The Economic Background of City Councilmembers *

Graham Straus,† *UCLA*

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Abstract

Is local politics shaped by groups and interests or party and ideology? Classic literature posits that local politics differs from national politics and centers on groups and interests rather than ideology, especially in settings with nonpartisan elections. A separate literature casts doubt on this, finding a connection between partisan voting, local ideology, and policy mimicking the federal level and without reference to groups and interests. In this paper, I use a large original dataset on the professional backgrounds of city councilors to provide a link between the evidence for both theories. I look at city council candidates from all 477 cities in California between 1996 and 2021, observing both candidates' career histories through their ballot designations and party affiliations through their public voter records. I find that liberal cities have more career politicians, non-profit workers, and service-based professionals running for and holding office, while conservative cities have more military and law enforcement workers and business types running for and holding office. Career politicians, non-profit workers, and service-based professionals are more likely to be registered as Democrats and military and law enforcement workers and business types are more likely to be registered Republicans. In this case group membership and party affiliation are tightly coupled.

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†PhD Candidate, Department of Political Science gpstraus@g.ucla.edu

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1 Introduction

A traditional view holds that local politics is different from national politics and centers on groups and interests not ideology, especially in settings where local officeholders are elected in nonpartisan elections. Anzia (2021) writes that "much of what is most important about local politics is probably not well explained by nationally forged partisan and ideological commitments." In this traditional view, scholars emphasize the importance of candidate identities beyond party, including occupation (Kirkland 2021; Carnes 2013), homeowner status (Einstein, Glick, and Palmer 2019; Hankinson 2018), race (Hajnal and Trounstine 2014; Barreto 2007), and gender (Holman 2014).

Some issues of local importance like zoning and city services do not have clear national parallels. In support of the traditional view of local politics are surveys that specifically ask questions about local policy areas and find that Republicans' and Democrats' local preferences can look more similar than dissimilar (e.g., Marble and Nall 2021; Jensen et al. 2021). Some studies show the partisanship of local elected officials does not drive various policy outcomes (e.g., Ferreira and Gyourko 2009; Thompson 2020).

A differing view casts doubt on this, finding a connection between partisan voting, local ideology, and policy mimicking the federal level and without reference to groups and interests. Warshaw (2019) writes that "it is now clear that partisanship and ideology have played important roles in local politics for at least the past few decades." This view emphasizes that in nonpartisan races candidates signal their party (Ferreira and Gyourko 2009) and learning about issue positions affects vote choice (Sances 2018). Cities elect politicians and policies that represent their ideological character (Tausanovitch and Warshaw 2014) and scholars have shown that local politics has nationalized in the sense that national party labels hold more sway in local politics than they once did (Hopkins 2018). Some studies show the partisanship of local elected officials does in fact drive policy outcomes (e.g., de Benedictis-Kessner, Jones, and Warshaw 2024; Einstein and Kogan 2016; de Benedictis-Kessner and Warshaw 2016).

To what extent can we separate candidates' party affiliations from their group memberships and personal interests? This article uses one particular local group and identity, occupation prior to office, to show that partisanship and background are tightly correlated and often inseparable. While there are many local groups and interests, I use occupation prior to office first because it is a salient identity for local elected officials, with recent research showing it weighs heavily in municipal politics (e.g. Kirkland 2021; Kirkland and Coppock 2018; Atkeson and Hamel 2020; Carnes 2013). Second, relative to other traits elected officials hold it is understudied because of sparse data availability. Finally, recent research on amateurism shows candidates are increasingly elected with no prior experience, which could put more emphasis on whatever it is they did for work before running (Porter and Treul 2024).

I expect people to be more likely to run for city council when they expect to win. This is because of high costs to running for office in the first place (Hall 2019). In other words, I expect the voters in cities to affect not only who wins office but also the composition of the candidate pool. I expect individuals from different occupations to have different political views that correlate with party. This is because people choose their sphere of work and choose their political party to align with their values and these sociological affiliations are often mutually reinforcing (Egan 2020).

To speak to the theoretical debate and mixed empirical evidence, I analyze an original panel dataset with hundreds of cities and thousands of California candidates. I observe candidates' occupations prior to office as well as their party affiliations. These are difficult traits to observe at scale in nonpartisan, local races. Candidates' occupations are coded based on their ballot designations. Ballot designations, required of all California candidates and meant to create a more informed electorate, must faithfully designate the candidate's primary occupation in a few words. Party affiliation is observed by looking up candidates in public voter files. I validate results on a smaller, cross-sectional national sample of large cities.

I find that the party character of the city is predictive of the career types who run and win; specifically, liberal cities have more career politicians, non-profit workers, and service-based professionals running for and holding office, while conservative cities have more military and law enforcement workers and business types running for and holding office. At the same time, the career type of the candidate is predictive of their individual party affiliation. Career politicians, non-profit workers, and service-based professionals are more likely to be registered as Democrats, whereas military and law enforcement workers and business types are more likely to be registered Republicans. In sum, any study that argues for a causal effect of electing an occupational class will struggle to rule out the effects of party, and any study that argues for a causal effect of electing a party member will struggle to rule out the effects of occupation. While this fact may not seem surprising, it has gone overlooked, and bringing data to this link synthesizes divergent theory.

2 Descriptive Results and Data

2.1 California Elections Data

The sample of California cities uses the California Elections Data Archive (*California Elections Data Archive (CEDA)* 2003). This database contains all city council candidates on the ballot in California between 1996 and 2021 and lists their ballot designations. Ballot designations in California offer candidates a few words to convey their most recent occupation. State law requires that candidates report faithfully on their most recent employment. Candidates have at times attempted to use the ballot designation to strategically represent themselves, and there have been legal challenges to proposed ballot designations (Nemerovski 2021). Strategic self-representation by candidates complicates the process of obtaining reliable occupation data from any source. For instance, candidates can lie or paint themselves in a favorable light on their websites or LinkedIn pages with no oversight, so gathering occupational data from these sources would likely be less reliable than the ballot designation.

The CEDA data runs from 1996 to 2021 offering occupational information on over 26,000 bids for seats on council in 477 cities both large and small.[1] Using the ballot designation to categorize candidates by occupation has precedent in the local politics literature (Atkeson and Hamel 2020) and has the advantage of using the same information voters see when profiling the candidates for themselves at the time of the election.

2.2 Categorizing Occupation

To classify candidate occupations, I use the coding schema developed by Carnes (2013). The nine categories that I use are: Politician or Staff Member (incumbent, Congressional staffer, city clerk), Business Owner/Executive (CEO, small business owner, financial advisor), Business Employee (insurance agent, realtor), Service-Based Professional (nurse, teacher), Technical Professional (engineer), Military or Law Enforcement (police, fire, retired Navy), Non-Profit Worker (management and employees), Lawyer (private practice, public defender), and Laborer/Worker (waiter, carpenter). I omit the category of “Farm Owner” from the Carnes (2013) coding because of my focus on cities and the natural bucketing of farm owner into business owner. I add in the category of “Non-Profit Worker” because of its frequency in the data and the close relationship between city governments and non-profits for local public goods provisioning (Mathews 2020). These nine categories are ideal for my analysis because they have precedent in the literature and strike a balance between being general enough to capture large segments of the sample but not too general so as to obscure the information that was on the ballot designation to begin with.[2] More detailed examples of each category are available in the appendix.

[1] 26,821 out of 29,997 candidates — 89.4% — have classifiable ballot designations. Candidates missing ballot designations or with undescriptive ballot designations (e.g. “unemployed”) are dropped.

[2] An intercoder reliability test between two Research Assistants using a random sample of 100 ballot designations yielded a Cohen’s kappa value of .606, or moderate to substantial agreement (McHugh 2012).

2.3 Descriptive Results

Table 1: **California City Councils Occupational Category Frequency**

Category	All Candidates		Elected		Unelected	
	n	%	n	%	n	%
Politician or Staff Member	8786	33.71%	6022	52.77%	2764	18.86%
Business Employee	4422	16.97%	1168	10.24%	3254	22.21%
Business Owner/Executive	3669	14.08%	1300	11.39%	2369	16.17%
Service-Based Professional	3010	11.55%	960	8.41%	2050	13.99%
Technical Professional	2369	9.09%	648	5.68%	1721	11.75%
Non-Profit Worker	1314	5.04%	380	3.33%	934	6.37%
Military or Law Enforcement	1190	4.57%	541	4.74%	649	4.43%
Lawyer	1003	3.85%	335	2.94%	668	4.56%
Laborer/Worker	300	1.15%	57	0.50%	243	1.66%

Many city council candidates come from a political job. "Politician or Staff Member" is by the most frequent category in the California sample in Table 1. The incumbency advantage — well documented at the city council level (Trounstine 2011) — is on display in these data. Some, like Paul Krekorian in Los Angeles, come to city council from the state legislature. Some work their way up through the ladder of city government, for example, Mitch O'Farrell first worked as a staff member for then-councilmember Eric Garcetti before running his own campaign.

Many city councilmembers can be considered business employees and executives. The rate is over 21% in the elected sample. This is slightly lower than the 32% rate at which elected mayors are business executives in recent samples (Kirkland 2021). There are far fewer self-advertised lawyers on city council than in Congress. Over 30% of the 118th House are lawyers, and conditional on running lawyers are twice as likely to win a seat in Congress than people with other backgrounds making lawyer the most common prior occupation in

Congress (Bonica 2020). However, the data in Table 1 suggest a different story at the city council level. More people on council come from service-based professions, like nursing or teaching for example, than come from the legal profession.

These descriptive results are notable on their own because they show the breadth and diversity of pathways to city council. However, the question at hand is whether these categories appear at differential rates in cities depending on how Republican or Democratic those cities are. In the next section I measure, for each city, the fraction of candidates and officeholders who fall into the nine career categories and plot those fractions against measures of city-level partisanship and ideology.

