1318	323
First Wave	2,812 (72.93%)	2,042 (76.48%)	544 (82.67%)
Second Wave	1,044 (27.07%)	628 (23.52%)	114 (17.33%)

Notes: (1) Sent applicants include all emails that successfully sent (on the sender side). For example, sent applicants include emails that bounced due to a number of reasons such as invalid emails or corporate spam filters. *(2) Received applicants* include all emails believed to have been received by the intended recipient. This group excludes emails where one or more of the emails from the applicant pair bounced or reached an unintended company or recipient. Thus, the number of received applicants in column two is slightly lower than received applicants in column one, which includes applications where only one of the two applications sent. *(3) Matched applicants* is a subset of received applicants for which we also have data on the company's partisan leanings based on FEC contributions by individuals therein. The number of firm contacts is one half the total number of applicants, which in the case of (2) and (3) is slightly higher than the number of unique firms secondary to firm-deduplication errors across multiple employer lists (Table 3.6).

3.2.12 Formal Models

In this analysis, I specifically evaluate how the alignment of a job applicant's political partisanship with that of the firm being applied to affects the likelihood of receiving a callback for a given job. To evaluate the likelihood that an applicant receives a callback, I use logistic regression models, a type of maximum likelihood estimation often used for estimating the probability of a binary event happening or not. In this case, I model the probability that a given fictitious applicant will receive a callback. This type of logistic regression modeling for binary outcomes has been conducted in similar experimental correspondence-audit studies (Gaddis 2015; Pedulla 2016; Tilcsik 2011). A number of other studies use related models, such as the probit model or exact logistic regression, as well as other models, such as linear or Heckman models (Gift and Gift 2015; Kang et al. 2016; Rivera and Tilcsik 2016: 1110).

Logistic Regression Model:

$$\eta_i = logit(\pi_i) = log\Big[\frac{\pi_i}{(1-\pi_i)}\Big] = \beta_0 + \beta_1 x_1 + \ldots + \beta_j x_i \tag{3.1}$$

Logistic Regression Model in Terms of Odds-Ratios:

$$\begin{aligned} \frac{\pi_i}{(1-\pi_i)} &= \exp(\beta_0 + \beta_1 x_1 + \ldots + \beta_j x_i) \\ \pi_i &= \frac{\beta_0 + \beta_1 x_1 + \ldots + \beta_j x_i}{1 + \exp(\beta_0 + \beta_1 x_1 + \ldots + \beta_j x_i)} \end{aligned} \tag{3.2}$$

for $i = 1, \ldots, n$ job applicants;

$j = 1, \ldots, j$ coefficients;

where $\pi_i = Prob\Big\{\text{Callback}_i\Big\}$ for a given applicant i in the set of observations $Y_i \sim B(n_i, \pi_i)$; as predicted by regression covariates x and regression coefficients β. Using these models, in combination with supporting descriptive statistics, I evaluate the evidence relative to my hypotheses on affective polarization and partisan homophily. More generally, I establish the effects of partisan bias and applicant prestige in the general case where firm partisanship is unknown. Collectively, this research underscores the role of political partisanship, especially affective polarization and partisan homophily, in structuring entry into firms. More generally, this work illustrates how political partisanship might shape careers.

3.3 Analysis

Before diving into the modeling analysis of the experiment, first consider the results for all received applicants. Recall that all received applicants are those applicants for whom an application was successfully sent and we may know the partisanship of the firm, but in most cases, firm partisanship is unknown (*c.f.* column two in Table 3.8).

3.3.1 Overall Findings Without Partisan Matching

If we assess the results for all received applicant pairs, there was not a significant difference by applicant partisanship (Republican, neutral, or Democrat) or applicant prestige. Despite the lack of significance, higher prestige applicants received slightly more callbacks, as did Republican applicants. I display discrete bar plots for results by party and prestige in Appendix C, Table C.5. Below, we can discern this same pattern, but also appreciate that some differences might exist at the intersection of partisanship and prestige (Table 3.1).

Namely, we see a statistically significant difference in the callback rates of low prestige Democratic applicants compared to low prestige Republican applicants. In some ways, this may seem curious. On one hand, there is more variation in callback rates for low prestige applicants, and overall they have lower callback rates than high prestige applicants on balance, with the caveat that such results are not statistically significant. Taken another way, for low

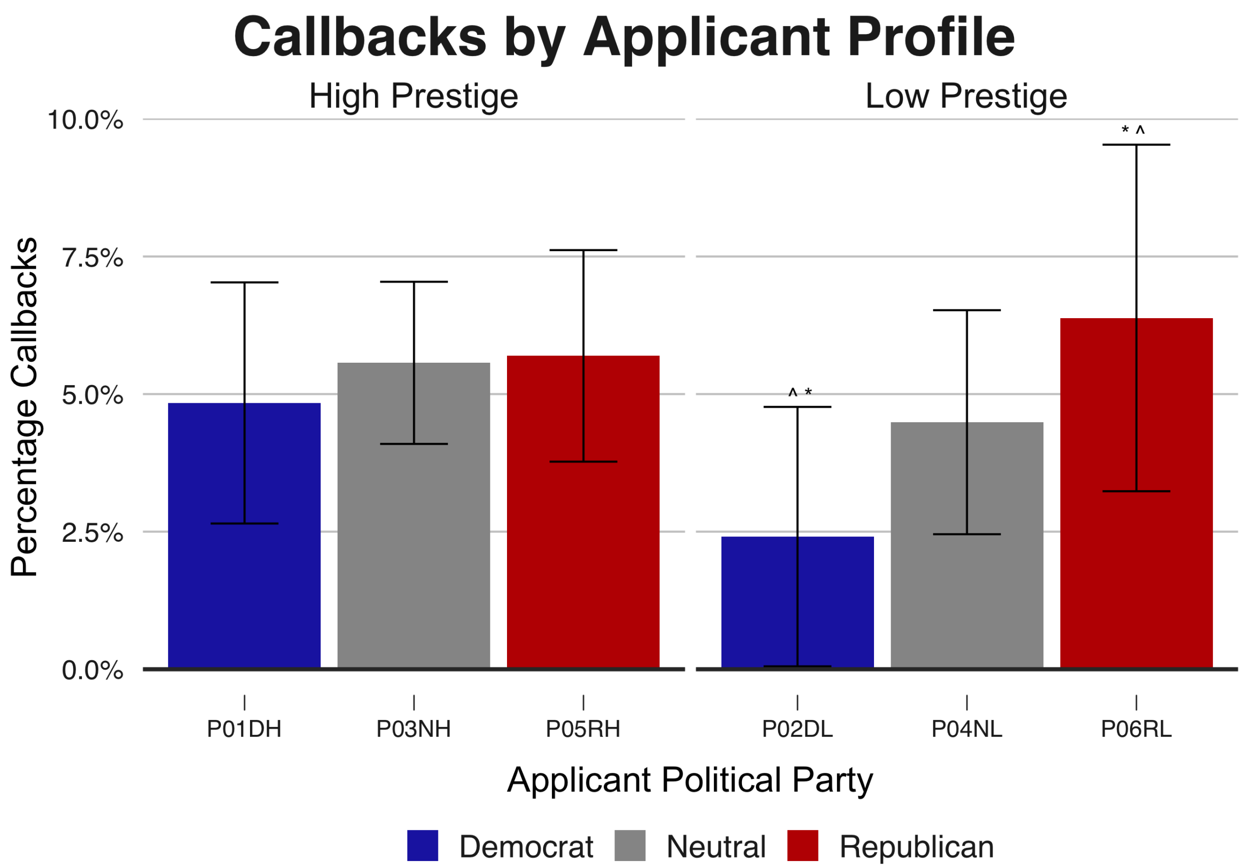


Figure 3.1: Results of the Experiment by Applicant Prestige and Party

Notes: N = 2670, all received applicant-pairs. Mean callback rate with 95% confidence interval displayed. Confidence intervals generated for each group (bar) using a one-sample t-test with the default two-sided option in R. This yields a confidence interval equivalent to the 95% CIs generated from a two-sample t-test with unequal variance in Stata. Two-sample t-tests for unequal variance calculated between each applicant partisanship and the other two partisan types within each firm party. The only significant difference is between low prestige Democratic and low prestige Republican applicants.

*p $<$ .05; **p $<$ .01; ***p $<$ .001

prestige applicants to receive a callback, matching on other dimensions, such as partisanship might matter more, but it should be noted that this same pattern does not necessarily hold true for the smaller sample of matched applicants, which I evaluate in the section below.[45]

[45] As indicated, the statistically significant difference between low prestige Democratic applicants compared to low prestige Republican applicants only appears in the larger received applicants dataset. In the smaller matched applicants dataset, the statistical significance dissolves, although the general pattern of more callbacks for low prestige Republican applicants over low prestige Democratic applicants holds (Appendix C, Table C.6).

3.3.2 Evaluating Affective Polarization and Partisan Homophily in Matched Applicants

Turning to the primary analysis surrounding the evaluation of affective polarization and partisan homophily, we should keep several points in mind. First, we must recall that we would like to evaluate two discrete mechanisms of political partisanship, namely affective polarization (specifically its negative valence of animus towards out-party members) and partisan homophily, or the preference for copartisans. This given framework collectively presumes that copartisans will receive more callbacks than opposing-partisans—and this difference will be significant. To better understand the power of the mechanisms, as well as a better differentiate which lever is more powerful, we can make comparisons with respect to an employer's preference for politically neutral applicants. In other words, we must attune to how neutral applicants compare to either copartisans or opposing partisans. Understanding this difference can help to reveal which driver is more important for individual applicants in labor market entry.

To appreciate this difference, consider the experimental results in Figure 3.2. Here, we can see that politically neutral applicants have a callback rate of 10.63%. Note that this is about the same callback rate as all applicants in the FEC-matched subsample, 10.49% (Table 3.8).[46] Yet, whether applicants match with the partisanship of the firm or oppose it matters. Copartisans receive more callbacks (16.87%) and opposing-partisans receive fewer callbacks (4.14%) on balance. When comparing the callback rate of mismatched partisans to matched partisans, we see that the difference is statistically significant ($p < 0.001$), indicating a significant firm-level difference between a preference for copartisans and an aversion toward out-partisans. Thus, when trying to differentiate which mechanism has more leverage, we can see that while opposing partisans have a significant disadvantage compared to neutral

[46]The astute observer may note that this rate is slightly higher than the callback rate for all received applicants. In part, this reflects a process of data collection, particularly the manual search process, which prioritized determining the partisanship for applicant pairs where at least one of the applicants had a callback. Such observations were most relevant since at least in these cases, the response indicated the email had definitively been received and did not simply silently pass to a spam folder or a persistent but outdated email without a valid automated reply.

applicants ($p < 0.01$), copartisans do not necessarily have a parallel advantage. Although copartisans have a higher callback rate than neutral applicants, the difference is not significant at the $p < 0.05$ level, only the $p < 0.1$ level. Consistent with past studies, affective polarization is a more powerful driver of behavior than partisan homophily, and collectively, there exists a significant difference between these response patterns.

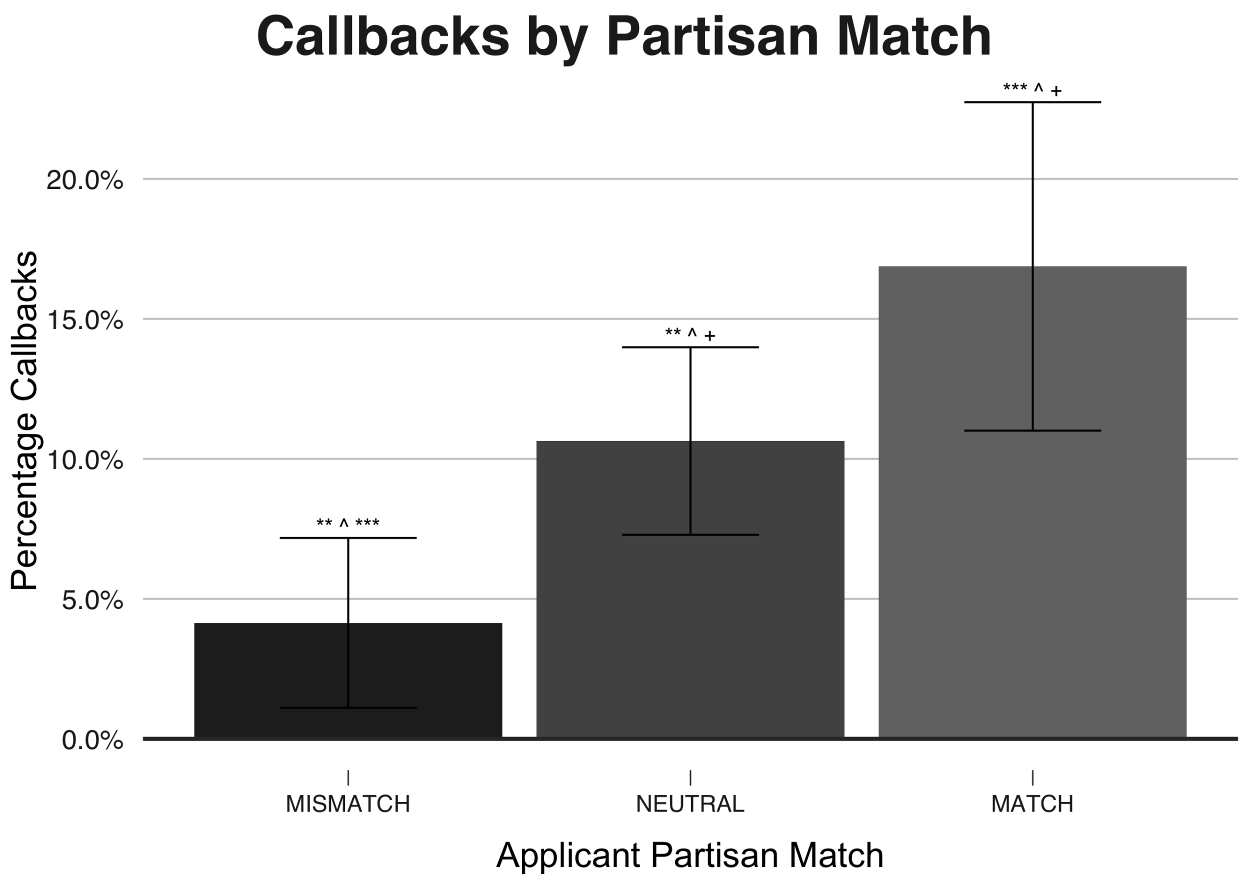


Figure 3.2: Experimental Results by Partisan Matching Status with the Company

Notes: All firms: N = 658 applicants. Results are only for applicants applying to companies with an identified partisan profile. Identifying that partisan profile is a considerable effort, incorporating analyzed data from the Federal Election Commission (Mausolf 2020a), as well as supplemental data on additional companies using the Center for Responsive Politics (2020). Mean callback rate with 95% confidence interval displayed. Confidence intervals generated for each group (bar) using a one-sample t-test with the default two-sided option in R. This yields a confidence interval equivalent to the 95% CIs generated from a two-sample t-test with unequal variance in Stata. Two-sample t-tests for unequal variance calculated between each applicant partisanship and the other two partisan types within each firm party. The p-value for each t-test is displayed in the figure above the CI upper bound with notation following the form $p1\hat{\ }p2$, where p reflects the significance seen below. The p-values, $p1\hat{\ }p2$, are the results for the group in question relative to the alternative two groups $group1\hat{\ }group2$, maintaining the consistent order (mismatch, neutral, match). *p < .05; **p < .01; ***p < .001

Indeed, these results show that affective polarization, in the sense of both partisan animosity and partisan homophily, operate at the firm level. Because this behavior is by definition partisan, and past studies have shown that Democratic and Republican firms have differences in firm-level behavior (Mausolf 2020a), we might wonder what differences in applicant callback patterns, if any, exist on the basis of firm partisanship. Examining the results in Democratic and Republican firms (Figure 3.3) reveals several important findings. First, the callback rate is higher in Democratic firms. Second, in both Democratic and Republican firms, there is a significant difference in the callback rate for opposing partisans versus copartisans, $p < 0.05$ and $p < 0.001$, respectively. Similarly, in both Democratic and Republican firms, opposing partisans face a callback disadvantage compared to neutral applicants, $p < 0.05$ in both cases. Only in Republican firms, however, do copartisans receive a significant callback advantage over neutral applicants, $p < 0.05$. Thus, echoing the overall results, we can see the results of affective polarization, especially the partisan animus experienced by opposing partisans for both Democratic and Republican firms.

Yet, from the applicant perspective, another façade emerges (Figure 3.4). Republican applicants, for instance, experience a smaller difference in callback rates on the basis of whether they match or mismatch with the partisanship of the firm. By contrast, Democrats see a large and highly significant difference in their callback rates, depending on whether they align with the partisanship of the firm. In this respect, the comparative risk of including a partisan signal is higher for Democratic applicants than Republican applicants if they inadvertently misjudge the partisanship of the firm. These results shed additional light on the overall higher callback rates for Republican applicants (Figure 3.1). If there are more Republican than Democratic firms, and out-party Republicans are less penalized than out-party Democrats, this could on balance offer some explanation for the slightly higher rates of callbacks for Republicans over Democrats in the experiment.

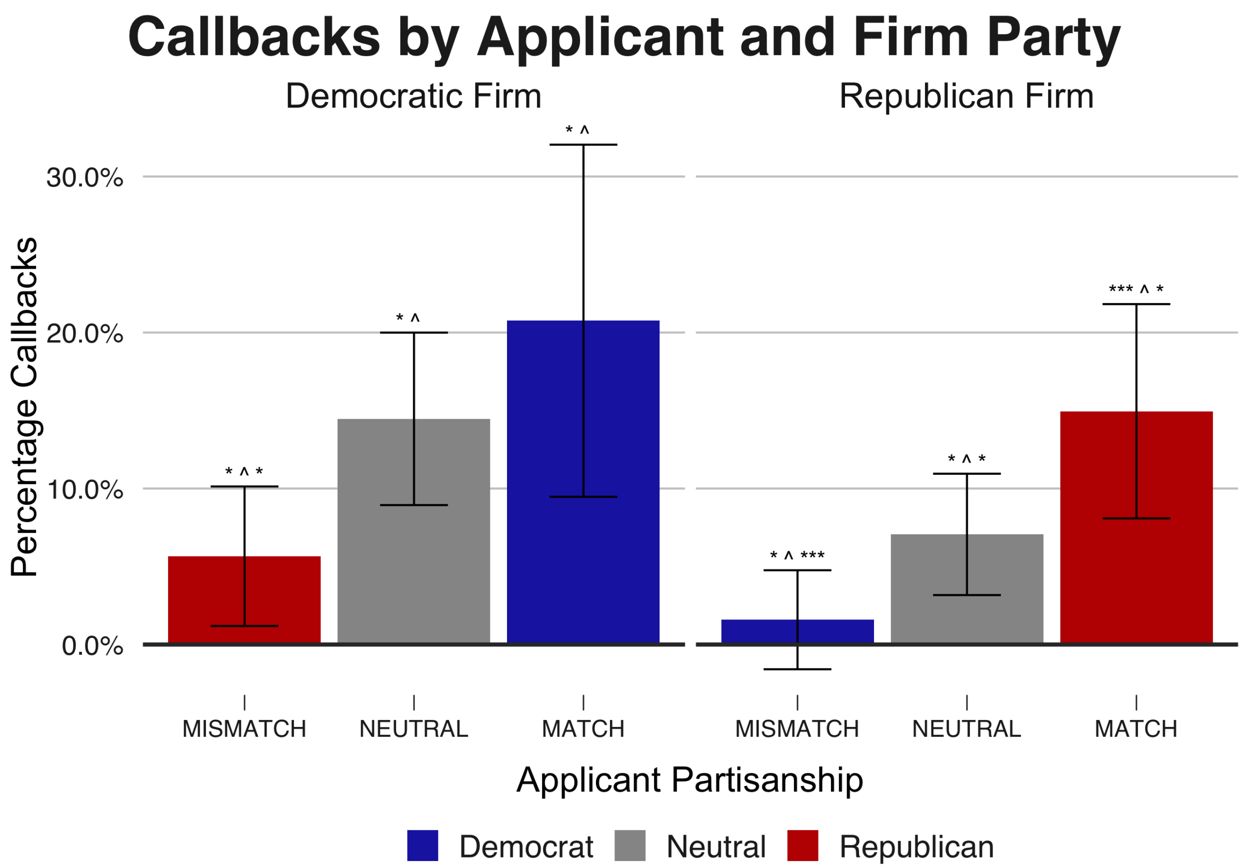


Figure 3.3: Callbacks by Applicant and Firm Partisanship

Notes: All firms: N = 658 applicants, Democratic Firms: N = 318 applicants, Republican firms: N = 340 applicants. Callback results displayed by the partisanship of the firm applied to and the partisanship of the application. As described, each firm received a matched pair of applicants (one partisan, one neutral). Mean callback rate with 95% confidence interval displayed. Confidence intervals generated for each group (bar) using a one-sample t-test with the default two-sided option in R. This yields a confidence interval equivalent to the 95% CIs generated from a two-sample t-test with unequal variance in Stata. Two-sample t-tests for unequal variance calculated between each applicant partisanship and the other two partisan types within each firm party. The p-value for each t-test is displayed in the figure above the CI upper bound with notation following the form $p1\hat{}p2$, where p reflects the significance seen below. No stars are displayed for insignificant results. The p-values, $p1\hat{}p2$, are the results for the group in question relative to the alternative two groups $group1\hat{}group2$, maintaining the consistent order (mismatch, neutral, match).

*p < .05; **p < .01; ***p < .001

3.3.3 Matched Partisans Models

Although bivariate evaluations certainly elucidate the perils of partisanship in job applications, we would be remiss not to consider the results of multivariate modeling. As previously stated, I conducted a number of multivariate logistic regression models of the likelihood that a fictitious applicant receives a callback. In the main analysis, these models, like the figures above, reflect the results for the 658 applicants for whom I also had data on the partisanship

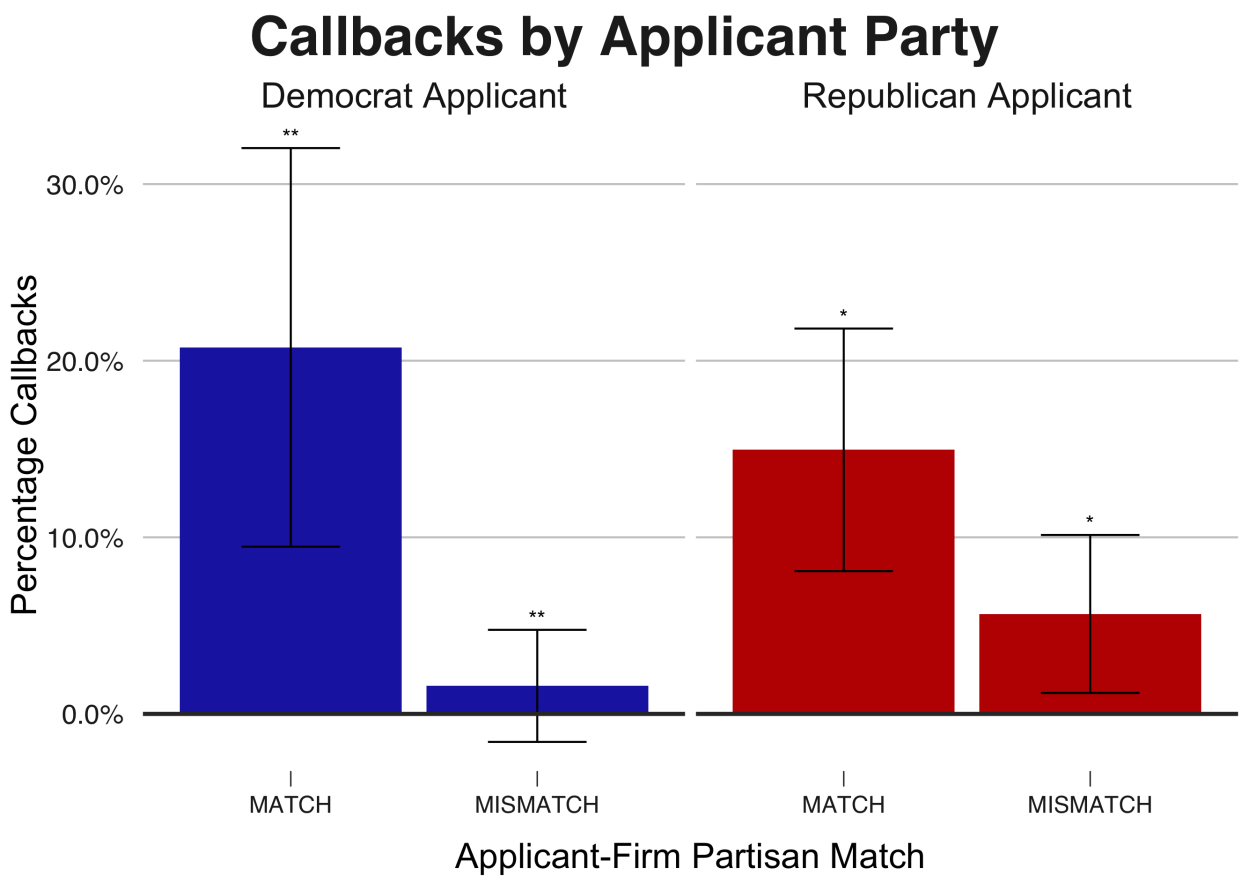


Figure 3.4: Callbacks by Applicant Party and Matching Status

Notes: N = 658. Mean callback rate with 95% confidence interval displayed. Two-sample t-tests for unequal variance calculated between partisan mismatches and matches within each applicant party. The p-value for each t-test is displayed in the figure above the CI upper bound.
*p < .05; **p < .01; ***p < .001

of the firm to which they had applied. In these models, we examine effects both within and between applicant pairs.[47] Examining the results, a lucid pattern shines through the shadows. Reflecting the discretized findings shown in the previous figures, mismatched partisan applicants—that is, fictitious applicants whose party opposes that of the firm receiving the application—are significantly less likely to receive a callback ($p < 0.001$), compared to the reference group of matched partisans, also known as copartisans. As seen in Table 3.9, these main effects remain robust under multiple parameterizations.[48]

[47]In Appendix C, I include discrete models for only matched pairs of Republican/neutral applicants and Democratic/neutral applicants as well as discrete models for only applicants applying to either Republican or Democratic firms.

[48]Likewise, the patterns remain if we examine the outcome (1) only for applicants applying to Republican firms (Table C.1), (2) only for applicants applying to Democratic firms (Table C.2), or (3) for only applicants

Table 3.9: Logit Models of the Likelihood that a Job Applicant Receives a Callback, Matched Applicants, Odds Ratios Displayed

	Pr{Applicant Receives Callback}			
	(1)	(2)	(3)	(4)
Applicant Partisan Matching				
Mismatched Partisan	0.171***	0.173***	0.163***	0.163***
Neutral Applicant	0.522*	0.526*	0.507*	0.509*
(Ref: Matched Partisan)				
Firm Partisanship				
Democratic Firm	2.052**	2.054**	1.901*	2.341**
(Ref: Republican Firm)				
Applicant Prestige				
High Prestige	1.480	1.489	1.415	1.477
(Ref: Lower Prestige)				
Job Type				
MS: Computer Scientist		0.818	0.819	0.786
MBA: Analyst or Manager		0.830	0.891	0.827
(Ref: Ph.D. Data Scienctist-Quant)				
Region				
Midwest				1.279
South				1.028
West Coast				0.521+
(Ref: East Coast)				
Experiment Features				
Received Order: Second			1.116	1.124
Resume Version: B			1.109	1.117
Experiment Wave: Second Wave			0.420+	0.434+
Constant	0.117***	0.126***	0.139***	0.131***
N	658	658	658	658
Log Likelihood	-209.025	-208.748	-206.332	-203.976
AIC	428.049	431.496	432.663	433.952

Notes: N = 658. Matched applicants are those applicants who applied to a firm where the partisanship of the firm could be determined, resulting in three match conditions (mismatch, neutral, and match) based on the partisanship of the firm (Democratic or Republican) and the partisanship of the test applicant (Democratic or Republican) and control applicant (Neutral).
+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001

The patterns also remain if we alternate the reference group to neutral applicants (Appendix C, Table C.4). As before, opposing partisans are less likely to receive a callback, and copartisans are more likely to receive a callback when compared to neutral applicants. Across both sets of models, we can see that the relative statistical strength of the effects is greater for opposing partisans than either neutral applicants (Table 3.9) or copartisans (Table C.4). In other words, we have higher confidence in the findings suggesting affective polarization in the sense of partisan animus ($p < 0.001, p < 0.01$) versus the findings supporting a lesser disadvantage

applying to unique firms (Table C.3), all of which are found in Appendix C. In each case, opposing partisans are less likely to receive a callback than copartisans.

of partisan neutrality ($p < 0.05$) or the advantage of partisan homophily ($p < 0.05$). In sum, although these models support both affective polarization and partisan homophily, we comparatively find higher statistical confidence in affective polarization.

Apart from the primary results on affective polarization and partisan homophily, we can also assess the effects (or lack thereof) for alternative model explanations. As previously suggested, the results differ depending on the type of firm to which an applicant applies. For instance, consistent with the above bivariate analysis, applicants to Democratic firms were more likely to receive a callback in each model, ceteris paribus (Table 3.9). Thus, those applying to Democratic firms were more likely to receive a callback, controlling for an applicant's partisan matching status, suggesting that Republican applicants to Democratic firms had better callback prospects than Democratic applicants to Republican firms. The exact explanation for this phenomenon is not entirely clear. Perhaps, some typically Democratic firms, such as technology firms, have a greater demand for highly skilled, technologically proficient applicants than the Republican firms in the study, or conversely, because these positions require difficult to acquire skills and credentials, they may be less sensitive to dimensions such as partisanship, provided you otherwise have a highly qualified resume. Thus, the demand for highly specialized, highly skilled applicants might dampen the effects of political partisanship.

This latter supposition dovetails with a subsequent finding. For the jobs applied to in this study, I did not find clear evidence that firms prefer higher versus lower prestige applicants. In part, this may reflect the fact that skills remain more salient than prestige for technical jobs. Nonetheless, fitting in politically proved more important than applicant prestige, and these partisan effects vary by the partisanship of the firm. Generally, this analysis did not reveal any effects by job type, resume and cover material version, or the order in which applicants were received. Only a weak association ($p < 0.1$) exists suggesting that West Coast applicants were less likely to receive a callback, as were applicants applying in the second experimental wave. Both findings, while not meeting the standard $\alpha < 0.05$ threshold, illuminate potential improvements or experimental considerations, which I expand upon in the discussion.

3.4 Discussion

Political partisanship permeates and serves as a potential barrier or benefit in the job-application process in corporate America. In this analysis, I demonstrate in particular, that an individual job applicant's partisanship—while a salient signal—critically relies upon dyadic partisan mechanisms, chiefly affective polarization (Iyengar and Westwood 2015; Iyengar et al. 2019), and secondarily, partisan homophily (Huber and Malhotra 2017; Iyengar et al. 2018). As we have seen, applicants are at a statistically significant advantage when their partisanship aligns with that of the firm, proving more likely to receive a callback than either politically neutral or opposing partisan applicants. Indeed, these findings augment a litany of studies showing partisan or political homophily in various contexts (Huber and Malhotra 2017; Iyengar et al. 2018), or more generalized studies revealing homophily or affinity for like others in the workplace (Ibarra 1992, 1995; McPherson et al. 2001), particularly in job applications (Rivera 2012b).

Yet, more pivotal than the findings for partisan homophily, we witness the greater salience of affective polarization. In the analysis, I demonstrate that job applicants, whose partisanship opposes the partisan majority of the firm, remain significantly less likely to receive a callback compared to politically neutral applicants, or those who align with the partisanship of the firm. The findings underscore past analyses that reveal the power of affective polarization (Gift and Gift 2015; Iyengar and Westwood 2015; Iyengar et al. 2019; Mason 2015), particularly studies which reaffirm the import of partisan animus as the primary lever in affective polarization (Iyengar and Krupenkin 2018), especially as it relates to resume evaluation (Gift and Gift 2015; Iyengar and Westwood 2015). Regarding resume evaluation, my findings substantiate those of Iyengar and Westwood (2015), which showed a preference for copartisans over opposing partisans in resume evaluation. My results importantly differ from Iyengar and Westwood (2015). Iyengar and Westwood (2015) used a survey panel of respondents versus an experiment on employers; the applicants were high school seniors versus graduate-degree holders; and the outcome was scholarships, not a jobs.

Turning to studies that experimentally evaluate affective polarization in job callbacks, Gift and Gift (2015) show that affective polarization, especially aversion to opposing partisans, negatively affects job market callbacks (Gift and Gift 2015). Like Gift and Gift (2015), I similarly demonstrate that opposing partisan applicants prove less likely to receive a callback than politically neutral applicants. Although my work likewise exemplifies the greater salience of affective polarization (partisan animus) than partisan homophily, unlike Gift and Gift (2015), I also demonstrate that copartisans are more likely to receive a callback than neutral applicants. To underscore a key differentiation, my research here is the first study to illustrate that affective polarization and partisan homophily can operate at the firm level, illustrating the importance of matching or mismatching with the partisanship of the firm. Such dyadic partisan bias at the firm level deserves additional consideration, particularly for future studies of labor market political discrimination.

In part, a likely explanation for finding statistically stronger effects (both for partisan homophily and affective polarization) resides in a methodological distinction in the evaluation of dyadic partisan effects. In short, I show that the job market prospects of applicants are not simply a function of applicant partisanship and the partisanship of a given geographic region (Gift and Gift 2015), but rather, that the alignment or divergence of the applicant and firm partisanship also matters. In other words, since partisan animus is a stronger effect than partisan homophily (Iyengar and Krupenkin 2018), the null findings of partisan homophily in Gift and Gift (2015) follow, particularly given the partisan heterogeneity that exists across firms (Bonica 2016; Gupta and Wowak 2017; Mausolf 2020a).

Although my research clearly augments the literature on affective polarization (Iyengar and Krupenkin 2018; Iyengar and Westwood 2015; Iyengar et al. 2019), especially correspondence-audit studies of affective polarization (Gift and Gift 2015), I also demonstrate the importance of considering the partisanship of the firm in this dyadic process, and in so doing, I underscore the relevance of firm partisanship in understanding labor market and workplace dynamics. That partisanship can affect workplace dynamics is not inherently unique. For instance, we have seen how partisanship differentially affects copartisan versus cross-partisan workplace conversations (Cowan and Baldassarri 2018), how partisanship, especially affective polarization transcends a multitude of social interactions (Iyengar et al. 2019), and how fitting into organizational culture has pivotal effects on persisting or faltering in the workplace (DiMaggio 1992; Goldberg et al. 2016; King et al. 2010; Rivera 2012b; Rivera and Tilcsik 2016; Stinchcombe 1965). Yet, more often than not, evaluations of affective polarization exclude firms or organizational culture. My work seeks to emphasize the importance of this dimension, as well as highlight the need to consider partisanship in future analyses of organizational diversity.

Drawing further parallels to the analysis of organizations and prior audit studies of diversity, my work elucidates some clarity vis-à-vis the theoretical puzzle of whether organizations would embrace partisan diversity or instead preference partisan homogeneity. Given the findings that both indicate a preference for copartisans and bias against partisan minorities, my research suggests that organizations did not efficiently preempt partisan discrimination, if any efforts were implemented at all, such as best-faith efforts or other diversity initiatives designed to forestall future regulation, compliance reviews, or litigation (Dobbin and Sutton 1998; Kalev and Dobbin 2006; Kalev et al. 2006; Skaggs 2008). Although the data cannot illustrate whether these firms had or actually implemented any training or efforts to mitigate partisan bias, if those efforts were in place, the results suggest they were not effective. In part, this might reflect the lack of protection for political partisanship under current EEOC law (U.S. Equal Employment Opportunity Commission 2020), despite the fact that employees have previously pursued litigation at least partially on these grounds (Copeland 2019; McCabe 2019).[49] Even without such protections, efforts to combat partisan bias might prove difficult since, as previously mentioned, this bias can operate implicitly. Nevertheless, it is worth reiterating, that partisan animus appears to be a slightly weaker, although still significant effect in Democratic firms. This may reflect a positive halo effect of differences in diversity training or compliance in Democratic versus Republican firms and that this state softens but does not eliminate partisan discrimination in these firms (Dobbin et al. 2011; Kalev and Dobbin 2006).

Beyond regulatory incentives, my results similarly do not support the idea that companies might view partisan diversity as a valued form of diversity with potential upsides in innovation, unlike the case for functional diversity (Ancona and Caldwell 1992; Burt 2000, 2004), or the potential benefits seen on teams with disciplinary diversity (Wu et al. 2019), even though in some contexts, political diversity might offer higher quality work (Shi et al. 2019). Consistent with most other studies, my work instead suggests that the majority of studied firms instead perceive partisan diversity, like diversity on other salient social dimensions, as a disadvantage. This supposition aligns with studies revealing a number of negative externalities stemming from diversity on key social dimensions, including increased discord, ineffective communication, and lower productivity (DiTomaso et al. 2007; Reagans and McEvily 2003; Williams and O'Reilly 1998), as well as lower retention and less satisfaction (Boone et al. 2004; Elvira and Town 2001; Milliken and Martins 1996; Tsui et al. 1991; Walton et al. 2015). Likewise, my work substantiates studies suggesting analogous upsides to homogeneity (Meyerson et al. 1996; Reagans and McEvily 2003; Rivera 2012b).

Although my study does not speak specifically to whether partisan diversity would incur benefits or deficits, firms in their action, collectively embrace a position which might be explained by either a rational expectation to (1) minimize the costs of diversity *a la* affective

[49]See also the National Labor Relations Board settlement agreement in the matter of Google, Case 32-CA-164766.

polarization or (2) garner the benefits of organizational or cultural fit secondary to partisan homophily. To the extent these perspectives exist, neither would seem to be dissuaded by the potential although legally nebulous grounds on which partisan discrimination might be pursued. My findings, while suggestive in clarifying this puzzle, deserve further research to more directly outline how partisan biases, such as affective polarization and partisan homophily, translate to perceptions of organizational fit and the benefits or deficits of diversity versus homogeneity in the workplace.

Methodologically, this work augments a bevy of studies utilizing correspondence-audits in the evaluation of workplace discrimination, which often emphasize race, ethnicity, gender, social class, culture, and sexual orientation (Bertrand and Mullainathan 2004; Correll et al. 2007; Gaddis 2015; Kang et al. 2016; Pedulla 2016; Rivera 2012b; Rivera and Tilcsik 2016; Tilcsik 2011). Alongside Gift and Gift (2015), my work extends correspondence-audit studies to include partisan discrimination. Although the primary focus of my research was evaluating partisan bias, I also included variation on applicant prestige, controlling for skill. Although Gaddis (2015) finds a callback advantage for those with elite credentials, race generally mattered more than prestige. Although I also did not find any significant advantage for high prestige applicants, like Gaddis (2015), I found that my main effect, in this case, partisanship, outweighed prestige. Following the notion that the effects of partisanship outweigh those of race (Iyengar and Westwood 2015), the null finding for prestige makes sense, particularly since my research design isolates prestige while controlling for skill and exemplifying a high level of both hard and soft skills that prestige so often approximates. That all my fictitious applicants also had hard to obtain technical skills, applied technical experience, and graduate degrees likely also assuaged employer concerns for low prestige applicants, compared to the bias that low prestige applicants with only a college degree might otherwise incur. Although such findings might appear to complicate findings of social or cultural capital, we must recall that while attending elite, or otherwise selective schools, is often entangled in social and cultural capital (Coleman 1988; DiMaggio and Mohr 1985;

Lareau 2003; Stevens 2007), any skills, whether soft skills or hard technical skills that are shaped by social and cultural capital are fixed across levels of prestige in this experiment. In this way, my study simply suggests that when educational and occupational prestige is isolated from the skills, it may not be as deterministic as some studies suggest (Rivera 2011, 2012b). At the same time, the results are consistent with several past studies. For example, Dale and Krueger (2002) do not find any systematic benefit of attending a selective versus unselective school, and James et al. (1989) finds that more important than college prestige is mathematics ability, GPA, and obtainment of a technical degree, qualities all applicants in my study had. Another important facet is how we define high prestige. For instance, in both this study and Gaddis (2015), many of the high prestige universities would likely have received ridicule from the participants in (Rivera 2011: 78), where attending a lesser Ivy League school suggested failure and only a "super-elite" Ivy such as Harvard, Princeton, or Yale would suffice. Resolving this question would require further experimental analysis that manipulates applicant prestige at super-elite universities versus other prestige tiers controlling for applicant skills, social, and cultural capital. Experimentally, however, as noted here and Rivera and Tilcsik (2016), conducting experiments with only super-elite applicants has certain challenges.

Of course, I must also recognize a number of potential caveats. First, although the computational design and deployment of the correspondence by emailed resumes and cover letters afforded many benefits, because response hinged on email delivery to an appropriate contact, the process of finding such a contact (and then having a valid email), proved challenging, and potentially hurt the response rate. Although traditional online application methods may have yielded a better response rate compared to emails, they would have proved challenging to execute at scale without human error and likely many months to send thousands of tailored, randomized applications and cover letters. Second, and related to the callback, finding recently posted jobs likely affected callback rates. Although I ran multiple web scrapers for various job fields and prioritized more recent job postings for companies, in hindsight, I would prioritize more restrictions on the recency of job postings. For example, to maximize potential response, it may have been better to iteratively work in batches such that, I only applied to jobs posted in the past week, rather than proceed in larger bulk batches where some jobs applied to had been posted for a number of weeks and perhaps had many qualified applicants already in the pipeline.

Additionally, dyadic analyses prove doubly difficult since information is also needed on the firm. In the case of firm partisanship, determining the partisan leaning of the modal employee proves challenging in its own right (*c.f.* Bonica 2016; Mausolf 2020a), and even these analyses might not have as recent a partisan profile as optimal and may need supplementation to garner partisan profiles for additional companies. As such, beyond the standard caveats around the experimental design, we must also consider any errors in the partisan inference for the firm, as well as any selection biases or other random errors in the inclusion or missingness of firms for which partisanship could be determined. Furthermore, we might also expect complex randomness in firm response dynamics. For instance, the partisanship of the firm recipient might oppose that of the typical employee, thus affecting results. Similarly, responsiveness might vary depending on the number of firm employees the email passes through before a decision is made to respond. Of course, if the participants suspected the evaluation of partisan discrimination (or conversely were oblivious to the partisan signal), they might also simply respond favorably to both applicants. Lastly, the type of analyses chosen could also affect the results. Although many of these errors are difficult, or even impossible to detect, I nonetheless suggest that given the overall experimental robustness, demonstration of effects using various analytic approaches, the general consistency with the existing theory on affective polarization, and the preregistration of the study design, that the results prove veritable.

In sum, I have demonstrated in this analysis that job market candidates face the ramifications of political partisanship in job applications, particularly those of affective polarization and partisan homophily. Although applicants are more likely to receive a callback when their partisanship aligns with a firm, compared to an applicant who remains neutral, or otherwise conceals their partisanship, such actions also pose substantial risks. In particular, the misapprehension of the firm's dominant partisanship can quickly denigrate an applicant's prospect of receiving a callback. That is, firms, more often than not, passed over otherwise qualified applicants whose partisanship opposed that of the firm. Office politics have always existed, although now, in an era of rising partisan and affective polarization, it is not simply a quotidian turn of phrase, but rather a salient social fact, dictating which applicants are suitable and welcome to join a given firm.

CHAPTER 4

Party in the Boardroom: The Role of Affective Polarization in Corporate Board Appointments

When pondering office politics, we might at first envision apolitical jockeying to curry favor, the office rumor mill, and less savory careerist machinations. However, given the rising tide of political partisanship in American society, another conception comes to mind. In this study, I ask how the partisan behavior of a corporate board of directors affects the likelihood of appointing a Democrat or a Republican to that board. Indeed, we have witnessed a proverbial inundation of partisanship and polarization across both the scientific press and the news media (Bail et al. 2018; Douthat 2020; Iyengar et al. 2019; Klein 2020; Macy et al. 2019; Pew Research Center 2016), affecting everything from cultural values, romantic entanglements, and economic behavior (DellaPosta et al. 2015; Gift and Gift 2015; Huber and Malhotra 2017; Iyengar and Westwood 2015; McConnell et al. 2018). Although polarization can have many meanings (*c.f.* Baldassarri and Gelman 2008; Fiorina and Abrams 2008; Iyengar et al. 2019; McCarty et al. 2006), I specifically focus on affective polarization, defined as "the tendency of people identifying as Republicans or Democrats to view opposing partisans negatively and copartisans positively" (Iyengar and Westwood 2015:691), although the term more often denotes partisan animus, the "phenomenon of animosity between the parties…known as affective polarization" (Iyengar et al. 2019: 130). Adopting this convention, I likewise refer to partisan animus as affective polarization. For clarity, I denote the antipodal process of viewing copartisans favorably as partisan homophily, a term often used in the study of romantic relationships, which more generally refers to the tendency of similar others to cluster or associate (Huber and Malhotra 2017; Iyengar et al. 2019; Lazarsfeld and Merton 1954; McPherson et al. 2001). Yet, to understand how these phenomena might affect corporate board appointments, we must more closely examine the literature on affective polarization and partisan homophily.

4.1 Unpacking the Role of Affective Polarization and Partisan Homophily in Corporate Boards

With this preliminary understanding of affective polarization and partisan homophily, let us inquire how these partisan processes affect organizational behavior, particularly the action of corporate board members to either add a new board member or replace an existing board member, where the latter process is alternatively referred to as board member swaps or board member succession. Although partisanship—especially affective polarization—can affect economic behavior (Carlin and Love 2013; Iyengar and Westwood 2015; McConnell et al. 2018), shape resume evaluation or job applicant callbacks (Gift and Gift 2015; Iyengar and Westwood 2015; Mausolf 2020b), or structure inter-firm business relationships, executive compensation, and corporate social responsibility (Gupta and Briscoe 2019; Gupta and Wowak 2017; Stark and Vedres 2012), we have little understanding of how partisan mechanisms, such as affective polarization or partisan homophily, shape corporate board appointments. In fact, given Bonica's (2016) assertion on the "prevalence of bipartisan boardrooms," and the potential benefits of promoting board member diversity (DiTomaso et al. 2007; Dobbin and Jung 2011; Hambrick et al. 1996), we might indeed question whether partisanship should affect board member appointments. Consider a related trend in the corporate board interlock literature, where political unity in campaign contributions is weakened by the decline of the inner circle (Burris 2005; Chu and Davis 2016; Useem 1984), resulting in greater partisan heterogeneity across interlocked directors (Burris 2005; Chu and Davis 2016), but increased partisan homogeneity within corporate boards, where partisan political contributions are more likely to align (Burris 2005; Chu and Davis 2016). Yet, the puzzle lies at the exact confluence of dichotomous theories and empirical findings suggesting the possibility that boardrooms might exhibit either partisan heterogeneity (bipartisanship or diversity) or conversely embrace partisan homogeneity. My research seeks to address this question and illustrate the power of party in the boardroom, especially the partisan mechanisms of affective polarization and partisan homophily.

