VRscores:
A New Measure and Dataset of Workforce Politics Using Voter Registrations*

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Abstract

This paper introduces VRscores, a workplace-level measure of employee partisanship constructed by linking U.S. voter registrations to electronically available worker profiles covering 2012 to 2024. The resulting organizational-level dataset captures the partisanship of 24.5 million workers across more than 534,000 employers with at least five matched employees. We release this employer-level dataset, along with parallel datasets reporting VRscores at the firm, occupation, industry, and metropolitan statistical area (MSA) levels. We show that VRscores cover substantially more employees and organizations than donation-based approaches to measuring political ideology. We also show that VRscores are more representative of the U.S. workforce in terms of partisanship, seniority, occupation, and industry. Finally, we demonstrate that VRscores and donation-based measures are only moderately correlated ($r = 0.51$) and that they classify one in five organizations differently with respect to whether they lean Democratic or Republican.

Keywords: nonmarket strategy, human capital, politics at work, corporate political activity, stakeholders

1 Introduction

A growing body of work considers how employees' political attitudes, beliefs, and identities might shape organizational outcomes. Early studies in this area focused on those within organizations' upper echelons, arguing that CEOs', board members', and top management team members' political ideologies shape diverse outcomes such as corporate social responsibility (Chin et al. 2013), executive compensation (Gupta and Wowak 2017), gender equality (Carnahan and Greenwood 2018), and responses to social activism (Briscoe et al. 2014, McDonnell and Cobb 2020). More recently, scholars have considered how the political ideologies of rank-and-file workers relate to outcomes including turnover (Bermiss and McDonald 2018, White et al. 2025), worker attraction and productivity (Burbano 2021, Carpenter and Gong 2015), personnel decisions (Mohliver and Raines 2024), sociopolitical activity (Gupta et al. 2017, Li and Disalvo 2023, McKean and King 2024, Wowak et al. 2022), and openness to external social activists (Gupta and Briscoe 2020).

To date, nearly all observational studies in this literature have operationalized employees' ideology using employees' political donations. This donations-based approach takes advantage of the fact that the Federal Election Commission (FEC) requires public disclosure of individual political donations to political campaigns and parties. The general approach is to aggregate donations from individual donors who report a common employer.[1] This measure is then scaled to reflect the proportion of donations flowing to one party (i.e., Democratic campaigns, committees, and/or the Democratic party) relative to the total donations to both major political parties (i.e., both Democratic and Republican recipients). This approach has been very influential, allowing scholars to open fruitful lines of research. As shown in Figure 1, we document 42 papers which use political contribution data and which appear in top management journals between 2013 and 2024.[2]

However, recent work draws attention to possible limitations regarding the coverage of donations-based measures, the validity of donations as indicators of ideology, and the appropriateness of focusing on ideology rather than identity. With regard to coverage, exceedingly few workers donate (Barber IV and

[1]Variants of this measure may focus on specific types of employees within a company, e.g., board members, executives, or other sub-populations of interest. They may also consist of one or more different measures, such as the number of donations, the dollar amount, or the number of distinct recipients.

[2]The papers are individually listed in Table A1. The journals were *Academy of Management Review* (AMR), *Academy of Management Journal* (AMJ), *Administrative Science Quarterly* (ASQ), *Management Science* (MS), *Organization Science* (OS), and *Strategic Management Journal* (SMJ). We searched each journal using the keywords "donat*," "democrat*," and "republic*"; we did not find any empirical papers in AMR. We include all papers appearing in these journals from 2010 to 2024 (first paper appeared in 2013), which includes papers in strategy and management as well as accounting, finance, and marketing. This does not include a number of relevant papers which are published in other disciplinary journals.

Blake 2024, Stuckatz 2022a, Teso 2025), and donors tend to be demographically distinct from non-donors (Grumbach and Sahn 2020, Grumbach et al. 2022, Bonica and Grumbach 2024) and hold extreme and atypical political views (Bafumi and Herron 2010, Barber 2016a,b, Barber et al. 2024, Broockman and Malhotra 2020, Meisels et al. 2024). At the same time, recent work emphasizes how donations may not necessarily capture enduring political beliefs or attitudes, but instead represent strategic attempts to gain access (Barber IV and Blake 2023, Gordon et al. 2007, Kalla and Broockman 2016, Werner 2015), or reflect coercion from workplace superiors (Babenko et al. 2020, Hertel-Fernandez 2018). More broadly, in the years since the inception of the donations-based approach, political scientists have increasingly identified political identity, rather than political ideology, as a key, stable driver of political attitudes and behaviors (Achen and Bartels 2016, Iyengar et al. 2012, Mason 2018).

In this paper, we introduce VRscores ("voter registration scores") as a novel measure of organizational partisanship, which (1) provides significantly larger and more representative coverage across and within workplaces, (2) is less vulnerable to issues of strategic self-presentation, and (3) more directly captures workers' political identities. Our strategy takes advantage of the fact that voter registrations in the United States are publicly accessible and that the majority of registered voters can be linked to one of the two major political parties. By merging voter registration data with newly available large-scale data on employee work histories (see Frake et al. 2024), we are able to identify the partisanship and place of employment for 45.3 million workers. After restricting to employers with at least five employees in our dataset, our public dataset contains the organizational partisanship of more than 534,000 employers based on 24.5 million workers.

After detailing how VRscores are created, we conduct a series of benchmarking exercises demonstrating VRscores' coverage advantages. First, because most of the working population is registered to vote while only very few donate, VRscores capture far more workers (24.5 million in 2024) than donations-based measures (1.3 million donors during the most recent two-year Federal election cycle). This larger sample yields a broader set of employers (534,000 vs. 100,000) and significantly deeper coverage of each employer (45.9 registered voters per firm versus 25.5 donors). Second, we show that the sample of employees used to construct VRscores is more representative of the US workforce in terms of partisan makeup, job category, and seniority. Whereas donations-based measures are heavily weighted towards relatively elite occupations and employees, VRscores better incorporate the political leanings of employees across occupations and throughout organizational hierarchies. We also show that donations-based measures are only moderately correlated with each other and that VRscores deliver substantively different estimates regarding the distribution of left versus right ideology and partisanship within organizations.

We then review work suggesting that donations reflect strategic motivations rather than deeply held beliefs or values. While Ansolabehere et al.'s (2003) influential work is often cited to claim that donations are purely ideologically motivated, empirical work in the intervening decades casts doubt on this assertion (Gordon et al. 2007, Kalla and Broockman 2016, Meisels et al. 2024). In particular, we detail work indicating that incentives for strategically motivated giving may exist for both (1) managers who wish to gain access to policymakers (Barber IV and Blake 2024, Steel 2024, Teso 2025) and (2) rank-and-file workers in response to pressure from superiors (Babenko et al. 2020, Hertel-Fernandez 2018, Stuckatz 2022a).

Next, we briefly summarize developments in political science in which scholars increasingly favor conceptions of political *identity* over political *ideology* for explaining political attitudes and behaviors (Iyengar et al. 2012). Notably, this work characterizes the majority of Americans as "ideologically innocent," and illustrates how political attitudes, beliefs, and behaviors often flow downstream from political identity (Achen and Bartels 2016, Barber and Pope 2019, Kinder and Kalmoe 2017). We encourage scholars who use VRscores to characterize these scores as measures of political identity (i.e., "organizational partisanship") rather than political ideology.

Having presented the advantages of VRscores, we discuss their possible limitations. These include the fact that VRscores can only capture workers with online professional profiles who are registered voters, as well as the possibility of strategic voter registration. While we acknowledge these limitations, we argue that measurement error from these limitations is significantly lower than the analogous challenges that arise with the donations-based approach.

To close, we detail a range of applications for VRscores. In particular, we highlight how VRscores might be used to address underexplored questions regarding how the distribution of employees' partisanship relates to organizational outcomes including performance, sociopolitical positioning, and corporate social responsibility. We also suggest that VRscores will be useful not only to management and strategy researchers, but also to economists, political scientists, sociologists, and scholars in other business disciplines. We do not advocate the abandonment of donations as an object of study but instead highlight cases where it will be instructive to combine and compare VRscores with donations-based measures.

2 VRscores: A Registration-Based Measure of Partisanship

To begin, we detail the underlying data sources as well as the process by which they are combined to create VRscores. We term our measure "VRscores" (voter registration scores), in parallel with Bonica's (2014) widely-used "CFscores" (campaign finance scores) from the Database on Ideology, Money in Politics, and Elections (DIME).

2.1 Voter Registration Files

Political parties in the United States do not maintain nationwide member rolls. Instead, each state maintains its own voter roll. In a majority of states, these rolls record each voter's party affiliation, if any. Like most other scholars, we rely on a vendor which aggregates voter files across all 50 states and Washington, D.C.[3] Our data comes from the nonpartisan vendor L2 Data, which has been widely used in academic research (e.g., Brown and Enos 2021, Imai et al. 2022). For every registered voter, the data contains information on geography (i.e., address), past turnout history, and partisan affiliation. In 30 states (and Washington, D.C.), voters may formally choose to be a member of a party during the registration process.

In the remaining states, L2 models partisanship based on fields such as past turnout in partisan primaries, historical data releases, or demographic modeling. These modeled partisan data have been widely used in political science research and have been validated with surveys (Igielnik et al. 2018). Additionally, given that a large majority of registered voters who do not register as either Democratic or Republican consistently behave like partisans (Klar 2014, Klar and Krupnikov 2016, Keith et al. 1992, Petrocik 2009), we follow the methodology developed by Brown and Enos (2021) and impute partisanship for non-partisans. Our application of this methodology is detailed in the appendix. In short, we impute partisanship based on primary participation as well as Bayesian methods using precinct-level electoral returns as well as demographic variables. Our final data release contains VRscores measures with and without these imputed partisans, allowing scholars to choose which approach they prefer and/or to check the sensitivity of using one approach over the other.

[3] While it is possible to download or purchase these data from each state individually, it is logistically complicated and expensive to do so.

2.2 Online Worker Profiles

We measure work history with data from Revelio Labs, a vendor that aggregates online employment details from internet sites such as LinkedIn. Revelio data are increasingly used in management as well as other fields (e.g., Li et al. 2022, Frake et al. 2024). For each individual in the dataset, Revelio records details related to both the specific position (i.e., the job) and the employer (i.e., the company). Position-level data include occupation and seniority. Revelio uses reported job titles to assign jobs to O*NET-SOC codes. Seniority is likewise assigned to one of seven categories ranging from entry-level to senior executive based upon a model which incorporates job title, individual job history, and years of experience. We also rely upon position-level geographic data (i.e., metropolitan statistical area [MSA] of the job) to facilitate the matching process. Employer-level (company) data fields include the employer name and ultimate corporate parent, as well as the industry (NAICS). Revelio standardizes company names across variant spellings and maps subsidiaries to their ultimate corporate parent.

2.3 Merging Strategy

We detail the merging strategy by which we combine L2 and Revelio in the appendix. Briefly, we use an ensemble linkage strategy that combines two complementary techniques: probabilistic and LLM-driven matching. First, we segment the datasets according to metropolitan statistical area (MSA), limiting potential matches to cases where the employment location and residential address fall within the same MSA. Second, we execute probabilistic record matching based on concordance patterns across comparison attributes including names, birth dates, and gender. We do so via Python's Splink package (Linacre et al. 2022), which implements the Fellegi–Sunter probabilistic matching framework (Fellegi and Sunter 1969) as adapted by Enamorado et al. (2019). Our second method utilizes the fuzzylink R package (Ornstein 2024) to conduct embedding-based semantic linkage. This approach proved adept at identifying matches overlooked by the probabilistic approach. In instances where the methods yield inconsistent results, we give precedence to combinations with higher match probabilities and, in the rare case of a tie, randomly select which match to include in our data.

Our ensemble matching approach links 45.34 million Revelio users to voter registrations. Restricting to positions that remain active in 2024 yields 39.94 million workers across 4.14 million employers, or roughly 25% of the $\approx$ 160 million people in the 2024 US workforce. Our VRscores dataset further excludes employers with fewer than five matched workers. In the resulting employer-year panel, we track 24.53 million unique workers across 534,392 employers (an average of 45.9 matched workers per firm), equal to about 15% of the US workforce in 2024. This coverage compares favorably to prior work by Colonnelli et al. (2022), who rely upon administrative data (including a unique tax ID number) and are able to match 7.8% of Brazilian workers with a political party. Our matching approach also yields a larger number of matched workers than a contemporaneous study which follows a different matching approach based on slightly different source data (Chinoy and Koenen 2024). To gauge the quality of our matching procedure, We present illustrative matches in the Appendix (see Table A3).

2.4 Aggregating to Calculate VRscores

Using this matched dataset, we calculate a VRscore for each employer that measures the aggregate partisan balance of its employees. Formally, a VRscore is defined as the number of employees who are Republican (R) over the number of employees who are either Democrats (D) or Republicans (R):

$$\text{VRscore} = \frac{\sum_{i=1}^{n} \mathbb{I}(e_i = R)}{\sum_{i=1}^{n} \mathbb{I}(e_i = D) + \sum_{i=1}^{n} \mathbb{I}(e_i = R)}. \tag{1}$$

The choice of Republicans as the focal partisan group is mostly arbitrary, but has the feature of moving rightward from zero when plotted. Because VRscores are a two-party measure, researchers can calculate an alternative version focused on Democrats by simply subtracting the VRscore from 1.

2.5 Public Dataset of VRscores

As a resource for scholars, we release the full VRscores dataset.[4] The public data contains our full merge and year-specific VRscore estimates from 2012–24 for all organizations with at least five matched workers. This public dataset comprises several components. In addition to core VRscores, we also include linking identifiers where available. We also include replication code to reproduce the microdata as well as the figures and tables in this paper. Appendix Table A2 provides a sample of the data for the 50 largest firms in our sample.

To respect source licensing, the public release uses VRID as the employer identifier. RCIDs, ultimate-parent RCIDs, and crosswalk fields (e.g., GVKEY, ticker, exchange, FactSet identifiers, CUSIP, company URLs, LinkedIn URLs, NAICS codes/descriptions, and headquarters fields) are excluded from the public

[4]The data are available to view in the anonymized version of our website at https://pow-anon.vercel.app/. They are also available for download at https://dataverse.harvard.edu/previewurl.xhtml?token=6b2aaf09-ee12-4e75-b830-36889c01800e.

files and are available to Revelio licensees via a restricted crosswalk.

2.6 Industry- and Occupation-Level Patterns in VRscores

Having described how VRscores are calculated, we next visualize these scores to show how partisans are distributed across and within industries and occupations. In these and all other cross-sectional analyses, we focus on the 2024 snapshot. Figure 2 visualizes this variation: Panel A plots the Republican share of workers *across* industries, and Panel B shows the distribution of firms *within* selected industries.

Figure 3 displays the Standard Occupational Classification (SOC) hierarchy as a sunburst, shading each node by the imputed two-party Republican share in 2024. This visualization highlights clear ideological clustering: education, social-service, and creative occupations (e.g., Miscellaneous Social Scientists & Related Workers at 23% Republican) are deep blue, while extraction, construction, transport, and maintenance roles are shaded deep red (e.g., oil and gas drill operators reach roughly 70% Republican). Management and business services are more balanced, with customer-facing and administrative functions slightly right of center and technical/professional staff slightly left of center. Because node sizes scale with employment, the figure makes clear that the largest labor pools occupy the middle of the distribution, with pockets of strongly partisan work at both extremes.

We also find notable geographic variation in workforce partisanship. Appendix Figure A9 illustrates the partisan lean of workers across US regions, shading metropolitan areas by their VRscore Republican share. Broadly, coastal and urban areas tend to have more Democratic-leaning workforces, whereas many inland regions lean more Republican. This geographic pattern mirrors well-known red/blue regional splits.

These analyses show that VRscores recover clear, interpretable patterns in the political composition of the workforce (see also Chinoy and Koenen 2024, Frake et al. 2024). The industry beeswarms and occupational sunburst together summarize broad differences across sectors and job families and, crucially, reveal within-industry and within-occupation dispersion that researchers can leverage. In addition to the organization-level data release, we also release industry, occupation, and MSA level VRscores.

3 Coverage Differences in Donations-based Measures versus VRscores

Next, we benchmark VRscores against donations-based measures across several dimensions. First, we examine the coverage of VRscores in terms of breadth of employee coverage (i.e., number of employees captured overall), breadth of employer coverage (i.e., number of employers present in the data), and depth of coverage within employers (i.e., number of employees per employer). Second, we benchmark the representativeness of VRscores versus donations-based measures in terms of political partisanship and the labor market roles of those covered. Third, we directly examine the correlation between VRscores and donations-based measures of aggregate employee partisanship.

3.1 Breadth and Depth of Coverage

To compare the coverage of VRscores and donations-based measures of ideology, we first construct a donations-based metric. We access donations data from the Federal Election Commission and focus on the donations from the latest election cycle for which data were available at the time of our analysis (the 2023-2024 general election cycle). We then group individual donors by their (self-reported) employer. As the self-reported field is non-standardized (Stuckatz 2022b), we first apply a detailed cleaning function to standardize employer names, the details of which are reported in the appendix. Overall the procedure produces 623,716 canonical employers, of which 58,869 consist of two or more raw variants. For the VRscores data, we aggregate positions active in 2024 by RCID.

Figure 4 compares, for 2024, the number of workers per employer in VRscores to the number of 2023-2024 FEC donors per employer. Note that the y-axis in this figure is on a log scale, so each labeled point is an order of magnitude larger than the previous point. Two patterns stand out. First, VRscores offer substantially *broader* coverage, capturing many more employers than the donations-based series. Second, VRscores provide *deeper* within-firm coverage: organizations that appear in the VRscores data typically have far more matched workers than FEC donors.

Figure 5 further disaggregates the dimensions along which VRscores outperform donations-based measures. Again, we include only organizations with five or more employees in each dataset. We show that VRscores cover significantly more workers. VRscores contain data on approximately 24.5 million unique workers, compared to 1.3 million workers in the donations-based approach. This order-of-magnitude difference reflects the broader coverage of voter registration data. While over three-quarters of employed Americans are registered to vote (Schaffner et al. 2023), only a very small proportion make political donations (Stuckatz 2022b). Second, VRscores cover many more unique employers (500,000 versus 100,000) with at least 5 identified workers than donations-based measures. This is consistent with Barber IV and Blake (2023), who estimate that as many as 60% of firms have no political donors among their employees.

Finally, VRscores also outperform donations-based measures in terms of the number of workers *within* each firm. To make this comparison, we conduct a perfect match of employers and only compare those for which we have five registered voters and five FEC donors. On average, VRscores cover 46 workers per employer, whereas donations-based metrics calculate the firm average based on 26 individual employee donors.

Beyond this relative comparison with donations-based approaches, we also examine breadth and depth against some absolute metrics. First, we confirmed that our data covers all companies listed in the 2025 US Fortune 500 and S&P 500. Second, we gathered the list of all publicly traded companies using Compustat. After removing ETFs, indices, and other financial securities that technically constitute publicly traded companies but do not have employees, we estimate that we cover approximately 90% of all publicly traded US companies.

Finally, we gauge within-firm coverage where we can benchmark against third-party headcount. We match public companies across Compustat, Revelio, and VRscores using the Compustat firm identifier (GVKEY), and compare average headcount per firm by source. Figure A8 reports: (i) Compustat's most recent 2024 headcount from WRDS; (ii) Revelio headcounts for both the All-users extract and the MSA-only extract (recall, we only attempt to match workers who reside in MSAs); and (iii) VRscores headcounts based on positions active in 2024 in the matched Revelio/L2 dataset, rolled up to the parent GVKEY. On these matched samples, VRscores headcounts average roughly 9% of Compustat and 19% of Revelio (All) among all public firms (Panel A), and about 12% of Compustat and 20% of Revelio (All) for the Fortune 1,000 subset (Panel B). Relative to the MSA-only Revelio extract, the corresponding coverage is approximately 27% and 28%, respectively.

3.2 Representativeness

We next investigate how employee donors compare with non-donors in terms of representativeness along both political and labor-market-related dimensions. To do this, we return to the matched dataset used to assemble company-level VRscores and take advantage of additional data fields from L2 and Revelio. First, L2 records whether individual registered voters made political contributions during the past four electoral cycles. We use this field to split our matched sample into donors and non-donors. We then compare donors and non-donors in our sample in terms of their political partisanship (from L2) and the nature of their employment (from Revelio). We benchmark political representativeness using high-quality survey data (the 2022 Cooperative Election Survey) and employment details using figures from the Bureau of Labor

Statistics (BLS) and the Census Bureau's American Community Survey (ACS).

3.2.1 Partisan Representativeness

First, in Figure 6, we compare the 2024 partisan composition of workers using two VRscores series—one based on registered partisanship and one using imputed partisanship—against the partisan composition of FEC donors aggregated to employers (RCID). We benchmark each to the 2022 Cooperative Election Study, which allows us to examine self-identified party identification for validated voters in full-time or part-time employment. The panels report the shares of Democrats, Independents/Other, and Republicans; the VRscores series restrict to employers with at least five matched workers active in 2024, and the FEC series restricts to employers with at least five distinct donors in the 2023–2024 cycle.

