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Duality in Diversity: How Intrapersonal and Interpersonal Cultural Heterogeneity Relate to Firm Performance

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Abstract

How does cultural heterogeneity in an organization relate to its underlying capacity for execution and innovation? Cultural diversity is commonly thought to present a tradeoff between task coordination and creative problem solving, with diversity arising primarily through cultural differences between individuals. In contrast, we propose that diversity can also exist within persons when individuals hold multiple cultural beliefs about the organization. We refer to these different forms as interpersonal and intrapersonal cultural heterogeneity. We argue that the former tends to undermine coordination and portends worsening firm profitability, while the latter facilitates creativity and supports greater patenting success and more positive market valuations. To evaluate these propositions, we use computational linguistics to identify cultural content in employee reviews of nearly 500 publicly traded firms on a leading company review website and then develop novel, time-varying measures of cultural heterogeneity. Our empirical results lend support for our two core propositions, suggesting the need to rethink the performance tradeoffs of cultural heterogeneity: it may be possible to reap the creativity benefits of higher intrapersonal heterogeneity and, at the same time, the efficiency benefits of lower interpersonal heterogeneity.

Keywords: organizational culture, cultural diversity, organizational innovation, firm performance, intrapersonal diversity

Whether deliberately cultivated or naturally arising, every organization develops a culture—a system of meanings and norms shared by its members. An organization's culture can influence the success of its members and the organization as a whole through its effects on individuals' motivation and commitment,

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interpersonal coordination, and groups' creativity and innovation (Chatman and O'Reilly, 2016). Although organizational scholars often ask how the content or intensity of culture relates to performance—for example, how shared beliefs and norms about the importance of cross-functional collaboration can boost or diminish firms' profitability—a growing literature has focused instead on the consequences of cultural diversity for organizational productivity and vitality. Research in this vein examines when a diversity of ideas and beliefs is conducive to organizational success and when it is instead detrimental.

Different literatures have provided varied and inconsistent answers to this question. One line of work sees cultural heterogeneity as an obstacle to firms' performance. Research on cultural strength, for example, emphasizes the importance of cultural agreement among organizational members. This perspective indicates that incompatibilities in employees' beliefs and normative expectations can impede their ability to coordinate tasks (Kotter and Heskett, 1992; Denison and Mishra, 1995; Weber and Camerer, 2003), thereby producing a negative relationship between cultural diversity and firms' performance. In contrast, research by economic and cultural sociologists typically views cultural diversity as an advantage. This perspective conceptualizes diversity as a reflection of the cultural ''toolkit'' available to individuals (Swidler, 1986). When organizational members have access to a broad array of cultural resources, the organization is assumed to have a greater capacity for creativity and innovation to address changing, uncertain, and competing environmental demands (Hallett and Ventresca, 2006; Stark, 2011).

This tension is also manifest in work on demographic diversity. Although it has primarily focused on diversity in ascribed characteristics such as sex or age and in functional experiences, this literature has also called attention to deep-level differences in how people think and what they believe about group and organizational culture (Harrison, Price, and Bell, 1998). Whereas some studies have highlighted demographic diversity's negative implications for performance through the facilitation of conflict and coordination inefficiencies, others have focused on its positive effects on collective learning and creativity (Fiol, 1994; Lau and Murnighan, 1998; Page, 2007; van Knippenberg and Schippers, 2007).

Taken together, these literatures suggest that cultural diversity presents a fundamental tradeoff: culturally diverse firms are better at creative problem solving, but this capability comes at the cost of decreased coordination and efficiency. Empirical support for such a tradeoff, however, remains meager and unsettled. We begin to reconcile these divergent theoretical perspectives and mixed empirical findings by drawing on the core insight that cultural diversity is not a one-dimensional construct. Existing literature has conceptualized this diversity exclusively through the prism of differences between individuals, but heterogeneity can also exist within persons (Bunderson and Sutcliffe, 2002; Morris, Chiu, and Liu, 2015; Goldberg, Hannan, and Kovács, 2016). Building on this insight, we propose that there are two distinct forms of cultural diversity in organizations: that stemming from misalignment among members' cultural perceptions of the organization and that arising from the breadth of cultural resources they use to understand and make sense of the organization.

To illustrate, imagine a world in which there are only two possible beliefs, A and B, about how work ought to be done. Then imagine two hypothetical organizations. In the first organization, half of the employees espouse only belief A and the other half espouse only belief B. In the second organization, all

employees espouse both beliefs. The two organizations could at first appear to be equally culturally diverse, because inside each organization, each belief is held by an equal number of people. (Beliefs A and B are each held by 50 people in the first organization and are each held by 100 people in the second organization.) But the nature of this diversity varies between them. In the first organization, heterogeneity stems from divergent cultural beliefs between people or *interpersonal heterogeneity*. In the second organization, heterogeneity stems instead from individuals having more than one cultural belief about the organization or *intrapersonal heterogeneity*. Interpersonal and intrapersonal heterogeneity are interrelated but analytically distinct.

Integrating insights from demographic diversity, group learning, and cultural sociology, we argue that interpersonal and intrapersonal heterogeneity are related to different organizational outcomes. Consistent with work on the organizational consequences of cultural strength (e.g., Kotter and Heskett, 1992), we theorize that interpersonal heterogeneity will be linked to a firm's coordination and execution capabilities and thus to indicators of performance such as profitability. In contrast, drawing on group learning research (e.g., Page, 2007) and the toolkit theory of culture (e.g., Swidler, 1986), we posit that intrapersonal heterogeneity will be tied to a firm's capacity for creative exploration and therefore to patenting success and market expectations of future growth. Dividing cultural heterogeneity into its interpersonal and intrapersonal components reveals that there need not be a tradeoff between organizational coordination and innovation—for example, a culture with low interpersonal but high intrapersonal heterogeneity can facilitate coordination without necessarily undermining creative problem solving and innovation.

Empirically, the methods most commonly used to study organizational culture—chiefly self-reports (O'Reilly, Chatman, and Caldwell, 1991) and participant observation (Kunda, 2009; Turco, 2016)—can yield rich insight but are not well suited to generating dynamic measures of cultural heterogeneity for a large, diverse sample of firms. In part for this reason, prior work examining the link between culture and firm performance has tended to rely on cross-sectional designs and has mostly sidestepped questions about the dynamic interplay between the two. Moreover, survey-based methods highlight variation among respondents (O'Reilly, Chatman, and Caldwell, 1991) but are less well suited to detecting differences in intrapersonal heterogeneity across organizations. To overcome these limitations, we apply the tools of computational linguistics to derive novel, time-varying measures of interpersonal and intrapersonal heterogeneity for a sample of nearly 500 publicly traded companies on Glassdoor (www.glassdoor.com)—a career intelligence website that allows employees to evaluate and write reviews about their firms. In so doing, we explore the relationship between cultural heterogeneity and different performance outcomes in a comprehensive, longitudinal dataset of the largest U.S. firms.

CULTURAL HETEROGENEITY AND FIRM PERFORMANCE

Why Cultural Heterogeneity Matters

Organizational scholars often understand culture as a ''system of publicly and collectively accepted meanings'' (Pettigrew, 1979: 574) that a group—including

a formal organization—develops in response to challenges of external adaptation and internal integration. These meanings manifest in the form of deeply rooted assumptions and beliefs about the world, as well as in the normative and behavioral expectations that these assumptions and beliefs prescribe (Schein, 2010). Individuals learn to recognize, internalize, and conform to the organization's cultural code through the ongoing process of socialization and enculturation (Van Maanen and Schein, 1979; Ashford and Nurmohamed, 2012; Srivastava et al., 2018).

Organizational culture has been characterized along multiple dimensions—such as content, or which specific beliefs and behavioral norms are prevalent, and intensity, or the degree to which members are willing to sanction non-conforming behavior and reward normatively compliant behavior—that have varying implications for firms' performance (Chatman and O'Reilly, 2016). The content of cultural values, beliefs, and norms is important because it influences how people work to accomplish tasks in firms. For example, a company feeling a sense of urgency to introduce a disruptive technology might prioritize speed, autonomy, and tolerance of mistakes over other considerations. Although we acknowledge that the content of such norms and the intensity with which they are reinforced can have important consequences, our investigation focuses instead on a different cultural feature: heterogeneity, or the variety and distribution of ideas, beliefs, and normative expectations held by organizational members. For the disruptive company example, a cultural heterogeneity perspective would focus less on specific values such as speed or autonomy and more on the variety and distribution of all prevailing ideas and beliefs in the organization.

Our focus on heterogeneity is consistent with the distributive approach to analyzing organizational culture (Harrison and Carroll, 2006), which acknowledges that culture's role in organizational success is often idiosyncratic, such that the cultural content associated with success varies by industry and by a firm's choice of competitive strategy. Moving fast may be conducive to success for an organization competing in a fast-paced and undetermined technology market but not for a hospital in which minor errors can have devastating implications. Although the effects of cultural heterogeneity on performance may also vary across competitive contexts, we anticipate that the relationship between heterogeneity and performance will be more stable and consistent across empirical settings than will the link between specific beliefs or norms and organizational performance. Thus, consistent with previous work that has focused on the distribution of culture, we propose that cultural heterogeneity has implications for firm performance that are independent of cultural content and intensity.