4.1.1 Resolving Boardroom Ideology and Partisanship

Fundamentally, a key to answering these empirical questions on affective polarization, partisan homophily, and analyses of boardrooms, rests at a nexus surrounding the conflation of ideology and partisanship. Although ideology and party are correlated (Bonica 2013, 2014, 2016), ideology refers to a set of positions on political issues whereas party refers to identification with a political party (Campbell et al. 1960; McCarty et al. 2006), which many scholars argue shapes ideological beliefs (Barber and Pope 2019; Goren 2005). Despite tightly clustered ideological polarization among party elites (Hetherington 2001; McCarty et al. 2006), ideological beliefs among average citizens are not similarly polarized and in fact remain highly heterogeneous, with overlap existing even across party divisions (Baldassarri and Goldberg 2014; DiMaggio et al. 1996; Fiorina and Abrams 2008). As such, many of the reports of heightened polarization actually reflect increases in party sorting or partisan polarization (Macy et al. 2019; Mausolf 2020a), increased ideological clarity as structured by increasing partisan division (Baldassarri and Gelman 2008; Baldassarri and Goldberg 2014; Barber and Pope 2019; Mason 2015), or animosity between parties as a result of affective polarization (Iyengar and Krupenkin 2018; Iyengar and Westwood 2015; Pew Research Center 2016). Furthermore, partisan mechanisms, such as affective polarization, operate irrespective of underlying, unexpressed ideological beliefs (Iyengar and Westwood 2015). That is, animosity toward opposing partisans and preference for copartisans exist implicitly, exceeding the effects of race, and occurs on the sole basis of a partisan signal (Iyengar and Westwood 2015). For these reasons, we must take analyses conflating party and ideology with some incredulity, alongside the understanding that the existence of partisan diversity does not preclude partisan discrimination, a fact familiar to scholars of race.

4.1.2 Disentangling Competing Partisan Mechanisms

Ergo, when we turn our attention to what lessons can be gleaned from scholars, such as Bonica (2016), several insights emerge. Extending his past analyses, which design a novel method for mapping ideological scores for incumbent and challenger candidates, political action committees (PACs), and individual contributors (Bonica 2013, 2014), Bonica next turns to assess the ideological distribution of individual Fortune 500 directors (Bonica 2016). Among other findings, Bonica (2016) reveals that "compared to corporate PACs, corporate elites are more ideological" but have "substantial heterogeneity... both across and within firms" (367). Most relevant, however, to this study, Bonica (2016) also demonstrates "the prevalence of bipartisan boardrooms" (367). Digging into the results, however, we can see that not all firms are created equal. For instance, although many boards have some ideological diversity, many other boards, such as Apple or Marathon Petroleum, are comprised of primarily liberals or conservatives (Bonica 2016), and given ideological heterogeneity even among a homogenous group of partisans (Baldassarri and Gelman 2008; Baldassarri and Goldberg 2014; Fiorina and Abrams 2008), suggests that such firms may have high partisan homogeneity, a finding demonstrated in Mausolf (2020a). Even by Bonica's (2016) analysis, however, the plurality of Republican corporate boards gave at least half of their political contributions to Republican political committees (Bonica 2016: 388). In this way, firms could be considered bipartisan, but many firms also seem to have a dominant party. Although Bonica (2016) operates within an ideological framework, his supposition that ideological heterogeneity might result from either non-ideological rationales, or by design to correct ideological imbalances, proves useful (Bonica 2016: 390). As I have elsewhere stated, party rather than ideology proves a far more salient constraining force (Barber and Pope 2019; Goren et al. 2009), and partisan behaviors, such as affective polarization and partisan homophily, seem more likely to shape board decisions than ideology since these biases can operate implicitly (Iyengar and Westwood 2015; Iyengar et al. 2019). Thus, board member selection might be influenced by partisanship, such that a board may be more likely to appoint a new board member whose partisanship aligns with that of the board and similarly less likely to appoint a board member whose partisanship diverges from that of the board.

Both of these latter hypotheses align with the idea of affective polarization and partisan homophily. A preference for copartisans would theoretically result in a situation of board member appointments aligning with the extant board. Yet, we would also generally expect the aversion toward opposing partisans to more often than not result in a lower likelihood of opposing partisans joining the board and a higher likelihood of copartisans joining the board, at least when only considering the appointment of known partisans. We could achieve better adjudication between these parallel but discrete mechanisms through experimental studies (Gift and Gift 2015; Iyengar and Westwood 2015; Mausolf 2020b), or by having better data about the exact selection pool for given board member appointments. For instance, as I describe in the data and methods section below, we can make inferences about corporate board member appointments by examining changes in board composition across two time periods. Such data, however, only show the positive outcome of board member selection. For example, we have no data about who may have been considered for a board appointment but was not ultimately selected.

Adjudicating between affective polarization and partisan homophily would further require data about those without any partisan signaling, and simply having an unknown party identity (from the analyst's perspective) is not equivalent to a board member having truly no ostensible partisan leaning since many partisan and other political attributes can be inferred by cultural preferences (DellaPosta et al. 2015). Outside of experiments or observational data an order of magnitude better than what is currently available, it may be difficult to disentangle the antipodal forces of partisan animus versus partisan homophily. In the end, both theories of affective polarization (in the sense of animus toward opposing partisans) and partisan homophily, or preference for copartisans (Huber and Malhotra 2017; Iyengar and Krupenkin 2018; Iyengar and Westwood 2015; Iyengar et al. 2019; Mausolf 2020b), suggest that incoming board members, whether those appointments are an addition or succession, will more likely to be copartisans than opposing partisans.

Although I argue that affective polarization and partisan homophily present one of the most compelling political rationales for selecting board members, we must also consider alternative possibilities. Here, the prospect raised by Bonica (2016), in which corporate boards may intentionally correct partisan imbalance has some merit. Rather than ideology, however, I contend that partisan rebalancing could prove more likely, particularly if considered from the perspective in which corporate board appointments reflect intentional signaling to shareholders (Dobbin and Jung 2011; Khurana 2002; Krawiec and Broome 2008). From this perspective, a strategic partisan rebalancing of a board parallels a similar phenomenon of corporate political action committees (PACs) supporting both parties (Bonica 2016; Hacker and Pierson 2010; Tripathi et al. 2002), or revolving door politics wherein corporate boards appoint former government officials and government leaders appoint former corporate titans (Hacker and Pierson 2010; Kuttner 2010; Luechinger and Moser 2014). To the extent that partisan rebalancing of corporate boards exists, I expect the process would be responsive to transitions in partisan control of U.S. presidential administrations. To account for this possibility in the analysis, I include a control for the U.S. presidential party in the models.

4.2 Folding In Theories of Board Diversity and Board Appointments

Outside of affective polarization, partisan homophily, and alternative partisan perspectives, I augment these theories with the research on organizational diversity, particularly as it relates to board member appointments. Here, two key but interrelated perspectives exist in relation to board appointments. The first is considering how diversity can positively or negatively alter board dynamics, and the second is using board appointments as an outward signal. Both perspectives, while discrete, offer parallel expectations that ground the initial hypotheses on partisan board appointments via affective polarization and partisan homophily.

Regarding the first idea of board diversity, we encounter a raft of studies, including a number of reviews and meta-analyses, which conclude that despite some evidence supporting benefits in innovation or creativity from functional diversity (Ancona and Caldwell 1992; Burt 2000), in most cases of organizational, team, or group diversity, particularly along salient social dimensions, we see substantial negative effects on "social integration, communication, and conflict" (DiTomaso et al. 2007; Jackson, Joshi, and Erhardt 2003; Williams and O'Reilly 1998: 115).[1] However, we can examine how diversity appointments on corporate boards affect firm dynamics and valuation. On this front, although some studies find positive effects of gender, racial, or ethnic diversity appointments to firm performance (Carter, Simkins, and Simpson 2003), these might simply reflect a reverse causality of successful firms appointing female or minority directors, particularly since more robust longitudinal evaluations show negative effects on firm performance and stock valuation (Adams and Ferreira 2009; Dobbin and Jung 2011).[2] Related to Adams and Ferreira (2009), important dimensions of diversity, be they gender, political ideology, or partisanship, can affect not just executive pay, but also the governance styles of directors and what leadership qualities they value (Adams and Ferreira 2009; Cheng and Groysberg 2016; Chin et al. 2013; Gupta and Briscoe 2019; Gupta and Wowak 2017; Gupta et al. 2017). Consistent across this evidence, however, whether considering the demonstrable detriments to performance, firm valuation, and board

[1]Multiple review articles conclude that diversity, especially on key social dimensions, has primarily negative effects. Consider the *Annual Review* article by DiTomaso et al. (2007), or publications in organizational behavior and management literature, such as Williams and O'Reilly (1998), which reviews over 80 studies and 40 years of research or Jackson et al. (2003) which also consults 63 studies on the topic.

[2]See, for example, the extended discussion throughout Dobbin and Jung (2011) and Adams and Ferreira (2009) about reverse causality and spurious results of positive effects, once longitudinal data and robust modeling is implemented, showing in actuality, negative effects for diversity appointments, in this case, gender diversity.

dynamics—or differences in leadership priorities and governance style—all suggest that corporate boards would, on balance, prefer to associate with similar others—in this case copartisans—and be averse to those who deviate from the typical appointee—in this case opposing partisans.

Yet, these arguments lead to an alternative albeit supportive perspective that board appointments serve as salient signals. When thinking about CEO appointments, for instance, Khurana (2002) argues that when a corporate board deliberates on the selection and appointment of a CEO, they consider what external signal that selection will send to external audiences, including institutional investors, Wall Street analysts, business media, and firm competitors. Translating the executive perspective to board members, Krawiec and Broome (2008) argue that the appointment of a board member serves as a valuable signal to shareholders, among other external audiences, a perspective adopted and expanded upon by Dobbin and Jung (2011). Integral to this argument, although boards might seek to signal a commitment to diversity and equality by appointing women or minorities to the board and thereby appease certain contingents (Dobbin and Jung 2011; Krawiec and Broome 2008),[3] such actions can also backfire if institutional investors interpret this signal as one indicating a prioritization of diversity over profits (Dobbin and Jung 2011).

Although most research articulates the downsides of diversity (Jackson et al. 2003; Williams and O'Reilly 1998), or even that corporate board diversity might negatively affect performance or firm profitability (Adams and Ferreira 2009), some studies instead suggest that a board's diversity appointments do not alter board dynamics, such as "efficacy or monitoring capabilities," or directly alter firm profitability and by consequence, stock prices

[3]For example, in their interviews with corporate boards of directors, Krawiec and Broome (2008) find that directors believed the "presence of women and minorities on the board sent an important, positive signal to labor" and other corporate constituents (453). See also Dobbin and Jung (2011). These ideas also have a connection to the social movements literature, wherein firms and directors can respond to mobilization objectives (Davis et al. 2008; McDonnell, King, and Soule 2015), although such studies often assess mobilization and corporate diversity (Olzak and Ryo 2007), or mobilization and firm shareholder value (King and Soule 2007), versus the interplay between corporate board diversity, firm performance, and shareholder value as argued in Dobbin and Jung (2011).

(Dobbin and Jung 2011: 837). Rather, the appointment of diversity candidates to the board of directors activates institutional investor bias, which directly and negatively affects stock valuation (Dobbin and Jung 2011).

Given the widespread and significant salience of partisan discrimination, particularly animus against imposing partisans via affective polarization (Iyengar and Krupenkin 2018; Iyengar and Westwood 2015; Iyengar et al. 2019), we might also expect that a corporate board appointment of a known partisan, particularly a partisan minority, might induce institutional investors to sell, or otherwise devalue the stock, not because such an appointment would necessarily affect the firm performance, but rather because investors are biased against those in the opposing political party. Although this study does not speak to how partisan board member appointments affect stock valuation, and indeed such studies are lacking,[4] the confluence of affective polarization (Iyengar et al. 2019), with the idea of institutional investor bias against board members' sociodemographic features (Dobbin and Jung 2011), and the idea that board member appointments can directly impact stock value (Dobbin and Jung 2011; Luechinger and Moser 2014), reify the idea that board appointments act as important signals (Dobbin and Jung 2011; Khurana 2002; Krawiec and Broome 2008). In this way, beyond board members' own partisan bias via affective polarization or partisan homophily, board members might additionally consider the signal that would be sent by and the consequences that could follow the appointment of an opposing partisan to the board.

Beyond affective polarization—or alternative perspectives of partisan homophily, diversity, and organizational culture—a host of additional possibilities exist that might explain the partisan selection of board members. For instance, the industry or sector in which a firm operates might map to specific policy positions and accordingly reflect a partisan

[4] As mentioned, studies have examined how gender diversity impacts stock value (Dobbin and Jung 2011), how firm value under Democratic versus Republican presidencies is higher (Camyar and Ulupinar 2013), or how corporate appointments of former government officials leads to an increase in stock value (Luechinger and Moser 2014). Less, however, is known about the general impact of in-partisan and out-partisan board appointees and stock valuation.

predilection. To account for this possibility, therefore, a subset of models includes controls for firm sector. We might expect, for instance, that technology firms might on balance be more Democratic, and energy sector firms, especially oil and gas companies, might lean Republican—a supposition which aligns with current empirical findings with some notable exceptions (Bonica 2014, 2016; Mausolf 2020a).[5]

Similarly, extant corporate board features might also shape the likelihood of appointing a Republican versus Democratic board member. For instance, corporate board diversity features, such as the proportion of the corporate board that is female, black, Hispanic, or non-white minority could potentially alter partisan behavior. As shown in Mausolf (2020a), Republican firms are significantly associated with having boards of directors that do not have any minorities or women. Although polarized Democratic firms did not necessarily have a converse association, it is possible that an increased number of women and minorities on the board of directors could decrease the likelihood of appointing Republican board members. We might also expect having a higher number of board members with an international background to have a similar effect. Moreover, having a board whose members are more advanced in age may negatively affect the likelihood of appointing Democrats. Conversely, the overall size of the board might have positive effects for Democratic appointment. With a larger board, there is a lower risk of partisan rebalancing from appointing an opposing partisan than in a comparatively smaller board. Lastly, the type of board appointment would logically affect the admission of partisan members. Chiefly, for cases of board member succession, the likelihood of appointing a copartisan or opposing partisan might depend on

[5]Consider the energy sector, for instance. Bonica (2014) shows that employees in the oil, gas, coal industry tend to have conservative CFscores, and that board members in these firms, such as Marathon Petroleum, are highly conservative (Bonica 2016), a finding aligning with those in Mausolf (2020a), that likewise shows that oil and gas companies like Marathon Petroleum or ConocoPhillips are polarized Republican firms, that is, are highly homogenous in consisting almost exclusively of Republicans, not just in executives but also in managers and all other employees. Yet, not all energy companies are Republican, and in fact, some companies, especially those in alternative energies, such as solar or wind, gravitate toward the Democratic Party (Mausolf 2020a). Likewise, not all technology firms are overwhelmingly Democratic and may, in fact, reflect an amphibious mixture of Democrats and Republicans (Mausolf 2020a). If caveats such as this exist for stereotypically partisan industries, other categories might prove even less prognostic. For these reasons, firm sector might not be the best predictor of board partisanship appointments.

whether the swap in question is equal—that is, a replacement of an outgoing board member with someone matching that member's partisanship—or unequal, where the incoming board member's party opposes the outgoing board member's partisanship.

4.3 Data and Methods

Data for this project comes from several data sources. The corporate board membership data comes from the Institutional Shareholder Services (ISS) - Directors Dataset (2007-2018), which has a variety of information on corporate boards of directors. Both the ISS and a related dataset, known as BoardEx, largely draw upon U.S. Securities and Exchange Commission filings and have been used in a number of studies looking at boards of directors and their activity (Chu and Davis 2016; Gupta and Wowak 2017).[6] While the BoardEx dataset has benefits when examining complex network dynamics and corporate interlocks, for my purpose of examining how the immediate board's partisanship affects board appointments, the ISS more than suffices and has added benefits, such as containing race and ethnicity data.

To execute this project also requires data on the political partisanship of board members. For this, I draw upon two primary data sources, namely the FEC - Corporate Politics data (Mausolf 2020a) and the DIME - Avenues of Influence data (Bonica 2016), which I detail below. Although these datasets vary in their construction and data coverage, both evolve from the same base data provided from the Federal Election Commission (FEC), which provides details on individual contributions to political committees as well as committees' itemized expenditures to other committees and candidates. Studies using some derivation of the FEC data to examine corporate elites (executives or board members) have emerged in multiple studies (Bonica 2016; Briscoe et al. 2014; Chin et al. 2013; Gupta and Briscoe 2019; Gupta and Wowak 2017; Gupta et al. 2017; Mausolf 2020a).

[6]Other commonly used datasets for researching corporate leadership include ExecuComp, particularly for studying executive compensation (Bertrand and Hallock 2001; DiPrete et al. 2010). Chin et al. (2013) also utilize both ExecuComp and RiskMetrics (now known as ISS) in a limited capacity.

4.3.1 ISS Directors Data Subset

For this study, I analyze a subset of the Institutional Shareholder Services (ISS) - Directors Dataset (2007-2018). In particular, I restrict my initial dataset to companies for which I have corresponding FEC campaign finance data, as described in (Mausolf 2020a), which contains firm-level data for a subset of 378 of the Fortune 400 companies as well as individual-level and contribution-level data for individuals within these companies. The final dataset analyzed in this paper reflects a smaller subset of companies, since I only include companies passing a certain board member missingness threshold. Substantively, this means that I am able to match the board member identity to a named individual in one of the partisanship datasets. For the majority of individuals therein, I am able to determine their partisanship using one of the two partisan data sources, the FEC - Corporate Politics data and the DIME - Avenues of Influence data from Mausolf (2020a) and Bonica (2016), respectively.

4.3.2 FEC - Corporate Politics (CP) Data

In this paper, I utilize data from Mausolf (2020a), which employs a method of determining the political partisanship, as well as the strength of that partisanship (partisan polarization), for firms and their subunits using Federal Election Commission (FEC) data. For brevity, I refer to this dataset as FEC-CP. This data comes into play at several points in the data preparation pipeline. First, as described above, I restrict the ISS directors dataset to include only the 378 companies found in the FEC-CP data. Second, I incorporate available firm-level metrics on partisan polarization from Mausolf (2020a). Third, beyond firm-level metrics, I also utilize information on individual partisanship by election cycle and overall individual partisanship, which is joined with the ISS data (described below). Lastly, I utilize political committee partisanship information in the FEC-CP data to supplement the DIME-AOI data, whose original partisanship measures are limited.

4.3.3 DIME - Avenues of Influence (AOI) Data

Like the FEC-CP data, the DIME-AOI data used in Bonica (2016) contains a variety of political data on individual contributors, particularly corporate board members, originally derived from the FEC. Although Bonica (2016) emphasizes board member ideology, the data also contains data on contributor partisanship, such as total individual contributions to the Democratic and Republican Party or the recipient's party if available. Likewise, there is data on contributor ideology, and in some cases linking data on the political committee, which I use to determine the partisanship of a given contribution using the FEC-CP data from Mausolf (2020a). Critically, we also have the full names of individual contributors and the company for which they work, which in the case of Bonica (2016) are all members of Fortune 500 boards of directors. When examining the DIME-AOI data, provided online for replication, Bonica (2016) includes two primary datasets, "bod_fortune_500" and "bod_fortune_500_cont_records," which I hereafter refer to as DM1 and DM2, respectively. Whereas DM1 contains summary-level metrics for board members at Fortune 500 companies, DM2 contains contribution-level records for board members. DM2 is, therefore, a preferable dataset since information derived thereof can contain board member partisanship measures by election cycle (as well as summary partisanship measures). DM1 can only signal the overall partisanship of a board member across all election cycles and cannot be supplemented by the FEC-CP data.

4.3.4 Deriving Individual Partisanship

As previously mentioned, to understand the role of partisanship in board member events, such as additions, swaps, or drops, we must first know the partisanship of board members. Although we might not be able to determine the partisanship of every board member (Gupta and Wowak 2017), we can certainly determine the partisanship for most board members, which I achieve using both the FEC-CP data as well as the DM1 and DM2 datasets from the

DIME-AOI data (Bonica 2016; Mausolf 2020a). Below, I describe the methods for obtaining standardized partisanship measures across these datasets.

DIME-AOI-DM1. Since the DM1 only provides summary-level data for individual partisans, deriving partisanship relies on the data columns therein, chiefly *dime.cfscore*, *total.dem*, *total.rep*, *total*, and *pct.to.dems*. From these variables, I generate three discrete measures of partisanship. First, I derive a *majority party* measure using *total.dem*, *total.rep*, and *total*,[7] such that the individual's party is determined by the party to which they have given the most contributions if the total is greater than zero. Similarly, I created a measure, *percentage Democrat party*, which relies on *pct.to.dems*,[8] such that the individual is a Democrat if ≥ 0.500 of contributions are to Democrats; otherwise, they are presumed to be Republican. Lastly, I derive the measure *CFscore party* from *dime.cfscore*, which is the "Contributor common-space CFscore" per the DIME-AOI codebook (Bonica 2016). As shown in (Bonica 2014: Appendix Figures 1-2), the contributor CFscore cut-point of 0 approximately divides the contributor CFscore scale $[-2, 2]$ between Democrats $[-2, 0)$ and $[0, 2]$ Republicans. I use this cut-point to create a partisanship measure using the *contributor CFscore*. I create an overall partisanship measure utilizing if-else logic to rank-order the three DM1 partisanship measures (*majority party*, *percentage Democrat party*, and *CFscore party*) to fill non-null values.[9] The resulting binary *party* measure [DEM, REP] excludes null values.

DIME-AOI-DM2. Since DM2 has contribution-level data, we may glean additional partisanship detail with supplementation from the FEC-CP data. Supplementation occurs through a series of joins using the DM2 dataset's *recipient.party* column, which contains the names of the FEC committees (or candidates). This identifying data links to the FEC-CP and comes directly from the FEC (Federal Election Commission 2018a). From the FEC-CP

[7]The measure *majority party* is denoted in code using *pct_party*.

[8]The measure *percentage Democrat party* is denoted in code using *pct_dem_party*.

[9]In other words, where the *majority party* is not null, the new variable *party* equals the *majority party* else, where *percentage Democrat party* is not null, party equals percentage Democrat party, else party equals *CFscore party* (excluding null values).

data, I can derive two datasets: (1) containing the committee name, election cycle, and party and (2) containing the candidate name, election cycle, and party. Using a series of left-joins, anti-joins, and unions, I first join DM2 with the FEC-CP by committee name and cycle, followed by another join using candidate name and cycle. In this way, for matching cases, I have a *party_ID* column, which is used throughout the FEC-CP data (Mausolf 2020a). This *party_ID* column is the first generated partisanship measure for DM2.[10] Next, I use the DM2 column *recipient.party*, recoded into "DEM", "REP", and "IND/OTH" results. As was the case in DM1, in DM2, I create a third measure of partisanship *CFscore party* using the aforementioned DEM/REP cut-point of 0. As before, I create an overall partisanship measure that utilizes if-else logic to rank-order the three DM2 partisanship measures (*party_ID*, *recipient party*, and *CFscore party*) to fill non-null values, respectively. This party variable is subsequently recoded into three district values [DEM, IND/OTH, and REP] with corresponding [-1, 0, 1] values.

To mirror the output of DM1, I summarize these character and numeric party variables in two ways. Recall, the original DM2 data is at the contribution level. This data is transformed to provide each individual with two collective partisanship measures: (1) *cycle_party*, the overall partisanship [DEM, REP] for a given election cycle, and (2) *party*, a given individual's dominant partisanship across all election cycles. Following prior cut-points, partisanship in both cases follows the convention such that Democrats have a party mean < 0 and Republicans have a party mean ≥ 0.

FEC-CP. The manipulation needed to derive concordant party measures in the FEC-CP is minimal. In its original state, each unique individual per firm has the possibility of a *party_ID* and *partisan_score* for each election cycle (Mausolf 2020a). Those variables generally have low missingness. After converting *partisan_score* to a second party measure,

[10]The measure *party_ID* as described in Mausolf (2020a) primarily consists of DEM or REP values, but may have other parties, unresolvable party concatenations, such as UNK_DEM_REP or other unknown values.

the two measures were combined into a singular *party_cycle* measure, which I subsequently recoded into three district values [DEM, IND/OTH, and REP] with corresponding [-1, 0, 1] values. Prior to calculating final party metrics, the individual's name underwent additional cleaning to facilitate matching to the names in the ISS data.

4.3.5 Matching Measures of Partisanship to Board Members

Having described the datasets and preparation, I now turn to the method of matching board member identities in the ISS with measures of individual partisanship in the FEC-CP and DIME-AOI. Some similar studies, such as Gupta and Wowak (2017), utilize methods such as fuzzy matching to align names in board member and FEC data. Although fuzzy matching can probabilistically join both full and partial matches of names, there is no guarantee that the names matched would pass a qualitative evaluation.[11] Rather than accidentally create these mismatch errors, I instead chose to perform a series of successive joins between the ISS and either the FEC-CP or one of the two DIME-AOI datasets using discrete join methods (Appendix D, Table D.1 and Table D.2).[12] This procedure has the added benefit of explicitly matching individuals. In most cases, the join includes the full name and firm.

To perform joins by name, I first worked to clean and standardize name formatting across the three partisanship datasets (FEC-CP, DM1, DM2) as well as the board member dataset (ISS). Although the exact changes for each dataset varied, each received some common treatments, such as switching the name to lowercase and stripping whitespace padding. Although the original FEC-CP data had previously been cleaned such that there were unique individuals (by full name) per firm and election cycle (Mausolf 2020a), the original name cleaning, while efficient for its purpose, was not optimized for joining datasets by name. In

[11] For example in testing fuzzy matching in Python in earlier versions of this analysis as well as in Mausolf (2020a), a number of errors were found in qualitatively reviewing fuzzy match results. See also the post-fuzzy-matching qualitative evaluation needed in Gupta and Wowak (2017).

[12] As I describe below, I include two tables in Appendix D, Table D.1 and Table D.2, which detail the exact join methods used and how many matched observations come from the FEC-CP, DM1, and DM2.

particular, I extracted suffixes from the FEC-CP data full names, which were additionally split into first and last name columns. Where any newly cleaned full name duplicates occurred, I retained the version of the individual with the most contributions.[13] Both of the DIME-AOI datasets (DM1, DM2) had already highly processed names and needed minimal cleaning to optimize matching with the ISS. For the ISS, a substantial amount of cleaning was needed. For example, I utilized regular expressions to extract titles, degrees, and suffixes from the full names of board members. Similarly, I also extracted nicknames from full names. For the first name column, I removed nicknames and middle initials, among other changes. Last name columns also had any lingering titles or suffixes removed. Beyond the original cleaned full name, I also generated supplemental full name columns using variations of the cleaned name elements, for example, (A) first name + last name or (B) nickname + last name. In this way, I had several permutations of full names as well as discrete first and last name columns for which I could attempt explicit joins with the partisanship datasets.

In total, I utilize twenty discrete join methods, and I perform these joins following two approaches regarding the fluidity or constancy of partisanship, namely (1) allowing an individual's partisanship to vary by election cycle and (2) assuming an individual's partisanship is fixed and reflective of their dominant party identity. For the primary analysis, I use the first approach, although I also perform analyses assuming the latter fixed partisanship, which appear in Appendix D. For both approaches (1) and (2), I perform the aforementioned sequence of joins, where the exact join method and number of cases resulting from each method are detailed in Appendix D, Table D.1 and Table D.2. For quality control purposes, I set a board-missingness threshold of 0.30. In other words, I only kept companies for subsequent analysis if I could match at least 70% of the board member identities to an

[13]The original FEC-CP data that had been reduced to unique individuals by cleaned full name, firm, and cycle collapsed all individual contributions for that person, averaging the *party_ID* and *partisan_score* for each contribution. For this reason, simply recalculating the mean of any new duplicate names would prove ill-advised and could inaccurately distort the overall partisanship. Since recalculating means with the original data was not readily available, the safer practice was dropping the result with fewer contributions. For example, if an individual made 25 contributions with one version of their name, but only two contributions with another name variation, I kept the version with the most contributions.

identity in one of the partisanship datasets. Because not every identity in the partisanship datasets (FEC-CP, DM1, DM2) was known, this translates to only analyzing boards where approximately 70% or more of the board has known partisanship.

4.3.6 Outlining (1) Variable Partisanship and (2) Fixed Partisanship Determination and Imputation

At first, the distinction between (1) variable partisanship and (2) fixed partisanship may seem obvious. Yet, to fully understand the distinction requires a better understanding of the determination of partisanship for these methods and how the datasets impact this determination. Recall, for example, the three partisanship datasets, FEC-CP: 1980-2018, DM1: 2002-2012, and DM2: 1980-2014. Although we could perform joins by election cycle using the FEC-CP data and DM2 data, for any join methods involving DM1, joining by cycle is impossible since that dataset summarizes activity across multiple election cycles. In this case, any joins for variable partisanship are the same as those performed for fixed partisanship. Furthermore, the FEC-CP covers the greatest time period compared to either DIME-AOI datasets. Thus, I first attempt to determine partisanship using the FEC-CP before falling back to the DM1 or DM2. Ignoring differences in each dataset's election cycle coverage, substantial gaps for individuals also exist within each dataset. For instance, some individuals might not have any discernible partisanship. In other cases, we might only have information about an individual in a single election cycle. Using the (2) fixed partisanship approach, the determination of partisanship reflects the binary (REP/DEM) conversion of either (A) the mean partisanship across all available election cycles (for FEC-CP and DM2) or (B) the expressed partisanship for an individual in DM1.

Of course, the approach differs in determining (1) variable partisanship. For instance, to determine an individual's partisanship for missing election cycles, I adopt a two-phase imputation approach: (1) first using forward fill imputation, and (2) second using backward fill imputation. All imputation of values occurs by company and individual. In other words, only known values of partisanship for an individual are used in determining their partisan expression in other cycles. If an individual has no known party identity, the value remains unknown. When data is forward filled, a given value is carried forward to fill missing values until another known value is encountered or no future values exist for that individual. Forward filling values makes logical sense. We would assume an individual retains their expressed partisan value into the future unless presented with evidence to the contrary. For example, if an individual were a Republican in 2016, we would assume they were also a Republican in 2018. Yet, taken alone, forward filling values is not enough. If we only have one observation for an individual, in this example, that they were a Republican in 2016, only future values, would be filled using forward fill, as described above. Because we have no information to the contrary, we might presume they were also a Republican in 2008-2014. This is an example of backward filling.

Formally, when data is backward filled, a given value is carried backward to fill missing values until another known value is encountered or no prior values exist for that individual. In the case of a single value, the order does not matter. Yet, in the case of two or more values where at least one party switch occurs, the order greatly matters. Consider the example in Table 4.1. Compared to the original method of determining overall partisanship, the forward fill, backward fill method differs primarily in the scenario where an individual makes one or more partisan transitions across cycles. If an individual is consistently the same partisan in one or more election cycles, there is no difference.

4.3.7 Determining Board Change Events

After determining parties, we must calculate board events. But first, we must define a board change event. Simply put, a board change event reflects an ostensible difference in the composition of the board as determined by its members. A board change transpires when

Table 4.1: Examining How Forward Fill (FFILL), Backfill (BFILL) Order Matters

Firm	Individual	Cycle	Party	Party (FFILL, BFILL)	Party (BFILL, FFILL)
C01	E01	2004	nan	REP	REP
C01	E01	2006	REP	REP	REP
C01	E01	2008	nan	REP	DEM
C01	E01	2010	nan	REP	DEM
C01	E01	2012	DEM	DEM	DEM
C01	E01	2014	nan	DEM	DEM
C01	E01	2016	nan	DEM	DEM
C01	E01	2018	nan	DEM	DEM

Notes: Example of how the two-phase imputation method occurs, grouped by company and individual. The utilized two-phase approach occurs in the order (1) forward fill (FFILL), (2) backward fill (BFILL) as represented in the column 'Party (FFILL, BFILL).' The other column 'Party (BFILL, FFILL)' illustrates why the order the steps are executed matter.

one or more changes occur in the set of board members between two time periods. If a set of board members is constant, no change exists. Thus, determining a board change event evolves from comparing the sets of all given board members within a firm at two points in time. As previously mentioned, this data comes from the ISS, which delimits the individual board members for a firm annually. Thus, we might minimally determine board change events by examining the set of board members each year with the set of board members in the prior year. We might alternatively express this comparison as a yearly comparison of board change events using a one-year lag. Below, I expand upon the prospect of relaxing the one-year lag to incorporate alternative lag possibilities.

Now that we understand that board events are changes in the set composition of a corporate board between two times, however, I must explain how practically this change is calculated. All changes are calculated using a self-designed code repository developed in *Python*, which for every firm, creates two lists of (a) current board members and (b) prior board members (for a given year-lag) for each available year of comparison, dependent on the number of lag-years included (Mausolf 2020g). The comparison of the two lists is not dependent on the order of the board members and uses a cleaned, lowercase version of the full name to prevent registering false change events from board-member name variations. When comparing two board sets, two elemental types of board change are possible. New board members may be added or dropped, and these events are not mutually exclusive. For example, two new board members may be added and only one old member is dropped. In most cases, the comparison of two board member sets reveals a large intersection of persistent board members. Where no new members are added and no old members are dropped, no board change occurs, and the intersection of persistent members is equal to the board set at either time period.

Thus, the set comparison of boards at two time periods results in the following possibilities from the combination of No Change (NC), Addition (A), or Drop (D) events: $[NC] \oplus [A \vee D]$, where $A \cup D \neq \varnothing$, $A = \varnothing \vee A = [A_1, \ldots, A_n]$, $D = \varnothing \vee D = [D_1, \ldots, D_n]$. In other words, we can have either no change or some non-empty combination of additions and drops. Where we have an equal number of additions and drops, this would be recoded as a swap. To give a few examples, suppose we have the following supersets of board change events: $\Big($[ADD, ADD, ADD], [DROP, DROP]$\Big)$, $\Big($[ADD], $\varnothing_{\text{DROP}}\Big)$, $\Big(\varnothing_{\text{ADD}}$, [DROP, DROP]$\Big)$. These supersets of events would be resolved as follows: [SWAP, SWAP, ADD], [ADD], [DROP, DROP]. Of course, a host of other possibilities exist, especially as the period between comparison boards increases. Nonetheless, the resolution of this process results in a dataset of board events.

The astute observer will note that the above process of codifying board change events relies upon the names of board members. The names of added, dropped, swapped, and persistent board members, while perhaps interesting, lacks generalizable utility in that names do not confer partisanship. To extract this information, I utilized a solution of creating two columns, one for the current board and one for the prior board, which contained a dictionary using board member names as keys, and board member parties as the values. Combined with discrete columns articulating added and dropped board member names, I could thus generate columns specifying the party of the added and dropped board members, which I utilize in the subsequent analysis. Recalling that not all board members have a known party identity, we have occurrences where the party of the added board member or the dropped board member has an unknown party identity. Although missing board partisanship could perhaps be either crudely imputed using the board mean or with a more advanced multiple imputation with chained equations approach, such approaches would to a great extent simply reify the hypothesized outcome (that added board members are more likely to match the board party). Therefore, the statistically conservative approach is to simply perform the analysis of board member appointments for only known partisans.

4.3.8 Board Change Event Lag Periods

As previously indicated, although board change events rely upon the comparison of a current board and a prior board occurring in the past, referred to as the lag, l, the period of lag varies. Practically, what sort of phenomena could be reflected by a multiyear lag? For instance, if a board simply adds and drops one member over a one-year lag, we would classify this event as a swap. Yet, a board likely makes changes outside of an annual calendar, and may, in fact, go through multiyear transition periods. Consider a board that adds and drops one member in 2013, adds two members in 2014, and drops two members in 2015. A one-year lag would show the following events: {2013: [SWAP], 2014: [ADD, ADD], 2015: [DROP, DROP]}; whereas a two-year lag would reveal: {2014: [SWAP, ADD, ADD], 2015: [SWAP, SWAP]}; and a three-year lag would show: {2015: [SWAP, SWAP, SWAP]}. In point of fact, depending on the lag set, we see discrete sets of board events.

Analytically, we could simply select a given lag-year and do analysis for that lag-year set of data only. For instance, we could analyze the data only for lag year, $l = 1$, $l = 2$, or $l = 4$. Since the ISS data is annual data, with included years of 2007-2018, if a given company has a board for each of these years, the range of possible lag years, $l = [1 \dots 11]$. Examining a single year lag may capture a certain phenomenon but overlook others if board member compositional changes could theoretically evolve over several years. So I may best analyze the scenarios, I designed code to calculate board change events for every range of lag years available to a firm, $l = [1 \ldots N]$, where N equals the number of included years for a firm less one. As I elaborate below, there are several approaches to analyzing the number of possible lag years, and I include both approaches, including full lag-year ranges $[1, 11]$, as well as single-year lags, among other possibilities, reserving most of the additional analyses for the appendix.

4.3.9 Cross-Classified Random Effects Logistic Regression Models

In this analysis, I ask how the partisanship of a firm's board influences the decision to admit either a new Democratic or Republican board member, and whether that likelihood varies by whether the board member is simply an additional member or succeeding an outgoing member of the board. Although the primary analysis utilizes multivariate, multi-level modeling, I also provide a number of descriptive statistics of the study variables as well as some bivariate graphs to illustrate the underlying phenomena. Before turning to the formal models, consider the descriptive statistics that result from the above data pipeline (Table 4.2).

To formally model how the partisanship of a firm's board influences the addition or succession of new board members of a given party, I conduct a type of longitudinal modeling known as cross-classified random effects (CCRE) logistic regression models (Raudenbush and Bryk 2002), used in educational studies, age-period-cohort analyses, and electoral studies (Park and Jensen 2007; Yang and Land 2006, 2006). Given the binary outcome variables, I utilize logistic regression, a type of hierarchical generalized linear model, which can be extended with cross-classified random effects (Caren, Ghoshal, and Ribas 2011; Raudenbush and Bryk 2002).

This type of hierarchical generalized linear model includes both level-1 fixed effects for primarily board-level features as well as level-2 cross-classified random effects for intersecting

Table 4.2: Descriptive Statistics, Board Member Events, 2007-2018: Party-Cycle

	1-Year Lag	2-Year Lag	2-4-Year Lags	All-Year Lags
Board Events				
Add	1,105 (24.07%)	1,298 (20.78%)	3,842 (17.70%)	10,031 (14.98%)
Drop	1,075 (23.42%)	1,267 (20.28%)	3,747 (17.26%)	9,628 (14.38%)
Swap	1,760 (38.34%)	3,484 (55.78%)	13,855 (63.83%)	46,371 (69.27%)
Equal Swap	644 (14.03%)	1,192 (19.08%)	4,768 (21.97%)	16,531 (24.69%)
Unequal Swap	1,116 (24.31%)	2,292 (36.70%)	9,087 (41.87%)	29,840 (44.58%)
No Change	650 (14.16%)	197 (3.15%)	261 (1.20%)	913 (1.36%)
New Board Members				
Republicans	1,055 (36.82%)	1,807 (37.79%)	6,924 (39.13%)	22,484 (39.86%)
Democrats	583 (20.35%)	961 (20.10%)	3,366 (19.02%)	10,049 (17.82%)
Unknown	1,227 (42.83%)	2,014 (42.12%)	7,407 (41.85%)	23,869 (42.32%)
Dropped Board Members				
Republicans	1,142 (40.28%)	1,947 (40.98%)	7,253 (41.21%)	22,657 (40.46%)
Democrats	667 (23.53%)	1,127 (23.72%)	4,309 (24.48%)	14,220 (25.39%)
Unknown	1,026 (36.19%)	1,677 (35.30%)	6,040 (34.31%)	19,122 (34.15%)
Event Match				
Match	1,780 (45.18%)	2,742 (45.33%)	9,740 (45.42%)	30,148 (45.66%)
Unmatched	2,160 (54.82%)	3,307 (54.67%)	11,704 (54.58%)	35,882 (54.34%)
Missing	650 (14.16%)	197 (3.15%)	261 (1.20%)	913 (1.36%)
Board-Level Metrics (Mean)				
Median Age	62.97 ± 3.49	63.01 ± 3.41	63.05 ± 3.37	63.03 ± 3.32
Female Proportion	0.20 ± 0.09	0.20 ± 0.09	0.21 ± 0.09	0.22 ± 0.09
Black / Hispanic Proportion	0.11 ± 0.09	0.12 ± 0.09	0.12 ± 0.09	0.13 ± 0.09
Minority Proportion	0.20 ± 0.17	0.19 ± 0.15	0.17 ± 0.13	0.17 ± 0.12
Non-USA Proportion	0.03 ± 0.06	0.04 ± 0.06	0.03 ± 0.06	0.03 ± 0.06
Board Size	11.38 ± 2.12	11.40 ± 2.05	11.40 ± 2.00	11.38 ± 1.97
Median Outside Board Ties	0.99 ± 0.56	0.99 ± 0.55	0.99 ± 0.55	0.98 ± 0.54
Board Party X Events				
Democratic Board	1,092 (23.79%)	1,411 (22.59%)	4,593 (21.16%)	13,203 (19.72%)
Republican Board	3,498 (76.21%)	4,835 (77.41%)	17,112 (78.84%)	53,740 (80.28%)
Firm Party X Events				
Polarized Democratic	444 (13.39%)	556 (12.19%)	1,926 (12.06%)	5,917 (12.01%)
Amphibious Firm	2,143 (64.63%)	3,001 (65.78%)	10,485 (65.63%)	32,338 (65.62%)
Polarized Republican	729 (21.98%)	1,005 (22.03%)	3,565 (22.31%)	11,029 (22.38%)
U.S. Presidential Party				
Democrat	3,286 (71.59%)	4,840 (77.49%)	16,193 (74.60%)	39,258 (58.64%)
Republican	1,304 (28.41%)	1,406 (22.51%)	5,512 (25.40%)	27,685 (41.36%)
Observations				
N	4590	6246	21705	66943
Firms	274	273	273	274
Sectors	14	14	14	14
Years	11	10	10	11
Lag Years	1	1	3	11
Time Period and Lags				
Year Range	2008, 2018	2009, 2018	2009, 2018	2008, 2018
Years Included (w/lag)	2007, 2018	2007, 2018	2007, 2018	2007, 2018
Lag Range	1, 1	2, 2	2, 4	1, 11

Notes: Descriptive statistics calculated for discrete lag years. That is, each column uses a discrete set of year lag(s) as follows: 1-year lag, 2-year lag, 2-4-year lags, and 1-11 (all) year lags. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles.

random variation of the fixed effects, namely how the modeled effects might vary by both firm and election cycle. Each model takes the following general form:

Level 1 - within-cell model:

$$\eta_{ijk} = \beta_{0jk} + \sum_{p=1}^{P} \beta_p X_p \tag{4.1}$$

Level 2 - between-cell model:

$$\beta_{0jk} = \ \gamma_0 + u_{0j} + v_{0k},\ u_{0j} \sim N(0, \tau_{u0}), v_{0k} \sim N(0, \tau_{v0}) \tag{4.2}$$

Combined model:

$$\eta_{ijk} = \gamma_0 + \sum_{p=1}^{P} \beta_p X_p + u_{0j} + v_{0k},\ u_{0j} \sim N(0, \tau_{u0}), v_{0k} \sim N(0, \tau_{v0}) \tag{4.3}$$

for $i = 1, \ldots, n_{jk}$ board events within firms j and years k;
$j = 1, \ldots, 274$ firms;
$k = 1, \ldots, 11$ years;

where $\eta_{ijk} = log\Big[\frac{\pi_{ijk}}{(1-\pi_{ijk})}\Big]$ and $\pi_{ijk} = Prob\Big\{\text{New REP}|\text{DEM Board Member}_{ijk}\Big\}$ for a given board event i in firm j for year k; β_p reflects level-1 fixed-effect coefficients β_p for the vector X_p of board-event variables, such as the board's political party, the type of board event (addition or succession), as well as other company variables; for $p, \ldots, P$ variables, where P is the maximum number of level-1 variables for a given model; γ_0 is the intercept; and $u_{0j} \sim N(0, \tau_{u0})$, $v_{0k} \sim N(0, \tau_{v0})$ are the random intercepts, which have variances τ_{u0} and τ_{v0}.

In other words, our outcome, η_{ijk} can be thought of as the log odds of successfully adding a new Republican or Democratic board member. Since a number of outcomes are possible, I examine discrete models for the $Prob\Big\{\text{New REP Board Member}_{ijk}\Big\}$ and $Prob\Big\{\text{New DEM Board Member}_{ijk}\Big\}$. It should further be noted that in the above model, the exact number of board events i, firms j, and years k vary by the included number of covariates P as well as the fixed number of lag-years l included in the underlying board-level data pipeline. The astute observer will note that l is not included in equation 4.3, chiefly because it is fixed for the entire subset of data modeled. We can extend the primary model 4.3 by adding an additional random effect for the number of lag-years utilized in the board-level data-generation pipeline. That is, rather than restrict the number of lag-years, I decided to analyze every lag-year subset at once with an additional cross-classified random-intercept for the lag years, l:

$$\begin{aligned} &\text{Combined model:} \\ \eta_{ijkl} =& \gamma_0 + \sum_{p=1}^{P} \beta_p X_p + u_{0j} + v_{0k} + w_{0l}, \\ &u_{0j} \sim N(0, \tau_{u0}), v_{0k} \sim N(0, \tau_{v0}), w_{0l} \sim N(0, \tau_{w0}) \end{aligned} \tag{4.4}$$

for $i = 1, \ldots, n_{jkl}$ board events within firms $j,$ years $k,$ and lag years $l;$
$j = 1, \ldots, 274$ firms;
$k = 1, \ldots, 11$ years;
$l = 1, \ldots, 11$ lag-years;

where the specifications for equation 4.3 also apply to equation 4.4 for a given board event i in firm j for year k and lag-year l, with the additional caveat that the number of possible years k is inversely related to lag-years l. All modeling for equations 4.3 and 4.4 was calculated using the *glmer* function from the *lme4* package with the BOBYQA optimizer set in the glmerControl (Bates et al. 2015; Douglas Bates, Bolker, and Walker 2015). To reiterate a point made earlier, in all the models, as well as the bivariate analyses, I only evaluate data where the incoming or added board member has a known party identity.[14] Descriptive

[14]To clarify this point, all the models—for example, Table 4.3 and Table 4.4—as well as Figure 4.2, only perform analysis where the incoming or added board member has a known party identity. The two primary categories of board member appointments include board member additions and board member successions (alternatively referred to as a swap or replacement). Because swaps involve not only an incoming board member but also an outgoing board member, I only require that the incoming board member have a known party identity. The departing board member may have either a known or unknown party identity. Descriptive statistics for this specific subset of observations can be found in Appendix D, Table D.4. For simplicity, the bivariate graph, Figure 4.1, only contains cases where the incoming and outgoing board members have known

statistics for the entire analysis dataset, including persistent boards (no change over the lag period) and board drops is provided in Table 4.2), and a more selective subset reflecting data for only known incoming partisan board members is found in Appendix D, Table D.4. Collectively, the analysis will help illustrate the extent to which affective polarization and partisan homophily affect the appointment of new members to a firm's corporate board.