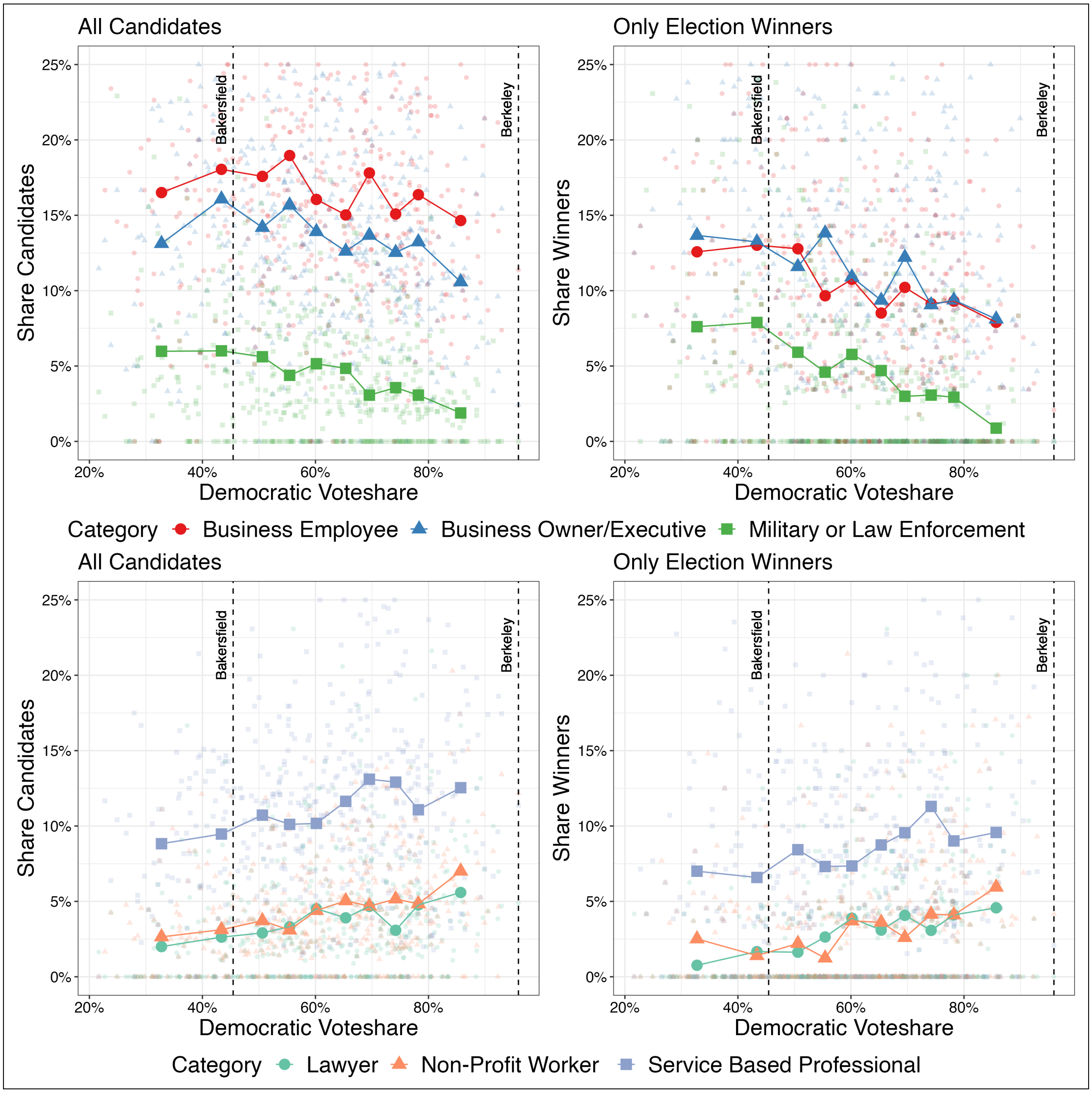
3 Candidate Occupation by City Ideology

3.1 Raw Data Visualization

Figure 1 shows the distribution of occupations on the y-axis and city-level Democratic vote-share from the 2020 presidential election along the x-axis. The figure demonstrates the trends of occupational categories across municipal partisanship. The graphs on the top row display three career categories that negatively correlate with Democratic partisanship and the graphs on the bottom row show three categories that positively correlate.

To make things more concrete, consider the city of Berkeley. About 95% of the two-party vote in Berkeley went to Democrats in 2020. Between 1996 and 2021 there are 123 candidates from Berkeley in the data. Fourteen of them (11.4%) have a business employee ballot designation, three of them (2.4%) have a business owner background, and zero are from military/law enforcement. There are small transparent red, blue, and green points displaying those proportions in the upper left graph in Figure 1. Fourteen (11.4%) are service-based professionals, fifteen (12.2%) are non-profit workers, and six (4.9%) are lawyers — all on display in the bottom left graph in Figure 1. There are 477 cities of data on display, with each occupation category in each city displayed by a small translucent point. The larger,

Figure 1: **California Cities' Distributions of Occupations Prior to Running for Office**



Graphs on the left ("All Candidates") use city data from 26,821 candidacies between 1996 and 2021. Graphs on the right ("Only Election Winners") filter down to only the 11,411 winners. Each large point is a vote share-decile average of cities' proportions of candidates or officeholders with a given career label. Three career categories appear in the top row of graphs (trending down with Democratic voteshare), and three categories below (trending up). For the three labels in neither set of figures, see the appendix.

dark points are voteshare-decile averages for each occupation across the whole sample. The left side graphs ("All Candidates") complete this exercise for all candidates and the right side graphs ("Only Election Winners") use only the officeholders to calculate proportions of council belonging to each career category.

Figure 1 shows that certain career backgrounds show up more in California's more liberal cities and certain other career backgrounds show up more in California's more conservative cities. The next section models and formalizes this relationship to rule out some potential sources of confounding. To see the same trends using alternate measures of city-level ideology, see the appendix.

3.2 Modeling

The raw data suggest occupational trends that follow the partisan composition of the city. But one concern is that the trends reflect the composition of the city residents and availability of careers more than they reflect varied preferences or differential candidate entry between cities.

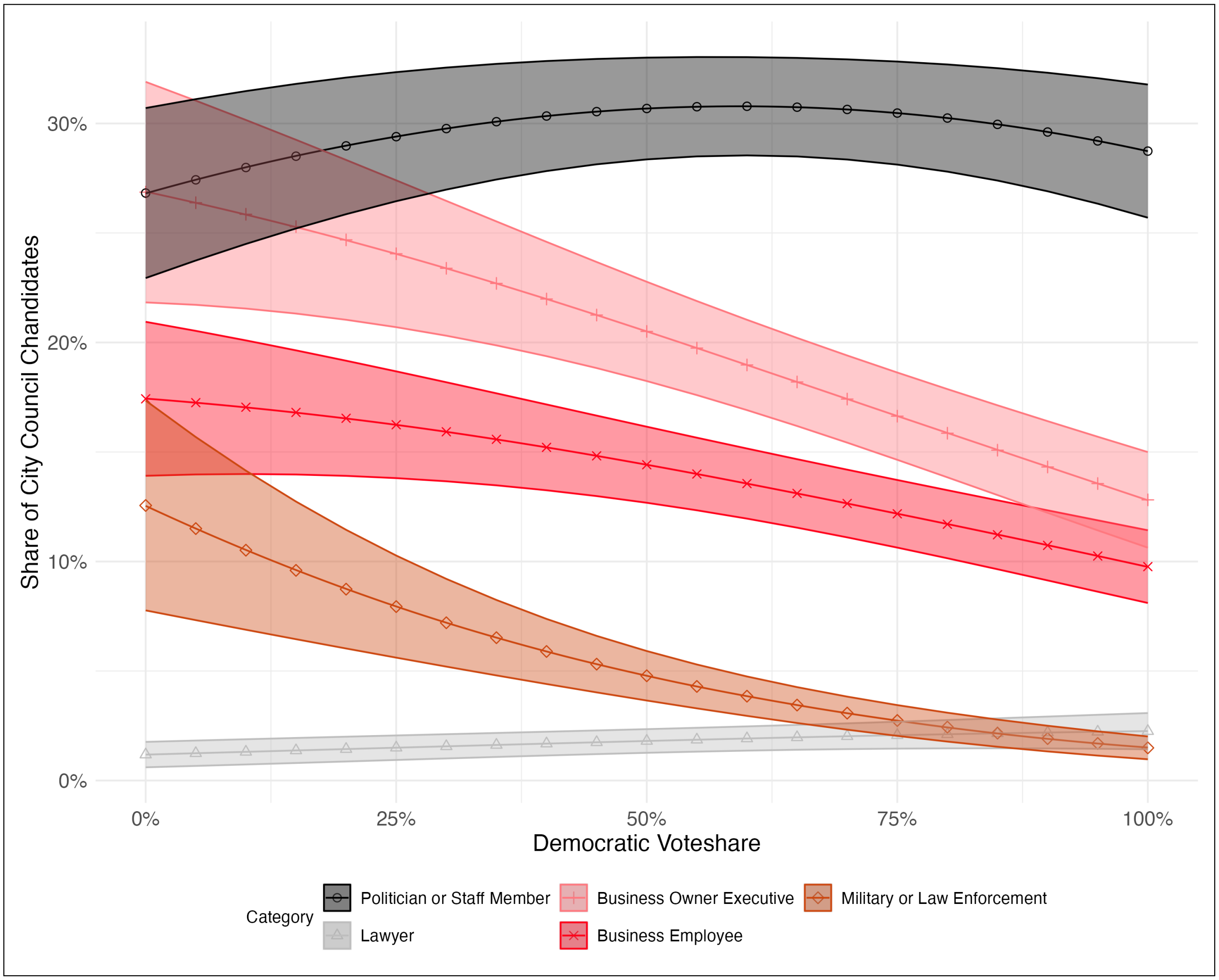
I use a multinomial logistic regression to model the share of each occupational category on the city's ideology and controls — including the citywide occupational distribution — to validate the patterns in the raw data. I measure city ideology using 2020 two-party Democratic voteshare. I include a host of city-level controls. For i indexing the 26,821 classified city council candidates, c indexing 477 cities, and t indexing year I estimate:

$$Y_{ict} \sim \beta_1 \text{Dem}_c + \mathcal{D}_c \beta_2 + \mathcal{O}_c \beta_3 + \delta_t + \epsilon_{ict}$$

The lefthand side Y_{ict} represents the occupational category for a candidate i. Dem_c is measured by aggregating 2020 precinct level Democratic two-party voteshare to the city level. $\mathcal{D}_c$ is a matrix of demographic census controls: income, population, race, and education. Income is median household income; the race categories are White, Black, Hispanic, and