Heterogeneous Perspectives on Cultural Heterogeneity

Organizational theorists who study cultural heterogeneity see it as both a blessing and a curse. Although work on organizational culture is vast and fragmented (Chatman and O'Reilly, 2016), two conflicting themes on the relationship between cultural heterogeneity and performance prevail. The first, most strongly associated with research on cultural strength, sees cultural heterogeneity as an impediment to organizational performance. This line of work conceptualizes culture as a solution to a complex coordination problem and views

heterogeneous cultures as detrimental to organizational performance because they undermine interpersonal integration and erode internal cohesion.

Two specific mechanisms undergird the theorized link between cultural strength and organizational performance. First, cultural homogeneity is assumed to promote interpersonal coordination by facilitating goal alignment and behavioral consistency (Gordon and DiTomaso, 1992; Kreps, 1996; Weber and Camerer, 2003). A lack of such alignment can produce coordination failures. For example, an employee working in accordance with a norm that encourages speed, autonomy, and a willingness to make mistakes will coordinate less well with another employee behaving in accordance with a norm emphasizing deliberateness, caution, and precision. Second, the absence of a unified and shared culture can generate fragmentation and a sense of personal estrangement. This can lead to conflict, as well as a decline in morale and a dampening of individual commitment and motivation (Martin, 1992; Jehn, Northcraft, and Neale, 1999).

In contrast, the benefits of cultural heterogeneity for organizational performance become apparent when culture is conceptualized as a set of cognitive resources that members deploy in adapting to external changes and competitive pressures. According to this perspective, cultural heterogeneity is an advantage rather than an obstacle. Core to this view is the assumption that creativity—the application of novel and useful solutions to problems (Amabile, 1988, 1996)—stems from the ability to recombine existing ideas in unconventional ways (Fleming, 2001; Uzzi et al., 2013; de Vaan, Vedres, and Stark, 2015). Drawing on these insights, researchers who emphasize the learning benefits of cultural diversity for performance argue that it promotes a capacity for creative problem solving and exploring a broader solution space. This capacity derives not only from the fact that culturally diverse teams draw on a breadth of ideas and interpretative lenses but also from the superadditive effects of this breadth: the novelty that emerges when ideas intersect and recombine (Page, 2007; Tadmor et al., 2012). The combination, for example, of a profit-oriented banking culture and a development-oriented social mission enabled the banks in Battilana and Dorado's (2010) study to pioneer commercial microfinance in Bolivia in the early 1990s.

Culturally heterogeneous organizations learn more effectively by fusing different schemas, scripts, and interpretive understandings to generate novel solutions. Cultural homogeneity, in contrast, can be detrimental to a firm's capacity for creativity for at least two reasons. First, employees in culturally uniform organizations are slower to recognize the need for change than their counterparts in organizations with diverse cultures (Lant and Mezias, 1992). Second, whereas cultural strength can foster first-order learning, such as determining how to more efficiently execute tasks that are known to be important for marketplace success, it can inhibit second-order learning—identifying which new tasks to take on in response to a new or changing competitive landscape (Denison, 1984).

These competing perspectives on the relationship between cultural heterogeneity and performance are echoed in research on relational demography, which has mostly examined the consequences of differences in ascribed traits (such as sex, race, and age) and in backgrounds (such as functional experience, education, and tenure) on group cohesion and performance (Pfeffer, 1983; Tsui, Egan, and O'Reilly, 1992). Research in this vein often assumes that

differences at the surface level, such as race and age, also reflect disagreements at a deeper level of attitudes and beliefs. When these attitudes and beliefs relate to shared meanings, assumptions, and normative expectations, they become the cognitive material that makes up organizational culture. As Harrison, Price, and Bell (1998) pointed out, demographic differences relate to attitudinal differences early in a group's life that tend to wane as members coordinate their cultural orientations over time.

Thus demographic diversity is not necessarily tantamount to cultural diversity. Nevertheless, work on the relationship between demographic diversity and performance echoes the tension pervading the literature on culture. Demographic differences, especially when different dimensions of categorical dissimilarity reinforce one another, foster subgroup conflict and erode group cohesion and performance (Lau and Murnighan, 1998). However, under certain conditions—such as functional interdependence—cultural heterogeneity can allow group members to bring together varying perspectives and ideas in ways that can enhance creativity and innovation (Jehn, Northcraft, and Neale, 1999; van Knippenberg and Schippers, 2007).

Interpersonal and Intrapersonal Cultural Heterogeneity

Taken together, these literatures suggest that cultural heterogeneity presents a fundamental tradeoff: culturally diverse firms are better at creative problem solving, but this capability comes at the cost of less coordination and efficiency. Yet empirical support for the existence of such a tradeoff is scant and inconclusive. Sørensen (2002), for example, theorized that the negative effects of cultural heterogeneity on firms' performance would attenuate in volatile contexts, which ought to favor firms with a greater capacity for adaptation; however, he found inconsistent support for this contention. Similarly, Kotrba et al. (2012) reported that the relationship between cultural heterogeneity and firms' performance is contingent on various other cultural attributes and varies by performance indicator (e.g., market-to-book ratio versus return on assets), while Burt et al. (2000) identified additional network-based market contingencies of strong cultures.

We argue that these mixed empirical findings in part reflect a theoretical shortcoming: the assumption that cultural heterogeneity is one-dimensional and arises predominantly from dissimilarities *between* people. The positive effects of heterogeneity on creativity and problem solving are often assumed to emerge from the combination of disparate beliefs that are otherwise distributed across individuals (Page, 2007). Prevailing organizational culture constructs also tend to emphasize between-person differences. Cultural consensus, for example, refers to the degree of agreement between group members about which normative expectations matter (Chatman and O'Reilly, 2016).

Yet heterogeneity can also exist *within* individuals. In team diversity research, Bunderson and Sutcliffe (2002) showed that heterogeneity derives not only from differences between people—the variety of functional experts on a team—but also within individuals—the aggregate functional breadth of team members. Extending this insight to the realm of organizational culture and drawing on the idea that culture is a toolkit of multiple and potentially inconsistent cognitive resources (Swidler, 1986), we propose that heterogeneity can arise in two conceptually distinct ways. The first is the familiar between-person

route, stemming from cultural misalignment between organizational members. The second is a heretofore unexamined within-person pathway, when organizational members subscribe to multiple and potentially incompatible beliefs and values.

Although within-person heterogeneity has been mostly overlooked by the literature on organizational culture, considerable evidence supports its existence. Firms commonly encourage their employees to adopt a broad and potentially inconsistent set of values. For example, Netflix's influential 126-page culture statement includes value statements ranging from freedom and autonomy to curiosity and responsibility.[1] Some of these values appear to be at odds with one another. For instance, Netflix emphasizes collective outcomes such as selflessness and teamwork but also the relentless pursuit of individual performance. The culture slide deck states, ''We're a team . . .'' and ''You seek what is best for Netflix, rather than best for yourself . . .,'' but then goes on to issue the stern warning that ''adequate performance gets a generous severance package.''

Formal statements and espoused values are, of course, often aspirational and do not necessarily represent employees' lived experiences. No one in Enron, as far as we know, officially endorsed malfeasance. There are nevertheless reasons to expect that, like formal mission statements, enacted culture can encompass a multiplicity of ideas, including ones that depart from official doctrine. Support for this view comes from two interrelated bodies of research. The first, from cultural sociology, holds that people are cognitively equipped to internalize and selectively deploy multiple, coinciding cultural frames. This approach conceives of culture as a loosely held repertoire or cultural ''toolkit'' (Swidler, 1986). Research in cognitive and cultural psychology generally supports this conceptualization. People often hold multiple and often inconsistent cognitive schemas (DiMaggio, 1997) and are capable of identifying with multiple cultural identities (Morris, Chiu, and Liu, 2015). Different situations invoke different cultural lenses. Participants in Swidler's (2001) study of romantic relationships, for example, at times described their bonds through a prism of love and selfless commitment and at others emphasized their relationships' rational and instrumental foundations. Thus individuals do not necessarily subscribe to a single and internally coherent cultural order. Rather, they embody multiple cultural models that are invoked by different institutional contexts (Hallett and Ventresca, 2006; Harding, 2007).

A second line of work demonstrates that people, especially in complex modern societies, acquire a capacity for polyculturalism stemming from their constant exposure to multiple and incongruent institutional orders. The normative assumptions governing relationships in the family, for example, are very different from those governing market transactions (Friedland and Alford, 1991). Consequently, people habitually draw symbolic boundaries between familial and economic relationships to resolve this incongruence (Zelizer, 2007).

Extending these arguments across levels of analysis, institutional sociologists have proposed that organizations, like individuals, often operate in multiinstitutional environments (Boltanski and Thévenot, 2006). For example, many companies cultivate a family-like ethos but draw on a market logic to manage

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[1] Downloaded more than 10 million times, the slide deck was hailed by Facebook's Chief Operating Officer, Sheryl Sandberg, as the ''most important document ever to come out of [Silicon] valley.''

labor relations. Employees intersect the different cultural orders on which such organizations are founded. Medical professionals, for example, must navigate the tensions between competing cultural logics that view medicine either through the lens of science or caregiving. The former emphasizes scientific authority and diagnostic success, whereas the latter conceptualizes quality health care as compassionate and preventive. Each prescribes different criteria for evaluating the legitimacy and desirability of behaviors and outcomes (Dunn and Jones, 2010).