4.4 Analysis

When considering whether affective polarization and partisan homophily can affect the appointment of corporate board members, let us first consider the bivariate pattern witnessed in board member events. Here, I specifically focus on the incoming board members in two types of board appointment events, additions and successions, which I alternatively refer to as swaps. Additionally, I consider the party of outgoing board member drops (excluding swaps).[15] In Figure 4.1, we can see the partisan pattern of incoming and outgoing board members demonstrated in both Democratic and Republican corporate boards.

Examining the results, we can see that Democratic boards are significantly more likely to appoint copartisan board members. We see these results for both board member successions and additions. Although we see significant differences for all Democratic board appointments, in the case of swaps, the incoming board member is a Democrat in 66.5% of cases compared to 58.4% of the cases for additions. Turning to the results for Republican boards, we see a similar pattern. For both board member swaps and additions, Republican boards have a significantly higher incidence of appointing incoming Republican board members. For

partisanship. Descriptive statistics for this alternative subset of observations can be found in Appendix D, Table D.3.

[15]Note that in this example, I only evaluate board member events that are specifically encoded as a drop. Thus, these are outgoing board members only from drops, not all outgoing board members from swaps and drops. A preliminary analysis considering all outgoing members shows similar results to only considering drops in isolation.

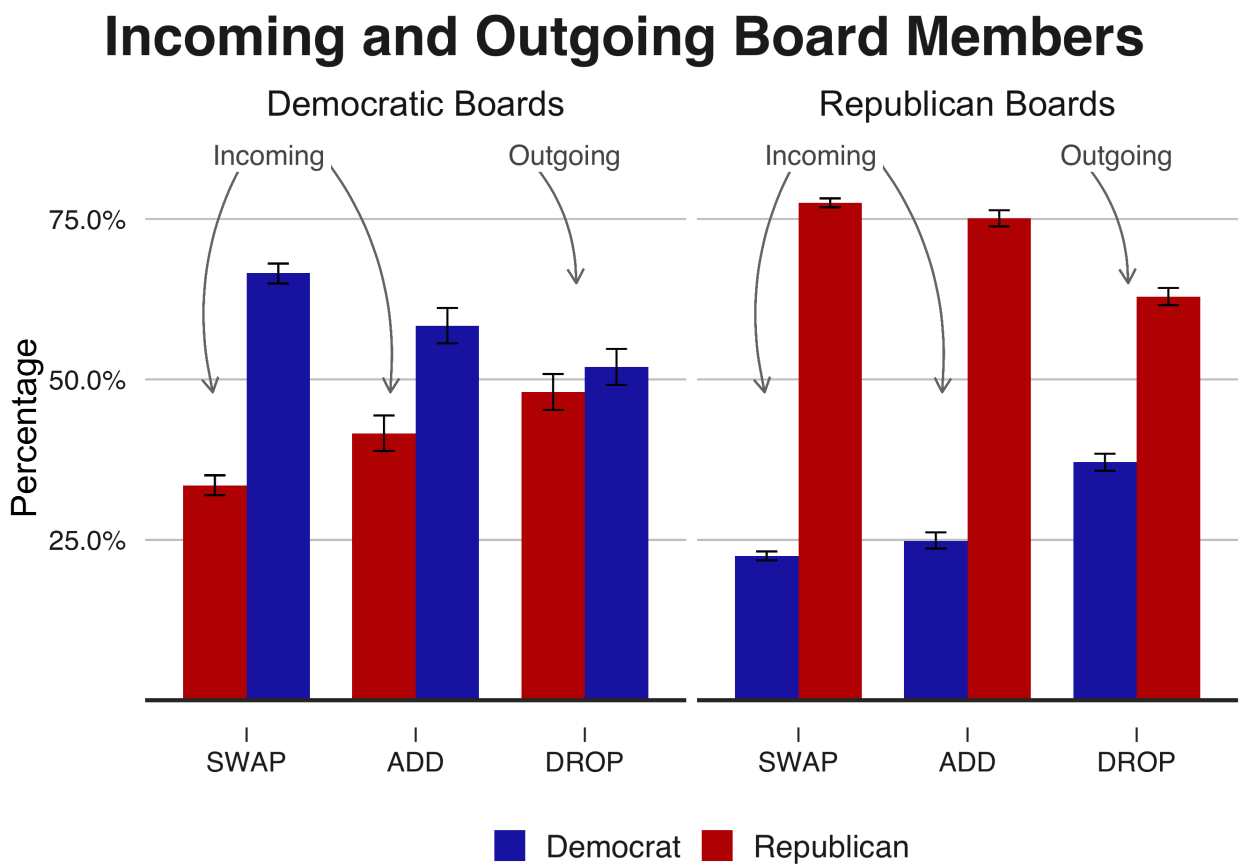


Figure 4.1: Incoming and Outgoing Board Members by Board Member and Board Party

Notes: Figure generated using all lags (1-year, 11-year) included. Error bars indicate a 95% CI. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles. For swaps or adds, the incoming board member is represented in the figure. For drops, the outgoing board member is represented. Collectively, we can see to what extent the party of the incoming or outgoing board member matches with the party of the firm's board. Only known partisans used. Specifically, all events with an unknown board member party in either the incoming or outgoing board member were dropped. N = 29,340 events. Republican board swaps, adds, drops: 13,799, 4,543, 5,016. Democratic board swaps, adds, drops: 3,534, 1,226, 1,222.

Republican boards, 77.5% of incoming board member swaps and 75.1% of board member additions were Republicans.

Synthesizing these patterns, we see that both Democratic and Republican boards favored copartisan appointments. These patterns exist for both board additions and swaps. The higher frequency of copartisan board appointments parallels the significantly less frequent occurrence of appointing opposing partisans. These patterns of affective polarization and partisan homophily, while evident in both Republican and Democratic boards, are more salient in Republican boards. In contrast to board appointments, we do not see evidence that boards are more likely to drop opposing partisans. In fact, Republican boards are significantly more likely to drop Republican board members. Democratic boards also have slightly higher rates of dropping copartisans but the results are not significant. Since copartisans are most frequently added, such results most likely reflect the need to drop copartisans in order to maintain a consistent board size. Although these drops are not part of an identified swap, they may be part of swaps using an alternative lag-year or instead precede future board additions. Nonetheless, we see patent partisan patterns in board member appointments in this bivariate analysis.

If we turn our attention to how these patterns might vary by year, we can glean additional insight. Consider how the level of partisanship has changed in recent years, starting with Democratic boards. Although Democratic boards are more likely to select a board member who matches the partisanship of the board (Figure 4.1)—that is appoint a Democratic board member in at least 50% of cases—this fact varies by year and whether the appointment is a swap or addition. Mirroring the trend seen in Figure 4.1, we can see that in Democratic firms, board member swaps more frequently exemplify partisan matching than board member additions (Figure 4.2). From 2008 to 2018, partisan matching in board member succession increased for Democratic firms and remained fairly stable year over year.

In contrast, we have seen a downward trend in partisan matching for board member additions in Democratic firms. In part, this trend may be related to the lesser frequency of Democratic board additions, compared to the increasing frequency of board member swaps in Democratic boards.[16] Although it proves difficult to disentangle, a possible explanation is that Democratic boards might elect to utilize board member succession more commonly than additions to bolster their Democratic ranks, relative to Republican boards. For Republican boards, the magnitude of partisan matching, both for board member succession and board member additions, has tended to increase over the years. When considering all boards, we

[16]To elaborate, whereas Democratic board member addition events increase from 31 to 205 between 2008 and 2018, Democratic board member swap events increase from 27 to 1079 over the same period. I visualize these trends in Appendix D, Figure D.1. To an extent, swaps would be expected to increase more than additions since multiple lag-years compound in successive years.

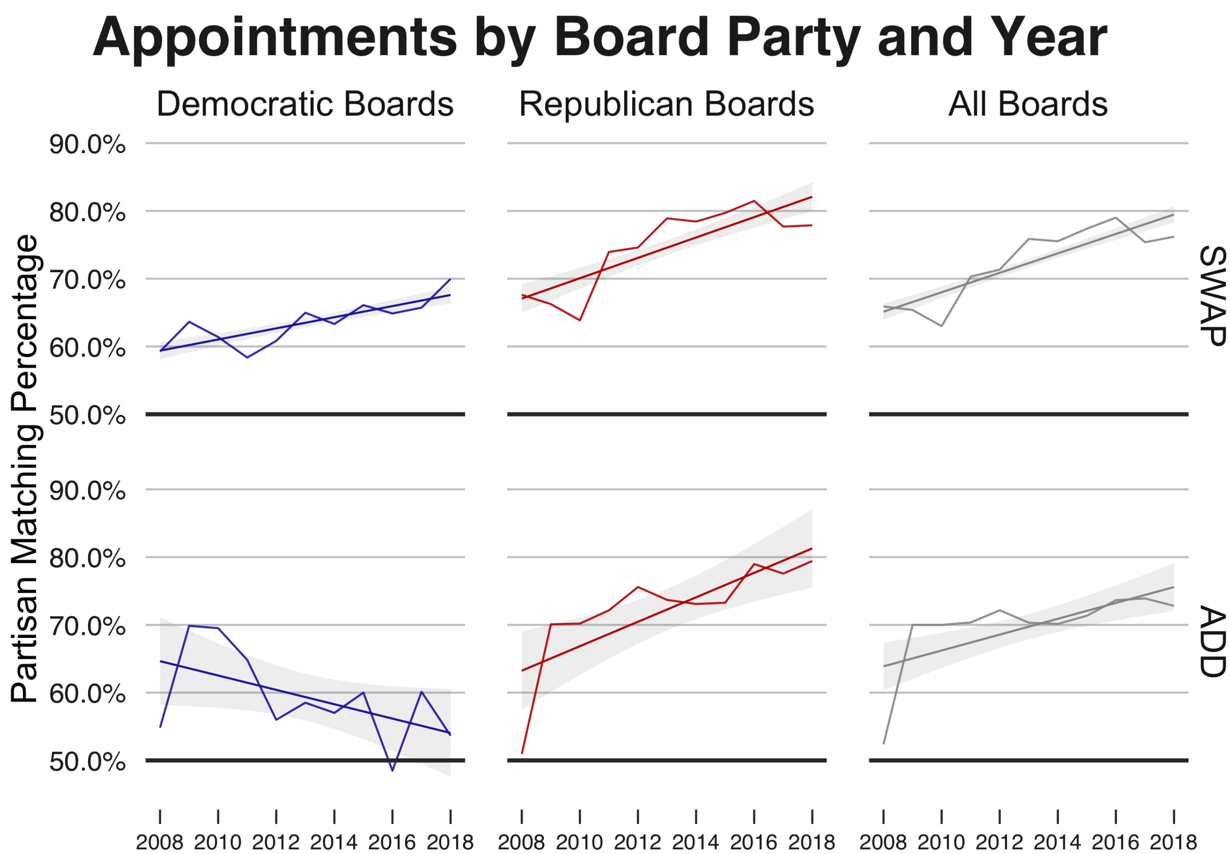


Figure 4.2: Partisan Matching for Board Appointments by Party and Year
Notes: Figure generated using all lags (1-year, 11-year) included. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles. Collectively, we can see to what extent the party of the incoming board member matches with the party of the firm's board. All events with an unknown board member party in the incoming board member were dropped, but unknown outgoing board party members were retained, which is the same approach adopted in the formal models. In the subplots, the yearly figure is plotted along with a GLM trend line and confidence interval calculated in R.

witness similar tends of intensified partisan matching from 2008 to 2018. Of course, a number of potential factors might be unaccounted for in these bivariate plots. To garner greater confidence in the results and their robustness, let us turn to the multivariate models.

Turning to the CCRE logit models, let us first consider the likelihood that a given board appoints a Republican board member (Table 4.3). Examining the models, we can see that not only is there a significantly higher likelihood that a Republican board will appoint a Republican board member, but the effect size is also fairly large ($OR = 3.85 - 4.18$) and highly significant $p < 0.001$ in each of the four models. In fact, besides stability across various model parameterizations (Table 4.3), these effects seem robust to multiple lag-year permutations as well as fixed versus variable partisanship, as displayed in Appendix D. If anything, we see even stronger effect sizes in the appendix models versus Table 4.3, which utilizes all available lag years. Models using only the one-year lag demonstrate a similar effect, ($OR = 3.58 - 4.24$), $p < 0.001$ (Table D.5), and those with a two-year lag are even stronger, ($OR = 4.86 - 5.25$), $p < 0.001$ (Table D.7). Models using fixed partisanship (versus the party-cycle measure) likewise, have stronger effects still. Keep in mind that for all these models, a Republican board has the reference group of a Democratic board. We can alternatively interpret these results as stating that Democratic boards have a significantly lower likelihood of appointing a Republican board member (Appendix D, Table D.9). Before diving into the results for the additional covariates, let us continue the discussion of primary partisan effects. Consider the results in Table 4.4, which shows the likelihood that a Democratic board member will be appointed. Examining the Republican board coefficient, we can see that a Republican board is significantly less likely to appoint a Democrat to the board ($OR = 0.24 - 0.26$), $p < 0.001$, compared to the reference group of a Democratic board. As before, we can alternatively interpret this to say that a Democratic board is significantly more likely to appoint a Democratic board member ($OR = 3.85 - 4.18$), $p < 0.001$, compared to a Republican board member (Appendix D, Table D.10).

Synthesizing the results seen across these models, board members are significantly more likely to be appointed when their partisanship matches the partisanship of the board. That is, copartisans are most likely to be appointed to the board. Democratic boards are more likely to appoint Democrats, while Republican boards are more likely to appoint Republicans. The opposite is also true. Opposing partisans remain significantly less likely to be appointed to a corporate board. Democrats have much lower odds of appointment to a Republican board, while Republicans similarly have low odds of appointment to a Democratic board. Although we might conclude that these results support a theory of partisan homophily, the results do not conversely exclude the affective polarization argument. In fact, as highlighted above, partisan homophily simply reflects a condition of association among like others, in this

Table 4.3: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Republican, 1-11-Year Lags, Odds Ratios Displayed

	Pr{New Board Member: Republican}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	1.264***	1.269***	1.349***	1.352***
Board Member Equal Swap	1.713***	1.716***	1.696***	1.678***
Republican Board	4.180***	4.071***	3.967***	3.848***
Democratic Firm			0.851	0.869
Republican Firm			1.678	1.383
Board Features				
Board Size (Log)		0.857	0.706*	0.680*
Median Age (Log)		0.441*	1.023	1.185
Proportion Female		0.481*	0.478*	0.444*
Proportion Black or Hispanic		0.150***		0.357*
Proportion Minority			0.338***	0.429***
Proportion Non-US				1.301
Median Outside Board Ties		0.883**	0.916	0.932
Firm Sectors				
Capital Goods				3.359
Conglomerates				0.267
Consumer Cyclical				0.487
Consumer Goods				0.869
Consumer/Non-Cyclical				0.656
Energy				0.472
Financial				0.473
Healthcare				0.673
Services				0.613
Technology				0.578
Transportation				0.533
Utilities				0.929
Other Features				
U.S. President (Democrat)		1.051	0.959	0.924
Constant	0.736*	50.261*	2.247	2.506
Level-2 Random Intercepts				
Firm Variance	3.132	3.198	2.735	2.471
Year Variance	0.06	0.082	0.052	0.058
Lag-Year Variance	0	0	0	0
N	32,533	32,533	24,899	24,624
Firms	269	269	209	202
Years	11	11	11	11
Lag-Years	11	11	11	11
Log Likelihood	-15,382.530	-15,355.190	-11,838.270	-11,674.410
AIC	30,779.060	30,736.370	23,706.540	23,406.810
BIC	30,837.790	30,845.440	23,828.380	23,642.040

Notes: Cross-classified random effects (CCRE) logistic regression model, all lags (1-year, 11-year) included. Cross-classified random intercepts include firm, year, and lag-year. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles.
*p < .05; **p < .01; ***p < .001

case, copartisans. We certainly see the more likely association of copartisans in corporate boards. Affective polarization commonly references partisan animus or aversion to those in the opposing party, which likewise finds support in the models.

Although I will elaborate on these findings in the discussion, at the moment, however, let us return to the additional conclusions that can be gleaned from the models beyond partisan homophily and affective polarization (Tables 4.3, 4.4). Consider how the type of appointment affects the likelihood of appointment for Republican versus Democratic board members. Recall that these models consider not only additions but also board member successions or swaps, namely equal swaps and unequal swaps. Checking Table 4.3, we can see that a Republican board member is significantly more likely to be appointed if the event is an addition, $(OR = 1.26 - 1.35)$, $p < 0.001$, or an equal swap (an equal partisan exchange), $(OR = 1.68 - 1.71)$, $p < 0.001$, which in this case would be an incoming Republican replacing an outgoing Republican board member. By extension, Republicans are less likely to be appointed in the event of an unequal swap, which in this case would be a Republican replacing a Democrat.

When considering the results for appointing a Democrat, a parallel albeit reverse set of findings exists. Democratic board members are less likely to be appointed following an addition event, $(OR = 0.74 - 0.79)$, $p < 0.001$, or an equal swap (Democrat replacing a Democrat), $(OR = 0.58 - 0.60)$, $p < 0.001$, compared to the reference group, wherein a Democrat succeeds a Republican board member. In part, these results shed additional light on Figure 4.2. We know from the models that Democratic boards are more likely to appoint Democratic board members and that Democrats are more often appointed when they succeed outgoing Republican members. The declining incidence of partisan matching for additions versus the increased partisan matching in swaps follows this interpretation from the multivariate models. Overall, while the type of event impacts a board member's odds of appointment, and these results are significant, they represent a considerably smaller effect than the partisanship of the firm's board.

Next, let us evaluate the results of other board features. Here, I focus on the results using other predictors of board diversity, particularly the proportion of the board that is

Table 4.4: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Democrat, 1-11-Year Lags, Odds Ratios Displayed

	Pr{New Board Member: Democrat}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	0.791***	0.788***	0.742***	0.740***
Board Member Equal Swap	0.584***	0.583***	0.590***	0.596***
Republican Board	0.239***	0.246***	0.252***	0.260***
Democratic Firm			1.176	1.151
Republican Firm			0.596	0.723
Board Features				
Board Size (Log)		1.167	1.416*	1.470*
Median Age (Log)		2.268	0.977	0.844
Proportion Female		2.078*	2.093*	2.251*
Proportion Black or Hispanic		6.663***		2.798*
Proportion Minority			2.959***	2.333***
Proportion Non-US				0.769
Median Outside Board Ties		1.132**	1.092	1.073
Firm Sectors				
Capital Goods				0.298
Conglomerates				3.734
Consumer Cyclical				2.052
Consumer Goods				1.151
Consumer/Non-Cyclical				1.524
Energy				2.116
Financial				2.113
Healthcare				1.486
Services				1.630
Technology				1.729
Transportation				1.875
Utilities				1.076
Other Features				
U.S. President (Democrat)		0.951	1.042	1.083
Constant	1.358*	0.020	0.447	0.399
Level-2 Random Intercepts				
Firm Variance	3.132	3.198	2.735	2.471
Year Variance	0.06	0.082	0.052	0.058
Lag-Year Variance	0	0	0	0
N	32,533	32,533	24,899	24,624
Firms	269	269	209	202
Years	11	11	11	11
Lag-Years	11	11	11	11
Log Likelihood	-15,382.530	-15,355.190	-11,838.270	-11,674.410
AIC	30,779.060	30,736.370	23,706.540	23,406.810
BIC	30,837.790	30,845.440	23,828.380	23,642.040

Notes: Cross-classified random effects (CCRE) logistic regression model, all lags (1-year, 11-year) included. Cross-classified random intercepts include firm, year, and lag-year. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles.
*p < .05; **p < .01; ***p < .001

female, black or Hispanic, or minority. First, consider the proportion of the board that is female. Here, we can see that as the board includes a greater proportion of women, we see a lower likelihood of appointing a Republican to the board, ($OR = 0.44 - 0.48$), $p < 0.05$

(Table 4.3), and a higher likelihood of appointing a Democrat ($OR = 2.08 - 2.25$), $p < 0.05$ (Table 4.4). Similarly, as the proportion of black or Hispanic or alternatively minority board members increases, we see a lower likelihood of appointing a Republican board member, ($OR = 0.15 - 0.36$), $p < 0.05 - 0.001$ and ($OR = 0.34 - 0.43$), $p < 0.001$, respectively. Conversely, we see opposite effects for the likelihood of appointing a Democrat. Of these effects, however, those for the proportion of minority board members appear most robust since they remain significant in at least one of the two possible models, $p < 0.05$ for the 1-year and 2-year lag models (Appendix D, Tables D.5-D.8).

Although we see effects for proportion female or proportion black or Hispanic in the main 1-11-year lag models, we see no significant effects for gender or black or Hispanic corporate board proportions in the more simplistic single 1-year or 2-year lag models (Appendix D, Tables D.5-D.8). In this way, although we see an effect under certain modeling constraints, because these effects only emerge in the scenario of increased event observations and do not appear in the more simplistic models using a single lag year, they should be considered somewhat tenuous as compared to the findings for board partisanship and event type which consistently appear across all modeled contexts.[17]

Apart from diversity features, we should also note several additional findings. Given the power of board partisanship, we do not seem to find any consistent effects for the magnitude of partisanship of the firm. For example, it seems to matter not whether the firm is a polarized Republican, polarized Democratic, or Amphibious firm, as described

[17] To provide additional context about the comparative significance vis-à-vis the number of observations, although the effect for both a Republican board and proportion minority are both $p < 0.001$, this fact would seem to equate their significance. For instance, a p-value of 0.000015 and 0.04 are both $p < 0.05$. In the same way, although both effects, have a probability $p < 0.001$ (Table 4.3), a Republican board has a z value $= 24.49 - 20.20, p < 2e - 16$, that is $p < 0.00000000000000022$, compared to the effects for a higher proportion minority board, which has a z value $= |3.65 - 5.20|$, $p < 0.00026 - 1.98e - 07$. By contrast, in the single-year lag model (Table D.5), the proportion minority has a z value $= |2.43|$, $p < 0.015$ in one model, while a Republican board still has a z value $= 8.06 - 11.01$, $p < 0.00000000000000022 - 0.00000000000000075$. In this way, not only is a Republican board several orders of magnitude more significant, but this significance remains stable across models using $N = 1,638 - 32,533$ events, whereas those for the strongest diversity predictor (minority proportion) largely erode.

in Mausolf (2020a), at least when using variable board partisanship. Truly, many of the so-called Amphibious firms (the reference group in the models), had overall Republican boards with occasionally Democratic-leaning employees (Mausolf 2020a). Generally, the power of the board's partisanship dominated, and in only a handful of the models with a simpler parameterization did we see any effects. Here, a polarized Republican firm predicted a higher likelihood of appointing a Republican board member, ($OR = 1.57 - 1.87$), $p < 0.05$, and a significantly lower likelihood of appointing a Democratic board member, ($OR = 0.64 - 0.54$), $p < 0.05$ (Appendix D, Tables D.11, D.12).

Models using fixed partisanship, however, reveal stronger effects, ($OR = 1.59 - 5.17$), $p < 0.01 - 0.001$ and ($OR = 0.63 - 0.19$), $p < 0.05 - 0.001$ for a Republican board's likelihood of appointing a Republican versus Democrat, respectively (Appendix D, Tables D.14-D.21). For the fixed partisan models, although the significance level and effect size varies, we witness the effects not simply in the simpler model parameterizations, but also a number of the more complex models (Models 3 or 4), often with a significance of $p < 0.001$ under different lag-periods. That the results chiefly exist for fixed partisan models is most likely associated with the fact that the clustering measure of firm partisanship employed from Mausolf (2020a) does not vary by election cycle, but rather is a summary measure after evaluating all election cycles for which data exists. Although the degree of partisan homogeneity in a firm has demonstrable, albeit weaker and less consistent effects, at least for variable partisanship, it nonetheless suggests that firms that are polarized Republican firms might have even more patent partisanship in their board member appointments. As opposed to firm partisanship, however, the models do not show much evidence to support that presidential election cycle, that is, the party of the U.S. president matters since we see only weakly significant effects, $p < 0.05$, in only two models among dozens. Similarly, no persistent, reliable effects exist for firm sector. These latter null findings underscore that in the matter of appointing known partisans to the corporate board of directors, the factors that matter most seem to be those characterizing the partisanship of the board, the firm, and the incoming board member.

4.5 Discussion

In this study, I evaluate the role of political partisanship, chiefly affective polarization and partisan homophily, in corporate board appointments. As we have seen across a series of bivariate and multivariate analyses, the results prove consistent with both affective polarization and partisan homophily hypotheses. Specifically, we see consistent robust effects suggesting that Republican corporate boards are more likely to appoint incoming Republican board members and are less likely to appoint Democratic board members. Likewise, Democratic board members are more likely to be appointed by Democratic corporate boards and less likely to be appointed by Republican boards. Collectively, these patterns support the generalized pattern that corporate boards are significantly more likely to appoint copartisan board members, which supports the partisan homophily hypothesis, and are significantly less likely to appoint opposing partisans, which supports the affective polarization hypothesis, in the sense of partisan animus.

From one perspective, these results extend the canon on partisan homophily (Huber and Malhotra 2017; Iyengar et al. 2018, 2019; Mausolf 2020b), or more generally the types of status homophily for which we see effects (Lazarsfeld and Merton 1954; McPherson et al. 2001). For example, Huber and Malhotra (2017) previously demonstrated political and partisan homophily on both the basis of political, ideological identity and partisan identity using the case of online dating, and Iyengar et al. (2018) shows political alignment in marital partnership to be "choice homophily" or "the individual-level propensity to choose similar others" versus "induced homophily," to use the terminology of (McPherson and Smith-Lovin 1987: 371). Although this study cannot possibly adjudicate whether the partisan homophily demonstrated by corporate boards is purely by choice or preference for copartisans or conversely avoidance of opposing partisans, among other possibilities, the results do augment the growing literature on the effects of partisan homophily in the workplace. For example, although Gift and Gift (2015) does not find partisan homophily in resume evaluation, rather finding affective polarization, we see in Mausolf (2020b), evidence of partisan homophily in resume callbacks. Copartisan applicants were more likely to receive a callback, that is, when the partisanship of the applicant matched the partisanship of the firm, compared to apolitical neutral applicants. Although we cannot make the same comparison to neutral applicants in this study, the results are nonetheless consistent with partisan homophily, except that rather than transpire for entry-level positions, we also see evidence of partisan homophily among corporate leadership.

At the same time, the results of this analysis are also consistent with affective polarization in the sense of partisan animus or aversion toward opposing partisans (Iyengar and Westwood 2015; Iyengar et al. 2019). In point of fact, although research on partisan homophily is limited, occurring in limited contexts, such as romance or resume evaluation (Huber and Malhotra 2017; Mausolf 2020b), manifest effects exist for affective polarization, which has previously appeared on a number of fronts, including denigrating trust, discounting economic rewards, or lowering wage-floor preferences (Carlin and Love 2013; Iyengar and Westwood 2015; McConnell et al. 2018), altering purchase behavior or market decisions (McConnell et al. 2018; Panagopoulos et al. 2016), creating an aversion to cross-party romantic entanglements (Iyengar et al. 2012; Kiefer 2017), or lowering the likelihood of scholarships or gaining first-round interviews while searching for employment (Gift and Gift 2015; Iyengar and Westwood 2015; Mausolf 2020b). Extending these results, we can now state that forces of affective polarization also appear to lower the likelihood that a potential board member will be appointed to a corporate board of directors.

The general trend of witnessing stronger effects of affective polarization than partisan homophily can, in part, be explained by the salience of partisan animus or partisan hostility toward opposing partisans over positive affect for copartisans (Iyengar and Krupenkin 2018). Yet, the difficulty also exists in the common use of affective polarization as synonymous with opposing party animus (Iyengar and Westwood 2015; Iyengar et al. 2019). To wit, affective polarization also captures the difference spanning attitudes toward copartisans versus opposing partisans (Iyengar and Westwood 2015; Iyengar et al. 2019). In fact, many of the aforementioned studies on affective polarization demonstrate this fact without being able to disentangle animus versus positive affect through, for example, a neutral partisan category. In fact, the effects are more often shown by contrasting the behavior experienced by opposing partisans versus copartisans, such as rewards or benefits for copartisans contra deficits for opposing partisans. From this perspective, although we cannot disentangle forces of attraction and aversion, the overarching pattern of preference for copartisans and aversion to opposing partisans in corporate board appointments remains consistent with the affective polarization canon (Iyengar et al. 2019), and thus extends its legacy to an important dimension of organizational behavior.

Shifting the focus to dimensions of organizational behavior and diversity, my results likewise make important contributions. Considering first the role of political diversity in organizations, these results present a foil to the quintessential ideological analysis by (Bonica 2013, 2014, 2016). In particular, although Bonica (2016) demonstrates ideological diversity, even among highly partisan firms, such as Marathon Petroleum (Bonica 2016; Mausolf 2020a), such results are not necessarily heterodox given the considerable ideological heterogeneity evident among homogenous partisans (Baldassarri and Gelman 2008; Baldassarri and Goldberg 2014; Fiorina and Abrams 2008). Similarly, the results do not necessarily countervail Bonica's (2016) assertion of bipartisan boardrooms, at least in one sense. Certainly, some types of firms are more bipartisan than others (Mausolf 2020a), and indeed both among overall Democratic or Republican boards, we see evidence that these boards on occasion appoint members of the opposing political party. Yet, in the sense that the term *bipartisan* connotes some echelon of magnanimous collaboration that transcends the frictions of partisanship, this is certainly not the case. Rather, despite having some degree of bipartisanship, in the sense that not all boards are in totality comprised of a single party, we see salient partisan behavior within these largely homogenous groups of partisans, such that the prospects of appointing someone from the opposing political party remains considerably less probable than appointing someone matching the party in the boardroom.

Reflecting how these findings relate to theories of diversity within firms, and especially corporate board membership, a number of points are worth discussion. Consistent with the general body of diversity literature, I likewise find that partisan diversity, like diversity on so many other key social dimensions, such as race, ethnicity, or gender, likewise presents a detrimental scenario for minorities in organizations (DiTomaso et al. 2007; Jackson et al. 2003; Williams and O'Reilly 1998). Of course, an important distinction here is that while many of the studies reviewed in organizational research consider performance outcomes, value, or dynamics (DiTomaso et al. 2007; Jackson et al. 2003; Williams and O'Reilly 1998), I simply evaluate the likelihood of appointment on the basis of partisanship. Since the perceived downfalls of diversity extend from denigrated communication, integration, and conflict associated with diversity on categorical dimensions, on which trust remains an integral part (Brewer 1981; Meyerson et al. 1996), and cross-party relationships instill diminished trust and increased hostility (Carlin and Love 2013; Iyengar and Westwood 2015), we would expect boards to more often discriminate against opposing partisans over copartisans, and to this end, my work is consistent with the general standing of diversity in organizational research. Of course, more research is needed to better understand how the existence of partisan minorities contributes to intra-firm dynamics and performance.

Considering board appointments specifically, prevailing evidence suggests the appointment of minorities, such as gender or minority members to the board, negatively impact firm performance and stock valuation (Adams and Ferreira 2009; Dobbin and Jung 2011). Likewise, boards might also consider what signal would be sent by the appointment of a board or other executive position to institutional investors or business media (Dobbin and Jung 2011; Khurana 2002; Krawiec and Broome 2008), which could directly, negatively impact stock price as a result of investor bias against the social identity of minority board appointees (Dobbin and Jung 2011). Since these prior findings suggest boards would preference non-diversity partisan appointees versus diversity partisan appointees, my findings are consistent with the supposition that can be derived from these studies on organizational diversity. Since corporate boards are indeed less likely to appoint partisan minorities, further research should be conducted to first consider to what extent the appointment of partisan minorities positively or negatively affects stock valuation, investor bias, or discourse from business media and analysts (*c.f.* Dobbin and Jung 2011; Khurana 2002). Research should also unpack board members' rationales in appointing copartisans versus opposing partisans along the lines of Krawiec and Broome (2008). Furthermore, although we have seen burgeoning research on how political ideology or partisanship affect corporate social responsibility or executive compensation (Briscoe et al. 2014; Chin et al. 2013; Gupta and Briscoe 2019; Gupta and Wowak 2017; Gupta et al. 2017), since as I have demonstrated, partisanship, chiefly affective polarization and partisan homophily, shape corporate board appointments and the partisan balance of boards, we need a better understanding of how the appointment of copartisan and opposing partisan members can shift dimensions of organizational behavior like corporate social responsibility or responsiveness to mobilization compared to prior firm behavior under prior instantiations of partisan diversity or homogeneity on corporate boards.

Beyond the diverse literature to which this study speaks, certain caveats, some of which have been previously highlighted, deserve mention. As perhaps evident in the data, methods, and analysis segments, performing this type of research using quantitative public records data proves challenging, just in determining the partisan leanings of firms, their employees, and boards of directors (Bonica 2016; Mausolf 2020a). As we have seen, a number of challenges persist, such as the ability to adequately capture repeated measures of individual partisanship for individuals spanning several election cycles. Although I have captured variable partisanship to an extent, the temporal partisan challenge, combined with the difficulties of linking external proprietary datasets on directors to this partisan data, creates a high bar to entry, a fact familiar to scholars in this space (Bonica 2016; Chu and

Davis 2016; Gupta and Wowak 2017; Gupta et al. 2017). This not only presents a barrier to future scholarship but also makes temporal analyses, such as those performed here, somewhat limited, given the caveats of variable partisanship. Nonetheless, since the models show that most variation exists across firms rather than time, combined with the consistent main effects using both fixed and variable partisanship, to an extent assuages concerns about the robustness of primary partisan effects. Similarly, the partisan effects prevail across multiple model permutations and do not seem to be adversely affected by the number of lag-years considered. As previously discussed, the same cannot be said for alternative effects like gender diversity. Lastly, an additional caveat exists in that the analysis can only consider the results for successful board appointments. We have no knowledge, for example, of the exact pool of all potential applicants (or their partisanship), which may have been considered for a board appointment prior to that event occurring. Such a scenario, while optimal, however, seems unlikely, at least at scale from a quantitative records perspective and implausible experimentally at this level of corporate leadership.

Collectively, although various caveats exist in any such study and disentangling positive affect versus partisan animus proves arduous, I demonstrate consistent effects of political partisanship, especially affective polarization, in corporate board appointments. These effects remain consistent both with affective polarization and partisan homophily hypotheses, and if we consider the vantage wherein we emphasize the differential experience faced by copartisans versus opposing partisans, I have demonstrated that political partisanship not only exists at the highest levels of corporate leadership, but indeed helps shape the likelihood of which board members are appointed, and thus not only who wields power in corporate America, but which party retains power for a given firm. The results of increasing affective polarization in firms suggest that corporate boards, if anything, will become more partisan in the future, not less. Given the power of corporations, and especially corporate boards, over both politics and the economy, such results underscore that we must better attune to the role of party in the boardroom.

CHAPTER 5

Conclusion - Reviewing the Structuring Role of Partisanship in Firms

In this dissertation, I explore the role of political partisanship in corporations, particularly the emergence of partisan polarization alongside two partisan mechanisms potentially contributing to this party sorting, namely affective polarization and partisan homophily. I achieve this research through a series of three empirical analyses, (1) computationally analyzing the extent and emergence of partisan polarization in firms, (2) experimentally testing affective polarization (partisan animus) and partisan homophily for job market callbacks for entry-level (graduate-degree) positions in firms, and (3) examining how these two partisan mechanisms transpire in late-stage careers when a firm appoints new members to their board of directors. Collectively, this research illustrates not only that partisanship polarization emerges in firms but also that affective polarization and partisan homophily shape multiple stages of the careers therein. These results suggest that political partisanship indeed acts as a structuring mechanism in firms. Below I summarize the detailed empirical findings, provide synthesis and interpretation of the findings, resolve the myriad puzzles postulated by this project, discuss how these results relate to the existing partisanship literature, and suggest directions for future research.

5.1 Summarizing the Empirical Findings

In the first empirical analysis, *Corporate Politics* (Mausolf 2020a), I demonstrate that political partisanship in organizations has increased in recent years, particularly after the 2012 presidential election. In particular, we see increasing partisan homogeneity within firms and increasing partisan polarization between firms. Increased within-firm partisan homogeneity exists not only among executives but also among other firm employees. Employees within firms increasingly gravitate toward a singular partisan pole. Through the use of time-series hierarchical cluster analysis, I identify three types of emergent partisan firms, namely, polarized Democratic, polarized Republican, and Amphibious firms, the latter of which alternate between weak Democratic and Republican states. Of these, the organizational types with the most notable changes occur among polarized Democratic and polarized Republican firms, which have become increasingly homogenous in the strength of their partisan attachments. Yet, these discrete partisan firm-types are not simply a political phenomenon but are also associated with differences in corporate behavior, particularly around firm diversity dimensions of corporate social responsibility. That we see organizational behavioral differences by firm partisanship in some ways proves prophetic for partisan differences seen in the subsequent empirical analyses.

In the second empirical analysis, *Office Politics* (Mausolf 2020b), we can see that an applicant's political partisanship matters, however, the process is dyadic, in that callback prospects for job applicants depend on how the partisanship of the applicant aligns with the partisanship of the firm. In particular, applicants whose partisanship opposes the firm are significantly less likely to receive a callback than either politically neutral applicants or applicants whose partisanship matches the firm. Likewise, applicants whose partisanship matches the firm are more likely to receive a callback than neutral applicants or opposing partisans. Although we see significant effects support both affective polarization (partisan animus) and partisan homophily, the results for affective polarization were overall stronger and more robust than those for partisan homophily. This determination is possible through the experimental design, through which I could make comparisons of the differential effects against an apolitical, neutral applicant.

Of course, a similar set of outcomes prevails in the third empirical analysis, *Party in the Boardroom* (Mausolf 2020c). Here, rather than examine graduate-degree holding applicants' callback success for entry-level positions, I instead examine how affective polarization and partisan homophily impact corporate board appointments (both board additions and board member succession). As before, corporate board members were more likely to be appointed when their partisanship aligned with the board. The increased likelihood of copartisan board member appointments practically manifests as follows. Incoming Republican board members were significantly more likely to be appointed by Republican boards, and incoming Democratic board members were significantly more likely to be appointed by Democratic boards. The converse is also true. Board members were significantly less likely to be appointed when their partisanship opposed the party of the board. Unlike the experimental analysis (Mausolf 2020b), we have neither a neutral board member nor insight into unsuccessful board member candidates and thus cannot disentangle effects for affective polarization versus partisan homophily. However, the same can be said for the majority of studies in affective polarization, which simply establish effects by looking at the difference in behavior toward opposing versus copartisans. My results likewise demonstrate a consistent preference for copartisans over opposing partisans, which is consistent with both affective polarization and partisan homophily hypotheses, and collectively substantiates the affective polarization literature.

Before turning toward a more substantive interpretive discussion of the findings, I must highlight another subtler point from the analyses, namely differences in ostensible behavior between Republican and Democratic firms. Taken in isolation, we might not think much of the differences, but collectively, a pattern emerges. Consider, for example, the pattern of party sorting in Republican firms (Mausolf 2020a). In the analysis, we witnessed increasing partisan polarization in Republican, Amphibious, and Democratic firms. Yet, the demonstrated increase in partisan homogeneity was greatest among Republican firms, particularly executives. Amphibious firm leadership, which was also leaned Republican, showed similar patterns, at least for executives. Democratic firms showed a lower partisan polarization, although, as noted, theses firms exhibited higher levels of similarity across occupational hierarchies than the other firm types. Given the higher level of partisan homogeneity in Republican firms, we might similarly expect that partisan mechanisms potentially contributing to partisan polarization, such as affective polarization and partisan homophily, might likewise prove more salient in Republican firms. Evidence from Mausolf (2020b, 2020c) suggests that this may be the case. For instance, recall the differences between Democratic and Republican firms in the experimental study. Although we witnessed partisan homophily—in this case, preference for copartisans over neutral applicants—for all firms in aggregate, the effects vary by firm-partisanship. We only see statistically significant effects for partisan homophily in Republican firms, not Democratic ones. Similarly, although we see significant effects for affective polarization (preference for neutral applicants and copartisans over opposing partisans) for all firms, the effects are stronger in Republican firms. Accordingly, Democratic applicants applying to a Republican firm face greater adversity than Republican applicants applying to a Democratic firm. Importantly, however, both are less likely to receive a callback than neutral applicants or copartisans. Turning to corporate board appointments (Mausolf 2020c), although we cannot so cleanly disentangle affective polarization versus partisan homophily, we again see the continued pattern of heightened partisanship in Republican firms. For example, we see markedly higher preferences for copartisans versus opposing partisans in considering board member succession at Republican versus Democratic firms. When we consider board additions, the difference in partisan predilections between firms is greater still. Across these discrete analyses, therefore, although we collectively see evidence of political partisanship, including partisan polarization, affective polarization, and partisan homophily, the manifested partisan effects are consistently greater in Republican firms.

5.2 Synthesizing and Interpreting the Results

Reflecting upon the empirical findings, we find evidence of increasing partisan polarization, especially increasing partisan homogeneity within Democratic and Republican firms, as well as demonstrable effects for two contributing partisan mechanisms: affective polarization and partisan homophily. Below, I attempt to synthesize these results and proffer some explanation for their relationship.

First, given the rise in partisan polarization (increasing partisan polarization across firms and increasing partisan homogeneity within firms), several explanations could propel these changes, most probable among them being an *activation hypothesis*, which suggests that the increased partisan and affective polarization occurring in society catalyze a ripple effect activating individuals' partisan behavior within firms. To briefly elaborate on this idea of an *activation hypothesis*, this idea does not have a singular origin, but rather emerges from a confluence of theories, chiefly in the study of organizations and political science. On the side of organizations, a common refrain in both neoinstitutionalism (DiMaggio and Powell 1983, 1991; Meyer and Rowan 1977) and old institutionalism (Selznick 1966) is the role that society can play in shaping both informal and formal processes or routines within organizations through the importation of external social and cultural frameworks and associated behaviors (Clemens 1993; Powell and Sandholtz 2012; Powell et al. 2005),[1] which in this case have a partisan basis.

On the side of partisanship and politics, discrete theories suggest that (A) the ideological polarization of political elites, such as members of Congress or the President of the United States, helps clarify the ideological stance and positions of parties in the conception of everyday Americans, and thereby increases the salience and sorting capacity of parties themselves (Hetherington 2001; Levendusky 2009). Although the increased salience of parties and party elites' ideological positioning can rouse internal conflict for individuals with diverse ideological positions, on the whole, such a process clarifies individuals' partisan allegiance and consequently can over time reshape ideological stances (Baldassarri and Goldberg 2014; Levendusky 2009), which is consistent with the idea of parties constraining individual

[1] I further elaborate on the importation of external frameworks and behaviors as it relates to organizations both in the Introduction (Chapter 1) as well as Mausolf (2020a), and Appendix A.

ideology (Barber and Pope 2019; Goren 2005; Goren et al. 2009). At the same time (B), the ideological extremism by party elites that catalyzes party sorting among everyday citizens varies by election cycle. In particular, we might expect candidate and news media coverage of ideologically extreme political rhetoric, alongside divisive political advertising to grow increasingly prevalent during election campaigns, which yields increased affective polarization, particularly partisan animosity in the advent and wake of Election Day (Sood and Iyengar 2016).[2] In this way, both partisan polarization and affective polarization have roots in political campaigning, which can thereby activate increased partisanship—both party sorting and affective polarization.

Although we would expect partisan activation among everyday Americans and that these processes would permeate firms, such activation would for several reasons likely be amplified within firms. First, my results suggest extant party sorting within firms prior to increasing partisan polarization after 2012. For example, we can see that classified Democratic and Republican firms already have a clear partisan leaning well before 2012 (Mausolf 2020a), and that corporate boards already exhibited partisan matching in board appointments during this same period (Mausolf 2020c). The existence of an ostensible majority party in firms creates an environment where partisan behavior of majority partisans can activate and amplify come campaign season. Such rising within-firm affective polarization—as facilitated by increasing partisan activation—would likely dampen within-firm dissent (Cowan and Baldassarri 2018), as such action would become increasingly perilous to work relations and employment. This is particularly true given the ire known opposing partisans can attract (Iyengar and Westwood 2015), including the career risks of not fitting in (Goldberg et al. 2016). The increased

[2]This might present an explanation for why we did not see robust effects, only occasionally significant effects, for the U.S. Presidential Party in Mausolf (2020c). Although campaigning in an election cycle could activate partisanship, these effects would likely be greatest immediately before an election or immediately after. Because many of the processes are captured on a two-year election cycle or a one or more year board appointment lag, surges in partisan behavior, such as contribution activity or partisan animus, might be less evident on the longer time scale analyzed, even if they gradually build over time. Additional analyses may also want to examine partisan activation, especially in campaign finance contribution behavior, on a daily time-scale, particularly in response to the partisan or ideologically extreme discourse by campaigning political elites.

discomfort and perceived peril for out-party members within firms could also expedite their need to transition to a firm more amenable to out-partisans' political predilections. In sum, the increased salience of parties and rousing animosity between parties, especially around electoral campaigns, would likely activate the overt expression of party loyalty by majority partisans within firms, and likewise increase expressions of hostility toward partisan minorities, silencing dissent of partisan minorities, and likely hastening their voluntary or involuntary departure from the firm.

Of course, partisan activation is just one of many possible suppositions. We might also consider a parallel process of spatial sorting or segregation, shown to be efficacious in other domains, such as income inequality or structural racism. The concentration of Democrats in coastal cities, for example, could have an effect, as could Republican companies that might have headquarters in the heartland. Such possibilities are not inconsistent with partisan activation and in fact would reify all of the aforementioned effects of increased party sorting and partisan biases stemming from increased partisan homogeneity in firms. By consequence, the increasing affective polarization in firms as activated by external political processes and perhaps spatial processes, not only bolsters the witnessed increase in partisan polarization (Mausolf 2020a), but also shapes careers, as documented in the analyses of entry into firms and effects on corporate board member additions (Mausolf 2020b, 2020c). In particular, we see experimental evidence consistent with these suppositions. Job applicants matching the partisan expression of firms received more callbacks for an interview, suggesting favor for copartisans, while applicants whose party identification opposed the firm received fewer callbacks. As discussed, these results prove consistent with the expectation for both partisan homophily and affective polarization. Important to note, however, is that these results emerge even among highly qualified advanced degree candidates with in-demand technical skills—exactly the type of candidate for which firms or recruiters might overlook their partisan predispositions. Lastly, with either adding new members to the corporate board or replacing existing board members, these processes likewise display significantly higher likelihoods for appointing copartisans than opposing partisans. Thus, we see that the decision of selecting an incoming board member is significantly and consistently affected by the partisanship of the board, thereby upholding both the ideas of partisan homophily and affective polarization.

