Political segregation in the US workplace

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Abstract

Using a novel dataset created by matching employment histories with voter registration data for 45.3 million workers, we provide the first large-scale estimate of workplace political segregation in the United States. We present four main findings. First, partisans are strongly segregated by workplace. The average Democrat's coworkers are 11.7 percentage points more Democratic than the average Republican's; the magnitude of workplace political segregation is similar to segregation by gender. There is considerable geographic variation in the extent to which individuals experience greater political segregation at work or in the neighborhoods where they live. Even after controlling for sorting by geography, industry, and occupation, substantial political segregation remains. Second, segregation is largest among those who are politically active and those who plausibly enjoy greater market power. Third Republicans experience significantly higher exposure to Democrats at work than vice versa, with the median Republican working in an environment where 50% of their coworkers are Democrats, compared to 32% of Republican co-workers for the median Democrat. Fourth, political workplace segregation has increased only modestly since 2012.

Keywords: partisan segregation, politics at work, polarization, labor markets, business and politics

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Political partisans in the United States are increasingly segregated along geographic and social dimensions. Partisans sort into predominantly “blue” or “red” regions, states, cities, and neighborhoods (Brown and Enos 2021, Brown et al. 2023, Lang and Pearson-Merkowitz 2015, Kaplan et al. 2022, Mummolo and Nall 2016). Democrats are more likely to attend college (Downey and Liu 2023, Zingher 2022) while Republicans are more likely to attend religious services (Mason 2015). Worshipers from both parties tend to share the pews with co-partisans (Malina and Hersh 2021, Margolis 2018). In marriage and courtship, partisans prefer copartisans and increasingly pass their political affiliation to their children (Huber and Malhotra 2017, Klofstad et al. 2013, Iyengar et al. 2018). Increased political segregation has coincided with rising “affective polarization”—i.e., the tendency of political partisans to dislike and distrust members of the opposing party (Iyengar and Westwood 2015, Iyengar et al. 2019)—raising concerns that declining inter-partisan contact contributes to partisan animosity (Ahler and Sood 2018).

Despite growing evidence of political segregation across many domains of everyday life, political segregation at work remains understudied. This gap is significant. For one, Americans spend far more waking hours at work than in any other activity (Bureau of Labor Statistics 2023). Crucially, this time at work constitutes a rare opportunity for the sort of sustained, cooperative, cross-partisan contact that may reduce prejudice across societal groups (Corno et al. 2022, Green and Hyman-Metzger 2024, Mutz and Mondak 2006). In fact, the workplace may be one of the few domains that meets Allport’s (1979) criteria for prejudice-reducing intergroup contact inasmuch as it is frequently characterized by relatively equal status among participants, a common group goal that requires cooperation across members of different groups, and the support of relevant authorities. Almost by definition, coworkers cooperate in teams to achieve a common objective that has been set by a superior. Residential neighbors, by contrast, often interact only superficially, and are less likely to interact at all if they are not copartisans (Parker et al. 2018). Moreover, employment frequently constitutes an important source of social identity (Akerlof and Kranton 2000), meaning that workplaces with partisan diversity may constitute sources of cross-cutting cleavages which strengthen democratic norms (Wojcieszak and Warner 2020).

Despite the apparent importance of workplace political segregation, research on this topic in the United States has focused on top managers or specific occupations or provided only small-scale experimental evidence that rank-and-file employees might sort by partisanship. Analyses of top managers reveal that boards of directors are increasingly politically homogeneous (Hoang et al. 2022, Fos et al. 2022). Experiments involving employee hiring suggest that rank-and-file employees prefer to work for companies that share their political ideology and/or partisanship (Carpenter and Gong 2015, Burbano 2020, McConnell et al. 2018) and that employers also prefer to hire politically like-minded candidates (Gift and Gift 2015, Colonnelli et al. 2024). Given the absence of legal protection or strong norms against political discrimination in hiring, scholars have theorized that workplace segregation may be more pronounced than segregation based on legally protected categories such as gender (Iyengar and Westwood 2015). Recent research suggests that, at least in Brazil, this is the case (Colonnelli et al. 2024). To date, however, there has been no large-scale estimate of the extent of political segregation in the US workplace.

We address this gap by merging administrative data from a national voter file with a separate dataset of online employee profiles from Revelio Labs (LinkedIn). We merge these datasets via an ensemble approach that uses longstanding probabilistic approaches (Enamorado et al. 2019, Fellegi and Sunter 1969) as well as more recent LLM-based techniques (Ornstein 2024). Full details of our source data and matching strategy can be found in the Methods section below. Our full dataset contains over 45.3 million unique workers. The primary analysis is performed on a 2024 snapshot of 31.0 million unique workers, representing 30% of attempted matches, 19% of registered voters, and 18% of the US workforce. To conduct temporal analysis, we also extend our 2024 matches backwards in time to construct a panel of position-years spanning 2012-2024. To the best of our knowledge, this dataset represents the broadest and most extensive coverage of partisanship in the US labor force.

Our coverage exceeds that of comparable studies. For instance, our dataset compares favorably to work-in-progress by Chinoy and Koenen (2024) and surpasses the 7.8% coverage of the Brazilian labor market achieved by Colonnelli et al. (2024).[1] When benchmarked against a nationally representative sample, our data compares well in terms of partisanship and gender. As is inherent to online profile data, our sample is moderately skewed towards white-collar industries and occupations. Despite this, our data constitutes a significant improvement on past attempts to characterize worker partisanship which rely upon political donation records (Bonica 2014, Gupta et al. 2017, Li and Disalvo 2022). Not only do very few workers donate (Stuckatz 2022a, Barber IV and Blake 2023), but donors tend be exceptionally old, white, and educated (Grumbach and Sahn 2020, Bonica and Grumbach 2022) and thus are likely far more unrepresentative of the overall employee population.

We present four key findings regarding political segregation in the US labor market. First, partisans

[1] Chinoy and Koenen (2024) are able to match 34.5 million workers using a different matching approach and source data, versus 45.3 million in our approach. Most of their analyses are conducted using a smaller analytical “coworker sample” of 20.3 million workers, versus 31.0 million in our approach.

are segregated by workplace. The average Democrat works in an environment that is 11.7 percentage points ($p < 0.001$, 95% CI: $[10.5, 12.9]$) more Democratic than the workplace of the average Republican. We also compare the extent of political segregation that individuals experience at work with residential political segregation they experience at home and find significant spatial variation. In some metropolitan areas, workers are more likely to encounter members of the opposing party at work, while in others, they are more likely to encounter out-partisans at home. After netting out sorting by occupation, industry, and geography, this political segregation is comparable and by some measures larger than estimates of gender segregation. Using fixed-effect regressions, we show that substantial political segregation persists even within narrowly defined labor markets. Our most restrictive specification finds that even controlling for gender, race, home census tract, industry, and occupation, a Republican is still likely to have about 3 percentage points more Republican co-workers relative to a Democrat.

Second, political segregation varies by worker characteristics. Notably, segregation is greater among workers who participate more in politics (e.g., by voting in Presidential primaries and/or making political donations). Segregation is also higher among workers who plausibly enjoy greater market power, including white workers, younger workers, workers in occupations that require greater training and preparation, and those in senior management roles. These patterns suggest that workers who care more about politics and have more employment options are more likely to sort themselves into politically homogeneous workplaces.

Third, we find that partisan-based workplace segregation has increased only very modestly between 2012-2024. New hires show some tendency to increasingly join firms where a higher share of coworkers share their partisanship.

Fourth, Republicans experience significantly higher exposure to Democrats at work than vice versa. This asymmetry in out-partisan exposure is driven in part by the fact—visible in nationally representative surveys as well as in our dataset—that Democrats comprise a greater share of workers than Republicans. This baseline difference is further magnified by political segregation. We close by discussing how the novel data and measures we present here can inform future work into the causes and consequences of workplace political segregation.

Results

Main Estimates

This paper examines the workplace experiences of individual employees rather than political composition of companies as a whole. Specifically, we focus on the extent to which the coworkers of a focal employee share this focal employee's partisanship. Given this focus, our methodology differs from existing work on company-level characteristics, such as political diversity within boards (Fos et al. 2022) or manager-employee dyads (Colonnelli et al. 2024). Instead, our approach most closely relates to work by Brown and Enos (2021) which captures geographic residential segregation using the partisanship of residential neighbors. We adopt a similar approach: for each worker, we conceptualize coworkers as the set of all positions that share a workplace—i.e., are at the same company and located within the same MSA (excluding the focal worker).

To define a worker's politics, we begin with voters who are formally registered with either the Democratic or Republican party and extend our analysis by imputing the likely partisan "lean" for registered independents, third-party members, and registered voters who decline to affiliate with any political party. Our approach to imputing partisan lean is motivated by research which suggests that true independents are rare; nearly all nominally "independent" voters consistently favor one of the two major parties (Keith et al. 1992, Klar 2014, Petrocik 2009). Our approach to imputation follows Brown and Enos (2021). We first assign partisan lean to unaffiliated voters with a recent past history of voting in either the Democratic or Republican primary. For voters registered with a third-party with a clear left-right ideology we assign them as "leaners" to the appropriately ideologically-aligned party.[2] For the remaining voters, we use a Bayesian modeling approach that incorporates both geographic and demographic imputation to impute voters' likely partisan lean.

In our main analysis, we focus on the most up-to-date snapshot of positions as of the time of our study. This sample comprises all positions that were active at any point from the start of 2024 through April 2025. Additional details on the source data, merge strategy, and imputation methodology are provided in the Methods section.

[2] For example, the Green Party is considered to lean Democratic while the Libertarian party is considered to lean Republican. We follow the party classifications of Brown and Enos (2021).

Formally, we define the share of Republican coworkers for a given position as:

$$ShareRep_{i,e,m} = \frac{\sum_{j=1,j\neq i}^{n_{e,m}} \mathbf{1}(p_j = \text{Rep})}{n_{e,m} - 1}$$

where $ShareRep_{i,e,m}$ is the share of coworkers for a worker's focal position i at employer e and MSA m that are Republicans (including Republican leaners).[3] The term $n_{e,m}$ is the number of positions in firm e in MSA m, and $p_j \in \{\text{Dem}, \text{Rep}\}$ is the partisanship of coworker j, such that $\mathbf{1}(p_j = \text{Rep})$ is equal to one if coworker j is a Republican and zero if she is a Democrat.

Because a focal worker must have at least one co-worker in order for our measure to be defined, our main analysis focuses on workplaces with at least two employees; our results are robust to a range of higher number-of-coworker inclusion thresholds. Sub-figure A of Figure 1 presents the kernel density plot of the overall distribution of the share of coworkers that are Republican, illustrating that the average worker (regardless of his or her party) experiences fewer Republicans (about 40.6%) and more Democratic coworkers (about 59.4%).

Sub-figure B of Figure 1 illustrates the degree of political segregation, showing that the average share of Republican coworkers varies significantly according to the partisanship of the focal worker. The mean Democrat's coworkers are 35.8% Republicans, while the mean Republican's coworkers are 47.5% Republicans—an 11.7 percentage point difference ($p < 0.001$, 95% CI: [10.5, 12.9]).

Geographic Variation in Workplace Segregation

Having established that political workplace segregation exists (Figure 1), we next examine how this segregation varies geographically. Our approach involves two key steps that allow us to separate workplace-specific sorting from residential sorting patterns.

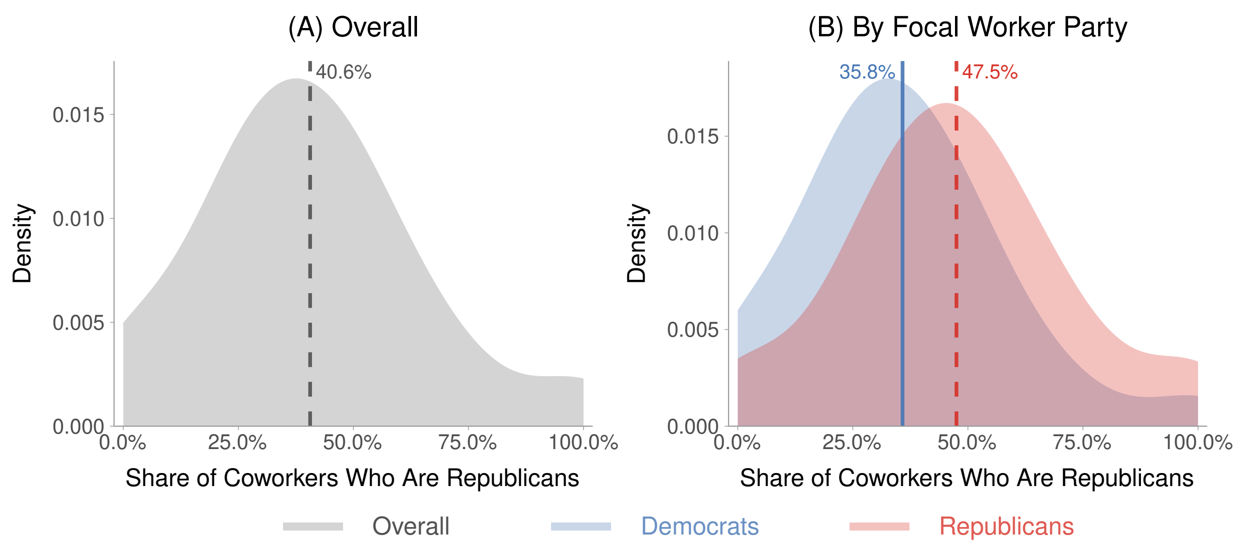
First, for each of the 366 metropolitan areas in our sample, we calculate each level of raw workplace segregation using the following specification:

$$ShareRep_{i,e,m} = \alpha_m + \beta_m Rep_{i,e,m} + \epsilon_{i,e,m}, \tag{1}$$

separately for each metropolitan area m. The coefficient β_m measures the raw partisan gap for each work-

[3] All analyses that refer to Democrats or Republicans include leaners unless otherwise specified.

Figure 1: Nationwide distribution of coworkers that are Republican, overall and by focal worker partisanship



NOTES: Sub-figure (A) presents the overall distribution of the share of coworkers who are Republicans across all positions. Sub-figure (B) presents the same distribution separately for Democratic and Republican focal workers, illustrating political segregation. Densities are estimated using a fixed bandwidth of 0.1; vertical lines indicate mean values (dashed gray in panel A; solid blue for Democrats and dashed red for Republicans in panel B). The sample is restricted to workers identified as Democrats or Republicans using imputed partisanship measures, and we include only workplaces with at least two employees. Republican coworker exposure is measured as the share of coworkers who are Republicans in the focal worker's establishment, calculated using two-party share measures. Analysis was conducted on our analytical sample of 37,200,614 positions for 30,965,666 workers. Figure A5 provides corresponding histograms.

ers' coworkers in each MSA. Panel A of Figure 2 maps these coefficients, revealing that while workplace segregation is a ubiquitous feature of the American workplace, its intensity varies significantly by region. The highest levels are heavily concentrated in the Deep South, with MSAs such as Montgomery, AL, and New Orleans, LA exhibiting the most pronounced sorting. High levels of segregation are also notable in the Industrial Midwest. In contrast, the lowest levels of sorting are found in the Great Plains and Mountain West.

The raw workplace segregation shown in Panel A, however, likely reflects two factors: (1) workplace-specific sorting and (2) the fact that Republicans and Democrats live and work in different neighborhoods within an MSA. To isolate workplace-specific patterns, we ask: "How much workplace segregation would we expect in each metro area given its level of residential segregation?" To answer this, we first formally measure residential segregation for each metro area (m) using the following model:

$$CensusTractRepShare_{i,m} = \alpha_m^{\text{res}} + \delta_m \text{Rep}_{i,m} + \epsilon_{i,m}^{\text{res}} \tag{2}$$

where $CensusTractRepShare_{i,m}$ is the Republican share of voters in individual i's residential census tract (estimated using the full voter file) and $\text{Rep}_{i,m}$ is an indicator variable for whether individual i is a Republican. The resulting coefficient, δ_m, captures the level of residential segregation for that MSA.

We then predict workplace segregation from residential segregation using:

$$\beta_m = \gamma_0 + \gamma_1 \cdot \delta_m + \nu_m, \tag{3}$$

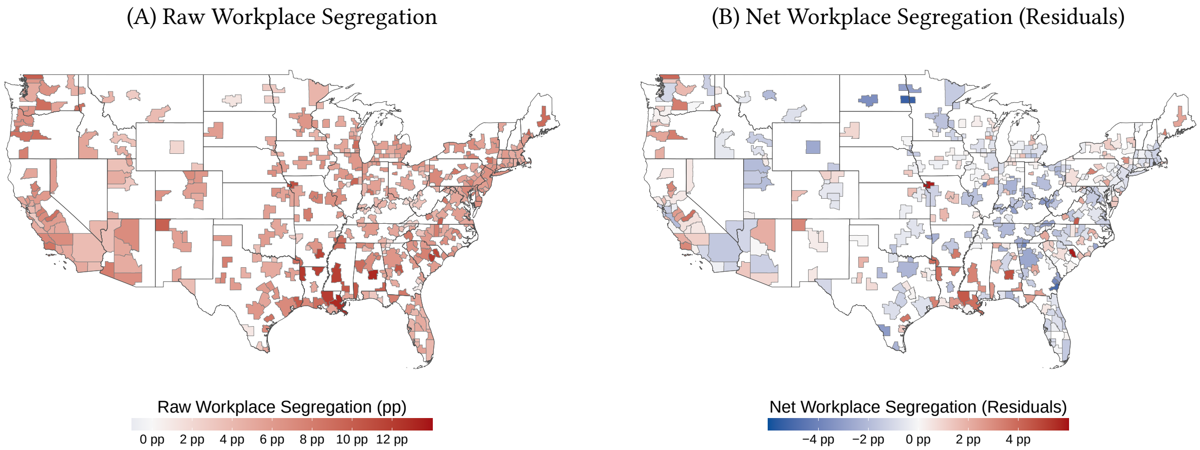
where β_m is the raw workplace segregation from Equation 1 and δ_m is the residential segregation coefficient from Equation 2. The residuals from this model, ν_m, represent the "net" workplace segregation that is unexplained by residential patterns. Negative residuals indicate that workers experience less political segregation at work than in their residential areas. Panel B of Figure 2 maps these residuals. The data suggest that net workplace segregation is systematically related to the economic and institutional character of an MSA. Large metropolitan areas consistently show negative residuals, with all of the largest 20 MSAs exhibiting less workplace segregation than their residential patterns would predict. This includes major "knowledge economy" and technology hubs like San Jose, CA, San Francisco, CA, Seattle, WA, Austin, TX, and Boston, MA exhibit negative residuals, suggesting that these areas have more political integration at work than within residential neighborhoods. Taken together, these analyses demonstrate that while raw workplace segregation follows broad regional contours, the underlying drivers are likely also tied to the specific economic and institutional characteristics of the metropolitan area. d

Political Segregation Across Industries and Occupations

The geographic variation in workplace segregation documented in Figure 2 suggests that broader political sorting processes influence where partisans work. However, workplace segregation may also reflect the fact that Republicans and Democrats systematically sort into different types of work—i.e., different industries and occupations—even if they live in the same areas.

To examine how partisanship varies across different types of work, Figure 3 presents ridge plots showing the distribution of Republican coworker exposure across selected industries and occupations. Panel A of Figure 3 shows the overall distribution of Republican coworker exposure, which is equivalent to Panel A of Figure 1. Panel B shows selected industries spanning the political spectrum, revealing dramatic differences in partisan exposure by industry and occupation. For example, workers in Museums and

Figure 2: Workplace Political Segregation Across Metropolitan Areas



NOTE: Panel A maps the MSA-specific coefficients β_m from Equation 1—the raw difference in Republican coworker exposure between Republican and Democratic workers in each metropolitan area. Panel B maps the residuals v_m from Equation 3—workplace segregation that cannot be explained by existing census tract measures of residential segregation (Equation 2). Red areas in Panel B have more workplace segregation than their residential patterns predict; blue areas have less. The analysis is based on approximately 37.2 million positions held by 31 million workers in 366 metropolitan areas; the contiguous US map shown here displays 363 of these MSAs. See Tables A1 and A2 in the appendix for complete MSA-level coefficients and residuals.

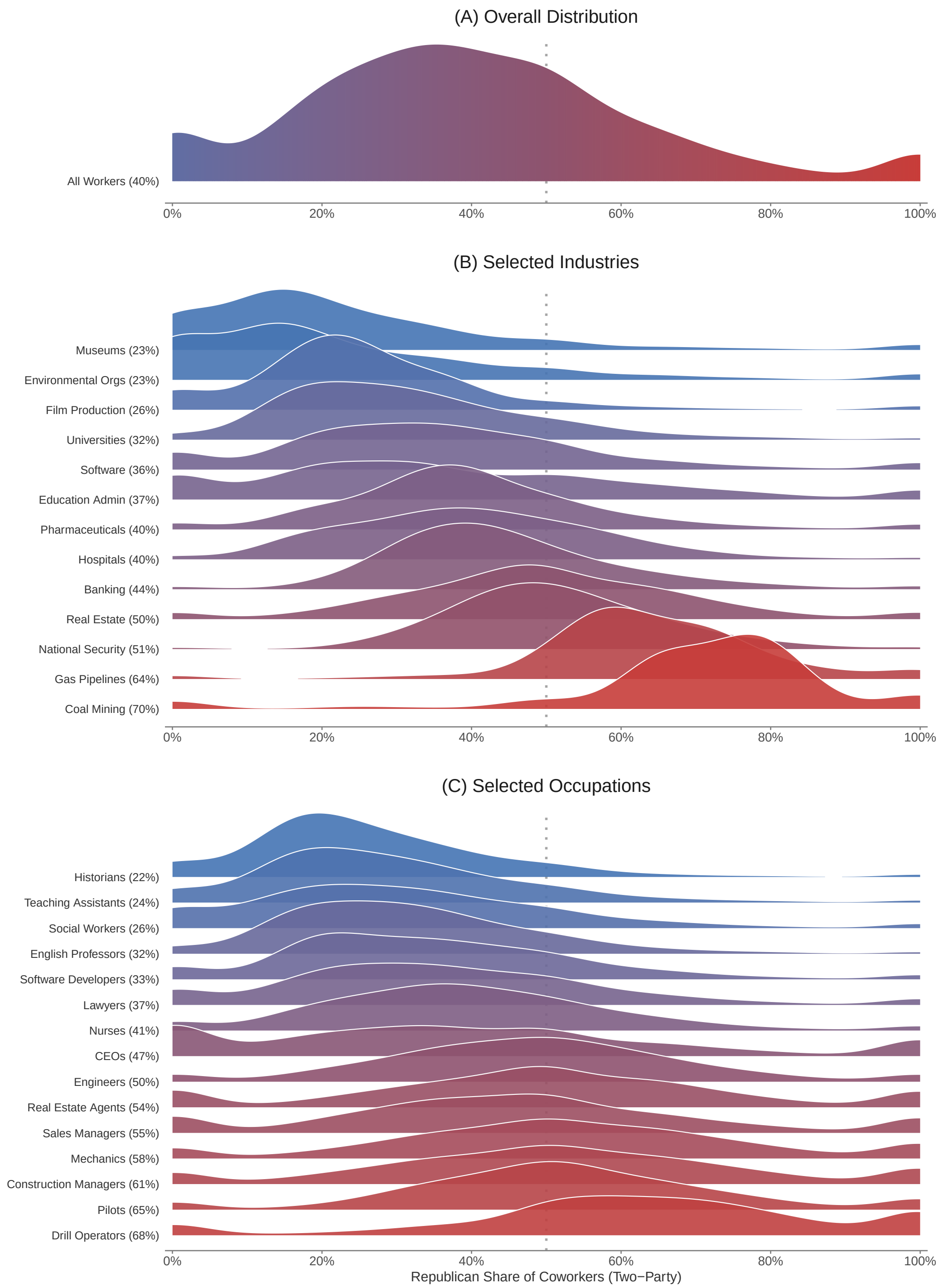
Environmental Organizations experience, on average, only 23% Republican coworkers. In contrast, those in Gas Pipelines and Coal Mining experience 64% and 70% Republican coworkers, respectively. Panel C shows selected occupations with similarly pronounced political sorting. Historians and Social Workers experience, on average, only 22% and 26% Republican coworkers. Meanwhile, Pilots and Drill Operators experience 65% and 68% Republican coworkers respectively. Ridge plots showing the distribution of Republican coworker exposure across all 2-digit NAICS industry codes and 2-digit SOC occupation codes are presented in Figures A7 and A8 in the appendix, respectively.