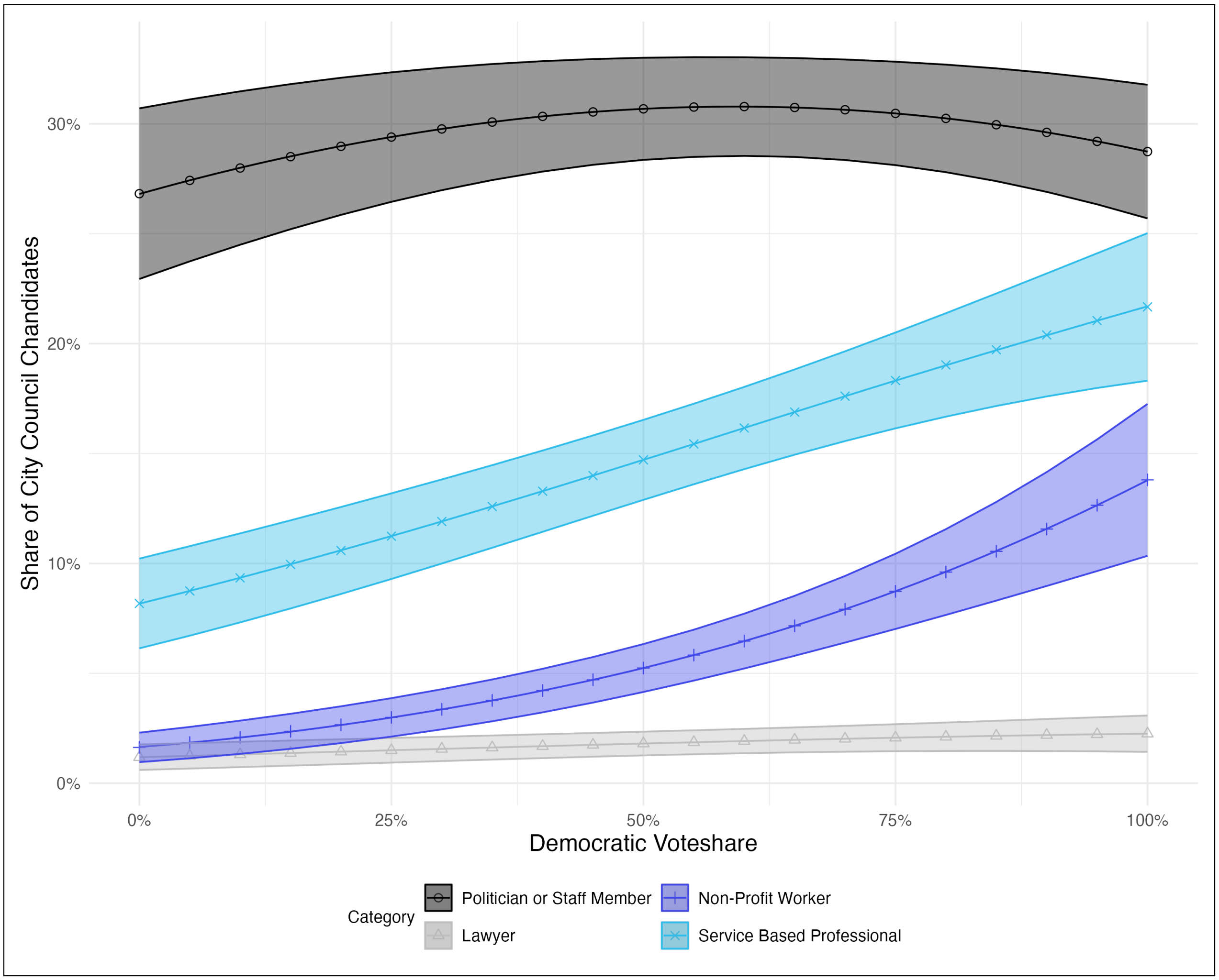
Asian; education is measured by the percentage of the city with a bachelors degree; and population is logged. $\mathcal{O}_c$ is the critical part of what this regression offers above the raw data, and it consists of two census measures of employment within a city. I observe the percent of the city in each "industry" — management, service, sales, construction, and transportation, and in each "type" — government, non-profit, private company, and self-employed (Manson et al. 2022). Specifically these data are from the ACS Occupation by Class of Worker for the Civilian Employed Population. Below are two figures using the model to predict shares of various occupational categories along a running variable of interest: city-level Democratic voteshare.

Figure 2: **Predicted Candidate Shares for California Cities (Republican Favored Careers)**



All controls set to median, year set to 2020. Democratic voteshare takes its full theoretical range. Model fit on 26,821 candidacies from 477 cities in California. Shading indiciates a 95% confidence band. For plain tabular regression coefficients see appendix.

Figure 3: **Predicted Candidate Shares for California Cities (Democratic Favored Careers)**



All controls set to median, year set to 2020. Democratic voteshare takes its full theoretical range. Model fit on 26,821 candidacies from 477 cities in California. Shading indicates a 95% confidence band. For plain tabular regression coefficients see appendix.

Figures 2 and 3 show results from using the model fit to predict the share of city council candidates in each occupational category across different city-level Democratic voteshares. On both plots, I display the predicted levels of candidates from Politician or Staff Member and Lawyer categories. For clarity I display predicted levels of Republican-favored occupational categories that decrease across the running variable in Figure 2 and, separately, Democratic-favored categories that increase in Figure 3.

The trends in the raw data in Figure 1 become more pronounced after adding in city-level controls. Business type candidates (owners and employees) and candidates coming from military and law enforcement are predicted to be relatively more abundant in California's more Republican cities. These three career labels show up less among candidates running in more Democratic cities. On the other hand, non-profit workers and service-based professionals appear on the ballot more frequently in California's more Democratic cities and less frequently in Republican cities.

This exercise shows that the ballot designated occupations do not show up in a way that is consistent with occupation-based descriptive representation. This aligns with research that shows poor descriptive representation in local politics along many dimensions (Vogl 2014; Ferreira and Gyourko 2014). These results suggest that knowing something about the ideological character of a place tells us something about the careers we'll be more likely to see in the pipeline to city council.

4 Candidate Party Affiliation by Candidate Occupation

Even if in the aggregate the partisanship of a city has occupational patterns associated with it, a remaining question concerns the party affiliations of the candidates themselves. In this section, I ask whether knowing something about the occupational background of a candidate tells us something about their likely party affiliation. In the nonpartisan local election environment it is reasonable to think that voters will be looking to any available information to infer candidate party affiliation. Existing work using experimental and observational evidence shows that party identification is a major consideration across partisan and nonpartisan ballot formats (Bonneau and Cann 2015), and indeed, voters do make inferences based upon career experience when making their decisions (Kirkland and Coppock 2018; Atkeson and Hamel 2020). This section uses data to probe how accurate those inferences are.

I look up California city council candidates in the L2 voter file to determine the party they affiliate with. The information I have on candidates is their first and last name and the city in which they run for city council. I merge in partisanship based on looking up each candidate in the full list of city voters. If I find a unique match, the process is done. If I find multiple name matches for a candidate in the city, I impute partisanship only if all name matches share the same partisan identification. This allows me to observe partisanship for 14,369 candidacies, or 53.6% of the sample.[3] See the appendix for identical results that observe party affiliation by matching candidates to the local government elections database (de Benedictis-Kessner et al. 2023).

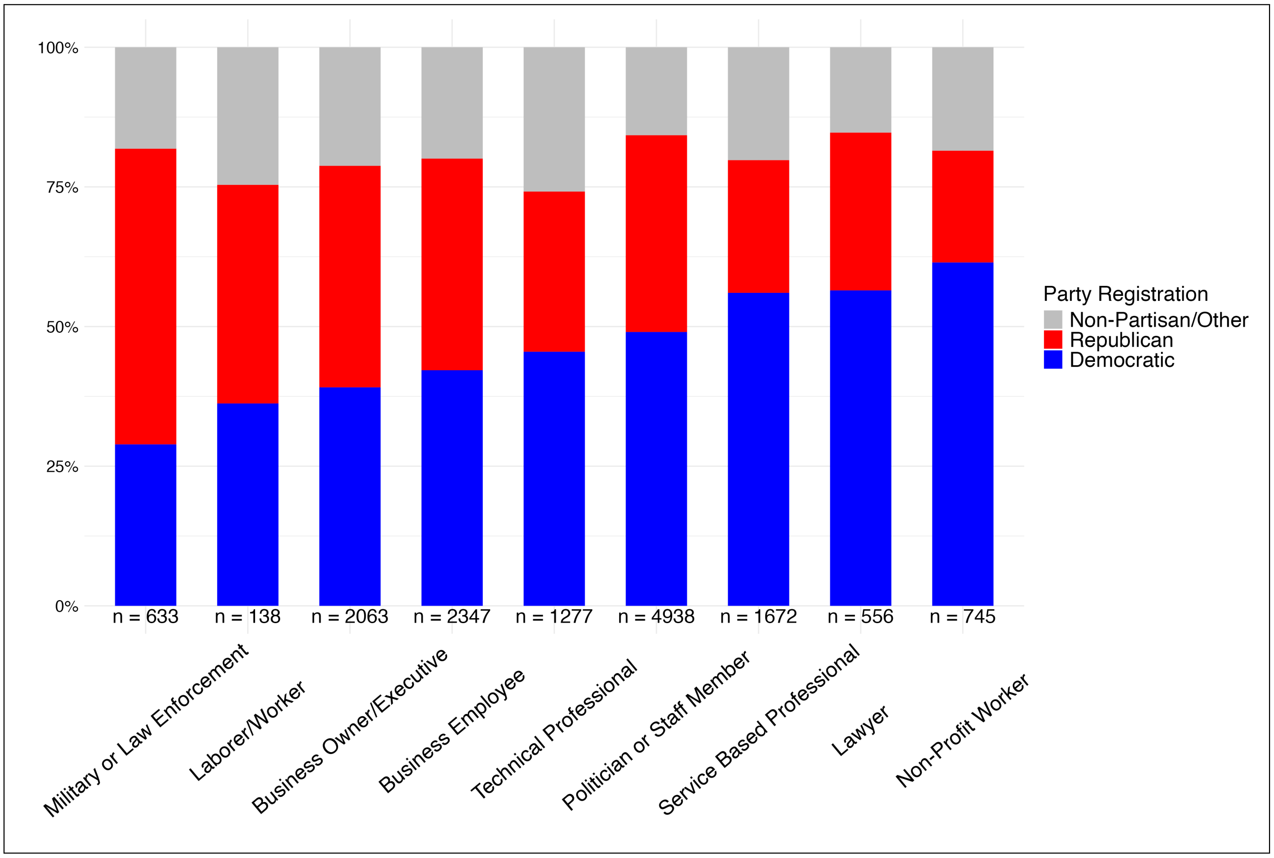
Table 2 shows data on the party-observed candidates: the percent of each occupational category that is Democratic, Republican, and Non-Partisan. Figure 4 presents the same information visually.

Table 2: **Voter File Partisanship Lookup**

Category	Democratic		Republican		Non-Partisan	
	n	%	n	%	n	%
Military or Law Enforcement	183	28.91%	335	52.92%	115	18.17%
Laborer/Worker	50	36.23%	54	39.13%	34	24.64%
Business Owner/Executive	807	39.12%	818	39.65%	438	21.23%
Business Employee	990	42.18%	889	37.88%	468	19.94%
Technical Professional	581	45.50%	366	28.66%	330	25.84%
Politician or Staff Member	2421	49.03%	1739	35.22%	778	15.76%
Service-Based Professional	937	56.04%	397	23.74%	338	20.22%
Lawyer	314	56.47%	157	28.24%	85	15.29%
Non-Profit Worker	458	61.48%	149	20.00%	138	18.52%

[3] Candidates identified in 467/477 cities. This method observes partisanship for candidates who are registered to vote in the city they run for office in and whose names on the ballot exactly match names in voter records.

Figure 4: **Voter File Partisanship Lookup**



All candidates in California sample for which reliable party information was available in the L2 voterfile.

Conditional on knowing a candidate's occupation, voters can make a better guess about that candidate's partisan identity. The distributions of party affiliations within each career category are significantly different ($\chi^2(16) = 447.49$, p-value $< 2.2\text{e-}16$). Military or law enforcement candidates tend to be more Republican and non-profit candidates tend to be more Democratic. When a business candidate appears on the ballot, voters do not suddenly become certain of their partisanship. However, compared to the distribution of party across say, service-based professionals, voters can guess Republican for the business candidate with more confidence.

In sum, knowing a candidate's occupation offers California voters some signal about the candidate's party identification. Voters use this fact (Adams, Lascher, and Martin 2021; Atkeson and Hamel 2020; Kirkland and Coppock 2018). Sourcing state voter records for candidate partisanship in nonpartisan California races allows for the powerful observation of both national partisan affiliation and occupational history. These two features of candidates are meaningfully correlated.