Institutional plurality begets friction and fragmentation in organizations when different individuals subscribe to distinct institutions, adopt different identities, and see the organizational mission through internally consistent but interpersonally incongruent lenses. Organizations can overcome this tension when their members cognitively fuse these different cultural components (Zilber, 2002; Battilana and Dorado, 2010; Besharov, 2014). In fact, cultural plurality can be a source of advantage. Work by cultural sociologists has found that multivocal actors (Padgett and Ansell, 1993) and cultural objects (Griswold, 1987) derive power from their capacity to engender multiple meanings while retaining coherence.

Bringing together the two broad perspectives—one that emphasizes heterogeneity's roots in group composition and the other that focuses on the breadth of cultural repertoires available to individual actors—we argue that cultural heterogeneity comprises two analytically distinct dimensions: interpersonal and intrapersonal. By interpersonal heterogeneity we refer to misalignment in cultural perceptions among the individuals who make up the organization.[2] By intrapersonal heterogeneity we mean the breadth of cultural beliefs to which those individuals subscribe.

To illustrate this distinction, we return again to our stylized example in which there are only two possible cultural beliefs, A and B. Figure 1 illustrates the demographic makeup of two hypothetical organizations, each represented by a circle. The organization on the left, comprising individuals who adopt either belief A or belief B, exhibits high interpersonal heterogeneity but low intrapersonal heterogeneity. Its culture exhibits low alignment across individuals, and individuals themselves tend to subscribe to a smaller set of cultural beliefs. The organization on the right, in contrast, is characterized by high intrapersonal heterogeneity and low interpersonal heterogeneity. Individuals maintain a variety of beliefs about how to accomplish work in the organization and exhibit high alignment about the importance of those beliefs. Distinguishing between these two components of heterogeneity helps to uncover an important insight: organizations with broad within-person cultural repertoires need not be characterized by high levels of between-person differences.

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[2] Interpersonal heterogeneity is related to but conceptually distinct from the construct of organizational subcultures, i.e., clusters of individuals who share similar beliefs that differ from those held by people in other clusters. In the extreme case of an organization with no interpersonal heterogeneity—i.e., in which all members hold exactly the same cultural beliefs—it is, of course, not possible for subcultures to exist. Yet in organizations whose members hold divergent cultural beliefs, subcultures may or may not exist. For example, in the extreme case of an organization in which each member holds a single cultural belief that no one else holds, interpersonal heterogeneity is high, but there are no subcultures. In the analyses that appear in Online Appendix A (http://journals.sagepub.com/doi/suppl/10.1177/0001839219844175), we nevertheless include a robustness check that accounts for the presence of organizational subcultures.

Figure 1. Example of interpersonal and intrapersonal cultural heterogeneity of beliefs A and B among members of two organizations.
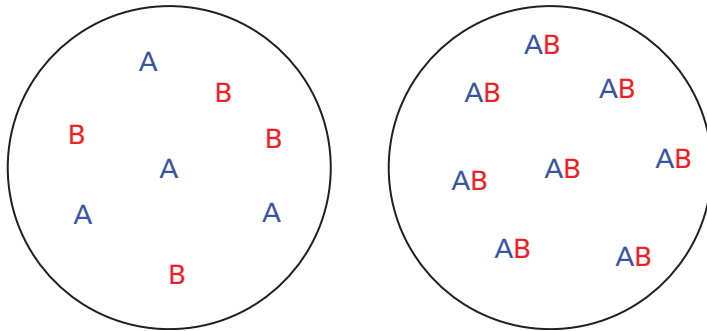
Netflix, for example, has developed a variety of human resource practices that complement its broad cultural mission. The company places a strong emphasis on hiring and dismissal on the basis of cultural fit and, at the same time, institutes formal procedures and behavioral norms that are consistent with the mission and breadth of values it espouses (McCord, 2014). Netflix, in other words, invests in cultivating low interpersonal heterogeneity and high intrapersonal heterogeneity. Insofar as these practices are effective, they should produce a culture that is both consensual and broad.

Performance Implications of the Two Forms of Cultural Heterogeneity

Seen in this light, the tradeoff between organizational coordination and problem-solving capacity no longer seems unavoidable. If cultural heterogeneity comprises two dimensions—interpersonal and intrapersonal—then culture can facilitate coordination without necessarily undermining creative problem solving and innovation. Consistent with this logic, each dimension of heterogeneity should promote different organizational outcomes. Drawing on the literature on cultural strength, we propose that interpersonal heterogeneity will weaken an organization's coordination and cohesion and will therefore undermine its capacity for effective execution. We therefore anticipate:

> **Hypothesis 1 (H1):** All else equal, interpersonal cultural heterogeneity will be negatively related to a firm's capacity for efficient execution.

Interpersonal heterogeneity and its negative effects on individual and organizational performance have been extensively researched. Hypothesis 1 is broadly consistent with prior work on cultural strength and consensus in organizations. To our knowledge, however, no prior studies have systematically compared—as we do here—differences in interpersonal heterogeneity across organizations over time and studied the implications of these differences for performance.

Our core argument about intrapersonal heterogeneity, which has not been previously examined in organizational research, is that because creativity and innovation stem from the recombination of previously unrelated ideas, a wide cultural toolkit should—all else equal—be conducive to individual creativity

(Amabile, 1988). Previous work has conceived of such recombination as arising from interpersonal exchange—as a function of teams rather than of individuals (de Vaan, Vedres, and Stark, 2015). We shift attention to the cultural resources available to individuals and the recombinant innovation they can engage in as a result. Creative recombination is ultimately something that individuals do (Amabile, 1988; Sauermann and Cohen, 2010), although organizations create contexts that can facilitate or inhibit this creativity (Amabile et al., 1996; Taggar, 2002).

Prior work on cultural heterogeneity has assumed that organizations enable creativity by forming culturally varied teams (e.g., Pieterse, van Knippenberg, and van Dierendonck, 2013). We propose that organizations can also facilitate creativity—whether deliberately or organically—by increasing the representation of members who espouse a broad set of beliefs. Evidence for a link between intrapersonal heterogeneity and individual creativity comes from cultural psychology. Multicultural individuals, for example, exhibit a capacity for high integrative complexity and creative output by virtue of constant exposure to different national cultures (Tadmor, Galinsky, and Maddux, 2012).

The recombinant advantages of intrapersonal cultural heterogeneity should also manifest in organizations whose members have access to broad cultural toolkits. Performing complicated tasks often requires individuals to draw on and integrate multiple and sometimes conflicting cultural ideas about how work is or should be done, and historical accounts of inventors and entrepreneurs often place them at cultural crossroads. For example, the hackers of the early computer industry intersected the seemingly antithetical worlds of cold war military research culture and 1960s counterculture, ushering in new technologies and organizational forms to translate these technologies into products (Turner, 2010). This ability to combine multiple perspectives was presumably also conducive to creative entrepreneurship for the machine operators in Stark's (2011) study of a Hungarian factory in the late 1980s. Operating in a cultural context that valued technical skills but also promoted an anti-bureaucratic, relationship-oriented ethos, these factory workers were successful in forging innovative partnerships and pursuing semi-private enterprise under Hungary's late-communist ''second-economy'' legislation. As both of these examples illustrate, organizations whose members draw on broader cultural toolkits tend to exhibit a greater capacity for creativity and innovation. Thus we hypothesize:

> Hypothesis 2 (H2): All else equal, intrapersonal cultural heterogeneity will be positively related to a firm's capacity for creativity and innovation.

How organizations transform innovative ideas into positive organizational outcomes differs from how they facilitate individual creativity. The generation of novel ideas requires divergent thinking and complex integration, which we contend can be catalyzed by intrapersonal heterogeneity. In contrast, selecting which of these ideas to act on and doing so effectively requires other forms of information-processing and problem-solving capacities (Berg, 2016). We do not hypothesize about the group processes that enable teams to translate creative ideas into organizational outcomes, as those have been studied elsewhere (e.g., Woodman, Sawyer, and Griffin, 1993; Taggar, 2002). Rather, we posit

that intrapersonal cultural heterogeneity is conducive to innovative output through its relationship with individual creativity.[3]

Language as a Window into Cultural Heterogeneity

In operationalizing the two constructs—interpersonal and intrapersonal heterogeneity—we begin with the premise that organizational culture can be detected in the language used by members (Crémer, Garicano, and Prat, 2007; Pinker, 2007). The relationship between language and culture is complex. A useful way of conceptualizing this relationship draws on the distinction between culture's behavioral and cognitive dimensions (Mobasseri, Goldberg, and Srivastava, 2019). In terms of the behavioral dimension, language can be thought of as a set of norms that facilitate interpersonal coordination and that people adhere to when they want to fit into an organization. Weber and Camerer (2003), for example, experimentally demonstrated that linguistic conventions formed by individuals solving a coordination task increase group efficiency but also serve as an impediment when groups with different conventions are combined. In more recent work, Srivastava et al. (2018) and Goldberg et al. (2016) developed a language-based measure of cultural fit and, using an e-mail corpus and personnel records from a mid-sized firm, demonstrated that compliance with linguistic norms is positively related to individual attainment.