This occupational and industrial sorting represents a key mechanism through which partisans may experience workplace segregation even within the same geographic area. Workers choosing careers aligned with their political values or being drawn to industries and occupations with compatible worldviews would generate partisan workplace clustering independent of residential sorting patterns.

Accounting for Geography, Occupation, and Industry

Having documented political segregation across geography (Figure 2), industries, and occupations (Figure 3), we now turn to our central analytical question: do workers sort into politically homogeneous workplaces beyond what would be expected from their residential, occupational, and industrial choices? Our

Figure 3: Ridge plots showing partisan compositions across occupations and industries



NOTE: Ridge plots show the distribution of Republican coworker share (two-party) across selected industries (Panel B) and occupations (Panel C), with Panel A showing the overall distribution across all observations. Panel B displays selected industries. Panel C displays selected occupations. Vertical line indicates political balance (50% Republican). Kernel density estimates use fixed bandwidth = 0.05. The full sample covers 37.2 million positions held by 31 million workers.

empirical strategy involves estimating increasingly restrictive specifications of Equation 4, progressively adding fixed effects to examine political sorting net of other types of sorting. We estimate:

$$ShareRep_{i,e,m} = \alpha + \beta Rep_{i,e,m} + \boldsymbol{\lambda_j} + \epsilon_{i,e,m} \tag{4}$$

which is nearly identical to Equation 1 but adds a vector of fixed effects, $\boldsymbol{\lambda_j}$.

We additionally re-estimate Equation 4 in two ways. First, to account for the over-representation of white-collar workers in our sample, we fit a version of Equation 4 which weights observations by occupation. Our weights use Bureau of Labor Statistics Occupational and Employment Wage Statistics (OWES) to adjust our sample to match the national distribution of workers across occupations, thus accounting for potential sample selection bias arising from differential rates of voter registration, LinkedIn profile availability, and matching success. We discuss both our sample benchmarking exercises and the weighting strategy in more detail in the Methods section.

Second, we also benchmark our estimates of political sorting against analogously estimated measures of gender segregation.[4] This analysis is run on our sample of 37.2 million positions held by 31 million workers. We repeat the analysis but replace (1) the outcome variable $ShareRep$ with the variable $ShareWomen$, which, for the focal position, is the share of women coworkers, and (2) the explanatory variable Rep with $Woman$, which is a dummy equal to one if the focal worker is a woman.

In line with Figure 1, the raw estimate for political segregation in Figure 4 shows political segregation is 11.7 percentage points ($p < 0.001$, 95% CI: $[0.105, 0.129]$) unweighted and 10.7 percentage points ($p < 0.001$, 95% CI: $[0.085, 0.129]$) when weighting to BLS. This is somewhat lower than the raw gender segregation estimate, at 15.6 percentage points ($p < 0.001$, 95% CI: $[0.152, 0.160]$). However, the patterns diverge markedly as we account for industry and occupation. Occupation fixed effects reduce political segregation modestly to 9.4 percentage points BLS-weighted ($p < 0.001$, 95% CI: $[0.072, 0.116]$) from 10.2 percentage points unweighted ($p < 0.001$, 95% CI: $[0.092, 0.112]$) while dramatically reducing gender segregation to 8.4 percentage points ($p < 0.001$, 95% CI: $[0.082, 0.086]$), indicating that occupational sorting explains much more of gender than political workplace segregation. Industry fixed effects show a similar but less pronounced pattern (political: 8.6 percentage points BLS-weighted, $p < 0.001$, 95% CI: $[0.066, 0.106]$, 9.6 percentage points unweighted, $p < 0.001$, 95% CI: $[0.076, 0.116]$); gender: 7.2 percentage

[4] Gender is obtained from voter registration records where available, or imputed by L2 using modeling techniques based on first names.

points, $p < 0.001$, 95% CI: $[0.070, 0.074]$). We also include geography fixed effects based upon workers' residential address. Census tract fixed effects reduce political segregation substantially to 5.3 percentage points BLS-weighted ($p < 0.001$, 95% CI: $[0.047, 0.059]$), 5.9 percentage points unweighted ($p < 0.001$, 95% CI: $[0.055, 0.063]$) while barely affecting gender segregation (15.5 percentage points, $p < 0.001$, 95% CI: $[0.151, 0.159]$), demonstrating that fine-grained geographic sorting plays a much more important role in political versus gender workplace segregation. The use of census tract fixed effects allows us to compare workers who live in the same neighborhood but work for different employers, thereby isolating workplace-specific political sorting from residential segregation patterns.

In Panel B, we combine occupation, industry, and geography fixed effects additively. Both types of segregation decline substantially, with BLS-weighted political segregation (2.4 percentage points, $p < 0.001$, 95% CI: $[0.022, 0.026]$) now lower than gender segregation (5.3 percentage points, $p < 0.001$, 95% CI: $[0.051, 0.055]$). Using interactive occupation-industry-census tract fixed effects yields similar results: political segregation (2.9 percentage points, $p < 0.001$, 95% CI: $[0.025, 0.033]$) is about the same as gender segregation (2.8 percentage points,$p < 0.001$, 95% CI: $[0.024, 0.032]$).

Our strictest specifications (Panel C) control for demographics. Models examining political segregation include gender and race/ethnicity fixed effects. Models examining gender segregation include race/ethnicity and partisanship fixed effects. The additive specification shows BLS-weighted political segregation (2.1 percentage points, $p < 0.001$, 95% CI: $[0.019, 0.023]$) below gender segregation (5.3 percentage points ($p < 0.001$, 95% CI: $[0.051, 0.055]$), while the interactive specification shows similar levels 3.1 percentage points ($p < 0.001$, 95% CI: $[0.017, 0.045]$) vs. 2.7 percentage points ($p < 0.001$, 95% CI: $[0.023, 0.031]$). This suggests that after accounting for occupational, industrial, geographic, and demographic sorting, political and gender workplace segregation are of similar magnitude. Importantly, the BLS-weighted results shown in Figure 4 are substantively similar to unweighted estimates, assuaging sample selection concerns.

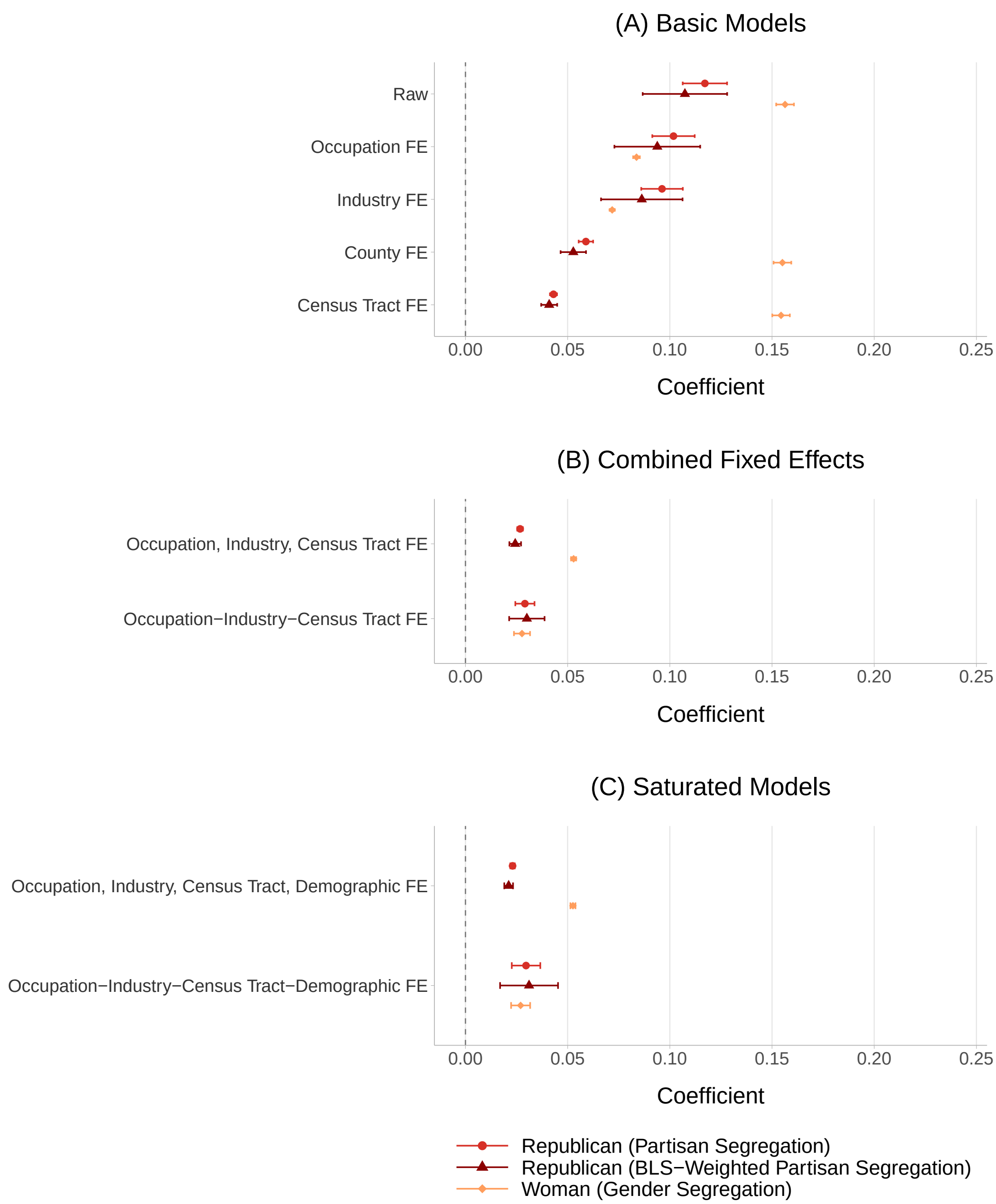
These fixed effects regressions quantify political sorting and provide descriptive insights into how political workplace segregation relates to other types of labor market sorting. However, it is important to note that these analyses do not isolate taste-based sorting along political lines. The analyses shown here focus on segregation within existing labor markets defined by geography, industry, and occupation, but it is also likely the case that labor market entry is endogenous in this context. Specifically, to the extent that workers' choices about where to live and what occupations and industries to pursue—and these decisions are at least in part motivated by politics—our observed estimates in these fixed effect analyses may be conservative underestimates of the true extent of taste-based sorting motivated by a preference for co-partisan co-workers. In the discussion section, we further discuss how these descriptive patterns might inspire future work that might further isolate the causes and consequences of political sorting across workplaces.

Specification Curves and Sensitivity Analysis

We made several methodological choices in calculating our estimates. We made these choices in light of our goal of understanding how workers experience their coworkers' partisanship in their workplaces and we discuss these choices in more detail in the Methods section. To demonstrate that our results are not contingent upon these choices, we conduct a multiverse analysis (specification curve) that systematically varies analytical specifications across multiple dimensions (Simonsohn et al. 2020). In the main analysis, we examine the two-party share while imputing Democratic or Republican partisan affiliation for workers who identify as independent, those affiliated with third parties, or those who do not disclose their partisanship, following Brown and Enos (2021). In Figure A9, we show that the results are qualitatively similar using measures of partisanship that rely on non-imputed voter registrations. Additionally, we demonstrate that our findings are robust to excluding workplaces with fewer than two, ten, or fifty matched workers. We also show that our results are robust to clustering standard errors at the MSA and employer level or simply estimating robust (non-clustered) standard errors. This multiverse analysis encompasses both our baseline specifications (equivalent to Equation 1) and full (additive) fixed effects models (equivalent to Equation 4), with results presented in Figure A9.

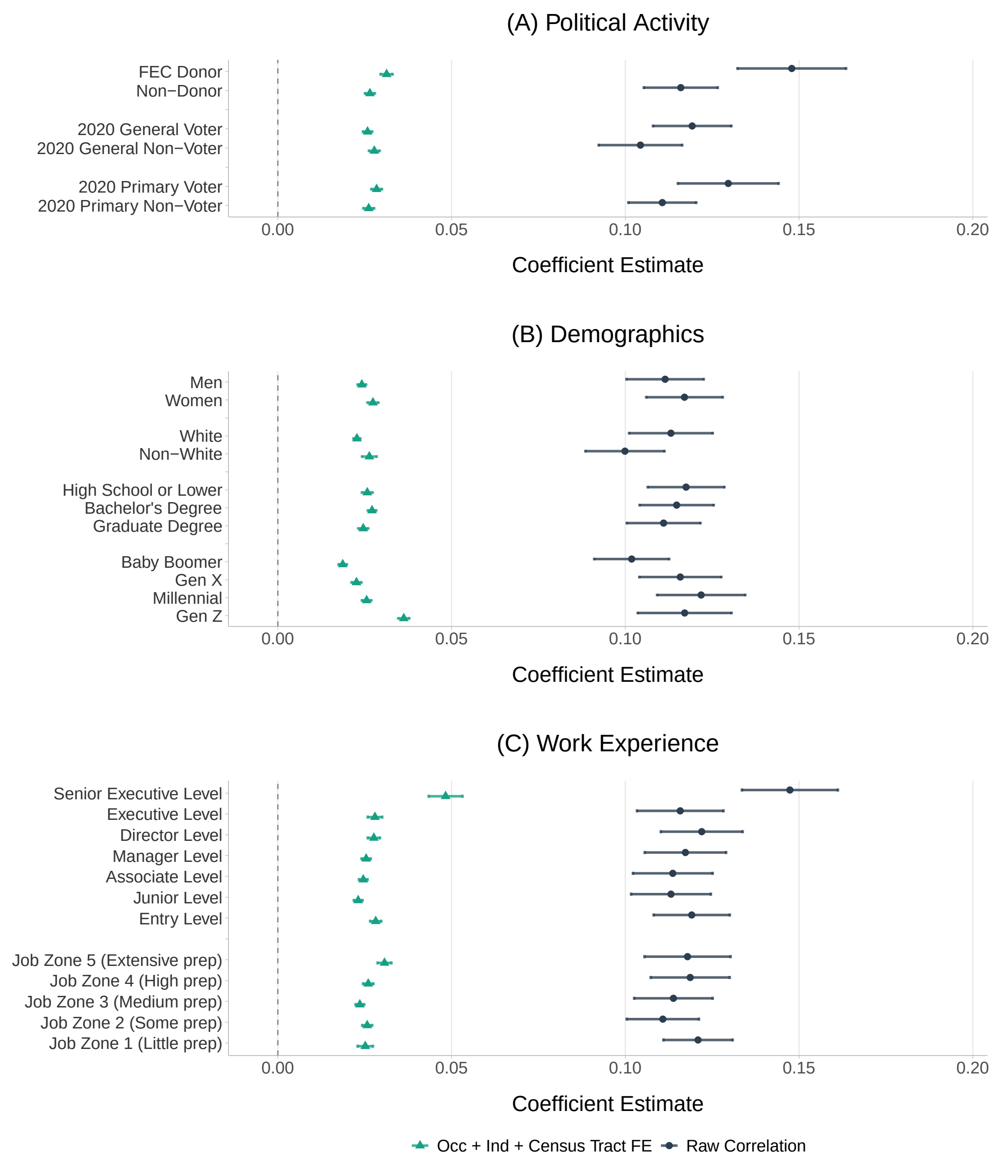
We also conduct sensitivity analysis around our decision to measure coworkers in terms of those that share a focal workers employer-MSA. While some companies (e.g., chain retailers) may have many locations within the same MSA, the population of workers within a given MSA represents an estimate of the population of workers with whom a focal worker could plausibly interact. Workers at the same company but in different MSAs are less likely to interact. To address potential measurement error that may arise when a firm has multiple establishments in a given MSA, we conduct sensitivity analysis restricting our sample to firms less likely to have multiple locations in a given MSA (employers with low overall number of workers and professional services firms); our results are robust to these restrictions (see Appendix Figure A10).

Figure 4: Estimated political segregation benchmarked against gender segregation



NOTES: Point estimates are from versions of Equation 1 and Equation 4 that differ in terms of whether they characterize political or gender workplace segregation and the fixed effects they include. All BLS–Weighted estimates are weighted using Bureau of Labor Statistics (BLS) Occupational Employment and Wage Statistics (OEWS) data to adjust for sample selection bias arising from voter registration, LinkedIn profile availability, and our matching methodology. Bars represent 95% confidence intervals. Standard errors are clustered by Metropolitan Statistical Area (MSA). Panel A shows individual fixed effects; Panels B and C use census tract fixed effects to control for fine-grained residential sorting patterns. In the saturated models (Panel C), demographic fixed effects are included as follows: political segregation models include gender fixed effects, while gender segregation models include partisanship fixed effects. All estimates use the fixest package in R. See Table A3 in the appendix for full regression results.

Figure 5: Examining heterogeneity



NOTES: This figure displays coefficients and confidence intervals from heterogeneity analysis of Republican workplace segregation across demographic and political groups. Each coefficient represents the estimated association between being a Republican and the share of Republican coworkers in the employer-MSA, estimated separately for each subgroup. The analysis includes 37.2 million positions held by 31 million workers. Error bars show 95% confidence intervals. All coefficients and standard errors are reported in Table A4 in the appendix.

Heterogeneity

Next, we examine heterogeneity in segregation by worker characteristics (see Figure 5). First, we examine heterogeneity in terms of political engagement, which reveals some of the strongest and most consistent patterns in our analysis. Political activity shows a clear gradient in workplace segregation: non-voters in the 2020 general election exhibit lower levels of segregation (10.4 percentage points, $p < 0.001$, 95% CI: $[0.092, 0.116]$) compared to general election voters (11.9 percentage points, $p < 0.001$, 95% CI: $[0.107, 0.131]$), while primary voters—who represent the most politically engaged segment of the electorate—display substantially higher segregation (13.0 percentage points, $p < 0.001$, 95% CI: $[0.116, 0.144]$). Most strikingly, those who have made donations above the FEC's $200 reporting threshold show the highest segregation levels of any group we examine (14.8 percentage points, $p < 0.001$, 95% CI: $[0.132, 0.164]$), with raw segregation coefficients 27% higher than non-donors (11.6 percentage points, $p < 0.001$, 95% CI: $[0.100, 0.120]$). This clear gradient from non-voters to donors suggests that political engagement itself, rather than simply partisan identity, drives workplace sorting behavior. These patterns are consistent with the idea that those who are most politically active place the greatest premium on working alongside those who share their partisanship and may be more willing to factor political considerations into their employment decisions.

Second, we examine heterogeneity by worker demographics and experience. Among demographic characteristics, women experience slightly higher segregation than men (11.7, $p < 0.001$, 95% CI: $[0.105, 0.129]$ vs. 11.1 percentage points, $p < 0.001$, 95% CI: $[0.099, 0.123]$) in raw estimates), while white workers exhibit somewhat higher segregation than non-white workers (11.3, $p < 0.001$, 95% CI: $[0.101, 0.125]$ vs. 10.0 percentage points, $p < 0.001$, 95% CI: $[0.088, 0.112]$)—a pattern that may reflect differences in labor market flexibility and employment options. Educationally, we observe a clear age gradient: Workers with high school education or lower show the highest raw segregation levels (11.8 percentage points, $p < 0.001$, 95% CI: $[0.106, 0.130]$), while those with bachelor's (11.5 percentage points, $p < 0.001$, 95% CI: $[0.105, 0.125]$) and graduate degrees (11.1 percentage points, $p < 0.001$, 95% CI: $[0.101, 0.121]$) show somewhat lower segregation. There is a similarly clear gradient across generations. Baby Boomers exhibit the lowest levels of segregation (10.2 percentage points, $p < 0.001$, 95% CI: $[0.090, 0.114]$), while Millennials show the highest (12.2 percentage points, $p < 0.001$, 95% CI: $[0.108, 0.136]$), with Gen X (11.6 percentage points, $p < 0.001$, 95% CI: $[0.104, 0.128]$) and Gen Z (11.7 percentage points, $p < 0.001$, 95% CI: $[0.103, 0.131]$) falling between these extremes. This suggests that younger cohorts, who entered the labor market during periods of heightened political polarization, may be more likely to sort into politically homogeneous workplaces.

Senior executive-level workers show the highest raw segregation (14.7 percentage points, $p < 0.001$, 95% CI: $[0.133, 0.161]$). This may be because senior executives have the greatest power to select into firms with coworkers who share their partisanship or shape/select the partisanship of their subordinates. When examining job zones—which capture the skill, education, and training requirements of occupations—we find a U-shaped pattern: jobs requiring little preparation (Zone 1: 12.1 percentage points, $p < 0.001$, 95% CI: $[0.111, 0.131]$) and jobs requiring the most extensive preparation (Zone 5: 11.8 percentage points, $p < 0.001$, 95% CI: $[0.106, 0.130]$) both exhibit high segregation, while middle-skill jobs show somewhat lower levels. However, after controlling for occupation, industry, and geography, workers in jobs requiring extensive preparation (Zone 5) show the highest segregation (3.1 percentage points, $p < 0.001$, 95% CI: $[0.028, 0.032]$), suggesting that highly skilled workers with substantial market power are particularly likely to sort into politically compatible workplaces.