In these ways, although perhaps the activation of party loyalty and partisan animus could create the appearance of increased partisan polarization (within-firm partisan homogeneity) by simply suppressing partisan minority expressions rather than encouraging minority party departure and favoring copartisan hiring, this scenario seems exceedingly unlikely as a singular rationale. In fact, the robust evidence for affective polarization and partisan homophily in affecting exactly who is welcome to enter the partisan firm and remain there as a valued member of the firm suggests that at multiple levels of the corporate hierarchy, political partisanship structures existing informal organizational routines, especially those around initial hiring or appointment to board membership. Given this evidence, and the above theoretical rationales, I also expect partisanship to have effects for involuntary departures (and voluntary ones), as well as other within-firm career transitions. Further research is certainly required, a subject to which I later return.

5.3 Unpacking Partisanship as an Organizational Structuring Mechanism

As I have just articulated, the evidence across the empirical chapters supports the thesis that political partisanship acts as an organizational structuring mechanism, one that not only affects the expressed partisan balance of firms but also shapes various stages of career, such as entry into firms or corporate board appointments. Relative to the overarching theoretical puzzles, let us first consider how we can resolve the conundrum of whether firms might attempt to mitigate partisan bias and promote partisan diversity or instead embrace partisan homogeneity.

5.3.1 Understanding the Puzzle of Partisan Diversity

Recall the argument which held that firms might try to preempt partisan discrimination to avoid future litigation or government regulation, as grounded in Dobbin and Sutton's (1998) *strength of a weak state* theory. Although firms have faced legal challenges alleging partisan bias (Copeland 2019; McCabe 2019),[3] and would, thus, be well advised to pursue best-faith initiatives to avoid partisan bias, such incentives seem at best to be ineffectual given the partisan biases clear in the analysis (Mausolf 2020b, 2020c). In all likelihood, these findings perhaps underscore the baseline importance of Equal Employment Opportunity Commission (EEOC) protection. I posit that the current lack of EEOC protection on partisan or political bases usurps firms' incentive to preempt partisan discrimination (U.S. Equal Employment Opportunity Commission 2020). This is particularly true for the majority of prominent firms in this study, which are already less likely to be found liable for discrimination even where EEOC protections exist (McDonnell and King 2018). Likewise, the documented effectiveness of federal compliance reviews, lawsuits, or EEOC charges in promoting diversity (Kalev and Dobbin 2006; Kalev et al. 2006; Skaggs 2008), appear to hold less merit for partisan discrimination given its currently tenuous legal footing. While my research does not contest these past findings, it suggests that to avoid discrimination, relying on firms' best-faith efforts is not alone sufficient without some minimal underlying legal basis to ground those efforts (Dobbin and Sutton 1998).

A second, also seemingly baseless, perspective, which might have encouraged firms to embrace partisan diversity, stems from the potential organizational, group, and team benefits of diversity. Much of this argument extends from arguments around dimensions of diversity, such as functional diversity—where, for instance, a team is comprised of individuals with varied job functions—particularly if they span structural holes in the firm and can, thus, leverage a diverse wealth of information and foster increased creativity and innovation

[3] National Labor Relations Board settlement agreement in the matter of Google, Case 32-CA-164766.

(Ancona and Caldwell 1992; Burt 2000, 2004). Likewise, disciplinary diversity, particularly on small teams, can lead to innovation (Wu et al. 2019). If partisan diversity followed the path of functional or disciplinary diversity, it could yield benefits in innovation and creativity. Evidence from open-source online contributions suggests partisan diversity could improve productivity in some cases (Shi et al. 2019), although it remains unclear how partisan diversity would operate in a corporate environment. Although more research is needed to test both the actual or perceived benefits of partisan diversity, even if those benefits exist, the results from this study suggest that affective polarization and partisan homophily would outweigh those considerations, since as we have seen, both board appointments and entry hiring reject partisan diversity in favor of partisan homogeneity (Mausolf 2020b, 2020c).

To reiterate a point, my research here cannot comment on whether partisan diversity or partisan homogeneity yields any benefits or deficits for organizations. I also cannot comment on how firm stakeholders perceive partisan diversity, or how the outlook of partisan minorities within firms affects this calculus. Instead, the puzzle of the dissertation emerges from the legal and performance rationales that would suggest firms might try to prevent partisan discrimination and promote partisan diversity in contrast to alternative performance and cultural rationales suggesting the opposite. The evidence suggests that, on balance, firms tend to discriminate against partisan minorities (opposing partisans) via affective polarization while favoring copartisans via partisan homophily (Mausolf 2020b, 2020c).

To comment on the other side of the puzzle, however, recall that many diversity and cultural rationales suggested the observed preference for partisan homogeneity over partisan diversity. Without even considering those perspectives, however, this supposition is clear from the affective polarization literature. This literature suggests that both overt hostility and aversion, as well as implicit bias, exists across party lines compared to positive feelings for copartisans (Iyengar and Westwood 2015; Iyengar et al. 2019). Such results align with the diversity and organizational culture literature in several ways. First, the consistent findings of negative effects for diversity, particularly along salient social dimensions, of which, we can include party identification, stem from the consistent, negative effects diversity yields in "social integration, communication, and conflict" (DiTomaso et al. 2007; Jackson et al. 2003; Williams and O'Reilly 1998: 115). Perhaps one reason these theories so cleanly intersect is that both draw upon similar theoretical impulses, such as homophily, intergroup contact, and social identity (Billig and Tajfel 1973; McPherson et al. 2001; Pettigrew 1998; Tajfel 1970; Tajfel and Turner 1979). Thus organizational diversity scholars, alongside scholars of affective polarization, when taken together, suggest that processes of affective polarization in society also prevail in organizations. Second, beyond avoiding the downfalls of diversity, homogeneity likewise has upsides in the readily available categorical trust, affinity, comfort, and communicative shortcuts at the disposal of similar others (Brewer 1981; Ibarra 1992, 1995; Meyerson et al. 1996; Reagans and McEvily 2003; Reagans and Zuckerman 2001). The positive work environment and improved performance from homogenous environments also facilitate improved employee satisfaction and commitment (Meglino et al. 1989; Reagans and McEvily 2003; Reagans and Zuckerman 2001), as opposed to the decreased satisfaction and higher turnover for diverse teams and particularly their minority members (Boone et al. 2004; Elvira and Town 2001; Milliken and Martins 1996; Tsui et al. 1991).

From a recruitment and cultural perspective, preferring similar others not only avoids costs of high turnover but also satisfies employees' desire to work with culturally and socially compatible colleagues, particularly in high-stress work environments with long hours (Rivera 2012b; Rivera and Tilcsik 2016). A lack of cultural fit might also engender a stalled career, or even termination (Goldberg et al. 2016; King et al. 2010; Stinchcombe 1965). As evidenced here, lacking the proper partisan fit with a firm lowers the likelihood of being hired to begin with or being appointed to a corporate board (Mausolf 2020c, 2020b). Both of these findings are consistent with other studies that find the lack of cultural or social fit lowers the likelihood of being hired (Rivera 2012b; Rivera and Tilcsik 2016). In relation to studies on diversity, my research is again consistent with the idea that firms would treat partisan diversity, like diversity on other salient social dimensions, as a disadvantage to be avoided if possible. Instead of preempting partisan discrimination and promoting partisan diversity, firms do the opposite, favoring copartisans while avoiding opposing partisans.

5.3.2 Toward a Perspective of Partisanship Within Organizations

Although these results help illuminate the founding puzzle in which conflicting organizational arguments could be made for firms to preempt or permit partisan bias, the results also underscore an additional puzzle of intellectual focus—that is, the relationship between politics and corporations. All too frequently, scholars adopt the perspective in which corporations and more generally the elites at the helm of capitalist enterprise orchestrate control over powerful institutions, including politics, the news media, as well as the issues to which citizens attune (Dahl 1963; Domhoff 2010; Hacker and Pierson 2010; Mayer 2016; Mills 1956). The emphasis on the power elite likewise generates a variety of research on the evolution and development of elites (Cookson Jr. and Persell 1986; Domhoff 2010; Levine 1980; Useem and Karabel 1986), their income or wealth (Bertrand 2009; Killewald, Pfeffer, and Schachner 2017; Piketty and Saez 2006), or even their political preferences and power (Bartels 2016; Gilens 2012; Page et al. 2013). Yet, such perspectives, while vital, overlook the role of politics, but especially partisanship, *within* organizations.

As previously detailed, this is not to say that scholarship on politics in organizations does not exist, only that again, the perspective is less prominent. Perhaps the closest analog to some of the research I conduct in this dissertation is the work performed by Bonica (2014, 2016), who outlines the ideological distributions of Fortune 500 board members (Bonica 2016), and the ideological distribution across different industries and professions using Federal Election Commission data (Bonica 2014). Instead of examining ideological composition or political polarization, I instead focus on partisan polarization at the firm level, identifying increasing partisan homogeneity within firms. I show these effects exist not only among executives but also other levels of the employment hierarchy. Given the high degree of ideological heterogeneity within parties (Baldassarri and Gelman 2008; Baldassarri and Goldberg 2014; Bonica 2013, 2014), the finding of increased partisan homogeneity in firms is not inconsistent with ideological diversity but expected. Where my work complicates or otherwise challenges Bonica (2016) is on the idea of bipartisanship, particularly bipartisan boards. Although some firms have less partisan homogeneity, even within polarized Republican or Democratic firms, partisan minorities often exist. Even though this implies a degree of bipartisan member composition, these boards do not necessarily follow the implied spirit of cooperation and amicability between opposing partisans. As I demonstrate, opposing partisans are significantly less likely to be appointed to a board compared to copartisans (Mausolf 2020c), and outside of corporate boards, we also see the effects of partisan homophily and affective polarization for entry-level job callbacks (Mausolf 2020b). In this way, although members of both parties often coexist, the antagonist spirit of partisanship—whether we are talking about party sorting, affective polarization, or partisan homophily—seems to pervade and indeed structure behavior within firms. In this way, my work suggests that scholars, beyond examining the external political consequences of firms, should additionally seek to understand how partisanship, and more generally politics operates *within* firms.

This latter point calls to question that recurring specter of parties and the effects of partisanship versus those of the ideology structured thereby (Barber and Pope 2019; Converse 1964; Goren 2005; Goren et al. 2009). Whereas the works of Bonica (2013, 2014, 2016) use a robust measure of both contributor and candidate political ideology, a number of other scholars simply use a measure of partisanship as a proxy for ideological belief (*c.f.* Gupta and Wowak 2017; Gupta et al. 2017), and thus the findings they portray are perhaps better described as findings of partisanship rather than ideology, despite the window dressing to the contrary. Indeed, even the titles to these articles convey notions of political parties and partisanship rather than ideology. Consider *The Elephant (or Donkey) in the Boardroom* (Gupta and Wowak 2017) or *Red, Blue, and Purple Firms: Organizational*

Political Ideology and Corporate Social Responsibility (Gupta et al. 2017). Red elephants and blue donkeys represent the designated totems and colors of the Republican and Democratic parties, respectively. Although the authors would like to suggest that "treating gifts to the Democratic (Republican) party... [reflect] liberal (conservative) beliefs," (Gupta et al. 2017: 1019), political science research reveals that party loyalty—not policy loyalty—is a more prevalent and consistent driver of ideological beliefs (Barber and Pope 2019). Such beliefs can be inconsistent and mutable to party cues (Barber and Pope 2019). In short, not only the symbolism in the article titles but also the underlying data and empirical science all reiterate that what Gupta and colleagues most accurately capture are the visceral effects of partisanship rather than ideology, which as shown by Bonica (2016), remains heterogeneous even on the boards of directors at highly partisan firms (Mausolf 2020a).[4] It is further worth noting that even though board members have ideological diversity, and some are liberals, the center of their liberal ideology is more akin to Bill Clinton or Andrew Cuomo than Bernie Sanders (Bonica 2016: 385). As members of the elite, their ideology and political preferences differ from everyday citizens (Bonica 2016; Page et al. 2013), illustrating another potential danger of inferring their ideology from a binary partisan signal. If we translate these scholars' findings back to the partisanship on which they were based, we can more clearly see the parallels to the research in this dissertation, which considers partisanship in its own right (Mausolf 2020a, 2020b, 2020c).

From this perspective—in which I consider several dimensions of firm or board partisanship—my work can be seen as extending the body of research generated by scholars in the space of organizational behavior and politics (Briscoe et al. 2014; Chin et al. 2013; Gupta and Briscoe 2019; Gupta and Wowak 2017; Gupta et al. 2017). For instance, Gupta et al. (2017) illustrate that "liberal," that is, Democratic firms, engage in more corporate social responsibility (CSR) than "conservative," that is, Republican firms. Among the CSR

[4]For instance, Bonica (2016) shows that even firms classified as polarized Republican firms (*c.f.* Mausolf 2020a), such as Marathon Petroleum, or conversely polarized Democratic firms, such as Apple, have a high degree of ideological heterogeneity on their boards of directors (Bonica 2016: 387).

measures, Gupta et al. (2017) include female representation in firm leadership, which I similarly show to be negatively associated with polarized Republican firms alongside several other CSR measures (Mausolf 2020a). Relatedly, while Gupta and Wowak (2017) arguably illustrate how board partisanship affects executive compensation, my research illustrates that the partisan composition of the board likewise affects the appointment of incoming board members (Mausolf 2020c). Because corporate boards are more likely to appoint copartisans (Mausolf 2020c), we would expect the pattern of increased partisan homogeneity of executives within firms (Mausolf 2020a). Moreover, we would also expect that organizational variation in behaviors that emerge from partisanship—such as corporate social responsibility (Chin et al. 2013; Gupta et al. 2017), executive compensation (Gupta and Wowak 2017), and responsiveness to mobilization (Briscoe et al. 2014; Gupta and Briscoe 2019)—would likewise not only perpetuate but perhaps intensify in future years.

Returning to an earlier point, I would like to emphasize that my study can only evaluate the effects of partisanship in its own right, since I do not have data on ideology. I contend that other scholars similarly using *only measures of partisanship* should have also adopted this same convention rather than claim that they found the effects of firm ideology. Collectively, I would like to challenge organizational scholars to properly disentangle the theory and measurement of partisanship versus ideology but nonetheless continue to examine the effects of politics operating within firms. As I have shown, partisanship, when studied in its own right is important. In particular, affective polarization and partisan homophily can have acute effects on the partisan composition and career prospects of those within firms. As argued in Appendix A, changes in attributes of a firms' human capital constitute a change in its organizational strategy and the structure that follows. Where these changes result in increasing partisan homogeneity and partisan behaviors, such as affective polarization and partisan homophily, we must exercise careful consideration. Because partisanship arguably affects several firm behaviors, including CSR, executive compensation, and federal elections, among other behaviors, a better understanding of how partisanship operates within firms is not only relevant but also essential to better understand down-ballot consequences of increasing partisanship within firms.

5.4 Expanding on the Legacy of Partisan and Affective Polarization Research

Returning to the most immediately proximal empirical findings, my research directly expands the realm of knowledge in the study of political partisanship (Baldassarri and Gelman 2008; Baldassarri and Goldberg 2014; Cowan and Baldassarri 2018), especially those in partisan polarization (Baldassarri and Gelman 2008; Fiorina and Abrams 2008; Lee 2015), and affective polarization (Iyengar and Westwood 2015; Iyengar et al. 2019, 2012). For scholars evaluating party sorting or partisan polarization, the results in (Mausolf 2020a, 2020b, 2020c), critically illustrate that although partisan polarization may already systemically pervade society, the labor markets and career trajectories found in firms are structured by societal partisanship and are increasingly becoming homogenous in their partisan composition in recent years. By consequence, we now face a situation in which individuals experience even less daily exposure to opposing partisans. Increased partisan segregation at work, while rooted in societal partisanship, likely contributes to cyclic, systemic effects, recalling alongside the allusion to segregation, a "vicious cycle" of partisanship compounding the issue of party sorting occurring across multiple physical and digital socioeconomic institutions.[5] In this way, carefully considering partisan polarization and partisan mechanisms within firms is essential.

Beyond partisan polarization, I show how the mechanisms of affective polarization and partisan homophily can be salient drivers of career prospects in their own right, both for entry into firms and corporate board appointments, findings that extend the canon of affective polarization research (Gift and Gift 2015; Huber and Malhotra 2017; Iyengar and Westwood

[5]To clarify the allusion, party sorting, partisan homogeneity, and partisan diversity have a clear analog to forces of racial segregation and systemic racism, as described, for instance, as a "vicious cycle" of the compounding effects of racial discrimination and poverty across institutions to create the truly disadvantaged (Wilson 1987: 57), or how such racial effects contribute to racial inequities for job applicants (Pager 2003), a fact I previously reference.

2015; Iyengar et al. 2018, 2019; Sood and Iyengar 2016). In particular, my research represents what appears to be the first study of affective polarization and partisan homophily *specific to processes within firms.* Although a few studies had previously examined how affective polarization affected college graduate job applicant callbacks (Gift and Gift 2015), or resume evaluation of high-school applicants using a survey panel (Iyengar and Westwood 2015), my study is the first to experimentally examine affective polarization and partisan homophily at the firm level (Mausolf 2020b). Recall, Gift and Gift (2015) only consider partisan matching between the applicant and the county wherein the job was located (in only two counties), whereas I examine how the applicant directly aligns with the partisanship of the firm at jobs around the country. Besides applying to jobs across the country, I also present results for highly qualified applicants holding graduate degrees with in-demand technical skills. Consistent with past research (Gift and Gift 2015; Iyengar and Krupenkin 2018), I find stronger results for affective polarization, that is, partisan animus against opposing partisans. Yet, I also demonstrate a distinguishable preference for copartisans over neutral applicants (Mausolf 2020b). In this way, I illustrate the efficacy of partisan homophily at the firm level, expanding the conception of partisan homophily among copartisans beyond studies of romance or financial rewards to now also include advantages in copartisan labor markets (Carlin and Love 2013; Huber and Malhotra 2017; Iyengar and Westwood 2015).

Although the study on corporate board appointments cannot as easily disentangle partisan animus versus partisan homophily, when we take the differential gap between these two phenomena to collectively represent affective polarization (Iyengar and Westwood 2015; Iyengar et al. 2019), my results likewise extend our knowledge of affective polarization at the firm level. Unlike the case for Mausolf (2020b), I am unaware of any similar study on affective polarization or partisan homophily that examines corporate board appointments or evaluates firm leadership. In many respects, my study purely expands the demonstrable domain of affective polarization to now include the likelihood of copartisan versus opposing partisan board member appointments. Although multiple scholars have previously remarked on partisan homogeneity or diversity in corporate boards (Bonica 2016; Burris 2005; Chu and Davis 2016), particularly from a network perspective, such comments have been more akin to observing its existence rather than assessing whether partisan mechanisms, such as affective polarization or partisan homophily, alter the likelihood of boards appointing copartisan versus opposing partisan members. Thus, my research here brings together research in sociology, organizations, and political science by leveraging intersecting theories to explain the emergence of extant corporate board behavior. My work extends the spectrum of economic phenomena shaped by affective polarization (*c.f.* Gift and Gift 2015; Iyengar and Westwood 2015; McConnell et al. 2018; Panagopoulos et al. 2016).

Still, while Mausolf (2020b) and Mausolf (2020c) exemplify that affective polarization and partisan homophily can structure career prospects in firms, myriad pressing possibilities for future research exist in firms. For example, the correspondence audit study illustrates a preference for copartisan versus opposing partisans in job applicant callbacks. Yet, an in-person audit experiment, such as (Pager 2003; Pager and Western 2012), or an in-depth interview study with hiring managers or board members, such as (Krawiec and Broome 2008; Rivera 2012b, 2012a), could yield additional insights into how these mechanisms operate at different stages of the application process and how those tasked with making these determinations conceive of copartisan versus opposing partisan applicants. Another space deserving of research is the question of how affective polarization shapes both voluntary and involuntary exit from firms. For example, Goldberg et al. (2016) assess a similar question using culture, which could be pursued along partisan dimensions. Likewise, many studies have evaluated satisfaction and turnover, especially for minority applicants (Boone et al. 2004; Elvira and Town 2001; Milliken and Martins 1996; Tsui et al. 1991), or support networks within firms for racial or gender minorities (Ibarra 1992, 1995). Moreover, research could be conducted to better understand similar phenomena for partisan minorities using a theoretical framework of affective polarization and partisan homophily.

Undeniably, many future directions of research exist to expand upon our knowledge of political partisanship in firms, particularly for affective polarization and partisan homophily, which structures partisan polarization in firms alongside the increasing activation of partisanship in society. That these effects and relationships may be cyclical and compounding impresses the need to better understand these complex dynamics. As I have demonstrated, political partisanship acutely operates as a structuring mechanism in firms, shaping not only the partisan composition and organizational behavior of firms, but pivotally affecting the careers of employees and leaders therein. And so enters the partisan firm, where political partisanship influences exactly who is welcome to join a given firm, proceed therein, and rise through the ranks as a valued employee.

APPENDIX A

Appendix Chapter 1: Theorizing Shifts in the Corporate Organizational State

A.1 Toward a Theory of Organizational Change

A theory of organizational change—or conversely the lack thereof (inertia)—depends on the organizational perspective adopted. We can broadly conceive two major theoretical camps, chiefly an "adaptational" camp and a "selection" camp (Barnett and Carroll 1995). Whereas the adaptational camp generally views organizational change and variation as the primary result of organizational leaders formulating and revising strategy in response to environmental stimuli, selection theorists posit that organizations—particularly larger organizations—express considerable stability or "inertia," and that this hesitance to adapt acts as a selection mechanism of organizational survival, such that organizational change, if and when it occurs, carries significant risk of organizational decay (Barnett and Carroll 1995; Hannan and Freeman 1977, 1984). I take a *selection perspective* to theorize processes of organizational change and organizational inertia, such that these processes can affect decisions in hiring, board member replacement, and the behavior of individuals therein. Following the organizational theory, I integrate these largely disparate theories to establish how political partisanship structures what I shall term the corporate organizational state.

In adopting the selection perspective—perhaps most famously advanced by Hannan and Freeman (1984), Hannan and Freeman (1977)—I concede and will in fact exploit a caveat admitted by Hannan and Freeman (1977), that organizational leaders and other actors can respond to environmental changes, which accounts for *some* variability in organizations:

> Clearly, leaders of organizations do formulate strategies and organizations do adapt to environmental contingencies. As a result at least some of the relationship between structure and environment must reflect adaptive behavior or learning. But there is no reason to presume that the great structural variability among organizations reflects only, or even primarily adaptation. (Hannan and Freeman 1977:930).

Herein, the emphasis is on structural "pressures," chiefly "structural inertia," a term widely used in the literature (Hannan and Freeman 1977, 1984). Originating from works by Burns and Stalker (1961) or Stinchcombe (1965), *inertia* refers to the idea that an organization, once set in motion, will perpetuate on its organizational trajectory.[1] For example, Stinchcombe (1965) writes, "if [organizational] resources for current operations come from endowments,...the organization may last much past the time when its structure was competitive...a particular case of a 'sunk cost', which generally gives older organizations an advantage" (168). This idea combined with Stinchcombe's (1965) "liability of newness" (148), parallels Hannan and Freeman (1977), where in Stinchcombe's (1965) words, endowments from the organization's past perpetuate into current operations (that is, inertia), such that this old structure reflects a failure to adapt to the point that the organization is less than optimally competitive but nonetheless generally advantaged over new organizations. Thus, inertia maintains stability and limits organizational change or adaptation.

A.1.1 Conceptualizing Organizational Change and Stability

Yet, to better understand organizational change or its analog of organizational inertia, we must first have a conception of what constitutes organizational change. Simply put, organizational change can be conceived "in terms of both its process and content" (Barnett and Carroll 1995:217), where process explains how material changes transpire and content refers to the

[1]In many ways, organizational inertia parallels the concept in physics, often referred to as Newton's first law, the law of inertia. Stinchcombe (1965), for example, writes that "organizations which are founded at a particular time must construct their social systems with the resources available...Once...set up in a particular area, they may preserve their structures" (168-169).

existence of measurable differences in an organization, particularly an organization's strategy or structure over a given temporal period. Before attempting to glean processual change, I will better elucidate two key aspects of an organization's foundational content, namely its *strategy and structure*.

A.1.1.1 Organizational Strategy and Structure

I adopt a broad definition of organizational strategy, following Chandler (1962), who defines strategy "as the determination of the basic long-term *goals and objectives* of an enterprise, and the adoption of *courses of action* and the *allocation of resources* necessary for carrying out these goals" (13, emphasis added). Chandler's (1962) definition of organizational strategy and its three quintessential elements—(1) goals and objectives, (2) course of action, and (3) allocation of resources—closely foreshadows Hannan and Freeman's (1984) four key organizational dimensions or core values.[2] When combined with Chandler's (1962) definition of organizational structure, the alignment is even more apparent:

> *Structure* can be defined as the design of the organization through which the enterprise is administered. This design, whether formally or informally defined has two aspects. It includes, first, the lines of authority and communication between the different administrative offices and officers and, second, the information and data that flow through these lines of communication and authority. (Chandler 1962:14)

By developing the ways in which Chandler (1962) adumbrates Hannan and Freeman (1984), I establish the requisite basis for subsequent theory to understand the content of organizational

[2] Several caveats are noted. For example, despite closely paralleling Chandler's (1962) definition of organizational strategy, Hannan and Freeman (1984) do not cite the work in the bibliography or acknowledge awareness of the work. This is not to say the work did not influence Hannan and Freeman (1984). For example, Hannan and Freeman (1984) cite Chandler's later work, Chandler (1977). Leading up to their discussion of core issues, Hannan and Freeman (1984) draw upon Downs's (1967) use of " 'organizational layers'," such as "actions," "decision-making rules," and "institutional rules," which also does not appear to cite or reference Chandler (1962). That is, the parallel between Chandler (1962) and Hannan and Freeman (1984) could be simply coincidental. For clarity, I submit the original articulation by Hannan and Freeman (1984):

change and how processually, organizations can both exhibit inertia while experiencing structural adaptations that affect strategy and structure.

> The core aspects of organization are (1) its stated *goals*—the bases on which legitimacy and other resources are mobilized; (2) *forms of authority* within the organization and the basis of exchange between members and the organization; (3) *core technology*, especially as encoded in capital investment, infrastructure, and the skills of members; and (4) *marketing strategy* in a broad sense—the kinds of clients (or customers) to which the organization orients its production and the ways in which it attracts resources from the environment. (156)

I begin with the first core values, which most clearly mirror Chandler (1962). Ostensibly Hannan and Freeman's (1984) "stated *goals*", mirrors Chandler's (1962) preeminent pillar of strategy, "goals and objectives," both in meaning and rank as the most important feature of organizational strategy. Whereas Chandler (1962) envisions an organizational core around both strategy and the structure that follows, Hannan and Freeman (1984) articulates core organizational dimensions that fuse strategy and structure, a point raising Hannan and Freeman's (1984) second core dimension, "*forms of authority*. . . and the basis of exchange between members" (156). Most directly, this second core dimension reflects an element of Chandler's (1962) conception of organizational structure, namely "lines of authority and communication between the different administrative offices and officers" (14). Returning to strategy, Hannan and Freeman's (1984) "*core technology*" includes "capital investment, infrastructure, and the skills of members", a passage directly reflecting Chandler's (1962) "allocation of resources," which "include financial capital; physical equipment such as plants, machinery, offices, warehouses. . . .and, most important of all, the technical, marketing, and administrative skills of its personnel" (14). Similarly, I argue that Chandler's (1962) "courses of action" comprises the general procedures for operationalizing resources in pursuit of organizational goals—a point reflected in Hannan and Freeman's (1984) broad conception of "marketing strategy." For both Chandler (1962) and Hannan and Freeman (1984), organizational goals act as the cornerstone of strategy with other core features playing supporting roles to achieve those objectives.

Beyond these clear parallels, the authors concur that "an organization's initial configuration on these…dimensions commits it to a certain form…and to a long-term strategy" (Hannan and Freeman 1984:156).[3] These dimensions, which Chandler (1962) defines as organizational strategy and which Hannan and Freeman (1984) states establishes strategy, relegate the organization "to a certain form of environmental dependence," in other words, a certain structure.[4] To put the point acutely, "structure follows strategy" (Chandler 1962:14). I utilize this central insight and the alignment of Chandler (1962) with Hannan and Freeman (1984) on strategy and structure to orient my theory of organizational state change.

A.1.2 Structure Follows Strategy

Augmenting the above theory, I formalize these theories to develop a model of organizational state change, where the *organizational state is a specific organizational strategy and structure anchored in a specific temporal state.* Let S indicate organizational *strategy* and s indicate *structure.* Since *strategy* informs an organization's *structure* (Chandler 1962), we can express this idea with the following notation. $S \rightarrow s$. Temporally, if the structure follows the strategy, for any organizational strategy at time zero, there exists a structure that emerges at time zero, plus some time interval ϵ, and this condition constitutes the organizational state at time zero plus ϵ, denoted $t0\delta$ when referring to a time-indexed organizational state:

$$\left(\forall\ S_{t0}\ \exists\ s_{t0+\epsilon}\right) \equiv O_{t0\delta}$$

[3] Hannan and Freeman's (1984) statement also echos Stinchcombe's (1965) expression of environmental dependence: "organizations which are founded at a particular time must construct their social systems with the resources available…Once…set up in a particular area, they may persevere their structures" (168-169).

[4] As noted, Hannan and Freeman's (1984) core dimensions include in Chandler's (1962) perspective dimensions of core *strategy* as well as *structure*. Resolving the seeming disparity is fairly straightforward. Chandler (1962) understands that initial configuration of strategy leads to initial structure. Hannan and Freeman (1984) also sees the second dimension (which is structural) as following from the first dimension (strategy). We can formalize this process mathematically.

This implies that any future change to strategy, S, will alter the existing structure.[5] For example, imagine an organization's strategy as a MxN matrix of values, $S_{m,n}$:

$$S_{m,n} = \begin{bmatrix} V_{1,1} & V_{1,2} & \cdots & V_{1,n} \\ V_{2,1} & V_{2,2} & \cdots & V_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ V_{m,1} & V_{m,2} & \cdots & V_{m,n} \end{bmatrix}$$

Following, Hannan and Freeman (1984), an organization may have both core dimensions—which can be thought of as *typologies of core values*—as well as additional supplementary values that can be altered with less risk. In general, these values, whether a core value, $C_{m,n}$, or a periphery value, $V_{m,n}$, can be conceived as having a finite set of value attributes. Let this value be reflected as a MxN matrix of value attributes:

$$V_{m,n} = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,n} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m,1} & a_{m,2} & \cdots & a_{m,n} \end{bmatrix} \equiv C_{m,n}$$

Coalescing Chandler (1962) and Hannan and Freeman (1984), an organization's defining strategy has certain core dimensions. Given Hannan and Freeman's (1984) designated importance of core organizational values, I will signify the importance of these values by

[5] At the initial configuration, structure following strategy is presented as deterministic in Chandler (1962). Chandler (1962) notes that strategy could theoretically change without a change to structure, but such a shift would only lead to economic inefficiency. For example, Chandler (1962) remarks, "growth without structural adjustment can only lead to economic inefficiency" (16). Since growth would comprise, for example, the expansion of one central headquarters to a second office with additional strategic resources (both infrastructure and human capital), it is all but inconceivable that such a shift would occur without also making updates to organizational structure, chiefly the lines of authority and channels of communication necessary for operations.

placing them on the diagonal of an organization's strategy matrix.[6] Thus, an organization's strategy at time zero can be written as follows:

$$S_{t0} = \begin{bmatrix} C_{1,1} = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,n} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m,1} & a_{m,2} & \cdots & a_{m,n} \end{bmatrix} & V_{1,2} & V_{1,3} & V_{1,4} & \cdots & V_{1,n} \\ V_{2,1} & C_{2,2} & V_{2,3} & V_{2,4} & \cdots & V_{2,n} \\ V_{3,1} & V_{3,2} & C_{3,3} & V_{3,4} & \cdots & V_{3,n} \\ V_{4,1} & V_{4,2} & V_{4,3} & C_{4,4} & \cdots & V_{4,n} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ V_{m,1} & V_{m,2} & V_{m,3} & V_{m,4} & \cdots & C_{m,n} \end{bmatrix}$$

where each core value $C_{i,j}$ or peripheral value $V_{i,j}$ can be expanded as a matrix of attributes of the form as shown in $C_{1,1}$ above. Such attributes constitute the key characteristics of the value comprising the organizational strategy.[7] Take for example, the core strategic value of an organization's human capital allocation (H_α)—a commonality between Chandler (1962) and Hannan and Freeman (1984)—$C_{i,j} = C_{H_\alpha}$.

Suppose the core value is arbitrarily constituted as *hiring an optimal number optimally qualified individuals to optimally execute the other core values* $\left(C_{1,1} \cdots C_{m,n}\right)$.[8] Then the attributes of that value are characterized by the hypothetical optima's that satisfy the

[6] In linear algebra, the diagonal of a matrix is used to derive and compute a variety of defining qualities of a matrix. Hence, placing core values along the diagonal helps signify the importance of these features to an organization's strategy.

[7] Note that in the strategy matrix $S_{m,n}$ there are m possible core values C. While Chandler (1962) outlines only three core components to strategy—(1) goals and objectives, (2) course of action, and (3) allocation of resources—and Hannan and Freeman's (1984) core dimensions only include three strategic dimensions, these *dimensions can be perceived as typologies rather than specific values*, e.g.: $C_{\text{Dimension}_1} = \left(C_{1,1} \cdots C_{i,j}\right)$, $C_{\text{Dimension}_2} = \left(C_{k,l} \cdots C_{m,n}\right)$. Organizational goals and objectives could include many individual goals, each of which would constitute an independent core value with unique value attributes.

[8] Optimality might be the expressed desire of *economic man*—a construct true in name only due to bounded rationality (March and Simon 1958). See also the discussion on following pages.

other core values, which necessarily vary by organization. Here, we arrive at a theoretical discontinuity based in pragmatism. Organizations do not express their strategy in matrix notation, and the exact expression of the core values will vary substantially by organization. Therefore, on the surface, an organization may keep all ostensible traces of its originating core values, in this example, human capital allocations. Such qualities exemplify the noted trends of high organizational inertia or stability (Hannan and Freeman 1977, 1984). Furthermore, while we might conceive of value attributes being expressed in terms of optimality, actors within organizations lack perfect information and have limited cognition, such that their rationality is "bounded," and objectives of optimality rather than being consistently met, are instead satisfied relative to known alternatives (DiMaggio and Powell 1991; March and Simon 1958).

At the same time, if the attributes constituting a knowably optimal (satisfactory) allocation of individuals shift, which might occur for example in organizational growth, so too does the realized form even if the surface-level expression of knowable optimality is stable. In our example, $C_{i,3} = \begin{bmatrix} a_{i,1} & a_{i,2} & a_{i,3} \end{bmatrix}$ or $C_{i,3} = \begin{bmatrix} a_{\text{optimal number}} & a_{\text{optimal qualifications}} & a_{\text{optimal execution}} \end{bmatrix}$. If any of these realized optima shift—that is, if there exist measurable disparities in *who* represents satisfactorily optimal human capital—so too does the core value shift and likewise the overall strategy and the structure that follows from it, constituting a change in the organizational state. Formally:

$$\forall a_{ij} \in C_{ij_{t0}} \neq, a_{ij} \in C_{ij_{t1}} \to \Delta_{a_{ij}} \implies C_{ij_{t0}} \neq C_{ij_{t1}} \implies S_{t0} \neq S_{t1}$$

$$\exists\ \Delta_{a_{ij}} : a_{ij_{t0}} \neq a_{ij_{t1}} \implies S_{t0} \neq S_{t1}$$

$$\because \forall\ S_{t0} \exists\ s_{t0+\epsilon} \implies \exists(S_{t0} \neq S_{t1}) \implies \exists(s_{t0+\epsilon} \neq s_{t1+\epsilon}) \implies \exists(O_{t0\delta} \neq O_{t1\delta})$$

$$\therefore \exists\ \Delta_{a_{ij}} \implies \exists\Delta_S \implies \exists\Delta_s$$

$$\therefore \exists\Delta_O \qquad \square$$

To reiterate the above point, *a change in the attributes of a core organizational value between two time points implies the existence of a change in organizational strategy, and therefore a* *shift in organizational structure—which constitutes a change in the organizational state.*

Note that this perspective is not inherently oppositional to Hannan and Freeman (1977, 1984). Whereas these authors make an argument about how and when changes or the lack thereof occur in organizational strategy and structure, the above formulation makes no comments to this effect. It simply states that *if* an attribute of a strategic value changes, whether the source is a *de facto* shift from structural inertia or an intentional shift from organizational leaders, that change in value attributes will alter the ensuing structural form and thus the organizational state comprised of strategy and structure.[9]

A.1.3 Structural Reproduction Leading to Strategic Shifts

Although strategy establishes an organization's initial structural form, that structure and its associated inertia while providing stability can also foster shifts in realized resources, such as human capital allocation, constituting a change in strategy and future structure. Upon first glance, this statement may strike the reader as both obtuse and tautological. Nonetheless, the postulation is consistent with the above outline of organizational state-change. To illustrate, let us return to the decision of human capital allocation, by which I will generally refer to strategic choices to recruit or terminate individuals to an organization and within an organization make decisions about the lateral, upward, or downward reallocation of existing personnel. In this scenario, I assume some existing organizational state $O_{t0\delta}$ (where $S_{t0} \exists s_{t0+\epsilon}$)[10]. Given the existing state $O_{t0\delta}$, let us assume some action in human capital allocation, denoted H_{α}. As suggested above, human capital allocation is a core strategic value, such that even if the *goal* or pretensive expression of the value is unadulterated, the

[9]Note that this change may be intentional or unintentional, and since the structure following strategy may be informal, structural shifts could be quite subtle and lead to decoupling.

[10]I use the term "organizational state" to refer to a specific organizational strategy and structure ($S_{t0} \exists s_{t0+\epsilon}$) at a given time. Given the subtleties to my definition of an organizational strategy and structure relative to changes in values and value attributes (stated or realized), organizational strategy and structure may update without radically altering the more general "organizational form," a term widely used in organizational literature (*c.f.* Hannan and Freeman 1977; Stinchcombe 1965).

measurable outcome or attributes of the expression may shift. Where both the expressed value and attributes remain stable and no measurable difference in outcome exists between states, the organizational state between two time periods remains unchanged.[11]

Where there exists stability in the core value *expression* and its attributes *but the realized outcome* of the value attribute changes, we have a condition such that high inertial pressure exists (since the core value expression and attributes are stable) but there is nonetheless a shift in the realized outcome of a value—in this case, human capital allocation Δ_{H_α}—and as a result a change in the organizational state. How might such a change evolve? I suggest two general processes or hypotheses for this scenario:

> *Hypothesis 1*: Given an organizational state $O_{t0\delta}$, there exists a *change in underlying societal human capital,* $\Delta_{Societal_{HC}}$, that influences the selection pool of human capital allocation, H_α, such that the realized outcome of human capital allocation shifts, Δ_{H_α}, implying a change in the organizational state, $\Delta_{O_{t1\delta}} \equiv \Delta_{[S_{t1}\ \exists\ s_{t1+\epsilon}]}$.
>
> *Hypothesis 2*: Given an organizational state $O_{t0\delta}$, there exists a *change in underlying societal values* $\Delta_{Societal_V}$ that influences informal organizational structure, $\Delta_{s_{t0+\epsilon}}$ but not strategy ($\nexists \Delta_{S_{t0}}$), such that the realized outcome of human capital allocation shifts Δ_{H_α}, implying a change in the organizational state, $\Delta_{O_{t1\delta}} \equiv \Delta_{[S_{t1}\ \exists\ s_{t1+\epsilon}]}$.

Graphically, I express these hypotheses in Table A.1. Yet to understand the above processes requires some additional grounding in existing theories of inertia, organizational choice, and subtleties at the intersection of old institutionalism and neoinstitutionalism.

[11] Conversely, of course, if the core value expression (or explicit attributes) shift, so does the strategy, structure, and organizational state. Such patent changes seem to be the predominate concern of (Hannan and Freeman 1977, 1984) to organizational survival and selection. The discussed change here is considerably more subtle and thus relates to how conditions of high inertial pressures still lead to organizational change.

Table A.1: Processes of Organizational State Change due to Social Environmental Shifts under Conditions of High Inertia

$$
\begin{array}{llll}
\text{Hypothesis}_1: & O_{t0\delta} & \mapsto & H_\alpha \to \Delta_{O_{t1\delta}} \\
 & & & \Uparrow \\
 & & & \Delta_{\text{Societal}_{HC}} \\
 & & & \\
\text{Hypothesis}_2: & O_{t0\delta} & \mapsto & \Delta_{s_{t0+\epsilon}} \to \Delta_{H_\alpha} \to \Delta_{O_{t1\delta}} \\
 & & & \Uparrow \\
 & & & \Delta_{\text{Societal}_{V}}
\end{array}
$$

A.1.4 The Role of Society in Institutionalism and Organizational Change

Understanding the role of human capital allocation relative to social environment or broad social structure requires a deeper explanation of the role of structure within corporate organizational forms. Herein, three concepts capture the quiddity of the above formulation: (1) organizational structure, (2) social structure, and (3) human capital allocation.[12]

A.1.4.1 Organizational Structure

Recalling Chandler (1962), organizational structure refers to both the lines of authority and communication between organizational members as well as the content of said communication. Accordingly, scholars concur that organizational structure has both formal and informal dimensions (Chandler 1962; Hannan and Freeman 1977, 1984; Meyer and Rowan 1977).[13] Although formal structure certainly operates within organizations, I posit that the role of

[12] Tension admittedly pervades the discussion of social structure and organizational structure given the debate over their origin and relationship. Arguably, from a societal emergence paradigm, the social and social contracts evolved from amalgamations of individuals and this step was antecedent to the emergence of simplistic and later complex organizations as would be evident from the readings of Durkheim and Mauss, Rousseau, Hobbes, and Weber. Despite the debate on origin, most scholars agree that organizational structure can both be shaped by individuals and shape individuals (Stinchcombe 1965), and more importantly, the collective social structure from which an organization develops sets inaugural organizational strategy and structure (Chandler 1962; Hannan and Freeman 1984); which thereafter can modify existing social structure, for example by generating or expanding new economies and markets and employing a labor force to that end.

[13] For example, Chandler (1962) writes, "*Structure*... whether formally or informally defined, has two aspects" (14).

society in the above hypotheses most acutely affects (directly or indirectly) the informal structures of organizations. By informal structures, I refer to elements of social structure that exist or operate independently from formally conveyed or explicitly defined "lines of authority" and supporting communication pursuant to organizational strategy. In the broader literature, such informal structure acquires a variety of designations, such as "habitualizations," "routines," "myths," or "repertoires" (Berger and Luckmann 1966; Clemens 1993; Hannan and Freeman 1984; Meyer and Rowan 1977).

To help frame the role of informal structure, Hannan and Freeman (1984) argue that organizational success demands both accountability and reliability, such that "reliable performance requires that an organization continually reproduce its structure" (154).[14] Although reproduction of structure could transpire through intentional deliberation, the reproduction of organizational structure often results from "institutionalization" and the implementation of standard procedures, or "routines" (Hannan and Freeman 1984:154). In such cases, structural reproduction perpetuates with little ostensible guidance, and by consequence, highly institutionalized organizations also exhibit high inertia—or torpid responsiveness to organizational threats and opportunities (Hannan and Freeman 1984). Here, *routines* often perpetuate informally and without guidance to reify and reproduce the exigent formal structure and strategy.

In many ways, the concepts of myths and ceremonies discussed by Meyer and Rowan (1977) relate to and illuminate the routinized process of institutionalization buttressing formal structure. The existence of routines is substantiated by myth and ceremony—whose origins are grounded in rational efficiency which exists in theory but not practice (March and Simon

[14] Hannan and Freeman (1984) emphasize that "reliability" and the related trait of "accountability" work to establish organizational legitimacy and establish its environmental persistence or survival, a perspective they advance contra "efficiency arguments," such as (Blau and Scott 1962; Thompson 1967). Thus, Hannan and Freeman's (1984) argument stands generally opposed to efficiency arguments and accordingly parallels the disabusal of economic rationality by Granovetter (1985) in pursuit of emphasizing the role of social relations for establishing economic success.

1958; Meyer and Rowan 1977).[15] Inefficiencies emerge from the inertia created, in part from these "rationalized myths," ceremonies, routines, or habitualized actions that prevail even after they are no longer efficient (Berger and Luckmann 1966; Hannan and Freeman 1984; Meyer and Rowan 1977; Stinchcombe 1965). In fact, a second purpose of these informal structures is to account for discontinuities or "decoupling" between expressed formal structure and lines of authority and daily enacted practice, a divide between the formal and informal structure (Meyer and Rowan 1977).

Although routines, myths, and ceremony help capture informal structure, the concept of "organizational repertoires" might also be applied (Clemens 1993). The term "organizational repertoires" refers to "the set of organizational models that are culturally or experientially available" (Clemens 1993:758). Although organizational models may refer to "examples of specific organizations" and their external actions as "governed by 'logics of appropriateness'. . . or institutional norms" (Clemens 1993:758; DiMaggio and Powell 1983; March and Olsen 1989:23–24), organizational models may also refer to the "templates for arranging relationships within an organization and sets of scripts for action" (Clemens 1993:758). It is this latter definition of organizational models as templates or scripts within an organization that best reflects my application of the term to internal organizational processes. The concept of organizational repertoires also captures Hannan and Freeman's (1984) argument that as part of the institutionalization process, organizations not only have routines but "sets of routines" and a "set of rules to switch between routines" (154). In sum, such sets of routines coalesce as "organizational memory" or as Hannan and Freeman (1984) define, "an organization's repertoire of routines. . . the set of collective actions that it can do from memory" (154; *c.f.* Nelson and Winter 1982). Critically, the malleability of repertoires lend itself to transfiguration not simply from experiential histories (Berger and Luckmann 1966) but also from a "common, culturally available repertoire" for situational interpretation

[15]For example, Meyer and Rowan's (1977) "rationalized myths" in organizational structures can trace their roots to economic rationality and exemplify a decoupling between formal and informal structure (343, 347).

and action (Clemens 1993:759).[16] In this way, the informal social structure of organizations may shift according to changing currents of societal understanding.