Yet language can also reveal a person's underlying beliefs and assumptions. For example, the language that activists and civil society organizations used in public discourse reflected deep cultural shifts in Americans' perceptions of nuclear energy in the 1980s (Gamson and Modigliani, 1989) and of Muslims in the period following the September 11, 2001 terrorist attacks (Bail, 2012). Building on these insights, we propose that organizational culture can be detected not only by observing the degree of linguistic compliance that members exhibit when communicating with each other—for example, in e-mails or text messages—but also in the language they use to describe the organization as a whole. In particular, we focus on the topics members use when describing their culture to each other and to outsiders. When explicitly talking about culture, organizational members consciously articulate the assumptions and beliefs they perceive are prevalent in their organization.

Whether measuring culture based on self-reports, implicit measures, or expressions of language, prior work has focused on specific categories, such as innovation, transparency, or collaboration, that were predefined by researchers or informants (e.g., senior leaders in the firm) (O'Reilly, Chatman, and Caldwell, 1991; Ehrhart and Naumann, 2004; Srivastava and Banaji, 2011). For example, Luo, Zhou, and Shon (2016) identified cultural topics such as innovation and quality in employees' reviews of firms on Glassdoor (the same site from which our data are drawn) and showed that different categories are correlated with employees' satisfaction and corporate performance in different industries.

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[3] Considering how innovation relates to execution naturally raises questions of how intrapersonal and interpersonal heterogeneity might jointly, rather than independently, shape organizational outcomes. We discuss this possibility and present supplementary analyses in Online Appendix B.

Although we acknowledge that certain cultural topics may matter more than others for success in a given industry sector, we propose that the distribution of cultural topics between and within individuals can nevertheless be independently related to firms' profitability and innovation. The novelty of our approach is that it neither privileges one set of cultural topics over others nor assumes that researchers and informants understand the culture better than the typical organizational member does. Instead, we assume that all topics used in discourse about the organization's culture are potentially informative.

Given a set of topics that organizational members use to describe culture in a given period, we define interpersonal heterogeneity as the dissimilarity of topics that group members mention in their characterizations. Organizations exhibit greater interpersonal heterogeneity when their members diverge from one another in describing the culture. We define intrapersonal heterogeneity as the breadth of topics used in individual members' cultural descriptions. Organizations exhibit greater intrapersonal heterogeneity when their members have access to and draw from a more diverse cultural toolkit.

METHOD

Data Sources and Sample

The data include all reviews of employers written by employees in the United States from January 2008 to July 2015 on the website Glassdoor.[4] Glassdoor is a career intelligence website that attracts a diverse audience primarily as a job search platform. It has an estimated 17 million unique users per month. While their identities as employees are authenticated by Glassdoor, reviewers are anonymous, thus making the reviews less susceptible to bias stemming from fear of retribution by employers. Reviews are either unsolicited or contributed by users searching for jobs in exchange for unlimited site access; see Online Appendix A (http://journals.sagepub.com/doi/suppl/10.1177/0001839219844175) for details. Popadak (2013) used similar review text from employees to construct longitudinal culture measures.[5]

We restricted the firm sample to publicly traded companies for which we have access to performance data from Compustat and firms with at least 50 employee reviews in one or more quarters to ensure that there were a sufficient number of reviews to calculate our culture measures. A small number of reviews were later dropped from this sample because they did not contain at least five words that were weighted by the latent Dirichlet allocation (LDA) culture model. Only firm/quarters with at least 25 reviews were used in estimated models. The resulting sample contains 512,246 reviews across 492 organizations. We lagged all predictors by one quarter to partially alleviate concerns of reverse causality and standardized the culture measures.

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[4] Accessible at www.glassdoor.com.

[5] Popadak's (2013) measures of organizational culture focused on specific cultural features, such as integrity, detail orientation, and adaptability, rather than the distribution of cultural content within and between employees. Nevertheless, she demonstrated that cultural attributes of organizations derived from the text of employees' reviews of firms on Glassdoor are highly correlated with popular, survey-based assessments of the workplace culture. This finding helps validate the use of Glassdoor reviews as a means to assessing aspects of a firm's changing organizational culture.

Measures

Dependent variables. Our hypotheses focus on the link between cultural heterogeneity and firms' capacity for efficient execution (H1) and creativity and innovation (H2). We link the capacity for efficient execution to firms' profitability, as measured by return on assets (ROA)—income before extraordinary items over total assets. ROA is commonly understood as a measure of profitability that indicates a firm's ability to effectively capitalize on its assets. We therefore used it as a reflection of a firm's capacity for efficient execution.

Creativity and innovation are more challenging to measure, and we consequently relied on two types of performance indicators: market valuation and patenting output. We measured the market's expectation of a firm's growth potential using Tobin's Q (TQ)—the market value of a firm's assets relative to their book value. Given the forward-looking nature of the market, this measure is commonly understood as an indicator of intangible capabilities and assets— from marketing prowess to innovative IT use (Bharadwaj, Bharadwaj, and Konsynski, 1999). Creativity and innovation are inherently linked to Tobin's Q. Investors tend to reward companies that exhibit creative business strategies and that pursue technological innovation (Kogan et al., 2017), and R&D intensity and patenting success are generally both positively associated with Tobin's Q (Hall, Jaffe, and Trajtenberg, 2005). Formally:

$$TQ = \frac{market\ value\ of\ assets}{0.9 * book\ value\ of\ assets + 0.1 * market\ value\ of\ assets} \quad (1)$$

Where market value of assets is defined as:

$$MV = book\ assets + $$
$$(market\ value\ of\ common\ equity - common\ equity - deferred\ taxes) \quad (2)$$

While Tobin's Q broadly captures a firm's potential for growth and innovation as judged by the market, we also measured innovation more directly via patenting success. Patents mark the creation of new knowledge and are well established as important innovation outcomes (Lanjouw and Schankerman, 2004). First, we measured a firm's ability to successfully produce patents by counting the total number of patents a firm applies for in a given quarter that are later approved. Second, we measured the mean number of backward citations made by the patents in a firm's portfolio in a given quarter, which is a common indicator of the technological importance and market value of the patents (Lanjouw and Schankerman, 2004).[6] Patents are required to cite relevant prior art, or backward citations to existing patents on which the focal patent builds. We logged the mean backward citations measure to account for skew.

Although patenting is a direct measure of innovation, it is not a perfect one. First, patenting captures technological innovation that can be protected as intellectual property, but a large proportion of innovation, such as marketing creativity or business strategy, is not reflected in patenting output. Second, industries

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[6] Given the recency of the data, we lack adequate data on forward citations, another measure of technological importance that counts the number of times that focal patents are cited by subsequent patents.

vary significantly in patenting volume. While patenting is extremely common in the pharmaceutical industry, for example, it is not in retail. Our measures of patenting, particularly patenting quality, therefore apply to only a relatively small subset of companies. Overall, we evaluated H2 by examining both Tobin's Q and patenting outcomes. Whereas Tobin's Q is a broad but noisy measure of innovation and creativity, patenting success provides a more direct but narrower indication of innovation.

Interpersonal and intrapersonal cultural heterogeneity. We developed language-based measures of cultural heterogeneity to capture variation in interpersonal and intrapersonal heterogeneity. We measured interpersonal heterogeneity and intrapersonal heterogeneity using free response text written by employees reviewing the firm. Following prior text analysis work, we treated each review as a ''bag of words,'' which assumes that we can identify topical content even after discarding word order. We then represented each review as a vector of unigram counts, which identifies how many times the review includes individual words. Together, these individual words form a set of the most popular words that appear across the entire text corpus.

Our empirical strategy consisted of two primary steps: (1) training a linguistic topic model to identify distinct dimensions of organizational culture mentioned in employees' reviews across the entirety of the Glassdoor data and (2) fitting that model to our analytic sample to identify the cultural dimensions mentioned in each employee review for the companies that we can track over time. We used a latent Dirichlet allocation (LDA) topic model (see Online Appendix C for technical details). LDA inputs a document-term matrix, for which the rows are reviews and the columns are unigram counts, and identifies distinct topics across the corpus by observing words that tend to co-occur frequently within each review. LDA then outputs a document-topic matrix, for which each review is assigned to a probabilistic mixture of topics, or a probability distribution giving the percentages across all topics $c \in C$ that the model estimates the review comprises.[7]

Training the LDA model allowed us to learn what topics employees across all organizations in the Glassdoor data collectively consider germane to organizational culture. Our model training approach required a key assumption: when employees write about firm culture, they sometimes explicitly use the word ''culture'' or a synonym and sometimes do not, but we could use the presence of a culture synonym as a label that indicates a given phrase contains content relevant to culture. Training the LDA model on text with these explicit references allowed the model to identify a set of cultural topics. The model was then fit to reviews in our analytic sample to identify the cultural topics in text containing either explicit or implicit culture references (see Online Appendix C for details).

The LDA model requires the researcher to choose the number of topics to output. Our goal in choosing the number of topics was not to maximize the coherence or distinctiveness of the topics, because we were not interested in the cultural content per se but in the distribution of content between and within

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[7] For further background and empirical examples of LDA in use, see DiMaggio, Nag, and Blei, 2013; Mohr and Bogdanov, 2013; Kaplan and Vakili, 2015; and Jha and Beckman, 2017.

reviewers. As such, we output a large number of topics—i.e., 500—to ensure we teased apart conceptually meaningful distinctions between cultural topics. This decision was informed by methodological research on LDA models— above some threshold, new topics only ''nibble away'' at existing topics rather than fundamentally alter the topic distribution. This suggests that more topics are preferable to fewer ones given our focus on the distribution of content (Wallach, Mimno, and McCallum, 2009: 8). Our cultural heterogeneity measures were highly correlated and our results were consistent using different numbers of topics (25, 50, 100, and 250).