Taken together, these heterogeneity patterns, paired with the preceding fixed effect analysis, suggest that workplace political segregation is not simply a mechanical result of residential, industry, or occupational sorting, but reflects active choices by workers who have both the motivation (political engagement) and opportunity (market power, flexibility) to select into politically compatible work environments.

Asymmetry in Out-Party Exposure

The density plots in Figure 1 establish that Democrats and Republicans work in systematically different environments: Republicans are substantially more likely to work alongside Republican coworkers than Democrats are. To examine the broader implications of this asymmetry for cross-party workplace contact, we analyze the distribution of both out-party and in-party exposure across the full range of worker experiences.

Democrats, on average, work in environments where 63% of their coworkers share their partisanship, while Republicans work in environments where only 44% of their coworkers share their partisanship. This translates to out-party exposure rates of 32% for Democrats and 50% for Republicans—a substantial 18 percentage point difference that reflects the fact that Democrats outnumber Republicans in the labor market, a feature of our sample and nationally representative estimates (see the Sample Benchmarking subsection of our Methods section).

Figure 6: Distribution of in-party and out-party exposure, by political affiliation

NOTES: This figure displays the share of in-party and out-party exposure by decile. Analysis based on two-party exposure measures using imputed partisanship for 37.2 million positions held by 31 million workers. Values shown are the mean exposure rates within each decile. Out-party exposure measures Republican coworker share for Democrats and Democratic coworker share for Republicans. In-party exposure measures same-party coworker shares.

However, focusing solely on average exposure obscures important variation in cross-party contact across the distribution of workers. Figure 6 presents a granular analysis of this variation by displaying both out-party and in-party exposure across percentiles of the exposure distribution, separately for Democratic and Republican workers. The heatmaps reveal several important patterns that extend beyond simple averages.

First, the out-party exposure heatmap (top panel) shows that even among Democrats in the highest deciles of Republican exposure—those most likely to work alongside Republicans—out-party contact remains relatively modest. By contrast, Republicans in the highest deciles of Democratic exposure experience substantially higher levels of cross-party contact, with some Republicans working in heavily Democratic environments. This asymmetry reflects the dual influence of Democratic workers' numerical advantage and workplace sorting patterns.

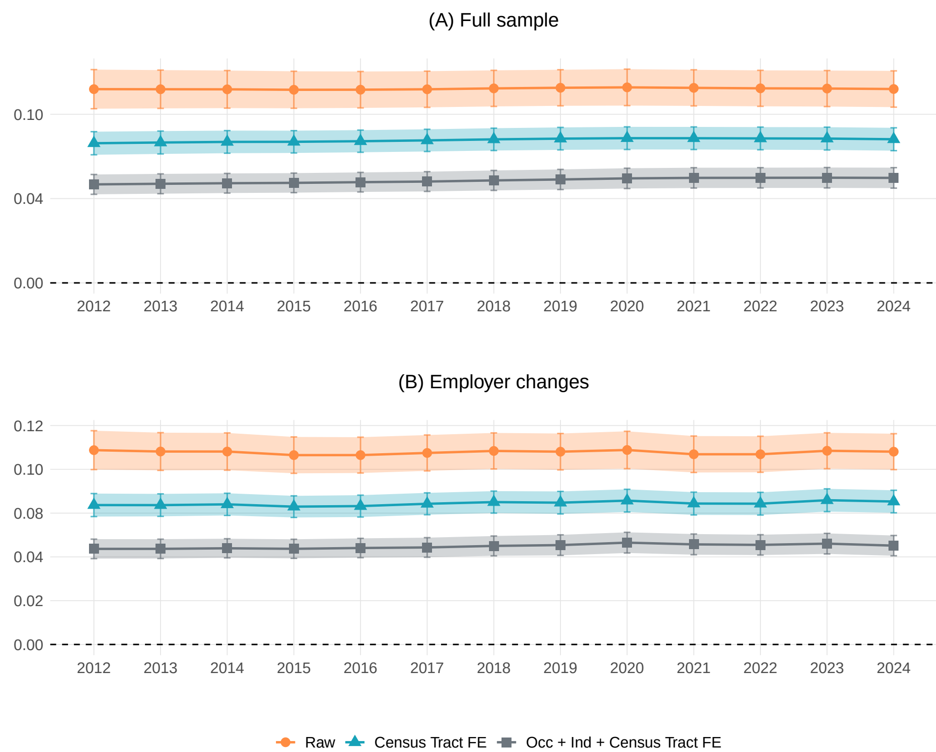
Second, the in-party exposure heatmap (bottom panel) reveals the mirror image: Democrats consistently experience higher same-party contact across nearly all percentiles, while Republicans show greater variation in their in-party exposure. The most isolated Republicans (those in the lowest percentiles of Republican exposure) work in dramatically different environments than the most isolated Democrats, highlighting how political workplace segregation affects the two parties differently.

This distributional analysis demonstrates that political workplace segregation creates systematically different experiences for Democratic and Republican workers. While both parties exhibit workplace sorting, Republicans are more likely to find themselves in politically heterogeneous work environments, whereas Democrats are more likely to work primarily alongside other Democrats. These patterns have important implications for theories of workplace contact and political polarization, as they suggest that opportunities for cross-party interaction are distributed unequally across the political spectrum.

Temporal Trends

Next, we examine temporal trends in workplace segregation by partisanship. We examine temporal trends using the panel of position-years described in the Methods section. We then re-estimate Equations 1 and 4 with census tract fixed effects, as well as the variant that includes occupation, industry, and census tract fixed effects. We plot the by-year estimates in Figure 7. While the degree of overall political segregation increased modestly over the past decade, the relative stability of this estimate may reflect the fact that job changes occur infrequently. Accordingly, we repeat this analysis but restrict the sample

Figure 7: Longitudinal analysis



NOTES: This figure presents coefficients from longitudinal regression analysis of Republican workplace segregation from 2012–2024. Panel A shows results for the full sample of all position-years. Panel B shows results restricted to workers experiencing employer changes, measured as a starting a new position. Three model specifications are shown: Raw estimates with no fixed effects, Census Tract FE models, and Occ-Ind-Census Tract FE models. The dependent variable is the percentage of Republican coworkers in the MSA-employer cell, calculated using only Democrats and Republicans (imputed). Standard errors are clustered by MSA. Complete regression results are reported in Table A5 in the appendix.

to instances where workers start a new position, meaning they are either (1) entering the labor market for the first time or (2) switching employers. These results are reported in Panel B of Figure 7. For the raw estimate, the degree of segregation remained essentially flat, declining slightly from 11.1% in 2012 ($p < 0.001$, 95% CI: [0.099, 0.123]) to 11.0% in 2024 ($p < 0.001$, 95% CI: [0.100, 0.120]). The census tract fixed effects estimate shows a modest upward trend from 8.0% ($p < 0.001$, 95% CI: [0.074, 0.086]) in 2012 to 8.2% ($p < 0.001$, 95% CI: [0.076, 0.088]) in 2024, an increase of 0.2 percentage points over 12 years. The occupation-industry-census tract fixed effects estimate shows a similar modest increase from 5.5% ($p < 0.001$, 95% CI: [0.049, 0.061]) in 2012 to 5.6% ($p < 0.001$, 95% CI: [0.050, 0.062]) in 2024, rising by 0.18 percentage points. Overall, the substantive magnitude of change is relatively small. One limitation of our data is that we cannot capture individuals who moved, changed registration status, or were not registered in 2024.

Discussion

Recent years have witnessed an outpouring of research examining the extent, origins, and consequences of political segregation across various geographic and social domains (Brown and Enos 2021, Huber and Malhotra 2017, Iyengar et al. 2018). Despite the workplace's potential for fostering prejudice-reducing, cross-partisan contact (Allport 1979, Mutz and Mondak 2006), very little is known regarding political segregation across workplaces. This paper addresses this gap by providing the first large-scale measurement of the extent of political segregation in the US workplace. As we show here, the magnitude of political segregation is larger than analogous estimates of political residential segregation, and similar in magnitude to workplace segregation based upon gender. Moving beyond our main, "raw" estimate, we present measures which include fixed effects for geography, industry, and occupation. Our cross-metropolitan analysis (Figure 2, Panel B) reveals that residential and workplace segregation co-vary across metropolitan areas, though substantial variation in workplace segregation patterns across areas remains. We show that even after accounting for geographic, industry, and occupational political segregation, workplaces remain significantly sorted by partisanship. Importantly, these results are robust to re-weighting our sample using BLS occupational data to address potential selection bias in our data as well as a wide range of alternative estimation and measurement decisions. These analyses provide confidence that our findings reflect genuine workplace sorting patterns rather than sampling artifacts.

Our findings illuminate the need for future research into the *causes* and demonstrate the *consequences* of workplace political segregation. First, regarding *causes*, political segregation may be driven by individual choices (or constraints) on where those from difference political groups live as well as the occupations and industries in which they work. This does not mean that political segregation is merely incidental or that politics do not play a role. Partisans may make politically-informed decisions about where to live and in which industry and/or occupation to seek employment based on their perception of the political makeup of these domains. For example, Democrats may seek out big-city jobs in education or media in order to work alongside other Democrats. Moreover, copartisan workers may make similar choices that are correlated with—but not necessarily driven by—partisanship. Research on political residential sorting finds that political homophily is largely driven not by explicit political bias but by the tendency of opposing partisans to prefer different neighborhood amenities (Martin and Webster 2020). Similarly, Republicans and Democrats may hold different worldviews that lead them towards different occupations and industries. Political segregation by geography, industry, and occupation may be mutually reinforcing. For instance, the tendencies of Democrats to live in more urban areas and Republicans to live in more rural regions may shape industry and occupation choices, which in turn may further influence or constrain the ability of these workers to relocate to other geographic regions.

Second, political segregation could arise during the hiring process as a result of employers' or job seekers' preferences for copartisan coworkers. Experimental evidence suggests that employers prefer to hire copartisans and discriminate against members of the opposing party (Gift and Gift 2015, Colonnelli et al. 2024). While employers cannot legally discriminate based on characteristics such as gender, race, or age, political partisanship is not a protected category at the Federal level nor in most US states. Political discrimination in the hiring process need not necessarily be motivated by copartisans favoritism. Employers may prefer workers who match the majority party to promote a harmonious and collaborative workplace (Barber IV and Blake 2023). Job seekers may also show greater propensity to seek work at employers where they believe most coworkers will share their partisanship. This may be driven by job seekers' desire to work alongside copartisans and/or concern that they will face discrimination at the hands of outpartisans. As companies increasingly take public stances on salient political issues, it may become easier for job seekers to infer and thus select into applicant pools based on the political composition of coworkers. Our heterogeneity analyses provide correlational evidence consistent with this mechanism. Workers who are more politically engaged (and thus plausibly more likely to care about their coworkers' partisanship) and who hold more labor market power (and are thus better able to realize these preferences) are more politically segregated.

Third, partisan segregation could be driven by processes that occur after job seekers join employers. Workers in the political minority within their employer may either come to adopt the majority partisanship over time (socialization) or they may be more likely to leave (differential attrition). Prior literature suggests that both effects can and do occur. Political socialization as a result of peer influence has been documented within residential neighborhoods (Brown 2023), colleges (Firoozi 2025), and explicitly political workplaces (i.e., politicians' offices) (Jones 2013), whereas differential attrition by political "misfits" has been shown in several workplace contexts (Bermiss and McDonald 2018, Hassell et al. 2023). However, work-in-progress suggests that this socialization may be modest and limited to non-partisans (Chinoy and Koenen 2024).

Beyond elucidating the drivers of workplace political sorting, future research can investigate its *consequences*. First, research is urgently needed to understand the relationship between workplace political segregation and affective polarization. The workplace is perhaps uniquely well-suited to foster the type of intergroup contact which can potentially reduce prejudice (Allport 1979, Mutz and Mondak 2006). Given growing concerns surrounding sharp rises in political discord and affective polarization in the United States (Iyengar et al. 2019), understanding whether the workplace serves as a locus of prejudice-reducing cross-partisan contact is imperative. While we have emphasized political segregation in presenting our results, the data we present also point to significant levels of outpartisan exposure, especially among Republicans. On this front, a critical question left unanswered by our study is whether workplaces with less political segregation are in fact more likely to foster meaningful cross-partisan contact and whether these interactions decrease affective polarization. To address this question, subsequent inquiry could use surveys to identify conversation networks as well as the extent and nature of workplace conversations around politics.

Second, workplace political segregation may be linked to the growing tendency of businesses to take public positions on controversial social issues. These stances have appeared puzzling, given that the benefits from appealing to like-minded stakeholders are often outweighed by the negative reactions from opposing stakeholders (Burbano 2020, Hou and Poliquin 2023). One suggestion is that employees may drive firms' engagement with controversial political issues (Li and Disalvo 2022). Research mapping political segregation to corporate sociopolitical activism may be able to elucidate whether corporate sociopolitical positioning is primarily a strategic response to workers' demands as opposed to a unilateral expression of top managers' beliefs or values (Hurst 2023, Mohliver et al. 2023).

Finally, workplace political segregation may affect firm performance. On one hand, political homogeneity arising from political segregation might enhance firm performance. Employees who feel politically misaligned with upper management or their peers may be less economically productive (Besley and Ghatak 2005, Carpenter and Gong 2015, McConnell et al. 2018, Spenkuch and Xu 2023) and more likely to exit the firm (Bermiss and McDonald 2018, Hassell et al. 2023). Moreover, if workers value politically homogeneous workplaces where they are in the majority, they may even accept a lower wage for jobs in these workplaces (McConnell et al. 2018). On the other hand, political segregation might erode firm performance. Studies of labor force segregation based upon gender have shown that resulting (mis)allocations of talent across industries and occupations can hinder economic growth (Hsieh et al. 2019). To the extent that political sorting may also result in a sub-optimal allocation of talent (Roy 1951), political segregation may have significant economic consequences. Understating the relationship between political segregation and firm productivity, innovation, and profitability represents an important frontier for future scholarship.

Methods

Data and Code Availability

The Revelio and L2 datasets used in this paper are commercial datasets whose license terms prohibit disclosure. To facilitate transparency into the analytical methods used in this paper, we provide a partial random sample of observations that have been anonymized to protect individual privacy and comply with licensing agreements. Key variables have been perturbed with noise to further safeguard individual identities, and all identifiers have been hashed.

We provide the R code used to produce the figures and tables in the main body of this article to demonstrate the methodology used throughout this paper. Combined with the sample data provided, this code can be used to demonstrate and evaluate the methods used in this paper, provide transparency into the research process, and allow researchers to understand and potentially adapt the methods used here for their own work. However, the figures and tables produced using this code and the sample data will not replicate those that appear in the paper.

Data and code for peer review are available at the Harvard Dataverse: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/1K7OUZ.

Overview

We estimate political segregation in the workplace by linking state voter registration files with a database of online worker profiles. This approach significantly improves upon previous studies of workplace partisanship in the United States in terms of the number and representativeness of workers it captures. Most existing research on firm-level political partisanship (and ideology) relies upon data from legally-mandated public disclosure of individual political donations by the Federal Election Commission (FEC). Because these public campaign finance disclosures contain names, addresses, job titles, and employer information, researchers have used data on partisan donations to measure firm-level partisanship and/or as a proxy for political ideology (e.g., Li 2018, Stuckatz 2022b). Many prior studies leverage the extensive Database on Ideology, Money in Politics, and Elections (DIME) data, developed by Bonica (2014), which not only captures this donation data, but also precisely characterizes donors' ideology based on the ideology of the candidates to whom they donate.[5]

The major trade-off for this measurement precision is narrow and skewed coverage. The vast majority of Americans do not donate to political campaigns, let alone in amounts large enough that historically required disclosure. As a result, donations-based measures cover a narrow and demographically unrepresentative slice of the US population—one that is not only far more politically engaged, but also far whiter, wealthier, and older than the US population as a whole (Grumbach and Sahn 2020, Bonica and Grumbach 2022). Thus, while DIME and other campaign finance-based datasets may provide good coverage for highly-educated, wealthy, and politically-engaged professions such as lawyers (Bonica et al. 2016) and doctors (Bonica et al. 2020), it is less representative when looking at employees or companies in general (Kagan et al. 2025).

In addition to questions about representativeness, linking FEC data with companies can also be technically challenging. FEC data is based upon reports filed by political campaigns or other political organizations, which must make a good faith effort to collect accurate information from their donors. However, unlike the voter file, where registered voters must provide their exact legal name in order to vote, there is nothing preventing donors from providing variants or nicknames. Company names are also not standardized, nor can corporate parents easily be linked with subsidiaries (Stuckatz 2022b). Donors may choose to withhold information, leading donation filings to read only that information has been "requested." Furthermore, donors may also give technically accurate but misleading information about their employment, such as listing a position in an industry trade association rather than their primary employer—a tactic that is especially common among firms facing reputational challenges (Shanor et al. 2022).

Given both the limited coverage and technical challenges involved with linking FEC disclosures with companies, previous efforts to link individual workers' partisanship with their employer have been orders of magnitude smaller than the data we present here. For instance, Stuckatz (2022b) deploys extensive code to standardize and parse Federal campaign contributions from 2003 to 2016 and was able to identify only 85,109 individuals across 874 political action committees (PACs) associated with publicly traded companies (see also Teso 2025). In another analysis, Barber IV and Blake (2023) estimated that 60% of US companies have no donors that appear in DIME.

[5]Political partisanship and ideology are theoretically distinct concepts, although they are highly correlated in the modern US political landscape. One major strength of the DIME data is that it can make fine-grained ideological distinctions between more moderate and more extreme members of the same party. As we discuss, our measure of partisanship greatly expands coverage but at the cost of a coarser measurement.

For some studies—such as those which focus on the ideology of the "upper echelons" within a firm or those which are primarily concerned with PAC contributions—these campaign finance measures may be appropriate. When it comes to capturing the general employee population, we believe our approach provides more comprehensive coverage compared to existing donation-based measures. We discuss the representativeness of our sample in more detail in the Sample Benchmarking section, below.

L2 Voter File

Our first data source is the national voter file. In the United States, individuals' vote choices are secret, but whether or not they register or turn out to vote is a matter of public record. Voters' registration and turnout history, combined with demographic and contact information, are widely used by political campaigns, commercial data vendors and marketers, and, increasingly, by academic researchers (Hersh 2015). 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. Voter file data have been widely used in political science, economics, and other fields, often by merging these data with other datasets to study topics such as voter turnout (Barber and Holbein 2022, Bonica et al. 2021), as well the political makeup of various professions and groups, including board members (Kempf and Tsoutsoura 2021), college students (Firoozi 2025), government bureaucrats (Spenkuch and Xu 2023), patent examiners (Raffiee et al. 2023), physicians (Hersh and Goldenberg 2016), the police (Ba et al. 2022), religious leaders (Malina and Hersh 2021), and spouses (Hersh and Ghitza 2018). Our voter file comes from the nonpartisan vendor L2 Data, extracted and processed in November 2024, and contains information on approximately 185 million registered voters in the United States. Estimates from the 2022 Cooperative Election Study suggest that approximately 73% of the overall US adult population are registered to vote; among those currently employed, it is 76%.

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

Partisanship

Unlike many other countries, (e.g., Brazil; see Colonnelli et al. 2024), political parties in the United States do not maintain nationwide member rolls. Instead, L2's information on partisan identification come from a variety of sources, which vary by state (Barber and Holbein 2022). States fall into three categories:[6]

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

- 30 states (and Washington, D.C.) register voters by party.
- 11 states do not formally register voters by partisanship, but do record whether voters chose to vote in either party's primary and classify voters in this manner.[7]
- Nine states provide no information on partisan registration, and L2 models partisan affiliations based upon ethnicity, geography, and other data.[8]

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. 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).

Partisanship Imputation

In our main analysis, we impute the partisanship of workers who are registered as independents, non-partisans, or with third parties. Among registered voters in our sample, about one-third are not registered as Democrats or Republicans. However, party registration potentially understates de-facto partisan segregation, as many 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 non-partisans using a multi-step approach, detailed in Figure 8. First, we begin with the partisan estimates provided by L2, as described previously. Second, 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. Third, we assign members of third-parties as "leaning" towards the party that most closely matches the ideology of their preferred third party. For example, the Green, Socialist, and Working Family Party are mapped to the Democratic party, while the American Independent, Libertarian, and Reform parties are mapped to the Republican party. We adopt the party classifications from Brown and Enos (2021).

Approximately 10–30% of voters remain unclassified at this point, depending upon the state. To model the partisan lean of these voters, we rely upon a Bayesian approach (Brown and Enos 2021) which incorporates fine-grained information about the local partisan geography as well as demographic modeling. First,

[7] These states are Georgia, Illinois, Indiana, Michigan, Mississippi, Ohio, South Carolina, Tennessee, Texas, Virginia, and Washington.