A.1.4.2 Social Structure

Accordingly, the role of the *social*, particularly social structure, is at the heart of these analyses for both informing and being shaped by organizational structure.[17] Fortunately, this supposition has broad theoretical and empirical backing. For instance, in both neoinstitutionalism (DiMaggio and Powell 1983, 1991; Meyer and Rowan 1977) and old institutionalism (Selznick 1966) we see traces of the role society can place on the social reproduction of processes in organizational structure. Despite the frictions on the adaptation-selection fault line, such arguments are integral to concepts of inertia and organizational reproduction in Meyer and Rowan (1977) and Hannan and Freeman (1984).[18] Apart from the literature on neoinstitutionalism and old institutionalism, we also see support for the general idea that processes in society can permeate organizations in studies on mobilization or organizational diversity (Davis et al. 2008; Dobbin and Sutton 1998).

[16] While the particularities of each definition and purpose of informal organizational structure vary, we importantly note that these perspectives (1) underscore the salience of social relationships in reifying formal organizational structure and objectives, (2) indicate a process of "institutionalization," and (3) contribute to "isomorphism" (Hannan and Freeman 1984; Meyer and Rowan 1977). For example, both Hannan and Freeman (1984) and Clemens (1993) tie this idea of organizational repertoires to isomorphism. Clemens (1993) writes, "if one recognizes an established *repertoire* of acceptable forms instead of a single institutional rule, a process of institutional isomorphism can also promote change within a social system" (Clemens 1993:771). Clemens (1993) use of "institutional isomorphism" most directly follows from DiMaggio and Powell (1983), which delineates two major types of isomorphism, "competitive isomorphism" as associated with Hannan and Freeman (1977) and "institutional isomorphism" associated with Meyer and Rowan (1977; DiMaggio and Powell 1983:149–50).

[17] Social structure can take on many definitions across various theoretical perspectives. One definition comes from Berger and Luckmann (1966), who argue the following: "The social reality of everyday life is thus apprehended in a continuum of typifications, which are progressively anonymous as they are removed from…face-to-face interaction. Social structure is the sum total of these typifications and of the recurrent patterns of interaction established by means of them. As such, social structure is an essential element of the reality of everyday life" (47-48).

[18] Although neo-institutionalist theories (DiMaggio and Powell 1983; Meyer and Rowan 1977) occasionally face criticism as adaptational perspectives contending that "organizational structures are rationally adapted to prevailing normatively endorsed modes of organizing" (Hannan and Freeman 1984:150), such dismissals overlook valuable insights regarding broader societal impacts upon organizational structure.

If internal organizational structures, conceived as organizational repertoires, are malleable to external societal influences, such as changing societal values, these processes might in turn affect the processes of human capital allocation outlined in the example of organizational-state change. While human capital allocation and relatedly social capital prove incredibly complex subjects with entire dedicated subfields in sociology and economics (Becker 1964; Becker and Tomes 1986; Coleman 1988) , from an organizational vantage, a basic tenet compatible with the above explication on organizational repertoires is that in order to be hired, maintain employment, or advance in an organization, individuals must "be socialized, careers molded, and power allocated to defend the value" (Stinchcombe 1965:167), that is *fit* with the company (King et al. 2010). I posit socialization is acute in highly competitive and elite organizations (DiMaggio and Powell 1991; Rivera 2012b). Those lacking "elite socialization" and proper pedigree brook a significant disadvantage for entry into and progression in the corporate hierarchy (Cookson Jr. and Persell 1986; Karabel 2005; Levine 1980; Rivera 2011; Stinchcombe 1965; Useem and Karabel 1986). While integrally reflecting internal processes of informal organizational structure, the phenomenon suggests two meaningful analytic points: the first being a point of adding new human capital resources—hiring or recruitment; the second being internal progression or appointment within firms. A central insight here is that labor markets reflect the "matching of persons to jobs" (Kalleberg and Sørensen 1979; Schneider 1987; Sørensen and Kalleberg 1981:52; Tilly and Tilly 1998). In other words, there must be an initial fit between the individual, organization, and role, such that the individual is satisfactory qualified in the confines of bounded rationality and the individual is willing to accept the position on the agreed upon terms between the employer and employee (March and Simon 1958; Sørensen and Kalleberg 1981).

In determining satisfactory fit, a number of subjectives enter the equation. Some subjectives regard the qualifications of the human capital, such as degree, skills, or the institutional prestige of the credentialing entity (Altonji et al. 2012; Dale and Krueger 2002; Gaddis 2015; Hoekstra 2009). Yet, the ultimate decision also relies upon biases or discrimination on sociodemographic dimensions, such as race (Bertrand and Mullainathan 2004; Gaddis 2015; Kang et al. 2016), gender or motherhood (Correll et al. 2007; England et al. 1988; Pedulla 2016; Williams 1992), sexual orientation (Tilcsik 2011) social class (Rivera and Tilcsik 2016), or culture (Rivera 2012b). As I have suggested in this dissertation, political partisanship also plays an important role (Mausolf 2020b, 2020c). Given organizations' predilection for reliability and accountability (Hannan and Freeman 1984), social networks enhance hiring prospects since a connection from an embedded social tie carries more credibility, ceteris paribus (Erickson 2001; Granovetter 1973, 1974, 1985; Lin and Dumin 1986; Smith 2005).

To these ends, the perceived optimality and acceptability of individuals will necessarily vary by (1) the general commonality of such a trait among otherwise qualified individuals, and (2) the perceived acceptability of these traits from those within the firm, which will depend upon the organizational repertoires existent in the firm, meaning both the situationally derived experiences of those in the organization and the culturally available perceptions at their disposal. In both the latter cases, this will be contingent upon broader societal values.

The (1) first situation reflects the first general hypothesis, such that human capital allocation will change as a result of social shifts in the underlying base of relevant human capital. Many examples of these changes could result, but they often transpire as the result of shifts from entry into and attrition during educational pipelines that endow individuals with the base level of requisite human capital necessary to satisfy employers in the matching of persons to jobs. For example, a marked increase in the proportion of women graduating with STEM degrees could change the profile of underlying human capital, such that previously gender imbalanced firms begin to display gender equity in the younger cohorts technicians. If such cohort and gender change correlate with shifts in party identification, these changes could result in an altering of the corporate political state. The extant partisan leaning of firms, often differentiated by certain industry subsets in Mausolf (2020a), for example, suggests there may have already been some sorting in the pathways that lead individuals to pursue careers in some firms.

In the (2) second situation, the informal structure or organizational repertoire *shifts prior to changes in human capital allocation.* This may occur either from internal or externally derived processes (Clemens 1993). As I argue in much of the dissertation, societal changes in rising political partisanship, especially partisan polarization and affective polarization (Baldassarri and Goldberg 2014; Fiorina and Abrams 2008; Iyengar et al. 2019; Mason 2015), in combination with potential partisan activation of individuals following political polarization of elites and electoral campaigns (Hetherington 2001, 2009; Sood and Iyengar 2016), particularly suggest that processes in society can permeate within organizations and lead to expressed partisanship within firms, such as the recent trends in increasing partisan expression in polarized Republican firms (Mausolf 2020a). Likewise, the demonstrated affective polarization and partisan homophily affecting entry into firms and corporate board appointments suggest prior shifts in existing employees partisan outlook affect future behavior in human capital allocation. Internally, changes in hiring repertoires will be based upon changing situational experiences for a given attribute. Since, the organizational state is given and assumed to remain fixed, the internally derived repertoires are assumed to remain constant barring any differential experiences occurring within an organization or its subunits that would reallocate action scripts toward one group but not another. Thus, the latter case of externally derived shifts in either situational experience or culturally available narratives proves most likely, and as hypothesized, this would generate a shifting of culturally available societal values relative to the given model of human capital allocation. Further exploration is of course needed and we might expect interaction between these two generalized organizational state change hypotheses, but nonetheless, evidence suggests that external societal processes, in this case changes in partisanship, can effect change in the corporate organizational state and a rise in political partisanship manifested within firms.

APPENDIX B

Appendix Chapter 2: Methods Supplement

B.1 Alternative Approaches: Hierarchical Cluster Analysis (HCA)

An alternative approach to this analysis would be to conduct a traditional hierarchical clustering analysis utilizing data for different election cycles in a matrix, rather than using a time series algorithm such as dynamic time warping (DTW) to compute the distance matrix. For example, we might perform HCA clustering using discrete temporal periods. As seen previously, AGNES, Ward's method models performed the best: (Table B.1).

Table B.1: HCA Model Evaluation for Three Time Periods

	Model Coefficient		
Model, Method	1980-2002	2004-2018	2010-2018
AGNES, UPGMA	0.659	0.513	0.563
AGNES, WPGMA	0.732	0.617	0.611
AGNES, Single Linkage	0.590	0.436	0.475
AGNES, Complete Linkage	0.831	0.756	0.791
AGNES, Ward's Method	0.916	0.927	0.940
Diana	0.812	0.738	0.773

Source: FEC 2018a, 2018b.
Notes: N = 211, 335, 334 Firms. Based on data from 89,633; 472,840; 374,717 (Individuals X Firm X Election Cycle) for 1980-2002, 2004-2018, and 2010-2018 respectively. This data represents individual-level data aggregated from individual contributions (contribution-level data). Companies had an inclusion threshold of $n = 10$, such that each Firm X Election Cycle must have >= 10 individuals with a known major party ID and known partisan score.

I ran the (AGNES, Ward's method, $K = 3$) model on a subset of the data, using a variety of partisan score and party identity aggregate measures for each firm by occupational hierarchy and election cycle. This results in an N X 192 matrix (data frame) such that each company is a single observation with 192 columns reflecting discrete variables for each partisan metric, occupational hierarchy, and cycle combination. Here N reflects the number of firms, which for

HCA (2004-2018), is N = 335. In these analyses, rather than use the full partisan polarization measure, I simply used the variance of the partisan identity and partisan score.

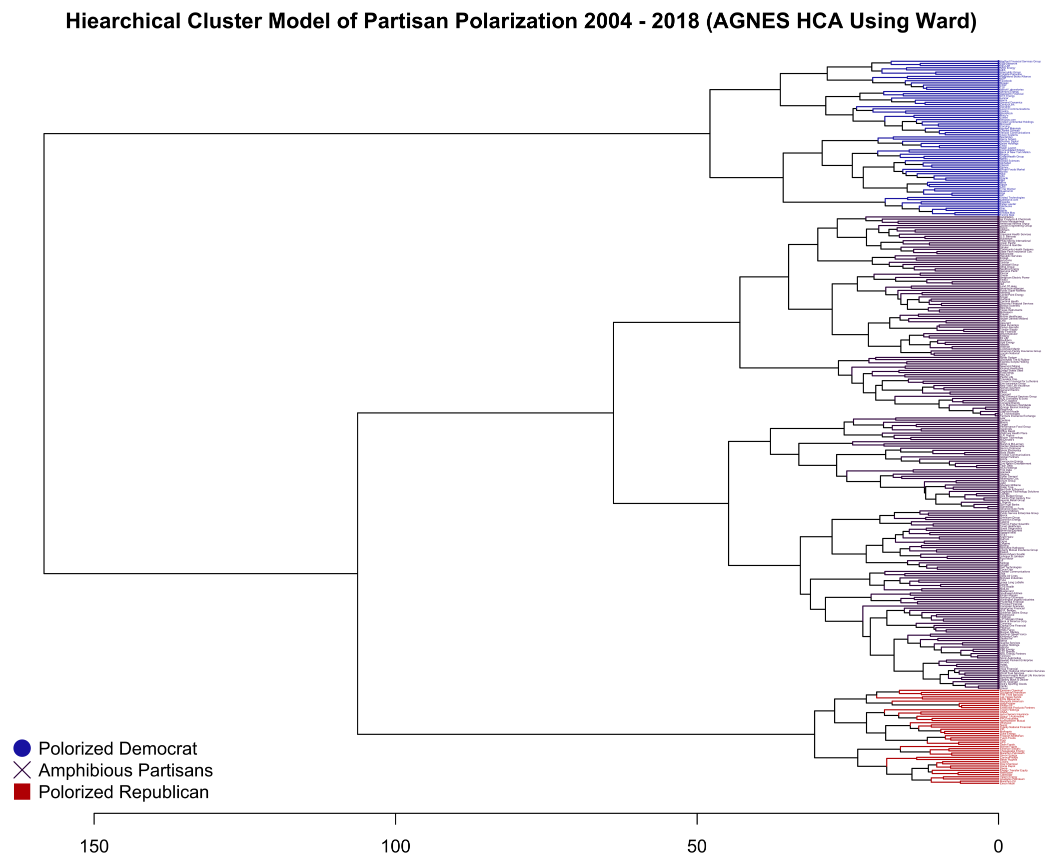


Figure B.1: Result of HCA AGNES-Ward Clustering Model for Fortune 400 Companies, 2004-2018

Notes: Hierarchical cluster analysis (HCA), AGNES algorithm, using Ward's method for individual-level firm data, 2004-2018. K=3 clusters requested following optimal cluster analysis for different time periods. AGNES Ward's method selected, agglomerative coefficient = 0.88.

From Figure B.1, we see similar firms such as Marathon Oil, Dean Foods among partisan Republican firms. Similarly, polarized Democratic companies include large technology and advertising companies such as Apple and Alphabet (Google). Below are the partisan polarization and partisanship plots for these HCA Clustered Firms.

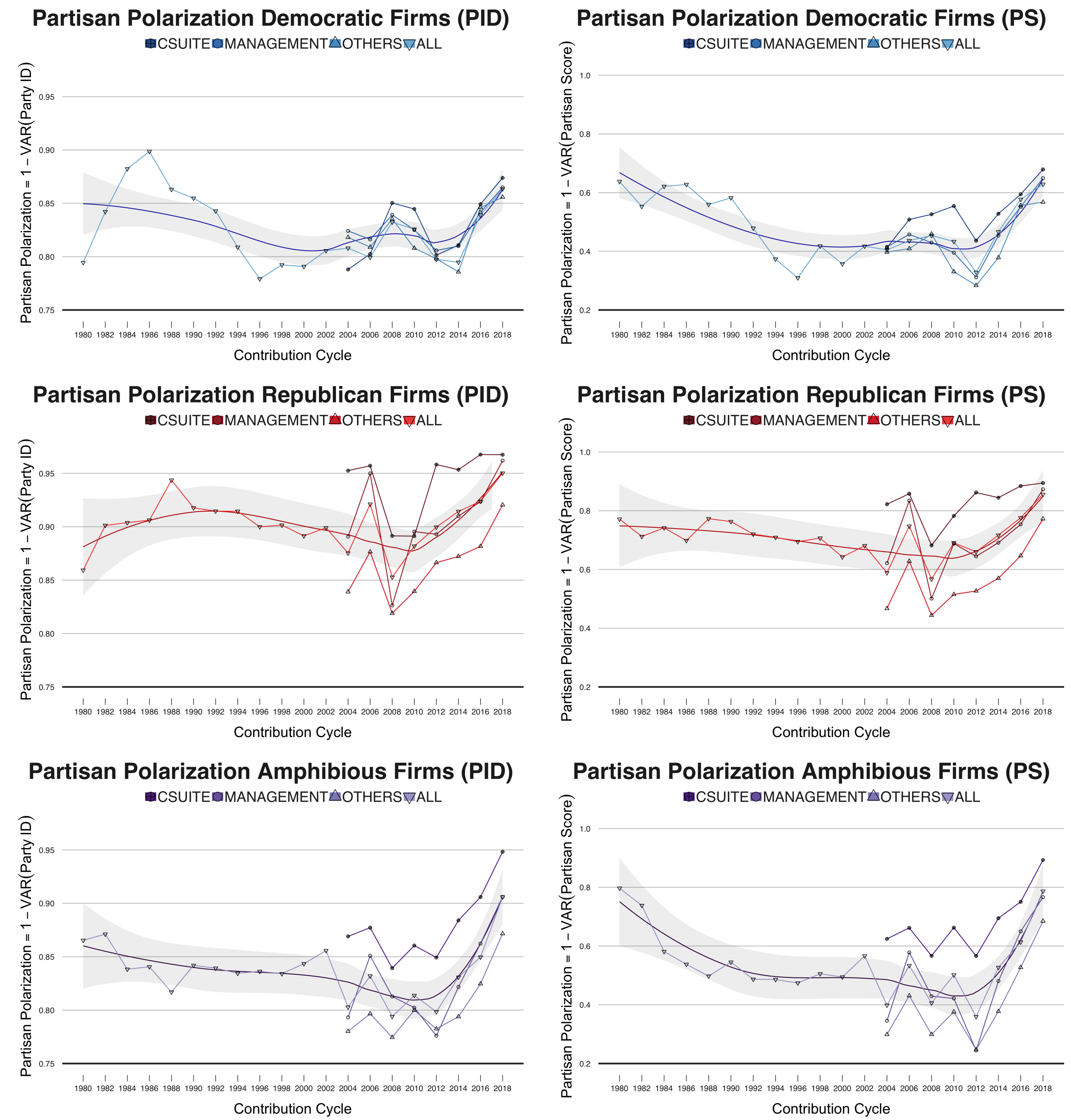


Figure B.2: Partisan Polarization Levels (by Partisan Metric) in Identified Democratic, Amphibious, and Republican Firms

Notes: Partisan polarization calculated using *party id* or *partisan score* for Democratic, Amphibious, and Republican firms. Partisan profile classified using hierarchical cluster analysis (HCA), AGNES algorithm, using Ward's method for individual-level firm data, 2004-2018. Each subplot represents one of those three identified clusters or the data for all firms (no clustering).

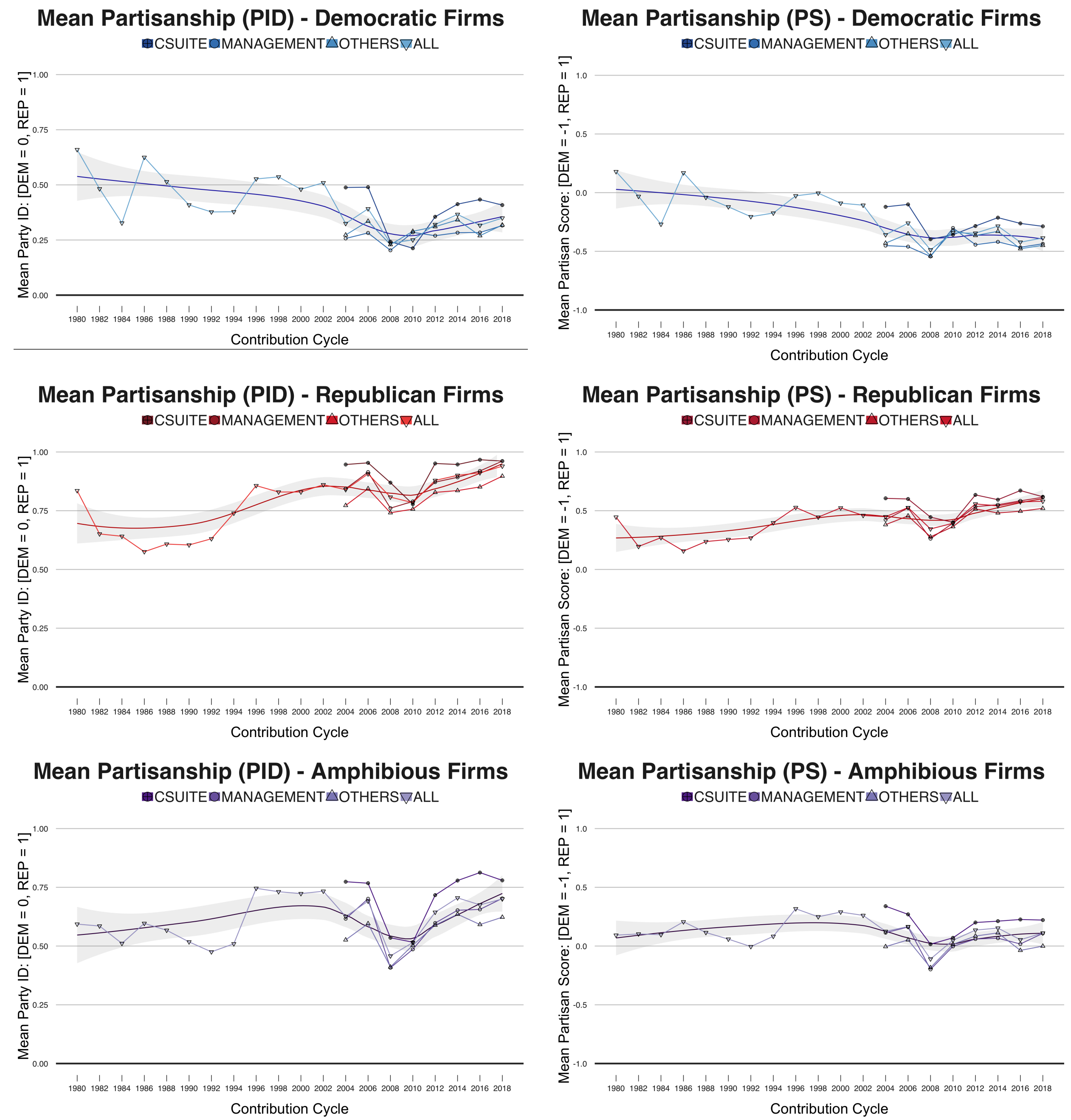


Figure B.3: Mean Partisanship in AGNES (2004-2018) Democratic, Amphibious, and Republican Firms

Notes: Mean partisanship calculated using either *party identity [DEM = 0, REP = 1]* or *partisan score [DEM = -1, REP = 1]* for Democratic, Amphibious, and Republican firms. Firms classified using (HCA) AGNES, Ward's method, 2004-2018, N = 335 Firms.

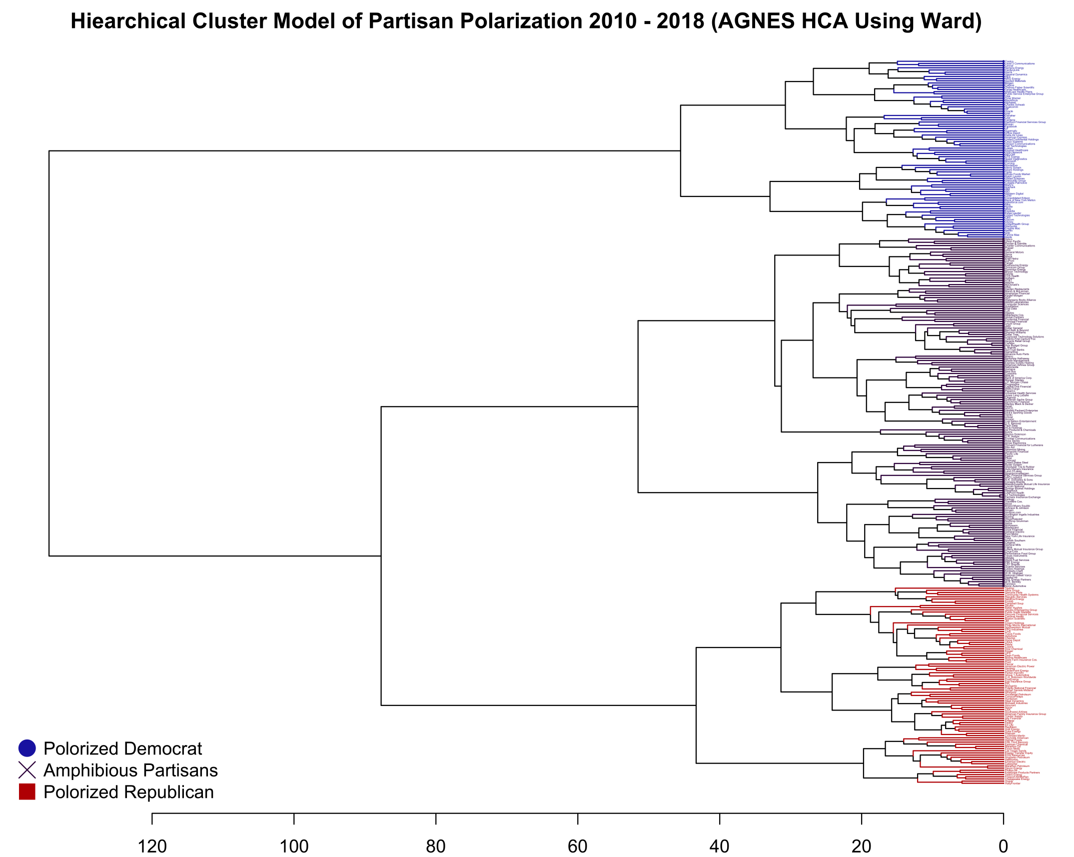


Figure B.4: Result of HCA AGNES-Ward Clustering Model for Fortune 400 Companies, 2010-2018

Notes: Hierarchical cluster analysis (HCA), AGNES algorithm, using Ward's method for individual-level firm data, 2010-2018. K=3 clusters requested following optimal cluster analysis for different time periods. AGNES Ward's method selected, agglomerative coefficient = 0.94.

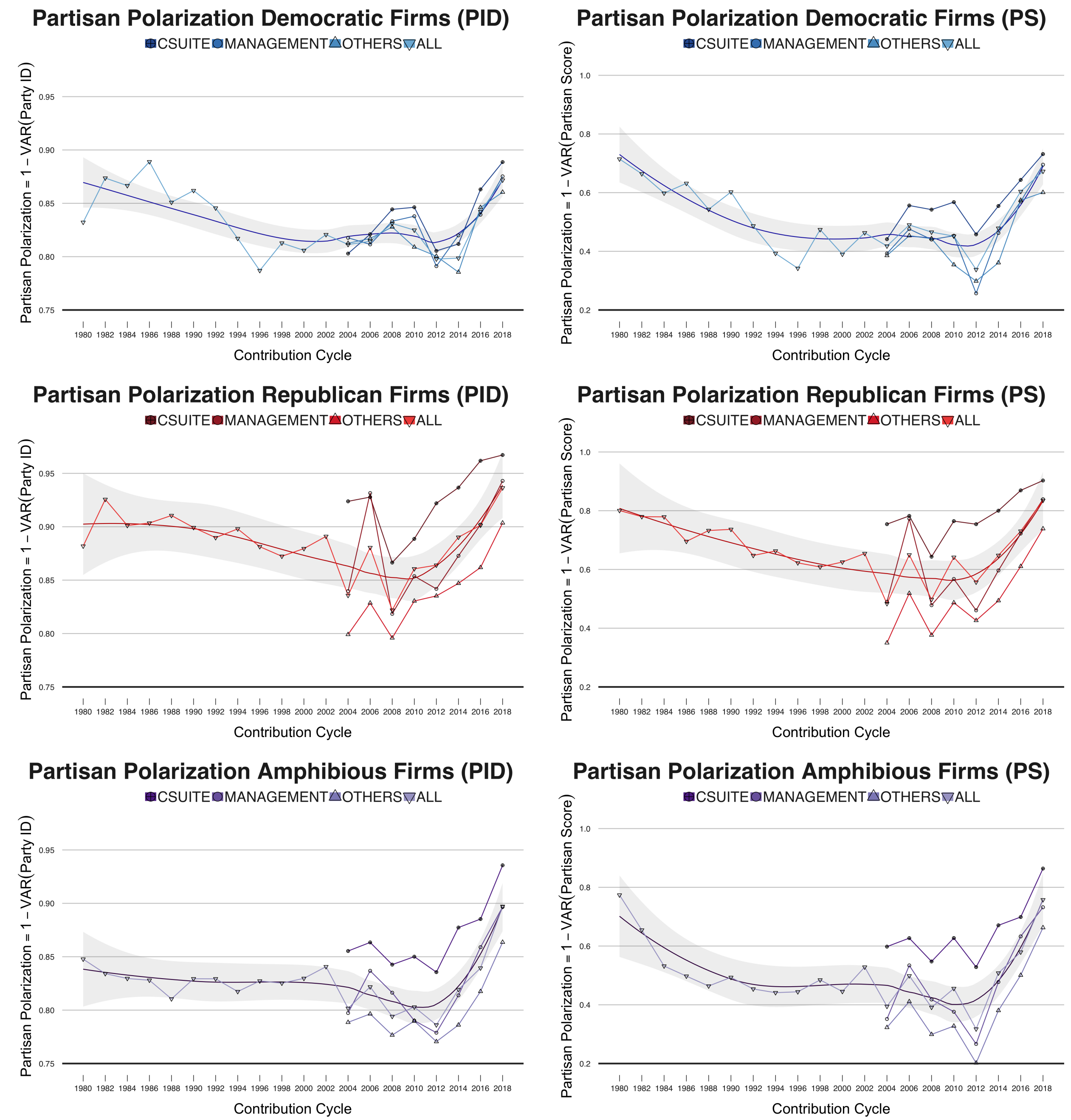


Figure B.5: Partisan Polarization in AGNES (2010-2018) Identified Democratic, Amphibious, and Republican Firms

Notes: Partisan polarization calculated using *party id* or *partisan score* for Democratic, Amphibious, and Republican firms. Partisan profile classified using hierarchical cluster analysis (HCA), AGNES algorithm, using Ward's method for individual-level firm data, 2010-2018. Each subplot represents one of those three identified clusters or the data for all firms (no clustering). N = 334 Firms.

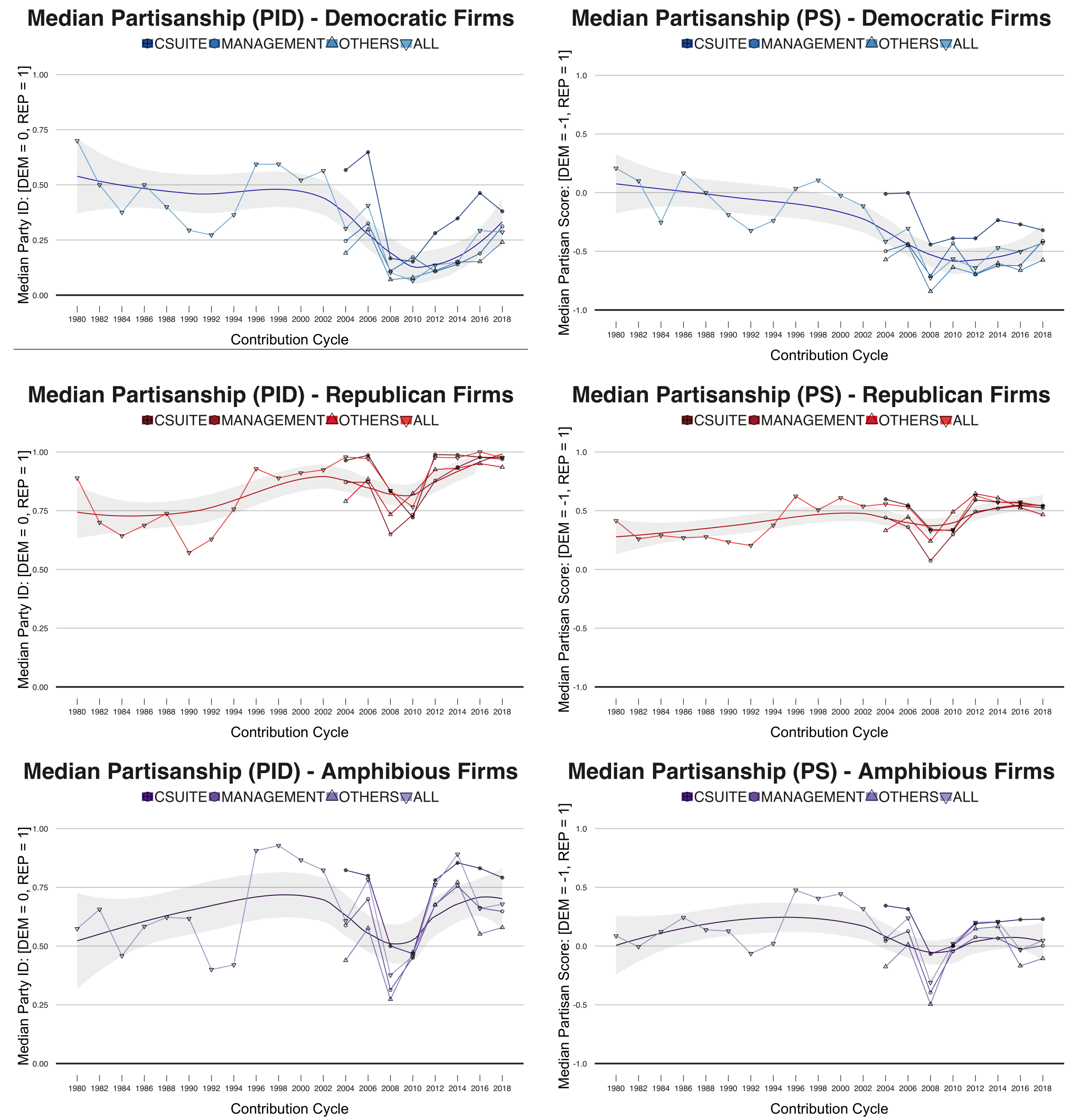


Figure B.6: Median Partisanship in AGNES (2010-2018) Democratic, Amphibious, and Republican Firms

Notes: Median partisanship calculated using either *party identity [DEM = 0, REP = 1]* or *partisan score [DEM = -1, REP = 1]* for Democratic, Amphibious, and Republican firms. Firms classified using (HCA) AGNES, Ward's method, 2010-2018, N = 334 Firms.

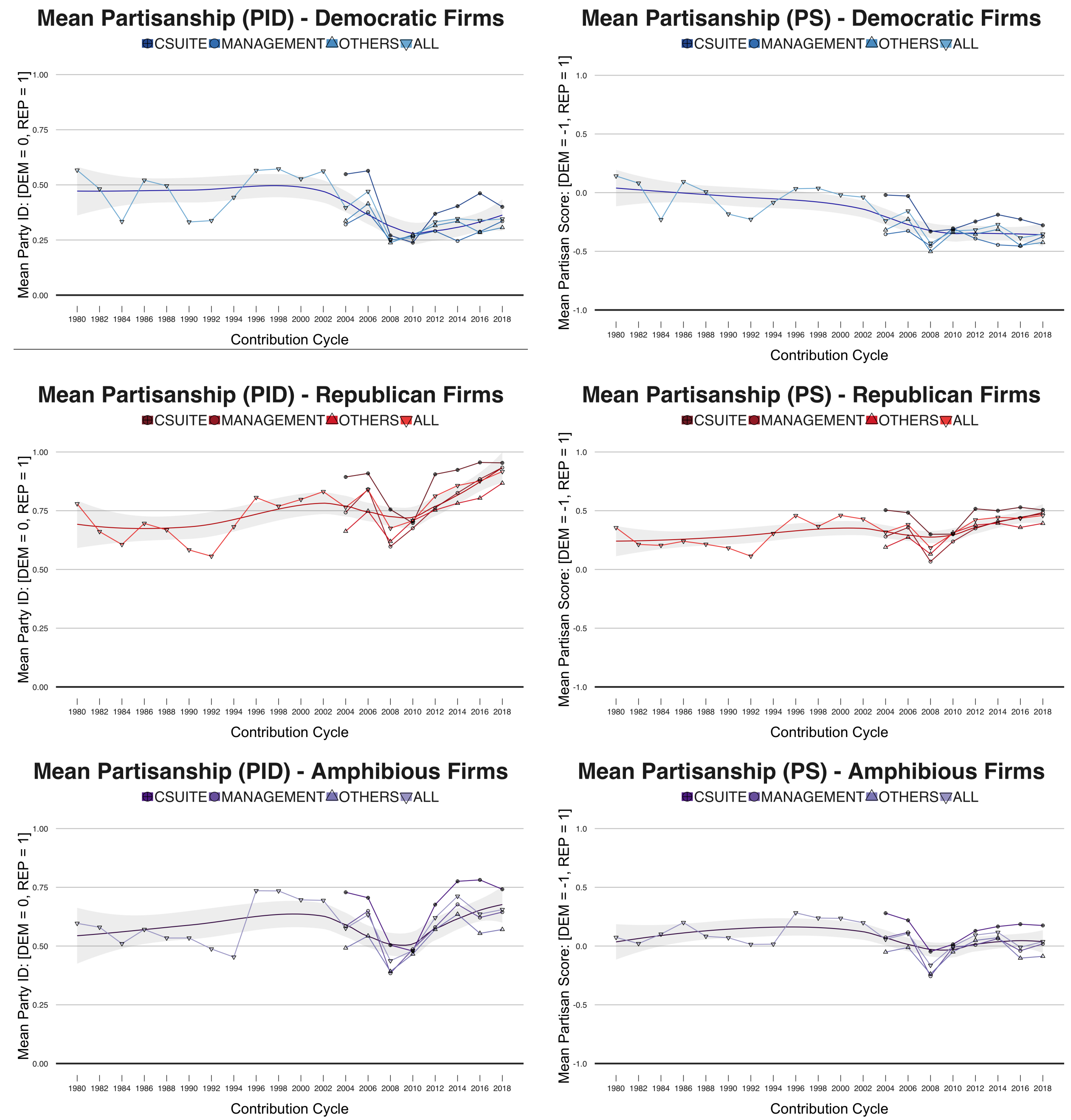


Figure B.7: Mean Partisanship in AGNES (2010-2018) Democratic, Amphibious, and Republican Firms

Notes: Mean partisanship calculated using either *party identity [DEM = 0, REP = 1]* or *partisan score [DEM = -1, REP = 1]* for Democratic, Amphibious, and Republican firms. Firms classified using (HCA) AGNES, Ward's method, 2010-2018, N = 334 Firms.

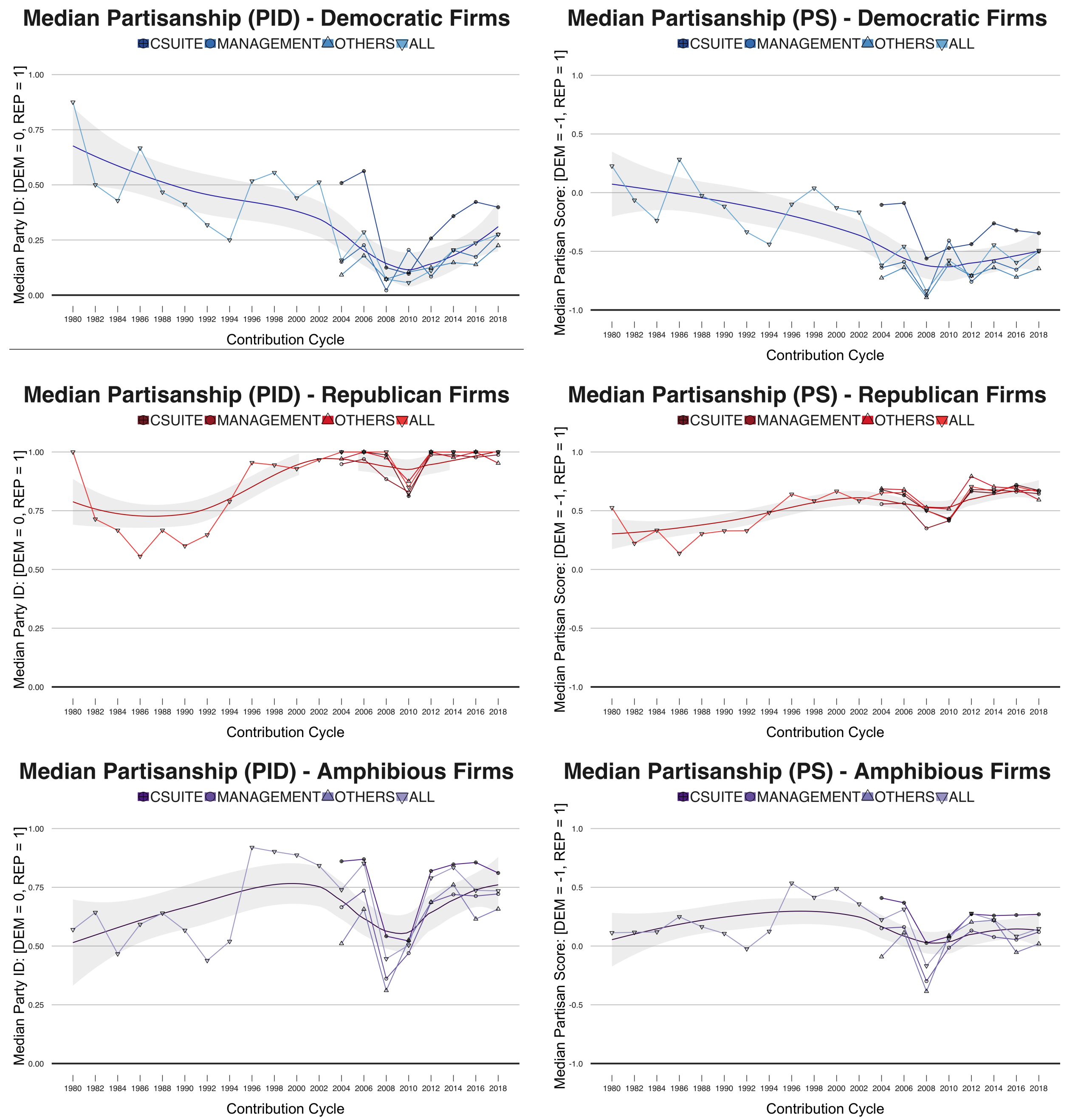


Figure B.8: Median Partisanship in AGNES (2004-2018) Democratic, Amphibious, and Republican Firms

Notes: Median partisanship calculated using either *party identity [DEM = 0, REP = 1]* or *partisan score [DEM = -1, REP = 1]* for Democratic, Amphibious, and Republican firms. Firms classified using (HCA) AGNES, Ward's method, 2004-2018, N = 335 Firms.

B.2 Data Without Minimal Thresholds

Table B.2: Individual Partisans at Fortune 400 Companies (No Threshold), 1980-2018

	1980-2018	1980-1988	1990-1998	2000-2008	2010-2018
Major Party ID					
DEM	199,790 (36)	5,073 (47)	17,883 (41)	56,226 (43)	120,608 (33)
REP	355,462 (64)	5,830 (53)	26,023 (59)	75,225 (57)	248,384 (67)
Unknown	14,731 (3)	665 (6)	1,993 (4)	4,498 (3)	7,575 (2)
Partisan Score					
minimum	-1.00	-1.00	-1.00	-1.00	-1.00
median (IQR)	0.17 (-0.54, 0.51)	0.04 (-0.28, 0.77)	0.18 (-0.29, 0.87)	0.12 (-1.00, 0.81)	0.17 (-0.14, 0.43)
mean (sd)	0.05 ± 0.68	0.10 ± 0.66	0.12 ± 0.70	-0.01 ± 0.79	0.06 ± 0.63
maximum	1.00	1.00	1.00	1.00	1.00
Unknown	3,451 (1)	234 (2)	481 (1)	939 (1)	1,797 (0)
Individual Contributions	3,881,136	20,426	85,813	325,807	3,449,090
minimum	1	1	1	1	1
median (IQR)	2.00 (1.00, 8.00)	1.00 (1.00, 2.00)	1.00 (1.00, 2.00)	1.00 (1.00, 2.00)	4.00 (1.00, 13.00)
mean (sd)	6.81 ± 14.59	1.77 ± 1.89	1.87 ± 2.48	2.40 ± 4.19	9.16 ± 17.28
maximum	3057	38	54	109	3057
Firms	371	202	267	337	370
N	569,983	11,568	45,899	135,949	376,567

Source: FEC 2018a, 2018b.
Notes: N = 569,983 (Individuals X Firm X Election Cycle) represents individual-level data aggregated from individual contributions (contribution-level data). Individual contributions detail each contribution sub_ID for all individuals in the requested firms, in each election cycle 1980-2018. Categorical data, such as party identity, reports the number for each cell, followed by a percentage: N (%). Companies were previously filtered for quality control. In contrast to the table in the paper, no threshold exists for companies to appear in this table. Each Firm X Election Cycle must have only one or more individuals (who may or may not have attached partisan measures).

B.3 Robustness Checks: Constant 1980 Firms

As one of several robustness checks, I wanted to evaluate the overarching patterns of increasing partisanship after 2012, as well as the apparent decline in partisanship from the 1980s through the 1990s. Was this simply a function of compositional changes in the included Fortune 400 companies? For example fewer companies appear in the 1980 data than in recent years (since the companies were determined using the most recent F1000 list).

A second possibility regards variance as the result of the number of individuals in the data. If measures of partisan polarization fluctuate due to the number of individuals contributing within a firm for an election cycle, we might also see shifts in partisan polarization. A common issue is that fewer individuals in a firm contribute funds during non-presidential election cycles. If too few individuals exist, the measure of partisan polarization may not be robust.

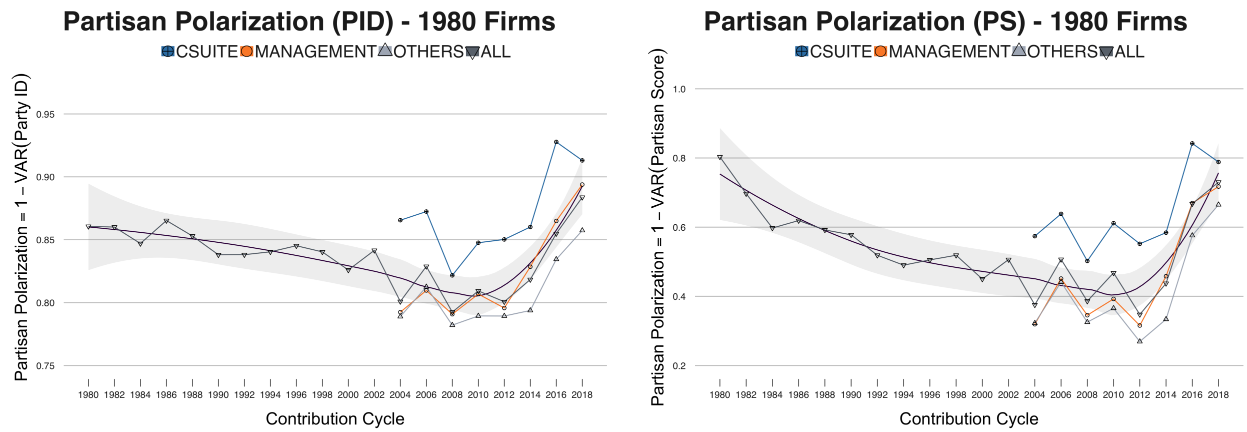


Figure B.9: Robustness Check: 1980 Constant Firms

Notes: Average partisanship calculated using either *party identity [DEM = 0, REP = 1]* or *partisan score [DEM = -1, REP = 1]* for all 1980 constant firms, N >= 10 individuals. The minimum election cycle individuals was determined using the most sparse measure of individuality, having >= 10 individuals with a binary partisan identity (DEM or REP). The above charts reflect the 27 firms which had >= 10 individuals (by party id) in every election cycle 1980-2018. Thus, the changes represented are for a constant set of firms.