Both VRscores track the CES benchmark much more closely than the FEC donor distribution. In the FEC series, a large fraction of observations fall into the Independent/Other category because donations without a clear partisan affiliation (including third-parties, issue committees, or donors who give to both sides) are coded as Independent/Other. As a result, the FEC Democratic and Republican shares are markedly lower than both the VRscores series and the population benchmark. By contrast, the VRscores registered and imputed variants differ in how unaffiliated registrants are treated, with imputation modestly increasing the partisan shares. While our main VRscore is a two-party Republican share (excluding Others from the denominator), we also report the share of "Others" as supplemental information. By contrast, it is not clear how to incorporate Independents/non-partisans in donations-based measures.[5]

3.2.2 Labor Market Representativeness

Next, we examine the labor market representativeness of donors versus matched registered voters. We benchmark along two dimensions. First, we look at the level of individual workers and compare the larger set of workers who are registered voters with the smaller set of workers who make political donations. Second, we look at the level of employers and compare coverage across sectors of the economy.

We first assess labor market representativeness by comparing donors to non-donors across 2-digit Standard Occupational Classification (SOC) codes in Figure A6. Next, we use the Job Zone classifications developed by the US Department of Labor. The Job Zone typology groups occupations into five areas based

[5]While one can infer that those who donate to both parties are Independent (as we do here), the common practice of treating non-donors as politically "neutral" has little empirical backing as most Americans express support for one of the two major parties despite never having made political donations (Keith et al. 1992, Klar and Krupnikov 2016).

on the levels of education, experience, and on-the-job training required to perform the job. Job Zone One represents entry-level jobs with little or no formal education or preparation needed (e.g., landscaping or housekeeping) while Zone Five occupations require extensive preparation, usually in the form of graduate school (e.g., lawyers or physicians). Figure 7 illustrates the distribution of matched registered voters and donors across the job zone classifications, along with a population benchmark from Bureau of Labor Statistics (BLS) figures from May 2024.

Given that both the likelihood of registering to vote and the likelihood of having a professional online presence are positively associated with education, income, and socioeconomic status (Verba et al. 1995), it is not surprising that both measures are somewhat skewed toward workers in higher zones. Both the overall registered voter sample and the donor employee sample under-represent workers in occupations which require less preparation (Zones One and Two), although the extent of the coverage gap is substantially larger for donors than our matched sample of registered voters. The most dramatic coverage skew is found for workers in the highest Zone. While the BLS estimates that only around 7% of workers fall into this category, about one-third of donors fall into this category, meaning donations-based metrics dramatically overweight the politics of a numerically small but highly elite subset of the workforce (see also Stuckatz 2022a, Teso 2025).

We next examine how donors compare to non-donors regarding their positions within organizational hierarchies. We take advantage of the seniority variable created by Revelio, which classifies individuals' seniority into seven levels based upon their job title and years of relevant experience. Panel (b) of Figure 7 shows that the population of donors is significantly skewed towards managers, directors, and executives, while matched registered voters are skewed towards entry- and junior-level workers. While we lack a direct population-level benchmark, the distribution of VRscores—i.e., one that includes far more junior workers than senior executives—appears to comport far better with how most organizations are structured. By contrast, the donor sample is more uniformly distributed across seniority levels, providing further evidence that the donor base is unrepresentatively senior.

Finally, we examine the distribution of matched registered voters versus donors across industry sectors compared to baseline population figures from the 2022 American Community Survey (ACS). Figure A5 shows that donors are significantly more likely to come from Information, Finance, and Professional Services, while matched registered voters are significantly more likely to come from Leisure and Hospitality and Retail Trade. These patterns bear similarities to the preceding two exercises, indicating that donors are relatively more concentrated in jobs that require more education and provide higher pay. While the preceding exercises highlighted concerns that donations-based measures may be less representative than VRscores at accurately representing individuals within specific firms, Figure A5 suggests that analyses based upon donation scores may capture a set of employers which are unrepresentative vis-à-vis the economy as a whole. Specifically, measures based on donations may include only employers in certain types of industries where workers are generally more educated and better-compensated.

3.3 Intertemporal Stability

As a brief aside, we also highlight the intertemporal stability of VRscores. Donations are, by definition, discrete, election-specific actions, characterized by significant intertemporal variation. Registered partisanship, in contrast, is an enduring, generally stable individual characteristic. To demonstrate how this individual-level stability translates to organizational stability, we calculate the within-employer standard deviation of VRscores and then plot the distribution of these values in the appendix Figure A3a. This shows that year-to-year partisan mix of a given employer tends to vary only modestly (with a median within-firm standard deviation under 10 percentage points), indicating that workforce partisanship is a persistent organizational attribute.

3.4 Direct Employer-Level Comparison

Having documented significant differences in the breadth, depth, and representativeness of the individual employees who comprise VRscores relative to donations-based measures, we now compare the company-level measures directly. This comparison requires matching organizations between our dataset and FEC donations dataset. We match organizations across datasets by reusing the canonical employer names generated for Figure 4 and replicating that text-cleaning in VRscores before performing a deterministic join, resulting in 4,141 distinct organizational matches between our datasets.

3.4.1 Correlation Analysis

In Figure 8, we examine the correlation between the percentage of Republican employees (2-party share) across firms using both VRscores (x-axis) and the donations-based metric (y-axis). We find only a moderate correlation between these measures ($r = 0.51$), suggesting that the political composition of employee donors is meaningfully distinct from the overall aggregate balance of employees. In addition to the overall correlation, the scatterplot also reveals that more than one in five (22%) organizations differs between the two measures in whether they are classified as majority-Democrat or majority-Republican.[6] These substantial discrepancies further underscore the distinction between VRscores and prior existing donations-based approaches as well as the need for researchers to carefully consider which measure is most appropriate for their topic of inquiry.

Next, we compare the VRscores dataset to the Mannor and Busenbark (2025) donations-based indicators of political ideology (DIPI) measures by matching the two datasets on Compustat's GVKEY. Because DIPI only covers publicly-traded companies, this comparison is only amongst publicly-traded firms with a valid GVKEY in VRscores and DIPI. In Figure A2, we compare the 2024 VRscores with the most recent version of the DIPI data (2022). Each panel plots the share of Republicans in VRscores against the share of Republican donors in DIPI (using their ten-year measures). Panel (A) compares employee-level VRscores to employee donations, while panels (B)–(D) compare VRscores to donations from top management teams (TMTs), CEOs, and boards, respectively. Agreement between the two measures is moderate for employees (correlation = 0.51, 73% consistent) and somewhat lower for executives and directors (correlations = 0.30–0.36).

As a final exercise to illustrate substantive differences in these measures, we chart, in Figure 9, the distribution of the share of workers that are Republicans for these matched sets of firms, separately as measured using the donations-based approach and VRscores. This figure shows that the donations-based measure follows a bimodal distribution, with nearly all firms classified as very heavily Republican or Democratic. In contrast, the distribution of VRscores has much more mass across the middle of the distribution. This exercise demonstrates that VRscores capture significant levels of political diversity in organizations that donations-based measures characterize as overwhelmingly right or left leaning. More generally, it indicates that employers in the United States are not as politically homogeneous or polarized in terms of their workforce as the donations-based measure might suggest.

We also assess whether these differences persist across firms of varying sizes. Appendix Figure A4 replicates the comparison in Figure 9 for subsamples defined by firm size cutoffs. Across small, medium, and large employers, the donations-based metric consistently exhibits a more bimodal pattern (i.e., either overwhelmingly Republican or Democratic), whereas the VRscores distributions remain more centered. In other words, the tendency for VRscores to capture greater within-firm political diversity holds at different firm size thresholds.

[6]We also conduct the same analysis using the share of donation dollars rather than the number of individual donors; the results are nearly identical and are shown in Figure A1.

4 Donations May Be Strategic Rather than Expressive

Having empirically demonstrated coverage advantages of VRscores, we next consider conceptual challenges arising from the fact that donations may be strategic rather than expressive. Inferring ideological preferences from observed donations requires assuming that donors give to candidates who they perceive as ideologically aligned with themselves. This assumption is frequently justified with reference to Ansolabehere et al. (2003), which reasons that because the average donation is too small to impact election results, donors have no incentive to give except to candidates who mirror their ideological preferences. Referencing this work, for instance, Chin et al. (2013:207) argue that "[a]lthough some political giving is motivated by a desire for influence, political scientists have concluded that donations from individuals…are overwhelmingly motivated by personal ideology." Similarly, Wowak et al. (2022) argue that "Political psychologists have concluded that individuals' political donations are expressions of ideological preferences or personal value systems, rather than efforts to obtain political favors" (567). A recent methodological paper describing the donations-based measure (Mannor and Busenbark 2025) makes this same claim.

Work in the decades since Ansolabehere et al. (2003) challenges the conclusion that personal ideology is the only significant driver of political donations. Gordon et al. (2007), for example, point out that if donations are primarily expressive, donors would give even to poor quality candidates in uncompetitive elections, as long they are a close ideological fit. Empirically, this is not the case. Instead, donors take into account strategic electoral considerations such as candidate electability and district competitiveness (Meisels et al. 2024). Similarly, donors also prefer to give to candidates in their home districts even if they may be less ideologically aligned relative to candidates in other districts (Bouton et al. 2024).

Beyond this general evidence that donations are strategic, there is more specific evidence that career and employment concerns induce strategic giving. Within this work, one strand of literature has examined donations by executives. Kim et al. (2025), for example, links 75 million lobbying reports and campaign contributions, showing that senior corporate officials are significantly more likely to make donations to elected officials whom they lobby in the future. In related work, Teso (2025) confirms that corporate elites are more likely to donate to Congress members whom their companies are lobbying and who sit on committees with oversight over their companies' industries.[7] Richter and Werner (2017) show that

[7] Anecdotal reports also confirm that both corporate elites and politicians view executives' personal donations as substitutes for one another: for example, Clawson et al. (1998) report one instance in which staff for Senator John Kerry solicited personal donations from executives in lieu of donations from their corporate PAC after Senator Kerry promised not to accept corporate

CEOs use political donations, in lieu of PACs, to circumvent regulatory or public scrutiny while accessing politicians. Work-in-progress by Barber IV and Blake (2023) provides direct evidence of strategic giving, showing a significant discontinuity in how much and to which parties workers donate when they become CEOs or join boards.

Other work substantiates the strategic advantages of these actions, showing how donations yield material benefits to those who make them. For example, Kalla and Broockman (2016) show via a randomized field experiment that access-seeking organizations were significantly more likely to be granted meetings with members of Congress when they revealed that members of their staff had donated to the member. Using large-scale donations data, Steel (2024) shows that CEOs who strategically donate to influential lawmakers can diminish the severity of regulatory enforcement penalties.

If strategic giving were limited to top executives, this might be less concerning, especially in cases where scholars remove top executives when calculating donations-based measures. However, strategic incentives to donate are not limited to upper echelons, since managers frequently influence the donation patterns of rank-and-file subordinates. In a series of national surveys, Hertel-Fernandez (2018) estimates that nearly 25% of workers have had a manager try to mobilize them in support of a political cause or candidate and that 50% of managers report attempting to mobilize subordinates. This pressure tends to push employees towards positions that will benefit their employer but are inconsistent with their personal beliefs (Hertel-Fernandez 2017). Babenko et al. (2020) illustrates how this pressure manifests in donations, demonstrating that candidates supported by firm CEOs also receive more support from these CEOs' subordinates. Stuckatz (2022a) presents similar evidence, illustrating that workers adjust their donations patterns to match the donation patterns of their employer's Political Action Committees (PACs). Interviews with private equity professionals suggest that workers' mimicry of their superiors' donation patterns may reflect not only coercion, but also strategic attempts to curry favor with superiors (Bermiss and McDonald 2018).

Both sets of mechanisms—i.e., top-down pressure from superiors or strategic impression management on the part of subordinates—are made possible by the fact that donations are more publicly visible than voting registrations. At many employers, executives may explicitly solicit donations from subordinates and co-workers by circulating a list of the company's preferred candidates (Li 2018). Furthermore, the website OpenSecrets makes donation records accessible such that anyone can lookup the political donations for anyone else—including, for example, executives who wish to see whether their subordinates supported the

PAC dollars (cited in Teso 2025:28).

company's preferred candidate. By contrast, there is often no straightforward analogue to looking up a single voter's partisan registration. While one can purchase an individual states' entire voter rolls, many states charge substantial fees and may restrict access to parties with a valid need-to-know (e.g., political campaigns or researchers).

5 Ideology versus Identity

So far, we have outlined reasons why VRscores may be more accurate in capturing the partisan skew than donations-based approaches are in capturing ideological skew; the former provides better coverage across and within firms and is less vulnerable to strategic manipulation. However, it is important to underscore that donations-based approaches seek to measure different constructs. While donations-based approaches aim to capture political *ideology*—meaning enduring, stable, sets of political attitudes, beliefs, and values—VRscores capture political *identity*, meaning the political group to which one belongs, generally understood as one's political partisanship (Jost 2006, Iyengar et al. 2012, Swigart et al. 2020). Leaving aside concerns over empirical accuracy, we also highlight developments in the field of political science that increasingly favor conceptions of political identity over political ideology when characterizing the drivers of political polarization and behavior.

Trepidation regarding the measurement and prevalence of political ideology dates at least to Converse (1964), who demonstrated that self-reported political attitudes, values, and beliefs were surprisingly unstable and inconsistent among the majority of the public. In a more contemporary version of this analysis, Kinder and Kalmoe (2017) illustrate that most Americans are "ideologically innocent" in the sense that they lack organized, constrained belief systems along liberal-conservative dimensions. In and alongside this work, scholars have increasingly shown the advantages of considering political identity, as it constitutes a temporally stable individual attribute with consistent predictive power for political attitudes, beliefs, and behaviors (Green et al. 2002, Iyengar et al. 2012). This line of research has proven especially fruitful in elucidating the drivers of affective polarization (Mason 2018), explaining how ostensibly non-political questions or contexts take on a partisan valence (Benton et al. 2021), and demonstrating how political beliefs and values can flow downstream from political identities (Barber and Pope 2019). Summarizing a huge body of work, Achen and Bartels (2016) propose that an identity-based conception of political behavior is superior to the "folk theory of democracy" wherein actions and attitudes follow sequentially from stable, coherent political ideologies.

While a comprehensive discussion of the theoretical and empirical nuances of the ideology versus identity debate is beyond the scope of this paper,[8] we wish to emphasize that our approach directly captures political identity in the form of political partisanship. While partisanship and ideology are undoubtedly connected, we invite scholars who use VRscores to characterize these scores as a measure of political identity (i.e., "organizational partisanship") rather than a measure of political ideology since they more directly capture the former.

6 Limitations of VRscores

While we argue that there are strong empirical and theoretical reasons to use VRscores, these measures are not flawless. Here, we discuss what we see as their three most notable limitations.

6.1 VRscores Only Capture Online Workers

First, VRscores can only capture workers with online profiles on websites such as LinkedIn.[9] Obviously, not all workers use LinkedIn. In particular, LinkedIn use is particularly common in many white-collar industries (e.g., professional services and finance) and far less common in more blue-collar industries (e.g., agriculture and manufacturing) (Frake et al. 2024, Chinoy and Koenen 2024). While the industry skew of VRscores compares favorably to donations-based measures (which are even more skewed towards white-collar industries), this remains a limitation that scholars should bear in mind. Improving on this dimension represents an opportunity for future research.

6.2 VRscores Only Capture Registered Voters

Another concern is that VRscores only capture registered voters, omitting the nearly one-in-four employed American workers who are not registered to vote (Frake et al. 2024, Schaffner et al. 2023). The population of workers that are not registered voters is comprised of two principal groups: workers who are legally ineligible to register to vote and workers who are eligible to vote but decline to do so.

The most notable group of non-eligible voters are non-citizens, who constitute a non-negligible portion of the US workforce. Moslimani and Passel (2024) estimate that there are approximately 22 million authorized and 8.3 million unauthorized immigrant workers. Together, these constitute nearly 18% of the

[8]For such a discussion, see work-in-progress by Bruno et al. (2025).

[9]Revelio describes its data collection process as aggregating "publicly available professional profiles," which may include international competitors to LinkedIn such as Germany's XING; in the United States, we believe that nearly all of its employment information is sourced from LinkedIn.

workforce. The actual number of workers without the right to vote is likely somewhat lower, as nearly half of all authorized immigrants are naturalized US citizens with the right to vote. The significance of this limitation may depend upon the specific research question, as companies, industries, and occupations differ in the extent to which they employ non-citizen workers, as well as the extent to which non-citizens may be politically active.[10] Notably, since non-citizens are legally prohibited from making political donations, this limitation is equally applicable to the donations-based approach.[11]

The (non-)coverage of eligible-but-unregistered voters is more theoretically nuanced and depends upon which dimension of politics the research question considers. For studies explicitly interested in partisanship, a reliance upon voter data means that, very strictly speaking, there is no missing data since non-registered voters do not have a registered partisanship to be measured. In cases in which researchers wish to characterize the political beliefs and attitudes of employees in aggregate—including those not captured by VRscores—researchers must make auxiliary assumptions. The extent to which this matters will vary greatly from across contexts based upon the proportion of non-registered or ineligible voters and the comparability of registered voters and non-registered voters. Additional considerations that may inform how researcher navigate this issue include the fact that non-registered voters are far less politically engaged in general (Verba et al. 1995).

6.3 Voters May Register Strategically

Another concern is that registered partisanship, like political donations, may sometimes reflect strategic calculation rather than true political identity. This may occur for several reasons. First, individuals who reside in deep blue or red states with closed primaries may choose to register with the majority party, rather than the party with which they truly identify, in order to vote in competitive partisan primaries.[12]

[10] For example, higher education and Silicon Valley technology firms may employ large numbers of non-citizen workers who are likely very politically active, whereas agricultural firms may employ large numbers of immigrants—including some without legal employment authorization—who may be less politically engaged.

[11] Beyond non-citizens, VRscores also do not capture those who have been legally disenfranchised—most notably, convicted felons. Felons without the right to vote comprise about 2% of the full population and an even smaller fraction of the working population (Hwang and Phillips 2024, Stewart 2022). Although this population is not captured by voter registrations, it is unlikely that donations-based measures will perform meaningfully better at capturing this group. While there does not appear to be any specific legal prohibition on campaign donations by convicted felons, it seems unlikely that a large number of convicted felons are active campaign donors.

[12] State parties differ in the eligibility to vote in partisan primaries. Some states offer "open" primaries in which any registered voter in the state may choose to vote in that party's primary. Others are "closed" or "semi-closed" and are open only to voters who are registered to that party and/or who were previously unaffiliated with any party. Finally, some states have non-partisan primaries with a single ballot which lists all candidates (Brown and Enos 2021). States with closed or semi-closed primaries are Arizona, Alaska (only Republicans), Colorado, Connecticut, Delaware, D.C., Florida, Idaho, Kansas, Kentucky, Maine, Maryland, Massachusetts, Nebraska, Nevada, New Hampshire, New Jersey, New Mexico, New York, North Carolina, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Dakota, Utah, and West Virginia.

While some voters probably do engage in this form of strategic registration, recent analysis suggests this practice is very rare. In the 2022 Cooperative Election Survey (Schaffner et al. 2023), an estimated 1% of US adults identified as members of a political party but also stated that they were registered with the opposing political party. This already-small figure may be driven more by voter inattention or long-term political shifts rather than strategic motivations, as other work argues that party affiliation is more driven by "true" preferences and only very rarely by strategic considerations with regard to primary access (Guo 2023). Consistent with this idea, voters moving from "open" to "closed" primary states are no more likely to change their partisanship than voters moving from states with similar primary election procedures (Cantoni and Pons 2022). Second, just as political donors may avoid disclosing their employer to avoid scrutiny (Shanor et al. 2022), individuals may also be aware that their party registration is public and may thus tailor their official registration due to social pressure. In practice, this also appears unlikely. While it is technically possible for everyday citizens to access voter registrations (i.e., to investigate one's colleagues), many states place restrictions on access that make it expensive and time-consuming to access voter rolls.[13]

7 Potential Applications for VRscores

We believe VRscores will facilitate research into a wide range of questions, including those of direct interest to management and strategy scholars, as well as broader questions regarding business, politics, and democracy that cut across academic disciplines.