[8] These states are Alabama, Hawaii, Minnesota, Missouri, Montana, North Dakota, Wisconsin, and Vermont.

we calculate a Bayesian geographic prior that is based upon precinct-level electoral returns. As precinct-level returns were not yet available in all states for 2024, we use 2020 returns. We attempt to assign voters to a precinct using spatial joins with the R sf package; in the rare cases where we are unable to do so, we use county-level returns. This approach largely mirrors that done by Brown and Enos (2021). We depart slightly from their procedure by not incorporating the number of registered Republicans and Democrats and instead relying only upon vote totals for the Republican and Democratic candidates.[9]

Second, we incorporate information about voters' demographics. We begin with a large-scale, high-quality survey (the 2020 Cooperative Election Study) 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 (non-leaner) independent.[10]

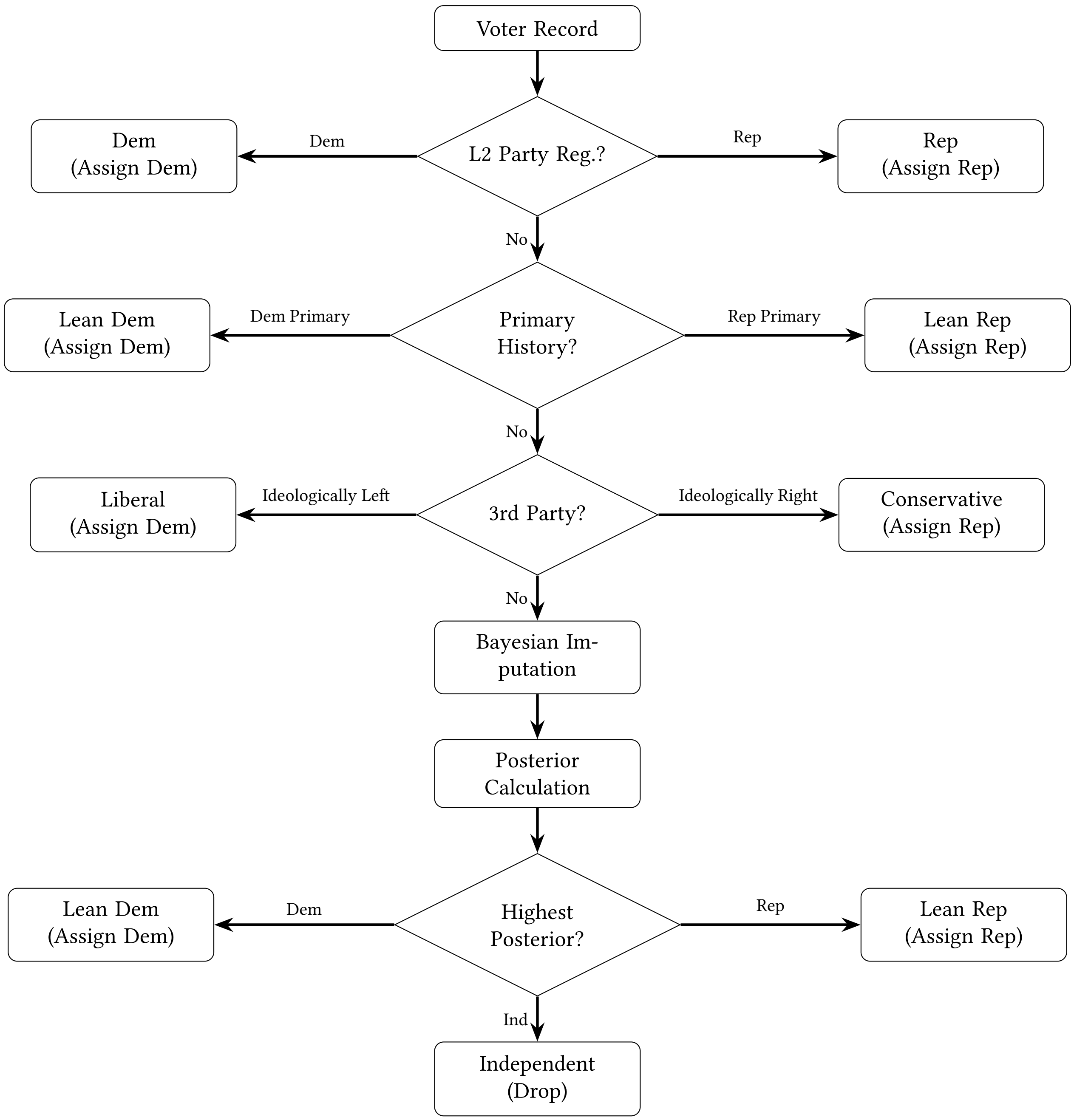
We then use Bayes' formula to incorporate the demographic information and the geographic prior to estimate the probability that each "independent" voter actually leans Democratic or Republican. We assign each voter as "leaning" towards the partisan label with the highest probability (i.e., Republican, Democratic, or Independent).[11] This imputation procedure classifies the majority of initially unaffiliated voters as Democratic or Republican leaners, with only a small fraction remaining as true independents.

[9] Based upon personal communication with one of the authors, we confirmed that this approach delivers comparable results.

[10] In cases where race data are missing in L2, we use only age, gender, and voter registration status.

[11] In the highly unlikely event that all probabilities are equal, we default to independent.

Figure 8: Compact flowchart of the hierarchical partisan imputation process



Gender

Gender classification in L2 combines direct collection and probabilistic imputation. 27 states directly include gender in their voter registration files, while 22 states and Washington, D.C., do not collect this information.[12] California includes gender in voter files, but the field is missing for a majority of registered voters.

For voters where gender is not directly provided, L2 implements probabilistic gender imputation based on first name frequency distributions. This approach uses administrative records and Census data to calculate the probability that individuals with specific first names are male or female, then assigns gender based on the higher probability. When first names are ambiguous (roughly equal gender probabilities), L2 incorporates middle name information to improve classification accuracy.[13]

Geographic Controls

To match datasets and control for residential sorting, 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.

We use census tract assignments—derived from L2's geocoding home addresses to Census tract boundaries—to implement geographic controls. Census tracts represent small, relatively homogeneous areas designed to contain 1,200-8,000 residents with similar demographic and socioeconomic characteristics. This allows us to compare workers who live in the same neighborhood but work for different employers.

Political Participation

All political participation variables come from L2. To measure registered voters' degree of political participation, we use L2 data on voters' turnout in general and primary elections. We also include a binary indicator for whether the individual was a political donor, based upon whether they gave at least one donation to a political campaign, as captured under FEC donation requirements.

[12] The states which include gender are Alabama, Alaska, Colorado, Connecticut, Florida, Georgia, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Massachusets, Maryland, Michigan, North Carolina, New York, Pennsylvania, Rhode Island, South Carolina, Tennessee, Texas, Virginia, Washington, and West Virginia.

[13] Personal communication with L2.

Worker Profiles from Revelio Labs

Prior work in other national contexts has leveraged administrative tax or pension data to study workplace partisanship (e.g, Colonnelli et al. 2024). In the United States, federal administrative data are not publicly available and are made available to researchers only under certain narrow circumstances. Statutory guidelines for the use of personally-identifiable tax or social security microdata for research purposes likely preclude their use for studies which focus on political partisanship. For example, researcher data access often relies upon sampling or the use of synthetic and/or coarsened anonymized data, neither of which would be suitable for our purposes.[14] Because these data are not available, we rely upon data on job positions from Revelio Labs. Revelio is a workforce intelligence company which uses proprietary technology to compile individual employment records based upon online professional profiles (i.e., LinkedIn), as well as job postings.[15] The Revelio data we use contain information on individual job positions, including the date on which they started and ended. 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 extracts names and professional information directly from LinkedIn profiles as they appear on the platform. However, we recognize that LinkedIn names may differ from legal names used in voter registration due to professional naming preferences, nicknames, maiden names, or cultural naming conventions. To address this challenge, we implement name cleaning using the `nominally` Python library, which standardizes name formats, handles common variations, and parses complex name structures. This preprocessing substantially improves matching accuracy compared to using raw LinkedIn name data.

[14] There have been notable cases where researchers have gained access to IRS data to study less politically-charged topics such as economic mobility (e.g., Chetty et al. 2014), but these have only been for subsets (i.e., individual birth cohorts) rather than the entire US workforce, as well as on research topics which are comparatively less politically sensitive relative to partisan politics.

[15] Revelio data have been been used in a variety of studies in management, accounting, and other disciplines to study topics including ESG reporting and workplace diversity (Ahn et al. 2023, **?**, Cai et al. 2022, **?**, Fadhel et al. 2021), the drivers and consequences of employee turnover (Arif et al. 2022, Leung et al. 2023, Li et al. 2022), corporate culture (Pacelli et al. 2023), and the influence of individual work history and life experiences on business outcomes (Agarwal et al. 2023, Gao et al. 2023).

Employer Information

Revelio relies on LinkedIn's entity relationships and implements name disambiguation and entity resolution to address the fundamental challenge that the same company may appear with multiple name variations across LinkedIn profiles (e.g., "BofA," "Bank of America," "BoA," "Bank of America Corp"). Using machine learning algorithms trained on business registration records, SEC filings, and other commercial databases, Revelio groups variant employer names into standardized entities.

Industry Classification

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. The resulting classifications provide comprehensive industry coverage but represent another area of proprietary processing that we treat as authoritative.

Occupation Classification

Job titles from LinkedIn are mapped to standardized O*NET-SOC occupation codes using Revelio's proprietary natural language processing pipeline. This system analyzes job titles, job descriptions (when available), and contextual information from job postings to predict the most appropriate occupation code. The model incorporates information about job responsibilities, required skills, and industry context to improve classification accuracy.

Seniority and Career Progression

Revelio estimates career seniority using a seven-category classification ranging from entry-level positions (interns, trainees) to senior executive roles (C-suite). This classification combines multiple information sources: (1) current job title analysis using NLP models trained to recognize seniority indicators, (2) individual employment history showing career progression patterns, and (3) estimated age based on years of employment history. The age estimation itself represents a significant methodological challenge, as LinkedIn does not provide birth dates, requiring Revelio to infer age from career duration and typical education-to-work transition patterns.[16]

Ensemble Matching Strategy

Merging datasets is not a new challenge in social science research (Enamorado 2021). This particular application presents unique challenges, however. First, the Revelio data are sourced from online employment profiles, rather than from government or administrative sources. As a result, we lack the individual identifiers—dates of birth (DOBs), social security numbers (SSNs), or home addresses—that are commonly used to link datasets. Furthermore, individuals may use an entirely separate name professionally (e.g., a nickname, middle name, or maiden name) that does not correspond to the legal name they use when registering to vote. While social scientists have developed methods for linking administrative datasets, these are typically designed to address partially missing data, data entry errors (e.g., typos), or inconsistencies (e.g., inconsistent usage of abbreviations), rather than cases where bridging data fields are almost entirely absent. A second related challenge is the sheer size of the data. Limiting to observations within MSAs, the L2 voter file contains approximately 177 million voter records and the Revelio data contain approximately 103 million distinct users, meaning that a brute force attempt to merge the two datasets would involve $\sim 1.8 \times 10^{16}$ (18 quadrillion) pairwise comparisons.

To address these challenges, we implement a novel ensemble matching approach that combines two complementary methodologies: probabilistic record linkage using the Fellegi-Sunter framework and large language model (LLM)-based semantic matching. Our data snapshots combine the most recent available data from both sources. In L2, we use voter file extracts processed in November 2024, while in Revelio we use employment data captured in April 2025.[17]

Data Preprocessing

We begin by partitioning both the Revelio and L2 records by metropolitan statistical area (MSA). We exclude records where the work or home address are located outside of an MSA or where location data are missing.[18] This is done for both practical reasons to make the computation feasible, as well as theoretical

[16] Personal communication with Hakki Ozdenoren, Revelio Labs.

[17] This means that we only match workers who were currently registered to vote as of the 2024 L2 extract. Most notably, individuals who had work history but who died before the L2 extract date are likely removed from the voter rolls and thus not available to be matched.

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

reasons—MSAs are constructed by the Census Bureau to capture commuting patterns, so it is reasonable to limit our matches to cases where the work location (as reported in Revelio) and home address (as reported in L2) are within the same MSA. For MSAs which span multiple states, we attempt to match job positions with voter registrations for all states associated with that MSA (e.g., we would attempt to match job positions located in the Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA with voters registered in the MSA in PA, NJ, DE, and MD).

Probabilistic Matching (Splink)

Our first matching approach uses Splink version 3.9.8 with a DuckDB backend to implement probabilistic record linkage following the Fellegi-Sunter framework (Fellegi and Sunter 1969). This approach estimates the probability that two records refer to the same individual based on the agreement patterns across multiple comparison variables. We use string comparison functions, including exact matches, Damerau-Levenshtein distances (threshold ≤ 1), and Jaro-Winkler similarity scores (thresholds ≥ 0.8 and ≥ 0.9) for first and last names. Additional comparisons include birth dates (exact year, ± 1 year, and ± 10 year matches), middle names (using name comparison functions), and exact gender matches. All comparisons incorporate term frequency adjustments to account for the relative commonness of names and demographic characteristics. The model uses blocking on last name to reduce computational complexity, with expectation-maximization to estimate match probabilities. For large MSAs, we implement name binning strategies (grouping by first letters of last names) to manage memory requirements during model training.

LLM-Based Matching (FuzzyLink)

Our second approach uses the fuzzylink R package to perform embedding-based semantic matching powered by large language models. This method uses GPT-4o-mini-2024-07-18 for match classification and OpenAI's text-embedding-3-large model (256 dimensions) to generate semantic embeddings of names. The approach blocks on gender and last name, then uses embedding similarity to identify potential matches. We provide specific instructions to the LLM to ignore professional titles, suffixes, case differences, punctuation, accents, name order variations, and minor misspellings while focusing on whether names likely refer to the same person. This method is particularly effective at capturing matches missed by traditional string-based approaches, such as those involving nicknames, initials, or alternative name presentations common in professional contexts.

Ensemble Integration

We combine the results from both matching approaches using an ensemble strategy that maximizes coverage while maintaining match quality. Our algorithm prioritizes matches with the highest match probability by removing duplicate Revelio user IDs (keeping the highest match probability), then removing duplicate voter IDs (again keeping the highest match probability). For ties, we prioritize records with quality indicators (e.g., Revelio's *is_bad_user* flag). If there are still ties, we randomly select which match to include.

Our ensemble approach yields about 45.3 million unique matched workers representing approximately 31.8% of Revelio users and 18.9% of registered voters, constituting the largest matched employer-voter dataset ever constructed.

Sample Attrition and Waterfall Analysis

The construction of our analytical dataset involves substantial but methodologically necessary attrition at each processing stage. We document this process through waterfall charts (presented in Appendix Figures A11 and A12) that track observation losses from initial data sources to final analytical sample.

Beginning with 102.6 million unique workers in Revelio's US MSA workforce and 176.7 million registered voters in L2, our ensemble matching process successfully links 44.2% of Revelio workers and 27.2% of L2 voters, resulting in the loss of 57.3 million Revelio workers and 128.6 million L2 voters. This substantial but expected attrition reflects the conservative nature of our matching approach, which prioritizes precision over recall to ensure high match quality. The differential retention rates between datasets reflect their distinct population coverage: Revelio captures employed workers with LinkedIn profiles, while L2 encompasses all registered voters regardless of employment status or online presence.

Subsequent filtering steps create our 2024 analytical cross-section. We make a number of restrictions include: (1) requiring non-missing values for partisan exposure measures, imputed partisanship scores, and demographic variables (gender, age); (2) restricting to workplaces with at least two employees to enable meaningful coworker exposure calculations; (3) requiring complete workplace characteristics including valid industry (NAICS) and occupation (O*NET-SOC) classifications; (4) restricting to workers classified as Democrats or Republicans using our imputed partisanship methodology, excluding independents and third-party registrants; and (5) requiring valid geocoded residential addresses for census tract assignment to enable geographic fixed effects.

Our final analytical sample comprises 31 million unique individuals from the Revelio perspective and 34.8 million from the L2 perspective, representing 30.2% and 18.6% retention, respectively. The difference between these final counts reflects the fact that L2 identifiers are state-specific. Therefore, a person who registers to vote in two states over their lifetime will receive two L2 identifiers.

Summary Statistics

Summary statistics for our working dataset are presented in Table 1. Our final analytical sample comprises 37.2 million observations representing 31 million unique individuals working across 366 metropolitan statistical areas. The sample spans 1,013 industries and 383 occupations (Throughout the paper, we refer to employer-MSA combinations as "workplaces"). Consistent with the highly skewed distribution of employees across employers in the United States, most employers have a small number of workers, although a small number of employers are very large, with workplace sizes averaging 904 employees.

After applying our partisanship imputation methodology to assign probable Democratic or Republican affiliation to all workers, our analytical sample comprises 59.1% Democrats and 40.9% Republicans. The sample is 53.5% female and 39.1% non-white, with a mean age of 43 years. Political engagement is high, with 81.6% having voted in the 2020 general election and 3.6% having made federal campaign contributions. While the proportion of Democrats appears larger than estimates of the share of the population who identify as Democrats, it is consistent with large-scale survey data which measure partisan *registration* (as opposed to self-identification) among employed individuals. We discuss this at greater length in the Sample Benchmarking section, below.

Our main analysis reported in the Results section uses a snapshot of the most current workforce identifiable using our data. This sample comprises positions that were reported as active at any point from the start of 2024 through our Revelio sample's end date in April 2025. In instances where a given worker has multiple positions within the same firm during this period we prioritize the position that is ongoing or with the latest end date. This avoids double counting a worker's experience in a given firm.

We also use our merged data to create an unbalanced panel of positions spanning 2012 to 2024. We do so by considering all positions active at any point between 2012 to 2024, inclusive (not just those in active employment as of 2024), held by workers we were able to match to the November 2024 L2 state-level voter files. We then use the start and end dates for each position to define unique position-year dyads. Here, units

Table 1: Summary statistics: Political workplace segregation analysis

Variable	N	Mean	Std. Dev.	Min	Max
Sample Characteristics					
Total Positions	37,200,614				
Unique Individuals	30,965,666				
MSAs	366				
Counties	1,392				
Census Tracts	72,252				
Workplace Characteristics					
Occupations	383				
Industries	1,013				
Workplace Size (MSA-level)	37,200,614	904	2,504	2	27,257
Workplace and Geographic Shares					
Republican Coworker Share (Two-Party)	37,200,614	0.406	0.239	0.000	1.000
Democratic Coworker Share (Two-Party)	37,200,614	0.586	0.242	0.000	1.000
Female Coworker Share (Benchmark)	37,200,614	0.530	0.253	0.000	1.000
Residential Republican Share	36,247,950	0.429	0.216	0.000	1.000
Individual Characteristics					
Republican (imputed)	15,235,660	0.410	0.492	0.000	1.000
Democrat (imputed)	21,964,961	0.590	0.492	0.000	1.000
Woman	19,896,974	0.535	0.499	0.000	1.000
Non-White	14,564,332	0.392	0.488	0.000	1.000
Age (2020)	36,845,511	42.8	16.5	14	96
Education					
High School or Lower	19,975,345	0.537	0.499	0.000	1.000
Bachelor's Degree	11,425,430	0.307	0.461	0.000	1.000
Graduate Degree	5,799,839	0.156	0.363	0.000	1.000
Seniority Levels					
Seniority Level 1	14,004,717	0.376	0.484	0.000	1.000
Seniority Level 2	9,320,556	0.251	0.433	0.000	1.000
Seniority Level 3	3,856,483	0.104	0.305	0.000	1.000
Seniority Level 4	3,861,352	0.104	0.305	0.000	1.000
Seniority Level 5	4,614,299	0.124	0.330	0.000	1.000
Seniority Level 6	1,169,624	0.031	0.175	0.000	1.000
Seniority Level 7	373,583	0.010	0.100	0.000	1.000
Political Activity					
2020 General Election	30,353,382	0.816	0.388	0.000	1.000
2020 Presidential Primary Voter	11,206,016	0.301	0.459	0.000	1.000
FEC Donor	1,316,417	0.035	0.185	0.000	1.000

NOTES: This table presents summary statistics for the political workplace segregation analysis dataset used across Figures 1-5 and 7. The sample is restricted to Democrats and Republicans (imputed partisanship) working in establishments with 2 or more employees.

of analysis are position-years, rather than simply positions, such that the same position appears separately in each year in which it was active at any time. Figure A4 charts the number of observations by year. The panel dataset statistics are similar to those for the 2024 cross-sectional data. Since our main objective is to estimate the most current degree of segregation in the United States labor market, we conduct our main benchmarking analysis and segregation estimates with respect to the 2024/2025 merged data. We use this panel of workers in the analysis described in the Temporal Trends subsection, above.

Sample Benchmarking

We benchmark our merged sample against external population data to assess representativeness and identify potential sources of bias. This benchmarking is crucial for understanding the generalizability of our results and informs our weighting methodology. We conduct three types of comparisons: demographic representativeness using the Cooperative Election Study (CES), industry coverage using the American Community Survey (ACS), and occupational coverage using Bureau of Labor Statistics (BLS) data.

Political and Demographic Representativeness:

Because our sample draws from registered voters with LinkedIn profiles, we face potential selection bias along both political and demographic dimensions. To assess political representativeness, we compare our sample to the 2023 Cooperative Election Study, a large-scale, nationally representative survey. Since our measure of partisanship relies on official party registration rather than self-reported partisanship, we benchmark against the population of registered voters in the CES who report working full- or part-time.

Table 2 shows that our merged sample closely matches the population of working registered voters on key political dimensions. Among registered voters, our sample contains 41% Democrats compared to 43% in the CES, and 29% Republicans compared to 32% in the CES. The share of independents and third-party registrants (30% vs. 25%) is also comparable. This close alignment provides confidence that our findings reflect genuine workplace sorting patterns rather than systematic political bias in our data sources.

Demographically, our sample shows some differences from population benchmarks. While our racial composition (61% white, 39% nonwhite) is reasonably representative compared to working registered voters (72% white, 28% nonwhite), it somewhat over-represents nonwhite workers. Gender representation in our sample (53% women, 47% men) aligns well with the broader working population, though it slightly over-represents women compared to registered voters specifically.

Table 2: Sample demographics vs. 2023 CES

	(1) Our Merged Sample	(2) Working Reg. Voters	(3) Working Gen. Pop.	(4) Gen. Pop.
Party				
Democrat	0.41	0.43	0.34	0.32
Other	0.30	0.25	0.39	0.40
Republican	0.29	0.32	0.27	0.28
Race/Ethnicity				
White	0.61	0.72	0.69	0.69
Nonwhite	0.39	0.28	0.31	0.31
Gender				
Woman	0.53	0.48	0.52	0.51
Man	0.47	0.51	0.47	0.48

NOTES: All columns except "Our Merged Sample" are calculated using the 2023 Cooperative Election Study (CES) and are weighted to either the population of registered voters (columns (2) and (3)) or general population (column (4)). Respondents who report working full- or part-time are included in columns 2 and 3. Our merged sample statistics are calculated using the full matched sample (including Democrats, Republicans, and Others/Independents), not the analytical sample used in other analyses, which is restricted to Democrats and Republicans only. This allows us to compare to population benchmarks that include all partisan categories. Our merged sample uses unimputed party registration from voter files (not our imputed partisanship measures used in other analyses). This ensures comparability with benchmark data, where independents who may lean Democratic or Republican are classified as independents/other, not as partisans. Statistics on party identification differ between registered voters and the general population because partisan identity is measured by registration for the sample and for registered voters but by survey responses (self-reported) for the general population. Race/ethnicity is based upon L2 categories in the sample and upon self-reported race in all other columns; missing modeled race is excluded from race calculations only. Gender does not sum to 100% because a small portion report a gender other than male or female in the CES and a small fraction of records in our merged sample are missing gender.

Industry Coverage

Our reliance on LinkedIn profiles creates systematic over-representation of white-collar industries and under-representation of blue-collar sectors. Table 3 compares our sample's industry composition to 2023 American Community Survey data. Professional sectors where LinkedIn usage is common—Financial Activities (+8 percentage points), Information Technology (+6 percentage points), and Manufacturing (+4 percentage points)—are substantially over-represented. Conversely, industries where online professional profiles are less common show significant under-representation: Construction (-5 percentage points), Leisure and Hospitality (-5 percentage points), and Retail Trade (-3 percentage points).