The topics identified by the LDA model have face validity as cultural dimensions that capture the linguistic signatures of ideas, beliefs, and normative expectations that organizational members hold. One way to validate LDA topics is to examine the words that are most highly weighted within each topic (DiMaggio, Nag, and Blei, 2013). Table 1 shows the highest-weighted words for four handpicked and four randomly selected LDA topics, as well as simple labels we chose that generally capture the underlying meanings of the topics. The first set was handpicked based on its highly distinctive culture content, and the randomly selected set is representative of average LDA topics. The LDA topics appear to be germane to organizational culture, lending support for our unsupervised learning approach.

After identifying cultural topics using this training set of phrases with explicit cultural references, we fit the LDA model to the reviews in our sample. In contrast to clustering methods, LDA is a mixed-membership approach, which assigns each document to a probability distribution over multiple topics. Figure 2 illustrates LDA's assignment of each review in the analytic sample to a mixture of multiple culture topics, represented as a topic probability distribution over the set of cultural topics. The model predicts that two reviews with similar topic probability distributions contain similar content.

We measured interpersonal heterogeneity by assessing the degree to which a firm's employees in a given quarter characterize the firm using dissimilar cultural topics. (Online Appendix C provides a series of measurement validation checks.) After fitting the LDA model to the reviews in our analytic sample, each review i is represented as a probability distribution p indicating the relative proportion of each cultural topic c estimated as present in the review text.

Table 1. Highest-weighted Words for Selected LDA Culture Topics

Number	Label	Words
		Selected topic
10	production quality v. quantity	qualiti product high produc deliv commit counter deliveri emphasi quantiti
16	entrepreneurial norms	entrepreneuri thrive initi spirit dynam motiv collabor starter creativ individu
33	travel and multiculturalism	travel opportun world countri meet experi chanc interact abroad global
35	social interaction	social fun event activ interact lot frequent aspect regular includ
		Random topic
473	performance recognition	perform reward recognit recogn incent individu consist mediocr contribut resul
415	organizational structure	compani exist virtual anymor bought parent basic built longer sold
399	fun work environment	fun cowork great cool amaz outgo hang toy lightheart easygo brilliant train hip
481	workplace challenges	challeng work interest reward present demand inher tackl workplac

Figure 2. Stylized example of LDA's mixed membership topic assignment.*

May 8, 2008

"VMware is a fun place to be; it's aggressively growing, and it strives to provide a comfortable work environment"

★★★★★ ▾   Current Employee - Software Engineer in Palo Alto, CA

■ Recommends   ■ Approves of CEO

Pros

VMware is a fun place to be during the day. The company is growing, and their technology has lots of room to grow and improve. The employees are diverse in age and culture; and everyone is friendly. This is helpful as many of us are new to the Bay Area. Everyone in the company is smart, works hard, and pulls their weight. There's a culture of collaboration; and a degree of freedom in selecting one's work. VMware provides a great set of on-site perks: free soda & other healthy beverages, on-site expresso machines, plenty of healthy snacks, pinball machines, a friday "beer bash", and plenty of games like pool, ping-pong, and foosball tables.

Show Less

Cons

Although virtualization is an interesting and exciting field; some of the periphery work can be burdensome. Because the stock is volatile; recent hires will become very wealthy before other employees who have stock options that are severely underwater. Some employees underestimate the tangible advantages of competitors' products; like Parallels and Microsoft HyperV. Occasionally, perks are changed without employee involvement; to the chargin of those who chose VMware for a specific perk. A weakness is that VMware's products built by Unix people are difficult for Windows/Mac-centric users; and products built by Windows people are difficult for Unix/Mac-centric users. The cubicle areas can be noisy.

Show Less

Topic Distribution
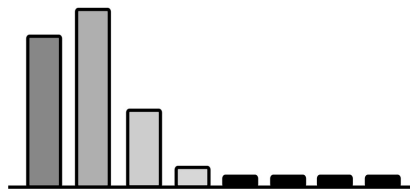
* Words associated with different topics, represented by different shades of gray, can be aggregated to yield a probability distribution over topics.

We defined interpersonal heterogeneity for a given firm/quarter as the mean Jensen–Shannon (JS) divergence between the LDA probability distributions for all unordered pairs of reviews i,j for that firm/quarter, formally:

$$InterH = \frac{\sum_{i,j} JS(p_i, p_j)}{\sum_{i,j}}, \; for \; all \; \{i,j | i < j\} \qquad (3)$$

where the JS divergence between the two probability distributions is defined as:

$$JS(p_i, p_j) = \frac{1}{2} KL(p_i, M) + \frac{1}{2} KL(p_j, M) \tag{4}$$

and where $M = \frac{1}{2}(p_i + p_j)$ and $KL(p_i, M)$ is the Kullback–Leibler divergence of M from p_i:

$$KL(p_i, M) = \sum_{c \in C} p_i(c) log_2 \frac{p_i(c)}{M(c)} \tag{5}$$

JS divergence is a symmetric measure of the dissimilarity of two probability distributions. It is well suited for comparing sparse, power-law distributions of words observed in natural language and has been used previously to measure the similarity of organizational members' language use (Goldberg et al., 2016; Srivastava et al., 2018).

We measured intrapersonal heterogeneity by assessing the degree to which a firm's employees discuss a broad versus narrow set of cultural topics (see Online Appendix C). Each review i is represented as a probability distribution p indicating the relative proportion of each cultural topic c estimated as present in the review text. We applied the Herfindahl index, a popular measure of concentration, to these probability distributions and calculated the mean Herfindahl score across all reviews for a given firm/quarter. Formally:

$$\bar{H} = \frac{\sum_i \sum_{c \in C} (p_i^c)^2}{\sum_i} \tag{6}$$

After taking the inverse, higher values indicate that employees discuss a broader range of cultural topics, while lower values indicate a narrower, concentrated set of topics. We took the natural log of the mean Herfindahl index because the measure has a highly skewed distribution. Intrapersonal heterogeneity for a firm/quarter is formally defined as:

$$IntraH = 1 - \ln \bar{H} \tag{7}$$

Figure 3 provides a stylized example of how our measures of interpersonal and intrapersonal heterogeneity capture systematic differences in the LDA topic probability distributions across individual reviews in a given firm-period. Using a (hypothetical) case of a firm that had three employee reviews, Panel A illustrates that firm-periods with low interpersonal heterogeneity feature reviews with more similar topic distributions. Conversely, high interpersonal heterogeneity firm-periods have reviews with more dissimilar topic distributions. Panel B, drawing on a similarly hypothetical example, illustrates that low intrapersonal heterogeneity firm-periods have reviews with more concentrated topic distributions on average, while high intrapersonal heterogeneity firm-periods have reviews with on average more uniformly distributed topic distributions.

Our language-based model of cultural heterogeneity has two advantages over survey-based culture measures. First, it allows us to measure dimensions of organizational culture longitudinally for a large, diverse set of organizations, which

Figure 3. Stylized illustration of interpersonal and intrapersonal heterogeneity.
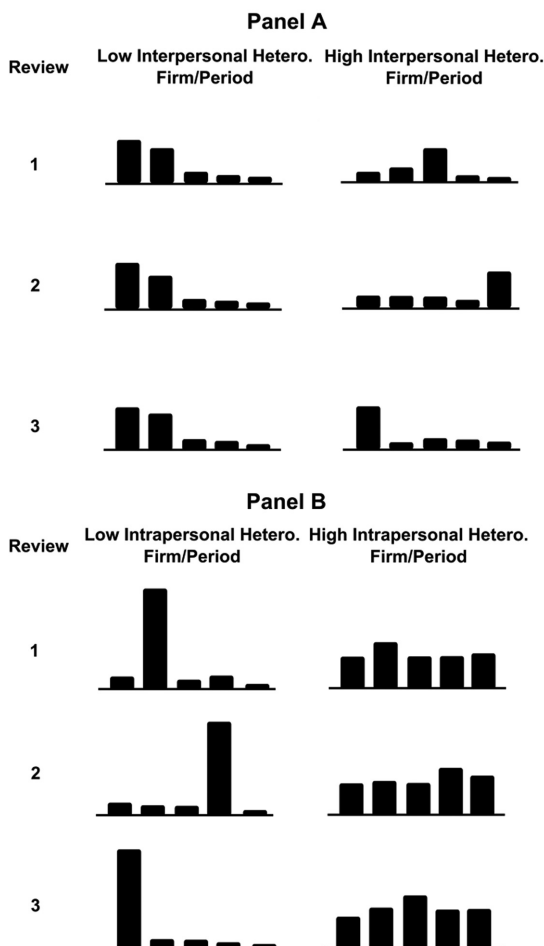
would be difficult using more expensive and time-intensive survey methods. Second, the model inductively identifies topics that employees consider germane to organizational culture. We do not require the researcher to make a priori assumptions about the cultural topics that broadly characterize organizations.

Given that the employees who wrote Glassdoor reviews were not selected through random sampling from the population of firm employees, Online Appendix A includes robustness checks to address the impact of non-random selection of employees into writing Glassdoor reviews that could bias our findings. We found no evidence that either the number or composition of reviewers systematically changes with firm performance and no evidence that the cultural heterogeneity measures themselves vary with the number or composition of reviewers.