7.1 Performance

First, VRscores can serve as a valuable tool for understanding how workers' partisanship relates to organizational performance. While an extensive literature has considered how the racial and gender composition of workplaces relates to financial performance (Dezső and Ross 2012, Hoogendoorn et al. 2013, Karpowitz et al. 2024, Richard 2000), much less is known regarding the possible relationships between financial performance and political composition. This gap is critical in light of the fact that political sorting across workplaces is similar in magnitude to segregation by race and gender (Chinoy and Koenen 2024, Colonnelli et al. 2022, de Figueiredo et al. 2024, Frake et al. 2024). On the one hand, political diversity could yield benefits, such as expanded perspectives that can enable creative problem-solving or better relationships with other politically

[13]States typically do not allow access to individual records, but instead sell the entire voter roll to interested parties, such as researchers, political parties, and data brokers. Many states charge significant access fees of hundreds or thousands of dollars; data vendors also charge significant fees and may have burdensome methods of accessing the data (e.g., by physically mailing a CD-ROM).

diverse stakeholders. Given evidence of political segregation across occupations (Frake et al. 2024) as well as evidence of preferences for copartisan coworkers (Hurst and Lee 2024, Gift and Gift 2015, Roth et al. 2022), failure to cultivate a politically diverse workplace may make it difficult to attract or retain workers. On the other hand, political diversity may dampen performance by sparking conflict and disagreements among employees, leading to lower productivity and higher turnover (Barber IV and Blake 2024, Bermiss and McDonald 2018, Swigart et al. 2020).

Taking a different perspective, future work might examine how political composition changes as a result of performance. Shared victories in workplace contexts might erode distrust across political lines, raising the salience of "cross-cutting" workplace identities over partisan identities (Mutz and Mondak 2006, Van Assche et al. 2023). This may reduce internal divisions or turnover related to political disagreement, contributing to united but politically diverse workplaces. Alternatively, improved labor market conditions arising from good performance could increase employees' market power, facilitating political minorities' ability to switch into workplaces with a greater share of copartisan coworkers.

7.2 Sociopolitical Positioning and Corporate Social Responsibility

Additionally, VRscores provide a tool for understanding the connection between rank and file workers and employers' inclination to take stances on divisive sociopolitical issues. Existing theories regarding sociopolitical positioning point to the key role that workers play in shaping these decisions (Hurst 2023, Mohliver et al. 2023). Using the donations-based approach, some work has begun to empirically examine these relationships (Li and Disalvo 2022, McKean and King 2024, Seo 2024). Research leveraging VRscores will be able to provide further insight regarding the connection between workers' partisanship and employers' sociopolitical stance taking. Future work might also use VRscores as an outcome variable, examining, for example, how stance-taking on the political left or right shapes the longer-term political composition of the employee population. Relatedly, VRscores can be used to further understand the connection between workers' politics and employers' social responsibility (Gupta et al. 2017). One extension might be to examine CSR-related outcomes among the large number of employers for which there are no donors, but which we are able to calculate a VRscore. These could provide insight into the roles of employees within smaller, local organizations in shaping social outcomes.

7.3 Broader Sociopolitical Outcomes

Finally, while strategy and management scholars comprise our main audience for this paper, we believe VRscores will also be of use to the growing number of scholars across the social sciences who study the role of firms and their employees in the broader political landscape (e.g., Chinoy and Koenen 2024, Li and Disalvo 2022). In the same way that Bonica's (2014) CFscores have become a staple for studying money in politics, we believe VRscores can become a staple in studying business and politics, not only among management and strategy scholars, but also scholars in marketing, organizational behavior, finance, as well as other non-business-school disciplines such as political science, psychology, economics, and sociology. Each of these disciplines now have active research communities examining the role of partisan politics in workplace settings. In fact, beyond the firm-level outcomes of most interest to management scholars, VRscores can be used to examine broader sociopolitical phenomena including electoral outcomes, voter turnout, campaign strategy, affective polarization, and more.

7.4 Studying Donations

In presenting VRscores, we do not argue that scholars should abandon the study of political donations. Political donations are a critical object of study in and of themselves. For example, donations can be used as an outcome variable for characterizing firms' non-market strategy (Li and Disalvo 2022), or an explanatory variable that may (or may not) allow firms to achieve key strategic objectives (Werner 2015). Neither of these approaches requires assuming that donations capture deeply-held political identity or ideology.

Moreover, insights might be gleaned by combining donations and voter-based measures of worker politics. For example, do partisan workers donate to outpartisan candidates to match the donation behavior of coworkers or employer PACs? When PACs and upper-echelons donate in ways contrary to the partisanship of the broader employee population, does this "mismatch" have downstream implications for employees' effort or turnover? Another avenue may be to test for a firm-level analog to Bafumi and Herron's (2010) theory of "leapfrog representation," wherein small numbers of exceptionally politically active donors disproportionately drive firms' sociopolitical actions. Scholars may also find it useful to combine donations and voter registrations to create multidimensional measures of organizational politics. For example, employers with high shares of registered Democrats as well as high numbers and shares of donations to Democratic candidates might be characterized as exceptionally left-leaning.

Finally, there may be cases where donations might reasonably be used to capture workers' political identities or ideologies. For example, prior studies have shown that donations provide significant coverage of highly-detailed, comprehensive professional databases of lawyers (Bonica et al. 2016, Carnahan and Greenwood 2018),and doctors (Kim 2024). Notably, these studies do not use donations to characterize the political ideology or identity of entire organizations and focus on populations for which questions over strategic donations seem less salient. If scholars are specifically interested in capturing ideology, we suggest using CFscores from the DIME database (Bonica 2014), which permit fine-grained distinctions.

8 Conclusion

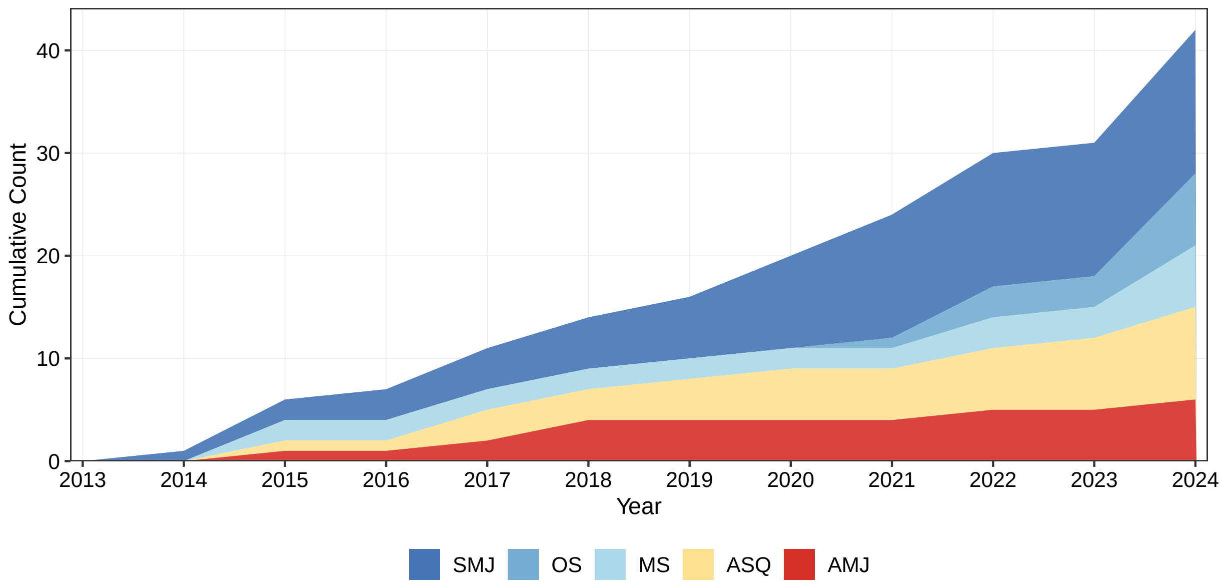
Our study makes several contributions towards understanding how employees' political partisanship shapes organizational outcomes. First, we describe a novel methodology for linking voter files to workers, allowing scholars to characterize workers' partisanship for a sizable share of the US labor market. Second, we use this methodology to create a measure of workplace partisanship, VRscores. Third, we demonstrate—both empirically and conceptually—the advantages of VRscores relative to donations-based measures. VRscores provide far broader and deeper coverage of the workforce and more representative sampling across organizational levels and industries. Finally, we discuss a range of potential uses for this new measure, describing how it may be applied to questions related to firm performance, innovation, sociopolitical stance taking, corporate social responsibility, and even broader political phenomena.

Our article is closely related to literature that has used donations-based approaches to examine the role of workers' political ideologies in shaping organizational outcomes. This literature has made critical contributions, drawing attention to important questions and providing preliminary evidence that workers may shape their employers' engagement with social issues (Gupta et al. 2017, Li and Disalvo 2022, McKean and King 2024). This paper complements and extends this work, demonstrating that donations-based measures of ideology are heavily skewed towards wealthier workers higher up in organizational hierarchies and presenting VRscores as a measure of partisanship that better captures rank-and-file workers.

Notably, some contemporary work has begun to merge voter files and worker profiles to study related questions, including estimates of the overall degree of political partisan segregation in the United States (Chinoy and Koenen 2024, Frake et al. 2024), as well as more specific studies on inventors (de Figueiredo et al. 2024), patent examiners (Raffiee et al. 2023), and startups (Kovacs and Sels 2024). While our data provide a firm-level breakdown of political composition across employers, it does not examine the causes of political sorting across employers. Some work highlights how labor market political sorting may be downstream from sorting that occurs across geographies, occupations, and industries (Frake et al. 2024), while other work points to the potential impact of partisan language in the course of recruiting (Chinoy and Koenen 2024, Hurst and Lee 2024, Roth et al. 2022). More work is needed to understand these origins. We hope VRscores can be used in future work to provide further insight on these questions.

In the context of growing political polarization, employers are entering the political arena in unprecedented ways (Barari 2024, Grossmann and Hopkins 2024, Larcker et al. 2018). Given the potentially critical role that workers play in shaping these actions, it is critical to have wide-reaching, representative measures of workers' politics. While there is much to be done regarding how employees' politics shape organizational and societal outcomes, we believe VRscores will be useful in these efforts and advance the growing body of research on this important topic.

Figure 1 Cumulative Number of Papers Using Political Donations Data in Top Management Journals

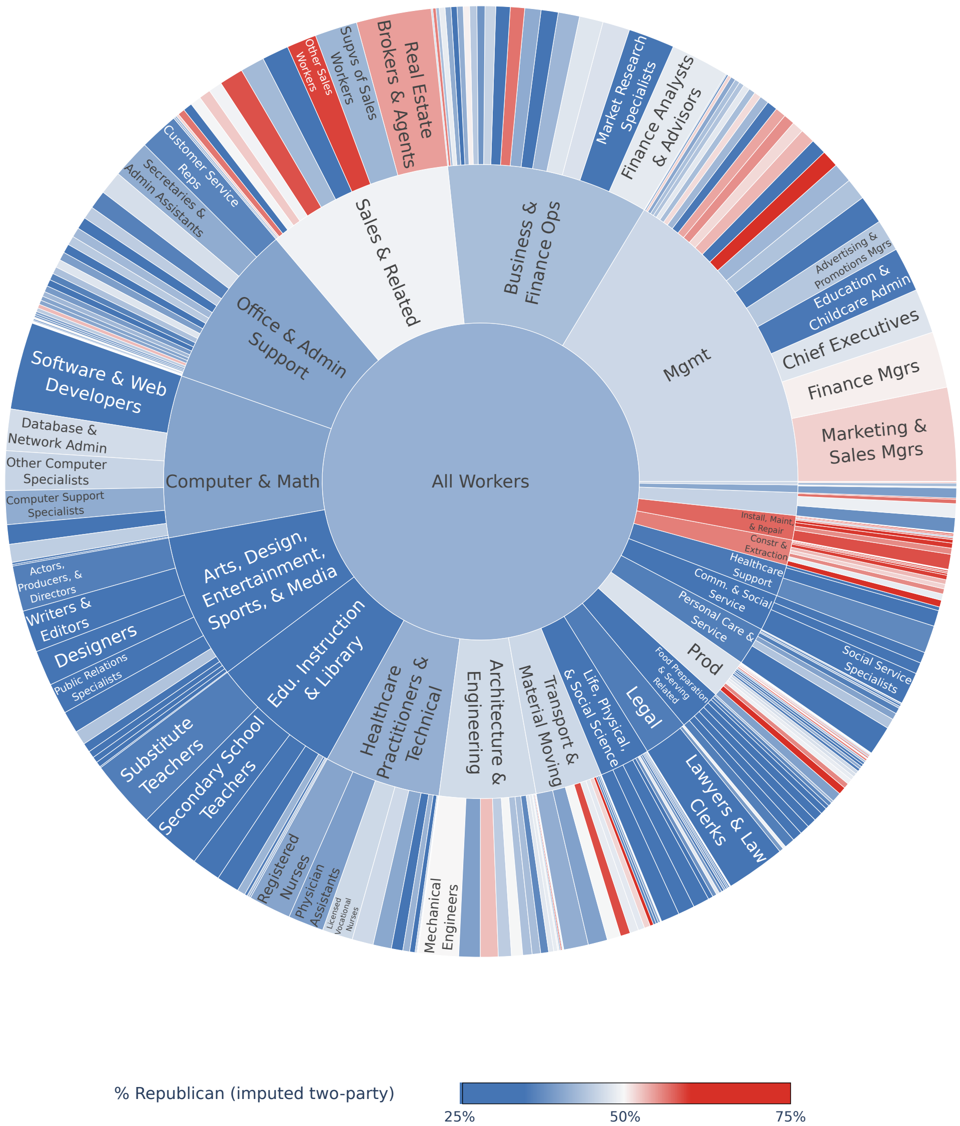


NOTE: AMJ: Academy of Management Journal; MS: Management Science; OS: Organization Science; ASQ: Administrative Science Quarterly; SMJ: Strategic Management Journal.

Figure 2 Distribution of VRscores by Industry and Organization (2024)

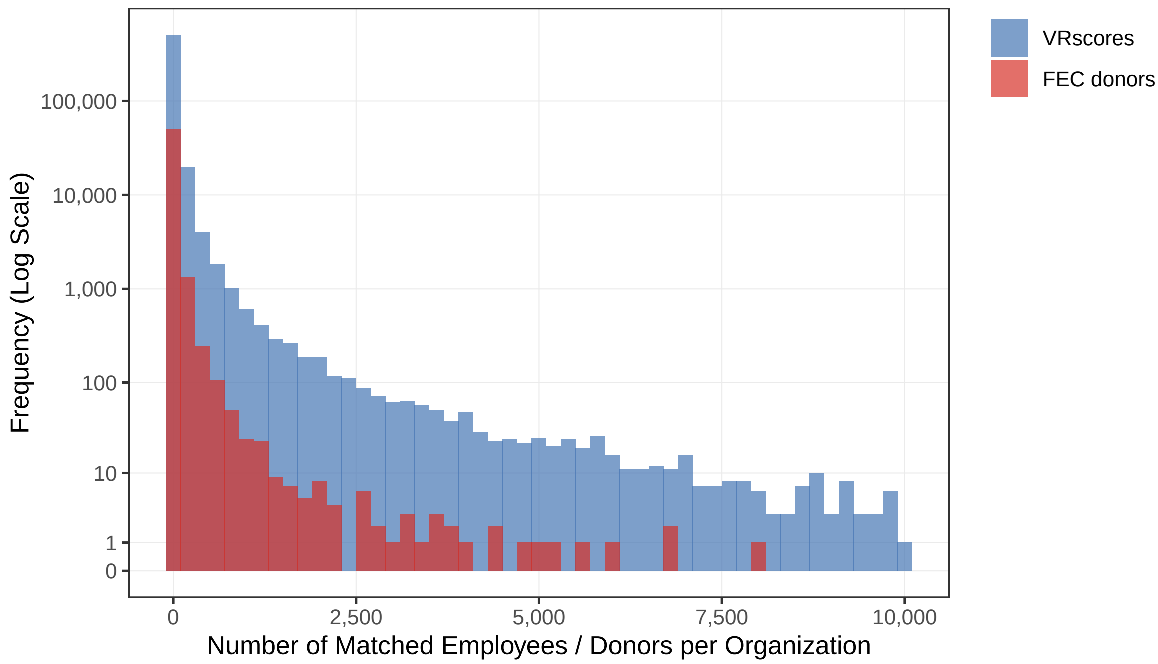
NOTE: Plot depicts imputed two-party VRscores. For workers not registered as Democrats or Republicans, partisanship was imputed. The sample excludes workers whose partisanship could not be reliably imputed as Democratic or Republican. Points are scaled to reflect the number of workers. Figures in parentheses reflect the average two-party imputed VRscore.

Figure 3 Partisanship of Occupations in VRscores (2024)



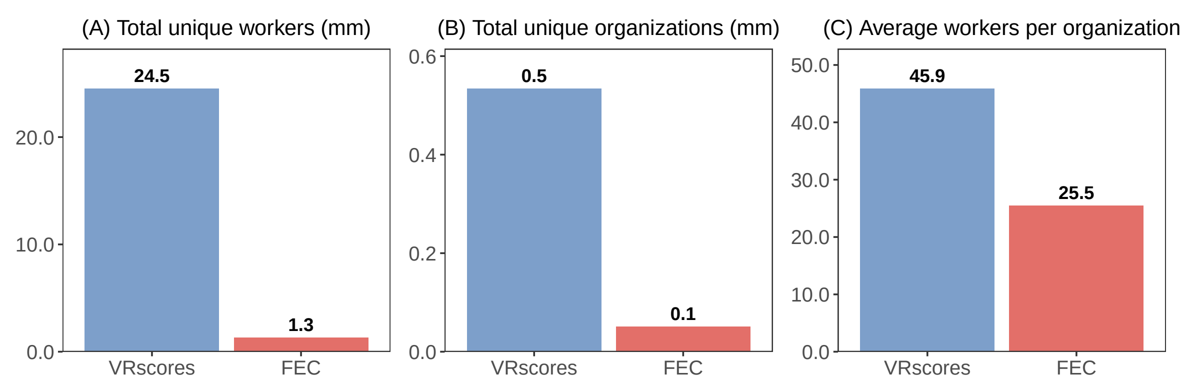
This sunburst plot aggregates the 2024 VRscores panel to the Standard Occupational Classification (SOC) hierarchy. The center shows the average VRscore across all workers with a valid occupation code in the dataset (about 0.7% of workers do not have a valid occupational code assigned by Revelio); the first ring displays SOC major groups (2-digit), and the second ring displays SOC broad occupations (4-digit). Fine-grained SOC detailed occupations (6-digit) are included in the public dataset but are not plotted here to preserve readability. Slice area reflects the number of matched workers in each group. Colors encode the imputed two-party Republican share: blue shades indicate Democratic-leaning occupations, white indicates parity, and red shades indicate Republican-leaning occupations. Occupational labels are suppressed for groups representing less than about 1% of total employment.

Figure 4 Distribution of Employees per Employer (FEC versus Revelio/L2) *(log scale)*



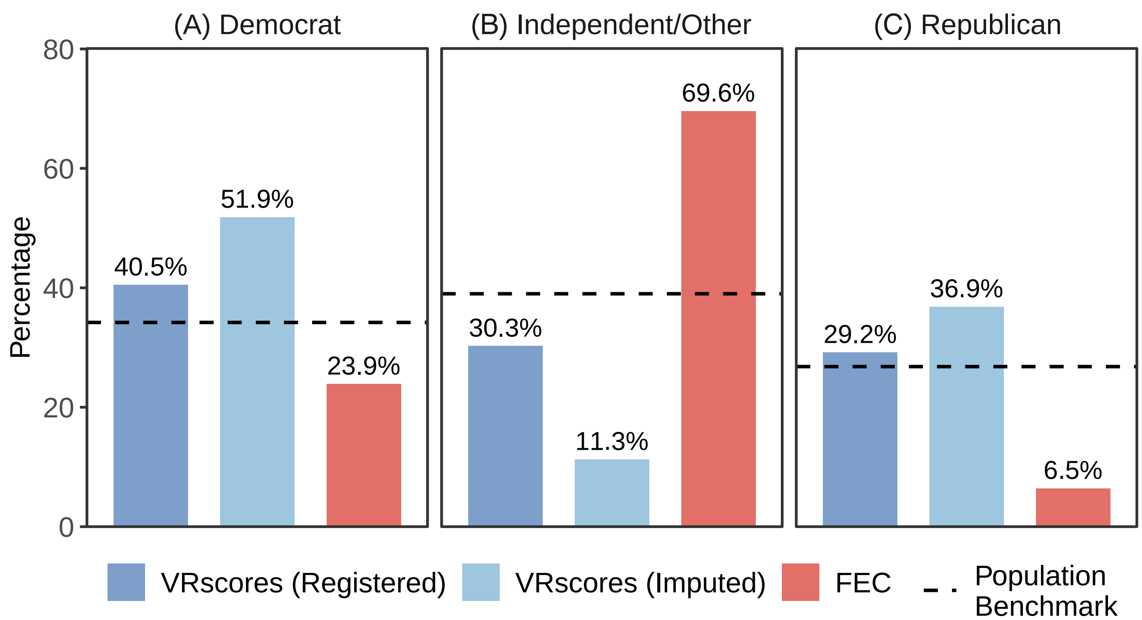
NOTE: The figure compares the number of matched registered-voter employees per company in the 2024 VRscores data with the number of matched donors per employer in the 2024 FEC data. The y-axis uses a $\log(n+1)$ (natural-log) transform so zero and single-count bins remain visible, and the x-axis is truncated at 10,000; both series exclude organizations with fewer than 5 matched employees or donors. VRscores positions active in 2024 are rolled up to companies using the `rcid`.