5 Validation: Large Cities (National Sample)

The results thus far have shown that in a longitudinal sample of California cities and candidates, city ideological character is predictive of aggregate occupational classes, and individual occupational classes are predictive of candidate party affiliation. In order to validate results on a national sample, I gathered data on 97 large cities that maintain websites for their councils.[4] For each member of the city council serving in 2022, I gathered their most prominent occupation prior to serving on city council. So if in their biography they mention graduating college, becoming a teacher, and then going on to finish law school and work in private practice, I categorize their pre-council career as lawyer.[5] The cross-sectional sample of large cities with occupation coded from web biographies is an effort to generalize the principal findings which come from the longitudinal sample of 477 California cities using ballot designations.

The model for the national cross-sectional data is a similar multinomial logistic regression model. In this model I can only look at city councilmembers elected to office (as opposed to the full set of candidates above) and only in one year, 2022. For i indexing the 877 classified city council officeholders and c indexing 97 cities I estimate:

$$Y_{ic} \sim \beta_1 \text{Dem}_c + \mathcal{D}_c \beta_2 + \mathcal{O}_c \beta_3 + \epsilon_{ic}$$

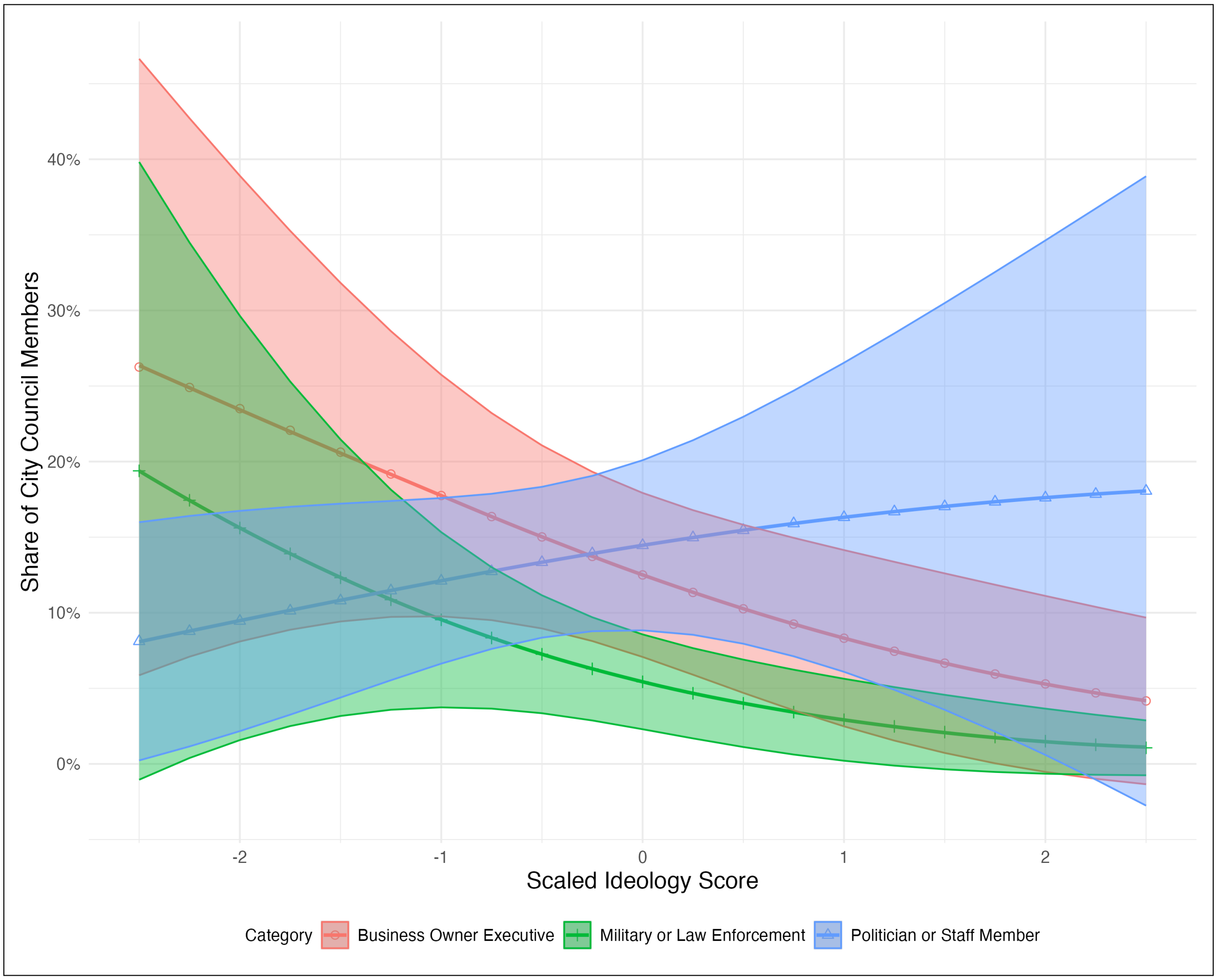
The census controls, both demographic and occupational, are the same as above. Dem_c is the scaled ideology score from Tausanovitch and Warshaw (2014). The score developed

[4] 97 of the 100 most populous cities have detailed information on their city councils available.

[5] The biographies I use to categorize officeholders are written by the officeholders themselves. Therefore the data is susceptible to inaccuracy insofar as officeholders write their biographies strategically. I assume that officeholders do not, in general, lie about what they did for work before running for office. One RA assisted in gathering data from city council websites.

by Tausanovitch and Warshaw (2014) is composed of stratified survey responses, it is highly correlated with two-party voteshare, and its use in the local politics literature is widespread.

Figure 5: **Predicted Candidate Shares for National Sample**



All controls set to median. The normalized (sd = 1) ideology score runs from Conservative (negative) to Liberal (positive). Model fit on 877 candidates from 97 cities in the United States. Shading indicates a 95% confidence band. For full tabular regression coefficient results see Appendix A.

There is more uncertainty because the sample size is less than 3% as large as the California sample and only includes officeholders, yet even in a limited, cross-sectional sample of currently serving city councilmembers a similar pattern emerges. Predicted shares for three key categories are displayed in Figure 5. Liberal cities have more people on council who come from some other political office and conservative cities have more business owners, executives, and military and law enforcement personnel serving on council. The results of the national modeling exercise align nicely with existing work from Kirkland and Coppock (2018), which finds in a conjoint experiment, "Republicans respond to the removal of partisan information by giving greater weight to job experience while Democrats respond by giving greater weight to political experience." The national exercise relies on one year of data from fewer than 1,000 city councilmembers and so it is not as strong as the California evidence. However, it is suggestive that the patterns and trends shown in the main results of the paper are not unique to California.

6 Discussion

In an era of increasing amateurism in politics (Porter and Treul 2024), when voters reference other candidate qualities to evaluate competence (Kirkland and Coppock 2018; Atkeson and Hamel 2020), understanding the interactions between a group or identity like occupation and candidate party affiliation is crucial. Existing theory disagrees on the relative importance of national party labels and local group membership in explaining municipal representation and policy patterns.

This piece has shown how party and one particular group — occupation — are tightly coupled in a recent sample of thousands of city council candidates and officeholders across California. First, cities that differ ideologically attract different kinds of candidates to run on average: more liberal cities have more service-based professionals like teachers and nurses, longstanding political types, and non-profit workers running for and winning office. More conservative cities have more military and law enforcement workers and business types running for and winning office. And at the individual candidate level, career labels from ballot designations signal party affiliation.

Designs that use regression discontinuity to show how party affects local politics (de Benedictis-Kessner and Warshaw 2016; de Benedictis-Kessner, Jones, and Warshaw 2024) assume that other observed and unobserved candidate characteristics are smooth at the cutpoint; in other words, that when a Republican wins by a razor thin margin, she only differs from the Democrat who loses by a razor thin margin by party. The same is true in the opposite direction for regression discontinuity work using occupation (Kirkland 2021). Some covariates are easier to test for smoothness around the discontinuity because of data availability, like race and gender, but many are more difficult to measure and go uncontrolled for despite their impact: union membership, occupational history, prior elected experience, family status, homeowner status, and more.

The documented association between occupation and party adds context to many existing findings in local political economy. Voters see candidate occupation through a partisan lens (Adams, Lascher, and Martin 2021), they weigh occupation in nonpartisan elections (Kirkland and Coppock 2018), and they punish and reward candidates based on endorsements from professional associations. For instance, police union endorsements, once an electoral boost across the board, have polarized voters in recent local elections. The police union endorsement now helps conservative candidates and hurts liberal candidates (Gaudette 2024).

Future work should expand to a national analysis and examine whether places have a different idea of what a "pre-political" career is. Do the California associations in this piece hold in other states? How do occupational trends vary between nonpartisan and partisan election formats? Is it true that in liberal places non-profit jobs are considered political pipelines and imbued with a certain prestige whereas in conservative places military and law enforcement jobs are considered political pipelines and have elevated status? How do the jobs we have change our ideological views? Researchers ought to use more specific occupational categories to better understand how the economic backgrounds and more detailed life experiences of politicians guide their work in office.

The strong correlation between party and occupation suggests that neither theories of local politics as driven by groups and identity nor theories of strong nationalized partisanship can rule out the other. Instead, the research designs used to study local politics need to capture the rich breadth of affiliations that candidates bring to the table.

References

Adams, Brian E., Edward L. Lascher, and Danielle Joesten Martin. 2021. “Ballot Cues, Business Candidates, and Voter Choices in Local Elections.” *American Politics Research* 49(March): 186–197.

Anzia, Sarah F. 2021. “Party and Ideology in American Local Government: An Appraisal.” *Annual Review of Political Science* 24(1): 133–150.

Atkeson, Lonna Rae, and Brian T. Hamel. 2020. “Fit for the Job: Candidate Qualifications and Vote Choice in Low Information Elections.” *Political Behavior* 42(March): 59–82.

Barreto, Matt A. 2007. “İSí Se Puede! Latino Candidates and the Mobilization of Latino Voters.” *American Political Science Review* 101(August): 425–441.

Bonica, Adam. 2020. “Why Are There So Many Lawyers in Congress?” *Legislative Studies Quarterly* 45(2): 253–289.

Bonneau, Chris W., and Damon M. Cann. 2015. “Party Identification and Vote Choice in Partisan and Nonpartisan Elections.” *Political Behavior* 37(1): 43–66.

California Elections Data Archive (CEDA). 2003.

Carnes, Nicholas. 2013. *White-Collar Government: The Hidden Role of Class in Economic Policy Making*. Chicago Studies in American Politics Chicago, IL: University of Chicago Press.

de Benedictis-Kessner, Justin, and Christopher Warshaw. 2016. “Mayoral Partisanship and Municipal Fiscal Policy.” *The Journal of Politics* 78(October): 1124–1138.

de Benedictis-Kessner, Justin, Daniel Jones, and Christopher Warshaw. 2024. “How Partisanship in Cities Influences Housing Policy.” *American Journal of Political Science* (March): ajps.12856.

de Benedictis-Kessner, Justin, Diana Da In Lee, Yamil R. Velez, and Christopher Warshaw. 2023. “American Local Government Elections Database.” *Scientific Data* 10(December): 912.