Table 3: Industry coverage vs. 2023 ACS

Supersector (NAICS Sector #)	**Merged Sample**	**2023 ACS**	**Difference**
Education and Health Services (61, 62)	0.20	0.23	-0.03
Financial Activities (52, 53)	0.15	0.07	+0.08
Manufacturing (31-33)	0.14	0.10	+0.04
Professional and Business Services (54-56)	0.13	0.12	+0.01
Public Administration (92)	0.09	0.05	+0.04
Information (51)	0.08	0.02	+0.06
Retail Trade (44-45)	0.08	0.11	-0.03
Leisure and Hospitality (71, 72)	0.04	0.09	-0.05
Transportation, Warehousing, and Utilities (22, 48-49)	0.03	0.06	-0.03
Wholesale Trade (42)	0.03	0.02	+0.01
Other Services (except Public Administration) (81)	0.02	0.05	-0.03
Construction (23)	0.02	0.07	-0.05
Natural Resources and Mining (11 and 21)	0.01	0.02	-0.01

NOTES: Population totals are based upon estimates from the 2023 American Community Survey (ACS) DP03 tables. Differences may reflect our dataset coverage but may also be due to differences in the underlying population being measured: our merged sample aims to cover the population of registered voters, while the ACS aims to reflect the entire population, including those who are not registered or not eligible to vote (e.g., non-citizens).

Occupational Skill Distribution

The industry patterns suggest our sample is skewed towards higher-skill occupations. Table 4 shows coverage across O*NET job zones, which measure the education, experience, and training requirements for different occupations. Our sample dramatically over-represents high-skill positions: Zone 4 occupations (requiring considerable preparation) comprise 41% of our sample versus 25% of the population (+16 percentage points), and Zone 5 occupations (requiring extensive preparation) represent 14% versus 5% (+9 percentage points). Conversely, we substantially under-represent lower-skill positions, with Zone 1 and

Zone 2 occupations showing deficits of 5 and 21 percentage points, respectively.

Table 4: Coverage by occupation type (O*NET zones) vs. 2023 BLS

O*NET Zone	Merged Sample	Population	Difference
Zone One	0.02	0.07	-0.05
Zone Two	0.21	0.42	-0.21
Zone Three	0.22	0.22	+0.00
Zone Four	0.41	0.25	+0.16
Zone Five	0.14	0.05	+0.09

NOTES: Population figures come from Bureau of Labor Statistics (BLS) estimates from the May 2023 BLS data release, which are merged with O*NET Zone codes from onetonline.org. O*NET Zones group occupations based upon the level of education, experience, and on-the-job training required to do a job. O*NET Zone classifications are used in government reporting and for official purposes (e.g., US immigration visa eligibility).

These benchmarking results reveal systematic selection bias that could affect our segregation estimates. The over-representation of high-skill, white-collar occupations might artificially inflate political segregation estimates if such workers have more opportunity to sort into politically similar workplaces.

However, our political benchmarking provides reassurance that the most critical dimension for our analysis—partisan representativeness—is well-preserved. The close alignment between our sample and population benchmarks on party registration suggests that while some occupational bias exists, it does not systematically favor one party over another in ways that would fundamentally undermine our segregation estimates.

BLS Weighting Methodology

To address the systematic occupational bias identified in our benchmarking analysis, we implement a weighting scheme using Bureau of Labor Statistics (BLS) Occupational Employment and Wage Statistics (OEWS) data. Our sample may be systematically unrepresentative due to differential rates of: (1) voter registration across demographic groups, (2) LinkedIn profile availability and usage patterns, and (3) matching success rates in our ensemble approach. Most notably, professional occupations appear over-represented relative to blue-collar occupations, potentially biasing our segregation estimates.

Our weighting methodology proceeds in several steps. First, we map O*NET occupation codes from our dataset to 2-digit Standard Occupational Classification (SOC) major occupation groups used by BLS, enabling us to link our observations to official employment statistics. Second, we standardize metropolitan area names to match BLS area definitions used in the OES data, accounting for variations in MSA naming conventions between our data sources.

Third, we calculate the observed distribution of workers across occupation-MSA combinations in our analytical sample, creating empirical proportions for each SOC major group within each metropolitan area. Fourth, we extract benchmark employment distributions from the 2024 BLS OES data, using metropolitan-area-specific employment counts where available and falling back to national proportions for areas not covered in the metro OES data.

Finally, we calculate sampling weights as the ratio of BLS benchmark proportions to our observed sample proportions for each occupation-MSA combination. Formally, for occupation o in metropolitan area m, the weight is defined as:

$$w_{o,m} = \frac{BLS\_Proportion_{o,m}}{Sample\_Proportion_{o,m}} = \frac{\frac{BLS\_Employment_{o,m}}{\sum_{o,m} BLS\_Employment_{o,m}}}{\frac{LinkedIn\_Count_{o,m}}{\sum_{o,m} LinkedIn\_Count_{o,m}}}$$

where $BLS\_Employment_{o,m}$ represents the official employment count from BLS OES data for occupation o in MSA m, and $LinkedIn\_Count_{o,m}$ represents the number of matched workers in our sample for the same occupation-MSA combination. These weights effectively up-weight under-represented occupation-MSA cells and down-weight over-represented cells, adjusting our sample to match the national occupational distribution.

Ethical Considerations

This study links publicly available data sources using names and metropolitan area information to match US voter registration records with LinkedIn employment profiles. All data sources consist of publicly accessible government records (voter files), publicly available internet profiles (LinkedIn), or imputed data based on these publicly available sources. Because this study did not involve the collection of original data and used only publicly accessible information, it was assessed by an Institutional Review Board at one of the authors' institutions (a prominent R1 university in the United States) as exempt from human subjects review.

Data processing and analysis were conducted on secure university servers with dual-factor authentication and appropriate data security protocols. While the source data are publicly accessible, they contain sensitive personal information including residential addresses and employment details. To protect individual privacy, we do not release individual-level data, use only aggregate analytical results, and have anonymized all released data samples in compliance with commercial licensing agreements. The replication dataset contains no direct personal identifiers and cannot be used to re-identify specific individuals.

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Online Appendix

for

Political segregation in the US workplace

List of Figures

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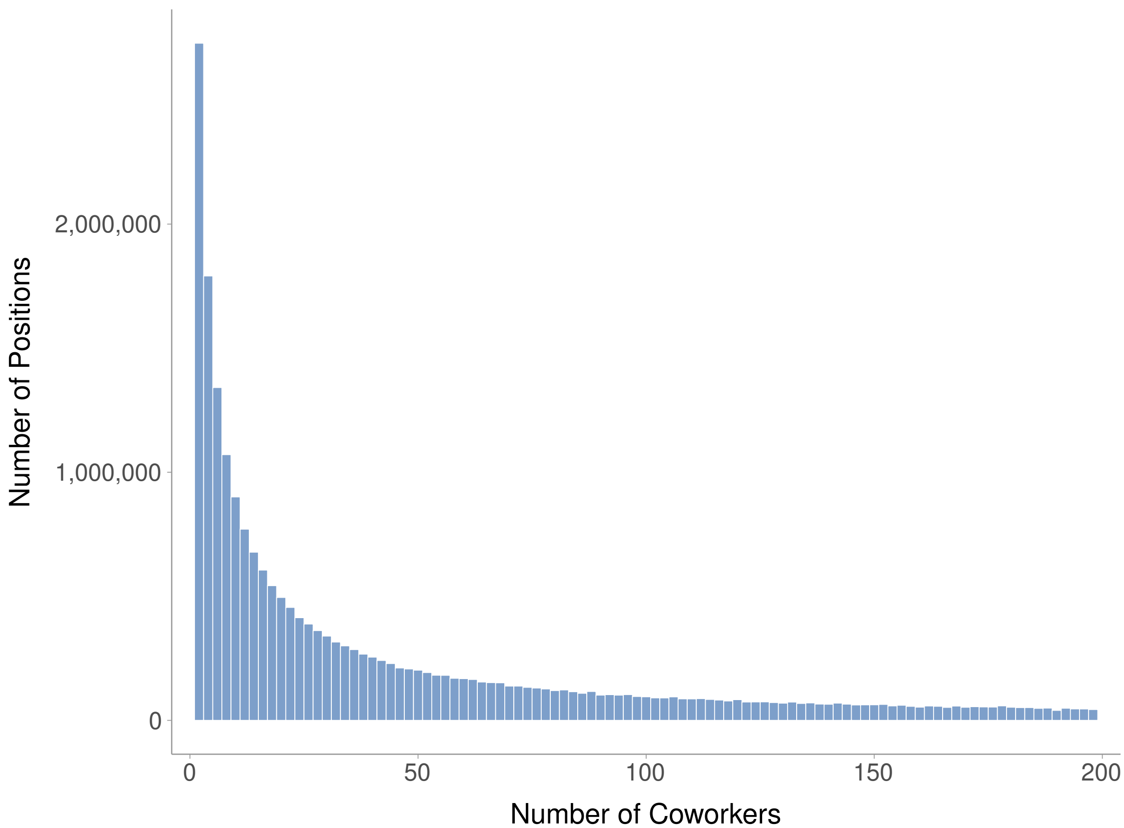
Figure A1: Voter file match rate, by age

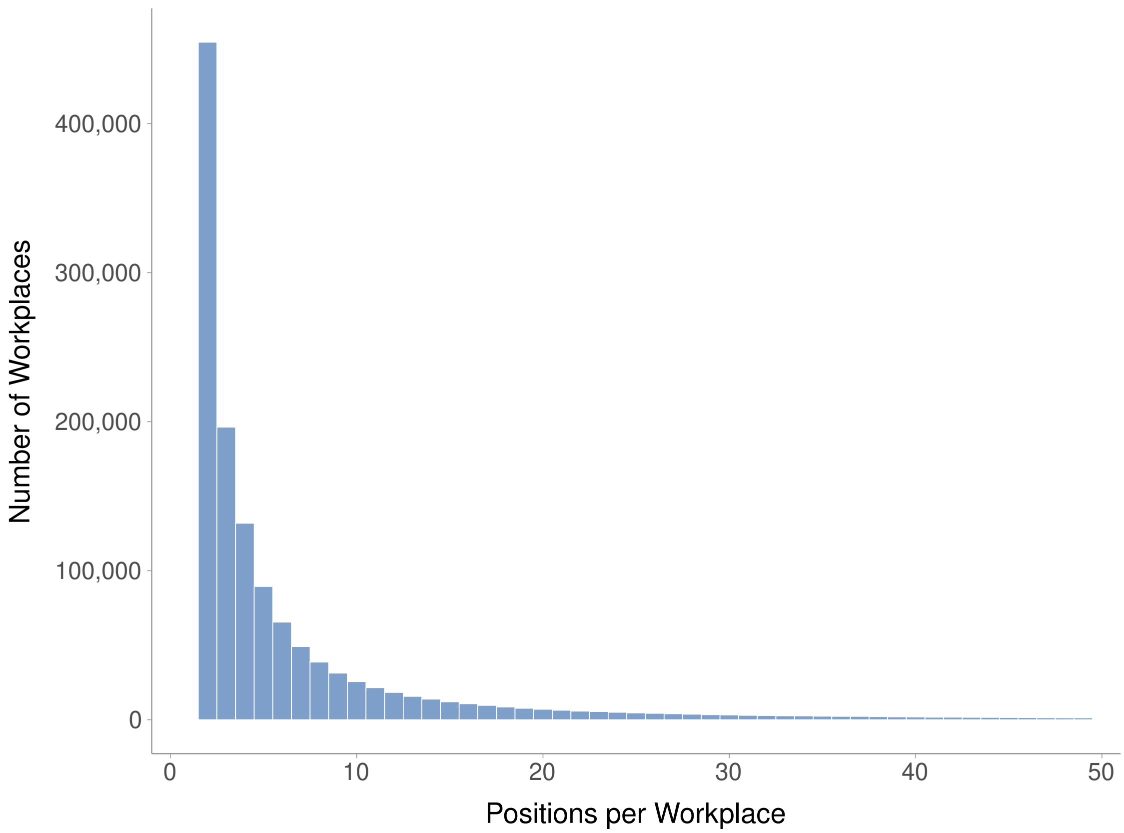
NOTES: This figure depicts the portion of L2 voter file records which we are able to match using our ensemble matching methodology that combines probabilistic record linkage (Splink) and LLM-based semantic matching (FuzzyLink). Match rate is highest for those in their late 20s and early 30s, likely because these voters are most likely to be in employment and have active LinkedIn profiles. They may also be more likely to appear on online job postings and professional social media platforms.

Figure A2: Number of coworkers per position



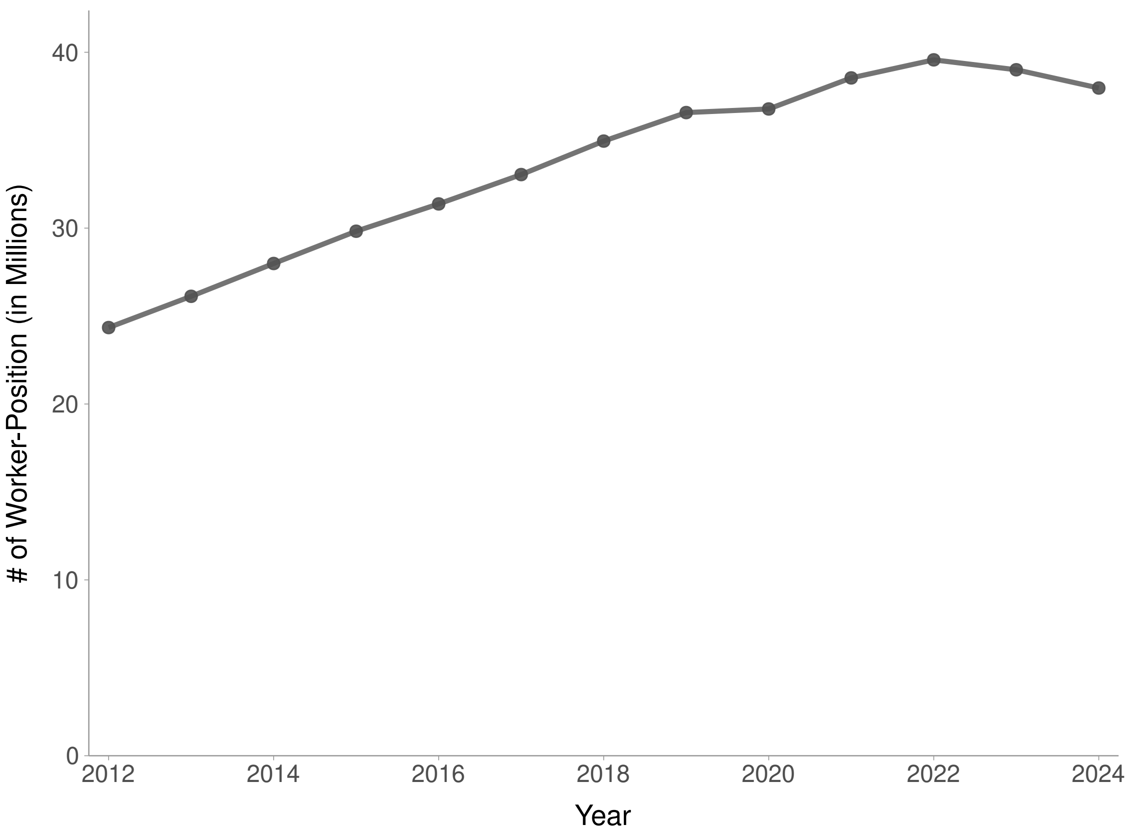
NOTES: For each employment position in the analytical dataset, this figure depicts the number of coworkers at the same workplace (i.e., at the same employer and MSA). Note that positions are not necessarily individual workers; a worker may have multiple positions as they change jobs or concurrently if they work multiple jobs. This figure excludes positions where the number of coworkers is greater than 200 to improve readability.

Figure A3: Number of positions per workplace



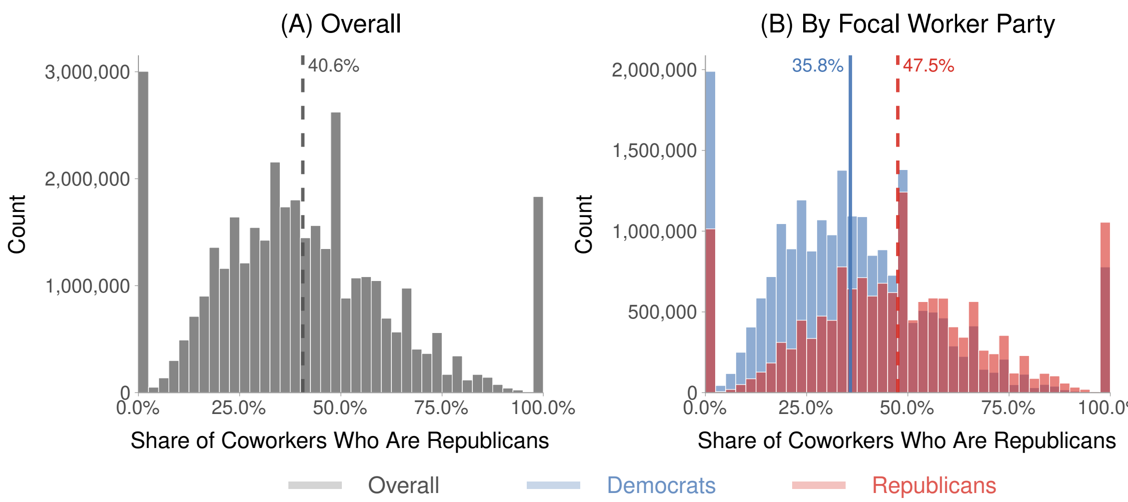
NOTES: Units of analysis are workplaces (employer-MSA dyads). This figure shows the distribution of workplace sizes based on the number of matched positions for each employer-MSA combination. The figure excludes employer-MSAs with more than 50 matched positions to improve readability, representing a small fraction of all workplaces in our sample. Our analytical sample includes workplaces ranging from 2 to several thousand employees, reflecting the highly skewed distribution typical of employer sizes in the US economy.

Figure A4: Number of positions per year



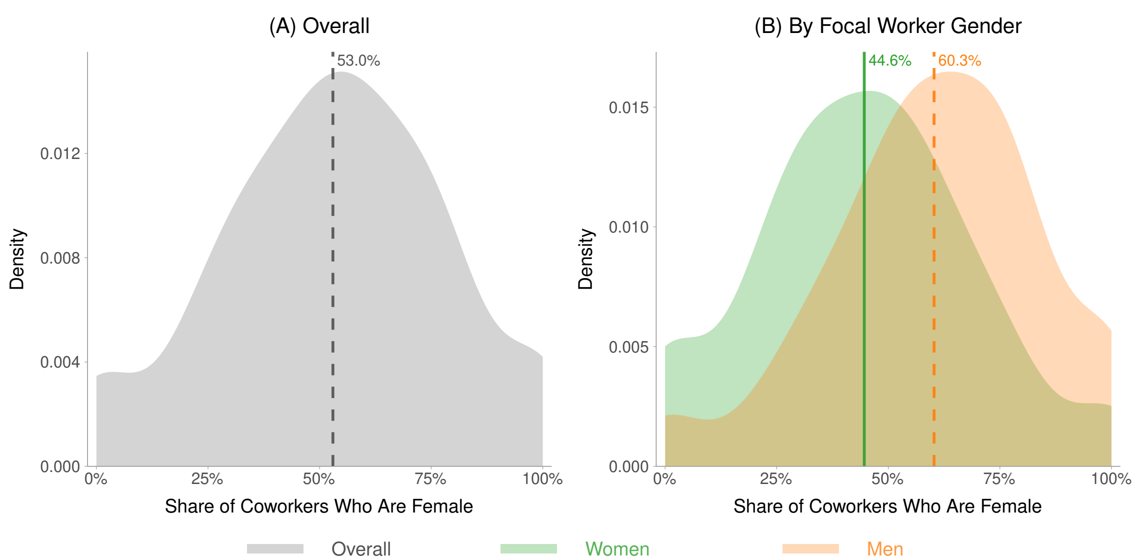
NOTES: Each point indicates the number of position-year observations in our panel dataset spanning 2012–2024. The panel is constructed by extending our April 2025 matches backwards in time using historical Revelio position data. The increase over time likely reflects growth in the size of the US labor force, growth in LinkedIn usage, and the fact that those who entered the workforce more recently are more likely to use LinkedIn.

Figure A5: Histograms of coworker partisanship



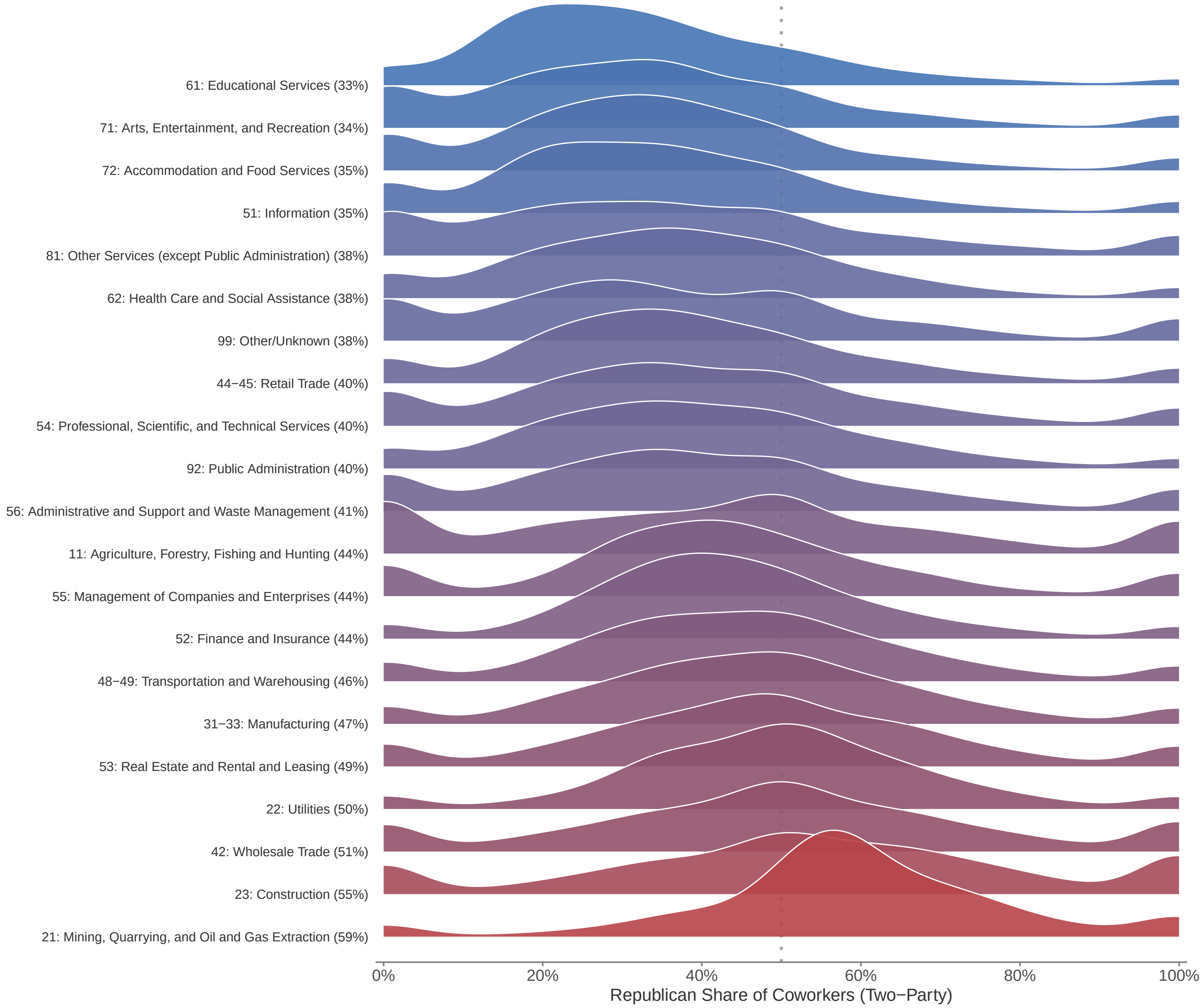
NOTES: Panel A shows the overall distribution of Republican coworker share. Panel B displays Republican coworker share separately for Democratic and Republican focal workers. All distributions use histogram format with vertical lines indicating group means. These patterns complement Figure 1 in the main text, which presents the same data using kernel density plots.