Figure 5 Comparison of FEC and VRscores



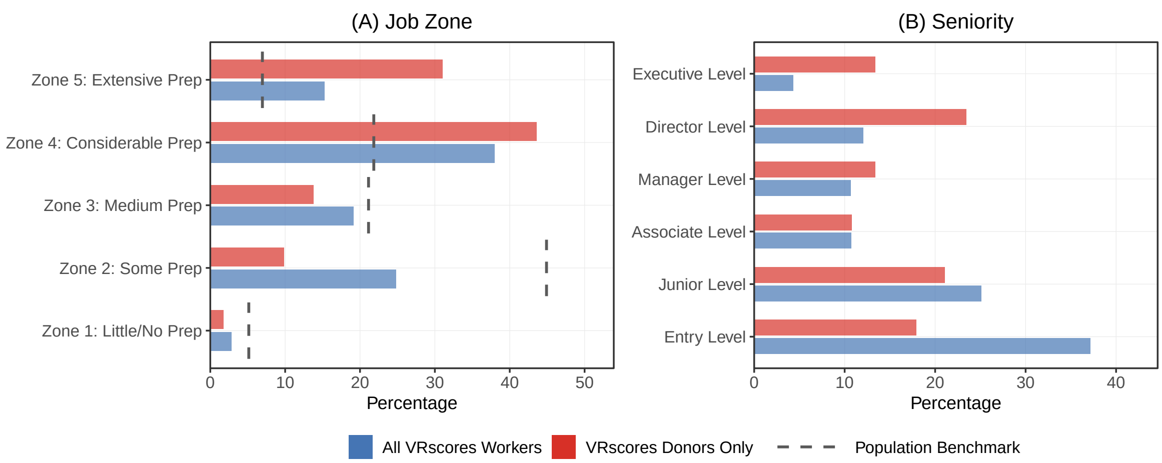
NOTE: VRscores totals are computed from the 2024 matched panel by aggregating employees at the company `rcid`; FEC totals aggregate 2024 donors to the canonical employer groups described in Figure 3 (lowercasing, punctuation removal, standardized corporate suffixes, token blocking, and TF–IDF clustering). Both datasets retain only employers with at least five matched employees or donors.

Figure 6 Demographic Comparison by Political Affiliation



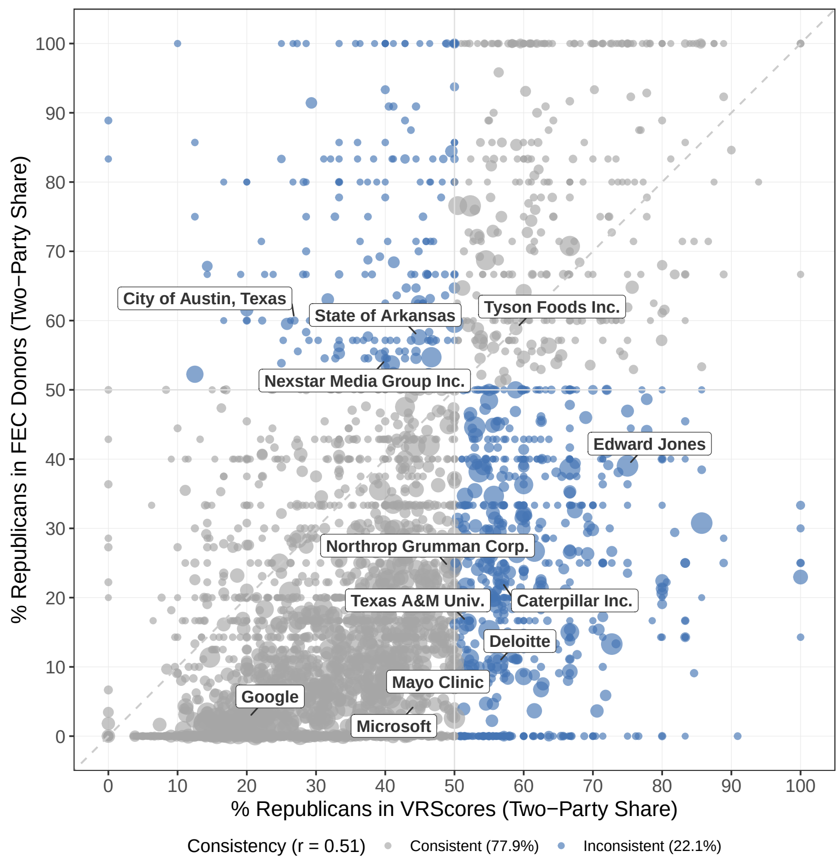
NOTE: Figure compares the 2024 partisan composition of the VRscores dataset, FEC donors, and population-level benchmarks drawn from the 2022 Cooperative Election Study (2024 CES not yet available). We plot two VRscores series—one using only registered partisanship and one using imputed partisanship—each restricted to employers with at least five matched workers whose positions are active in 2024. The FEC series aggregates by employer, which are defined in the same way as Figure 3 (lowercasing, punctuation removal, standardized corporate suffixes, token blocking, TF–IDF clustering), retaining only organizations that have at least five distinct donors over the 2023–2024 federal cycle. Donor partisan counts reflect sums by committee affiliation; individuals who contribute to both Democratic and Republican committees appear in each corresponding total. FEC Donor partisanship reflect the affiliation of the donation; contributors and committees without a clear Democratic or Republican lean (including blanks, third-parties, and issue organizations) fall into the Independent/Other category. Dotted lines denote CES voter-registration partisanship among labor-force participants, which may differ from self-identification. While neither dataset perfectly matches the CES benchmark, both VRscores series hew far more closely to the population than the FEC donor distribution.

Figure 7 Distributions of Workers by Job Zone and Seniority



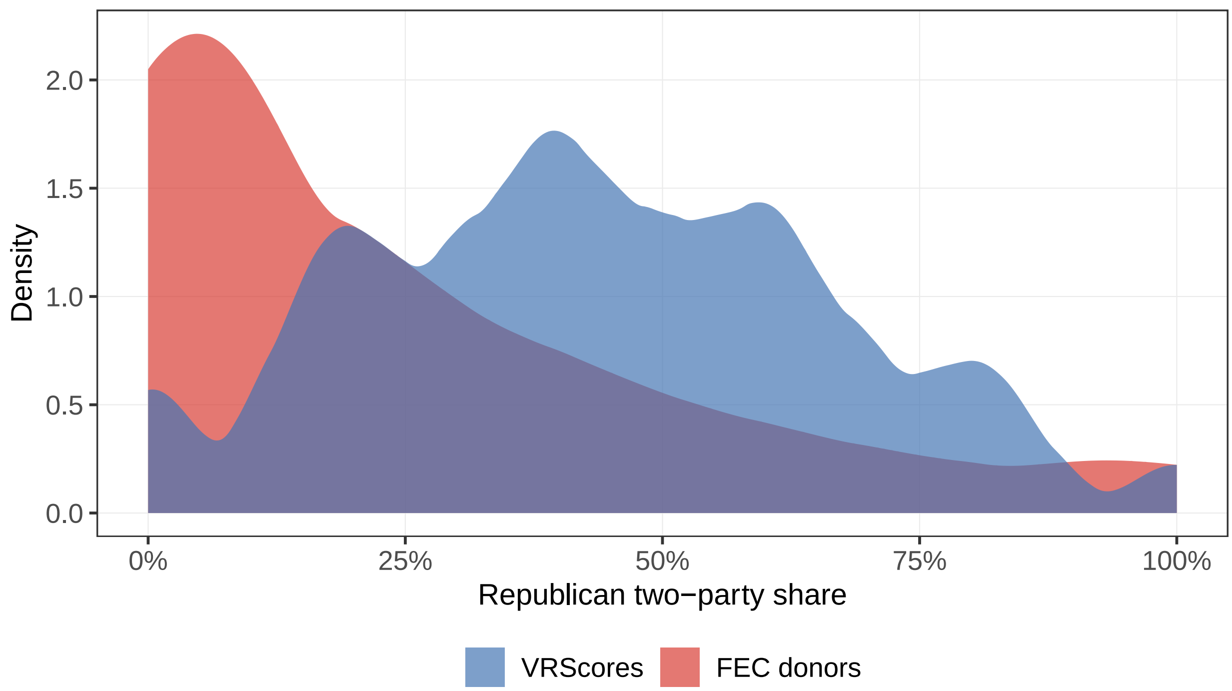
NOTE: Figure compares the 2024 occupational mix of the VRscores workforce ("All VRscores Workers") with the subset identified by L2 as reportable FEC donors ("VRscores Donors Only"). Counts are based on distinct individuals whose positions are active in 2024. Panel (A) groups workers by O*NET Job Zone. The dashed benchmark is derived from the BLS May 2024 Occupational Employment and Wage Statistics release ('national_M2024_dl.xlsx'). Panel (B) groups workers by Revelio seniority. We combine Revelio's level 6 (Executive) and level 7 (Senior Executive) into the 'Executive Level'.

Figure 8 Correlation Between VRscores and Donations-based Measure of Firm Politics



NOTE: This scatterplot compares Republican two-party shares derived from the 2024 VRscores dataset (x-axis) with the 2024 FEC employer aggregates (y-axis). We match organizations across datasets by reusing the canonical employer names generated for Figure 4 and replicating that text-cleaning in VRscores before performing a deterministic join. The figure keeps only matches with at least 5 two-party workers in the VRscores snapshot and at least 5 two-party donors in the FEC data, leaving 4,141 distinct employers. Labels highlight several large, notable firms across quadrants. Figure A1 repeats the exercise weighting the FEC axis by donation amounts (dropping employers with fewer than $100 in two-party giving), and the patterns are substantively unchanged.

Figure 9 Distribution of Share of Republican Workers for VRscores versus Donations-based Measure (Employee Donors)



NOTES: Kernel density plots compare 2024 Republican two-party shares for all VRscores employers (imputed party labels with more than 5 matched workers active in 2024; 485,610 organizations) to FEC employers (more than 5 unique donors in the 2023–2024 cycle; 16,711 organizations). VRscores shares are computed from imputed Democratic and Republican worker counts. Densities are estimated with a biweight kernel (bandwidth adjustment 2).

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A Appendix Figures and Tables

Description of Appendix Figures

Figure A1: Correlation Between VRscores and Donations-based Measure of Organization Politics (Based on Donation $) Scatterplot comparing the Republican two-party share from VRscores (x-axis) with the Republican share of two-party donation dollars (y-axis) at the employer level.

Figure A2: Comparing VRscores Republican Share (2024) to DIPI Donations-based Republican Share (2022) Four panels matching firms by GVKEY: (A) VRscores vs employee donations; (B) VRscores vs TMT donations; (C) VRscores vs CEO donations; (D) VRscores vs board donations. Each panel reports the Pearson correlation and agreement in majority-party classification.

Figure A3: Within-organization Temporal Stability of VRscores (2012–2024) Histograms of within-firm standard deviations for annual VRscores using organizations with at least five employees in every year, shown separately for non-imputed and imputed series.

Figure A4: Distribution of Share of Republican Workers for VRscores versus Donations-based Measure at Different Size Thresholds Kernel density plots comparing two-party Republican shares from VRscores and from donations-based measures under minimum employer-size thresholds of 5, 25, and 100 matched workers.

Figure A5: Comparison of Workforce by Industry Supersector (2024) Bar charts comparing industry composition for all VRscores workers versus the subset who are donors, against ACS population benchmarks. Donors are over-represented in Finance, Information, and Professional Services; under-represented in Leisure/Hospitality and Retail.

Figure A6: Comparison of Workforce by Occupation (2-Digit SOC Major Group, 2024) Side-by-side occupational distributions for all VRscores workers and donors, benchmarked to BLS OEWS major groups.

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Figure A8: Average Headcount per Firm: Overall vs. Fortune 1000 Coverage Mean headcount per firm from Compustat, Revelio (All and MSA-only), and VRscores, shown for (A) all matched public firms and (B) the Fortune 1000 subset.

Figure A9: VRscores Republican Two-Party Share by MSA (2024) US maps shading MSAs by Republican two-party share for (A) imputed and (B) non-imputed VRscores.

Description of Appendix Tables

Table A1: Papers Using Campaign Finance Data in Top Management Journals List of 42 studies (2013–2024) using donations data, indicating the focal population (e.g., CEO, TMT, board, employees) and the construction of ideological measures.

Table A2: Top 50 Companies by Employee Count Largest employers in VRscores with registered and imputed partisan shares, including two-party percentages.

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Table A7: Top 15 MSAs by VRscores Employment (2024) Largest MSAs by employment, with Republican two-party shares using registered and imputed series.

Table A8: VRscores Occupation Summaries (2024) Partisan shares by SOC major group and the top 15 detailed occupations by employment.

Table A9: VRscores Industry Summaries (2024) Partisan shares by two-digit NAICS sectors and the top 15 detailed industries by employment.

Table A1 Papers Using Campaign Finance Data

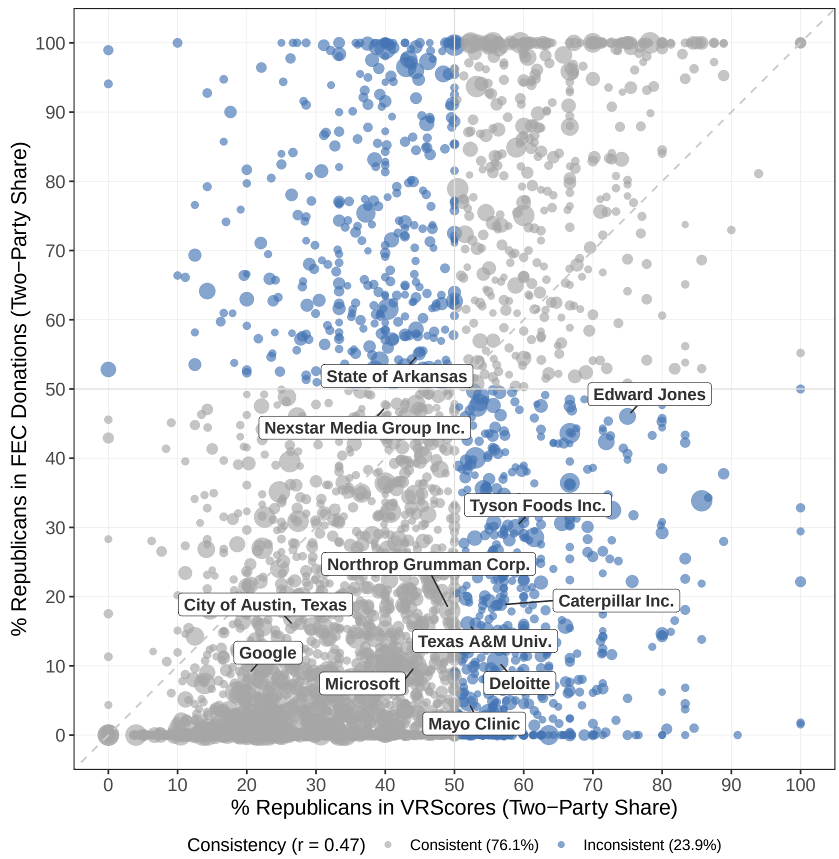
	Paper	CEO	BOD	TMT	PAC	Managers	Employees	Org. Ideo.	Method
1	Benton, Cobb, and Werner (2021)				✓				Chin et al. (2013) 4-part average
2	Bermiss and McDonald (2018)						✓	✓	Net partisan balance of donations ($)
3	Briscoe, Chin, and Hambrick (2014)	✓						✓	Chin et al. (2013) 4-part average
4	Briscoe and Joshi (2017)					✓			Chin et al. (2013) 4-part average
5	Busenbark, Bundy, and Chin (2023)	✓	✓						Chin et al. (2013) 4-part average
6	Carnahan and Greenwood (2018)			✓					Chin et al. (2013) 4-part average and DIME CFscores (Bonica 2014)
7	Chin, Hambrick, and Treviño (2013)	✓							Chin et al. (2013) 4-part average
8	Chin and Semadeni (2017)	✓							Chin et al. (2013) 4-part average
9	Christensen, Dhaliwal, Boivie, and Graffin (2015)			✓					Net partisan balance of donations ($)
10	Christensen, Jin, Sridharan, and Wellman (2022)				✓				Net partisan balance of donations ($)
11	DesJardine, Shi, and Werner (2024)		✓						Net partisan balance of donations ($)
12	Dewan, Simons, and Wernicke (2024)	✓							DIME CFscores (Bonica 2014)
13	Evans, Prado, Rizzo, and Zambrana (2024)					✓			Net partisan balance of donations ($)
14	Fewer and Tarakci (2024)	✓							Chin et al. (2013) 4-part average (squared)
15	Graffin, Hubbard, Christensen, and Lee (2020)	✓							Net partisan balance of donations ($)
16	Gupta and Briscoe (2020)							✓	Chin et al. (2013) 4-part average
17	Gupta, Briscoe, and Hambrick (2017)							✓	Chin et al. (2013) 4-part average
18	Gupta, Briscoe, and Hambrick (2018)	✓						✓	Chin et al. (2013) 4-part average
19	Gupta, Fung, and Murphy (2021)	✓							Chin et al. (2013) 4-part average
20	Gupta, Nadkarni, and Mariam (2019)	✓							Chin et al. (2013) 4-part average

	Paper	CEO	BOD	TMT	PAC	Managers	Employees	Org. Ideo.	Method
21	Gupta and Wowak (2017)		✓						Chin et al. (2013) 4-part average
22	Gupta, Wowak, and Boeker (2022)		✓						DIME CFscores (Bonica 2014) (modified 4-part average)
23	Huang, Lei, Wang, and Xing (2024)			✓					Net partisan balance of donations ($) (squared)
24	Hutton, Jiang, and Kumar (2015)			✓	✓				Net partisan balance of donations ($) (weighted by pay-based rank at firm)
25	Keum and Meier (2024)	✓							Any donation to Republican or Democratic Federal candidate
26	Lungeanu and Weber (2021)	✓							Chin et al. (2013) 4-part average
27	McDonnell and Werner (2016)				✓				Net partisan balance of donations ($) (squared)
28	McKean and King (2024)	✓		✓			✓		Chin et al. (2013) 4-part average
29	Minefee, McDonnell, and Werner (2021)						✓		Chin et al. (2013) 4-part average
30	Mkrtchyan, Sandvik, and Zhu (2024)	✓							Net partisan balance of donations
31	Park, Boeker, and Gomulya (2020)		✓						Net partisan balance of donations
32	Petrenko, Aime, Ridge, and Hill (2016)	✓							Chin et al. (2013) 4-part average
33	Semadeni, Chin, and Krause (2022)	✓							Chin et al. (2013) 4-part average
34	Seo (2024)						✓		DIME CFscores (Bonica 2014)
35	Shi, Connelly, Mackey, and Gupta (2019)		✓						Chin et al. (2013) 4-part average
36	Shi, Gao, and Aguilera (2021)				✓				Net partisan balance of donations ($)
37	Shi, Xia, and Meyer-Doyle (2022)		✓						Net partisan balance of donations ($)
38	Tilcsik, Anteby, and Knight (2015)						✓		DIME CFscores (Bonica 2014) (by industry)
39	Werner (2015)	✓							Net partisan balance of donations ($)
40	Wowak and Busenbark (2024)	✓						✓	Chin et al. (2013) 4-part average

	Paper	CEO	BOD	TMT	PAC	Managers	Employees	Org. Ideo.	Method
41	Wowak, Busenbark, and Hambrick (2022)						✓		Number and $ value of donations to Democrats
42	Zhang (2022)	✓							Chin et al. (2013) 4-part average
	Total	**19**	**7**	**5**	**5**	**2**	**6**	**6**	

Checkmarks refer to population of interest: CEO, board of directors, top management team (TMT), the corporation's public action committee (PAC), managers or other supervisory employees, employees as a whole, or the concept of "organizational ideology".