To help counteract both issues, I examined whether the trend in increasing partisan polarization still appeared if I kept a constant set of firms which (A) existed in 1980, with (B) at least 10 individuals with a recorded partisan identity, and (C) remain in the dataset each subsequent election cycle 1982-2018 with the condition (B). I denote these 1980 constant firms. The results are similar to those seen when all firms with at least 10 partisans are examined, as shown in the main paper.

B.4 FEC Individual Contributor Data Collection

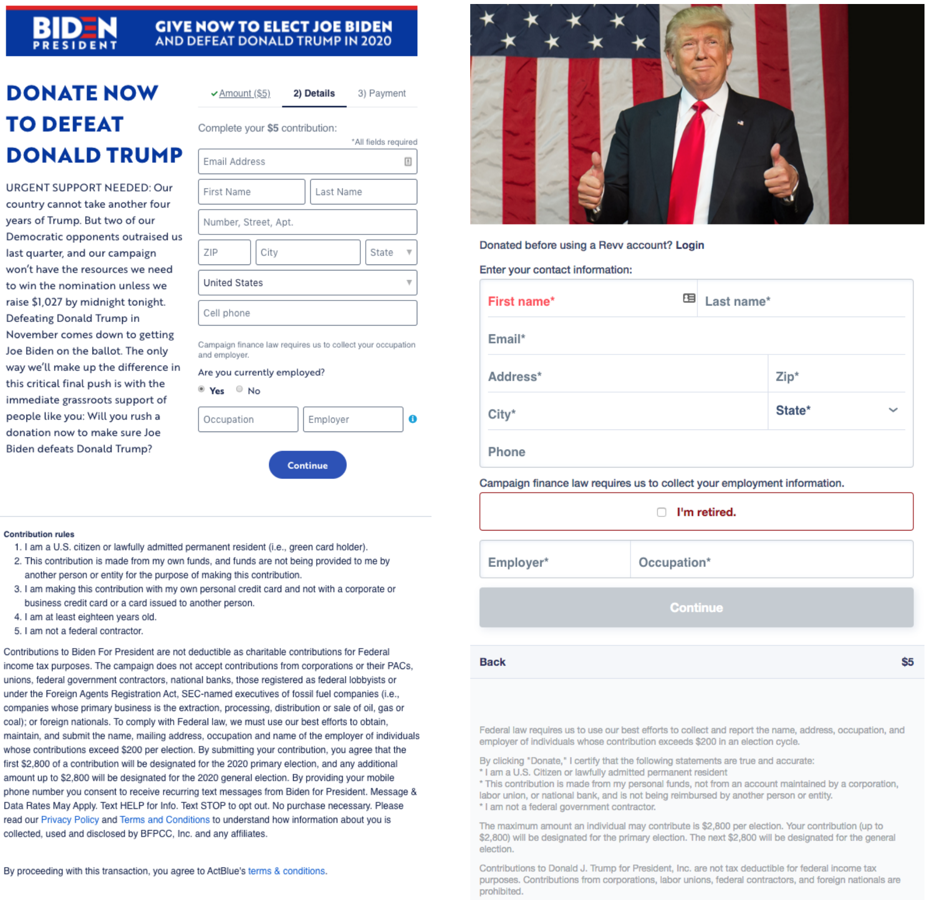


Figure B.10: Example of Data Collected in FEC Individual Contributions

Notes: As previously noted, the FEC requires that "for each contribution that exceeds $200, either by itself or when added to the contributor's previous contributions made during the same calendar year, records must identify that contribution by: Amount; Date of receipt; and Contributor's full name and mailing address, occupation and employer" (Federal Election Commission 2018c). As we can see in these contribution forms (to be filled out by the individual contributor), such information is required even for small donations, in this example, $5.00, regardless of prior contribution history. As described in the research methodology, both "occupation" and "employer" prove critical to identifying individuals at the firms in question. Yet, the forms have idiosyncrasies in the collection. For example, the form for Joe Biden asks "Are You Currently Employed," with options for (1) "Occupation" and (2) "Employer" only listed if you check *yes*. The form for Donald Trump lists (1) "Employer" and (2) "Occupation" along with a box to check if you are retired. For unemployed or formerly employed individuals, such differences would likely result in different data entry. In the case of Biden, we would likely see no data for occupation or employer. For Trump, we might see something along the lines of "unemployed" or "laid off" / "NA," among many possibilities. Similarly, individuals with multiple jobs have no clear way to input those options, and some individuals may incidentally put their employer in the occupation field (or vice versa).

APPENDIX C

Appendix Chapter 3: Experimental Methods Supplement

C.1 Example Experimental Materials

Subject: Data Scientist Opening - Facebook
From: Ryan Connor McGrath <ryancrmcgrath@gmail.com>
To: officepoliticsaudit
Date Sent: Sun, 31 Mar 2019 16:11:02 -0700 (PDT)
Date Received: Sun, 31 Mar 2019 16:11:04 -0700 (PDT)
Attachments: Resume_Ryan_Connor_McGrath.pdf

Hi Jonathan,

I am writing in response to your notice for the Data Scientist opening at your Menlo Park office. I am a doctoral candidate in computer science at Stanford University, where I specialize in studying recurrent neural networks for cloud computing. Facebook has excellent careers in data science and artificial intelligence, and I am confident, together, we would be a great match.

As a computer scientist, I have both the theoretical knowledge and applied experience to make a difference at Facebook. If you peruse my resume, you'll notice that I have not only developed enhanced RNN algorithms in Java, but I have also used Python, Spark, and SQL to apply deep neural nets and streamline ETL pipelines as a data science intern for both Airbnb and Microsoft. Collectively, my background in computer science as well as statistical and mathematical modeling gives me first-hand experience into the crux of today's complex puzzles in data science and their applications at the frontier of artificial intelligence.

Although I have a number of methodological strengths and my doctoral degree underscores my ability to tackle multifaceted problems, independence has its limits. Therefore, I also strive to work as a team player, whether it's by working with colleagues at Airbnb and Microsoft to communicate data-driven solutions or spearheading fundraising initiatives and leading a diverse set of students during my tenure as president of the Cal Associated Students. I think you will agree that my programming and mathematical background—combined with my outgoing charisma and penchant for team leadership—makes me a valuable recruit for the position at Facebook.

Jonathan, I am excited about this opportunity at Facebook and eager to discuss next steps. Attached, please find a copy of my resume. I look forward to speaking with you soon so that we can discuss the position further.

All the best,

Ryan

Ryan Connor McGrath
Ph.D. Candidate, Department of Computer Science
Stanford University
763.354.1118 | ryancrmcgrath@gmail.com

Figure C.1: Version A Cover Letter for P03NH to Hypothetical Data Science Job

Subject: Position | Data Scientist
From: Graham Spencer Andersen <grahamsrandersen@gmail.com>
To: officepoliticsaudit
Date Sent: Sun, 31 Mar 2019 16:10:24 -0700 (PDT)
Date Received: Sun, 31 Mar 2019 16:10:26 -0700 (PDT)
Attachments: Resume_Graham_S_Andersen.pdf

Dear Jonathan Williams:

I hope this email finds you well. I recently came across the Data Scientist position at Facebook’s Menlo Park office. As a Ph.D. candidate in electrical engineering and computer science at the University of California-Berkeley, I research the application of nonparametric bound estimation for deep reinforcement learning, a type of computer vision. Given, Facebook’s opportunities in machine learning and data science, I would love to contribute my talents.

With my background in computer science, I exhibit both the academic theory and pragmatic qualifications to be impactful at Facebook. As evidenced in my resume, I have used my dissertation to develop a C++ library that optimizes deep learning. Moreover, I have applied my computational skills in Python, SQL, and Hadoop to improve ETL server efficiency and provide impactful analytics during my summer data science internships at Google and Uber. Both within and outside the workplace, I embrace collaboration, such as my efforts at Google and Uber to share actionable data intelligence or my past initiatives as vice president of the UCLA Bruin Democrats to direct fundraisers and organize student activities.

In combination, my collaborative skills and computational abilities in artificial intelligence, mathematics, and statistics illustrate the value I can bring to Facebook, and I would be delighted to continue the conversation. To that end, I have attached my resume for review. I hope to hear from you shortly.

Sincerely,

Graham S. Andersen
Ph.D. Candidate
Department of Electrical Engineering and Computer Sciences
The University of California, Berkeley
Phone: (616) 528-3153

Figure C.2: Version B Cover Letter for P01DH to Hypothetical Data Science Job

Ryan Connor McGrath

353 Serra Mall, Gates 438, Stanford, CA 94305 | 763.354.1118 | ryancrmcgrath@gmail.com

Education

2019	Ph.D.	Stanford University, Computer Science ◇ Thesis: *Adaptive Computational Offloading in the RNN Algorithm* ◇ Keywords: Recurrent Neural Networks, Artificial Intelligence, Parallel Computing
2015	M.S.	Stanford University, Computer Science, GPA: 3.95
2013	B.S.	University of California, Berkeley, Mathematics, GPA 3.86

Skills

Programming	◇ Python, C++, Java, Scala, R, Spark, Hive, SQL, PHP ◇ HTML, CSS, JSON, Node.js, Flask, Shiny ◇ Vim, Atom, Sublime, LaTeX, Git, SSH, Mac, Linux, Windows
Analysis	◇ Machine Learning; Recurrent Neural Networks; Parallel Computing; Tera and Giga Data; Time Series, Longitudinal Models; Natural Language Processing; Web-Scraping

Professional Experience

2014-Present — Stanford University, Stanford, CA
Graduate Research Assistant, Department of Computer Science
◇ Developed an enhanced LSTM algorithm in **Java** for deep learning. Supervised 3 junior programmers.
◇ Applied machine learning and RNN models to parallelized GPU clusters using **Python**, **Spark**, and **C++**, improving performance on complex pattern recognition tasks.

Jun-Sep 2018 — Airbnb, San Francisco, CA
Data Science and Analytics Intern
◇ Reduced computational complexity while improving precision by 15% in modeling facial recognition on a distributed **Spark** cluster using **Python** and **SQL**.

Jun-Sep 2017 — Microsoft, Redmond, WA
Data Scientist/Machine Learning, Intern
◇ Improved backend development of an ETL pipeline with **PHP** and **SQL**.
◇ Developed a predictive machine learning dashboard with **Python** and **SQL** to provide consumer insights to project managers.

2012-2013 — University of California, Berkeley, Berkeley, CA
Research Assistant, Department of Mathematics
◇ Conducted original research, synthesized literature, and assisted with proofs on network topologies.

Leadership, Awards, and Honors

2014-2019 — Stanford University
◇ Marshall Dissertation Completion Fellowship, Kaggle Competition Finalist, CVPR Presenter.

2009-2013 — University of California, Berkeley
◇ Graduated *magna cum laude*, Phi Beta Kappa, Dean's List.
◇ Spearheaded fundraising campaigns and managed student events as president of the Cal Associated Students.

Additional Information

Languages:	English (native), French (proficient), Portuguese (elementary)
Office:	Microsoft: Word, PowerPoint, Access, Outlook, Excel; Adobe: Acrobat Pro, InDesign, Lightroom; Google: Slides, Sheets, Documents, Gmail, Drive; Project management: Salesforce CRM, Trello, Basecamp; Other: Tableau, Gephi, Atlas.ti
Interests:	Squash, Cycling, Travel, Hiking, Winter Sports

Figure C.3: Version A Resume for P03NH to Hypothetical Data Science Job

Graham S. Andersen

Address: 253 Cory Hall
Berkeley, CA 94720
Phone: (616) 528-3153
Email: grahamsrandersen@gmail.com

Education

Ph.D.	University of California, Berkeley, Electrical Engineering and Computer Science ○ Thesis: *Nonparametric Bound Estimation in Deep Reinforcement Learning*, a thesis which develops and applies deep reinforcement learning, artificial intelligence, algorithmic efficiency.	2019
M.S.	University of California, Berkeley, Statistics, GPA: 3.94	2015
B.S.	University of California, Los Angeles, Applied Mathematics, *summa cum laude*, GPA 3.91	2012

Work Experience

University of California, Berkeley, Berkeley, CA — 2013-Present
Graduate Research Assistant, Department of Electrical Engineering and Computer Science
○ Authored a mathematical proof for nonparametric bound estimation and wrote a *C++* library to demonstrate the algorithm's utility for deep reinforcement learning.
○ Maintained server data integrity and engineering for fellow researchers' machine learning projects.

Google, Mountain View, CA — May-Aug 2018
Data Science Intern
○ Optimized an ETL pipeline using *SQL* and improved the efficiency of deep learning models by 21% using a combination of *Python* and *C++*, thereby reducing server costs in both memory and computation time.
○ Deployed appropriate machine learning and computational methodologies in *Python* to furnish project partners with impactful measurement strategies and analytic insights.

Uber, San Francisco, CA — May-Aug 2017
Data Science, Computer Vision Intern
○ Harnessed *SQL*, *Hadoop*, and *Python* to drive impactful predictive analytics.
○ Collaborated with data engineers and junior developers in the creation of *Python* and *Django* based machine learning dashboards, which I shared with project leads to improve product strategy.

University of California, Los Angeles, Los Angeles, CA — 2011-2013
Research Assistant, Department of Applied Mathematics
○ Distilled prior mathematical research and worked with graduate fellows to devise proofs necessary for a paper on N-dimensional hypergraphs.

Honors, Awards, and Accomplishments

University of California, Berkeley — 2013-2019
○ Dissertation Improvement Grant, Department Hackathon Facilitator, KDD Presenter.

University of California, Los Angeles — 2008-2012
○ Latin honors - *summa cum laude*, Phi Kappa Phi, President's List.
○ Organized campus activities and directed fundraisers as vice president of the UCLA Bruin Democrats.

Technical Skills

○ Python, Java, C++, Julia, R, SQL, Hadoop, PrestoSQL
○ HTML, JavaScript, CSS, Markdown, JSON, Django, Tableau
○ Sublime, Emacs, Secure Shell, Git, Linux
○ Deep Reinforcement Learning, Machine Learning, NLP
○ Distributed Computing, Large Data, Data-Mining
○ Time Series, Multilevel Modeling

Supplemental Qualifications

○ *Languages*: *German* (advanced), *Spanish* (beginner)
○ *Business*: SAP CRM, Asana, Slack
○ *Microsoft Office*: Excel, Word, PowerPoint, Outlook, Access
○ *Google*: Slides, Sheets, Documents, Gmail, Drive

Figure C.4: Version B Resume for P01DH to Hypothetical Data Science Job

C.2 Supplemental Figures and Models

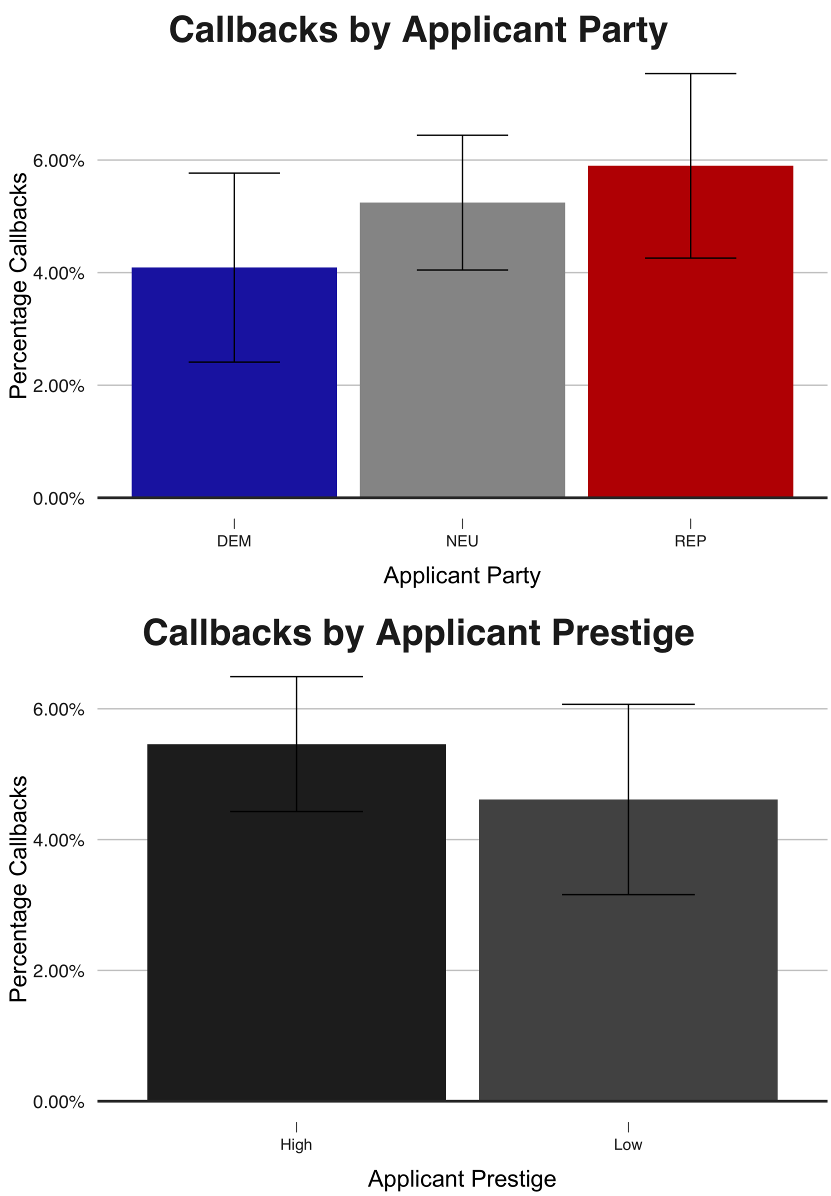
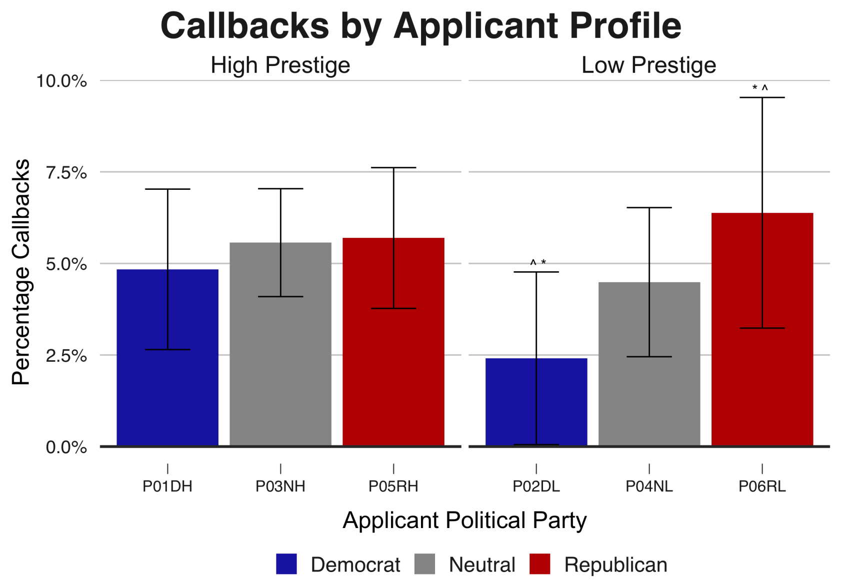


Figure C.5: Experimental Results by Applicant Partisanship and Prestige

Notes: N = 2670. Mean callback rate with 95% confidence interval displayed. Confidence intervals generated for each group (bar) using a one-sample t-test with the default two-sided option in R. This yields a confidence interval equivalent to the 95% CIs generated from a two-sample t-test with unequal variance in Stata. Two-sample t-tests for unequal variance calculated between each applicant partisanship and the other two partisan types within each firm party. No significant differences exist in either subplot.

(1) Received Applicants (N = 2670)



(2) Matched Applicants (N = 658)

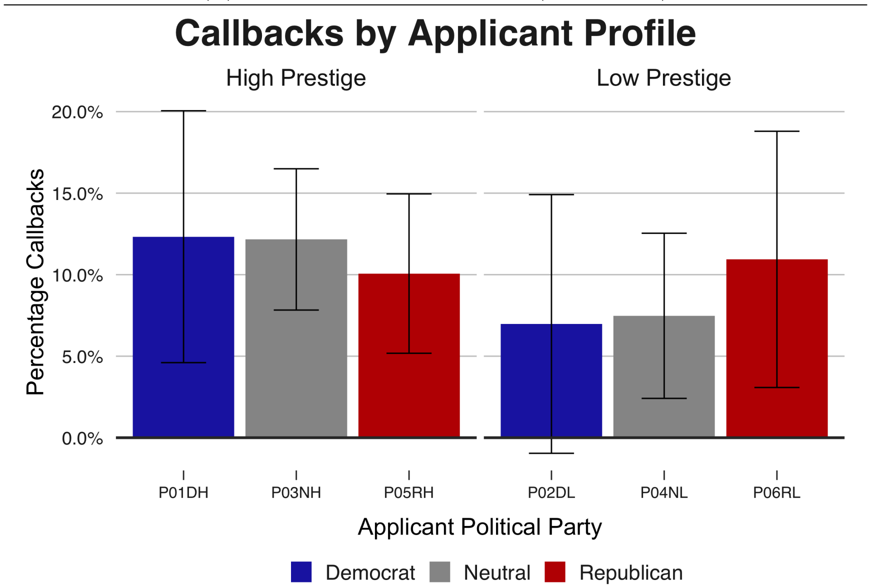


Figure C.6: Comparison of Callbacks using Party X Prestige for (1) Received Applicants versus (2) Matched Applicants

Notes: Mean callback rate with 95% confidence interval displayed. Confidence intervals generated for each group (bar) using a one-sample t-test with the default two-sided option in R. This yields a confidence interval equivalent to the 95% CIs generated from a two-sample t-test with unequal variance in Stata. Two-sample t-tests for unequal variance calculated between each applicant partisanship and the other two partisan types within each firm party.
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table C.1: Logit Models of the Likelihood that a Job Applicant Receives a Callback at a Republican Firm, Matched Applicants, Odds Ratios (OR) Displayed

	Pr{Applicant Receives Callback}			
	(1)	(2)	(3)	(4)
Applicant Partisan Matching				
Mismatched Partisan	0.091*	0.107*	0.094*	0.093*
Neutral Applicant	0.431*	0.454+	0.424*	0.420*
(Ref: Matched Partisan)				
Applicant Prestige				
High Prestige	0.970	1.050	0.925	1.017
(Ref: Republican Firm)				
Job Type				
MS: Computer Scientist		0.805	0.817	0.785
(Ref: Lower Prestige)				
MBA: Analyst or Manager		0.173*	0.210*	0.209*
Region				
Midwest				1.557
(Ref: Ph.D. Data Scienctist-Quant)				
South				0.790
West Coast				0.312
Experiment Features				
Received Order: Second			1.499	1.611
(Ref: East Coast)				
Resume Version: B			1.401	1.366
Experiment Wave: Second Wave			0.376	0.381
Constant	0.180***	0.229**	0.200**	0.183**
N	340	340	340	340
Log Likelihood	-93.653	-89.604	-87.286	-85.363
AIC	195.305	191.208	192.572	194.727

Notes: N = 340. Republican firms only. Matched applicants are those applicants who applied to a firm where the partisanship of the firm could be determined, resulting in three match conditions (mismatch, neutral, and match) based on the partisanship of the firm (Democratic or Republican) and the partisanship of the test applicant (Democratic or Republican) and control applicant (Neutral).
+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Table C.2: Logit Models of the Likelihood that a Job Applicant Receives a Callback at a Democratic Firm, Matched Applicants, Odds Ratios (OR) Displayed

	Pr{Applicant Receives Callback}			
	(1)	(2)	(3)	(4)
Applicant Partisan Matching				
Mismatched Partisan	0.220**	0.222**	0.224**	0.227**
Neutral Applicant	0.630	0.639	0.643	0.651
(Ref: Matched Partisan)				
Applicant Prestige				
High Prestige	1.941+	2.032+	2.002+	1.917
(Ref: Republican Firm)				
Job Type				
MS: Computer Scientist		0.822	0.812	0.791
(Ref: Lower Prestige)				
MBA: Analyst or Manager		1.860	1.842	1.655
Region				
Midwest				0.770
(Ref: Ph.D. Data Scienctist-Quant)				
South				1.201
West Coast				0.590
Experiment Features				
Received Order: Second			0.909	0.909
(Ref: East Coast)				
Resume Version: B			0.924	0.929
Experiment Wave: Second Wave			0.606	0.571
Constant	0.170***	0.143***	0.166***	0.206**
N	318	318	318	318
Log Likelihood	-114.287	-112.573	-112.175	-110.960
AIC	236.573	237.147	242.350	245.919

Notes: N = 318. Democratic firms only. Matched applicants are those applicants who applied to a firm where the partisanship of the firm could be determined, resulting in three match conditions (mismatch, neutral, and match) based on the partisanship of the firm (Democratic or Republican) and the partisanship of the test applicant (Democratic or Republican) and control applicant (Neutral).
+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Table C.3: Logit Models of the Likelihood that a Job Applicant Receives a Callback, Matched Applicants, OR Displayed, Deduplicated Firms

	Pr{Applicant Receives Callback}			
	(1)	(2)	(3)	(4)
Applicant Partisan Matching				
Mismatched Partisan	0.173***	0.175***	0.166***	0.166***
Neutral Applicant	0.525*	0.530*	0.513*	0.515*
(Ref: Matched Partisan)				
Firm Partisanship				
Democratic Firm	2.058**	2.057**	1.905*	2.323**
(Ref: Republican Firm)				
Applicant Prestige				
High Prestige	1.483	1.494	1.428	1.496
(Ref: Lower Prestige)				
Job Type				
MS: Computer Scientist		0.821	0.819	0.792
MBA: Analyst or Manager		0.831	0.883	0.820
(Ref: Ph.D. Data Scienctist-Quant)				
Region				
Midwest				1.271
South				1.019
West Coast				0.528
(Ref: East Coast)				
Experiment Features				
Received Order: Second			1.111	1.120
Resume Version: B			1.111	1.119
Experiment Wave: Second Wave			0.448+	0.460+
Constant	0.118***	0.128***	0.138***	0.131***
N	646	646	646	646
Log Likelihood	-207.748	-207.478	-205.421	-203.165
AIC	425.495	428.956	430.841	432.331

Notes: N = 646. Matched applicants are those applicants who applied to a firm where the partisanship of the firm could be determined, resulting in three match conditions (mismatch, neutral, and match) based on the partisanship of the firm (Democratic or Republican) and the partisanship of the test applicant (Democratic or Republican) and control applicant (Neutral). Only unique, deduplicated firms included. Although the original models include unique applicant pairs, because of errors in deduplicating list-ids, several firms received more than one pair of applications for different open positions to different firm contacts. These cases were removed from these models.
+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Table C.4: Logit Models of the Likelihood that a Job Applicant Receives a Callback, Matched Applicants, OR Displayed, Neutral Reference Group

	Pr{Applicant Receives Callback}			
	(1)	(2)	(3)	(4)
Applicant Partisan Matching				
Mismatched Partisan	0.328**	0.330**	0.322**	0.320**
Matched Partisan	1.915*	1.900*	1.974*	1.966*
(Ref: Neutral Applicant)				
Firm Partisanship				
Democratic Firm	2.052**	2.054**	1.901*	2.341**
(Ref: Republican Firm)				
Applicant Prestige				
High Prestige	1.480	1.489	1.415	1.477
(Ref: Lower Prestige)				
Job Type				
MS: Computer Scientist		0.818	0.819	0.786
MBA: Analyst or Manager		0.830	0.891	0.827
(Ref: Ph.D. Data Scienctist-Quant)				
Region				
Midwest				1.279
South				1.028
West Coast				0.521+
(Ref: East Coast)				
Experiment Features				
Received Order: Second			1.116	1.124
Resume Version: B			1.109	1.117
Experiment Wave: Second Wave			0.420+	0.434+
Constant	0.061***	0.067***	0.070***	0.067***
N	658	658	658	658
Log Likelihood	-209.025	-208.748	-206.332	-203.976
AIC	428.049	431.496	432.663	433.952

Notes: N = 658. Matched applicants are those applicants who applied to a firm where the partisanship of the firm could be determined, resulting in three match conditions (mismatch, neutral, and match) based on the partisanship of the firm (Democratic or Republican) and the partisanship of the test applicant (Democratic or Republican) and control applicant (Neutral).
+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001

APPENDIX D

Appendix Chapter 4: Additional Tables and Figures

D.1 Expanding on the Matching Measures of Partisanship to Board Members

To elaborate on the method described in the main paper, I iteratively perform a series of successive joins between the ISS and either the FEC-CP or one of the two DIME-AOI datasets using discrete join methods. This method has the added benefit of explicitly matching individuals. In the majority of cases, the join includes the full name and firm. In total, I utilize twenty discrete join methods.

In brief, this method works as follows. First I attempt an inner join between the ISS and given dataset (FEC-CP, DM1, DM2) on a specified set of left and right join columns and drop all rows not joined on the right side. Once the first join is performed, I perform an anti-join between the original dataset and the latest join. That is, I isolate all rows in the ISS that were not found in the most recent join. Subsequently, the process repeats using a different join method. In total, 20 discrete merge methods are performed. The majority of these joins occur using a company id and some version of the full name, including variations of a full name as a single column or combinations of the full name from first and last name columns. Similarly, most joins first try to find the individual using the primary company id in the ISS data. However, a handful of individuals have a second company at which they are employed. Methods 1-9 rely on the primary company id. Methods 10-18 rely upon the alternative id. These joins mirror joins 1-9 but use the alternative company id instead. The last two joins capitalize on a general search using the DIME-AOI datasets.

According to Bonica (2016), DIME-AOI data only contains board members at Fortune

Table D.1: Summary Matched Partisans by Source and Join: Measure, Fixed-Party

Merge Type	Partisan Data	Left Columns	Right Columns	Count
1A	FEC-CPD	'cid_master', 'fullname_clean_pure'	'cid_master', 'fullname_fec'	$7,977$
1B	FEC-CPD	'cid_master', 'fullname_clean_simple'	'cid_master', 'fullname_fec'	0
1C	FEC-CPD	'cid_master', 'fullname_clean_nickname'	'cid_master', 'fullname_fec'	1
1D	FEC-CPD	'cid_master', 'fullname_clean'	'cid_master', 'fullname_fec'	0
1E	FEC-CPD	'cid_master', 'first_name_clean', 'last_name_clean'	'cid_master', 'full_first', 'last'	0
2A	DM2	'ticker', 'last_name_clean', 'first_name_clean'	'ticker', 'contributor.lname_clean', 'contributor.fname_clean'	$11,242$
2B	DM2	'ticker', 'last_name_clean'	'ticker', 'contributor.lname_clean'	594
3A	DM1	'ticker', 'last_name_clean', 'first_name_clean'	'ticker', 'last.name_clean', 'first.name_clean'	$6,462$
3B	DM1	'ticker', 'last_name_clean'	'ticker', 'last.name_clean'	736
1A (Alt)	FEC-CPD	'alt_cid_master', 'fullname_clean_pure'	'cid_master', 'fullname_fec'	463
1B (Alt)	FEC-CPD	'alt_cid_master', 'fullname_clean_simple'	'cid_master', 'fullname_fec'	0
1C (Alt)	FEC-CPD	'alt_cid_master', 'fullname_clean_nickname'	'cid_master', 'fullname_fec'	1
1D (Alt)	FEC-CPD	'alt_cid_master', 'fullname_clean'	'cid_master', 'fullname_fec'	0
1E (Alt)	FEC-CPD	'alt_cid_master', 'first_name_clean', 'last_name_clean'	'cid_master', 'full_first', 'last'	0
2A (Alt)	DM2	'alt_ticker', 'last_name_clean', 'first_name_clean'	'ticker', 'contributor.lname_clean', 'contributor.fname_clean'	11
2B (Alt)	DM2	'alt_ticker', 'last_name_clean'	'ticker', 'contributor.lname_clean'	0
3A (Alt)	DM1	'alt_ticker', 'last_name_clean', 'first_name_clean'	'ticker', 'last.name_clean', 'first.name_clean'	8
3B (Alt)	DM1	'alt_ticker', 'last_name_clean'	'ticker', 'last.name_clean'	0
2A (Gen)	DM2	'last_name_clean', 'first_name_clean'	'contributor.lname_clean', 'contributor.fname_clean'	$1,667$
3A (Gen)	DM1	'last_name_clean', 'first_name_clean'	'last.name_clean', 'first.name_clean'	197

Notes: All joins are inner joins between the left-side ISS dataset and a right-side partisan dataset denoted in the table. For each join left and right columns are indicated. Joins performed for analyses using the *party* measure.

500 companies, and based on our knowledge of board networks (Chu and Davis 2011, 2016), board members often serve on the boards of multiple firms. Following this premise, board members in the ISS not yet found in the prior 18 joins, were generally searched for among the DM1, and DM2 datasets using the full name (first and last name) without regard for the given company limitation. Table D.1 further describes the joins that occur for the party measure. In first creating the joins for the *party measure*, the FEC-CP, DM1, and DM2 were (1) loaded for the set of possible join columns, as well as the party measure, (2) deduplicated, and (3) had NA values dropped in all columns except the party measure.

This process resulted in a certain allocation of joins from each method and dataset in an optimized order. To best replicate this method when performing the joins by cycle, a special series of prior joins was performed on the FEC, DM1, and DM2 data, such that each deduplicated identity X firm X cycle observation inherited additional rows for each election cycle in the ISS data (2008-2018). In this way, the FEC, DM1, and DM2 datasets each had not only all years natively found in those datasets but also every year in the ISS, where those cycles may or may not intersect. Ostensibly, this method initially results in a number of missing party-cycle observations, which are then imputed (grouped by individual and firm) using the aforementioned two-phase forward-fill, back-fill method. When this data is then joined with the ISS, we have a full range of cycles for each identity. In this way, applying the same series of merge methods (but additionally joining on election cycle) results in a similar allocation of observations from each dataset for the various methods (Table D.2).

Table D.2: Summary Matched Partisans by Source and Join: Measure, Party-Cycle

Merge Type	Partisan Data	Left Columns	Right Columns	Count
1A	FEC-CPD	'cid__master', 'fullname__clean__pure', 'cycle'	'cid__master', 'fullname__fec', 'cycle'	$7,949$
1B	FEC-CPD	'cid__master', 'fullname__clean__simple', 'cycle'	'cid__master', 'fullname__fec', 'cycle'	0
1C	FEC-CPD	'cid__master', 'fullname__clean__nickname', 'cycle'	'cid__master', 'fullname__fec', 'cycle'	1
1D	FEC-CPD	'cid__master', 'fullname__clean', 'cycle'	'cid__master', 'fullname__fec', 'cycle'	0
1E	FEC-CPD	'cid__master', 'first__name__clean', 'last__name__clean', 'cycle'	'cid__master', 'full__first', 'last', 'cycle'	0
2A	DM2	'ticker', 'last__name__clean', 'first__name__clean', 'cycle'	'ticker', 'contributor.lname__clean', 'contributor.fname__clean', 'cycle'	$11,235$
2B	DM2	'ticker', 'last__name__clean', 'cycle'	'ticker', 'contributor.lname__clean', 'cycle'	594
3A	DM1	'ticker', 'last__name__clean', 'first__name__clean'	'ticker', 'last.name__clean', 'first.name__clean'	$6,490$
3B	DM1	'ticker', 'last__name__clean'	'ticker', 'last.name__clean'	743
1A (Alt)	FEC-CPD	'alt__cid__master', 'fullname__clean__pure', 'cycle'	'cid__master', 'fullname__fec', 'cycle'	462
1B (Alt)	FEC-CPD	'alt__cid__master', 'fullname__clean__simple', 'cycle'	'cid__master', 'fullname__fec', 'cycle'	0
1C (Alt)	FEC-CPD	'alt__cid__master', 'fullname__clean__nickname', 'cycle'	'cid__master', 'fullname__fec', 'cycle'	1
1D (Alt)	FEC-CPD	'alt__cid__master', 'fullname__clean', 'cycle'	'cid__master', 'fullname__fec', 'cycle'	0
1E (Alt)	FEC-CPD	'alt__cid__master', 'first__name__clean', 'last__name__clean', 'cycle'	'cid__master', 'full__first', 'last', 'cycle'	0
2A (Alt)	DM2	'alt__ticker', 'last__name__clean', 'first__name__clean', 'cycle'	'ticker', 'contributor.lname__clean', 'contributor.fname__clean', 'cycle'	11
2B (Alt)	DM2	'alt__ticker', 'last__name__clean', 'cycle'	'ticker', 'contributor.lname__clean', 'cycle'	0
3A (Alt)	DM1	'alt__ticker', 'last__name__clean', 'first__name__clean'	'ticker', 'last.name__clean', 'first.name__clean'	8
3B (Alt)	DM1	'alt__ticker', 'last__name__clean'	'ticker', 'last.name__clean'	0
2A (Gen)	DM2	'last__name__clean', 'first__name__clean'	'contributor.lname__clean', 'contributor.fname__clean'	$1,667$
3A (Gen)	DM1	'last__name__clean', 'first__name__clean'	'last.name__clean', 'first.name__clean'	197

Notes: All joins are inner joins between the left-side ISS dataset and a right-side partisan dataset denoted in the table. For each join left and right columns are indicated. Joins performed for analyses using the *party__cycle* measure.

Table D.3: Descriptive Statistics, Board Member Events, 2007-2018: Party-Cycle, Only Known Partisans Subset

	1-Year Lag	2-Year Lag	2-4-Year Lags	All-Year Lags
Board Events				
Add	644 (33.11%)	754 (26.79%)	2,238 (22.92%)	5,769 (19.66%)
Drop	689 (35.42%)	802 (28.50%)	2,404 (24.62%)	6,238 (21.26%)
Swap	612 (31.47%)	1,258 (44.71%)	5,123 (52.46%)	17,333 (59.08%)
Equal Swap	386 (19.85%)	736 (26.15%)	3,000 (30.72%)	10,230 (34.87%)
Unequal Swap	226 (11.62%)	522 (18.55%)	2,123 (21.74%)	7,103 (24.21%)
New Board Members				
Republicans	810 (64.49%)	1,317 (65.46%)	4,941 (67.12%)	15,804 (68.41%)
Democrats	446 (35.51%)	695 (34.54%)	2,420 (32.88%)	7,298 (31.59%)
Dropped Board Members				
Republicans	820 (63.03%)	1,289 (62.57%)	4,623 (61.42%)	14,251 (60.46%)
Democrats	481 (36.97%)	771 (37.43%)	2,904 (38.58%)	9,320 (39.54%)
Event Match				
Match	1,127 (57.94%)	1,744 (61.98%)	6,285 (64.36%)	19,625 (66.89%)
Unmatched	818 (42.06%)	1,070 (38.02%)	3,480 (35.64%)	9,715 (33.11%)
Board-Level Metrics (Mean)				
Median Age	62.99 ± 3.45	63.11 ± 3.39	63.19 ± 3.37	63.11 ± 3.36
Female Proportion	0.20 ± 0.09	0.20 ± 0.09	0.21 ± 0.09	0.22 ± 0.09
Black / Hispanic Proportion	0.12 ± 0.09	0.12 ± 0.09	0.12 ± 0.09	0.13 ± 0.09
Minority Proportion	0.20 ± 0.17	0.19 ± 0.16	0.17 ± 0.13	0.17 ± 0.12
Non-USA Proportion	0.04 ± 0.06	0.03 ± 0.06	0.03 ± 0.06	0.03 ± 0.05
Board Size	11.48 ± 2.15	11.40 ± 2.04	11.37 ± 1.99	11.36 ± 1.98
Median Outside Board Ties	1.01 ± 0.55	1.00 ± 0.54	1.01 ± 0.54	0.99 ± 0.53
Board Party X Events				
Democratic Board	470 (24.16%)	655 (23.28%)	2,122 (21.73%)	5,982 (20.39%)
Republican Board	1,475 (75.84%)	2,159 (76.72%)	7,643 (78.27%)	23,358 (79.61%)
Firm Party X Events				
Polarized Democratic	185 (12.46%)	240 (11.24%)	850 (11.34%)	2,568 (11.29%)
Amphibious Firm	966 (65.05%)	1,407 (65.90%)	4,922 (65.67%)	14,975 (65.86%)
Polarized Republican	334 (22.49%)	488 (22.86%)	1,723 (22.99%)	5,193 (22.84%)
U.S. Presidential Party				
Democrat	1,440 (74.04%)	2,234 (79.39%)	7,444 (76.23%)	17,698 (60.32%)
Republican	505 (25.96%)	580 (20.61%)	2,321 (23.77%)	11,642 (39.68%)
Observations				
N	1945	2814	9765	29340
Firms	271	269	270	271
Sectors	14	14	14	14
Years	11	10	10	11
Lag Years	1	1	3	11
Time Period and Lags				
Year Range	2008, 2018	2009, 2018	2009, 2018	2008, 2018
Years Included (w/lag)	2007, 2018	2007, 2018	2007, 2018	2007, 2018
Lag Range	1, 1	2, 2	2, 4	1, 11

Notes: Descriptive statistics calculated for discrete lag years. That is, each column uses a discrete set of year lag(s) as follows: 1-year lag, 2-year lag, 2-4-year lags, and 1-11 (all) year lags. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles. All events with an unknown board member party in either the incoming or outgoing board member were dropped. This is the same approach taken in Figure 4.1.

Table D.4: Descriptive Statistics, Board Member Events, 2007-2018: Party-Cycle, Formal Models Subset

	1-Year Lag	2-Year Lag	2-4-Year Lags	All-Year Lags
Board Events				
Add	644 (39.32%)	754 (27.24%)	2,238 (21.75%)	5,769 (17.73%)
Swap	994 (60.68%)	2,014 (72.76%)	8,052 (78.25%)	26,764 (82.27%)
Equal Swap	386 (23.57%)	736 (26.59%)	3,000 (29.15%)	10,230 (31.44%)
Unequal Swap	608 (37.12%)	1,278 (46.17%)	5,052 (49.10%)	16,534 (50.82%)
New Board Members				
Republicans	1,055 (64.41%)	1,807 (65.28%)	6,924 (67.29%)	22,484 (69.11%)
Democrats	583 (35.59%)	961 (34.72%)	3,366 (32.71%)	10,049 (30.89%)
Dropped Board Members				
Republicans	380 (38.23%)	789 (39.18%)	3,141 (39.01%)	10,508 (39.26%)
Democrats	232 (23.34%)	469 (23.29%)	1,982 (24.62%)	6,825 (25.50%)
Unknown	382 (38.43%)	756 (37.54%)	2,929 (36.38%)	9,431 (35.24%)
Event Match				
Match	1,149 (70.15%)	1,990 (71.89%)	7,519 (73.07%)	24,311 (74.73%)
Unmatched	489 (29.85%)	778 (28.11%)	2,771 (26.93%)	8,222 (25.27%)
Board-Level Metrics (Mean)				
Median Age	62.77 ± 3.38	62.89 ± 3.32	63.01 ± 3.30	63.07 ± 3.29
Female Proportion	0.19 ± 0.09	0.20 ± 0.09	0.20 ± 0.09	0.22 ± 0.09
Black / Hispanic Proportion	0.11 ± 0.08	0.12 ± 0.08	0.12 ± 0.09	0.13 ± 0.09
Minority Proportion	0.21 ± 0.18	0.19 ± 0.16	0.17 ± 0.13	0.17 ± 0.12
Non-USA Proportion	0.04 ± 0.07	0.04 ± 0.06	0.03 ± 0.06	0.03 ± 0.05
Board Size	11.82 ± 2.13	11.70 ± 2.01	11.60 ± 1.96	11.55 ± 1.92
Median Outside Board Ties	1.01 ± 0.56	0.99 ± 0.54	1.00 ± 0.55	0.99 ± 0.54
Board Party X Events				
Democratic Board	416 (25.40%)	671 (24.24%)	2,297 (22.32%)	6,573 (20.20%)
Republican Board	1,222 (74.60%)	2,097 (75.76%)	7,993 (77.68%)	25,960 (79.80%)
Firm Party X Events				
Polarized Democratic	141 (11.30%)	218 (10.39%)	796 (10.18%)	2,584 (10.38%)
Amphibious Firm	818 (65.54%)	1,406 (67.02%)	5,222 (66.79%)	16,536 (66.41%)
Polarized Republican	289 (23.16%)	474 (22.59%)	1,801 (23.03%)	5,779 (23.21%)
U.S. Presidential Party				
Democrat	1,236 (75.46%)	2,350 (84.90%)	8,457 (82.19%)	20,932 (64.34%)
Republican	402 (24.54%)	418 (15.10%)	1,833 (17.81%)	11,601 (35.66%)
Observations				
N	1638	2768	10290	32533
Firms	269	269	269	269
Sectors	14	14	14	14
Years	11	10	10	11
Lag Years	1	1	3	11
Time Period and Lags				
Year Range	2008, 2018	2009, 2018	2009, 2018	2008, 2018
Years Included (w/lag)	2007, 2018	2007, 2018	2007, 2018	2007, 2018
Lag Range	1, 1	2, 2	2, 4	1, 11

Notes: Descriptive statistics calculated for discrete lag years. That is, each column uses a discrete set of year lag(s) as follows: 1-year lag, 2-year lag, 2-4-year lags, and 1-11 (all) year lags. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles. All events with an unknown board member party in the incoming board member were dropped, but unknown outgoing board party members were retained, which is the same approach adopted in the formal models as well as Figure 4.2.