Figure A6: Gender segregation kernel density plots



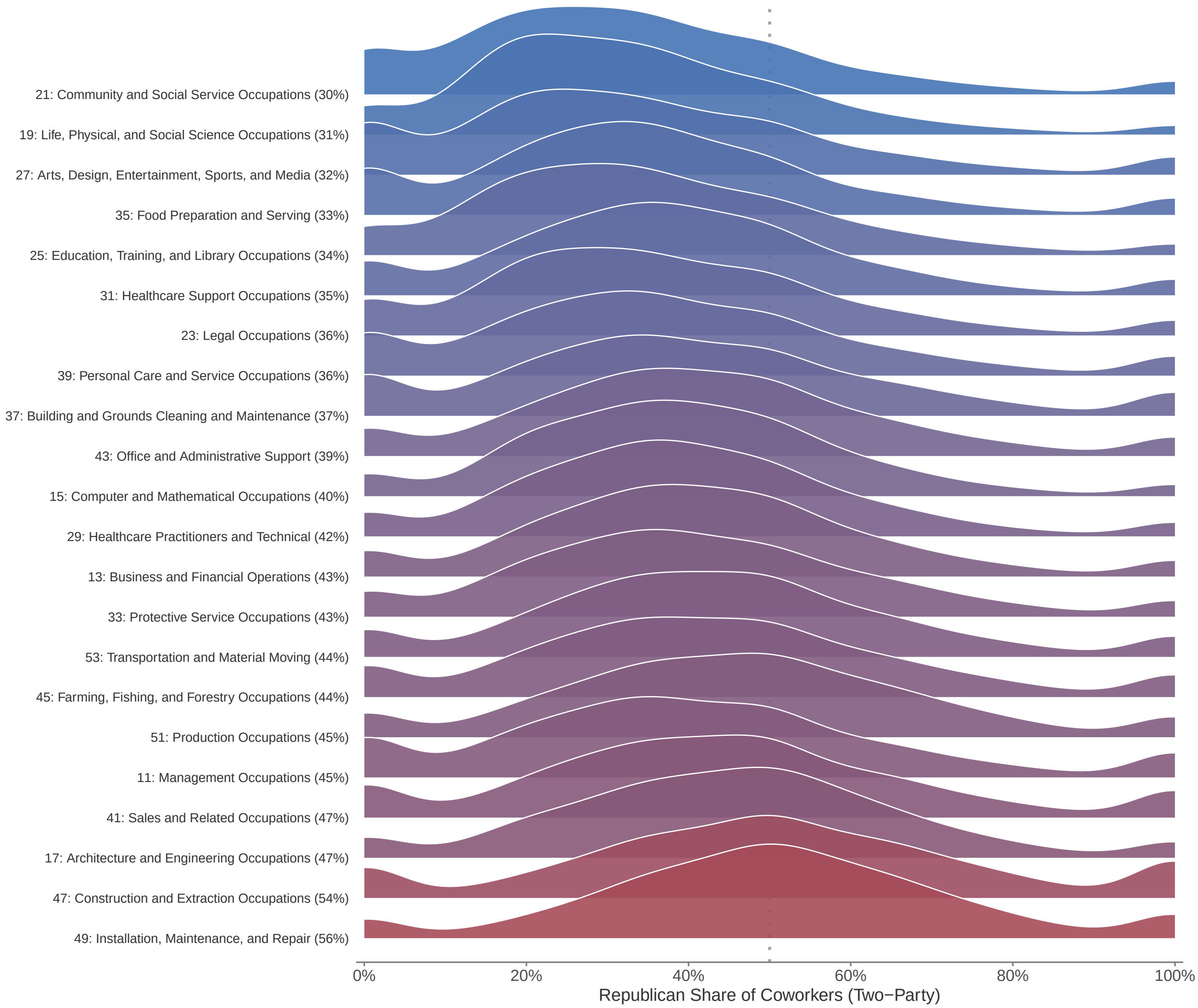
NOTES: Panel A shows the overall distribution of the share of women coworkers across all positions in our analytical sample. Panel B presents this distribution separately for women and men focal workers, illustrating gender-based workplace segregation. The mean woman worker's coworkers are disproportionately women compared to the mean man's coworkers, demonstrating systematic gender sorting in the workplace. Both plots are kernel density plots estimated using a fixed bandwidth of 0.10; vertical lines indicate mean values for each group. This analysis complements our main political segregation analysis by providing a benchmark for comparison, as illustrated in greater detail in Figure 4 in the main text.

Figure A7: Ridge plots showing political composition across 2-digit industry codes (NAICS)



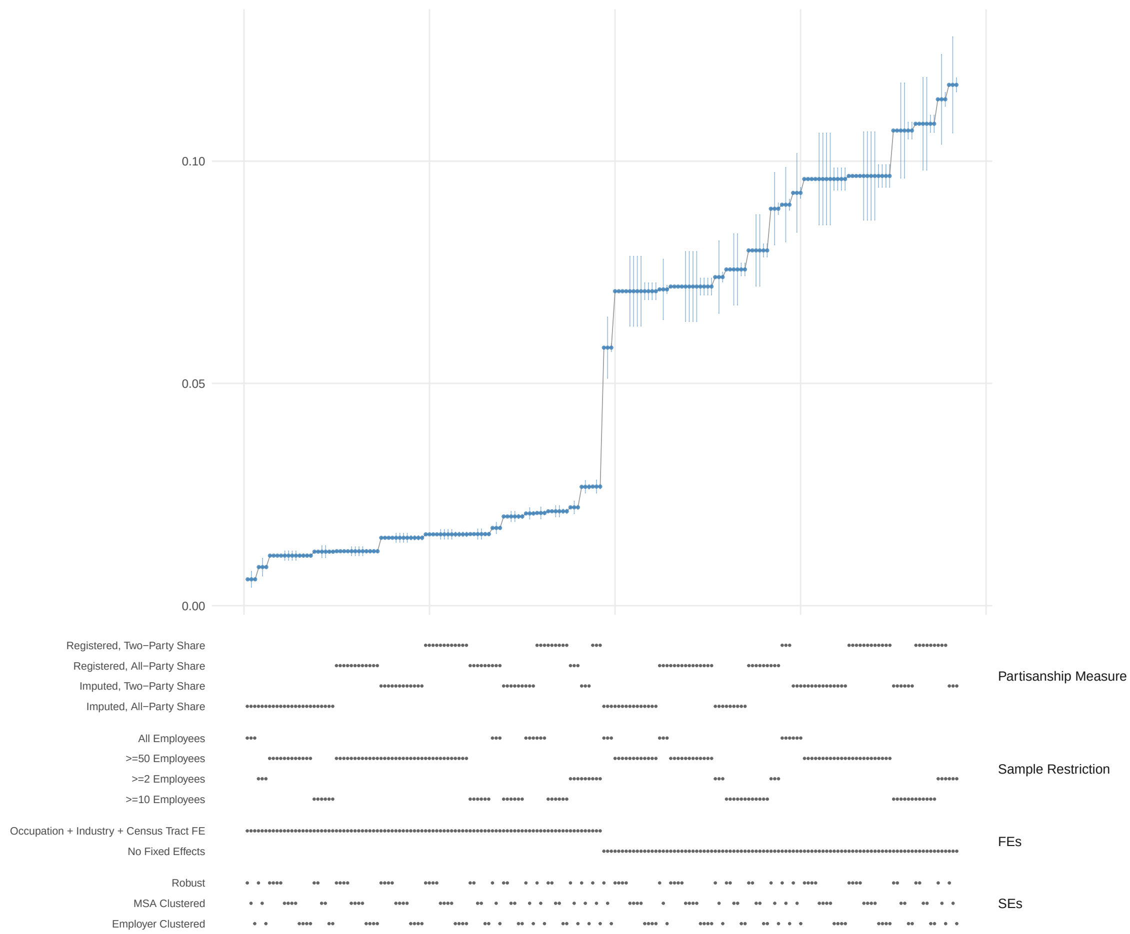
NOTES: Ridge plot shows the distribution of Republican coworker share (two-party) across 2-digit NAICS industry codes. Industries are ordered by Republican share from highest (bottom) to lowest (top), with percentages shown in parentheses. Only industries with at least 500 observations are included. Vertical dotted line indicates political balance (50% Republican). Kernel density estimates use fixed bandwidth = 0.05. The sample covers workers in industries meeting the minimum observation threshold from our analytical sample of 37.2 million positions held by 31 million workers.

Figure A8: Ridge plots showing political composition across 2-digit occupation codes (SOC)



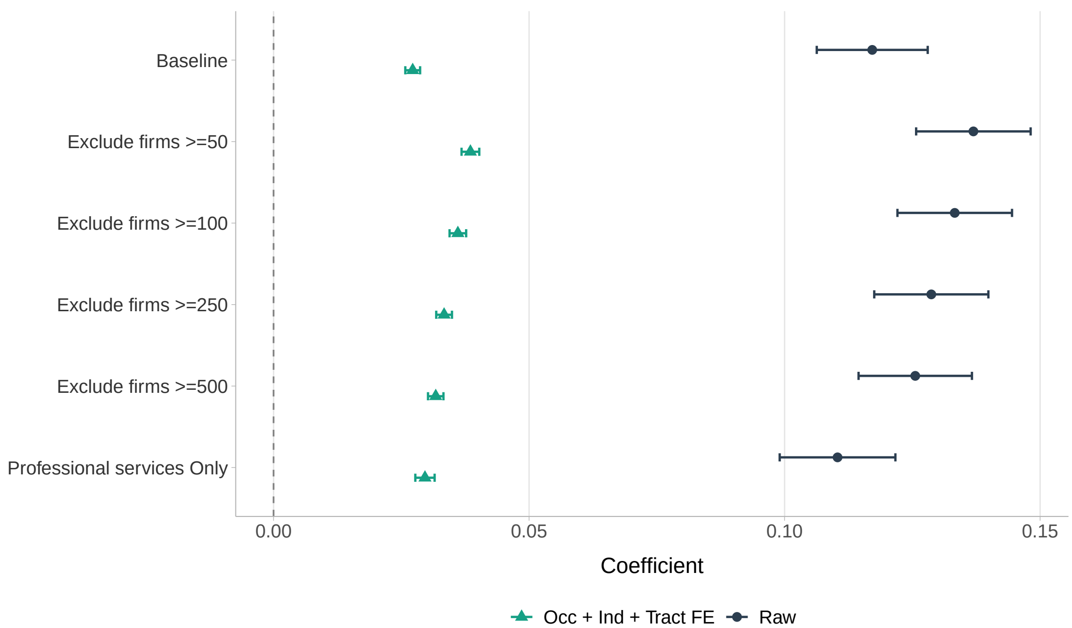
NOTES: Ridge plot shows the distribution of Republican coworker share (two-party) across 2-digit SOC occupation codes. Occupations are ordered by Republican share from highest (bottom) to lowest (top), with percentages shown in parentheses. Only occupations with at least 500 observations are included. Vertical dotted line indicates political balance (50% Republican). Kernel density estimates use fixed bandwidth = 0.05. The sample covers workers in occupations meeting the minimum observation threshold from our analytical sample of 37.2 million positions held by 31 million workers.

Figure A9: Multiverse specification curve analysis



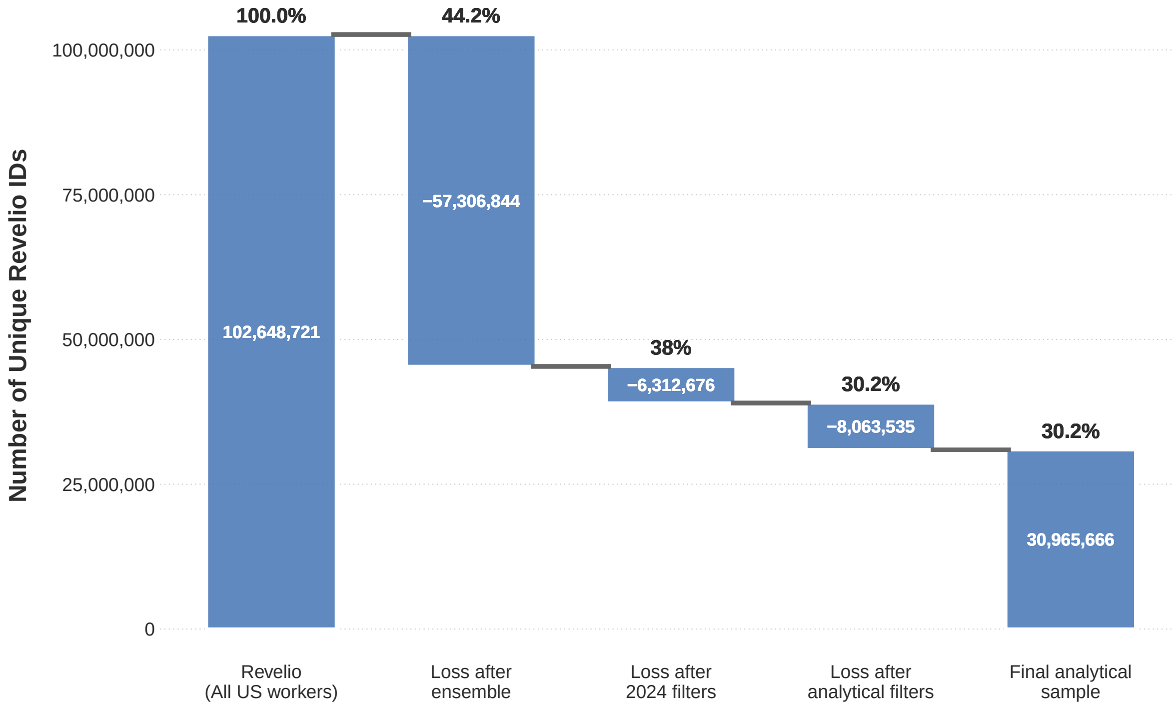
NOTES: This figure displays robustness checks for our estimates of political workplace segregation using a multiverse analysis approach. Each point represents a coefficient estimate from a different analytical specification, systematically varying methodological choices including fixed effects structure, sample restrictions, clustering assumptions, and reference categories. The upper panel shows the distribution of effect sizes across all specifications, while the lower panel indicates which analytical choices were used for each estimate. Our main findings are robust across the vast majority of reasonable analytical specifications.

Figure A10: Robustness to multi-office firms



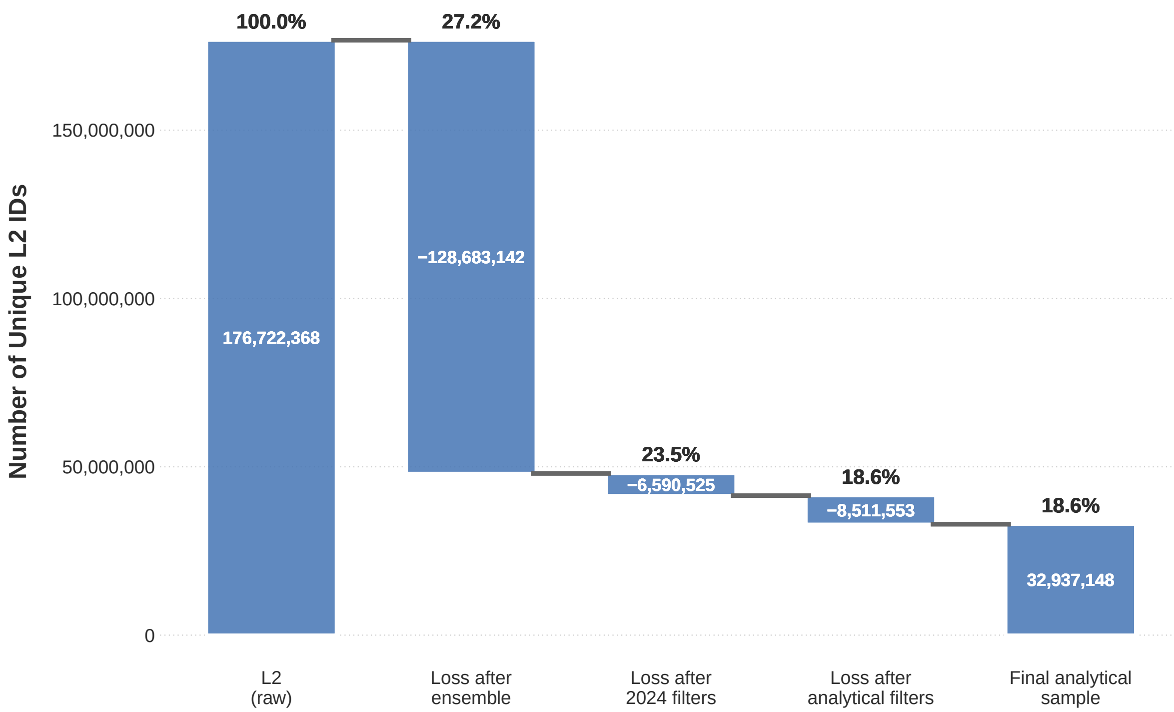
NOTES: This figure presents a sensitivity analysis to address the concern that our firm-MSA workplace definition may introduce measurement error for large, multi-location firms. We re-estimate our main segregation coefficient under several sample restrictions: excluding large firms of various size thresholds and isolating professional service firms (NAICS 54), which are less likely to have heterogeneous, geographically dispersed offices within an MSA. Both raw and full fixed-effects (Occ + Ind + Tract FE) models are shown. Notably, restricting to smaller firms yields larger coefficient estimates, which could reflect either reduced measurement error (as smaller firms are less likely to have multiple establishments within an MSA) or genuinely higher segregation levels in smaller firms. Regardless of interpretation, the robustness of segregation across firm size categories suggests our main findings are not artifacts of measurement error from multi-office firms. Detailed results are reported in Table A7.

Figure A11: Sample attrition waterfall chart: Revelio dataset



NOTES: This waterfall chart tracks the progression of unique individuals from the initial Revelio dataset through ensemble matching and analytical filtering to the final sample. Starting population: 102.6 million unique US workers within Metropolitan Statistical Areas. Step 1 (Ensemble Matching): Successful matching with L2 voter file using combined Splink and FuzzyLink methodologies. Step 2 (2024 Filters): Application of temporal and data quality filters active positions in 2024. Step 3 (Analytical Filters): Application of final analytical sample restrictions, including non-missing key variables, workplaces with at least 2 employees, and restriction to Democrats and Republicans (imputed).

Figure A12: Sample attrition waterfall chart: L2 dataset



NOTES: This waterfall chart tracks the progression of unique individuals from the initial L2 voter file through ensemble matching and analytical filtering to the final sample. Starting population: 177 million registered voters from processed MSA-specific datasets. Step 1 (Ensemble Matching): Successful matching with Revelio employment data using combined Splink and FuzzyLink methodologies. Step 2 (2024 Filters): Application of temporal and data quality filters for active positions in 2024. Step 3 (Analytical Filters): Application of final analytical sample restrictions including non-missing key variables, workplaces with at least 2 employees, and restriction to Democrats and Republicans using imputed partisanship. Note that final analytical sample size is not the same as that shown in Figure A11 because in a small fraction of cases, the same worker has multiple unique L2 voter IDs, which occurs because L2 assigns a new voter ID when an individual moves states.