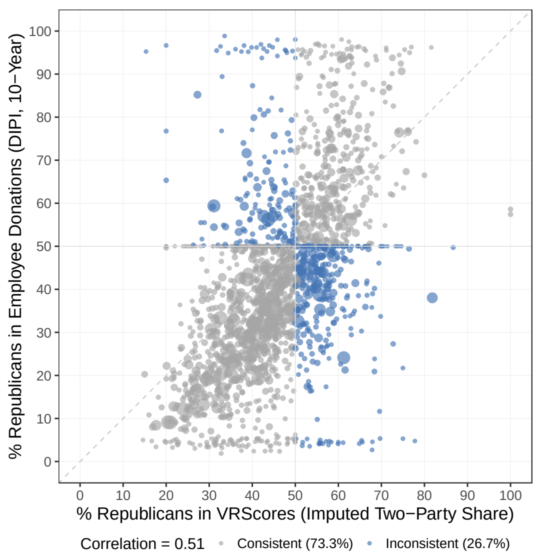
Figure A1 Correlation Between VRscores and Donations-based Measure of Firm Politics *(Based on Donation $)*



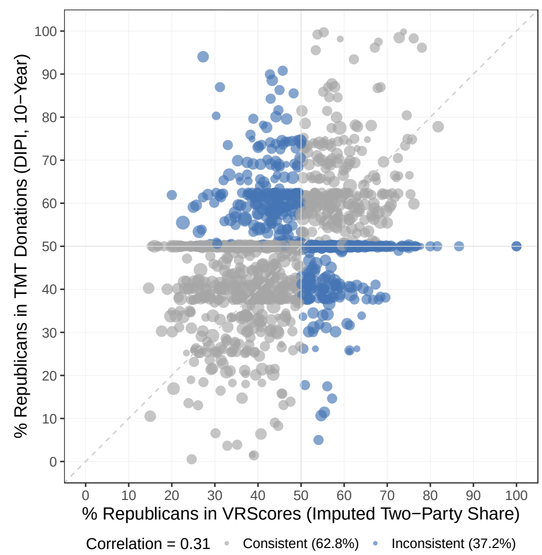
NOTE: This donation-weighted scatterplot compares 2024 VRscores two-party worker share (x-axis) with the FEC measure (y-axis), but each point reflects the Republican share of two-party donation dollars. As in the Figure 8, we match employers by reusing the canonical names produced for Figure 4 and replicating that cleaning for VRscores. We retain employers with at least 5 two-party VR workers, at least 5 two-party FEC donors, and at least $100 in two-party contributions, leaving 4,140 organizations.

Figure A2 Comparing VRscores Republican Share (2024) to DIPI Donations-based Republican Share (2022)

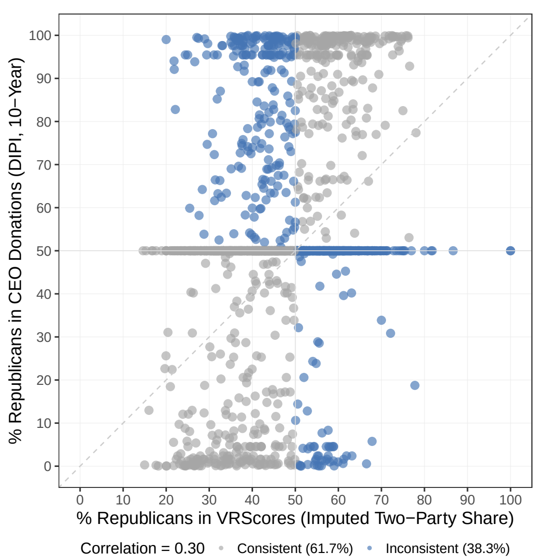
(a) VRscores vs. Employee Donations (10-Year)



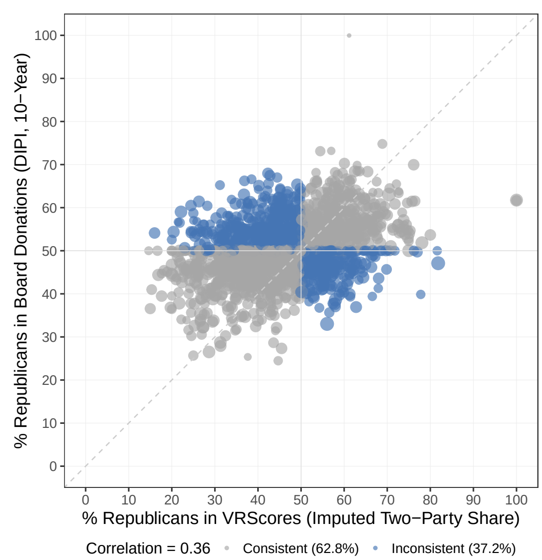
(b) VRscores vs. TMT Donations (10-Year)



(c) VRscores vs. CEO Donations (10-Year)



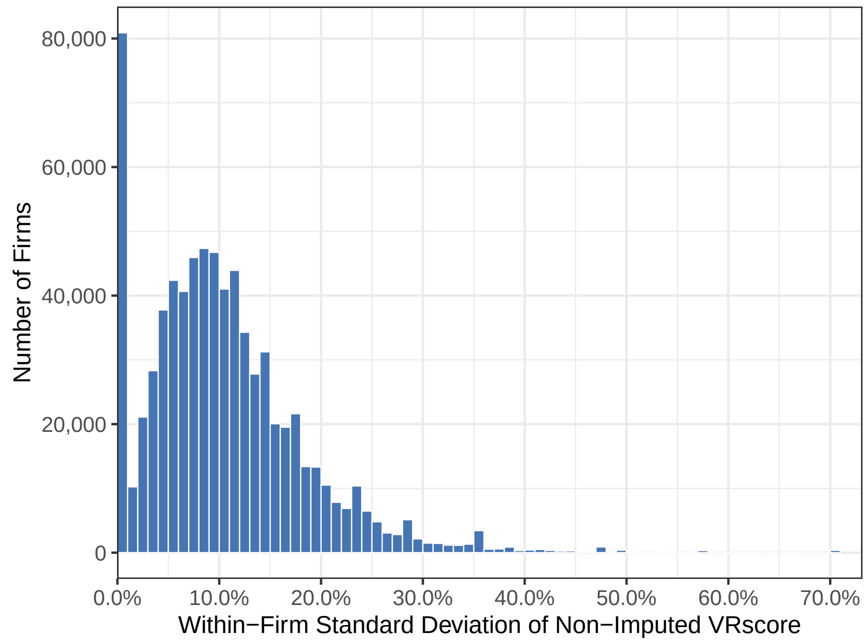
(d) VRscores vs. Board Donations (10-Year)



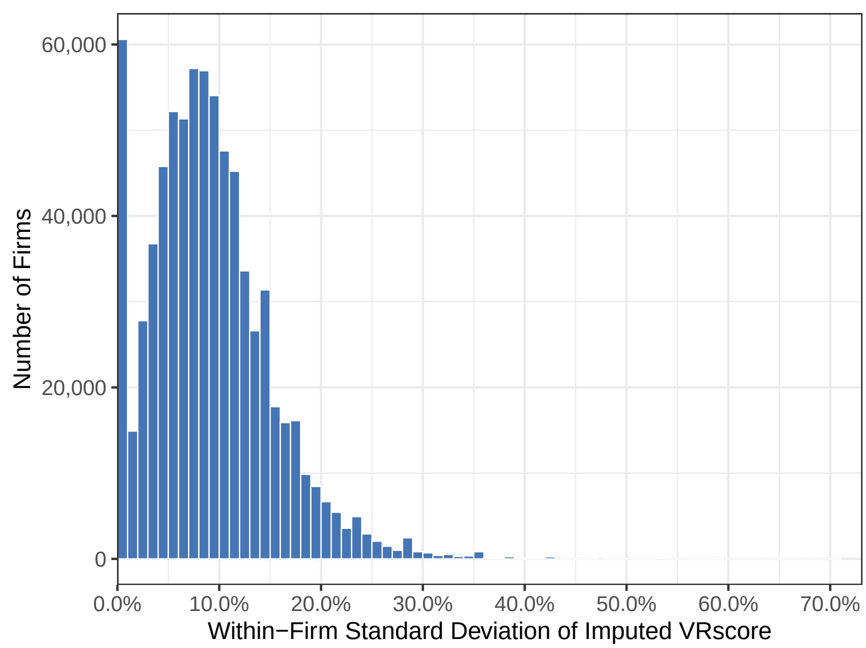
NOTE: VRscores values (x-axis) use the imputed two-party worker counts from the 2024 panel, restricted to firms with at least five imputed two-party workers. DIPI (donations-based indicators of political ideology) values (y-axis) come from the 2022 Organizational Leadership File (Mannor and Busenbark 2025), where each "10-year" measure pools individual contributions made between 2013–2022 before computing liberalism scores (0 = all GOP, 1 = all DEM). We reverse-code those scores so the y-axis reports percent Republican (to align the scale with VRscores). Gray markers indicate that VRscores and DIPI agree on the majority party, while blue bubbles represent disagreement. The legend also reports the Pearson correlation for each panel. Organizations are matched by GVKEY. The 2024 VRscores data contain 12,079 organizations with unique GVKEYs and the 2022 DIPI Organizational Leadership File contains (1,836 GVKEYs. plots show the 1,753 GVKEYs that exist in both datasets.

Figure A3 Within-organization temporal stability of VRscores (2012–2024)

(a) Non-Imputed VRscores

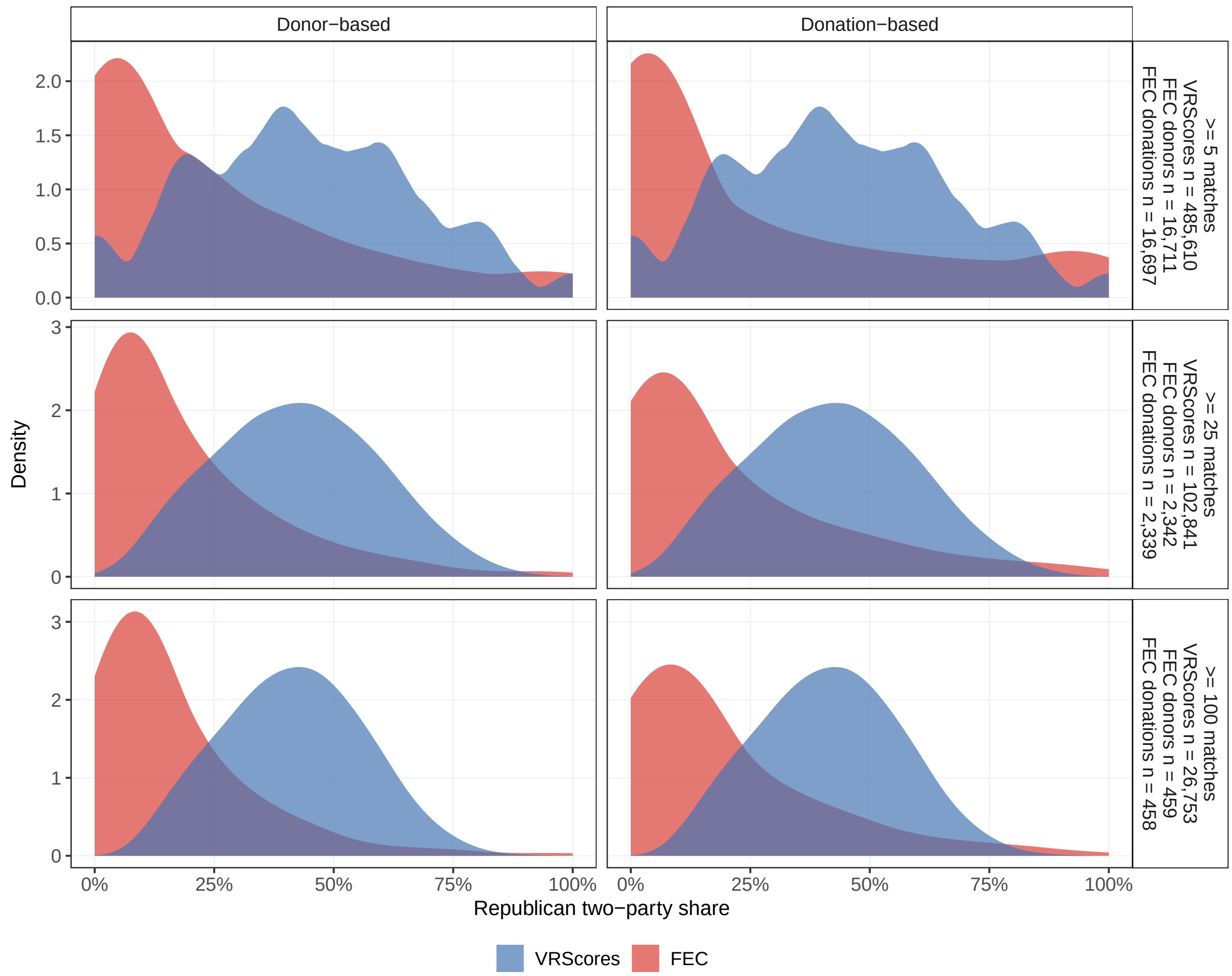


(b) Imputed VRscores



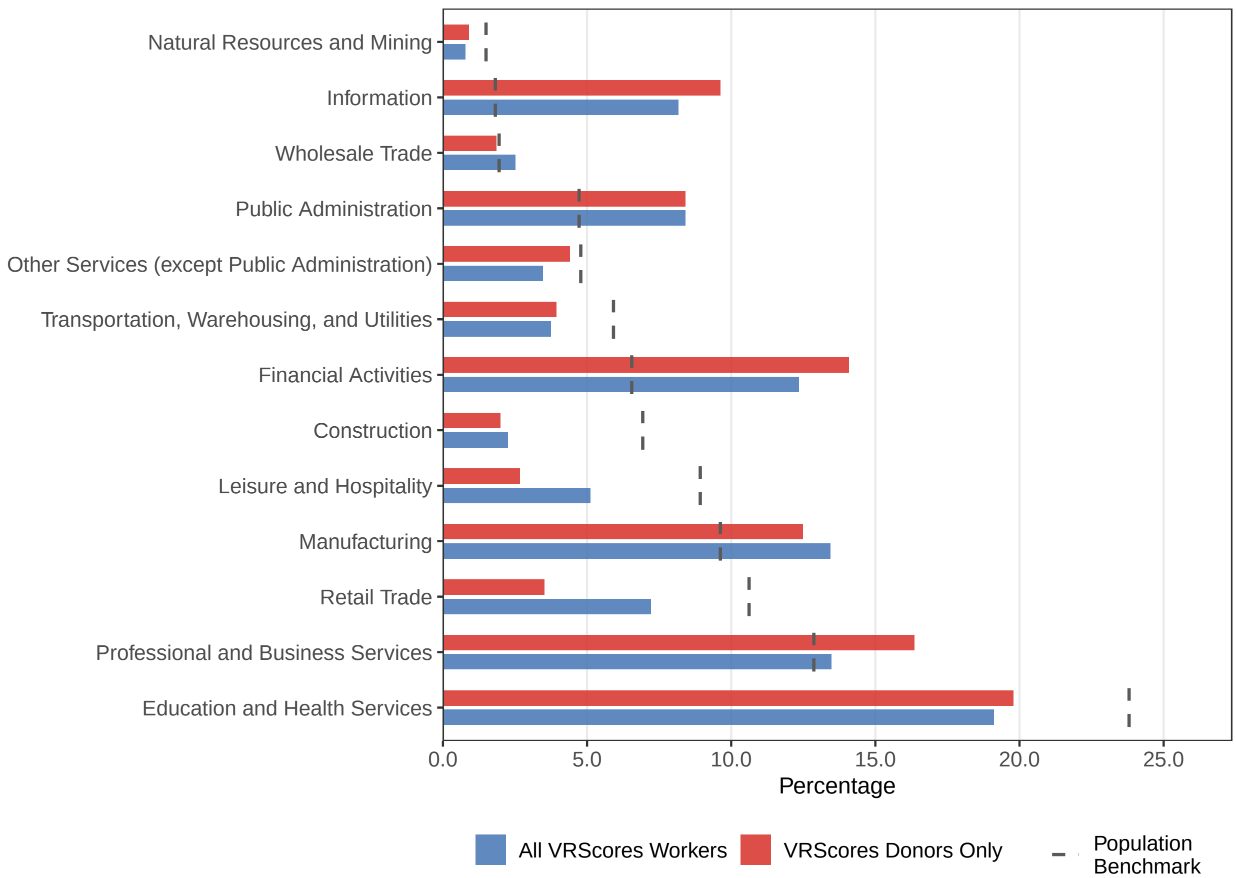
NOTE: Panels show the distribution of within-organization standard deviations for annual VRscores, using organizations with at least five employees in every year between 2012 and 2024. Non-imputed scores (top) have a median within-organization standard deviation of 9.4% and a 75th percentile of 14.3%. Imputed scores (bottom) have a median standard deviation of 8.4% and a 75th percentile of 12.3%. The fact that the distributions are concentrated near zero indicates that VRscores are relatively stable over time.

Figure A4 Distribution of Share of Republican Workers for VRscores versus Donations-based Measure at Different Size Thresholds



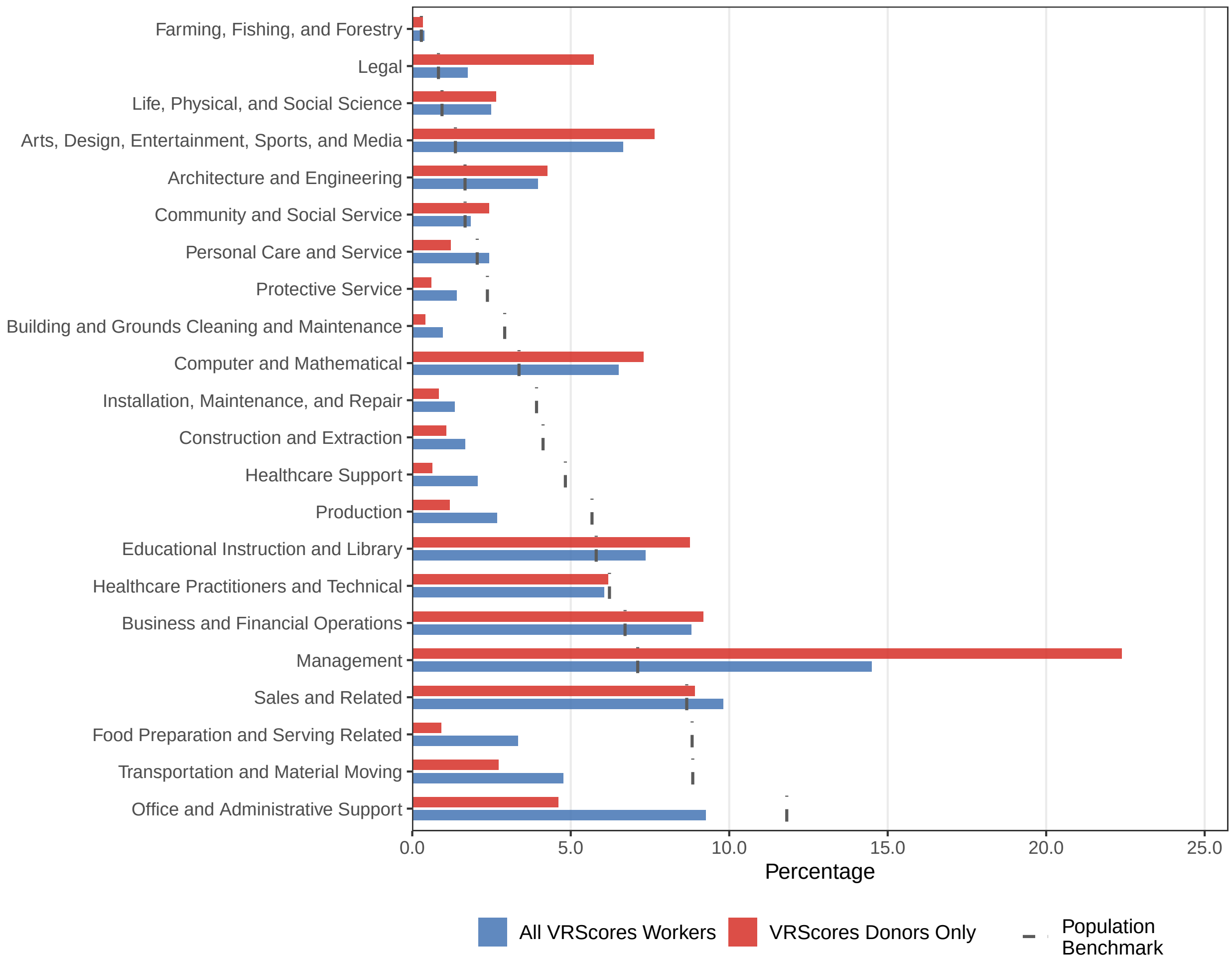
NOTES: These kernel density plots illustrate the distribution of the share of Republican workers as estimated with VRscores versus the donations-based measure across different firm size thresholds.

Figure A5 Comparison of Workforce by Industry Supersector (2024)



NOTE: Compares all VRscores workers active in 2024 with the subset who are donors within the 2024 snapshot. Dotted line shows national industry employment shares from the 2024 American Community Survey (ACS) 1-Year, Table S2407 (Industry by Class of Worker for the Civilian Employed Population 16 Years and Over). Supersectors are mapped from 2-digit NAICS. Counts include all unique positions active in 2024; workers with multiple concurrent positions may appear in more than one category. The ACS target population is all US workers, including those not registered or ineligible to vote.