Egan, Patrick J. 2020. “Identity as Dependent Variable: How Americans Shift Their Identities to Align with Their Politics.” *American Journal of Political Science* 64(3): 699–716.

Einstein, Katherine Levine, and Vladimir Kogan. 2016. “Pushing the City Limits: Policy Responsiveness in Municipal Government.” *Urban Affairs Review* 52(January): 3–32.

Einstein, Katherine Levine, David M. Glick, and Maxwell Palmer. 2019. *Neighborhood Defenders: Participatory Politics and America’s Housing Crisis*. Cambridge: Cambridge University Press.

Ferreira, Fernando, and Joseph Gyourko. 2009. “Do Political Parties Matter? Evidence from U.S. Cities.” *The Quarterly Journal of Economics* 124(February): 399–422.

Ferreira, Fernando, and Joseph Gyourko. 2014. "Does Gender Matter for Political Leadership? The Case of U.S. Mayors." *Journal of Public Economics* 112(April): 24–39.

Gaudette, Jennifer. 2024. "Polarization in Police Union Politics." *American Journal of Political Science (forthcoming)* .

Hajnal, Zoltan, and Jessica Trounstine. 2014. "What Underlies Urban Politics? Race, Class, Ideology, Partisanship, and the Urban Vote." *Urban Affairs Review* 50(January): 63–99.

Hall, Andrew B. 2019. *Who Wants to Run?: How the Devaluing of Political Office Drives Polarization.* Chicago Studies in American Politics Chicago, IL: University of Chicago Press.

Hankinson, Michael. 2018. "When Do Renters Behave Like Homeowners? High Rent, Price Anxiety, and NIMBYism." *American Political Science Review* 112(August): 473–493.

Holman, Mirya R. 2014. "Sex and the City: Female Leaders and Spending on Social Welfare Programs in U.s. Municipalities." *Journal of Urban Affairs* 36(4): 701–715.

Hopkins, Daniel J. 2018. *The Increasingly United States: How and Why American Political Behavior Nationalized.* Chicago Studies in American Politics Chicago, IL: University of Chicago Press.

Jensen, Amalie, William Marble, Kenneth Scheve, and Matthew J. Slaughter. 2021. "City Limits to Partisan Polarization in the American Public." *Political Science Research and Methods* 9(April): 223–241.

Kirkland, Patricia A. 2021. "Business Owners and Executives as Politicians: The Effect on Public Policy." *The Journal of Politics* 83(October): 1652–1668.

Kirkland, Patricia A., and Alexander Coppock. 2018. "Candidate Choice Without Party Labels:: New Insights from Conjoint Survey Experiments." *Political Behavior* 40(September): 571–591.

Manson, Steven, Jonathan Schroeder, David Van Riper, Tracy Kugler, and Steven Ruggles. 2022. "National Historical Geographic Information System: Version 17.0.".

Marble, William, and Clayton Nall. 2021. "Where Self-Interest Trumps Ideology: Liberal Homeowners and Local Opposition to Housing Development." *The Journal of Politics* 83(October): 1747–1763.

Mathews, Melissa A. 2020. "The Embeddedness of Nonprofit Leadership in Civic Governance." *VOLUNTAS: International Journal of Voluntary and Nonprofit Organizations* 31(February): 201–212.

McHugh, Mary L. 2012. "Interrater Reliability: The Kappa Statistic." *Biochemia Medica* 22(October): 276–282.

Nemerovski, Peter. 2021. "Occupational Hazard: A Critique of California's Ballot Designation Statute.".

Porter, Rachel, and Sarah A. Treul. 2024. "Evaluating (in)experience in congressional elections." *American Journal of Political Science* (March).

Sances, Michael W. 2018. "Ideology and Vote Choice in U.S. Mayoral Elections: Evidence from Facebook Surveys." *Political Behavior* 40(September): 737–762.

Tausanovitch, Chris, and Christopher Warshaw. 2014. "Representation in Municipal Government." *American Political Science Review* 108(August): 605–641.

Thompson, Daniel M. 2020. "How Partisan Is Local Law Enforcement? Evidence from Sheriff Cooperation with Immigration Authorities." *American Political Science Review* 114(February): 222–236.

Trounstine, Jessica. 2011. "Evidence of a Local Incumbency Advantage." *Legislative Studies Quarterly* 36(2): 255–280.

Vogl, Tom S. 2014. "Race and the Politics of Close Elections." *Journal of Public Economics* 109(January): 101–113.

Warshaw, Christopher. 2019. "Local Elections and Representation in the United States." *Annual Review of Political Science* 22(1): 461–479.

The Economic Background of City Councilmembers Appendix

October 3, 2024

Contents

A Ballot Designation Categorization Examples

Technical Professional	Business Employee	Service Based Professional
Architect	Businessman	Nurse
Engineer	Retired businessman	Teacher
Software engineer	Consultant	Educator
Physician	Contractor	Professor
Journalist	Realtor	Pastor

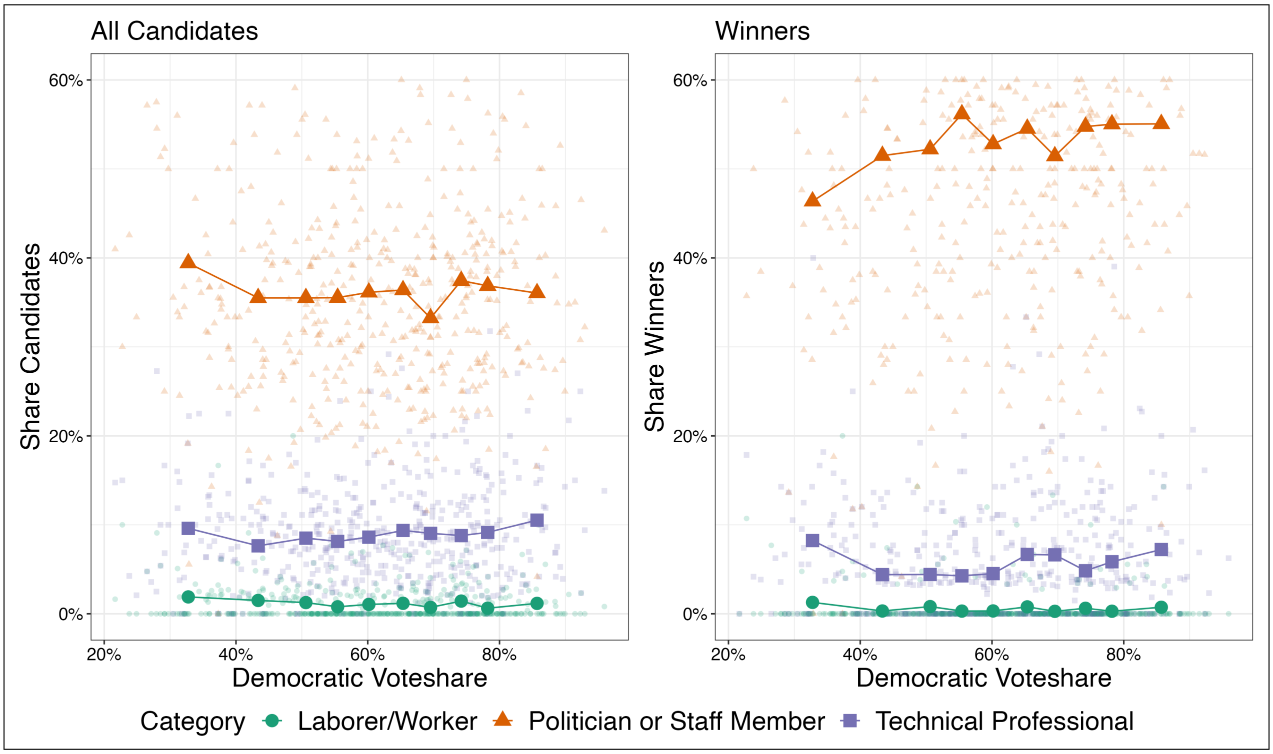
Non-Profit Worker	Laborer/Worker	Military or Law Enforcement
Nonprofit director	Waiter	Police officer
Community organizer	Carpenter	Firefighter
Grant writer	Farmer	Navy
Nonprofit executive	Utility worker	Sheriff
Development director	Painter	Captain

Politician or Staff Member	Business Owner	Lawyer
Incumbent	CEO	Attorney
Mayor	Small business owner	Private practice
Councilman	Retired business owner	Public defender
Councilmember	Executive director	Prosecutor
Assemblymember	Restaurant owner	Paralegal

B Raw Data

B.1 Additional Career Categories

Figure 1: **Supplementary Raw Data Display California Candidates and Winning Officeholders**

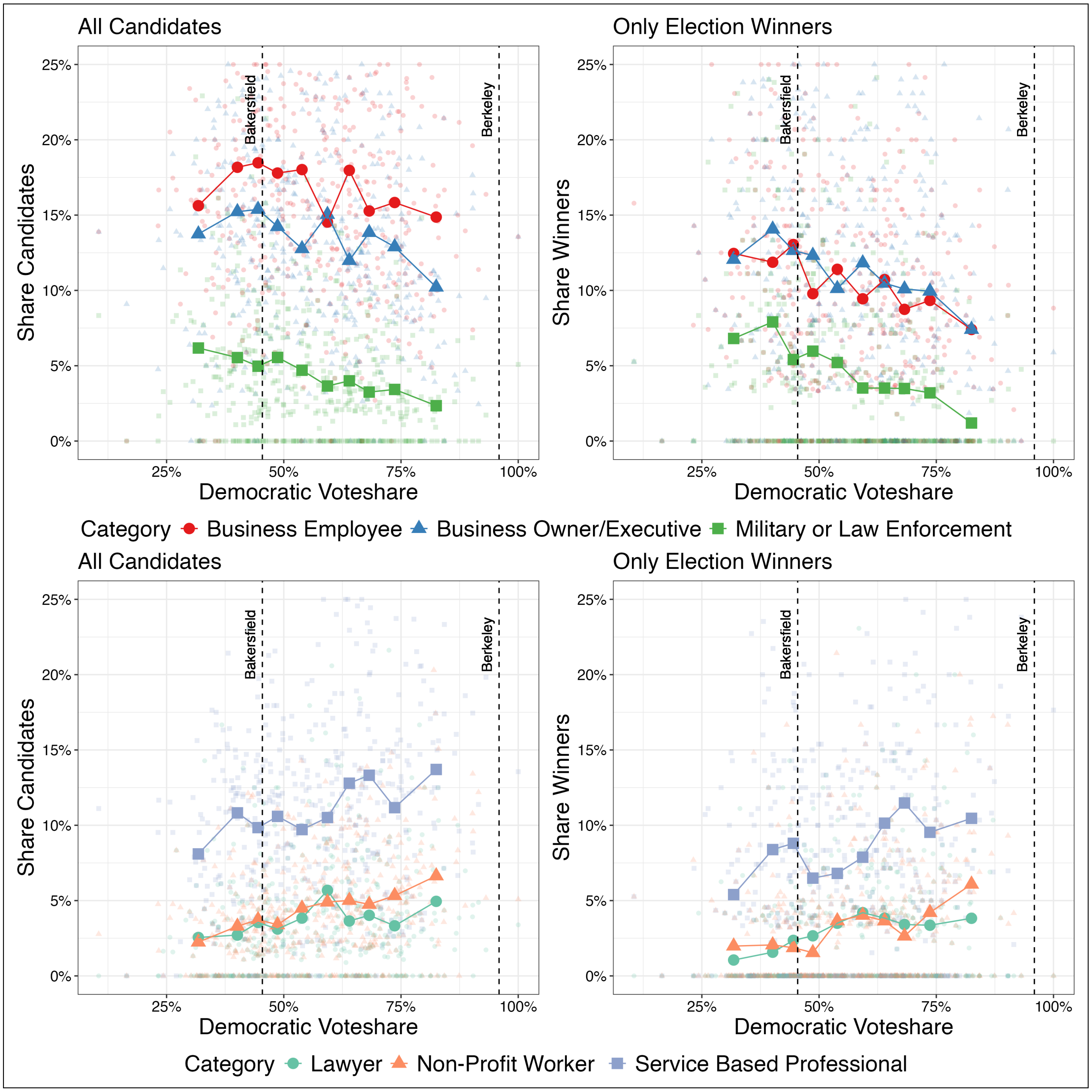


Additional career categories (Politician or Staff Member, Laborer/Worker, and Technical Professional) not displayed in the partisan trends in Figure 1 in the main text.