Table A1: Raw workplace segregation coefficients by MSA

MSA	Coef.	N	MSA	Coef.	N
Abilene TX	0.047	11,403	Lansing East Lansing MI	0.050	82,153
Akron OH	0.043	87,838	Laredo TX	0.010	15,619
Albany GA	0.049	924	Las Cruces NM	0.053	15,462
Albany Schenectady Troy NY	0.062	139,641	Las Vegas Paradise NV	0.042	286,194
Albuquerque NM	0.057	103,012	Lawrence KS	0.070	2,641
Alexandria LA	0.052	5,148	Lawton OK	0.037	7,134
Allentown Bethlehem Easton PA NJ	0.052	128,435	Lebanon PA	0.043	12,985
Altoona PA	0.046	12,569	Lewiston Auburn ME	0.096	7,028
Amarillo TX	0.060	26,509	Lewiston ID WA	0.088	3,392
Ames IA	0.069	14,505	Lexington Fayette KY	0.036	93,402
Anchorage AK	0.080	40,639	Lima OH	0.071	2,309
Anderson SC	0.064	16,313	Lincoln NE	0.068	56,504
Anderson IN	0.038	8,532	Little Rock North Little Rock Conway AR	0.064	88,474
Ann Arbor MI	0.049	100,324	Logan UT ID	0.056	14,368
Anniston Oxford AL	0.077	6,833	Longview TX	0.056	19,014
Appleton WI	0.046	35,666	Longview WA	0.061	3,823
Asheville NC	0.084	54,737	Los Angeles Long Beach Santa Ana CA	0.051	1,504,883
Athens Clarke County GA	0.056	4,739	Louisville Jefferson County KY IN	0.044	222,696
Atlanta Sandy Springs Marietta GA	0.064	506,999	Lubbock TX	0.079	44,635
Atlantic City Hammonton NJ	0.047	22,196	Lynchburg VA	0.052	30,157
Auburn Opelika AL	0.058	10,520	Macon GA	0.106	8,061
Augusta Richmond County GA SC	0.063	26,717	Madera CA	0.088	2,106
Austin Round Rock TX	0.054	502,298	Madison WI	0.053	143,143
Bakersfield CA	0.070	69,545	Manchester Nashua NH	0.047	42,946
Baltimore Towson MD	0.073	484,464	Manhattan KS	0.068	6,402
Bangor ME	0.092	9,621	Mankato North Mankato MN	0.059	13,363
Barnstable Town MA	0.062	20,932	Mansfield OH	0.043	1,757
Baton Rouge LA	0.121	113,591	Mcallen Edinburg Mission TX	0.027	35,092
Battle Creek MI	0.062	13,178	Medford OR	0.078	17,070
Bay City MI	0.069	8,277	Memphis TN MS AR	0.093	154,233
Beaumont Port Arthur TX	0.102	37,099	Merced CA	0.070	15,212
Bellingham WA	0.100	30,871	Miami Fort Lauderdale Pompano Beach FL	0.042	671,608
Bend OR	0.089	25,327	Michigan City La Porte IN	0.055	6,925
Billings MT	0.039	17,196	Midland TX	0.073	21,069
Binghamton NY	0.074	27,151	Milwaukee Waukesha West Allis WI	0.091	297,722
Birmingham Hoover AL	0.069	72,343	Minneapolis St. Paul Bloomington MN WI	0.064	747,594
Bismarck ND	0.012	11,493	Missoula MT	0.043	15,371
Blacksburg Christiansburg Radford VA	0.075	20,340	Mobile AL	0.105	51,398

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Table A1 – continued from previous page

MSA	Coef.	N	MSA	Coef.	N
Bloomington Normal IL	0.070	21,993	Modesto CA	0.078	31,255
Bloomington IN	0.089	23,917	Monroe LA	0.117	17,813
Boise City Nampa ID	0.053	109,143	Monroe MI	0.058	6,391
Boston Cambridge Quincy MA NH	0.053	810,347	Montgomery AL	0.132	54,025
Boulder CO	0.056	64,718	Morgantown WV	0.047	16,446
Bowling Green KY	0.046	16,898	Morristown TN	0.037	4,199
Bremerton Silverdale WA	0.058	27,621	Mount Vernon Anacortes WA	0.063	9,151
Bridgeport Stamford Norwalk CT	0.050	131,785	Muncie IN	0.044	11,256
Brownsville Harlingen TX	0.054	23,503	Muskegon Norton Shores MI	0.051	16,605
Brunswick GA	0.006	885	Myrtle Beach North Myrtle Beach Conway SC	0.067	37,004
Buffalo Niagara Falls NY	0.058	146,872	Napa CA	0.063	14,122
Burlington NC	0.071	17,032	Naples Marco Island FL	0.056	4,484
Burlington South Burlington VT	0.053	38,293	Nashville Davidson Murfreesboro Franklin TN	0.060	290,378
Canton Massillon OH	0.038	44,250	New Haven Milford CT	0.073	103,260
Cape Coral Fort Myers FL	0.043	76,331	New Orleans Metairie Kenner LA	0.131	165,493
Cape Girardeau Jackson MO IL	0.062	7,489	New York Northern New Jersey Long Island NY NJ PA	0.067	2,671,627
Carson City NV	0.044	4,017	Niles Benton Harbor MI	0.057	13,097
Casper WY	0.022	6,613	North Port Bradenton Sarasota FL	0.046	86,519
Cedar Rapids IA	0.055	39,681	Norwich New London CT	0.059	30,574
Champaign Urbana IL	0.096	29,627	Ocala FL	0.041	29,858
Charleston North Charleston SC	0.060	133,313	Ocean City NJ	0.068	5,785
Charleston WV	0.034	24,846	Odessa TX	0.057	10,107
Charlotte Gastonia Rock Hill NC SC	0.061	416,220	Ogden Clearfield UT	0.035	61,779
Charlottesville VA	0.058	43,247	Oklahoma City OK	0.059	185,320
Chattanooga TN GA	0.045	62,148	Olympia WA	0.046	33,631
Cheyenne WY	0.032	9,383	Omaha Council Bluffs NE IA	0.059	175,208
Chicago Joliet Naperville IL IN WI	0.062	1,306,474	Orlando Kissimmee Sanford FL	0.050	440,553
Chico CA	0.077	19,989	Oshkosh Neenah WI	0.050	22,715
Cincinnati Middletown OH KY IN	0.055	359,146	Owensboro KY	0.027	12,027
Clarksville TN KY	0.048	25,252	Oxnard Thousand Oaks Ventura CA	0.051	102,635
Cleveland Elyria Mentor OH	0.066	338,881	Palm Bay Melbourne Titusville FL	0.035	49,451
Cleveland TN	0.016	1,983	Palm Coast FL	0.039	7,936
Coeur Dalene ID	0.050	5,959	Panama City Lynn Haven Panama City Beach FL	0.033	8,338
College Station Bryan TX	0.065	32,738	Parkersburg Marietta Vienna WV OH	0.034	10,679
Colorado Springs CO	0.049	106,582	Pascagoula MS	0.046	9,391
Columbia MO	0.079	34,792	Pensacola Ferry Pass Brent FL	0.050	64,998
Columbia SC	0.078	122,718	Peoria IL	0.062	37,542
Columbus GA AL	0.051	6,245	Philadelphia Camden Wilmington PA NJ DE MD	0.059	989,093

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Table A1 – continued from previous page

MSA	Coef.	N	MSA	Coef.	N
Columbus OH	0.054	371,760	Phoenix Mesa Scottsdale AZ	0.049	619,224
Columbus IN	0.017	1,213	Pine Bluff AR	0.117	4,564
Corpus Christi TX	0.073	38,120	Pittsburgh PA	0.072	447,778
Corvallis OR	0.089	13,968	Pittsfield MA	0.041	11,958
Crestview Fort Walton Beach Destin FL	0.030	21,737	Pocatello ID	0.046	7,921
Cumberland MD WV	0.059	6,087	Port St. Lucie FL	0.057	43,662
Dallas Fort Worth Arlington TX	0.051	1,041,342	Portland South Portland Biddeford ME	0.060	61,758
Dalton GA	0.016	1,564	Portland Vancouver Hillsboro OR WA	0.066	423,183
Danville IL	0.041	1,214	Poughkeepsie Newburgh Middletown NY	0.060	67,585
Danville VA	0.099	3,265	Prescott AZ	0.052	12,127
Davenport Moline Rock Island IA IL	0.054	39,177	Providence New Bedford Fall River RI MA	0.045	200,612
Dayton OH	0.057	127,206	Provo Orem UT	0.031	98,612
Decatur AL	0.041	3,265	Pueblo CO	0.052	13,310
Decatur IL	0.013	1,479	Punta Gorda FL	0.039	5,301
Deltona Daytona Beach Ormond Beach FL	0.044	48,267	Racine WI	0.062	19,301
Denver Aurora Broomfield CO	0.057	592,424	Raleigh Cary NC	0.054	301,956
Des Moines West Des Moines IA	0.054	128,090	Rapid City SD	0.059	12,516
Detroit Warren Livonia MI	0.062	650,844	Reading PA	0.056	48,371
Dothan AL	0.098	12,714	Redding CA	0.053	13,862
Dover DE	0.060	14,973	Reno Sparks NV	0.059	62,975
Dubuque IA	0.058	13,624	Richmond VA	0.059	268,383
Duluth MN WI	0.043	32,902	Riverside San Bernardino Ontario CA	0.038	407,860
Durham Chapel Hill NC	0.049	130,366	Roanoke VA	0.045	45,624
Eau Claire WI	0.058	21,146	Rochester MN	0.045	30,757
El Centro CA	0.038	7,280	Rochester NY	0.064	169,658
El Paso TX	0.037	79,693	Rockford IL	0.055	33,126
Elizabethtown KY	0.019	12,648	Rocky Mount NC	0.077	12,223
Elkhart Goshen IN	0.069	17,482	Rome GA	0.040	1,092
Elmira NY	0.048	5,235	Sacramento Arden Arcade Roseville CA	0.061	347,084
Erie PA	0.056	34,608	Saginaw Saginaw Township North MI	0.069	21,206
Eugene Springfield OR	0.087	46,147	Salem OR	0.066	33,507
Evansville IN KY	0.038	40,516	Salinas CA	0.049	35,248
Fairbanks AK	0.067	7,649	Salisbury MD	0.068	10,337
Fargo ND MN	0.026	33,769	Salt Lake City UT	0.048	192,253
Farmington NM	0.099	6,272	San Angelo TX	0.060	10,452
Fayetteville NC	0.068	37,801	San Antonio New Braunfels TX	0.063	378,052
Fayetteville Springdale Rogers AR MO	0.049	70,100	San Diego Carlsbad San Marcos CA	0.051	579,379
Flagstaff AZ	0.070	14,658	San Francisco Oakland Fremont CA	0.040	712,616

Continued on next page

Table A1 – continued from previous page

MSA	Coef.	N	MSA	Coef.	N
Flint MI	0.060	35,248	San Jose Sunnyvale Santa Clara CA	0.029	370,043
Florence Muscle Shoals AL	0.072	11,711	San Luis Obispo Paso Robles CA	0.073	35,373
Florence SC	0.115	19,732	Sandusky OH	0.028	5,642
Fond Du Lac WI	0.068	2,142	Santa Barbara Santa Maria Goleta CA	0.086	52,540
Fort Collins Loveland CO	0.071	63,891	Santa Cruz Watsonville CA	0.064	18,286
Fort Smith AR OK	0.028	20,114	Santa Fe NM	0.058	14,373
Fort Wayne IN	0.064	61,102	Santa Rosa Petaluma CA	0.051	56,245
Fresno CA	0.060	84,309	Savannah GA	0.057	5,530
Gadsden AL	0.074	7,081	Scranton Wilkes Barre PA	0.052	55,340
Gainesville FL	0.062	49,312	Seattle Tacoma Bellevue WA	0.050	694,664
Gainesville GA	0.049	2,293	Sebastian Vero Beach FL	0.049	11,646
Glens Falls NY	0.062	10,597	Sheboygan WI	0.046	13,222
Goldsboro NC	0.075	9,111	Sherman Denison TX	0.032	10,771
Grand Forks ND MN	0.029	10,101	Shreveport Bossier City LA	0.122	37,618
Grand Junction CO	0.065	15,779	Sioux City IA NE SD	0.046	12,101
Grand Rapids Wyoming MI	0.056	153,334	Sioux Falls SD	0.052	39,330
Great Falls MT	0.028	6,042	South Bend Mishawaka IN MI	0.057	38,290
Greeley CO	0.063	26,711	Spartanburg SC	0.068	33,466
Green Bay WI	0.056	43,348	Spokane WA	0.046	76,486
Greensboro High Point NC	0.079	121,877	Springfield IL	0.060	23,010
Greenville Mauldin Easley SC	0.065	129,874	Springfield MA	0.061	70,324
Greenville NC	0.061	26,106	Springfield MO	0.080	60,823
Gulfport Biloxi MS	0.054	19,261	Springfield OH	0.041	10,504
Hagerstown Martinsburg MD WV	0.041	22,723	St. Cloud MN	0.057	22,976
Hanford Corcoran CA	0.051	6,444	St. George UT	0.049	12,412
Harrisburg Carlisle PA	0.057	99,466	St. Joseph MO KS	0.109	1,862
Harrisonburg VA	0.082	14,301	St. Louis MO IL	0.067	488,861
Hartford West Hartford East Hartford CT	0.054	165,391	State College PA	0.084	27,110
Hattiesburg MS	0.104	12,772	Stockton CA	0.047	57,379
Hickory Lenoir Morganton NC	0.034	34,085	Sumter SC	0.122	10,116
Hinesville Fort Stewart GA	0.019	852	Syracuse NY	0.071	96,943
Holland Grand Haven MI	0.057	41,646	Tallahassee FL	0.079	66,281
Honolulu HI	0.017	82,699	Tampa St. Petersburg Clearwater FL	0.044	455,253
Hot Springs AR	0.034	3,206	Terre Haute IN	0.043	15,269
Houma Bayou Cane Thibodaux LA	0.055	17,134	Texarkana TX Texarkana AR	0.092	8,743
Houston Sugar Land Baytown TX	0.072	883,640	Toledo OH	0.063	76,965
Huntington Ashland WV KY OH	0.020	18,721	Topeka KS	0.055	28,301
Huntsville AL	0.069	80,577	Trenton Ewing NJ	0.043	49,802

Continued on next page

Table A1 – continued from previous page

MSA	Coef.	N	MSA	Coef.	N
Idaho Falls ID	0.035	14,019	Tucson AZ	0.068	129,489
Indianapolis Carmel IN	0.057	333,814	Tulsa OK	0.053	137,695
Iowa City IA	0.068	30,393	Tuscaloosa AL	0.091	31,431
Ithaca NY	0.073	16,410	Tyler TX	0.064	25,740
Jackson MI	0.037	4,129	Utica Rome NY	0.055	24,523
Jackson MS	0.119	56,222	Valdosta GA	0.083	1,859
Jackson TN	0.053	1,496	Vallejo Fairfield CA	0.051	39,040
Jacksonville FL	0.056	253,502	Victoria TX	0.086	3,756
Jacksonville NC	0.021	7,296	Vineland Millville Bridgeton NJ	0.064	9,148
Janesville WI	0.042	15,668	Virginia Beach Norfolk Newport News VA NC	0.053	271,297
Jefferson City MO	0.077	18,476	Visalia Porterville CA	0.052	25,764
Johnson City TN	0.054	18,002	Waco TX	0.066	29,662
Johnstown PA	0.046	10,843	Warner Robins GA	0.065	2,378
Jonesboro AR	0.037	7,491	Washington Arlington Alexandria DC VA MD WV	0.052	1,020,303
Joplin MO	0.056	13,732	Waterloo Cedar Falls IA	0.060	19,243
Kalamazoo Portage MI	0.060	58,199	Wausau WI	0.051	14,545
Kankakee Bradley IL	0.072	7,610	Weirton Steubenville WV OH	0.030	7,238
Kansas City MO KS	0.054	420,379	Wenatchee WA	0.067	10,270
Kennewick Pasco Richland WA	0.053	32,787	Wheeling WV OH	0.052	8,873
Killeen Temple Fort Hood TX	0.060	46,607	Wichita Falls TX	0.049	8,319
Kingsport Bristol Bristol TN VA	0.024	16,509	Wichita KS	0.058	88,069
Kingston NY	0.088	10,388	Williamsport PA	0.065	12,984
Knoxville TN	0.053	99,462	Wilmington NC	0.058	57,273
Kokomo IN	0.029	9,637	Winchester VA WV	0.044	12,996
La Crosse WI MN	0.054	20,435	Winston Salem NC	0.054	24,794
Lafayette LA	0.090	39,755	Worcester MA	0.048	97,710
Lafayette IN	0.065	26,218	Yakima WA	0.089	18,094
Lake Charles LA	0.071	23,872	York Hanover PA	0.054	52,192
Lake Havasu City Kingman AZ	0.036	9,200	Youngstown Warren Boardman OH PA	0.054	43,587
Lakeland Winter Haven FL	0.051	62,662	Yuba City CA	0.069	8,451
Lancaster PA	0.079	72,073	Yuma AZ	0.079	10,388

NOTES: This table reports the raw MSA-level workplace segregation coefficients plotted in Figure 2a. Each coefficient represents β from the regression: $\text{pct\_rep\_imp\_cws\_emp\_msa\_dr}_i = \alpha + \beta \cdot \text{rep\_imp}_i + \varepsilon_i$ estimated separately for each MSA. Coefficients measure the additional percentage points of Republican coworkers that Republican workers have compared to Democratic workers within each MSA. Sample restricted to Democrats and Republicans only (imputed partisanship). 'N' represents the number of unique worker-employer-MSA records in the analysis. MSAs are sorted alphabetically.

Table A2: Net workplace segregation coefficients (residuals) by MSA

MSA	Residual	N	MSA	Residual	N
Abilene TX	-0.0204	10,722	Lansing East Lansing MI	-0.0097	80,667
Akron OH	-0.0232	86,657	Laredo TX	-0.0316	15,205
Albany GA	-0.0145	901	Las Cruces NM	0.0045	14,893
Albany Schenectady Troy NY	0.0007	136,197	Las Vegas Paradise NV	-0.0129	279,995
Albuquerque NM	0.0033	99,753	Lawrence KS	0.0024	2,581
Alexandria LA	-0.0194	4,990	Lawton OK	-0.0169	6,882
Allentown Bethlehem Easton PA NJ	-0.0035	124,798	Lebanon PA	-0.0041	12,701
Altoona PA	-0.0035	12,206	Lewiston Auburn ME	0.0339	6,926
Amarillo TX	0.0003	25,264	Lewiston ID WA	0.0340	3,312
Ames IA	0.0112	14,149	Lexington Fayette KY	-0.0166	90,998
Anchorage AK	0.0214	37,906	Lima OH	0.0174	2,279
Anderson SC	0.0091	15,590	Lincoln NE	0.0127	54,998
Anderson IN	-0.0139	8,323	Little Rock North Little Rock Conway AR	-0.0158	86,094
Ann Arbor MI	-0.0193	98,224	Logan UT ID	0.0033	13,777
Anniston Oxford AL	0.0201	6,642	Longview TX	0.0011	17,984
Appleton WI	-0.0056	35,082	Longview WA	0.0112	3,756
Asheville NC	0.0221	53,029	Los Angeles Long Beach Santa Ana CA	-0.0105	1,477,319
Athens Clarke County GA	-0.0192	4,547	Louisville Jefferson County KY IN	-0.0168	217,095
Atlanta Sandy Springs Marietta GA	-0.0270	483,767	Lubbock TX	0.0192	42,440
Atlantic City Hammonton NJ	-0.0100	21,779	Lynchburg VA	-0.0075	28,566
Auburn Opelika AL	0.0004	10,198	Macon GA	0.0238	7,654
Augusta Richmond County GA SC	-0.0013	25,507	Madera CA	0.0377	2,031
Austin Round Rock TX	-0.0128	478,044	Madison WI	-0.0076	140,462
Bakersfield CA	0.0110	68,222	Manchester Nashua NH	-0.0035	42,417
Baltimore Towson MD	-0.0033	473,764	Manhattan KS	0.0163	6,118
Bangor ME	0.0232	9,261	Mankato North Mankato MN	0.0013	13,011
Barnstable Town MA	0.0119	19,747	Mansfield OH	-0.0035	1,730
Baton Rouge LA	0.0444	110,782	Mcallen Edinburg Mission TX	-0.0230	33,573
Battle Creek MI	0.0148	12,967	Medford OR	0.0204	16,682
Bay City MI	0.0142	8,161	Memphis TN MS AR	-0.0003	151,817
Beaumont Port Arthur TX	0.0332	35,840	Merced CA	0.0239	14,607
Bellingham WA	0.0398	29,919	Miami Fort Lauderdale Pompano Beach FL	-0.0155	658,939
Bend OR	0.0343	24,368	Michigan City La Porte IN	0.0029	6,792
Billings MT	-0.0078	16,670	Midland TX	0.0128	19,784
Binghamton NY	0.0101	25,353	Milwaukee Waukesha West Allis WI	-0.0058	294,422
Birmingham Hoover AL	-0.0109	70,028	Minneapolis St. Paul Bloomington MN WI	-0.0177	732,754
Bismarck ND	-0.0360	11,207	Missoula MT	-0.0051	14,872
Blacksburg Christiansburg Radford VA	0.0230	19,513	Mobile AL	0.0270	50,365

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Table A2 – continued from previous page

MSA	Residual	N	MSA	Residual	N
Bloomington Normal IL	0.0094	21,629	Modesto CA	0.0258	30,774
Bloomington IN	0.0141	23,212	Monroe LA	0.0342	17,359
Boise City Nampa ID	-0.0050	105,940	Monroe MI	0.0067	6,304
Boston Cambridge Quincy MA NH	-0.0121	795,501	Montgomery AL	0.0463	52,415
Boulder CO	-0.0046	63,006	Morgantown WV	-0.0035	15,656
Bowling Green KY	-0.0044	16,098	Morristown TN	-0.0148	4,094
Bremerton Silverdale WA	0.0040	26,954	Mount Vernon Anacortes WA	0.0131	8,950
Bridgeport Stamford Norwalk CT	-0.0086	129,665	Muncie IN	-0.0124	10,993
Brownsville Harlingen TX	-0.0006	22,757	Muskegon Norton Shores MI	-0.0009	16,334
Brunswick GA	-0.0504	838	Myrtle Beach North Myrtle Beach Conway SC	0.0155	34,088
Buffalo Niagara Falls NY	-0.0030	144,237	Napa CA	0.0155	13,817
Burlington NC	0.0145	16,327	Naples Marco Island FL	-0.0009	4,335
Burlington South Burlington VT	-0.0021	37,249	Nashville Davidson Murfreesboro Franklin TN	-0.0208	283,392
Canton Massillon OH	-0.0216	43,638	New Haven Milford CT	0.0026	101,262
Cape Coral Fort Myers FL	-0.0075	71,754	New Orleans Metairie Kenner LA	0.0381	161,764
Cape Girardeau Jackson MO IL	0.0040	7,152	New York Northern New Jersey Long Island NY NJ PA	-0.0078	2,635,613
Carson City NV	-0.0031	3,901	Niles Benton Harbor MI	0.0065	12,825
Casper WY	-0.0265	6,492	North Port Bradenton Sarasota FL	-0.0037	83,575
Cedar Rapids IA	-0.0030	39,030	Norwich New London CT	0.0019	29,902
Champaign Urbana IL	0.0245	29,103	Ocala FL	-0.0101	28,821
Charleston North Charleston SC	0.0009	126,698	Ocean City NJ	0.0223	5,612
Charleston WV	-0.0162	23,666	Odessa TX	-0.0003	9,221
Charlotte Gastonia Rock Hill NC SC	-0.0094	401,922	Ogden Clearfield UT	-0.0198	60,432
Charlottesville VA	-0.0022	41,489	Oklahoma City OK	-0.0050	177,417
Chattanooga TN GA	-0.0261	60,518	Olympia WA	-0.0064	32,661
Cheyenne WY	-0.0150	9,158	Omaha Council Bluffs NE IA	-0.0019	170,694
Chicago Joliet Naperville IL IN WI	-0.0082	1,291,423	Orlando Kissimmee Sanford FL	-0.0079	425,545
Chico CA	0.0319	19,280	Oshkosh Neenah WI	-0.0037	22,413
Cincinnati Middletown OH KY IN	-0.0173	352,780	Owensboro KY	-0.0205	11,665
Clarksville TN KY	-0.0167	24,716	Oxnard Thousand Oaks Ventura CA	0.0018	100,375
Cleveland Elyria Mentor OH	-0.0134	334,527	Palm Bay Melbourne Titusville FL	-0.0158	47,673
Cleveland TN	-0.0312	1,953	Palm Coast FL	-0.0082	7,348
Coeur Dalene ID	0.0035	5,706	Panama City Lynn Haven Panama City Beach FL	-0.0165	7,973
College Station Bryan TX	0.0010	31,176	Parkersburg Marietta Vienna WV OH	-0.0167	10,381
Colorado Springs CO	-0.0070	104,736	Pascagoula MS	-0.0267	9,139
Columbia MO	0.0147	33,890	Pensacola Ferry Pass Brent FL	-0.0062	63,392
Columbia SC	0.0068	118,355	Peoria IL	-0.0009	36,904
Columbus GA AL	-0.0160	6,021	Philadelphia Camden Wilmington PA NJ DE MD	-0.0032	969,997