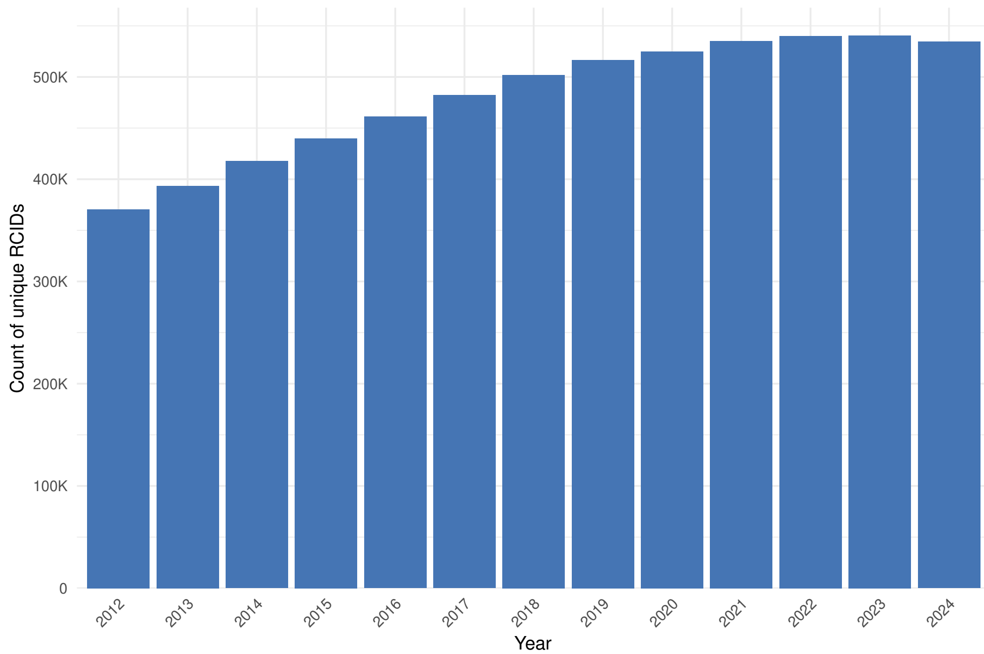
Figure A6 Comparison of Workforce by Occupation (2-Digit SOC Major Group, 2024)



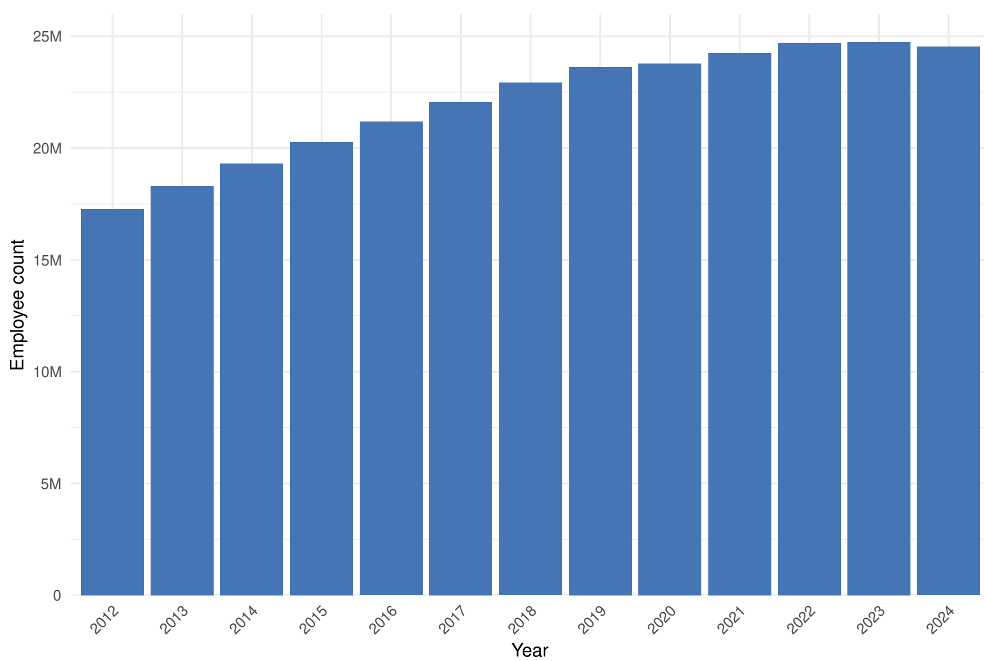
NOTE: Compares all VRscores workers active in 2024 with the subset who are donors within the 2024 snapshot, by SOC major group (2-digit). Dotted line shows national occupational employment shares from the US Bureau of Labor Statistics Occupational Employment and Wage Statistics (OEWS), May 2024 national file, aggregated to major groups. Counts include all unique positions active in 2024; workers with multiple concurrent occupations may appear in more than one category.

Figure A7 VR panel coverage over time

(A) Unique organizations per year



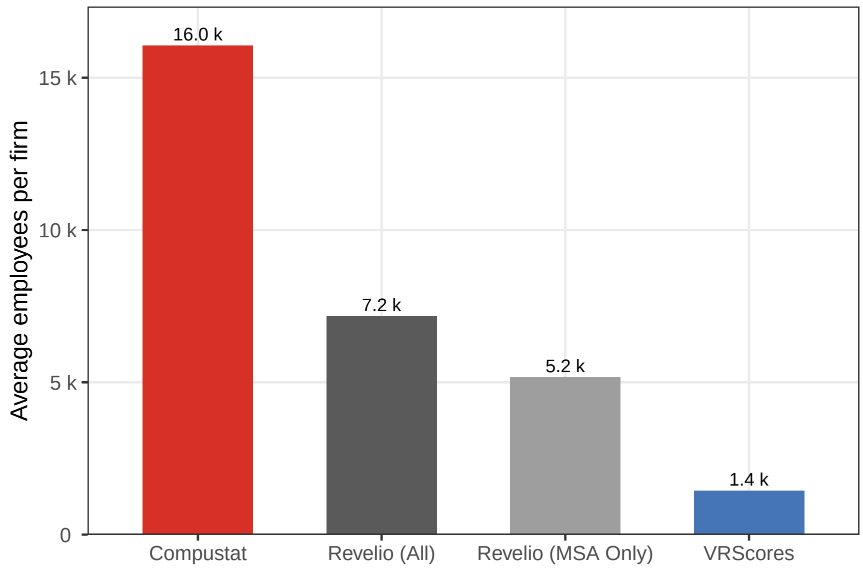
(B) Total employees per year



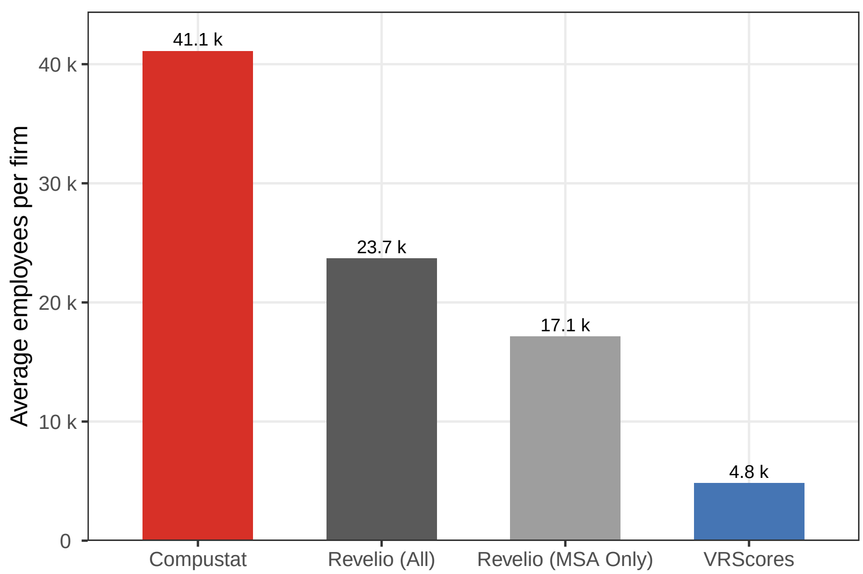
NOTE: Histograms summarize the VRscores panel spanning 2012–2024 (6.3 million organization-years). Panel (A) reflects the unique-organization counts (using RCID) by year. Panel (B) represents the total number of employees by year.

Figure A8 Average Headcount per Firm: Overall vs. Fortune 1000 Coverage

(a) All Matched Compustat Firms



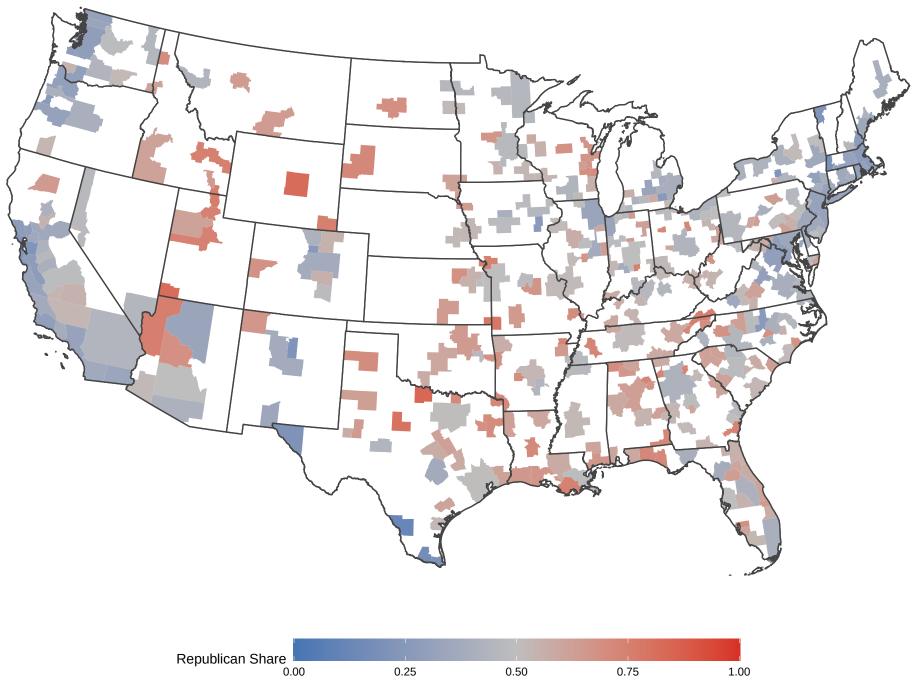
(b) Matched Fortune 1,000 Firms



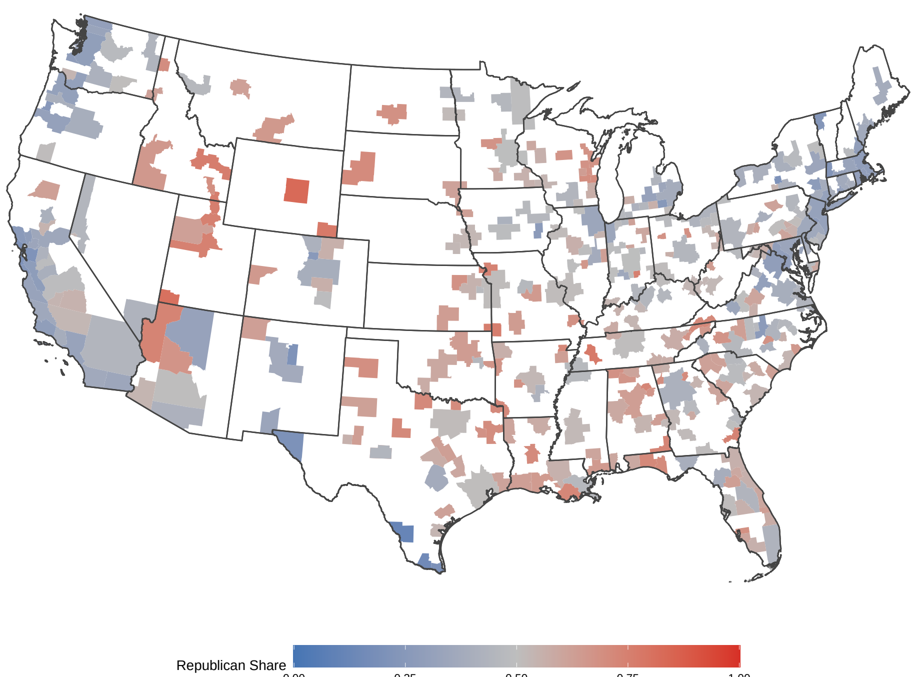
NOTE: Compustat headcounts come from the most recent headcount available from WRDS in 2024. Revelio metrics aggregate individual-level position records from the April 2025 Revelio release (all users and MSA-only extracts) after restricting to profiles with start dates on or before 31 December 2024, end dates on or after 1 January 2024 (or missing), US locations, and at least five active positions per GVKEY. VRscores represent the position active as of 2024 in the matched Revelio/L2 dataset, summed across subsidiaries and filtered to GVKEYs with more than five employees. Panel (A) covers the 3,810 public firms with non-missing employment in all sources. Panel (B) restricts to the 864 matched firms whose tickers appear in the 2024 Fortune 1000 list. Bars report mean employment per firm for each data source within the corresponding sample.

Figure A9 VRscores Republican Two-Party Share by MSA

(a) Imputed Republican Two-Party Share



(b) Non-Imputed Republican Two-Party Share



NOTE: Each panel shades US metropolitan statistical areas (MSAs) by the VRscore Republican share among two-party–affiliated Revelio workers in 2024. The non-imputed panel uses only observed partisan registrations; the imputed panel augments missing affiliations with the project's probabilistic assignments.

Table A2 Top 50 Companies by Employee Count

RCID	Company	Employees	Registered D%	Registered R%	Registered D2P%	Registered R2P%	Imputed D%	Imputed R%	Imputed D2P%	Imputed R2P%
1359692	Amazon.com, Inc.	97,894	45.5	19.1	70.4	29.6	58.1	24.3	70.5	29.5
1191500	Wells Fargo & Co.	65,611	38.2	30.0	56.0	44.0	52.2	38.6	57.5	42.5
674	The United States Army	64,625	34.3	32.9	51.0	49.0	41.4	40.5	50.6	49.4
22142783	Walmart, Inc.	63,868	37.6	27.9	57.4	42.6	46.0	36.5	55.8	44.2
1403686	US Department of Veterans Affairs	52,452	43.6	28.9	60.2	39.8	53.3	37.0	59.0	41.0
543448	JPMorgan Chase & Co.	51,222	42.4	25.2	62.7	37.3	55.9	31.6	63.9	36.1
207607	US Air Force	49,145	27.9	39.3	41.5	58.5	34.2	49.1	41.1	58.9
350953	Microsoft Corp.	47,684	49.4	19.4	71.8	28.2	63.1	23.8	72.7	27.3
739347	Target Corp.	45,542	43.7	22.6	65.9	34.1	56.2	28.6	66.3	33.7
393528	Bank of America Corp.	45,170	40.1	27.0	59.8	40.2	54.6	34.4	61.3	38.7
961524	The Boeing Co.	42,234	41.2	33.8	55.0	45.0	50.1	40.2	55.5	44.5
233459	Google LLC	42,127	50.7	13.8	78.6	21.4	68.0	17.9	79.2	20.8
1232095	Apple, Inc.	42,108	51.0	16.4	75.6	24.4	66.7	20.9	76.1	23.9
197643	US Navy	40,749	33.8	33.2	50.5	49.5	41.9	40.8	50.7	49.3
20937770	Deloitte LLP	40,325	42.6	24.5	63.4	36.6	56.8	30.0	65.5	34.5
97840	AT&T, Inc.	39,976	41.5	33.2	55.6	44.4	49.4	40.6	54.9	45.1
20939497	Kaiser Permanente, Inc.	39,495	52.4	19.5	72.9	27.1	67.1	25.4	72.5	27.5
20921805	Lockheed Martin Corp.	37,476	31.3	36.9	45.9	54.1	42.5	45.7	48.2	51.8
494205	The Home Depot, Inc.	31,685	40.1	27.7	59.1	40.9	50.3	35.5	58.7	41.3
1233227	The United States Postal Service	31,411	45.4	27.6	62.1	37.9	54.3	35.9	60.2	39.8
851738	Northrop Grumman Corp.	31,289	34.7	34.2	50.3	49.7	45.5	43.2	51.3	48.7
1037635	Starbucks Corp.	30,664	49.7	17.4	74.1	25.9	62.1	22.6	73.3	26.7
22142761	United Parcel Service, Inc.	29,013	38.1	31.3	54.9	45.1	47.5	39.4	54.7	45.3
20921455	Verizon Communications, Inc.	28,308	40.8	28.7	58.7	41.3	52.2	37.8	58.0	42.0
22173634	State Farm Mutual Automobile Insurance Co.	28,183	36.8	35.3	51.1	48.9	45.9	43.0	51.6	48.4
267301	Citigroup, Inc.	28,157	40.8	27.4	59.8	40.2	54.1	34.7	60.9	39.1
669531	FMR LLC (Fidelity Investments)	27,735	30.0	27.4	52.2	47.8	49.4	37.2	57.0	43.0
755148	Keller Williams Realty, Inc.	27,672	34.4	38.3	47.3	52.7	44.2	46.5	48.7	51.3
22142390	International Business Machines Corp.	27,467	38.9	30.1	56.4	43.6	52.0	38.9	57.2	42.8
1017034	CVS Health Corp.	26,922	40.8	23.5	63.5	36.5	55.1	30.9	64.1	35.9
1301557	Ernst & Young Global Ltd.	26,767	40.0	26.0	60.6	39.4	54.8	31.7	63.4	36.6
709929	PricewaterhouseCoopers LLP	26,398	38.6	26.4	59.4	40.6	54.6	32.0	63.0	37.0
777168	Lowe's Companies, Inc.	26,385	34.5	32.4	51.6	48.4	43.7	41.6	51.3	48.7
970845	Amazon Web Services, Inc.	25,987	45.1	19.5	69.9	30.1	59.4	24.4	70.9	29.1
166241	Walgreen Co.	25,031	42.6	23.0	64.9	35.1	55.1	29.0	65.5	34.5
1398143	General Motors Co.	24,580	44.6	32.7	57.7	42.3	51.8	39.3	56.9	43.1
1070638	UnitedHealth Group, Inc.	24,394	39.2	32.3	54.8	45.2	50.6	40.2	55.7	44.3
9119130	US Bank	24,224	35.7	34.5	50.8	49.2	47.7	42.3	53.0	47.0
1233178	Meta Platforms, Inc.	23,880	50.2	13.6	78.6	21.4	67.6	17.3	79.6	20.4
1230770	Accenture Plc	23,710	45.0	23.1	66.1	33.9	59.1	28.6	67.4	32.6
472640	Oracle Corp.	22,438	38.8	26.6	59.3	40.7	54.6	34.7	61.1	38.9
22142112	Capital One Financial Corp.	22,057	50.7	23.5	68.3	31.7	61.2	27.8	68.7	31.3
22142569	The PNC Financial Services Group, Inc.	22,040	42.5	32.7	56.5	43.5	51.5	39.9	56.4	43.6
1311350	Intel Corp.	21,800	36.7	22.0	62.5	37.5	55.2	30.3	64.6	35.4
1485785	Morgan Stanley	21,523	35.6	31.1	53.4	46.6	50.1	38.5	56.5	43.5
396968	RTX Corp.	20,664	29.6	32.3	47.8	52.2	45.0	42.8	51.3	48.7
296156	United States Marine Corps	20,571	29.0	35.4	45.0	55.0	36.9	44.3	45.5	54.5
1137889	Optum, Inc.	20,122	38.5	29.3	56.8	43.2	52.5	37.4	58.4	41.6
806872	FedEx Corp.	20,020	37.1	29.8	55.4	44.6	46.6	38.4	54.8	45.2
690100	KPMG LLP	19,466	39.0	27.5	58.7	41.3	53.6	33.6	61.5	38.5

Notes: RCID = Revelio Company ID. Employees is the total number of matched employees in VRscores. Registered percentages use voter registration to calculate partisanship; imputed percentages use imputed partisanship for people who are not registered as Democrats or Republicans. D2P% and R2P% are the two-party shares (exclude non-partisans from the denominator). The table lists the top 50 RCIDs by employee headcount in 2024.

Methods

Data and Code Availability

The Revelio and L2 datasets used in this paper are commercial datasets whose license terms prohibit disclosure. As mentioned elsewhere, we provide the public version of our dataset. To facilitate transparency into the methods used in this paper, we provide the code used to create the dataset and analyses reported in the paper. Data and code for peer review are available at the Harvard Dataverse: https://dataverse.harvard.edu/previewurl.xhtml?token=6b2aaf09-ee12-4e75-b830-36889c01800e. The data will be made publicly available via a public-facing website, an anonymized version of which is available here: https://politicsatwork.org/.

Overview

We calculate VRscores by linking state voter registration files with a database of online worker profiles.[14]

L2 Voter File

Our first data source is the national voter file. In the United States, whether or not individuals register to vote is public record. Data from these filings are widely used by political campaigns, commercial data vendors, and, increasingly, by academic researchers (Hersh 2015, Kempf and Tsoutsoura 2021, Spenkuch et al. 2023). In many states, these data can be accessed by contacting individual state and/or local officials, but researchers more typically rely on data vendors which aggregate, clean, and standardize the raw records received from election officials. We purchase data from the nonpartisan vendor L2 Data, extracted and processed in November 2024, containing information on approximately 185 million registered voters in the United States.