B.2 Alternate City Partisanship Measure: 2008 Election Results

The following figure replicates results from the main text but uses 2008 city-level election results instead of 2020 city-level election results to check that the results are not sensitive to choice of election year. The Pearson correlation coefficient between 2008 and 2020 California city-level election results is .943.

Figure 2: **Using 2008 Election Results for City-Level Democratic Voteshare**

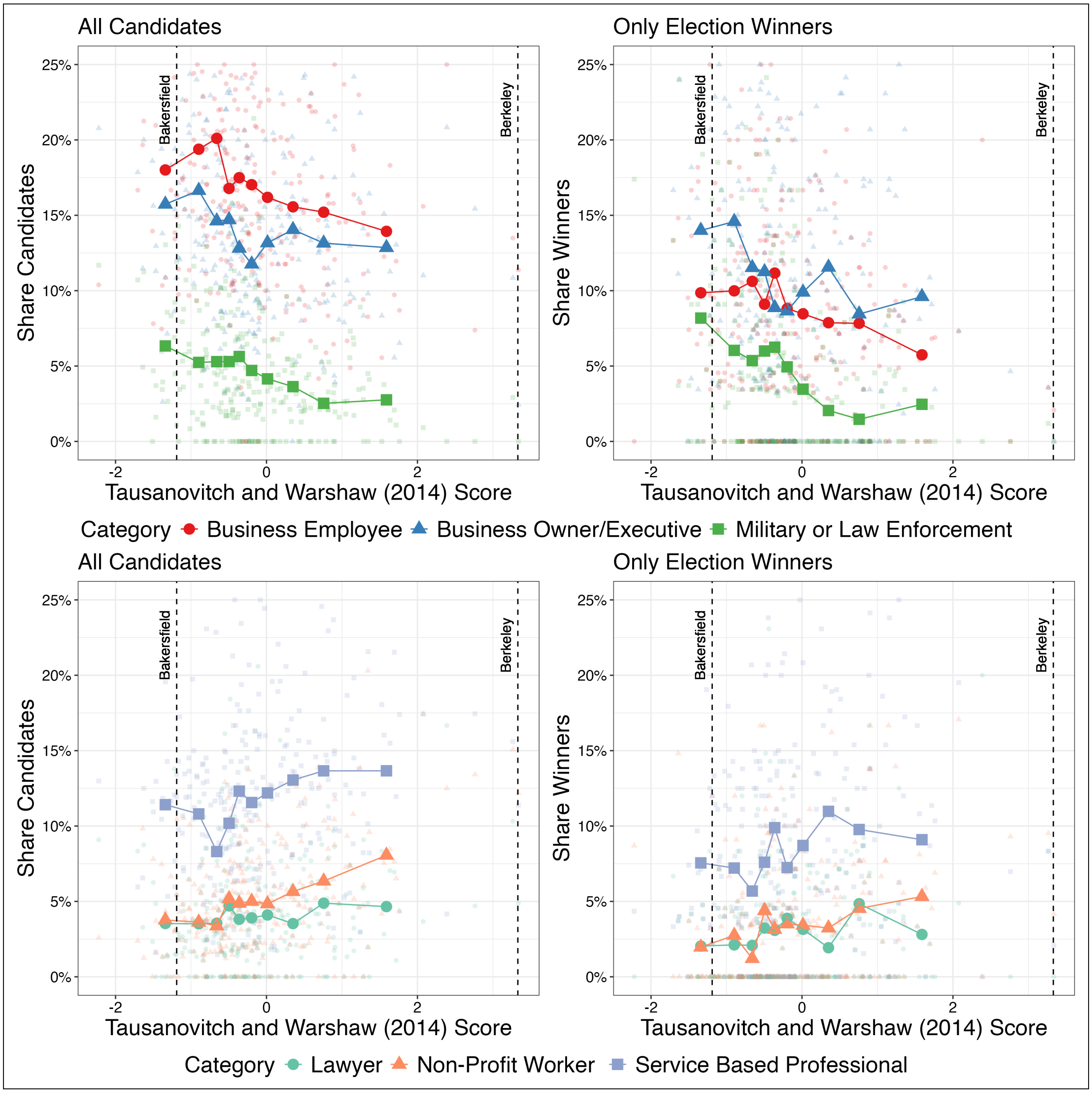


Graphs on the left ("All Candidates") use city data from 26,821 candidacies between 1996 and 2021. Graphs on the right ("Only Election Winners") filter down to only the 11,411 winners. Each large point is a vote share-decile average of cities' proportions of candidates or winners with a given career label. Three career categories appear in the top row of graphs (trending down with Democratic voteshare), and three categories below (trending up).

B.3 Alternate City Partisanship Measure: Scaled Survey-Based Results

The following figure replicates results from the main text but uses the scaled, survey-based ideological scores from Tausanovitch and Warshaw (2014) instead of 2020 city-level election results. More positive scores represent more liberal cities. This robustness check is to ensure that results are similar when using a survey-based measure of ideology instead of aggregated election results. Scores in Tausanovitch and Warshaw (2014) are available for only 271/477 cities in California.

Figure 3: **Using Tausanovitch and Warshaw (2014) City Ideology Scores Instead of Election Results**

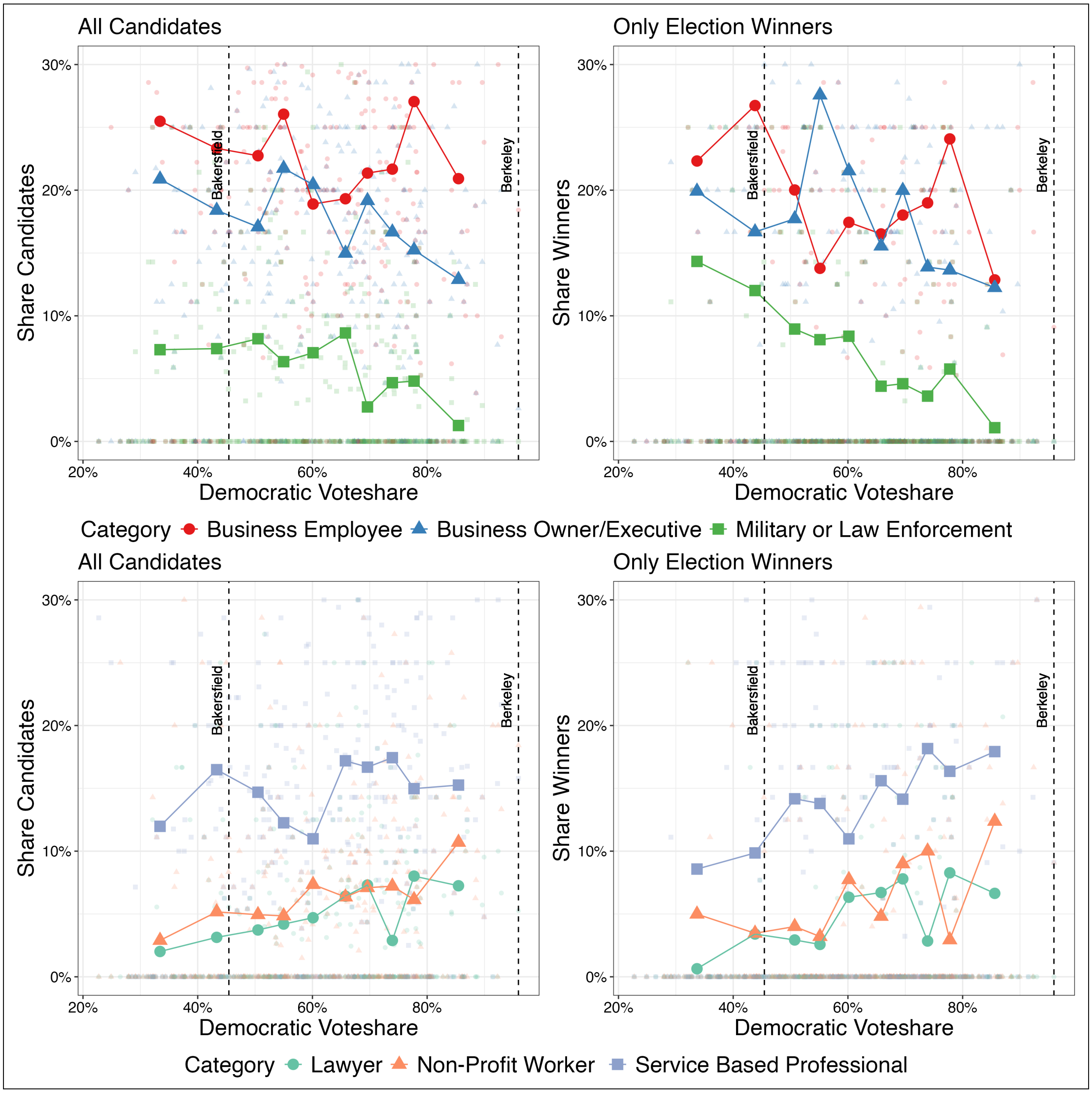


Graphs on the left ("All Candidates") use city data from 18,579 candidacies between 1996 and 2021. Graphs on the right ("Only Election Winners") filter down to only the 7,035 winners. Each large point is a vote share-decile average of cities' proportions of candidates or winners with a given career label. Three career categories appear in the top row of graphs (trending down with Democratic voteshare), and three categories below (trending up).

B.4 Open Seat Elections Only

The following figure replicates results from the main text but uses only elections in which there is no incumbent on the ballot. This limits the data to 6,025 candidates from 394 cities.