D.2 Supplemental Figures

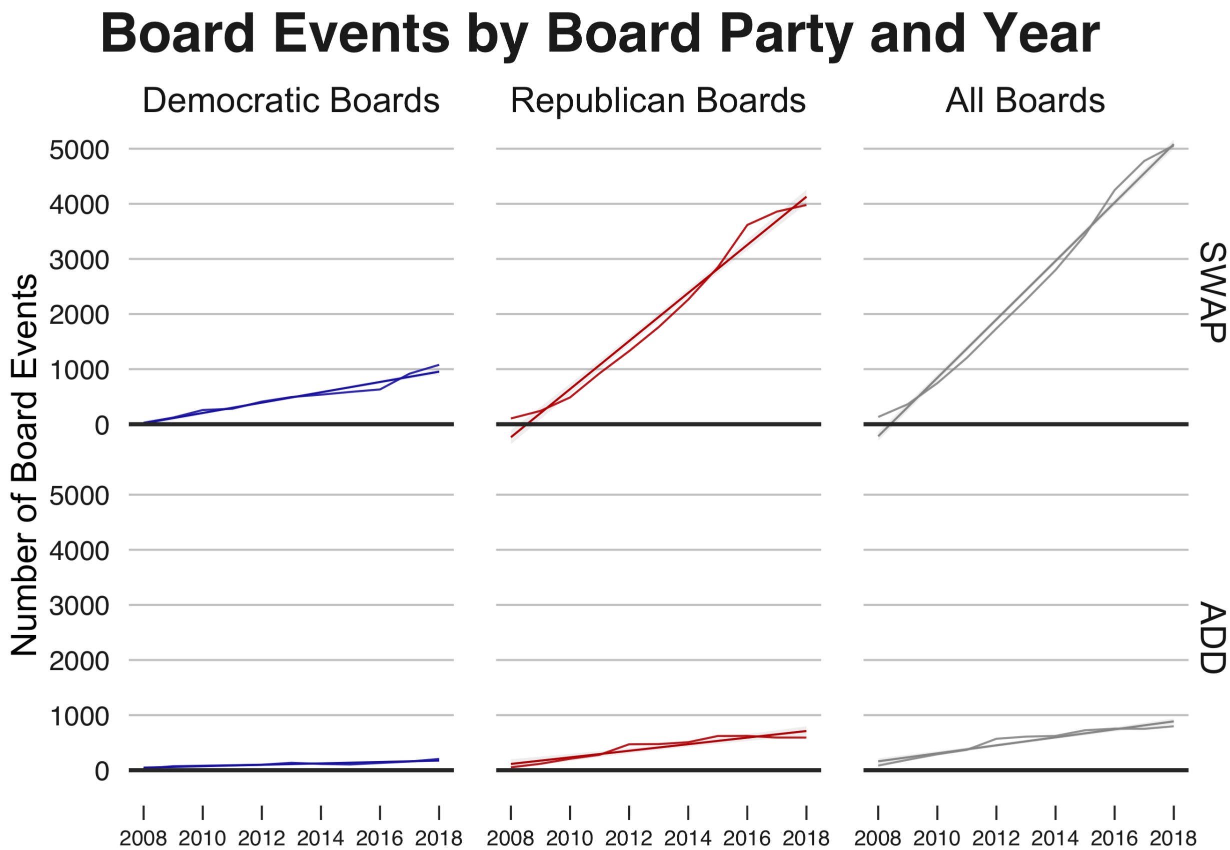


Figure D.1: Yearly Board Member Events by Event Type and Board Party

Notes: Figure generated using all lags (1-year, 11-year) included. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles. In the plot, we can see to the number of board events for swaps and additions. All events with an unknown board member party in the incoming board member were dropped, but unknown outgoing board party members were retained, which is the same approach adopted in the formal models. In the subplots, the yearly figure is plotted along with a GLM trend line and confidence interval calculated in R.

D.3 Additional CCRE Logistic Regression Models Using both the Time-Varying Party-Cycle Measure and the Fixed-Party Measure

Similar to the analysis in the main paper, the following models similarly utilize the *party-cycle* measure, which has the opportunity to change over time for individual board members, at least for those matched using either the FEC-CPD or DM2 datasets, as shown in Table D.2. Importantly, these tables exemplify that the effects found in the primary paper are not simply artifacts of including multiple lag-years, but instead similarly emerge when looking at a single lag-year definition in isolation. In this case, I include both a 1-year lag and a 2-year lag for comparison. To reiterate an earlier point, a 1-year lag means that board-event calculations capture change over a two-year period where those years are consecutive, for example, the changes between a firm's board in 2007 and a firm's board in 2008. By contrast, although a two-year lag also measures changes using two board-years, a two-year gap (versus a one-year gap) exists in calculating board events. To continue the example, a two-year lag would capture differences between a firm's board in 2007 and that firm's board in 2009. Beyond additional models showing the one-year or two-year lag, I also include additional models utilizing an alternative reference group for the partisanship of the board, that is, a reference group of a Republican board instead of a Democratic board. Otherwise, these models mirror those in the main analysis. I also include a simpler set of models with the same covariate parameterization but discrete lag-year periods. Lastly, I include a parallel set of models, which instead use the *fixed-party* measure instead of the variable *party-cycle* measure.

Table D.5: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Republican, 1-Year Lag, Odds Ratios (OR) Displayed

	Pr{New Board Member: Republican}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	1.110	1.115	1.012	0.969
Board Member Equal Swap	1.512**	1.531**	1.373	1.356
Republican Board	4.238***	4.333***	3.642***	3.583***
Democratic Firm			0.984	1.027
Republican Firm			1.698**	1.529*
Board Features				
Board Size (Log)		0.988	1.397	1.543
Median Age (Log)		3.806	3.557	2.985
Proportion Female		1.244	1.131	1.392
Proportion Black or Hispanic		1.130		1.314
Proportion Minority			0.402*	0.490
Proportion Non-US				0.352
Median Outside Board Ties		0.982	0.916	0.889
Firm Sectors				
Capital Goods				1.039
Conglomerates				0.266
Consumer Cyclical				0.348*
Consumer Goods				0.795
Consumer/Non-Cyclical				0.712
Energy				0.578
Financial				0.490
Healthcare				0.597
Services				0.477
Technology				0.412*
Transportation				0.495
Utilities				0.605
Other Features				
U.S. President (Democrat)		1.329*	1.233	1.201
Constant	0.576***	0.002	0.002	0.005
Level-2 Random Intercepts				
Firm Variance	0.126	0.113	0.106	0.04
Year Variance	0.021	0.003	0	0
N	1,638	1,638	1,248	1,222
Firms	269	269	204	197
Years	11	11	11	11
Log Likelihood	-981.837	-979.260	-739.202	-713.009
AIC	1,975.674	1,982.520	1,506.404	1,482.018
BIC	2,008.082	2,047.335	1,578.214	1,625.048

Notes: Cross-classified random effects (CCRE) logistic regression model with fixed 1-year lag. Cross-classified random intercepts include firm and year. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.6: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Democrat, 1-Year Lag, Odds Ratios (OR) Displayed

	Pr{New Board Member: Democrat}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	0.901	0.897	0.988	1.032
Board Member Equal Swap	0.661**	0.653**	0.728	0.737
Republican Board	0.236***	0.231***	0.275***	0.279***
Democratic Firm			1.016	0.974
Republican Firm			0.589**	0.654*
Board Features				
Board Size (Log)		1.012	0.716	0.648
Median Age (Log)		0.263	0.281	0.333
Proportion Female		0.804	0.884	0.718
Proportion Black or Hispanic		0.885		0.761
Proportion Minority			2.489*	2.042
Proportion Non-US				2.837
Median Outside Board Ties		1.018	1.091	1.125
Firm Sectors				
Capital Goods				0.962
Conglomerates				3.765
Consumer Cyclical				2.873*
Consumer Goods				1.258
Consumer/Non-Cyclical				1.404
Energy				1.730
Financial				2.039
Healthcare				1.674
Services				2.098
Technology				2.429*
Transportation				2.020
Utilities				1.652
Other Features				
U.S. President (Democrat)		0.753*	0.811	0.833
Constant	1.735***	563.757	639.359	212.550
Level-2 Random Intercepts				
Firm Variance	0.126	0.113	0.106	0.04
Year Variance	0.021	0.003	0	0
N	1,638	1,638	1,248	1,222
Firms	269	269	204	197
Years	11	11	11	11
Log Likelihood	-981.837	-979.260	-739.202	-713.009
AIC	1,975.674	1,982.520	1,506.404	1,482.018
BIC	2,008.082	2,047.335	1,578.214	1,625.048

Notes: Cross-classified random effects (CCRE) logistic regression model with fixed 1-year lag. Cross-classified random intercepts include firm and year. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.7: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Republican, 2-Year Lag, OR Displayed

	Pr{New Board Member: Republican}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	1.359**	1.382**	1.419**	1.426**
Board Member Equal Swap	1.901***	1.904***	1.879***	1.853***
Republican Board	5.253***	5.307***	4.915***	4.856***
Democratic Firm			1.013	1.047
Republican Firm			1.423	1.295
Board Features				
Board Size (Log)		0.817	0.916	0.861
Median Age (Log)		1.365	2.278	2.483
Proportion Female		1.533	1.696	1.969
Proportion Black or Hispanic		0.846		2.036
Proportion Minority			0.401*	0.408*
Proportion Non-US				0.288
Median Outside Board Ties		1.026	0.965	0.934
Firm Sectors				
Capital Goods				1.772
Conglomerates				0.667
Consumer Cyclical				0.566
Consumer Goods				0.852
Consumer/Non-Cyclical				0.806
Energy				0.613
Financial				0.588
Healthcare				0.746
Services				0.645
Technology				0.571
Transportation				0.605
Utilities				0.942
Other Features				
U.S. President (Democrat)		1.087	1.030	0.995
Constant	0.470***	0.179	0.020	0.024
Level-2 Random Intercepts				
Firm Variance	0.539	0.534	0.521	0.449
Year Variance	0.024	0.022	0.007	0
N	2,768	2,768	2,098	2,057
Firms	269	269	205	198
Years	10	10	10	10
Log Likelihood	-1,577.552	-1,577.046	-1,187.561	-1,152.853
AIC	3,167.103	3,178.092	2,403.122	2,361.706
BIC	3,202.659	3,249.202	2,482.204	2,519.319

Notes: Cross-classified random effects (CCRE) logistic regression model with fixed 2-year lag. Cross-classified random intercepts include firm and year. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.8: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Democrat, 2-Year Lag, OR Displayed

	Pr{New Board Member: Democrat}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	0.736**	0.724**	0.705**	0.701**
Board Member Equal Swap	0.526***	0.525***	0.532***	0.540***
Republican Board	0.190***	0.188***	0.203***	0.206***
Democratic Firm			0.987	0.955
Republican Firm			0.703	0.772
Board Features				
Board Size (Log)		1.225	1.091	1.161
Median Age (Log)		0.733	0.439	0.400
Proportion Female		0.652	0.590	0.508
Proportion Black or Hispanic		1.182		0.491
Proportion Minority			2.497*	2.452*
Proportion Non-US				3.468
Median Outside Board Ties		0.975	1.036	1.071
Firm Sectors				
Capital Goods				0.565
Conglomerates				1.500
Consumer Cyclical				1.766
Consumer Goods				1.173
Consumer/Non-Cyclical				1.240
Energy				1.632
Financial				1.700
Healthcare				1.341
Services				1.551
Technology				1.752
Transportation				1.654
Utilities				1.062
Other Features				
U.S. President (Democrat)		0.920	0.971	1.005
Constant	2.127***	5.597	49.199	41.977
Level-2 Random Intercepts				
Firm Variance	0.539	0.534	0.521	0.449
Year Variance	0.024	0.022	0.007	0
N	2,768	2,768	2,098	2,057
Firms	269	269	205	198
Years	10	10	10	10
Log Likelihood	-1,577.552	-1,577.046	-1,187.561	-1,152.853
AIC	3,167.103	3,178.092	2,403.122	2,361.706
BIC	3,202.659	3,249.202	2,482.204	2,519.318

Notes: Cross-classified random effects (CCRE) logistic regression model with fixed 2-year lag. Cross-classified random intercepts include firm and year. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.9: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Republican, 1-11-Year Lags, OR Displayed

	Pr{New Board Member: Republican}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	1.264***	1.269***	1.349***	1.352***
Board Member Equal Swap	1.713***	1.716***	1.696***	1.678***
Democratic Board	0.239***	0.246***	0.252***	0.260***
Democratic Firm			0.851	0.869
Republican Firm			1.678	1.383
Board Features				
Board Size (Log)		0.857	0.706*	0.680*
Median Age (Log)		0.441	1.023	1.186
Proportion Female		0.481*	0.478*	0.444*
Proportion Black or Hispanic		0.150***		0.357*
Proportion Minority			0.338***	0.429***
Proportion Non-US				1.301
Median Outside Board Ties		0.883**	0.916	0.932
Firm Sectors				
Capital Goods				3.360
Conglomerates				0.268
Consumer Cyclical				0.487
Consumer Goods				0.868
Consumer/Non-Cyclical				0.656
Energy				0.473
Financial				0.473
Healthcare				0.673
Services				0.614
Technology				0.578
Transportation				0.533
Utilities				0.929
Other Features				
U.S. President (Democrat)		1.052	0.959	0.924
Constant	3.077***	204.676**	8.915	9.631
Level-2 Random Intercepts				
Firm Variance	3.132	3.198	2.735	2.471
Year Variance	0.06	0.082	0.052	0.058
Lag-Year Variance	0	0	0	0
N	32,533	32,533	24,899	24,624
Firms	269	269	209	202
Years	11	11	11	11
Lag-Years	11	11	11	11
Log Likelihood	-15,382.530	-15,355.190	-11,838.270	-11,674.410
AIC	30,779.060	30,736.370	23,706.540	23,406.810
BIC	30,837.790	30,845.440	23,828.380	23,642.040

Notes: Cross-classified random effects (CCRE) logistic regression model, all lags (1-year, 11-year) included. Cross-classified random intercepts include firm, year, and lag-year. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.10: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Democrat, 1-11-Year Lags, OR Displayed

	Pr{New Board Member: Democrat}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	0.791***	0.788***	0.742***	0.740***
Board Member Equal Swap	0.584***	0.583***	0.590***	0.596***
Democratic Board	4.180***	4.071***	3.967***	3.848***
Democratic Firm			1.176	1.151
Republican Firm			0.596	0.723
Board Features				
Board Size (Log)		1.167	1.416*	1.470*
Median Age (Log)		2.267	0.977	0.843
Proportion Female		2.078*	2.094*	2.251*
Proportion Black or Hispanic		6.664***		2.798*
Proportion Minority			2.960***	2.333***
Proportion Non-US				0.769
Median Outside Board Ties		1.132**	1.092	1.073
Firm Sectors				
Capital Goods				0.298
Conglomerates				3.733
Consumer Cyclical				2.052
Consumer Goods				1.151
Consumer/Non-Cyclical				1.524
Energy				2.116
Financial				2.113
Healthcare				1.486
Services				1.630
Technology				1.729
Transportation				1.876
Utilities				1.076
Other Features				
U.S. President (Democrat)		0.951	1.042	1.083
Constant	0.325***	0.005**	0.112	0.104
Level-2 Random Intercepts				
Firm Variance	3.132	3.198	2.735	2.471
Year Variance	0.06	0.082	0.052	0.058
Lag-Year Variance	0	0	0	0
N	32,533	32,533	24,899	24,624
Firms	269	269	209	202
Years	11	11	11	11
Lag-Years	11	11	11	11
Log Likelihood	-15,382.530	-15,355.190	-11,838.270	-11,674.410
AIC	30,779.060	30,736.370	23,706.540	23,406.810
BIC	30,837.790	30,845.440	23,828.380	23,642.040

Notes: Cross-classified random effects (CCRE) logistic regression model, all lags (1-year, 11-year) included. Cross-classified random intercepts include firm, year, and lag-year. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.11: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Republican, Lag Year Sets, OR Displayed

	Pr{New Board Member: Republican}			
	1-2 Year Lags	1-4 Year Lags	1-6 Year Lags	1-8 Year Lags
	(1)	(2)	(3)	(4)
Board Member Added	1.238*	1.261***	1.244***	1.295***
Board Member Equal Swap	1.704***	1.713***	1.749***	1.740***
Republican Board	4.315***	4.280***	4.198***	4.084***
Democratic Firm	0.998	0.959	0.861	0.875
Republican Firm	1.571*	1.714*	1.800*	1.867*
Constant	0.548***	0.584**	0.605**	0.624**
Level-2 Random Intercepts				
Firm Variance	0.946	1.897	2.378	2.656
Year Variance	0.056	0.083	0.08	0.074
Lag Year Variance	0	0	0	0
N	3,346	9,067	15,373	20,852
Firms	206	208	209	209
Years	11	11	11	11
Lag Years	$[1, 2]$	$[1, 4]$	$[1, 6]$	$[1, 8]$
Log Likelihood	-1,870.259	-4,659.973	-7,534.939	-9,994.861
AIC	3,758.519	9,337.945	15,087.880	20,007.720
BIC	3,813.559	9,401.957	15,156.640	20,079.230

Notes: Cross-classified random effects (CCRE) logistic regression model with discrete multiyear lags. That is, each model uses a discrete set of year lags as follows: 1-2 year lags, 1-4 year lags, 1-6 year lags, and 1-8 year lags. Cross-classified random intercepts include firm, year, and lag years. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.12: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Democrat, Lag Year Sets, OR Displayed

	Pr{New Board Member: Democrat}			
	1-2 Year Lags	1-4 Year Lags	1-6 Year Lags	1-8 Year Lags
	(1)	(2)	(3)	(4)
Board Member Added	0.808*	0.793***	0.804***	0.772***
Board Member Equal Swap	0.587***	0.584***	0.572***	0.575***
Republican Board	0.232***	0.234***	0.238***	0.245***
Democratic Firm	1.002	1.042	1.162	1.143
Republican Firm	0.637*	0.584*	0.556*	0.536*
Constant	1.826***	1.713**	1.652**	1.601**
Level-2 Random Intercepts				
Firm Variance	0.946	1.897	2.378	2.656
Year Variance	0.056	0.083	0.08	0.074
Lag Year Variance	0	0	0	0
N	3,346	9,067	15,373	20,852
Firms	206	208	209	209
Years	11	11	11	11
Lag Years	$[1, 2]$	$[1, 4]$	$[1, 6]$	$[1, 8]$
Log Likelihood	-1,870.259	-4,659.973	-7,534.939	-9,994.861
AIC	3,758.519	9,337.945	15,087.880	20,007.720
BIC	3,813.559	9,401.957	15,156.640	20,079.230

Notes: Cross-classified random effects (CCRE) logistic regression model with discrete multiyear lags. That is, each model uses a discrete set of year lags as follows: 1-2 year lags, 1-4 year lags, 1-6 year lags, and 1-8 year lags. Cross-classified random intercepts include firm, year, and lag years. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.13: Descriptive Statistics of Analysis Data, Board Member Events, 2007-2018: Fixed-Party

	1-Year Lag	2-Year Lag	2-4-Year Lags	All-Year Lags
Board Events				
Add	1,105 (24.07%)	1,298 (20.78%)	3,842 (17.70%)	10,031 (14.98%)
Drop	1,075 (23.42%)	1,267 (20.28%)	3,747 (17.26%)	9,628 (14.38%)
Swap	1,760 (38.34%)	3,484 (55.78%)	13,855 (63.83%)	46,371 (69.27%)
Equal Swap	667 (14.53%)	1,242 (19.88%)	4,989 (22.99%)	17,294 (25.83%)
Unequal Swap	1,093 (23.81%)	2,242 (35.89%)	8,866 (40.85%)	29,077 (43.44%)
No Change	650 (14.16%)	197 (3.15%)	261 (1.20%)	913 (1.36%)
New Board Members				
Republicans	1,168 (40.77%)	1,989 (41.59%)	7,465 (42.18%)	23,909 (42.39%)
Democrats	470 (16.40%)	779 (16.29%)	2,825 (15.96%)	8,624 (15.29%)
Unknown	1,227 (42.83%)	2,014 (42.12%)	7,407 (41.85%)	23,869 (42.32%)
Dropped Board Members				
Republicans	1,217 (42.93%)	2,072 (43.61%)	7,788 (44.24%)	24,867 (44.41%)
Democrats	591 (20.85%)	1,000 (21.05%)	3,770 (21.42%)	12,002 (21.43%)
Unknown	1,027 (36.23%)	1,679 (35.34%)	6,044 (34.34%)	19,130 (34.16%)
Event Match				
Match	1,842 (46.75%)	2,816 (46.55%)	9,924 (46.28%)	30,247 (45.81%)
Unmatched	2,098 (53.25%)	3,233 (53.45%)	11,520 (53.72%)	35,783 (54.19%)
Missing	650 (14.16%)	197 (3.15%)	261 (1.20%)	913 (1.36%)
Board-Level Metrics (Mean)				
Median Age	62.97 ± 3.49	63.01 ± 3.41	63.05 ± 3.37	63.03 ± 3.32
Female Proportion	0.20 ± 0.09	0.20 ± 0.09	0.21 ± 0.09	0.22 ± 0.09
Black / Hispanic Proportion	0.11 ± 0.09	0.12 ± 0.09	0.12 ± 0.09	0.13 ± 0.09
Minority Proportion	0.20 ± 0.17	0.19 ± 0.15	0.17 ± 0.13	0.17 ± 0.12
Non-USA Proportion	0.03 ± 0.06	0.04 ± 0.06	0.03 ± 0.06	0.03 ± 0.06
Board Size	11.38 ± 2.12	11.40 ± 2.05	11.40 ± 2.00	11.38 ± 1.97
Median Outside Board Ties	0.99 ± 0.56	0.99 ± 0.55	0.99 ± 0.55	0.98 ± 0.54
Board Party X Events				
Democratic Board	837 (18.24%)	1,131 (18.11%)	3,844 (17.71%)	10,953 (16.36%)
Republican Board	3,753 (81.76%)	5,115 (81.89%)	17,861 (82.29%)	55,990 (83.64%)
Firm Party X Events				
Polarized Democratic	444 (13.39%)	556 (12.19%)	1,926 (12.06%)	5,917 (12.01%)
Amphibious Firm	2,143 (64.63%)	3,001 (65.78%)	10,485 (65.63%)	32,338 (65.62%)
Polarized Republican	729 (21.98%)	1,005 (22.03%)	3,565 (22.31%)	11,029 (22.38%)
U.S. Presidential Party				
Democrat	3,286 (71.59%)	4,840 (77.49%)	16,193 (74.60%)	39,258 (58.64%)
Republican	1,304 (28.41%)	1,406 (22.51%)	5,512 (25.40%)	27,685 (41.36%)
Observations				
N	4590	6246	21705	66943
Firms	274	273	273	274
Sectors	14	14	14	14
Years	11	10	10	11
Lag Years	1	1	3	11
Time Period and Lags				
Year Range	2008, 2018	2009, 2018	2009, 2018	2008, 2018
Years Included (w/lag)	2007, 2018	2007, 2018	2007, 2018	2007, 2018
Lag Range	1, 1	2, 2	2, 4	1, 11

Notes: Descriptive statistics calculated for discrete lag years. That is, each column uses a discrete set of year lag(s) as follows: 1-year lag, 2-year lag, 2-4-year lags, and 1-11 (all) year lags. Measure of board-member partisanship: *party*, which is fixed across election cycles.

Table D.14: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Republican, 1-Year Lag, Fixed-Party, OR Displayed

	Pr{New Board Member: Republican}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	1.420**	1.417*	1.299	1.279
Board Member Equal Swap	1.881***	1.885***	1.744**	1.853***
Republican Board	5.644***	5.691***	4.279***	4.462***
Democratic Firm			0.748	0.740
Republican Firm			1.866**	1.587*
Board Features				
Board Size (Log)		1.011	1.162	1.233
Median Age (Log)		1.074	5.760	6.602
Proportion Female		1.179	1.286	1.799
Proportion Black or Hispanic		0.420		0.650
Proportion Minority			0.661	0.749
Proportion Non-US				1.705
Median Outside Board Ties		1.011	0.919	0.874
Firm Sectors				
Capital Goods				1.007
Conglomerates				0.169
Consumer Cyclical				0.309*
Consumer Goods				0.605
Consumer/Non-Cyclical				0.621
Energy				0.606
Financial				0.527
Healthcare				0.571
Services				0.589
Technology				0.498
Transportation				0.350*
Utilities				0.635
Other Features				
U.S. President (Democrat)		1.265	1.171	1.127
Constant	0.496***	0.318	0.0003	0.0003
Level-2 Random Intercepts				
Firm Variance	0.065	0.075	0.014	0
Year Variance	0.002	0	0	0
N	1,638	1,638	1,248	1,222
Firms	269	269	204	197
Years	11	11	11	11
Log Likelihood	-890.108	-887.894	-678.226	-651.393
AIC	1,792.216	1,799.788	1,384.453	1,358.786
BIC	1,824.624	1,864.603	1,456.263	1,501.817

Notes: Cross-classified random effects (CCRE) logistic regression model with fixed 1-year lag. Cross-classified random intercepts include firm and year. Measure of board-member partisanship: *party*, which is fixed across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.15: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Democrat, 1-Year Lag, Fixed-Party, OR Displayed

	Pr{New Board Member: Democrat}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	0.704**	0.706*	0.770	0.782
Board Member Equal Swap	0.532***	0.531***	0.573**	0.540***
Republican Board	0.177***	0.176***	0.234***	0.224***
Democratic Firm			1.336	1.351
Republican Firm			0.536**	0.630*
Board Features				
Board Size (Log)		0.989	0.861	0.811
Median Age (Log)		0.932	0.174	0.151
Proportion Female		0.848	0.778	0.556
Proportion Black or Hispanic		2.382		1.539
Proportion Minority			1.512	1.335
Proportion Non-US				0.587
Median Outside Board Ties		0.989	1.088	1.144
Firm Sectors				
Capital Goods				0.993
Conglomerates				5.911
Consumer Cyclical				3.236*
Consumer Goods				1.653
Consumer/Non-Cyclical				1.609
Energy				1.651
Financial				1.897
Healthcare				1.751
Services				1.698
Technology				2.007
Transportation				2.859*
Utilities				1.576
Other Features				
U.S. President (Democrat)		0.791	0.854	0.887
Constant	2.016***	3.145	3,419.748	3,799.836
Level-2 Random Intercepts				
Firm Variance	0.065	0.075	0.014	0
Year Variance	0.002	0	0	0
N	1,638	1,638	1,248	1,222
Firms	269	269	204	197
Years	11	11	11	11
Log Likelihood	-890.108	-887.894	-678.226	-651.393
AIC	1,792.216	1,799.788	1,384.453	1,358.786
BIC	1,824.624	1,864.603	1,456.263	1,501.817

Notes: Cross-classified random effects (CCRE) logistic regression model with fixed 1-year lag. Cross-classified random intercepts include firm and year. Measure of board-member partisanship: *party*, which is fixed across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.16: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Republican, 2-Year Lag, Fixed-Party, OR Displayed

	Pr{New Board Member: Republican}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	1.486***	1.522***	1.443**	1.483**
Board Member Equal Swap	2.284***	2.303***	2.217***	2.302***
Republican Board	6.241***	6.274***	4.643***	4.615***
Democratic Firm			0.657	0.634
Republican Firm			1.953**	1.558
Board Features				
Board Size (Log)		0.767	0.855	0.791
Median Age (Log)		0.791	14.500*	18.971*
Proportion Female		1.978	2.372	2.718
Proportion Black or Hispanic		0.393		0.657
Proportion Minority			0.687	0.769
Proportion Non-US				0.908
Median Outside Board Ties		0.992	0.925	0.904
Firm Sectors				
Capital Goods				1.358
Conglomerates				0.432
Consumer Cyclical				0.445
Consumer Goods				0.618
Consumer/Non-Cyclical				0.889
Energy				0.602
Financial				0.522
Healthcare				0.507
Services				0.665
Technology				0.538
Transportation				0.378*
Utilities				0.911
Other Features				
U.S. President (Democrat)		1.117	0.989	0.920
Constant	0.489***	2.179	0.00001*	0.00001*
Level-2 Random Intercepts				
Firm Variance	0.681	0.703	0.528	0.478
Year Variance	0.002	0.002	0.004	0.002
N	2,768	2,768	2,098	2,057
Firms	269	269	205	198
Years	10	10	10	10
Log Likelihood	-1,439.578	-1,437.894	-1,100.955	-1,062.734
AIC	2,891.157	2,899.789	2,229.910	2,181.468
BIC	2,926.712	2,970.900	2,308.993	2,339.080

Notes: Cross-classified random effects (CCRE) logistic regression model with fixed 2-year lag. Cross-classified random intercepts include firm and year. Measure of board-member partisanship: *party*, which is fixed across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.17: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Democrat, 2-Year Lag, Fixed-Party, OR Displayed

	Pr{New Board Member: Democrat}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	0.673***	0.657***	0.693**	0.674**
Board Member Equal Swap	0.438***	0.434***	0.451***	0.434***
Republican Board	0.160***	0.159***	0.215***	0.217***
Democratic Firm			1.523	1.577
Republican Firm			0.512**	0.642
Board Features				
Board Size (Log)		1.304	1.168	1.264
Median Age (Log)		1.264	0.069*	0.052*
Proportion Female		0.506	0.416	0.368
Proportion Black or Hispanic		2.545		1.520
Proportion Minority			1.456	1.301
Proportion Non-US				1.102
Median Outside Board Ties		1.008	1.082	1.106
Firm Sectors				
Capital Goods				0.736
Conglomerates				2.316
Consumer Cyclical				2.247
Consumer Goods				1.618
Consumer/Non-Cyclical				1.124
Energy				1.660
Financial				1.915
Healthcare				1.972
Services				1.504
Technology				1.856
Transportation				2.643*
Utilities				1.098
Other Features				
U.S. President (Democrat)		0.895		1.087
Constant	2.046***	0.459	76,523.470*	108,935.000*
Level-2 Random Intercepts				
Firm Variance	0.681	0.703	0.528	0.478
Year Variance	0.002	0.002	0.005	0.002
N	2,768	2,768	2,098	2,057
Firms	269	269	205	198
Years	10	10	10	10
Log Likelihood	-1,439.578	-1,437.894	-1,100.957	-1,062.734
AIC	2,891.157	2,899.789	2,227.914	2,181.468
BIC	2,926.712	2,970.900	2,301.348	2,339.080

Notes: Cross-classified random effects (CCRE) logistic regression model with fixed 2-year lag. Cross-classified random intercepts include firm and year. Measure of board-member partisanship: *party*, which is fixed across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.18: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Republican, 1-11-Year Lags, Fixed-Party, OR Displayed

	Pr{New Board Member: Republican}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	1.338***	1.313***	1.403***	1.406***
Board Member Equal Swap	2.090***	2.092***	2.162***	2.177***
Republican Board	2.979***	2.864***	2.676***	2.636***
Democratic Firm			0.690	0.693
Republican Firm			5.168***	3.556**
Board Features				
Board Size (Log)		1.132	0.972	0.934
Median Age (Log)		0.330*	1.859	1.844
Proportion Female		0.553	0.707	0.668
Proportion Black or Hispanic		0.086***		0.147***
Proportion Minority			0.459***	0.730
Proportion Non-US				2.791*
Median Outside Board Ties		0.959	0.995	1.035
Firm Sectors				
Capital Goods				3.797
Conglomerates				0.246
Consumer Cyclical				0.263
Consumer Goods				0.563
Consumer/Non-Cyclical				1.989
Energy				0.419
Financial				0.394
Healthcare				0.486
Services				0.606
Technology				0.476
Transportation				0.348
Utilities				1.125
Other Features				
U.S. President (Democrat)		0.973	0.890	0.861
Constant	1.742**	210.047**	0.147	0.346
Level-2 Random Intercepts				
Firm Variance	6.148	6.224	4.79	4.319
Year Variance	0.009	0.018	0.008	0.018
Lag-Year Variance	0	0	0	0
N	32,533	32,533	24,899	24,624
Firms	269	269	209	202
Years	11	11	11	11
Lag-Years	11	11	11	11
Log Likelihood	-13,851.910	-13,822.500	-10,887.620	-10,698.570
AIC	27,717.830	27,670.990	21,805.240	21,455.130
BIC	27,776.560	27,780.060	21,927.080	21,690.370

Notes: Cross-classified random effects (CCRE) logistic regression model, all lags (1-year, 11-year) included. Cross-classified random intercepts include firm, year, and lag-year. Measure of board-member partisanship: *party*, which is fixed across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.19: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Democrat, 1-11-Year Lags, Fixed-Party, OR Displayed

	Pr{New Board Member: Democrat}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	0.747***	0.762***	0.712***	0.711***
Board Member Equal Swap	0.479***	0.478***	0.462***	0.459***
Republican Board	0.336***	0.349***	0.373***	0.379***
Democratic Firm			1.449	1.444
Republican Firm			0.194***	0.281**
Board Features				
Board Size (Log)		0.883	1.031	1.070
Median Age (Log)		3.032*	0.571	0.542
Proportion Female		1.809	1.376	1.498
Proportion Black or Hispanic		11.592***		6.786***
Proportion Minority			2.096***	1.369
Proportion Non-US				0.358*
Median Outside Board Ties		1.042	1.007	0.966
Firm Sectors				
Capital Goods				0.263
Conglomerates				4.061
Consumer Cyclical				3.809
Consumer Goods				1.777
Consumer/Non-Cyclical				0.503
Energy				2.390
Financial				2.540
Healthcare				2.059
Services				1.651
Technology				2.101
Transportation				2.875
Utilities				0.889
Other Features				
U.S. President (Democrat)		1.028		1.162
Constant	0.574**	0.005**	5.858	2.890
Level-2 Random Intercepts				
Firm Variance	6.148	6.224	4.788	4.319
Year Variance	0.009	0.018	0.013	0.018
Lag-Year Variance	0	0	0	0
N	32,533	32,533	24,899	24,624
Firms	269	269	209	202
Years	11	11	11	11
Lag-Years	11	11	11	11
Log Likelihood	-13,851.910	-13,822.500	-10,888.460	-10,698.570
AIC	27,717.830	27,670.990	21,804.920	21,455.130
BIC	27,776.560	27,780.060	21,918.640	21,690.370

Notes: Cross-classified random effects (CCRE) logistic regression model, all lags (1-year, 11-year) included. Cross-classified random intercepts include firm, year, and lag-year. Measure of board-member partisanship: *party*, which is fixed across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.20: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Republican, Lag Year Sets, Fixed-Party, OR Displayed

	Pr{New Board Member: Republican}			
	1-2 Year Lags	1-4 Year Lags	1-6 Year Lags	1-8 Year Lags
	(1)	(2)	(3)	(4)
Board Member Added	1.385**	1.314***	1.302***	1.366***
Board Member Equal Swap	2.049***	2.070***	2.162***	2.208***
Republican Board	4.902***	4.021***	3.363***	2.945***
Democratic Firm	0.706	0.735	0.666	0.685
Republican Firm	2.034**	3.076***	4.142***	4.891***
Constant	0.597**	0.829	1.034	1.172
Level-2 Random Intercepts				
Firm Variance	1.013	2.762	3.949	4.454
Year Variance	0.027	0.031	0.025	0.022
Lag Year Variance	0	0	0	0
N	3,346	9,067	15,373	20,852
Firms	206	208	209	209
Years	11	11	11	11
Lag Years	[1, 2]	[1, 4]	[1, 6]	[1, 8]
Log Likelihood	-1,724.902	-4,273.586	-6,905.128	-9,165.326
AIC	3,467.804	8,565.173	13,828.250	18,348.650
BIC	3,522.843	8,629.184	13,897.020	18,420.160

Notes: Cross-classified random effects (CCRE) logistic regression model with discrete multiyear lags. That is, each model uses a discrete set of year lags as follows: 1-2 year lags, 1-4 year lags, 1-6 year lags, and 1-8 year lags. Cross-classified random intercepts include firm, year, and lag years. Measure of board-member partisanship: *party*, which is fixed across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.21: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Democrat, Lag Year Sets, Fixed-Party, OR Displayed

	Pr{New Board Member: Democrat}			
	1-2 Year Lags	1-4 Year Lags	1-6 Year Lags	1-8 Year Lags
	(1)	(2)	(3)	(4)
Board Member Added	0.722**	0.761***	0.768***	0.732***
Board Member Equal Swap	0.488***	0.483***	0.463***	0.453***
Republican Board	0.204***	0.249***	0.297***	0.340***
Democratic Firm	1.416	1.361	1.501	1.461
Republican Firm	0.492**	0.325***	0.241***	0.204***
Constant	1.674**	1.206	0.967	0.854
Level-2 Random Intercepts				
Firm Variance	1.013	2.762	3.949	4.454
Year Variance	0.027	0.031	0.025	0.022
Lag Year Variance	0	0	0	0
N	3,346	9,067	15,373	20,852
Firms	206	208	209	209
Years	11	11	11	11
Lag Years	[1, 2]	[1, 4]	[1, 6]	[1, 8]
Log Likelihood	-1,724.902	-4,273.586	-6,905.128	-9,165.326
AIC	3,467.804	8,565.173	13,828.250	18,348.650
BIC	3,522.843	8,629.184	13,897.020	18,420.160

Notes: Cross-classified random effects (CCRE) logistic regression model with discrete multiyear lags. That is, each model uses a discrete set of year lags as follows: 1-2 year lags, 1-4 year lags, 1-6 year lags, and 1-8 year lags. Cross-classified random intercepts include firm, year, and lag years. Measure of board-member partisanship: *party*, which is fixed across election cycles.
*p < .05; **p < .01; ***p < .001

REFERENCES

Adams, Renée B. and Daniel Ferreira. 2009. "Women in the Boardroom and Their Impact on Governance and Performance." *Journal of Financial Economics* 94(2):291–309.

Altonji, Joseph G., Erica Blom, and Costas Meghir. 2012. "Heterogeneity in Human Capital Investments: High School Curriculum, College Major, and Careers." *Annual Review of Economics* 4(1):185–223.

An, Jisun, Daniele Quercia, and Jon Crowcroft. 2014. "Partisan Sharing: Facebook Evidence and Societal Consequences." Pp. 13–24 in *Proceedings of the second acm conference on online social networks*. New York, NY, USA: ACM. Retrieved (http://doi.acm.org/10.1145/2660460.2660469).

Ancona, Deborah Gladstein and David F. Caldwell. 1992. "Demography and Design: Predictors of New Product Team Performance." *Organization Science* 3(3):321–41.

Andrews, Kenneth T. 2004. *Freedom Is a Constant Struggle: The Mississippi Civil Rights Movement and Its Legacy*. Chicago: University of Chicago Press.

Andrews, Kenneth T. and Michael Biggs. 2006. "The Dynamics of Protest Diffusion: Movement Organizations, Social Networks, and News Media in the 1960 Sit-Ins." *American Sociological Review* 71(5):752–77.

Andrews, Kenneth T. and Neal Caren. 2010. "Making the News: Movement Organizations, Media Attention, and the Public Agenda." *American Sociological Review* 75(6):841–66.

Andris, Clio, David Lee, Marcus J. Hamilton, Mauro Martino, Christian E. Gunning, and John Armistead Selden. 2015. "The Rise of Partisanship and Super-Cooperators in the U.S. House of Representatives." *PLOS ONE* 10(4):1–14.

Bail, Christopher, Lisa Argyle, Taylor Brown, John Bumpuss, Haohan Chen, M.B. Fallin Hunzaker, Jaemin Lee, Marcus Mann, Friedolin Merhout, and Alexander Volfovsky. 2018. "Exposure to Opposing Views Can Increase Political Polarization: Evidence from a Large-Scale Field Experiment on Social Media." *SocArXiv*. Retrieved March 29, 2018 (10.17605/OSF.IO/4YGUX).

Baldassarri, Delia and Peter Bearman. 2007. "Dynamics of Political Polarization." *American Sociological Review* 72(5):784–811.

Baldassarri, Delia and Andrew Gelman. 2008. "Partisans Without Constraint: Political Polarization and Trends in American Public Opinion." *American Journal of Sociology* 114(2):408–46.

Baldassarri, Delia and Amir Goldberg. 2014. "Neither Ideologues nor Agnostics: Alternative Voters' Belief System in an Age of Partisan Politics." *American Journal of Sociology* 120(1):45–95.

Baltzell, E. Digby. 1958. *The Philadelphia Gentlemen*. Glencoe, IL: Free Press.

Baltzell, E. Digby. 1964. *The Protestant Establishment*. New York: Random House.

Barber, Michael and Jeremy C. Pope. 2019. "Does Party Trump Ideology? Disentangling Party and Ideology in America." *American Political Science Review* 113(1):38–54.

Barnett, William P. and Glenn R. Carroll. 1995. "Modeling Internal Organizational Change." *Annual Review of Sociology* 21:217–36.

Barrow, Lisa and Ofer Malamud. 2015. "Is College of Worthwhile Investment?" *Annual Review of Economics* 7(1):519–55.

Bartels, Larry. 2016. *Unequal Democracy: The Political Economy of the New Gilded Age*. 2nd ed. Princeton, NJ: Princeton University Press.

Bartels, Larry M. 2000. "Partisanship and Voting Behavior, 1952-1996." *American Journal of Political Science* 44(1):35–50.

Bartels, Larry M. 2002. "Beyond the Running Tally: Partisan Bias in Political Perceptions." *Political Behavior* 24(2):117–50.

Bartels, Larry M. and Simon Jackman. 2014. "A Generational Model of Political Learning." *Electoral Studies* 33:7–18.

Bates, Douglas, Martin Mächler, Ben Bolker, Steven Walker, R. Haubo Bojesen Christensen, Henrik Singmann, Bin Dai, Gabor Grothendieck, Peter Green, and Maintainer Ben Bolker. 2015. "Package 'Lme4'." *Convergence* 12(1):470–74.

Bebchuk, Lucian A. and Jesse M. Fried. 2004. *Pay Without Performance: The Unfulfilled Promise of Executive Compensation*. Cambridge, MA: Harvard University Press.

Bebchuk, Lucian A., Jesse M. Fried, and David I. Walker. 2002. "Managerial Power and Rent Extraction in the Design of Executive Compensation." *University of Chicago Law Review* 69:751–846.

Becker, Gary. 1964. *Human Capital*. New York, NY: Columbia University Press.

Becker, Gary S. and Nigel Tomes. 1979. "An Equilibrium Theory of the Distribution of Income and Intergenerational Mobility." *Journal of Polital Economy* 87(6):1153–89.

Becker, Gary S. and Nigel Tomes. 1986. "Human Capital and the Rise and Fall of Families." *Journal of Labor Economics* 4(3):1–39S.

Bello, Jason and Meredith Rolfe. 2014. "Is Influence Mightier Than Selection? Forging Agreement in Political Discussion Networks During a Campaign." *Social Networks* 36:134–46.

Berger, Peter L. and Thomas Luckmann. 1966. *The Social Construction of Reality: A Treatise in the Sociology of Knowledge*. Garden City, NY: Anchor.

Berndt, Donald J. and James Clifford. 1994. "Using Dynamic Time Warping to Find Patterns in Time Series." Pp. 359–70 in *KDD workshop*, vol. 10. Seattle, WA.

Bertrand, Marianne. 2009. "CEOs." *Annual Review of Economics* 1(1):121–50.

Bertrand, Marianne and Kevin F. Hallock. 2001. "The Gender Gap in Top Corporate Jobs." *Industrial and Labor Relations Review* 55(1):3–21.

Bertrand, Marianne and Emir Kamenica. 2018. "Coming Apart? Cultural Distances in the United States over Time." *National Bureau of Economic Research*. Retrieved February 19, 2020 (http://www.nber.org/papers/w24771).

Bertrand, Marianne and Sendhil Mullainathan. 2001. "Are Ceos Rewarded for Luck? The Ones Without Principals Are." *The Quarterly Journal of Economics* 116(3):901–32.

Bertrand, Marianne and Sendhil Mullainathan. 2004. "Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination." *American Economic Review* 94(4):991–1013.

Billig, Michael and Henri Tajfel. 1973. "Social Categorization and Similarity in Intergroup Behaviour." *European Journal of Social Psychology* 3(1):27–52.

Blau, Peter Michael and W. Richard Scott. 1962. *Formal Organizations: A Comparative Approach*. San Francisco: Chandler.

Bond, Robert and Solomon Messing. 2015. "Quantifying Social Media's Political Space: Estimating Ideology from Publicly Revealed Preferences on Facebook." *American Political Science Review* 109(1):62–78.

Bonica, Adam. 2013. "Ideology and Interests in the Political Marketplace." *American Journal of Political Science* 57(2):294–311.

Bonica, Adam. 2014. "Mapping the Ideological Marketplace." *American Journal of Political Science* 58(2):367–86.

Bonica, Adam. 2016. "Avenues of Influence: On the Political Expenditures of Corporations and Their Directors and Executives." *Business and Politics* 18(4):367–94.

Bonica, Adam. 2018. "Inferring Roll-Call Scores from Campaign Contributions Using Supervised Machine Learning." *American Journal of Political Science* 62(4):830–48.

Boone, Christophe, Woody Van Olffen, Arjen Van Witteloostuijn, and Bert De Brabander. 2004. "The Genesis of Top Management Team Diversity: Selective Turnover Among Top Management Teams in Dutch Newspaper Publishing, 1970-94." *Academy of Management Journal* 47(5):633–56.

Brewer, Marilynn B. 1981. "Ethnocentrism and Its Role in Interpersonal Trust." in *Scientific inquiry and the social sciences*, edited by M. B. Brewer and B. E. Collins. San Francisco, CA: Jossey-Bass.

Briscoe, Forrest Scott, M. K. Chin, and Donald C. Hambrick. 2014. "CEO Ideology as an Element of the Corporate Opportunity Structure for Social Activists." *Academy of Management Journal* 57(6):1786–1809.

Bromley, Patricia and Amanda Sharkey. 2017. "Casting Call: The Expanding Nature of Actorhood in Us Firms, 1960–2010." *Accounting, Organizations and Society* 59:3–20.

Brooks, David. 2020. "How Trump Wins Again." *New York Times*. Retrieved February 18, 2020 (https://www.nytimes.com/2020/02/06/opinion/trump-democrats-2020.html).

Bruni, Frank. 2020. "Bernie Sanders Prevails. Cue the Party Panic." *New York Times*. Retrieved February 18, 2020 (https://www.nytimes.com/2020/02/12/opinion/new-hampshire-primary-results.html).

Brunsson, Nils and Kerstin Sahlin-Andersson. 2000. "Constructing Organizations: The Example of Public Sector Reform." *Organization Studies* 21(4):721–46.

Burns, Tom E. and George Macpherson Stalker. 1961. *The Management of Innovation*. London: Tavistock.

Burris, Val. 2005. "Interlocking Directorates and Political Cohesion Among Corporate Elites." *American Journal of Sociology* 111(1):249–83.

Burt, Ronald S. 2000. "The Network Structure of Social Capital." Pp. 345–423 in *Research in organizational behavior*, vol. 22, edited by B. M. Straw and R. I. Sutton. New York: JAI.

Burt, Ronald S. 2004. "Structural Holes and Good Ideas." *American Journal of Sociology* 110(2):349–99.

Burton, Robert. [1651] 1927. *The Anatomy of Melancholy.* New York: Farrar & Rinehart.

Campbell, Angus, Philip E. Converse, Warren E. Miller, and Donald E. Stokes. 1960. *The American Voter.* New York: Wiley.

Camyar, Isa and Bahar Ulupinar. 2013. "The Partisan Policy Cycle and Firm Valuation." *European Journal of Political Economy* 30:92–111.

Caren, Neal, Raj Andrew Ghoshal, and Vanesa Ribas. 2011. "A Social Movement Generation: Cohort and Period Trends in Protest Attendance and Petition Signing." *American Sociological Review* 76(1):125–51.

Carlin, Ryan E. and Gregory J. Love. 2013. "The Politics of Interpersonal Trust and Reciprocity: An Experimental Approach." *Political Behavior* 35(1):43–63.