Below, we describe the variables we use from the L2 voter file:

Partisanship

L2's information on partisan identification comes from a variety of sources, which vary by state (Barber and Holbein 2022). States fall into three categories:[15]

- 30 states (and Washington, D.C.) register voters by party.

[14]The raw inputs are restricted to records with MSA assignments.

[15]See https://www.l2-data.com/wp-content/uploads/2024/09/State-by-State-Partisanship-Party.pdf.

- 11 states do not register voters by partisanship, but record whether voters chose to vote in either party's primary. This primary participation is the base for partisan classification. These states include Georgia, Illinois, Indiana, Michigan, Mississippi, Ohio, South Carolina, Tennessee, Texas, Virginia, and Washington.
- Nine states provide no information on partisan registration, and L2 models partisan affiliations based upon ethnicity, geography, and other data. These states are Alabama, Hawaii, Minnesota, Missouri, Montana, North Dakota, Wisconsin, and Vermont. Prior studies which make use of commercial voter file data have conducted robustness checks excluding states with imputed partisanship have found no difference in results. Moreover, a report by Pew Research which compared modeled data on commercial voter files with self-reported survey responses also found that modeled partisanship is correct in a majority of cases (Igielnik et al. 2018).

While these methods appear to provide accurate estimates of partisanship, scholars concerned about their accuracy may wish to conduct robustness tests in which they test sensitivity of results to removing observations from twenty states where L2 imputes partisanship, or, at least, the nine states where this is based on geographic and demographic characteristics.

Partisanship Imputation

Among registered voters in our sample, about one-third do not register with any party. However, party registration potentially understates de-facto partisan segregation, as many self-declared independents have clear partisan leanings (Keith et al. 1992, Klar 2014, Petrocik 2009). Following the methodology of Brown and Enos (2021), we impute partisan "lean" for these non-partisans. We start with the partisan estimates provided by L2. Next, for voters who are not classified as either Republican or Democrats, we identify whether they have a prior history of voting in either the Democratic or Republican political primary from 2012-2022, and assign them to the party in whose primary they most recently voted. We then classify members of third-parties as "leaning" towards the party that most closely matches the ideology of their preferred third party, using the classifications from Brown and Enos (2021). For example, the Green and Socialist parties are mapped to the Democratic party, while the Libertarian and Reform parties are mapped to the Republican party.

Following these steps, approximately 10–30% of voters remain unclassified. To model the partisan lean of these voters, we rely upon a Bayesian approach developed by Brown and Enos (2021) which incorporates fine-grained information about the local partisan geography as well voters' demographics. First, we calculate a Bayesian geographic prior based on precinct-level electoral returns. Since precinct-level returns were not yet available in all states for 2024, we use 2020 returns. We assign most voters to precincts and in the rare cases where we are unable to do so, we use county-level returns. Our approach is very similar to that laid out in Brown and Enos (2021), but we depart slightly from their procedure by relying only upon vote totals for the Republican and Democratic candidates.[16]

Second, we incorporate information about voters' demographics. We begin with the 2020 Cooperative Election Study, a large-scale, high-quality public opinion survey and use these data to estimate the conditional probabilities that an individual falls within a given demographically-defined stratum (defined by age bracket × race × gender × voter registration status) conditional upon them identifying as a Democrat, Republican, or true independent. Where race data are missing in L2, we use only age, gender, and voter registration status.

We then use Bayes' rule to combine the demographic and the geographic priors to estimate the probability that each "independent" voter actually leans Democratic or Republican. We assign each voter as "leaning" towards the partisan label with the highest probability (i.e., Republican, Democratic, or Independent).In the extremely rare cases where all probabilities are equal, we default to Independent. This procedure classifies most initially unaffiliated voters as Democrats or Republicans.

It is worth noting that, in conducting this methodology we sometimes impute partisanship for registered voters that L2 has already imputed as Independent or non-partisan, namely those in the 20 states for which voters do not report registration.

We release separate versions of VRscores that either include or do not include our imputed partisanship for Independents. Scholars can thus choose which measure they prefer and/or check the sensitivity of their results to both approaches.

Geography

To match datasets, we assign users to geographic areas. We match on MSA, which is assigned by Revelio based on the user's reported workplace. We assign L2 users to MSAs based on the HUD User (https://www.huduser.gov/) crosswalks, which link specific addresses to MSAs.

[16]In personal communication with the authors of Brown and Enos (2021), we confirmed this approach delivers comparable results.

Worker Profiles from Revelio Labs

Revelio compiles employment records via online professional profiles and job postings. Our particular Revelio dataset was captured in April 2025. After excluding records with missing data fields (MSA or employer), our Revelio data available for matching cover approximately 129 million positions, held by 103 million unique workers.

Below, we detail each of the variables we use from this dataset.

Names and Personal Information

Revelio captures identity and career data directly from individuals' LinkedIn profiles as displayed on the platform. However, the names presented on LinkedIn may not align with the legal names recorded in voter files, as users may adopt professional aliases, shortened versions, birth surnames, or names reflecting cultural practices. To mitigate this issue, we employ the nominally Python library for name normalization, which regularizes naming conventions, accommodates typical variants, and processes intricate name compositions. This data preparation step significantly enhances match quality relative to utilizing unprocessed LinkedIn name information.

Employer

Revelio leverages LinkedIn's organizational linkages and applies disambiguation techniques along with entity consolidation to tackle the core problem that identical firms can be represented through numerous naming variations within LinkedIn profiles (e.g., BofA," Bank of America," BoA," Bank of America Corp"). Through machine learning models trained on corporate registration documents, Securities and Exchange Commission submissions, and additional commercial data sources, Revelio consolidates alternative employer designations into uniform entity identifiers.

Occupation

LinkedIn job titles are translated into standardized O*NET-SOC occupational classifications through Revelio's proprietary text analysis framework. This framework evaluates position titles, role descriptions (where accessible), and contextual details from employment listings to determine the most suitable occupation designation. The algorithm integrates data regarding work duties, requisite competencies, and sectoral context to enhance categorization precision.

Industry

Revelio classifies employers into NAICS codes at the sector, subsector, and detailed industry levels. This process combines automated matching of employer names against commercial business databases with machine learning models used to predict industry codes based on company names, descriptions, and employee job titles.

Seniority

Revelio approximates professional seniority through a seven-tier categorization spanning from junior positions (interns, trainees) to top executive appointments (C-suite). This categorization synthesizes multiple data inputs: (1) analysis of current position titles via NLP algorithms designed to identify hierarchical markers, (2) examination of individual work histories revealing advancement trajectories, and (3) inferred age derived from employment tenure length. The age inference process itself poses a substantial methodological obstacle, given that LinkedIn does not supply birthdates, necessitating that Revelio extrapolate age from career span and conventional education-to-employment transition timelines.[17]

Ensemble Matching Strategy

To integrate L2 and Revelio, we deploy an innovative ensemble linkage strategy that merges two complementary techniques: probabilistic record matching employing the Fellegi-Sunter model and large language model (LLM)-driven semantic comparison. Our data incorporate the latest accessible information from both repositories. For L2, we utilize voter registry extracts compiled in November 2024, whereas for Revelio we employ workforce data obtained in April 2025.

Data Preprocessing

We initiate the process by segmenting both Revelio and L2 records according to metropolitan statistical area (MSA). We omit records where employment or residential addresses fall outside MSA boundaries or where geographic information is absent.[18]

This approach serves dual purposes: first, it allows computational tractability as matching all names across all metro areas is not feasible. Second it is conceptually justified, as MSAs are delineated by the

[17] We learned this in the course of personal communication with Revelio employee Hakki Ozdenoren.

[18] According to the 2021 American Community Survey (ACS) DP03 table, nearly 88% of Americans in the labor force live within an MSA.

Census Bureau to reflect commuting dynamics, making it logical to constrain our linkages to instances where the employment location (as documented in Revelio) and residential address (as documented in L2) fall within the same MSA. For MSAs that traverse state boundaries, we seek to link employment records with voter registrations across all states encompassed by that MSA (e.g., we would seek to link employment records situated in the Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA with voters living in the MSA across PA, NJ, DE, and MD).

The voter file inputs begin with state-level L2 `VM2Uniform` archives. We process these archives by decompressing the tabular extracts, recompressing them for efficient cluster processing, and converting each state to parquet. This conversion retains canonical L2 fields: voter identifier, name components, gender, birthdate, geography (ZIP, FIPS, etc.), party affiliation, etc. Spark is then used to filter these state-level parquets into MSA-specific extracts based on a ZIP/ZCTA crosswalk.

Revelio data are prepared analogously. Position records are restricted to observations with valid employer identifiers and MSA assignments, joined to the MSA crosswalk, and repartitioned by MSA. For the user data, we retain essential identity fields, drop records with missing first or last names, and append modeled birthdates provided by Revelio. We standardize full names by lowercasing, removing punctuation, and splitting tokens (into first, middle, and last names) using `nominally::parse_name`. Records with single-character first and last names are dropped unless paired with longer tokens (e.g., a middle name).

Probabilistic Matching (Splink)

We run probabilistic matching on a Slurm-managed high-performance cluster. Each job loads Spark 3.5.1 and Python 3.11 (Anaconda distribution) and executes Splink 3.9.8 with the DuckDB backend and its bundled similarity UDFs. The Python environment additionally pins `nominally` 1.1.0, `pandas`, `numpy`, and `duckdb`.

The matching workflow is executed per-MSA. For very large MSAs, jobs are split into alphabetic bins by last name to ensure computational tractability. The process begins in Spark (configured with Kryo serialization) to read the MSA-specific L2, Revelio user, and Revelio position parquets. This stage applies shared cleaning utilities and standardizes variable names to Splink's schema (`unique_id`, `firstname`, `lastname`, etc.). The resulting data frames are then converted to pandas to be processed by Splink's DuckDB backend.

Splink is configured with a random seed of 943,095, a match probability prior of 0.1, and an estimation sample size of 10^9. We estimate *m*- and *u*-parameters using the expectation-maximization (EM) algorithm, running the training twice for stability (blocking first on given name, then on last name) to refine match weights. For generating the final predictions, we use blocking on `lastname`. The comparisons mirror the Fellegi–Sunter specification: (i) first- and last-name exact matches, Damerau–Levenshtein distance ≤ 1, and Jaro–Winkler thresholds ≥ 0.9 and ≥ 0.8; (ii) a birthyear comparison with exact matches plus ± 1, ± 5, and ± 10 year tolerances; and (iii) middle-name and gender comparisons. All comparisons include term-frequency adjustments to down-weight common tokens. This process adjusts match probability assigned to the match by assigning a weight that is inversely proportional to the token's prevalence in the dataset. For example, a match on a relatively frequent last name (e.g., `Smith`) will receive a much lower match probability because the match provides substantially weaker evidence of a true link than a match on a rare last name (e.g., *Peixoto*), which would receive a higher match probability.

After training, the final model is saved. Predictions are generated using a match probability threshold of 0.1. These predictions are converted back to Spark to apply a deterministic deduplication routine. This routine resolves one-to-many and many-to-one ties by prioritizing the link with the highest match probability and, where applicable, dropping links to flagged users that Revelio has flagged as "bad users." The final set of deduplicated pairs is used to merge the full Revelio position records with the corresponding L2 voter records. These final position-level parquets, stored by MSA, form the input to the ensemble stage described below.

LLM-Based Matching (FuzzyLink)

Our second method utilizes the Ornstein's (2024) fuzzylink R package to conduct embedding-based semantic linkage driven by large language models. This technique employs `gpt-4o-mini-2024-07-18` for match determination and OpenAI's `text-embedding-3-large` model (256 dimensions) to produce semantic representations of names. The fuzzylink function is configured with `record_type = "person"`, `max_labels 5000`, and parallel processing enabled.

The matching process is stratified and blocked on two fields: derived gender (M or F) and the first three characters of the last name. Within these blocks, the model leverages embedding proximity to detect potential correspondences. We supply explicit directives to the LLM to disregard occupational titles, name suffixes, capitalizations, punctuation, diacritical marks, name sequencing variations, and trivial spelling errors while concentrating on whether names plausibly reference the same individual.

Following the per-chunk matching, we perform a multi-stage deduplication. First, matches are aggregated per-MSA and deduplicated to enforce a one-to-one relationship by retaining only the highest `match_probability` link for each `user_id` and, subsequently, for each LALVOTERID. Second, all MSA-level matches are combined into a global file and subjected to a final deduplication pass. This pass sorts all potential links by `match_probability`, `jw` (Jaro-Winkler), and `sim` (cosine similarity) in descending order, then drops duplicates by `user_id` and LALVOTERID to ensure a unique one-to-one match across the entire dataset. This LLM technique proves especially useful in identifying matches missed by conventional string-based methods, including those featuring diminutives, name abbreviations, etc.

Ensemble Integration

We integrate the outputs from both linkage techniques using an ensemble framework designed to optimize coverage while preserving match quality. To enforce a one-to-one match, our algorithm prioritizes links with the highest match probability. The deduplication process is applied sequentially: first, it resolves duplicate Revelio user IDs, and second, it resolves duplicate voter IDs. In both stages, only the link with the strongest probability is retained. Any remaining ties are broken by prioritizing records with data quality markers (e.g., using Revelio's *is_bad_user* flag); if matches are still equivalent, we arbitrarily select which link to retain. This ensemble framework produces approximately 45.3 million distinct matched workers, representing 44.1% of the 102.6 million Revelio users with MSA assignments and 26.1% of the 183.7 million MSA-assigned L2 voter registrations.

Public Dataset Construction

To prepare the final public VRscores dataset, we first exclude workers assigned to an RCID with fewer than five matches in a given year.

Next, we apply additional organization-level filters and perform validation. First, we used an LLM and did a manual review to identify invalid employers. This process flagged unusual names or terms like "unemployed," "student," or "retired," allowing us to remove approximately 1,500 bad RCIDs.

Following this cleaning, we performed an extensive manual validation and augmentation of the RCID-to-GVKEY mapping. We focused on large firms that did not have a GVKEY assigned by Revelio, and this manual process resulted in our adding approximately 3,200 additional RCID-to-GVKEY linkages for these firms. We caution researchers using this dataset for questions sensitive to corporate structure, such as mergers and acquisitions. The RCID-to-GVKEY mapping was performed and validated as of 2024. This static mapping is applied to all historical snapshots (e.g., 2012-2023). Consequently, for research where temporal changes in firm ownership and structure are critical, end users are responsible for implementing their own time-varying mapping and should not rely on our time-invariant linkage.

For the primary analysis in this paper, we filter the full 45.3 million matches to a 2024 snapshot, which includes 31.1 million employees with active positions in 2024. This sample is further limited to the 24.5 million individuals at RCIDs that meet the previously described 5-employee-match threshold. See Table A5 for details on the 2024 cross section of the public VRscores dataset.

Constructing the Panel

We construct an unbalanced panel of positions extending from 2012 to 2024. We do so by incorporating all positions held by matched individuals that were active at any point during this period. Each record is assigned to all relevant years based on its start and end dates. The resulting analytical unit is the position-year. Appendix Figure A7 summarizes this longitudinal coverage, plotting the number of unique organizations (panel A) and total matched employees (panel B) by year. Coverage increases steadily over time—as more workers create online profiles and as the labor force expands—but even in the earlier years, VRscores covers millions of workers. This temporal breadth allows researchers to observe within-firm partisan composition trends over time. See Table A6 for details.

MSA, Occupation, and Industry Cuts

In addition to the RCID panel, we construct year-level aggregates for metropolitan areas (MSAs), occupations (O*NET codes), and industries (NAICS). These cuts are derived from the same underlying position-year universe and apply the same core filters.

First, for each calendar year, we deduplicate to one active position per individual. We keep the position with the most recent end date (treating open-ended positions as the most recent), breaking ties by later start date and then by RCID. We exclude positions at RCIDs flagged as non-companies in our manually curated list.

MSA Panel

We assign positions to MSAs by preferring the position-level MSA when present and otherwise using the profile-level MSA. We drop empty or nonstandard labels and exclude any non-US territories and nonmetropolitan placeholders (e.g., "Nonmetropolitan Area," "Puerto Rico," etc.). We then aggregate all deduplicated workers active in the year to the MSA-year and retain MSA-years with at least 50 workers. See Table A7 for details.

Occupation Panel

We group deduplicated workers by ONET occupation code and label within each year. We retain occupation-years with at least 50 workers. This produces an occupation-year panel raw and imputed partisan shares, margins, and diversity metrics at the ONET code level. See Table A8 for details.

Industry Panel

We assign NAICS codes by joining positions to an Revelio's company crosswalk that maps RCIDs (Revelio's company identifier) with 6-digit NAICS codes and descriptions. We then group deduplicated workers by NAICS within each year and retain industry-years with at least 50 workers. As with the occupation panel, we report the same raw and imputed partisan shares, margins, and diversity metrics.

Across all three cuts (MSA, occupation, NAICS), the reporting window is 2012–2024 and the metrics are computed on the same deduplicated position-year base with the same exclusions of invalid RCIDs. Privacy and stability are enforced by only reporting cells with at least 50 workers. See Table A9 for details.

Donations

In order to compare the breadth and depth of coverage afforded by VRscores versus donations-based measures, we first construct a donations-based metric. We access donations data from the Federal Election Commission and focus on the donations from the latest election cycle for which data were available at the time of our analysis (the 2023-2024 general election cycle). We then group individual donors by their (self-reported) employer. As the self-reported field is non-standardized (Stuckatz 2022b), we first apply a detailed cleaning function to standardize employer names, the details of which are reported in the appendix. This involves converting all names to lowercase, removing special characters and punctuation, and standardizing commonly-used terms to describe corporate structures (e.g., "limited liability company" versus "LLC," “corporation" versus “corp."), replacing “and/plus” with “&”, and discarding cleaned names that are two or fewer characters. To consolidate spellings, we construct blocking keys that drop generic terms (e.g., “inc,” “llc,” “group,” “services”), alphabetize the remaining distinctive tokens, and retain short leading/trailing fragments. Within each block we compute character 3–4 gram TF–IDF vectors and treat employer names whose cosine similarity exceeds 0.94 as the same canonical employer.[19] Overall the procedure produces 623,716 canonical employers, of which 58,869 consist of two or more raw variants. For the VRscores data, we aggregate positions active in 2024 by `rcid`.

The rest of our benchmarking analysis involves comparisons with donations-based measures. We make many of the comparison based on the population of donors in our matched dataset. These donors are identified with a variable from LinkedIn that indicates where an individual made an FEC-reportable donation (i.e., a donation over $200 in the last electoral cycle).

Table A4 Variable Dictionary for the RCID-Year Panel

Column	**Type**	**Description**
`vrid`	string	VRscores employer identifier (VRID).
`rcid`	string	Revelio company identifier (not included in the public release; available in a restricted crosswalk for Revelio licensees).
`rcid_raw`	string	Raw RCID value prior to sanitisation (not included in the public release; available in a restricted crosswalk for Revelio licensees).
`year`	integer	Calendar year for the aggregated snapshot.
`company_name`	string	Employer name.
`final_parent_company`	string	Ultimate parent organisation name (not included in the public release; available in a restricted crosswalk for Revelio licensees). A parent may have many children RCIDs associated with it.
`final_parent_company_rcid`	string	RCID associated with the final parent (not included in the public release; available in a restricted crosswalk for Revelio licensees).
`gvkey`	string	WRDS Compustat GVKEY mapped to the employer (not included in the public release; available in a restricted crosswalk for Revelio licensees). Blank when no mapping is available.
`ticker`	string	Public equity ticker supplied by the Revelio crosswalk when available (not included in the public release; available in a restricted crosswalk for Revelio licensees).

[19]For example, “bank of america,” “bank of america corp,” and “bank of america inc” all collapse to the same employer, whereas “bank of america stadium” or “bank of new york” would be distinct employers because they are not similar enough).

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Column	Type	Description
exchange	string	Stock exchange or trading venue for the ticker (not included in the public release; available in a restricted crosswalk for Revelio licensees).
factset_entity_id	string	FactSet entity identifier for the company (not included in the public release; available in a restricted crosswalk for Revelio licensees).
factset_ultimate_parent_id	string	FactSet ID for the ultimate parent company (not included in the public release; available in a restricted crosswalk for Revelio licensees).
cusip	string	CUSIP identifier sourced from the crosswalk (not included in the public release; available in a restricted crosswalk for Revelio licensees).
url	string	Official company website (not included in the public release; available in a restricted crosswalk for Revelio licensees).
linkedin_url	string	LinkedIn company profile URL (not included in the public release; available in a restricted crosswalk for Revelio licensees).
naics_code	string	6-digit NAICS industry code (not included in the public release; available in a restricted crosswalk for Revelio licensees).
naics_desc	string	NAICS industry description associated with naics_code (not included in the public release; available in a restricted crosswalk for Revelio licensees).
headquarters_state	string	Headquarters state/region from the Revelio crosswalk (not included in the public release; available in a restricted crosswalk for Revelio licensees).
headquarters_city	string	Headquarters city from the Revelio crosswalk (not included in the public release; available in a restricted crosswalk for Revelio licensees).
headquarters_zip_code	string	Headquarters postal/ZIP code (string to preserve leading zeros; not included in the public release; available in a restricted crosswalk for Revelio licensees).
modal_state	string	Most common state across deduplicated worker positions for the RCID in the given year.
modal_city	string	Most common city across deduplicated worker positions.
modal_msa	string	Most common MSA across de-duplicated worker positions.
modal_zip_code	string	(Years with voter ZIP data only) Most common voter ZIP among matched workers.
employee_count	integer	Number of deduplicated workers attached to the RCID-year (minimum 5).
avg_match_probability	float	Average probabilistic score across all matched workers. This is a measure of match confidence.
dem_workers_raw	integer	Count of workers matched to L2 with Democratic party affiliation.