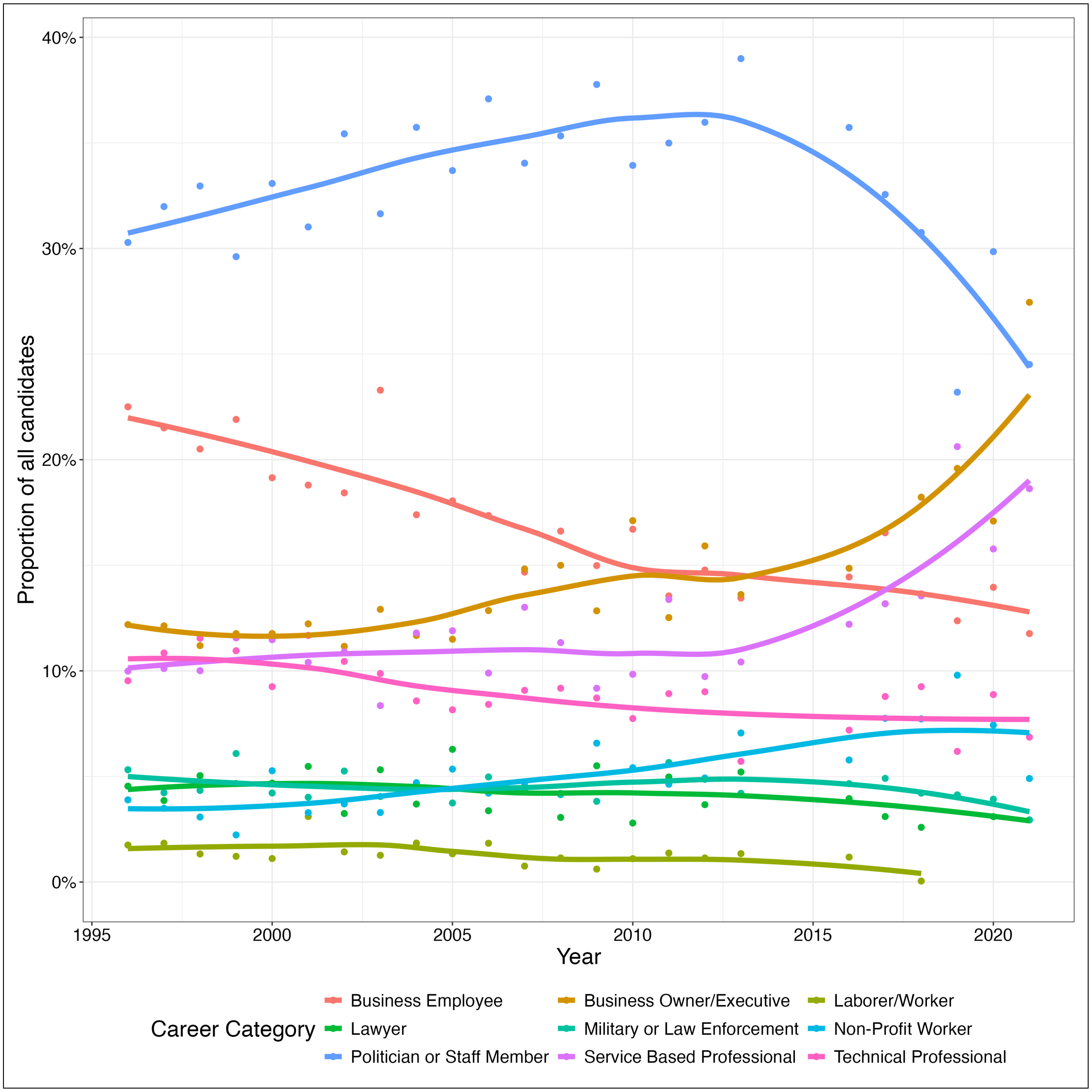
Figure 4: **Open Seat Elections Only**



Graphs on the left ("All Candidates") use city data from 6,025 candidacies between 1996 and 2021. Graphs on the right ("Only Election Winners") filter down to only the 2,050 winners. Each large point is a vote share-decile average of cities' proportions of candidates or winners with a given career label. Three career categories appear in the top row of graphs (trending down with Democratic voteshare), and three categories below (trending up).

B.5 Over Time Plot

Figure 5: **Proportion of All Candidates Belonging to Each Career Category Over Time**



Each point represents the proportion of all California candidates in a given career category in a given year.

C Modeling: Coefficients for Candidate Occupation by City Ideology Multinomial Logistic Regression Models

Table 1: **California Multinomial Logistic Regression Coefficients and Standard Errors**

Category vs. Business Employee:	Business Owner/Executive	Laborer/Worker	Lawyer	Military or Law Enforcement
(Intercept)	-1.292 (1.59)	5.097 (3.963)	-10.981 (2.671)	-5.494 (2.351)
Democratic Voteshare	-0.161 (0.222)	1.766 (0.549)	1.223 (0.348)	-1.552 (0.342)
1997	0.052 (0.18)	0.328 (0.39)	-0.211 (0.273)	-0.148 (0.262)
1998	0.008 (0.134)	-0.246 (0.311)	0.255 (0.187)	-0.147 (0.187)
1999	-0.006 (0.187)	-0.053 (0.468)	-0.062 (0.267)	0.23 (0.243)
2000	0.109 (0.128)	-0.289 (0.311)	0.14 (0.182)	-0.068 (0.18)
2001	0.189 (0.182)	1.003 (0.335)	0.227 (0.248)	-0.054 (0.268)
2002	0.101 (0.133)	-0.036 (0.3)	-0.142 (0.203)	0.196 (0.177)
2003	0.033 (0.198)	-0.09 (0.504)	0.008 (0.278)	-0.258 (0.3)
2004	0.211 (0.13)	0.29 (0.277)	0.042 (0.193)	0.119 (0.178)
2005	0.197 (0.167)	0.219 (0.392)	0.361 (0.218)	-0.021 (0.244)
2006	0.325 (0.128)	0.249 (0.277)	-0.011 (0.196)	0.18 (0.175)
2007	0.698 (0.171)	-0.179 (0.507)	0.251 (0.253)	0.409 (0.244)
2008	0.511 (0.126)	-0.166 (0.311)	-0.094 (0.202)	0.051 (0.183)
2009	0.529 (0.176)	-0.379 (0.554)	0.395 (0.239)	0.225 (0.259)
2010	0.629 (0.123)	-0.165 (0.311)	-0.166 (0.205)	0.284 (0.172)
2011	0.612 (0.188)	0.532 (0.43)	0.411 (0.258)	0.702 (0.245)
2012	0.691 (0.127)	-0.032 (0.312)	0.225 (0.195)	0.304 (0.178)
2013	0.665 (0.184)	0.532 (0.43)	0.431 (0.253)	0.401 (0.264)
2016	0.642 (0.128)	0.023 (0.308)	0.301 (0.191)	0.296 (0.179)
2017	0.405 (0.211)	-11.998 (221.948)	-0.388 (0.345)	0.38 (0.293)
2018	0.922 (0.119)	-3.135 (1.022)	-0.049 (0.197)	0.282 (0.172)
2019	1.037 (0.278)	-11.45 (297.867)	0.117 (0.433)	0.473 (0.43)
2020	0.828 (0.117)	-12.114 (86.146)	0.029 (0.184)	0.219 (0.17)
2021	1.46 (0.358)	-11.975 (431.669)	0.267 (0.662)	0.013 (0.66)
Logged Population	0.099 (0.02)	-0.025 (0.055)	0.198 (0.031)	0.125 (0.03)
White	-0.184 (0.416)	-0.302 (0.88)	1.577 (0.779)	-1.008 (0.565)
Black	-0.262 (0.716)	-4.599 (1.787)	0.395 (1.276)	0.439 (0.969)
Asian	-0.868 (0.479)	-1.048 (1.114)	1.897 (0.852)	-0.484 (0.658)
Hispanic	-1.029 (0.3)	-2.934 (0.733)	0.464 (0.514)	-0.29 (0.425)
Bachelors	0.209 (0.566)	-2.435 (1.564)	-0.621 (0.871)	0.531 (0.885)
Logged Income	-0.013 (0.122)	-0.151 (0.328)	0.164 (0.193)	0.325 (0.186)
Management	0.418 (0.797)	-4.58 (1.869)	3.122 (1.405)	-1.64 (1.151)
Service	0.659 (0.895)	-6.04 (2.157)	1.774 (1.62)	-0.348 (1.278)
Sales	1.459 (1.058)	-3.149 (2.493)	3.536 (1.868)	2.504 (1.517)
Construction	1.093 (0.797)	-1.922 (1.579)	2.84 (1.589)	1.139 (1.107)
Self Employed	-1.569 (0.688)	-7.256 (2.203)	3.981 (0.974)	0.31 (1.105)
Non-Profit Employed	0.159 (1.091)	-3.962 (2.936)	3.97 (1.675)	-0.576 (1.699)
Government Employed	-1.06 (0.519)	3.531 (1.188)	0.969 (0.859)	3.17 (0.708)

Reference outcome baseline category: Business Employee.

Table 1: **California Multinomial Logistic Regression Coefficients and Standard Errors (continued)**