Analytical Strategy and Estimation

We tested our hypotheses with two types of models. The first was a conventional OLS model with lagged independent variables (but when estimating

patent counts, we also used a negative binomial model). In addition to our main independent variables, we controlled for firm size, measured as logged value of assets, and number of reviews, logged, to account for systematic variation in cultural heterogeneity measures attributable to the number of reviews with which they were produced. We also included industry and quarter fixed effects, given that performance outcomes vary significantly by industry and over time. We clustered standard errors by firm to allow for correlation between observations of the same firm over time.

A second type of model relied on coarsened exact matching (CEM) (Iacus et al., 2012), which we used for two reasons. First, CEM allowed us to (partially) address concerns about endogeneity. CEM identifies firm observations that vary on the culture variable of interest but have the same or very similar values for each control variable. Conditional on identifying all variables that affect the relationship between cultural heterogeneity and performance, CEM helps to correct for selection bias. We acknowledge, however, that the relationship between culture and firm performance is likely to be complicated and potentially bi-directional. CEM moves us closer to causal estimates, but in the absence of exogenous variation in cultural heterogeneity or a compelling instrumental variable, we stop short of making a strong causal claim.

Second, we assumed that a substantial proportion of variation in the effects of cultural heterogeneity on performance is attributable to differences between firms—for example, to organizations' different emphases on cultivating cultural consensus. Moreover, culture is known to change slowly in firms. Although our data are comprehensive, they afford systematically observing within-firm cultural change over an extensive period of time for only a subset of companies. To properly estimate between-firm differences, our modeling strategy must account for other factors, such as industry, firm size, and period, which may result in nonlinear relationships between cultural heterogeneity and performance. CEM provides such a modeling approach by allowing us to match firms that are culturally different but otherwise similar.

We implemented CEM as follows. For each culture variable (interpersonal and intrapersonal heterogeneity), we first divided observations into high and low categories on the culture measure, defined by a value above or below the industry median.[8] We then matched these firms identified as high or low on the culture variable with others that were the same or very similar on observed characteristics to achieve covariate balance.

CEM allowed us to match exactly on some covariates and coarsely on other covariates when it was infeasible to produce exact matches. We matched exactly on industry, year, and quarter. We matched coarsely on firm assets as a firm size control and on number of reviews to account for the level of coverage on the Glassdoor website. For the firm performance outcomes and patent count, coarse matches were identified using the binning algorithm default for the *cem* command in Stata.[9] But the default binning algorithm did not produce enough matches for the mean backward citations outcome to run a meaningful

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[8] We identified high and low culture groups using industry medians because the distributions of interpersonal and intrapersonal heterogeneity vary substantially across some industries, where industry is defined by two-digit SIC code.

[9] Sturge's rule is the default algorithm, which is commonly used to determine the bin width when representing a probability distribution as a histogram.

statistical analysis because that outcome is conditional on a firm having patented in a given quarter. Thus we manually instructed the command to iden-tify matches using five equally spaced bins with respect to firm assets and three equally spaced bins with respect to the number of reviews. This proce-dure produced enough matches for analysis while also achieving balance on the covariates.

An attractive feature of CEM is that it can produce matched strata with an unequal number of high and low culture observations so as to maximize the total number of matched observations and thus increase estimation efficiency in the subsequent analysis. The CEM algorithm produced simple weights to adjust for these differences during estimation, which we applied in all models. We also included strata fixed effects in all models—we modeled variation in the performance outcomes between high and low culture observations within each stratum of matched observations. Finally, we once again clustered stan-dard errors by firm to allow for correlation between observations of the same firm over time.

RESULTS

Table 2 reports univariate statistics and bivariate correlations for the final analy-tical sample. Interpersonal heterogeneity and intrapersonal heterogeneity have a moderately high negative correlation. Consistent with hypothesis 1, interpersonal heterogeneity has a significant negative association with ROA. Consistent with hypothesis 2, intrapersonal heterogeneity has a significant positive correlation with Tobin's Q and patenting. Additionally, interpersonal heterogeneity has a moderately high positive correlation with firm size, and intrapersonal heterogeneity has a negative correlation with the number of Glassdoor reviews.

We report both OLS and CEM model results as our main findings. The matching strategy is successful in that it eliminates statistically significant dif-ferences in the observed covariates for observations with non-missing data across the four outcome variables. Table 3 shows t-tests on covariate means before versus after matching for both the interpersonal heterogeneity and intrapersonal heterogeneity matching across the four outcomes. Any large

Table 2. Univariate Statistics and Bivariate Correlations (N = 3,251)*

Variable	Mean	S.D.	(1)	(2)	(3)	(4)	(5)	(6)
1. ROA	1.45	2.51						
2. TQ	1.78	.78	.41•••					
3. Patent count	15.72	64.33	.14•••	.064•••				
4. Lag interpersonal hetero.	− .01	.99	−.16•••	−.29•••	− .061•••			
5. Lag intrapersonal hetero.	.02	.97	.031	.098•••	.13•••	− .56•••		
6. Lag log assets	10.21	1.96	−.12•••	−.46•••	.15•••	.40•••	− .042•	
7. Lag log # reviews	4.62	.68	.076•••	.045•	.0038	.081•••	−.18•••	.21•••

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

* Log of mean number of backward citations is not shown above because non-missing values are conditional on patenting. Mean: 2.22, S.D.: 1.01, # observations: 774.

Table 3. t-Tests on Covariate Means before and after Matching

Variable	Before matching t-test on means		Matched sample t-test on means
ROA	Low–high interpersonal hetero.		Low–high interpersonal hetero.
Lag log assets	− 4.52		− .75
Lag log # reviews	− 6.49		− .18
Strata		2515	
Matched strata		265	
Multivariate L1 distance	.9		.66
Low interpersonal hetero. obs.	1639		360
High interpersonal hetero. obs.	1644		375
TQ	Low–high intrapersonal hetero.		Low–high intrapersonal hetero.
Lag log assets	.55		1.01
Lag log # reviews	10.4		.54
Strata		2496	
Matched strata		255	
Multivariate L1 distance	.91		.72
Low intrapersonal hetero. obs.	1637		337
High intrapersonal hetero. obs.	1616		362
Log # patents	Low–high intrapersonal hetero.		Low–high intrapersonal hetero.
Lag log assets	.74		1.16
Lag log # reviews	10.27		.49
Strata		2537	
Matched strata		259	
Multivariate L1 distance	.92		.72
Low intrapersonal hetero. obs.	1668		346
High intrapersonal hetero. obs.	1644		368
# backward citations per patent	Low–high intrapersonal hetero.		Low-high intrapersonal hetero.
Lag log assets	.75		1.24
Lag log # reviews	6.45		.77
Strata		579	
Matched strata		111	
Multivariate L1 distance	.94		.85
Low intrapersonal hetero. obs.	426		166
High intrapersonal hetero. obs.	523		189

t-statistics for firm assets and number of Glassdoor reviews that exist before matching are sharply reduced to the point of nonsignificance after matching.

Table 4 shows regression results for models of ROA on interpersonal heterogeneity as tests of hypothesis 1. Model 1 shows that interpersonal heterogeneity has a significantly negative association with ROA in an OLS specification with quarter and industry fixed effects. Model 2 shows that the negative association holds in the matched sample. Thus we find support for hypothesis 1: firms higher in interpersonal heterogeneity exhibit lower profitability.

Table 5 shows regression results for models of Tobin's Q and the patenting outcomes on intrapersonal heterogeneity. Model 1 shows that intrapersonal heterogeneity has a significantly positive association with Tobin's Q in an OLS

Table 4. ROA on Interpersonal Heterogeneity*

	(1) OLS	(2) Matched
Lag interpersonal hetero.	− .38•••	− .33•
	(3.71)	(2.47)
Lag log assets	.22•	
	(2.08)	
Lag log # reviews	.27	
	(1.83)	
Constant	− .57	.39
	(.56)	(1.24)
Quarter FEs	Yes	No
Industry FEs	Yes	No
Stratum FEs	n/a	Yes
Firm/quarters	3283	735

• $p < .05$; •• $p < .01$; ••• $p < .001$.
* Absolute t-statistics are in parentheses; standard errors are clustered by firm.