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Column	**Type**	**Description**
`rep_workers_raw`	integer	Count of workers matched to L2 with Republican affiliation.
`other_workers_raw`	integer	Count of matched workers whose L2 party is neither Democratic nor Republican.
`party_known_workers_raw`	integer	Total count of workers with any L2 party assignment (Democratic, Republican, or other).
`dem_workers_imp`	float	Imputed Democratic worker count (`dem_imputed`) aggregated across employees.
`rep_workers_imp`	float	Imputed Republican worker count (`rep_imputed`) aggregated across employees.
`other_workers_imp`	float	Residual imputed nonpartisan count: `max(employee_count - dem_workers_imp - rep_workers_imp, 0)`.
`democrat_pct_raw`	float	Democratic share of the workforce using raw counts (`dem_workers_raw / employee_count`).
`republican_pct_raw`	float	Republican share of the workforce using raw counts.
`nonpartisan_pct_raw`	float	Share of workers without Democratic/Republican affiliation using raw counts.
`democrat_pct_two_party_raw`	float	Democratic share among workers with Democratic or Republican affiliation only (`dem_workers_raw / (dem_workers_raw + rep_workers_raw)`).
`republican_pct_two_party_raw`	float	Republican share among two-party workers.
`two_party_margin_raw`	float	Republican minus Democratic share among two-party workers (`(rep - dem) / (dem + rep)`). Positive values indicate a Republican lean.
`overall_margin_raw`	float	Republican minus Democratic share of the full workforce (`(rep - dem) / employee_count`).
`democrat_pct_imp`	float	Democratic share using imputed counts (`dem_workers_imp / employee_count`).
`republican_pct_imp`	float	Republican share using imputed counts.
`nonpartisan_pct_imp`	float	Residual nonpartisan share using imputed counts.
`democrat_pct_two_party_imp`	float	Democratic share among imputed two-party workers (`dem_workers_imp / (dem_workers_imp + rep_workers_imp)`).
`republican_pct_two_party_imp`	float	Republican share among imputed two-party workers.
`two_party_margin_imp`	float	Imputed two-party margin (`(rep_imp - dem_imp)/(dem_imp + rep_imp)`).
`overall_margin_imp`	float	Imputed overall margin (`(rep_imp - dem_imp) / employee_count`).
`political_diversity_raw`	float	$1 - \Sigma(p_i^2)$ for raw partisan shares; higher values indicate greater diversity.
`political_diversity_imp`	float	$1 - \Sigma(img_i^2)$ computed from imputed shares.

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Column	Type	Description
effective_parties_raw	float	Effective number of parties based on raw shares (inverse Herfindahl).
effective_parties_imp	float	Effective number of parties based on imputed shares.
latest_processed_at	timestamp	Most recent processing timestamp from the crosswalk rows feeding the RCID.

Table A3 Illustrative match outcomes across match-probability deciles.

Decile	Match Prob.	Source	Revelio First	Revelio Middle	Revelio Last	L2 First	L2 Middle	L2 Last	Birth Years (Rev (Rough) / L2)
10: [0.808, 1.000]	1.000	splink	Hayward		Coppe	Hayward	D	Coppe	1987 / 1955
10: [0.808, 1.000]	1.000	splink	Vlad		Agranovich	Vlad		Agranovich	1976 / 1963
10: [0.808, 1.000]	0.999	fuzzylink	Elvis		Garcia	Elvis		Garcia	1993 / 1971
9: [0.768, 0.808)	0.806	splink	Vickie		Ellison	Vickie	Louise	Ellison	1991 / 1970
9: [0.768, 0.808)	0.804	fuzzylink	Gary		Duncan	Gary	E	Duncan	1970 / 1963
9: [0.768, 0.808)	0.804	splink	Benjamin		Chadwick	Benjamin	David	Chadwick	1991 / 1991
8: [0.722, 0.768)	0.767	splink	Nicholas		Cyrus	Nicholas	Dawson	Cyrus	1985 / 1983
8: [0.722, 0.768)	0.767	splink	Cliff		Welles	Clifford	Y	Welles	1961 / 1948
8: [0.722, 0.768)	0.766	splink	Erin		Tansey	Erin	Ann	Tansey	1991 / 1980
7: [0.666, 0.722)	0.721	splink	Dominick		Greco	Dominick		Greco	1979 / 1967
7: [0.666, 0.722)	0.721	fuzzylink	Michael		Braun	Michael	Andrew	Braun	1988 / 1954
7: [0.666, 0.722)	0.718	fuzzylink	Amy		Teblum	Amy	Lynn	Teblum	1993 / 1978
6: [0.599, 0.666)	0.663	fuzzylink	Kaylan		Crawford	Kayla	Marie	Crawford	1991 / 1992
6: [0.599, 0.666)	0.660	splink	Danny		Flowers	Danny	Lee	Flowers	1979 / 1971
6: [0.599, 0.666)	0.660	splink	Susan		Mackiewicz	Susan	Marie	Mackiewicz	1966 / 1960
5: [0.516, 0.599)	0.598	splink	Christine		Nutter	Christine	Ella	Nutter	1990 / 1966
5: [0.516, 0.599)	0.594	splink	Danielle		Vaccaro	Danielle	Lorena	Vaccaro	– / 1991
5: [0.516, 0.599)	0.594	splink	David		Krane	David	Anthony	Krane	1996 / 1982
5: [0.516, 0.599)	0.592	splink	Sean		Musselman	Sean	Michael	Musselman	1993 / 1981
4: [0.420, 0.516)	0.514	splink	Caroline		Rosado	Caroline		Rosado	1975 / 1977
4: [0.420, 0.516)	0.512	splink	Lexi		Mitchell	Lexi	Sueann	Mitchell	1994 / 2000
4: [0.420, 0.516)	0.510	splink	Rhonda		Sorensen	Rhonda	Marie	Sorensen	1985 / 1971
3: [0.323, 0.420)	0.416	splink	Cheryl		Kasper	Cheryl	Marie	Kasper	1978 / 1966
3: [0.323, 0.420)	0.376	splink	Katie		Rahill	Katherine	Marie	Rahill	1994 / 1981
3: [0.323, 0.420)	0.368	splink	Rick		Schultheis	Richard	Thomas	Schultheis	1991 / 1954
2: [0.215, 0.323)	0.323	splink	Diane		Dotson	Diane	Marie	Dotson	1980 / 1969
2: [0.215, 0.323)	0.321	splink	Christian		Galvez	Crystian		Galvez	1996 / 1996
2: [0.215, 0.323)	0.249	fuzzylink	Mike		Quackenbush	Michael	Aaron	Quackenbush	1976 / 1976
1: [0.000, 0.215)	0.214	splink	Taylor		Jacobs	Taylor	Lindsey	Jacobs	1996 / 1998
1: [0.000, 0.215)	0.149	fuzzylink	Richie		White	Richard	W	White	1976 / 1935
1: [0.000, 0.215)	0.146	fuzzylink	Chuck		Tebussek	Charles	David	Tebussek	– / 1948

NOTES: As described in the text, the birth year measure from Revelio represents a very rough approximation based on length of time in the labor market. As illustrated in the table, this variable factored much less prominently than name in determining probable matches.

Table A5 Summary Statistics for VRscores Employers (2024)

Panel A: Coverage

Metric	Value
Employers represented	534,392
Matched employees (imputed)	24,533,608
Workers with two-party registration (raw)	69.7%
Workers with imputed two-party affiliation	88.7%
Unique MSAs represented	414
Unique NAICS industries	1,014
Unique occupations (O*NET)	383

Panel B: Employer Size Distribution and Partisan Mix

Size (workers)	Employers (count / share)	Employees (count / share)	Registered two-party share	Imputed two-party share
<10	259,464 / 48.6%	1,675,737 / 6.8%	69.9%	88.8%
10–24	160,523 / 30.0%	2,380,979 / 9.7%	69.9%	88.9%
25–49	55,618 / 10.4%	1,904,733 / 7.8%	70.0%	89.0%
50–99	28,823 / 5.4%	1,983,302 / 8.1%	70.2%	89.2%
100–249	17,887 / 3.3%	2,726,449 / 11.1%	70.2%	89.1%
250–499	6,081 / 1.1%	2,106,713 / 8.6%	69.9%	89.0%
500–999	3,165 / 0.6%	2,185,575 / 8.9%	69.8%	88.9%
1,000+	2,831 / 0.5%	9,570,120 / 39.0%	69.3%	88.3%

Panel C: Employer Partisan Balance (Imputed Two-Party)

Category	Share of employers	Share of workers (imputed two-party)
Employers majority Republican (imputed margin)	35.9%	27.1%
Employers majority Democratic (imputed margin)	56.6%	71.1%
Employers with equal imputed two-party share	7.5%	1.8%

Notes: Statistics use the 2024 VRscores employer-year panel (`rcid_panel_year_2024.parquet`). Headcounts rely on imputed partisan worker totals. Registered shares draw on raw (non-imputed) voter registration counts, while imputed shares use the imputed partisan headcounts. Panel B reports the share of workers in each size bin with Democratic or Republican affiliation using raw registrations ("Registered") and using the imputed affiliation measure ("Imputed"); the complements are workers registered outside the two major parties. Unique MSA and NAICS counts are based on modal assignments in the employer panel; occupation counts use distinct O*NET codes in the occupation-year panel. Partisan majorities classify each employer by the sign of the imputed two-party margin (Republican share minus Democratic share) among workers with two-party registration, and the worker shares rely on imputed two-party headcounts. Ties occur when the imputed two-party shares are exactly equal.

Table A6 VRscores Employer Panel Coverage by Year

Year	Employers	Employees	Workers two-party (raw share)	Workers two-party (imputed share)	Employers majority Republican (imputed)	Employers majority Democratic (imputed)
2012	370,426	17,269,623	72.3%	91.4%	40.9%	51.7%
2013	393,571	18,305,957	72.0%	91.1%	40.1%	52.5%
2014	417,604	19,310,604	71.6%	90.8%	39.3%	53.3%
2015	439,982	20,277,435	71.3%	90.5%	38.5%	54.1%
2016	461,191	21,175,482	71.0%	90.3%	37.8%	54.8%
2017	482,144	22,056,108	70.7%	90.0%	37.2%	55.5%
2018	502,104	22,923,980	70.5%	89.8%	36.6%	55.9%
2019	516,553	23,633,086	70.3%	89.5%	36.4%	56.2%
2020	525,013	23,784,580	70.1%	89.4%	36.3%	56.3%
2021	535,238	24,254,543	69.9%	89.1%	36.0%	56.5%
2022	539,944	24,705,857	69.8%	88.9%	35.9%	56.6%
2023	540,676	24,750,017	69.7%	88.7%	35.8%	56.7%
2024	534,392	24,533,608	69.7%	88.7%	35.9%	56.6%

Notes: Coverage statistics use employer-year panel files (`rcid_panel_year_YYYY.parquet`). Two-party shares reflect the proportion of workers with Democratic or Republican affiliation. Employer majority indicators rely on the imputed two-party margin.

Table A7 Top 15 MSAs by VRscores Employment (2024)

MSA	Workers (count / share)	Registered Rep two-party share	Imputed Rep two-party share
New York-Northern New Jersey-Long Island NY-NJ-PA MSA	1,839,116 / 10.1%	31.5%	31.9%
Chicago-Naperville-Joliet IL-IN-WI MSA	823,304 / 4.5%	33.9%	33.2%
Los Angeles-Long Beach-Santa Ana CA MSA	759,951 / 4.2%	32.2%	32.4%
Boston-Cambridge-Quincy MA-NH MSA	571,944 / 3.1%	28.9%	26.7%
Seattle-Tacoma-Bellevue WA MSA	557,885 / 3.1%	29.2%	29.1%
Washington-Arlington-Alexandria DC-VA-MD-WV MSA	551,650 / 3.0%	29.1%	29.4%
Dallas-Fort Worth-Arlington TX MSA	488,913 / 2.7%	51.2%	50.5%
Houston-Sugar Land-Baytown TX MSA	462,308 / 2.5%	50.6%	50.5%
Philadelphia-Camden-Wilmington PA-NJ-DE-MD MSA	454,922 / 2.5%	35.9%	36.0%
Minneapolis-St. Paul-Bloomington MN-WI MSA	360,095 / 2.0%	49.7%	46.7%
San Francisco-Oakland-Fremont CA MSA	351,687 / 1.9%	21.6%	22.2%
Detroit-Warren-Livonia MI MSA	331,203 / 1.8%	38.3%	39.7%
Phoenix-Mesa-Scottsdale AZ MSA	308,352 / 1.7%	50.3%	50.0%
Charlotte-Gastonia-Concord NC-SC MSA	308,017 / 1.7%	46.2%	44.5%
Denver-Aurora CO MSA	271,546 / 1.5%	39.3%	37.8%

Notes: Rankings use the 2024 VRscores employer-year panel. Counts are based on imputed partisan headcounts. The "Registered" column reports the Republican share among workers with observed two-party registration; the "Imputed" column reports the Republican share after applying the imputation to workers without partisan registration.

Table A8 VRscores Occupation Summaries (2024)

Panel A: SOC Major Groups

Occupation	Workers (count / share)	Registered Rep two-party share	Imputed Rep two-party share
11 Management Occupations	4,553,767 / 16.4%	47.0%	46.3%
13 Business and Financial Operations Occupations	2,857,004 / 10.3%	44.6%	43.4%
41 Sales and Related Occupations	2,639,389 / 9.5%	50.5%	49.4%
43 Office and Administrative Support Occupations	2,343,690 / 8.4%	40.5%	40.4%
15 Computer and Mathematical Occupations	2,292,865 / 8.3%	40.8%	40.4%
27 Arts, Design, Entertainment, Sports, and Media Occupations	2,064,119 / 7.4%	32.2%	32.6%
25 Educational Instruction and Library Occupations	1,857,490 / 6.7%	33.2%	33.7%
29 Healthcare Practitioners and Technical Occupations	1,648,663 / 5.9%	42.6%	41.7%
17 Architecture and Engineering Occupations	1,362,021 / 4.9%	48.1%	46.8%
53 Transportation and Material Moving Occupations	948,531 / 3.4%	46.2%	46.4%
19 Life, Physical, and Social Science Occupations	721,988 / 2.6%	31.0%	30.7%
23 Legal Occupations	628,627 / 2.3%	35.8%	35.9%
35 Food Preparation and Serving Related Occupations	614,049 / 2.2%	33.5%	33.6%
51 Production Occupations	570,056 / 2.1%	46.9%	47.6%
39 Personal Care and Service Occupations	543,965 / 2.0%	36.6%	36.1%
21 Community and Social Service Occupations	516,561 / 1.9%	28.8%	29.8%
31 Healthcare Support Occupations	446,004 / 1.6%	35.4%	35.5%
47 Construction and Extraction Occupations	359,709 / 1.3%	55.9%	56.0%
49 Installation, Maintenance, and Repair Occupations	344,758 / 1.2%	56.9%	57.2%
33 Protective Service Occupations	322,469 / 1.2%	46.3%	45.8%
37 Building and Grounds Cleaning and Maintenance Occupations	106,998 / 0.4%	40.1%	40.8%
45 Farming, Fishing, and Forestry Occupations	47,322 / 0.2%	46.2%	46.6%

Panel B: Top 15 Occupations by VRscores Employment

Occupation	Workers (count / share)	Registered Rep two-party share	Imputed Rep two-party share
Substitute Teachers, Short-Term	645,970 / 2.3%	36.0%	36.0%
Career/Technical Education Teachers, Secondary School	588,630 / 2.1%	33.7%	34.3%
Software Developers	534,862 / 1.9%	34.1%	33.2%
Sales Managers	531,824 / 1.9%	57.7%	56.5%
Chief Executives	402,850 / 1.4%	48.9%	48.6%
Acute Care Nurses	400,388 / 1.4%	41.6%	40.5%
Mechanical Engineers	380,520 / 1.4%	51.7%	50.0%
Real Estate Sales Agents	376,211 / 1.4%	56.1%	54.8%
Search Marketing Strategists	375,917 / 1.4%	36.3%	35.7%
Customer Service Representatives	367,530 / 1.3%	36.0%	36.7%
Marketing Managers	352,422 / 1.3%	46.6%	45.2%
Physician Assistants	336,159 / 1.2%	40.5%	39.6%
Real Estate Brokers	330,055 / 1.2%	56.1%	54.0%
Lawyers	313,954 / 1.1%	37.2%	37.5%
Social and Human Service Assistants	305,993 / 1.1%	25.0%	26.3%

Notes: Rankings use the 2024 VRscores occupation-year panel (`occupation_panel_year_2024.parquet`). Counts are based on imputed partisan headcounts. Share pairs report the Republican share among two-party workers and the share of workers outside the two major parties. The "Registered" column reports raw voter registration shares; the "Imputed" column reports shares after applying the imputation.

Table A9 VRscores Industry Summaries (2024)

Panel A: Two-Digit NAICS Sectors

Industry	Workers (count / share)	Registered Rep two-party share	Imputed Rep two-party share
31-33 Manufacturing	3,218,037 / 13.1%	49.1%	48.1%
54 Professional, Scientific, and Technical Services	2,754,473 / 11.2%	41.0%	40.4%
52 Finance and Insurance	2,537,544 / 10.4%	46.3%	44.9%
62 Health Care and Social Assistance	2,462,963 / 10.1%	38.5%	38.3%
92 Public Administration	2,387,359 / 9.7%	38.9%	39.5%
61 Educational Services	2,299,426 / 9.4%	32.6%	33.1%
51 Information	2,081,340 / 8.5%	35.9%	35.7%
44-45 Retail Trade	1,443,896 / 5.9%	40.7%	40.7%
81 Other Services (except Public Administration)	774,561 / 3.2%	37.7%	37.9%
56 Administrative and Support and Waste Management	717,610 / 2.9%	43.0%	42.9%
53 Real Estate and Rental and Leasing	701,282 / 2.9%	50.8%	49.3%
72 Accommodation and Food Services	634,904 / 2.6%	36.6%	36.9%
48-49 Transportation and Warehousing	597,712 / 2.4%	47.2%	47.3%
42 Wholesale Trade	558,785 / 2.3%	53.6%	52.7%
23 Construction	522,895 / 2.1%	56.5%	55.2%
71 Arts, Entertainment, and Recreation	400,116 / 1.6%	34.4%	34.6%
22 Utilities	201,405 / 0.8%	50.2%	49.7%
21 Mining, Quarrying, and Oil and Gas Extraction	124,743 / 0.5%	61.3%	60.9%
11 Agriculture, Forestry, Fishing and Hunting	51,862 / 0.2%	46.7%	46.2%
55 Management of Companies and Enterprises	23,130 / 0.1%	45.0%	45.1%

Panel B: Top 15 Industries by VRscores Employment

Industry	Workers (count / share)	Registered Rep two-party share	Imputed Rep two-party share
Colleges, Universities, and Professional Schools	1,759,194 / 7.2%	31.5%	32.0%
Software Publishers	1,042,541 / 4.2%	37.3%	36.7%
Executive and Legislative Offices, Combined	863,409 / 3.5%	38.2%	38.7%
General Medical and Surgical Hospitals	770,199 / 3.1%	40.5%	40.0%
Commercial Banking	557,324 / 2.3%	46.2%	44.9%
Portfolio Management and Investment Advice	387,527 / 1.6%	47.7%	44.9%
Other Computer Related Services	331,310 / 1.4%	42.9%	42.4%
Offices of Real Estate Agents and Brokers	315,955 / 1.3%	51.9%	50.1%
Offices of Lawyers	292,903 / 1.2%	35.1%	35.0%
Administration of Education Programs	289,512 / 1.2%	36.6%	37.0%
Engineering Services	279,529 / 1.1%	51.2%	50.2%
Elementary and Secondary Schools	276,195 / 1.1%	37.0%	36.9%
National Security	271,528 / 1.1%	51.2%	51.4%
Pharmaceutical Preparation Manufacturing	255,956 / 1.0%	42.7%	40.8%
All Other Miscellaneous Ambulatory Health Care Services	223,345 / 0.9%	37.5%	37.2%

Notes: Rankings use the 2024 VRscores employer-year panel. Counts are based on imputed partisan headcounts. The "Registered" column reports the Republican share among workers with observed two-party registration; the "Imputed" column reports the Republican share after applying the imputation to workers without partisan registration.