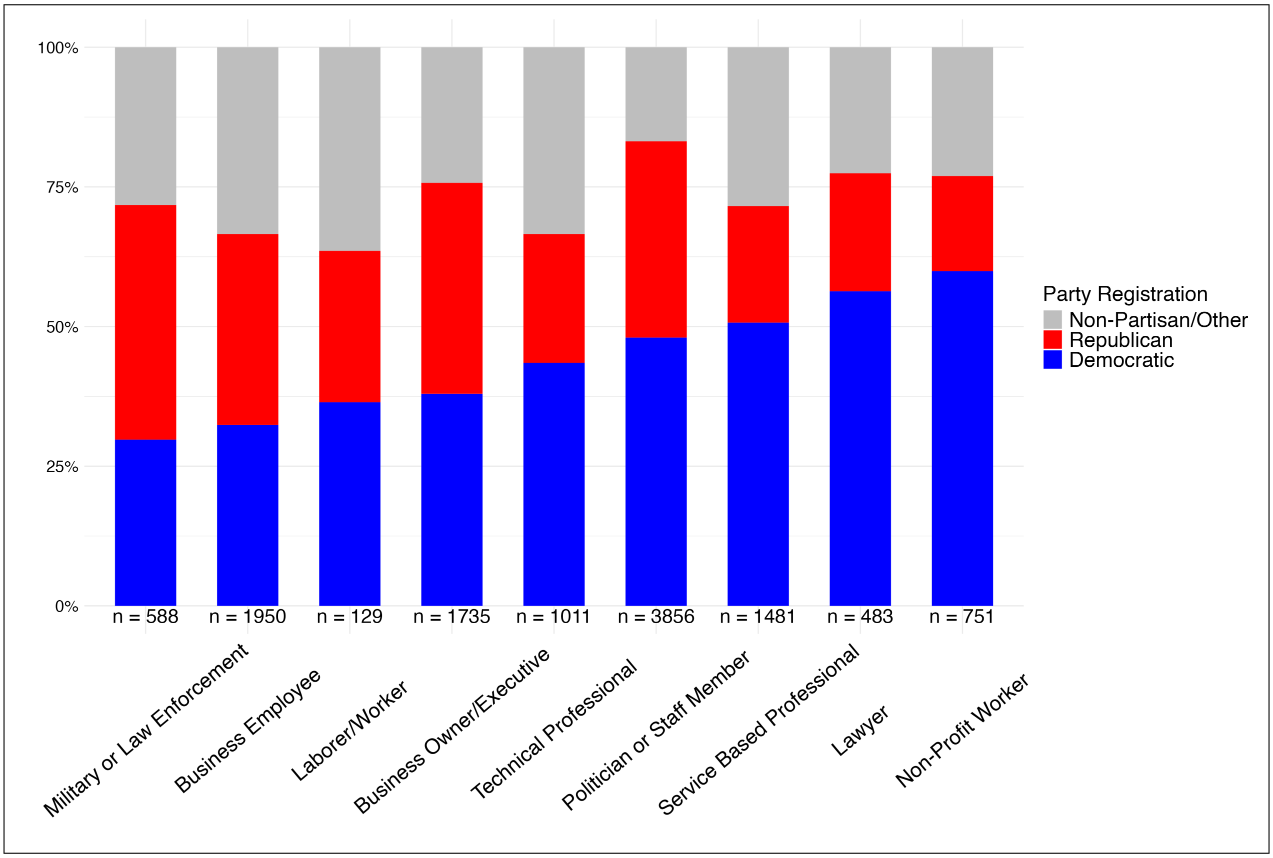
Category vs. Business Employee	Non-Profit Worker	Politician or Staff Member	Service Based Professional	Technical Professional
(Intercept)	-6.105 (2.342)	2.189 (1.284)	4.462 (1.655)	0.829 (1.784)
Democratic Voteshare	2.715 (0.319)	0.648 (0.18)	1.554 (0.23)	1.152 (0.244)
1997	-0.204 (0.286)	0.07 (0.14)	0.018 (0.191)	0.159 (0.189)
1998	-0.084 (0.215)	0.18 (0.103)	0.112 (0.141)	0.296 (0.139)
1999	-0.69 (0.348)	-0.014 (0.146)	0.138 (0.192)	0.146 (0.195)
2000	0.402 (0.185)	0.256 (0.099)	0.294 (0.133)	0.128 (0.139)
2001	-0.179 (0.293)	0.174 (0.145)	0.17 (0.193)	0.353 (0.189)
2002	0.139 (0.203)	0.356 (0.102)	0.282 (0.138)	0.292 (0.14)
2003	-0.341 (0.329)	0.006 (0.155)	-0.251 (0.226)	0.001 (0.217)
2004	0.416 (0.19)	0.411 (0.101)	0.412 (0.134)	0.151 (0.142)
2005	0.283 (0.232)	0.308 (0.13)	0.332 (0.17)	0.077 (0.185)
2006	0.353 (0.194)	0.46 (0.1)	0.247 (0.137)	0.149 (0.142)
2007	0.393 (0.255)	0.524 (0.142)	0.63 (0.179)	0.408 (0.194)
2008	0.375 (0.195)	0.456 (0.102)	0.428 (0.136)	0.262 (0.141)
2009	0.715 (0.234)	0.597 (0.14)	0.264 (0.193)	0.319 (0.196)
2010	0.677 (0.185)	0.42 (0.101)	0.304 (0.137)	0.104 (0.144)
2011	0.422 (0.268)	0.625 (0.152)	0.726 (0.189)	0.466 (0.207)
2012	0.636 (0.19)	0.594 (0.104)	0.385 (0.14)	0.383 (0.143)
2013	0.749 (0.242)	0.755 (0.149)	0.458 (0.197)	0.013 (0.229)
2016	0.817 (0.185)	0.61 (0.104)	0.64 (0.136)	0.164 (0.149)
2017	0.578 (0.269)	0.362 (0.171)	0.467 (0.214)	0.261 (0.237)
2018	1.168 (0.171)	0.511 (0.1)	0.798 (0.128)	0.485 (0.135)
2019	1.125 (0.344)	0.365 (0.264)	1.267 (0.279)	0.193 (0.369)
2020	1.051 (0.169)	0.452 (0.097)	0.916 (0.123)	0.406 (0.132)
2021	0.703 (0.553)	0.423 (0.359)	1.177 (0.383)	0.387 (0.487)
Logged Population	0.273 (0.026)	-0.071 (0.016)	0.08 (0.021)	0 (0.023)
White	0.166 (0.587)	-0.879 (0.324)	-0.53 (0.404)	0.734 (0.48)
Black	-1.1 (0.981)	-1.063 (0.566)	-1.505 (0.707)	-0.207 (0.831)
Asian	-0.319 (0.682)	-0.849 (0.377)	-0.706 (0.477)	0.736 (0.545)
Hispanic	-0.719 (0.43)	-0.86 (0.237)	-0.686 (0.3)	-1.425 (0.342)
Bachelors	-0.598 (0.837)	-0.744 (0.46)	0.19 (0.601)	-1.536 (0.619)
Logged Income	0.017 (0.178)	-0.036 (0.1)	-0.469 (0.129)	-0.114 (0.136)
Management	-0.977 (1.176)	0.174 (0.631)	-1.526 (0.812)	0.379 (0.893)
Service	-0.561 (1.309)	-0.537 (0.708)	-2.596 (0.907)	-1.515 (1.03)
Sales	-0.343 (1.638)	0.602 (0.841)	-1.785 (1.094)	-1.349 (1.183)
Construction	-0.082 (1.157)	0.012 (0.618)	-0.479 (0.76)	0.577 (0.888)
Self Employed	1.259 (1.025)	-0.647 (0.553)	-0.357 (0.747)	-0.896 (0.75)
Non-Profit Employed	3.299 (1.596)	1.204 (0.874)	1.318 (1.135)	-0.899 (1.205)
Government Employed	1.276 (0.767)	0.519 (0.413)	1.801 (0.532)	0.397 (0.567)

Reference outcome baseline category: Business Employee.

D Alternate Sourcing of Candidate Party Information

The main text used candidate party information from looking up candidates in the L2 voter file in the city in which they ran for office. Here is the same figure, but using data from the 44.7% of candidates who appear in the local elections database (de Benedictis-Kessner et al. 2023). This is to make sure that when using a different match procedure and different source voterfiles, the same baseline finding holds.

Figure 6: **Sourcing Candidate Partisanship from the American Local Government Elections Database (de Benedictis-Kessner et al. 2023)**



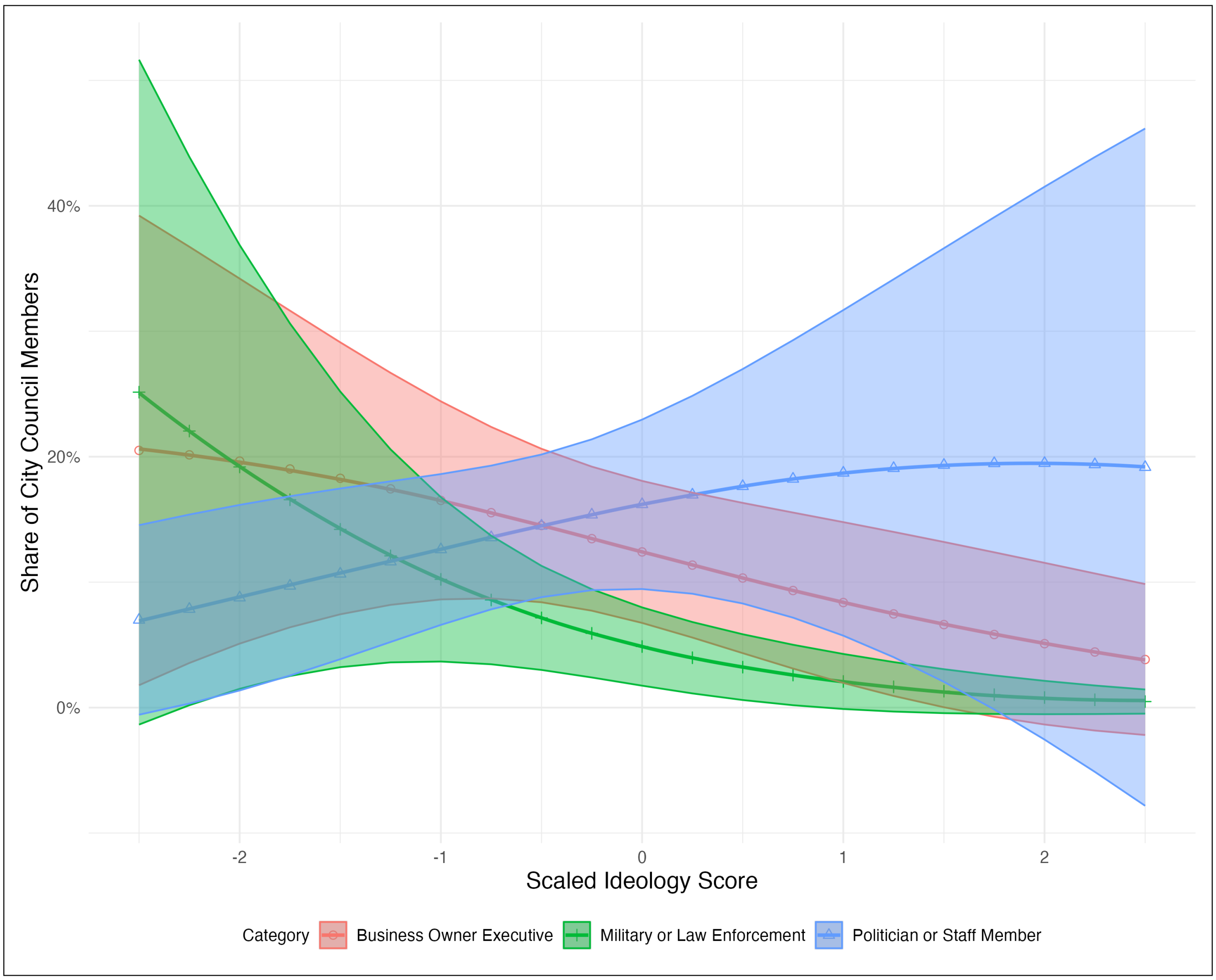
Party information is that which is available for California candidates from the Local Elections Database (de Benedictis-Kessner et al. 2023).

The career categories show significantly different partisan distributions ($\chi^2(16) = 606.91$, p-value $< 2.2\text{e-}16$)

E Validation: Large Cities (National Sample) — Nonpartisan Cities Only

The main text used a sample of 97 large cities across the country to validate the main results from the longitudinal California sample. The main text dataset used 877 city councilors from across the country from cities with nonpartisan and partisan elections. Here I limit the data to the 675 city councilors from only cities with nonpartisan elections. This means excluding Baltimore, MD, Buffalo, NY, Charlotte, NC, Baton Rouge, LA, Fort Wayne, IN, Indianapolis, IN, Jacksonville, FL, Louisville, KY, New York City, NY, New Orleans, LA, Philadelphia, PA, Pittsbrugh, PA, Tucson, AZ, and Winston-Salem, NC.

Figure 7: **Predicted Candidate Shares for National Cities (Nonpartisan Elections Only)**



Model fit on data limited to only officeholders in cites with nonpartisan elections.

References

de Benedictis-Kessner, Justin, Diana Da In Lee, Yamil R. Velez, and Christopher Warshaw. 2023. "American Local Government Elections Database." *Scientific Data* 10(December): 912.

Tausanovitch, Chris, and Christopher Warshaw. 2014. "Representation in Municipal Government." *American Political Science Review* 108(August): 605–641.