Carter, David A., Betty J. Simkins, and W. Gary Simpson. 2003. "Corporate Governance, Board Diversity, and Firm Value." *Financial Review* 38(1):33–53.

Center for Responsive Politics. 2020. "Search Opensecrets.org." *OpenSecrets.org.* Retrieved March 16, 2020 (https://www.opensecrets.org/search).

Chandler, Alfred. 1977. *The Visible Hand.* Cambridge, Massachusetts: Belknap Press of Harvard University Press.

Chandler, Alfred D. Jr. 1962. *Strategy and Structure.* Cambridge, Massachusetts: M.I.T. Press.

Chatman, Jennifer A., Jeffrey T. Polzer, Sigal G. Barsade, and Margaret A. Neale. 1998. "Being Different yet Feeling Similar: The Influence of Demographic Composition and Organizational Culture on Work Processes and Outcomes." *Administrative Science Quarterly* 43(4):749–80.

Chen, M. Keith and Ryne Rohla. 2018. "The Effect of Partisanship and Political Advertising on Close Family Ties." *Science* 360(6392):1020–4.

Cheng, J. Yo-Jud and Boris Groysberg. 2016. "7 Charts Show How Political Affiliation Shapes U.S. Boards." *Harvard Business Review.* Retrieved June 6, 2017 (https://hbr.org/2016/08/7-charts-show-how-political-affiliation-shapes-u-s-boards).

Chin, M. K., Donald C. Hambrick, and Linda K. Treviño. 2013. "Political Ideologies of Ceos: The Influence of Executives' Values on Corporate Social Responsibility." *Administrative Science Quarterly* 58(2):197–232.

Chu, Johan S. G. and Gerald F. Davis. 2016. "Who Killed the Inner Circle? The Decline of the American Corporate Interlock Network." *American Journal of Sociology* 122(3):714–54.

Chu, Johan S.G. and Gerald F. Davis. 2011. "Who Killed the Inner Circle? The Breakdown of the American Corporate Elite Network, 1999-2009." Retrieved November 1, 2016 (http://opensiuc.lib.siu.edu/pnconfs_2011/1).

Clemens, Elisabeth S. 1993. "Organizational Repertoires and Institutional Change: Women's Groups and the Transformation of U.S. Politics, 1890-1920." *American Journal of Sociology* 98(4):755–98.

Cohn, Nate. 2014. "Polarization Is Dividing American Society, Not Just Politics." *New York Times*. Retrieved February 25, 2020 (https://www.nytimes.com/2014/06/12/upshot/polarization-is-dividing-american-society-not-just-politics.html).

Coleman, James S. 1988. "Social Capital in the Creation of Human Capital." *American Journal of Sociology* 94(1):95–120.

Confessore, Nicholas and Justin Bank. 2019. "In the Trump Era, a Family's Fight with Google and Facebook over Disinformation." *New York Times*. Retrieved April 16, 2020 (https://www.nytimes.com/2019/08/21/us/facebook-disinformation-floyd-brown.html).

Conger, Kate and Sheera Frenkel. 2018. "Dozens at Facebook Unite to Challenge Its 'Intolerant' Liberal Culture." *New York Times*. Retrieved February 18, 2020 (https://www.nytimes.com/2018/08/28/technology/inside-facebook-employees-political-bias.html).

Converse, Philip E. 1964. "The Nature of Belief Systems in Mass Publics." Pp. 206–61 in *Ideology and discontent*, edited by D. E. Apter. New York: The Free Press of Glencoe.

Cookson Jr., Peter W. and Caroline Hodges Persell. 1986. *Preparing for Power: America's Elite Boarding Schools*. New York: Basic Books.

Copeland, Rob. 2019. "Fired by Google, a Republican Engineer Hits Back: 'There's Been a Lot of Bullying'." *Wall Street Journal*. Retrieved February 18, 2020 (https://www.wsj.com/articles/fired-by-google-a-republican-engineer-hits-back-theres-been-a-lot-of-bullying-11564651801).

Correll, Shelley, Stephen Benard, and In Paik. 2007. "Getting a Job: Is There a Motherhood Penalty?" *American Journal of Sociology* 112(5):1297–1338.

Cowan, Sarah K. and Delia Baldassarri. 2018. "It Could Turn Ugly: Selective Disclosure of Attitudes in Political Discussion Networks." *Social Networks* 52:1–17.

Dahl, Robert A. 1963. *Who Governs? Democracy and Power in an American City*. New Haven, CT: Yale University Press.

Dale, Stacy Berg and Alan B. Krueger. 2002. "Estimating the Payoff to Attending a More Selective College: An Application of Selection on Observables and Unobservables." *Quarterly Journal of Economics* 117(4):1491–1527.

Davis, Gerald F., Calvin Morrill, Hayagreeva Rao, and Sarah A. Soule. 2008. "Introduction: Social Movements in Organizations and Markets." *Administrative Science Quarterly* 53(3):389–94.

DellaPosta, Daniel, Yongren Shi, and Michael Macy. 2015. "Why Do Liberals Drink Lattes?" *American Journal of Sociology* 120(5):1473–1511.

DiMaggio, Paul. 1992. "Nadel's Paradox Revisited: Relational and Cultural Aspects of Social Structure." Pp. 118–42 in *Networks and organizations: Structure, form, and action*, edited by Nohria Nitin and R. G. Eccles. Boston, MA: Harvard Business School Press.

DiMaggio, Paul and John Mohr. 1985. "Cultural Capital, Educational Attainment, and Marital Selection." *American Journal of Sociology* 90(6):1231–61.

DiMaggio, Paul and Walter W. Powell. 1991. "Introduction." Pp. 1–38 in *The new institutionalism in organizational analysis*, edited by P. DiMaggio and W. W. Powell. Chicago: University of Chicago Press.

DiMaggio, Paul J. and Walter W. Powell. 1983. "The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields." *American Sociological Review* 48(2):147–60.

DiMaggio, Paul, John Evans, and Bethany Bryson. 1996. "Have American's Social Attitudes Become More Polarized?" *American Journal of Sociology* 102(3):690–755.

DiPrete, Thomas A., Gregory M. Eirich, and Matthew Pittinsky. 2010. "Compensation Benchmarking, Leapfrogs, and the Surge in Executive Pay." *American Journal of Sociology* 115(6):1671–1712.

DiTomaso, Nancy, Corinne Post, and Rochelle Parks-Yancy. 2007. "Workforce Diversity and Inequality: Power, Status, and Numbers." *Annual Review of Sociology* 33(1):473–501.

Dobbin, Frank and Jiwook Jung. 2011. "Corporate Board Gender Diversity and Stock Performance: The Competence Gap or Institutional Investor Bias?" *North Carolina Law Review* 89(3):809–38.

Dobbin, Frank and John R. Sutton. 1998. "The Strength of a Weak State: The Rights Revolution and the Rise of Human Resources Management Divisions." *American Journal of Sociology* 104(2):441–76.

Dobbin, Frank R., Lauren Edelman, John W. Meyer, W. Richard Scott, and Ann Swidler. 1988. "The Expansion of Due Process in Organizations." Pp. 71–100 in *Institutional patterns and organizations: Culture and environment*, edited by L. G. Zucker. Cambridge, MA: Ballinger; Ballinger.

Dobbin, Frank, Soohan Kim, and Alexandra Kalev. 2011. "You Can't Always Get What You Need: Organizational Determinants of Diversity Programs." *American Sociological Review* 76(3):386–411.

Domhoff, G. William. 2010. *Who Rules America: Challenges to Corporate and Class Dominance*. 6th ed. New York: McGraw Hill.

Douglas Bates, Martin Mächler, Ben Bolker, and Steve Walker. 2015. "Fitting Linear Mixed-Effects Models Using lme4." *Journal of Statistical Software* 67(1):1–48.

Douthat, Ross. 2020. "The Many Polarizations of America." *New York Times*. Retrieved February 25, 2020 (https://www.nytimes.com/2020/01/28/opinion/klein-lind-caldwell-book.html).

Downs, Anthony. 1957. *An Economic Theory of Democracy*. New York: Harper & Row.

Downs, Anthony. 1967. *Inside Bureaucracy*. Boston: Little, Brown.

Duckworth, Angela L., Christopher Peterson, Michael D. Matthews, and Dennis R. Kelly. 2007. "Grit: Perseverance and Passion for Long-Term Goals." *Journal of Personality and Social Psychology* 92(6):1087.

Durkheim, Émile. [1915] 1965. *The Elementary Forms of the Religious Life*. New York: Free Press.

Elvira, Marta and Robert Town. 2001. "The Effects of Race and Worker Productivity on Performance Evaluations." *Industrial Relations: A Journal of Economy and Society* 40(4):571–90.

England, Paula, George Farkas, Barbara S. Kilbourne, and Thomas Dou. 1988. "Explaining Occupational Sex Segregation and Wages: Findings from a Model with Fixed Effects." *American Sociological Review* 53(4):544–58.

Erickson, Bonnie H. 2001. "Good Networks and Good Jobs: The Value of Social Capital to Employers and Employees." Pp. 127–58 in *Social capital: Theory and research*, edited by N. Lin and K. S. Cook. New York: Aldine de Gruyter.

Federal Election Commission. 2018a. *Bulk Downloads*. Retrieved April 24, 2018 (https://www.fec.gov/files/bulk-downloads/index.html).

Federal Election Commission. 2018b. *Detailed Files About Candidates, Parties and Other Committees*. Retrieved April 24, 2018 (https://classic.fec.gov/finance/disclosure/ftpdet.shtml).

Federal Election Commission. 2018c. *Recording Receipts*. Retrieved May 30, 2018 (https://www.fec.gov/help-candidates-and-committees/keeping-records/records-receipts/).

Fiorina, Morris P. and Samuel J. Abrams. 2008. "Political Polarization in the American Public." *Annual Review of Political Science* 11(1):563–88.

Fiorina, Morris P., Samuel J. Abrams, and Jeremy C. Pope. 2005. *Culture War?: The Myth of a Polarized America*. New York: Pearson-Longman.

Fortune. 2018. *Fortune 500*. Fortune Media. Retrieved March 20, 2018 (http://fortune.com/fortune500/list/).

Frank, Robert H. and Philip J. Cook. 1995. *The Winner-Take-All Society: Why the Few at the Top Get so Much More Than the Rest of Us*. New York: Penguin Books.

Frum, David. 2020. "Bernie Can't Win." *The Atlantic*. Retrieved February 18, 2020 (https://www.theatlantic.com/ideas/archive/2020/01/bernie-sanderss-biggest-challenges/605500/).

Frydman, Carola. 2005. *Rising Through the Ranks: The Evolution of the Market for Corporate Executives, 1936-2003*. Cambridge, MA: Harvard University.

Frydman, Carola and Raven E. Saks. 2010. "Executive Compensation: A New View from a Long-Term Perspective, 1936-2005." *Review of Financial Studies* 23(5):2099–2138.

Gabaix, Xavier and Augustin Landier. 2008. "Why Has Ceo Pay Increased so Much?" *The Quarterly Journal of Economics* 123(1):49–100.

Gaddis, S. Michael. 2015. "Discrimination in the Credential Society: An Audit Study of Race and College Selectivity in the Labor Market." *Social Forces* 93(4):1451–79.

Gaddis, S. Michael. 2017. "How Black Are Lakisha and Jamal? Racial Perceptions from Names Used in Correspondence Audit Studies." *Sociological Science* 4(19):469–89.

Gant, Michael M. and Lee Sigelman. 1985. "Anti-Candidate Voting in Presidential Elections." *Polity* 18(2):329–39.

General Services Administration: 18F. 2017. *OpenFEC Api (Beta) Documentation*. Retrieved November 11, 2017 (https://api.open.fec.gov/developers/).

Gift, Karen and Thomas Gift. 2015. "Does Politics Influence Hiring? Evidence from a Randomized Experiment." *Political Behavior* 37(3):653–75.

Gilens, Martin. 2005. "Inequality and Democratic Responsiveness." *Public Opinion Quarterly* 69(5):778–96.

Gilens, Martin. 2012. *Affluence and Influence: Economic Inequality and Political Power in America*. Princeton, NJ: Princeton University Press.

Goldberg, Amir, Sameer B. Srivastava, V. Govind Manian, William Monroe, and Christopher Potts. 2016. "Fitting in or Standing Out? The Tradeoffs of Structural and Cultural Embeddedness." *American Sociological Review* 81(6):1190–1222.

Goren, Paul. 2002. "Character Weakness, Partisan Bias, and Presidential Evaluation." *American Journal of Political Science* 46(3):627–41.

Goren, Paul. 2005. "Party Identification and Core Political Values." *American Journal of Political Science* 49(4):881–96.

Goren, Paul, Christopher M. Federico, and Miki Caul Kittilson. 2009. "Source Cues, Partisan Identities, and Political Value Expression." *American Journal of Political Science* 53(4):805–20.

Granovetter, Mark. 1985. "Economic Action and Social Structure." *American Journal of Sociology* 91:481–510.

Granovetter, Mark S. 1973. "The Strength of Weak Ties." *American Journal of Sociology* 78(6):1360–80.

Granovetter, Mark S. 1974. *Getting a Job: A Study of Contacts and Careers*. Cambridge, MA: Harvard University Press.

Green, Donald Philip and Bradley Palmquist. 1990. "Of Artifacts and Partisan Instability." *American Journal of Political Science* 34(3):872–902.

Green, Donald, Bradley Palmquist, and Eric Schickler. 2002. *Partisan Hearts and Minds: Political Parties and the Social Identities of Voters*. New Haven, CT: Yale University Press.

Groenendyk, Eric. 2012. "Justifying Party Identification: A Case of Identifying with the 'Lesser of Two Evils'." *Political Behavior* 34(3):453–75.

Gupta, Abhinav and Forrest Briscoe. 2019. "Organizational Political Ideology and Corporate Openness to Social Activism." *Administrative Science Quarterly*.

Gupta, Abhinav and Adam J. Wowak. 2017. "The Elephant (or Donkey) in the Boardroom." *Administrative Science Quarterly* 62(1):1–30.

Gupta, Abhinav, Forrest Briscoe, and Donald C. Hambrick. 2017. "Red, Blue, and Purple Firms: Organizational Political Ideology and Corporate Social Responsibility." *Strategic Management Journal* 38(5):1018–40.

Hacker, Jacob S. and Paul Pierson. 2010. *Winner-Take-All Politics: How Washington Made the Rich Richer–and Turned Its Back on the Middle Class*. New York: Simon; Schuster.

Hallock, Kevin F. 1997. "Reciprocally Interlocking Boards of Directors and Executive Compensation." *Journal of Financial and Quantitative Analysis* 32(3):331–44.

Hambrick, Donald C., Theresa Seung Cho, and Ming-Jer Chen. 1996. "The Influence of Top Management Team Heterogeneity on Firms' Competitive Moves." *Administrative Science Quarterly* 41(4):659–84.

Hannan, Michael and John Freeman. 1977. "The Population Ecology of Organizations." *American Journal of Sociology* 82:929–64.

Hannan, Michael and John Freeman. 1984. "Structural Inertia and Organizational Change." *American Sociological Review* 49:149–64.

Heckman, James J. and Peter Siegelman. 1993. "The Urban Institute Audit Studies: Their Methods and Findings." Pp. 187–258 in *Clear and convincing evidence: Measurement of discrimination in america*, edited by M. Fix and R. J. Struyk. Washington, D.C.: Urban Institute Press.

Hetherington, Marc J. 2001. "Resurgent Mass Partisanship: The Role of Elite Polarization." *American Political Science Review* 95(3):619–31.

Hetherington, Marc J. 2009. "Putting Polarization in Perspective." *British Journal of Political Science* 39(2):413–48.

Hoekstra, Mark. 2009. "The Effect of Attending the Flagship State University on Earnings: A Discontinuity-Based Approach." *The Review of Economics and Statistics* 91(4):717–24.

Holcombe, A. N. 1911. "Direct Primaries and the Second Ballot." *American Political Science Review* 5(4):535–52. Retrieved (http://www.jstor.org/stable/1945022).

Huber, Gregory A. and Neil Malhotra. 2017. "Political Homophily in Social Relationships: Evidence from Online Dating Behavior." *The Journal of Politics* 79(1):269–83.

Ibarra, Herminia. 1992. "Homophily and Differential Returns: Sex Differences in Network Structure and Access in an Advertising Firm." *Administrative Science Quarterly* 37(3):422–47.

Ibarra, Herminia. 1995. "Race, Opportunity, and Diversity of Social Circles in Managerial Networks." *The Academy of Management Journal* 38(3):673–703.

Iyengar, Shanto and Masha Krupenkin. 2018. "The Strengthening of Partisan Affect." *Political Psychology* 39(S1):201–18.

Iyengar, Shanto and Sean J. Westwood. 2015. "Fear and Loathing Across Party Lines: New Evidence on Group Polarization." *American Journal of Political Science* 59(3):690–707.

Iyengar, Shanto, Tobias Konitzer, and Kent Tedin. 2018. "The Home as a Political Fortress: Family Agreement in an Era of Polarization." *The Journal of Politics* 80(4):1326–38.

Iyengar, Shanto, Yphtach Lelkes, Matthew Levendusky, Neil Malhotra, and Sean J. Westwood. 2019. "The Origins and Consequences of Affective Polarization in the United States." *Annual Review of Political Science* 22(1):129–46.

Iyengar, Shanto, Gaurav Sood, and Yphtach Lelkes. 2012. "Affect, Not Ideology: A Social Identity Perspective on Polarization." *Public Opinion Quarterly* 76(3):405–31.

Jackson, Susan E., Aparna Joshi, and Niclas L. Erhardt. 2003. "Recent Research on Team and Organizational Diversity: SWOT Analysis and Implications." *Journal of Management* 29(6):801–30.

James, Estelle, Nabeel Alsalam, Joseph C. Conaty, and Duc-Le To. 1989. "College Quality and Future Earnings: Where Should You Send Your Child to College?" *American Economic Review* 79(2):247–52.

Johnston, Richard. 2006. "Party Identification: Unmoved Mover or Sum of Preferences?" *Annual Review of Political Science* 9(1):329–51.

Kalev, Alexandra and Frank Dobbin. 2006. "Enforcement of Civil Rights Law in Private Workplaces: The Effects of Compliance Reviews and Lawsuits over Time." *Law &Amp; Social Inquiry* 31(4):855–903.

Kalev, Alexandra, Frank Dobbin, and Erin Kelly. 2006. "Best Practices or Best Guesses? Assessing the Efficacy of Corporate Affirmative Action and Diversity Policies." *American Sociological Review* 71(4):589–617.

Kalleberg, Arne L. and Aage B. Sørensen. 1979. "The Sociology of Labor Markets." *Annual Review of Sociology* 5(1):351–79.

Kang, Sonia K., Katherine A. DeCelles, András Tilcsik, and Sora Jun. 2016. "Whitened Résumés: Race and Self-Presentation in the Labor Market." *Administrative Science Quarterly* 61(3):469–502.

Kanter, Rosabeth Moss. 1993. *Men and Women of the Corporation*. New Edition. New York: BasicBooks.

Karabel, Jerome. 2005. *The Chosen: The Hidden History of Admission and Exclusion at Harvard, Yale, and Princeton*. Boston: Houghton Mifflin.

Karol, David. 2009. *Party Position Change in American Politics: Coalition Management*. New York: Cambridge University Press.

Kaufman, Leonard and Peter J. Rousseeuw. 1990. *Finding Groups in Data: An Introduction to Cluster Analysis*. Hoboken, NJ: John Wiley & Sons.

Keister, Lisa A. 2005. *Getting Rich: America's New Rich and How They Got That Way*. New York: Cambridge University Press.

Keister, Lisa A. 2014. "The One Percent." *Annual Review of Sociology* 40(1):347–67.

Khan, Shamus Rahman. 2011. *Privilege: The Making of an Adolescent Elite at St. Paul's School*. Princeton, NJ: Princeton University Press.

Khurana, Rakesh. 2002. *Searching for a Corporate Savior: The Irrational Quest for Charismatic Ceos*. Princeton, NJ: Princeton University Press.

Kiefer, Elizabeth. 2017. "'Til Trump Do Us Part: The Relationship Deal Breaker We Never Saw Coming." *Refinery29*. Retrieved February 29, 2020 (https://www.refinery29.com/en-us/2017/07/162856/talking-politics-with-partner-relationship-advice).

Killewald, Alexandra, Fabian T. Pfeffer, and Jared N. Schachner. 2017. "Wealth Inequality and Accumulation." *Annual Review of Sociology* 43(1):DOI: 10.1146/annurev–soc–060116–053331.

King, Brayden G. and Sarah A. Soule. 2007. "Social Movements as Extra-Institutional Entrepreneurs: The Effect of Protests on Stock Price Returns." *Administrative Science Quarterly* 52(3):413–42.

King, Brayden G., Teppo Felin, and David A. Whetten. 2010. "Perspective—Finding the Organization in Organizational Theory: A Meta-Theory of the Organization as a Social Actor." *Organization Science* 21(1):290–305.

Klar, Rebecca. 2020. "Ocasio-Cortez: Democrats Must 'Rally' Behind the Nominee 'No Matter Who It Is'." *The Hill*. Retrieved February 18, 2020 (https://thehill.com/homenews/campaign/481171-ocasio-cortez-democrats-must-rally-behind-the-nominee-no-matter-who-it-is).

Klein, Ezra. 2020. *Why We're Polarized*. New York: Avid Reader Press.

Klofstad, Casey A., Rose McDermott, and Peter K. Hatemi. 2013. “The Dating Preferences of Liberals and Conservatives.” *Political Behavior* 35(3):519–38.

Koger, Gregory, Seth Masket, and Hans Noel. 2009. “Partisan Webs: Information Exchange and Party Networks.” *British Journal of Political Science* 39(3):633–53.

Krawiec, Kimberly D. and Lissa Lamkin Broome. 2008. “Signaling Through Board Diversity: Is Anyone Listening?” *University of Cincinnati Law Review* 77:431–64.

Kuttner, Robert. 2010. *A Presidency in Peril: The Inside Story of Obama’s Promise, Wall Street’s Power, and the Struggle to Control Our Economic Future*. White River Junction, VT: Chelsea Green Publishing.

Lareau, Annette. 2003. *Unequal Childhoods: Class, Race, and the Family*. Berkeley: University of California Press.

Lareau, Annette. 2011. *Unequal Childhoods: Class, Race, and Family Life, 2nd Edition with an Update a Decade Later*. Berkeley, CA: University of California Press.

Laumann, Edward O. and David Knoke. 1987. *The Organizational State: Social Choice in National Policy Domains*. Wisconsin: University of Wisconsin Press.

Layman, Geoffrey C. and Thomas M. Carsey. 2002. “Party Polarization and ’Conflict Extension’ in the American Electorate.” *American Journal of Political Science* 46(4):786–802.

Lazarsfeld, Paul F. and Robert King Merton. 1954. “Friendship as a Social Process: A Substantive and Methodological Analysis.” Pp. 18–66 in *Freedom and control in modern society*, edited by M. Berger, T. Abel, and C. H. Page. New York: D. Van Nostrand.

Lee, Frances E. 2015. “How Party Polarization Affects Governance.” *Annual Review of Political Science* 18(1):261–82.

Levendusky, Matthew S. 2009. “The Microfoundations of Mass Polarization.” *Political Analysis* 17(2):162–76.

Levin, Murray B. and Murray Eden. 1962. “Political Strategy for the Alienated Voter.” *Public Opinion Quarterly* 26(1):47–63.

Levine, Steven B. 1980. “The Rise of American Boarding Schools and the Development of a National Upper Class.” *Social Problems* 28(1):63–94.

Levitt, Steven D. and Stephen J. Dubner. 2005. *Freakonomics: A Rogue Economist Reveals the Hidden Side of Everything*. New York: William Morrow.

Lin, Nan and Mary Dumin. 1986. "Access to Occupations Through Social Ties." *Social Networks* 8(4):365–85.

Lipset, Seymour M. 1960. *Political Man: The Social Basis of Modern Politics*. New York: Doubleday.

Lipsky, Michael. 1968. "Protest as a Political Resource." *American Political Science Review* 62(4):1144–58.

Luechinger, Simon and Christoph Moser. 2014. "The Value of the Revolving Door: Political Appointees and the Stock Market." *Journal of Public Economics* 119:93–107.

Macy, Michael, Sebastian Deri, Alexander Ruch, and Natalie Tong. 2019. "Opinion Cascades and the Unpredictability of Partisan Polarization." *Science Advances* 5(8).

Manza, Jeff and Clem Brooks. 1999. *Social Cleavages and Political Change: Voter Alignments and Us Party Coalitions*. New York: Oxford University Press.

March, James and Herbert Simon. 1958. *Organizations*. Cambridge, Massachusetts: Blackwell.

March, James G. and Johan P. Olsen. 1989. *Rediscovering Institutions: The Organizational Basis of Politics*. New York: Free Press.

Martin Maechler, Anja Struyf, Peter Rousseeuw and Erich Schubert. 2019. *Finding Groups in Data: Cluster Analysis Extended Rousseeuw et Al.* The Comprehensive R Archive Network. Retrieved May 6, 2019 (https://cran.r-project.org/web/packages/cluster/cluster.pdf).

Mason, Lilliana. 2015. "'I Disrespectfully Agree': The Differential Effects of Partisan Sorting on Social and Issue Polarization." *American Journal of Political Science* 59(1):128–45.

Mausolf, Joshua Gary. 2020a. "Corporate Politics: The Emergence of Partisan Polarization in Firms, 1980-2018." Working Paper, Department of Sociology, University of Chicago, Chicago, IL.

Mausolf, Joshua Gary. 2020b. "Office Politics: How Affective Polarization and Partisan Homophily Alter Hiring Decisions." Working Paper, Department of Sociology, University of Chicago, Chicago, IL.

Mausolf, Joshua Gary. 2020c. "Party in the Boardroom: The Role of Affective Polarization in Corporate Board Appointments." Working Paper, Department of Sociology, University of Chicago, Chicago, IL.

Mausolf, Joshua Gary. 2020d. "Preregistration - Office Politics: How Affective Polarization and Partisan Homophily Alter Hiring Decisions." *Center for Open Science*. Retrieved April 17, 2020 (https://osf.io/4d3xg/?view_only=900f9d4330e94bc0b16b6f5e868ae7a7).

Mausolf, Joshua Gary. 2020e. “Reproducible Code - Corporate Politics: The Emergence of Partisan Polarization in Firms, 1980-2018.” *GitHub*. Retrieved April 11, 2020 (https://github.com/jmausolf/OpenFEC).

Mausolf, Joshua Gary. 2020f. “Reproducible Code - Office Politics: How Affective Polarization and Partisan Homophily Alter Hiring Decisions.” *GitHub*. Retrieved April 11, 2020 (https://github.com/jmausolf/office_politics).

Mausolf, Joshua Gary. 2020g. “Reproducible Code - Party in the Boardroom: The Role of Affective Polarization in Corporate Board Appointments.” *GitHub*. Retrieved April 11, 2020 (https://github.com/jmausolf/iss_boards).

Mayer, Jane. 2016. *Dark Money: The Hidden History of the Billionaires Behind the Rise of the Radical Right*. New York: Doubleday.

McAdam, Doug. 1983. “Tactical Innovation and the Pace of Insurgency.” *American Sociological Review* 48(6):735–54.

McAdam, Doug and Yang Su. 2002. “The War at Home: Antiwar Protests and Congressional Voting, 1965 to 1973.” *American Sociological Review* 67(5):696–721.

McCabe, David. 2019. “Google Settles with U.S. over Workers’ Complaints It Stifled Dissent.” *New York Times*. Retrieved February 18, 2020 (https://www.nytimes.com/2019/09/12/technology/google-settlement-nlrb.html).

McCarty, Nolan, Keith T. Poole, and Howard Rosenthal. 2006. *Polarized America: The Dance of Ideology and Unequal Riches*. Cambridge, MA: MIT Press.

McConnell, Christopher, Yotam Margalit, Neil Malhotra, and Matthew Levendusky. 2018. “The Economic Consequences of Partisanship in a Polarized Era.” *American Journal of Political Science* 62(1):5–18.

McDonnell, Mary-Hunter and Brayden G. King. 2018. “Order in the Court: How Firm Status and Reputation Shape the Outcomes of Employment Discrimination Suits.” *American Sociological Review* 83(1):61–87.

McDonnell, Mary-Hunter, Brayden G. King, and Sarah A. Soule. 2015. “A Dynamic Process Model of Private Politics: Activist Targeting and Corporate Receptivity to Social Challenges.” *American Sociological Review* 80(3):654–78.

McPherson, J. Miller and Lynn Smith-Lovin. 1987. “Homophily in Voluntary Organizations: Status Distance and the Composition of Face-to-Face Groups.” *American Sociological Review* 52(3):370–79.

McPherson, Miller, Lynn Smith-Lovin, and James M. Cook. 2001. "Birds of a Feather: Homophily in Social Networks." *Annual Review of Sociology* 27(1):415–44.

Meglino, Bruce M., Elizabeth C. Ravlin, and Cheryl L. Adkins. 1989. "A Work Values Approach to Corporate Culture: A Field Test of the Value Congruence Process and Its Relationship to Individual Outcomes." *Journal of Applied Psychology* 74(3):424.

Meyer, John W. 2010. "World Society, Institutional Theories, and the Actor." *Annual Review of Sociology* 36(1):1–20.

Meyer, John W. and Patricia Bromley. 2013. "The Worldwide Expansion of 'Organization'." *Sociological Theory* 31(4):366–89.

Meyer, John W. and Brian Rowan. 1977. "Institutionalized Organizations: Formal Structure as Myth and Ceremony." *American Journal of Sociology* 83(2):340–63.

Meyerson, Debra, Karl E. Weick, and Roderick M. Kramer. 1996. "Swift Trust and Temporary Groups." Pp. 166–95 in *Organizations: Frontiers of theory and research*, edited by R. M. Kramer and T. R. Tyler. Thousand Oaks, CA: Sage.

Milliken, Frances J. and Luis L. Martins. 1996. "Searching for Common Threads: Understanding the Multiple Effects of Diversity in Organizational Groups." *Academy of Management Review* 21(2):402–33.

Mills, C. Wright. 1956. *The Power Elite*. New York: Oxford University Press.

Mizruchi, Mark S. 1996. "What Do Interlocks Do? An Analysis, Critique, and Assessment of Research on Interlocking Directorates." *Annual Review of Sociology* 22(1):271–98.

Mizruchi, Mark S. 2013. *The Fracturing of the American Corporate Elite*. Cambridge, MA: Harvard University Press.

Montero, Pablo and José A. Vilar. 2014. "TSclust: An R Package for Time Series Clustering." *Journal of Statistical Software* 62(1):1–41.

Mudge, Stephanie L. and Anthony S. Chen. 2014. "Political Parties and the Sociological Imagination: Past, Present, and Future Directions." *Annual Review of Sociology* 40(1):305–30.

Murphy, Kevin J. and Jan Zabojnik. 2004. "CEO Pay and Appointments: A Market-Based Explanation for Recent Trends." *American Economic Review* 94(2):192–96.

Murray, Joshua. 2017. "Interlock Globally, Act Domestically: Corporate Political Unity in the 21st Century." *American Journal of Sociology* 122(6):1617–63.

Nelson, Richard R. and Sidney G. Winter. 1982. *An Evolutionary Theory of Economic Change*. Cambridge: Belknap.

Nelson, Thomas E., Michele Acker, and Melvin Manis. 1996. “Irrepressible Stereotypes.” *Journal of Experimental Social Psychology* 32(1):13–38.

Nicholson, Stephen P., Chelsea M. Coe, Jason Emory, and Anna V. Song. 2016. “The Politics of Beauty: The Effects of Partisan Bias on Physical Attractiveness.” *Political Behavior* 38(4):883–98.

Olzak, Susan and Emily Ryo. 2007. “Organizational Diversity, Vitality and Outcomes in the Civil Rights Movement.” *Social Forces* 85(4):1561–91.

Padgett, John F. and Paul D. McLean. 2006. “Organizational Invention and Elite Transformation: The Birth of Partnership Systems in Renaissance Florence.” *American Journal of Sociology* 111(5):1463–1568.

Page, Benjamin I., Larry M. Bartels, and Jason Seawright. 2013. “Democracy and the Policy Preferences of Wealthy Americans.” *Perspectives on Politics* 11(1):51–73.

Pager, Devah. 2003. “The Mark of a Criminal Record.” *American Journal of Sociology* 108(5):937–75.

Pager, Devah. 2007. *Marked: Race, Crime, and Finding Work in an Era of Mass Incarceration*. Chicago, IL: University Of Chicago Press; University Of Chicago Press.

Pager, Devah and Lincoln Quillian. 2005. “Walking the Talk? What Employers Say Versus What They Do.” *American Sociological Review* 70(3):355–80.

Pager, Devah and Bruce Western. 2012. “Identifying Discrimination at Work: The Use of Field Experiments.” *Journal of Social Issues* 68(2):221–27.

Panagopoulos, Costas, Donald P. Green, Jonathan Krasno, Michael Schwam-Baird, Eric Moore, and Kyle Endres. 2016. “Risky Business: Does Corporate Political Giving Affect Consumer Behavior?” Paper presented at the Annual Meeting of the American Political Science Association, Philadelphia, PA, September.

Park, Jong Hee and Nathan Jensen. 2007. “Electoral Competition and Agricultural Support in OECD Countries.” *American Journal of Political Science* 51(2):314–29.

Pedulla, David S. 2016. “Penalized or Protected? Gender and the Consequences of Nonstandard and Mismatched Employment Histories.” *American Sociological Review* 81(2):262–89.

Pettigrew, Thomas F. 1998. "Intergroup Contact Theory." *Annual Review of Psychology* 49(1):65–85.

Pew Research Center. 2016. *Partisanship and Political Animosity in 2016: Highly Negative Views of the Opposing Party - and Its Members.* Retrieved October 14, 2017 (http://assets.pewresearch.org/wp-content/uploads/sites/5/2016/06/06-22-16-Partisanship-and-animosity-release.pdf).

Pfeiffer, Dan. 2020. "Dems Beware: Don't Be Like Mitt in 2012." *Politico*. Retrieved February 18, 2020 (https://www.politico.com/news/magazine/2020/02/17/dan-pfeiffer-mitt-romney-loss-2012-lessons-115340).

Piketty, Thomas. 2014. *Capital in the 21st Century.* Cambridge, MA: Harvard University Press.

Piketty, Thomas and Emmanuel Saez. 2006. "The Evolution of Top Incomes: A Historical and International Perspective." *American Economic Review* 96(2):200–205.

Piven, Frances Fox and Richard A. Cloward. 1977. *Poor People's Movements: Why They Succeed, How They Fail.* New York: Random House.

Politico. 2016a. *2016 Michigan Presidential Election Results.* Politico LLC. Retrieved December 6, 2018 (https://www.politico.com/2016-election/results/map/president/michigan/).

Politico. 2016b. *2016 Minnesota Presidential Election Results.* Politico LLC. Retrieved December 6, 2018 (https://www.politico.com/2016-election/results/map/president/minnesota/).

Politico. 2018a. *Michigan Election Results 2018.* Politico LLC. Retrieved December 6, 2018 (https://www.politico.com/election-results/2018/michigan/).

Politico. 2018b. *Minnesota Election Results 2018.* Politico LLC. Retrieved December 6, 2018 (https://www.politico.com/election-results/2018/minnesota/).

Poole, Keith T. 2005. *Spatial Models of Parliamentary Voting: Analytical Methods for Social Research.* New York: Cambridge University Press.

Poole, Keith T. and Howard Rosenthal. 1984. "The Polarization of American Politics." *The Journal of Politics* 46(4):1061–79.

Poole, Keith T. and Howard Rosenthal. 1997. *Congress: A Political-Economic History of Roll Call Voting.* New York: Oxford.

Powell, Walter W. and Kurt W. Sandholtz. 2012. "Amphibious Entrepreneurs and the Emergence of Organizational Forms." *Strategic Entrepreneurship Journal* 6(2):94–115.

Powell, Walter W., Douglas R. White, Kenneth W. Koput, and Jason Owen-Smith. 2005. "Network Dynamics and Field Evolution: The Growth of Interorganizational Collaboration in the Life Sciences." *American Journal of Sociology* 110(4):1132–1205.

Quillian, Lincoln. 2006. "New Approaches to Understanding Racial Prejudice and Discrimination." *Annual Review of Sociology* 32(1):299–328.

Raudenbush, Stephen W. and Anthony S. Bryk. 2002. *Hierarchical Linear Models: Applications and Data Analysis Methods, Second Edition*. Thousand Oaks, CA: Sage.

Reagans, Ray and Bill McEvily. 2003. "Network Structure and Knowledge Transfer: The Effects of Cohesion and Range." *Administrative Science Quarterly* 48(2):240–67.

Reagans, Ray and Ezra W. Zuckerman. 2001. "Networks, Diversity, and Productivity: The Social Capital of Corporate R&D Teams." *Organization Science* 12(4):502–17.

Reskin, Barbara F. and Debra Branch McBrier. 2000. "Why Not Ascription? Organizations' Employment of Male and Female Managers." *American Sociological Review* 65(2):210–33.

Reskin, Barbara F., Debra B. McBrier, and Julie A. Kmec. 1999. "The Determinants and Consequences of Workplace Sex and Race Composition." *Annual Review of Sociology* 25(1):335–61.

Rivera, Lauren A. 2011. "Ivies, Extracurriculars, and Exclusion: Elite Employers' Use of Educational Credentials." *Research in Social Stratification and Mobility* 29(1):71–90.

Rivera, Lauren A. 2012a. "Diversity Within Reach: Recruitment Versus Hiring in Elite Firms." *Annals of the American Academy of Political and Social Science* 639(1):70–89.

Rivera, Lauren A. 2012b. "Hiring as Cultural Matching: The Case of Elite Professional Service Firms." *American Sociological Review* 77(1):999–1022.

Rivera, Lauren A. and András Tilcsik. 2016. "Class Advantage, Commitment Penalty." *American Sociological Review* 81(6):1097–1131.

Ruef, Martin. 2000. "The Emergence of Organizational Forms: A Community Ecology Approach." *American Journal of Sociology* 106(3):658–714.

Russonello, Giovanni. 2020. "Moderates Search for a Savior." *New York Times*. Retrieved February 18, 2020 (https://www.nytimes.com/2020/02/12/us/politics/on-politics-michael-bloomberg.html).

Scher, Bill. 2020. "Hey Moderates, It's Time to Compromise-with Yourselves." *Politico*. Retrieved February 18, 2020 (https://www.politico.com/news/magazine/2020/02/12/democrats-2020-candidates-moderate-biden-buttigieg-klobuchar-new-hampshire-114460).

Schneider, Benjamin. 1987. "The People Make the Place." *Personnel Psychology* 40(3):437–53.

Sears, David. 1975. "Political Socialization." Pp. 93–154 in *Handbook of political science*, vol. 2, edited by F. I. Greenstein and N. W. Polsby. Reading, MA: Addison-Wesley.

Selznick, Philip. 1966. *TVA and the Grassroots*. New York: Harper Tourchbooks.

Shi, Feng, Misha Teplitskiy, Eamon Duede, and James A. Evans. 2019. "The Wisdom of Polarized Crowds." *Nature Human Behaviour* 3(4):329–36.

Sigelman, Lee and Michael M. Gant. 1989. "Anticandidate Voting in the 1984 Presidential Election." *Political Behavior* 11(1):81–92.

Singer, Natasha. 2018. "Did You Vote? Now Your Friends May Know (and Nag You)." *New York Times*. Retrieved February 18, 2020 (https://www.nytimes.com/2018/11/04/us/politics/apps-public-voting-record.html).

Skaggs, Sheryl. 2008. "Producing Change or Bagging Opportunity? The Effects of Discrimination Litigation on Women in Supermarket Management." *American Journal of Sociology* 113(4):1148–82.

Smith, Sandra Susan. 2005. "'Don't Put My Name on It': Social Capital Activation and Job-Finding Assistance Among the Black Urban Poor." *American Journal of Sociology* 111(1):1–57.

Snyder Jr., James M. 1990. "Campaign Contributions as Investments: The Us House of Representatives, 1980-1986." *Journal of Political Economy* 98(6):1195–1227.

Snyder Jr., James M. 1992. "Long-Term Investing in Politicians; or, Give Early, Give Often." *The Journal of Law and Economics* 35(1):15–43.

Solon, Gary. 1992. "Intergenerational Income Mobility in the United States." *American Economic Review* 82(3):393–408.

Sood, Gaurav and Shanto Iyengar. 2016. "Coming to Dislike Your Opponents: The Polarizing Impact of Political Campaigns." *SSRN*. Retrieved February 29, 2020 (https://ssrn.com/abstract=2840225).

Speake, Jennifer. 2008. *The Oxford Dictionary of Proverbs*. 5th ed. New York: Oxford University Press.

Stark, David and Balazs Vedres. 2012. "Political Holes in the Economy." *American Sociological Review* 77(5):700–722.

Stevens, Mitchell L. 2007. *Creating a Class: College Admissions and the Education of Elites*. Cambridge, MA: Harvard University Press.

Stinchcombe, Arthur L. 1965. "Social Structure and Organizations." Pp. 142–93 in *Handbook of organizations*, edited by J. G. March. Chicago: Rand McNally.

Strauss, Daniel. 2020. "'We Can Lose This Election': What Top Democrats Fear Could Go Wrong in 2020." *The Guardian*. Retrieved February 18, 2020 (https://www.theguardian.com/us-news/2020/jan/31/2020-will-trump-win-democrats-on-factors-losing-election).

Sunny He, Vivian Mo, Zachary Liu and Jonathan Zong. 2020. "Is Your News Feed a Bubble?" Retrieved February 19, 2020 (http://politecho.org/).

Sutton, John R. and Frank Dobbin. 1996. "The Two Faces of Governance: Responses to Legal Uncertainty in U.S. Firms, 1955 to 1985." *American Sociological Review* 61(5):794–811.

Sørensen, Aage B. and Arne L. Kalleberg. 1981. "An Outline of a Theory of the Matching of Persons to Jobs." Pp. 49–74 in *Sociological perspectives on labor markets*, edited by I. Berg. New York: Academic Press.

Tajfel, Henri. 1970. "Experiments in Intergroup Discrimination." *Scientific American* 223(5):96–103.

Tajfel, Henri and John C. Turner. 1979. "An Integrative Theory of Intergroup Conflict." Pp. 33–47 in *The social psychology of intergroup relations*, edited by W. G. Austin and S. Worchel. Monterey, CA: Brooks-Cole.

Tan, Michael Steinbach, Pang-Ning and Vipin Kumar. 2006. *Introduction to Data Mining*. Boston, MA: Pearson Addison-Wesley.

Thompson, James D. 1967. *Organizations in Action*. Edison, New Jersey: Transaction Publishers.

Tilcsik, András. 2011. "Pride and Prejudice: Employment Discrimination Against Openly Gay Men in the United States." *American Journal of Sociology* 117(2):586–626.

Tilly, Chris and Charles Tilly. 1998. *Work Under Capitalism*. Boulder, CO: Westview Press.

Timberg, Craig. 2020. "How Conservatives Learned to Wield Power Inside Facebook." *Washington Post*. Retrieved April 16, 2020 (https://www.washingtonpost.com/technology/2020/02/20/facebook-republican-shift/).

Tomaskovic-Devey, Donald and Ken-Hou Lin. 2011. "Income Dynamics, Economic Rents, and the Financialization of the U.S. Economy." *American Sociological Review* 76(4):538–59.

Tripathi, Micky, Stephen Ansolabehere, and James M. Snyder. 2002. “Are Pac Contributions and Lobbying Linked? New Evidence from the 1995 Lobby Disclosure Act.” *Business and Politics* 4(2):131–55.

Tsui, Anne S., Terri Egan, and Charles O’Reilly. 1991. “Being Different: Relational Demography and Organizational Attachment.” *Academy of Management Proceedings* 1991(1):183–87.

U.S. Equal Employment Opportunity Commission. 2020. “Who Is Protected from Employment Discrimination?” *USA.Gov*. Retrieved February 26, 2020 (https://www.eeoc.gov/employers/smallbusiness/faq/who_is_protected.cfm).

Useem, Michael. 1984. *The Inner Circle*. New York: Oxford University Press.

Useem, Michael and Jerome Karabel. 1986. “Pathways to Top Corporate Management.” *American Sociological Review* 51(2):184–200.

Van Knippenberg, Daan, Carsten K. W. De Dreu, and Astrid C. Homan. 2004. “Work Group Diversity and Group Performance: An Integrative Model and Research Agenda : Theoretical Models and Conceptual Analyses.” *Journal of Applied Psychology* (6):1008.

Walton, Gregory M., Mary C. Murphy, and Ann Marie Ryan. 2015. “Stereotype Threat in Organizations: Implications for Equity and Performance.” *Annual Review of Organizational Psychology and Organizational Behavior* 2(1):523–50.

Wang, Dan J. and Sarah A. Soule. 2016. “Tactical Innovation in Social Movements: The Effects of Peripheral and Multi-Issue Protest.” *American Sociological Review* 81(3):517–48.

Weichselbaumer, Doris. 2015. “Testing for Discrimination Against Lesbians of Different Marital Status: A Field Experiment.” *Industrial Relations: A Journal of Economy and Society* 54(1):131–61.

Williams, Christine L. 1992. “The Glass Escalator: Hidden Advantages for Men in the ’Female’ Professions.” *Social Problems* 39(3):253–67.

Williams, Katherine Y. and Charles A. O’Reilly. 1998. “Demography and Diversity in Organizations: A Review of 40 Years of Research.” Pp. 77–140 in *Research in organizational behavior*, vol. 20, edited by B. M. Straw and L. Cummings. Greenwich, CT: JAI.

Wilson, William Julius. 1987. *The Truly Disadvantaged : The Inner City, the Underclass, and Public Policy*. Chicago: University of Chicago Press.

WorldAtlas. 2018a. *Where Is Area Code 616?* worldatlas.com. Retrieved December 6, 2018 (https://www.worldatlas.com/na/us/mi/area-code-616.html).

WorldAtlas. 2018b. *Where Is Area Code 763?* worldatlas.com. Retrieved December 6, 2018 (https://www.worldatlas.com/na/us/mn/area-code-763.html).

Wright, Frederick. 1928. "Montreal." *American Political Science Review* 22(2):381–83. Retrieved (http://www.jstor.org/stable/1945472).

Wu, Lingfei, Dashun Wang, and James A. Evans. 2019. "Large Teams Develop and Small Teams Disrupt Science and Technology." *Nature* 566(7744):378–82.

Yang, Yang and Kenneth C. Land. 2006. "A Mixed Models Approach to the Age-Period-Cohort Analysis of Repeated Cross-Section Surveys, with an Application to Data on Trends in Verbal Test Scores." *Sociological Methodology* 36(1):75–97.