**Table 5. Tobin's Q/Patent Outcomes on Intrapersonal Heterogeneity***

	(1) TQ OLS	(2) TQ Matched	(3) Log # patents OLS	(4) # patents Neg. bin	(5) Log # patents Matched	(6) # back. cites OLS	(7) # back. cites Matched
Lag intrapersonal hetero.	.10•••	.11•	.14••	.28•••	.094•	.14••	.25•
	(3.69)	(2.18)	(2.76)	(3.43)	(2.13)	(3.05)	(2.39)
Lag log assets	− .11••		.21••	.83•••		.14•	
	(3.15)		(2.66)	(5.89)		(2.23)	
Lag log # reviews	.16••		.054	.071		− .15	
	(3.17)		(.54)	(.32)		(1.87)	
Constant	2.80•••	1.01•••	− 0.98	− 22.5•	− .0039	2.10•••	1.01
	(8.73)	(10.2)	(1.22)	(1.97)	(.07)	(4.32)	(1.60)
Quarter FEs	Yes	No	Yes	Yes	No	Yes	No
Industry FEs	Yes	No	Yes	Yes	No	Yes	No
Strata FEs	n/a	Yes	n/a	n/a	Yes	n/a	Yes
Firm/quarters	3253	699	3296	3296	714	949	355

• $p < .05$; •• $p < .01$; ••• $p < .001$.
* Absolute t-statistics are in parentheses; standard errors are clustered by firm.

specification with quarter and industry fixed effects. This positive association holds in model 2 using the matched sample. Model 3 shows that higher intrapersonal heterogeneity predicts greater patenting volume in an OLS specification. We also modeled the raw patent count in a negative binomial specification in model 4, which produces consistent results. Model 5 shows that this effect of intrapersonal heterogeneity on patenting volume holds with the matched sample. We find in model 6 that higher intrapersonal heterogeneity is associated with higher mean backward citations among the patents in a firm portfolio. This association holds in model 7 using the matched sample. Together, these results provide support for hypothesis 2: firms higher in

Figure 4. Predicted effects from CEM models of interpersonal and intrapersonal heterogeneity on firm performance and patent outcomes.
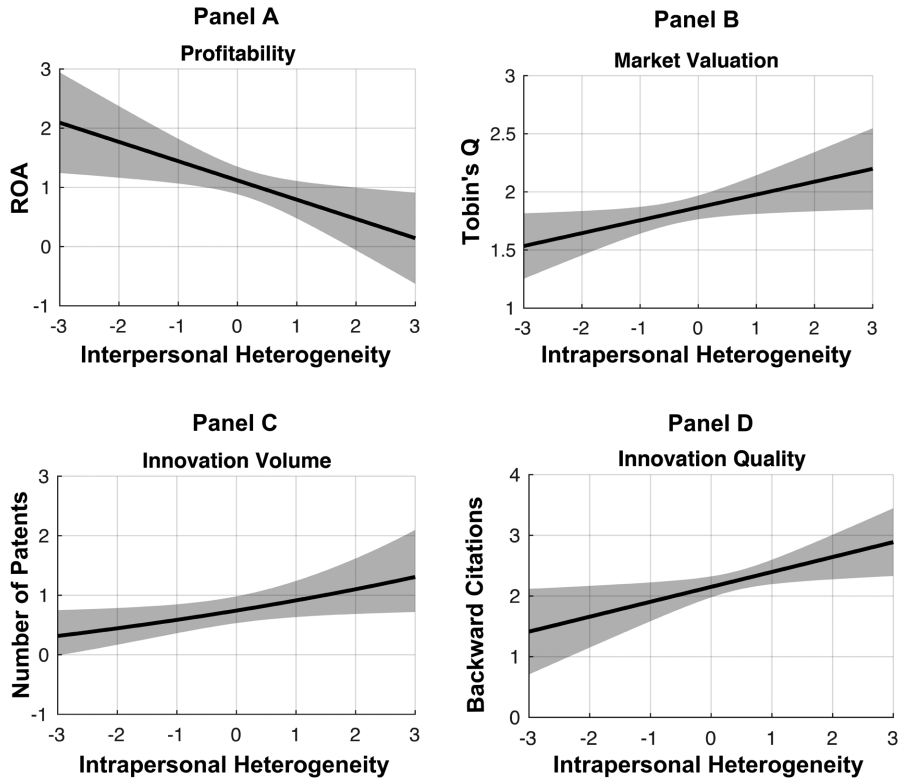
intrapersonal heterogeneity exhibit a greater capacity for creativity and innovation as reflected in their increased market valuation, larger patenting volume, and higher patent quality.

Figure 4 provides a visualization of the predicted effects of interpersonal and intrapersonal heterogeneity on firms' performance and patent outcomes for our CEM models. A one-standard-deviation increase in interpersonal heterogeneity reduces ROA by approximately .35 percent, which is equivalent to .13 standard deviations (Panel A). A one-standard-deviation increase in intrapersonal heterogeneity increases Tobin's Q by approximately .25 points, or .15 standard deviations (Panel B); increases patent count by roughly .2, or approximately .07 standard deviations (Panel C); and increases mean backward citations by approximately .28, or .25 standard deviations (Panel D).

Online Appendix B describes a series of alternative models that we used to explore the interrelationships between the two heterogeneity measures. We show that our main results for each heterogeneity measure hold when we control for the other measure and find no evidence of cross effects (i.e., interpersonal heterogeneity affecting growth/innovation or intrapersonal heterogeneity influencing productivity). Although we do not find evidence of a linear interaction effect between the heterogeneity measures, we present some preliminary findings based on indicator variables that point to possible nonlinear interrelationships, suggesting that this may be a promising avenue for future research.

Robustness Checks

We conducted four additional analyses to assess the robustness of our findings. First, to ensure that our measure of interpersonal heterogeneity is not simply a proxy for the presence of organizational subcultures, we used a clustering procedure to assess the extent to which each organization-quarter observation can be divided into cultural subgroups. The clustering procedure uses the K-means algorithm, based on our measure of cultural distance, to divide the population into clusters and then uses the gap statistic (Tibshirani, Walther, and Hastie, 2001) to assess the optimal division into subgroups. Including a control for the presence of subgroups did not materially change our results.

Second, given that both of our heterogeneity measures could be related to the overall level of cultural breadth in the organization, we used a variant of our intrapersonal heterogeneity measure that assesses the dispersion of topics discussed across all employee reviews. Specifically, we calculated the (logged) mean Herfindahl index across all employee reviews in a given firm/quarter and then took the inverse. High values indicate that employees discuss a broad range of cultural topics, while low values suggest a narrow range. Controlling for firm-level cultural breadth does not materially alter our results.

Third, to establish that our results are not driven by specific cultural categories and that our measure is robust to the selection of fewer than 500 topics, we ran a simulation analysis, which reveals a high degree of correspondence between measures based on randomly selected subsets of topics and measures based on our 500-topic model. These three analyses are presented in Online Appendix A.

Finally, we undertook a manual coding exercise using a 100-topic model and demonstrate in Online Appendix D that our algorithmically derived measures and results are nearly identical to those obtained via manual coding.

DISCUSSION

When is a diversity of ideas and beliefs beneficial for organizational success, and when is it detrimental? From a perspective that views organizations as solutions to complex coordination problems, cultural heterogeneity is mostly seen as a source of dissonance and friction. Through the lens of economic and cultural sociology, it is viewed as a necessary condition for creativity and innovation. We have shown that this tension can be resolved when we consider the duality in diversity—that it can take two analytically distinct forms. Prior research has emphasized heterogeneity between organizational members but mostly overlooked the heterogeneity that can exist within individuals. We conceptually separate the two forms and demonstrate that interpersonal heterogeneity—the extent to which organizational members diverge in their understanding of firm culture—is negatively associated with effective coordination and execution, whereas intrapersonal heterogeneity—the breadth of cultural beliefs about the organization that are held by individual members—is positively linked to creativity and the capacity for recombinant innovation.

Organizational Culture and Firm Performance

Our findings make several noteworthy contributions to the extensive and multidisciplinary literature that examines the link between organizational culture and

firm performance (e.g., Kotter and Heskett, 1992; Sørensen, 2002; Van den Steen, 2010). First, whereas much of this work has examined how specific cultural content—for example, norms of adaptability—relates to outcomes such as cash flow growth (Chatman et al., 2014), we demonstrate that the distribution of culture in an organization can have performance consequences independent of the organization's specific cultural content (cf. Carroll and Harrison, 1998). Our findings neither invalidate nor downplay the importance of studies that focus on specific organizational culture features. Yet the cultural content that matters for organizational success is known to vary considerably across competitive contexts, such as industry, geography, or regulatory environment. In contrast, a distributive approach to measuring culture such as ours uncovers linkages between culture and performance that would appear to be more generalizable across competitive contexts and over time.

Drawing on the sociological conceptualization of culture as a toolkit, we introduce to this literature a novel organizational culture construct: intrapersonal heterogeneity. Prevailing approaches to studying organizational culture have exclusively explored cultural heterogeneity through an interpersonal lens. Constructs such as cultural strength focus on the degree of normative consensus between organizational members and the intensity with which these norms are enforced interpersonally (Chatman and O'Reilly, 2016). In other words, cultural heterogeneity is assumed to inhere in differences between individuals. Heterogeneity within individuals has been largely overlooked by this literature, and existing measures and analytical models of cultural heterogeneity are not designed to provide the data that would be needed to measure within-person heterogeneity. For example, the Organizational Culture Profile—a widely used instrument for assessing cultural features—requires respondents to array cultural norms on a normal-like scale (O'Reilly, Chatman, and Caldwell, 1991). It therefore assumes a fixed within-person distribution of culture. Similarly, formal models of cultural distribution in organizations (e.g., March, 1991; Harrison and Carroll, 2006) often focus on interpersonal transmission, reducing culture to a one-dimensional scale.

We identify a complementary dimension of heterogeneity—that which exists within people—and demonstrate that considering the two forms in tandem helps to resolve the ambiguity that previously existed in the literature about how cultural heterogeneity relates to firm performance. Our findings suggest that the heterogeneity tradeoff assumed in previous research—that heterogeneity harms execution and productivity but helps creativity and innovation—may in fact be avoidable. Insofar as firms can increase intrapersonal heterogeneity while holding interpersonal heterogeneity constant, our theory predicts they will achieve greater innovation output without sacrificing short-term profitability. Conversely, if firms can decrease interpersonal heterogeneity without eroding its intrapersonal counterpart, we anticipate that they can improve profitability without compromising innovativeness. Exploratory findings reported in Online Appendix B seem to point in this direction.

The identification of two analytically distinct forms of cultural heterogeneity naturally raises questions about how deliberative organizational change efforts influence each dimension and how the two relate to each other over time. An extensive literature has explored the organizational determinants of strong, interpersonally homogeneous cultures. In contrast, because intrapersonal heterogeneity is a novel construct, its antecedents remain unclear. Nevertheless,

previous work has suggested that disparate cultural logics can be fused together when practices embody multiple meanings (e.g., Zilber, 2002) and that organizations can influence this process through hiring and socialization (e.g., Battilana and Dorado, 2010). It remains to be studied which organizational processes are effective at facilitating intrapersonal heterogeneity and how intentional attempts to broaden organizational members' cultural toolkits affect interpersonal heterogeneity. Might a deliberate focus on increasing within-person heterogeneity provide greater scope for shared understanding between people or instead sow interpersonal cultural discord? Conversely, how do managerial efforts aimed at diversifying the cultural makeup of a company's workforce affect intrapersonal heterogeneity?

Intrapersonal cultural heterogeneity, however, is not exclusively the purview of intentional managerial policies inside organizations. Rather, we expect that the breadth of individuals' cultural toolkits is shaped by their social experiences such that the diversity of social worlds individuals inhabit—whether by virtue of their personal history or network position—is positively related to their intrapersonal cultural diversity. This suggests that organizations play an important societal role in bridging or reinforcing cultural boundaries between different social groups, especially if increased labor market mobility is leading employees toward greater exposure to cultural multiplicity. Under some circumstances such exposure begets intrapersonal cultural breadth (Morris, Chiu, and Liu, 2015), but under others it serves to narrow cultural repertoires and entrench cultural divisions (Bail et al., 2018; Goldberg and Stein, 2018).

In the future, questions such as these will be easier to answer because of the methodological innovation we introduce: using unsupervised learning to identify cultural content in the language employees use to describe their organizations and deriving time-varying measures of organizational culture based on this language. Unlike traditional survey-based measures of culture, language-based measures of culture can be produced unobtrusively on a continuous basis and at scale. Whereas recent work in this vein has mined internal employee communications to characterize how individuals fit culturally in their organization (Goldberg et al., 2016; Doyle et al., 2017; Srivastava et al., 2018), the approach we develop here enables us to characterize the culture of the organization as a whole, to make comparisons across organizations, and to systematically track distributive cultural change within and across organizations.

Culture as Toolkits

Our work also injects greater theoretical precision into, and provides empirical support for, the theory of culture as toolkits (Swidler, 1986), which is one of the most influential perspectives in contemporary cultural sociology but also one that has been criticized as vague and susceptible to slippage in terminology (Lamont, 1992; Small, Harding, and Lamont, 2010). First, our intrapersonal heterogeneity construct represents a concrete manifestation of the somewhat hazy ''symbols, stories, rituals, and worldviews'' that constitute toolkits in Swidler's (1986: 273) theory. Although we acknowledge that toolkits may include a broader set of implements, we propose that a useful way to conceptualize toolkits—at least in the organizational context—is to focus on the breadth of topics employees draw on in describing their organization's culture.

Second, our approach offers a way to extend cultural toolkits to organizations and the fields in which they are embedded (Weber, 2005). Our method can be readily adapted to characterizing the (changing) distance between firms in the space of cultural topics. Complementing cultural compatibility analyses based on surveys (Stahl and Voigt, 2008), formal models (Van den Steen, 2010), and laboratory experiments (Weber and Camerer, 2003), language-based measures of cultural similarity between firms could be used to examine how culture influences success or failure at the interorganizational level—for example, in mergers and acquisitions (Weber and Camerer, 2003; Stahl and Voigt, 2008; Van den Steen, 2010; Bauer and Matzler, 2014), joint ventures, and alliances (Park and Ungson, 1997; Pothukuchi et al., 2002). Such measures could also be used to examine how the cultural distinctiveness or similarity of an organization relates to its strategic positioning and competitive advantage. Moreover, our measures can be aggregated to the field or industry level as a means to explore how toolkit breadth and composition relate to field-level dynamics.

Finally, whereas toolkit theory focuses on the repertoire of cultural resources individuals draw on to construct strategies of action, we make the micro-to-macro link between individual toolkits, group creativity, and organizational level outcomes. While the image of culture as toolkits has been widely influential in sociology, few studies have examined the relationship between the breadth of cultural toolkits and group-level outcomes. We argue that individuals with broad cultural repertoires are more likely to engage in recombinant innovation and demonstrate that this breadth is linked to organizational creativity and innovation. While our empirical examination focuses on for-profit organizations, we see no reason why it should not extend to other domains. Just as community-level ethnic integration relates to entrepreneurship and innovation (e.g., Samila and Sorenson, 2017), our findings suggest that communities—whether at the local or national level—whose members draw on a wide range of cultural elements will exhibit, all else equal, a greater capacity for innovation. Communities high in intrapersonal but low in interpersonal cultural heterogeneity might enjoy diversity's benefits, such as enhanced resilience, while avoiding the risk of coordination breakdowns and inefficiencies (Page, 2010).

More broadly, high intrapersonal but low interpersonal heterogeneity might allow nations to leverage the benefits of multiculturalism while still preserving an overarching sense of cultural cohesion and unity. For example, American society might not face a strict tradeoff between being a cultural ''melting pot,'' in which assimilation forces foster cohesion but stifle diversity, and being a multicultural ''salad bowl'' that preserves diversity but reifies cultural boundaries (Fischer and Mattson, 2009). The realization of cultural diversity's potential for macro-level innovation, however, might be stymied if people are increasingly engaging with cultural echo chambers that limit their exposure to cultural multiplicity, thereby narrowing their cultural toolkits (DellaPosta, Shi, and Macy, 2015).

Cultural Heterogeneity and Group Diversity

Although our conceptual arguments are not directly derived from research on relational demography and group diversity, we identify a number of important parallels between the two bodies of work. First, our distinction between the

interpersonal and intrapersonal forms of cultural heterogeneity echoes Bunderson and Sutcliffe's (2002) separation of dominant function diversity (a between-person comparison of functional expertise on a team) from intrapersonal functional diversity (based on within-person functional breadth). Our theory applies a similar distinction to cultural diversity in organizations.

At the same time, the constructs we have developed at the organizational level have implications for research on group effectiveness. Prior work focusing on cultural diversity in groups and teams has examined surface-level traits such as race and nationality, as well as deep-level values that are measured using proxies such as the national cultural distance between group members (Stahl et al., 2010). As this work has demonstrated, categorical differences between individuals on dimensions such as gender or occupational background can, but often do not, relate to differences in underlying beliefs (Harrison, Price, and Bell, 1998). The constructs we introduce offer the potential to more directly assess cultural diversity in groups. It remains to be explored how intrapersonal and interpersonal heterogeneity in work groups might relate to mechanisms such as group conflict, creativity, and social integration through which diversity—both ascribed and internalized—affects team performance.

Limitations and Future Directions

Given the nature of the data we analyze, this study has limitations that point to avenues for future research. First, the coarsened exact matching approach we use (Iacus et al., 2012) achieves balance between our treatment and control groups by matching on observed firm attributes. It does not, however, address potential threats to causal identification stemming from unobserved heterogeneity. Future research in this vein—especially studies that draw on data sets spanning longer time horizons and thus affording a window into changing firm cultures—could account for time-invariant unobserved heterogeneity by estimating within-firm models. Over the time horizon of our data set, employees' descriptions of firm culture in Glassdoor reviews simply do not exhibit sufficient temporal variance to support the use of within-firm estimates.

Also, although we report robustness checks that help to dispel concerns that our findings can be accounted for by compositional shifts in the kinds of employees who choose to comment about firm culture prior to changes in firms' performance, we cannot fully rule out the potentially confounding role of selection effects. We leave to future research the task of more thoroughly accounting for selection dynamics in employees' reviews. For example, researchers could draw on national survey panels to identify a representative set of employees at firms included in the Glassdoor data and ask them to rate their firm using the same pro and con questions used by Glassdoor.

In addition, any method of measuring culture necessarily makes simplifying assumptions about a complex, multifaceted phenomenon in order to gain analytical tractability. Our LDA topic modeling approach assumes that the importance of word order is negligible and infers the existence of cultural topics based on the co-occurrence of words within employees' reviews. This method may obscure some more-nuanced cultural meanings residing in the ordering of words and the relationships between specific words in sentences. Future research might look to alternative natural language processing tools, such as

word embedding models, to detect cultural meanings overlooked by topic modeling (Mikolov et al., 2013).

Conclusion

This study paves the way for novel investigations of the role of culture in organizational performance. Drawing on language as a window into organizational culture, it demonstrates that cultural heterogeneity can be a double-edged sword, with its interpersonal form foreshadowing a decline in profitability and its intrapersonal form heralding heightened market expectations of future firm growth and innovative output. At the same time, it highlights that the coordination–creativity tradeoff that culture presumably embodies is not inevitable. Understanding the duality in cultural diversity may help uncover organizational practices and interventions that simultaneously promote efficiency and innovation.

Supplemental Material

Supplemental material for this article can be found in the Online Appendix at http://journals.sagepub.com/doi/suppl/10.1177/0001839219844175.

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