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Table A2 – continued from previous page

MSA	Residual	N	MSA	Residual	N
Columbus OH	-0.0195	362,676	Phoenix Mesa Scottsdale AZ	-0.0133	591,543
Columbus IN	-0.0249	1,187	Pine Bluff AR	0.0355	4,445
Corpus Christi TX	0.0127	36,879	Pittsburgh PA	0.0066	434,234
Corvallis OR	0.0343	13,578	Pittsfield MA	-0.0083	11,469
Crestview Fort Walton Beach Destin FL	-0.0218	21,043	Pocatello ID	-0.0069	7,711
Cumberland MD WV	0.0111	5,848	Port St. Lucie FL	0.0012	41,353
Dallas Fort Worth Arlington TX	-0.0222	1,001,181	Portland South Portland Biddeford ME	0.0007	60,488
Dalton GA	-0.0393	1,532	Portland Vancouver Hillsboro OR WA	0.0016	414,552
Danville IL	-0.0090	1,177	Poughkeepsie Newburgh Middletown NY	0.0041	66,049
Danville VA	0.0438	3,211	Prescott AZ	0.0003	11,472
Davenport Moline Rock Island IA IL	-0.0024	38,528	Providence New Bedford Fall River RI MA	-0.0133	197,605
Dayton OH	-0.0104	124,599	Provo Orem UT	-0.0196	95,908
Decatur AL	-0.0243	3,186	Pueblo CO	-0.0056	12,897
Decatur IL	-0.0388	1,454	Punta Gorda FL	-0.0094	4,982
Deltona Daytona Beach Ormond Beach FL	-0.0129	46,620	Racine WI	0.0033	19,118
Denver Aurora Broomfield CO	-0.0051	577,593	Raleigh Cary NC	-0.0071	287,532
Des Moines West Des Moines IA	-0.0023	124,065	Rapid City SD	0.0090	12,085
Detroit Warren Livonia MI	-0.0071	637,510	Reading PA	0.0028	47,490
Dothan AL	0.0286	12,173	Redding CA	0.0056	13,337
Dover DE	0.0010	14,629	Reno Sparks NV	0.0044	61,127
Dubuque IA	0.0014	13,442	Richmond VA	-0.0064	258,873
Duluth MN WI	-0.0148	32,246	Riverside San Bernardino Ontario CA	-0.0157	396,496
Durham Chapel Hill NC	-0.0145	124,935	Roanoke VA	-0.0172	44,513
Eau Claire WI	0.0014	20,713	Rochester MN	-0.0127	30,235
El Centro CA	-0.0112	7,137	Rochester NY	0.0037	166,970
El Paso TX	-0.0105	78,004	Rockford IL	0.0018	32,712
Elizabethtown KY	-0.0300	12,302	Rocky Mount NC	0.0213	11,658
Elkhart Goshen IN	0.0097	17,209	Rome GA	-0.0150	1,060
Elmira NY	0.0005	5,150	Sacramento Arden Arcade Roseville CA	0.0038	336,505
Erie PA	0.0038	33,892	Saginaw Saginaw Township North MI	0.0151	20,921
Eugene Springfield OR	0.0230	45,316	Salem OR	0.0127	32,754
Evansville IN KY	-0.0183	39,493	Salinas CA	0.0003	34,626
Fairbanks AK	0.0088	6,811	Salisbury MD	0.0128	10,023
Fargo ND MN	-0.0533	32,849	Salt Lake City UT	-0.0150	188,298
Farmington NM	0.0314	5,543	San Angelo TX	0.0076	10,068
Fayetteville NC	0.0133	36,702	San Antonio New Braunfels TX	-0.0081	360,210
Fayetteville Springdale Rogers AR MO	-0.0118	67,962	San Diego Carlsbad San Marcos CA	-0.0022	566,918
Flagstaff AZ	0.0204	13,492	San Francisco Oakland Fremont CA	-0.0139	698,396

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Table A2 – continued from previous page

MSA	Residual	N	MSA	Residual	N
Flint MI	0.0012	34,563	San Jose Sunnyvale Santa Clara CA	-0.0200	361,911
Florence Muscle Shoals AL	0.0203	11,397	San Luis Obispo Paso Robles CA	0.0204	34,478
Florence SC	0.0585	18,999	Sandusky OH	-0.0247	5,529
Fond Du Lac WI	0.0233	2,100	Santa Barbara Santa Maria Goleta CA	0.0313	51,289
Fort Collins Loveland CO	0.0106	62,023	Santa Cruz Watsonville CA	0.0156	17,777
Fort Smith AR OK	-0.0241	19,476	Santa Fe NM	0.0057	13,499
Fort Wayne IN	-0.0004	59,727	Santa Rosa Petaluma CA	0.0036	54,160
Fresno CA	0.0061	82,640	Savannah GA	-0.0274	5,331
Gadsden AL	0.0117	6,901	Scranton Wilkes Barre PA	-0.0027	53,365
Gainesville FL	0.0042	46,971	Seattle Tacoma Bellevue WA	-0.0105	681,884
Gainesville GA	-0.0087	2,155	Sebastian Vero Beach FL	0.0002	11,133
Glens Falls NY	0.0119	10,343	Sheboygan WI	-0.0059	13,076
Goldsboro NC	0.0179	8,769	Sherman Denison TX	-0.0222	10,180
Grand Forks ND MN	-0.0300	9,909	Shreveport Bossier City LA	0.0385	36,548
Grand Junction CO	0.0158	15,463	Sioux City IA NE SD	-0.0147	11,885
Grand Rapids Wyoming MI	-0.0023	149,753	Sioux Falls SD	-0.0007	38,097
Great Falls MT	-0.0205	5,894	South Bend Mishawaka IN MI	0.0043	37,653
Greeley CO	0.0077	25,937	Spartanburg SC	0.0120	31,997
Green Bay WI	0.0055	42,639	Spokane WA	-0.0132	74,146
Greensboro High Point NC	0.0047	117,604	Springfield IL	-0.0002	22,664
Greenville Mauldin Easley SC	0.0101	123,337	Springfield MA	-0.0016	68,829
Greenville NC	0.0113	24,880	Springfield MO	0.0181	59,203
Gulfport Biloxi MS	-0.0113	18,752	Springfield OH	-0.0163	10,333
Hagerstown Martinsburg MD WV	-0.0119	22,154	St. Cloud MN	-0.0173	22,378
Hanford Corcoran CA	0.0039	6,310	St. George UT	0.0010	12,059
Harrisburg Carlisle PA	0.0025	96,895	St. Joseph MO KS	0.0583	1,788
Harrisonburg VA	0.0216	13,691	St. Louis MO IL	-0.0178	478,453
Hartford West Hartford East Hartford CT	-0.0079	162,341	State College PA	0.0329	25,859
Hattiesburg MS	0.0282	12,194	Stockton CA	-0.0029	55,855
Hickory Lenoir Morganton NC	-0.0185	32,486	Sumter SC	0.0659	9,752
Hinesville Fort Stewart GA	-0.0392	828	Syracuse NY	0.0124	95,265
Holland Grand Haven MI	0.0009	40,553	Tallahassee FL	0.0240	64,871
Honolulu HI	-0.0461	81,137	Tampa St. Petersburg Clearwater FL	-0.0120	440,921
Hot Springs AR	-0.0150	3,137	Terre Haute IN	-0.0115	14,868
Houma Bayou Cane Thibodaux LA	0.0004	16,611	Texarkana TX Texarkana AR	0.0385	8,441
Houston Sugar Land Baytown TX	-0.0074	850,554	Toledo OH	0.0019	75,659
Huntington Ashland WV KY OH	-0.0319	17,473	Topeka KS	-0.0038	27,655
Huntsville AL	0.0035	76,669	Trenton Ewing NJ	-0.0147	48,773

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Table A2 – continued from previous page

MSA	Residual	N	MSA	Residual	N
Idaho Falls ID	-0.0141	13,539	Tucson AZ	0.0089	125,033
Indianapolis Carmel IN	-0.0234	325,205	Tulsa OK	-0.0065	131,079
Iowa City IA	0.0063	29,805	Tuscaloosa AL	0.0160	30,342
Ithaca NY	0.0147	15,760	Tyler TX	0.0081	24,459
Jackson MI	-0.0156	4,065	Utica Rome NY	0.0043	23,969
Jackson MS	0.0327	54,859	Valdosta GA	0.0242	1,789
Jackson TN	-0.0179	1,459	Vallejo Fairfield CA	-0.0026	38,250
Jacksonville FL	-0.0062	244,070	Victoria TX	0.0357	3,538
Jacksonville NC	-0.0279	6,776	Vineland Millville Bridgeton NJ	0.0125	9,011
Janesville WI	-0.0070	15,474	Virginia Beach Norfolk Newport News VA NC	-0.0126	265,394
Jefferson City MO	0.0143	17,998	Visalia Porterville CA	0.0045	24,928
Johnson City TN	-0.0026	17,744	Waco TX	0.0047	28,829
Johnstown PA	-0.0018	10,517	Warner Robins GA	0.0116	2,262
Jonesboro AR	-0.0188	7,258	Washington Arlington Alexandria DC VA MD WV	-0.0147	998,607
Joplin MO	0.0111	13,226	Waterloo Cedar Falls IA	0.0018	18,954
Kalamazoo Portage MI	0.0042	57,006	Wausau WI	0.0027	14,391
Kankakee Bradley IL	0.0139	7,452	Weirton Steubenville WV OH	-0.0163	7,108
Kansas City MO KS	-0.0123	410,415	Wenatchee WA	0.0172	9,933
Kennewick Pasco Richland WA	-0.0002	32,046	Wheeling WV OH	0.0037	8,512
Killeen Temple Fort Hood TX	-0.0125	45,079	Wichita Falls TX	-0.0067	8,037
Kingsport Bristol Bristol TN VA	-0.0279	16,221	Wichita KS	-0.0034	85,748
Kingston NY	0.0292	10,100	Williamsport PA	0.0116	12,625
Knoxville TN	-0.0156	97,177	Wilmington NC	0.0034	53,959
Kokomo IN	-0.0261	9,401	Winchester VA WV	-0.0080	12,480
La Crosse WI MN	-0.0069	20,189	Winston Salem NC	-0.0126	23,916
Lafayette LA	0.0272	38,418	Worcester MA	-0.0077	96,035
Lafayette IN	0.0010	25,588	Yakima WA	0.0343	17,777
Lake Charles LA	0.0042	23,165	York Hanover PA	0.0006	51,047
Lake Havasu City Kingman AZ	-0.0109	8,688	Youngstown Warren Boardman OH PA	-0.0105	42,951
Lakeland Winter Haven FL	-0.0025	60,184	Yuba City CA	0.0223	8,214
Lancaster PA	0.0227	70,510	Yuma AZ	0.0133	9,863

NOTES: This table reports the net workplace segregation coefficients (residuals) plotted in Figure 2b. Each residual represents the unexplained workplace segregation after regressing MSA-level workplace segregation on residential segregation: $\text{WorkplaceSeg}_{msa} = \alpha + \beta \cdot \text{ResidentialSeg}_{msa} + \varepsilon_{msa}$. Positive residuals indicate MSAs with higher workplace segregation than predicted by residential patterns; negative residuals indicate lower workplace segregation than predicted. 'N' represents the number of unique worker-employer-MSA records in the analysis. MSAs are sorted alphabetically.

Table A3: Workplace Segregation by Political Affiliation and Gender

	Panel A: Basic Models				Panel B: Combined FE		Panel C: Saturated	
	Raw	Occ FE	Ind FE	Census Tract FE	Additive	Interactive	Additive	Interactive
Partisan Segregation								
Unweighted								
Coefficient	0.117***	0.102***	0.096***	0.059***	0.027***	0.029***	0.023***	0.030***
Std. Error	(0.006)	(0.005)	(0.005)	(0.002)	(0.001)	(0.002)	(0.001)	(0.004)
P-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	37,200,614	36,516,390	37,076,033	37,200,614	35,460,059	37,200,614	35,460,059	37,200,614
BLS-Weighted								
Coefficient	0.107***	0.094***	0.086***	0.053***	0.024***	0.030***	0.021***	0.031***
Std. Error	(0.011)	(0.011)	(0.010)	(0.003)	(0.001)	(0.004)	(0.001)	(0.007)
P-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	37,200,614	36,516,390	37,076,033	37,200,614	35,460,059	37,200,614	35,460,059	37,200,614
Gender Segregation								
Coefficient	0.156***	0.084***	0.072***	0.155***	0.053***	0.028***	0.053***	0.027***
Std. Error	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
P-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	37,200,614	36,516,390	37,076,033	37,200,614	35,460,059	37,200,614	35,460,059	37,200,614

NOTES: Standard errors in parentheses, p-values in brackets, clustered by MSA. The analysis sample is restricted to imputed Democrats and Republicans and excludes observations with missing values for any of the dependent or independent variables, including fixed effects. Panel A shows basic specifications with individual fixed effects. Panel B shows combined fixed effects for occupation, industry, and census tract. Panel C shows saturated models including demographic controls. Demographic controls include gender and race/ethnicity for Republican models; partisanship and race/ethnicity for gender models. Race/ethnicity categories include White, Black, Hispanic, Asian, Native American, Middle Eastern, and Other. Dependent variables: Republican share of coworkers (Democrat-Republican only) for partisan segregation; female share of coworkers for gender segregation. For each model, the degrees of freedom are over 34mm and in some cases much larger than this. *** p<0.001, ** p<0.01, * p<0.05.

Table A4: Political Workplace Segregation by Demographic and Political Groups

		Raw Correlation				Occ + Ind + Census Tract FE			
Group Category	**Group**	**Coef.**	**Std. Err.**	**P-value**	**N**	**Coef.**	**Std. Err.**	**P-value**	**N**
FEC Donations	FEC Donor	0.1479***	(0.008)	[0.000]	1,316,417	0.0313***	(0.001)	[0.000]	1,256,878
	Non-Donor	0.1160***	(0.005)	[0.000]	35,884,197	0.0265***	(0.001)	[0.000]	34,203,181
2020 General Election	2020 General Voter	0.1192***	(0.006)	[0.000]	30,353,382	0.0258***	(0.001)	[0.000]	29,006,289
	2020 General Non-Voter	0.1043***	(0.006)	[0.000]	6,847,232	0.0278***	(0.001)	[0.000]	6,453,770
2020 Presidential Primary	2020 Primary Voter	0.1296***	(0.007)	[0.000]	11,206,016	0.0284***	(0.001)	[0.000]	10,715,395
	2020 Primary Non-Voter	0.1106***	(0.005)	[0.000]	25,994,598	0.0262***	(0.001)	[0.000]	24,744,664
Gender	Men	0.1114***	(0.006)	[0.000]	17,303,640	0.0242***	(0.001)	[0.000]	16,536,346
	Women	0.1170***	(0.006)	[0.000]	19,896,974	0.0274***	(0.001)	[0.000]	18,923,713
Race	White	0.1131***	(0.006)	[0.000]	22,636,282	0.0228***	(0.001)	[0.000]	21,559,555
	Non-White	0.0999***	(0.006)	[0.000]	14,564,332	0.0263***	(0.001)	[0.000]	13,900,504
Education	High School or Lower	0.1175***	(0.006)	[0.000]	19,975,345	0.0257***	(0.001)	[0.000]	18,830,776
	Bachelor's Degree	0.1148***	(0.005)	[0.000]	11,425,430	0.0271***	(0.001)	[0.000]	11,023,978
	Graduate Degree	0.1110***	(0.005)	[0.000]	5,799,839	0.0246***	(0.001)	[0.000]	5,605,305
Generation	Baby Boomer	0.1018***	(0.006)	[0.000]	7,989,985	0.0187***	(0.001)	[0.000]	7,549,126
	Gen X	0.1158***	(0.006)	[0.000]	10,671,234	0.0226***	(0.001)	[0.000]	10,249,174
	Millennial	0.1218***	(0.007)	[0.000]	12,143,450	0.0256***	(0.001)	[0.000]	11,588,244
	Gen Z	0.1171***	(0.007)	[0.000]	4,946,460	0.0362***	(0.001)	[0.000]	4,734,228
Seniority	Entry Level	0.1191***	(0.006)	[0.000]	14,004,717	0.0282***	(0.001)	[0.000]	13,359,927
	Junior Level	0.1131***	(0.006)	[0.000]	9,320,556	0.0231***	(0.001)	[0.000]	8,901,651
	Associate Level	0.1137***	(0.006)	[0.000]	3,856,483	0.0246***	(0.001)	[0.000]	3,694,823
	Manager Level	0.1173***	(0.006)	[0.000]	3,861,352	0.0254***	(0.001)	[0.000]	3,701,175
	Director Level	0.1220***	(0.006)	[0.000]	4,614,299	0.0276***	(0.001)	[0.000]	4,308,918
	Executive Level	0.1158***	(0.006)	[0.000]	1,169,624	0.0279***	(0.001)	[0.000]	1,133,210
	Senior Executive Level	0.1474***	(0.007)	[0.000]	373,583	0.0483***	(0.003)	[0.000]	360,355
Job Zone	Job Zone 5 (Extensive prep)	0.1179***	(0.006)	[0.000]	4,714,352	0.0307***	(0.001)	[0.000]	4,583,923
	Job Zone 4 (High prep)	0.1187***	(0.006)	[0.000]	15,563,094	0.0260***	(0.001)	[0.000]	15,122,945
	Job Zone 3 (Medium prep)	0.1138***	(0.006)	[0.000]	7,675,239	0.0236***	(0.001)	[0.000]	7,447,929
	Job Zone 2 (Some prep)	0.1108***	(0.005)	[0.000]	7,603,305	0.0257***	(0.001)	[0.000]	7,373,681
	Job Zone 1 (Little prep)	0.1209***	(0.005)	[0.000]	960,400	0.0252***	(0.001)	[0.000]	931,581

NOTES: This table presents coefficients from regressions of Republican coworker share on Republican partisanship indicator, estimated separately for each demographic and political group. Raw Correlation shows results from $\text{RepCoworkerShare}_i = \alpha + \beta \cdot \text{Republican}_i + \varepsilon_i$ with standard errors clustered by MSA. Fixed Effects specification includes occupation, industry, and census tract fixed effects: $\text{RepCoworkerShare}_i = \alpha + \beta \cdot \text{Republican}_i + \gamma_{occ} + \delta_{industry} + \eta_{tract} + \varepsilon_i$ with standard errors clustered by MSA. P-values in brackets. N shows the number of observations used in each regression. Sample restricted to Democrats and Republicans only using imputed partisanship measures. For each model, the degrees of freedom are over 300,000 and in most cases much larger than this. *** p<0.001, ** p<0.01, * p<0.05.

Table A5: Longitudinal segregation estimates (2012–2024)

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Panel A: Full Sample													
Raw Model													
Coefficient	0.1149***	0.1149***	0.1148***	0.1145***	0.1146***	0.1148***	0.1154***	0.1157***	0.1160***	0.1157***	0.1154***	0.1153***	0.1150***
Std. Error	(0.0059)	(0.0058)	(0.0057)	(0.0056)	(0.0055)	(0.0055)	(0.0055)	(0.0055)	(0.0055)	(0.0055)	(0.0054)	(0.0055)	(0.0055)
P-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	18,688,932	20,070,108	21,503,705	22,894,813	24,053,406	25,283,214	26,678,941	27,836,793	27,786,139	28,994,796	29,652,878	29,053,918	28,151,078
Census Tract FE Model													
Coefficient	0.0828***	0.0833***	0.0836***	0.0837***	0.0840***	0.0845***	0.0851***	0.0856***	0.0858***	0.0858***	0.0857***	0.0856***	0.0852***
Std. Error	(0.0035)	(0.0035)	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0035)
P-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	18,688,932	20,070,108	21,503,705	22,894,813	24,053,406	25,283,214	26,678,941	27,836,793	27,786,139	28,994,796	29,652,878	29,053,918	28,151,078
Occ+Ind+Census Tract FE Model													
Coefficient	0.0584***	0.0588***	0.0591***	0.0593***	0.0597***	0.0601***	0.0608***	0.0613***	0.0620***	0.0623***	0.0623***	0.0624***	0.0623***
Std. Error	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)
P-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	18,446,121	19,816,557	21,239,907	22,622,857	23,776,118	24,997,634	26,386,759	27,542,094	27,492,112	28,702,271	29,354,483	28,752,884	27,849,041
Panel B: First Year at Position													
Raw Model													
Coefficient	0.1109***	0.1102***	0.1101***	0.1081***	0.1081***	0.1094***	0.1105***	0.1101***	0.1110***	0.1086***	0.1086***	0.1106***	0.1101***
Std. Error	(0.0057)	(0.0055)	(0.0054)	(0.0053)	(0.0052)	(0.0052)	(0.0052)	(0.0053)	(0.0054)	(0.0053)	(0.0052)	(0.0052)	(0.0052)
P-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	4,705,671	5,142,642	5,642,647	6,053,083	6,214,259	6,510,831	6,907,431	6,995,669	5,812,073	6,982,664	6,803,318	5,388,960	4,144,315
Census Tract FE Model													
Coefficient	0.0796***	0.0796***	0.0800***	0.0787***	0.0790***	0.0803***	0.0813***	0.0810***	0.0821***	0.0805***	0.0804***	0.0824***	0.0816***
Std. Error	(0.0033)	(0.0033)	(0.0032)	(0.0031)	(0.0032)	(0.0032)	(0.0032)	(0.0033)	(0.0033)	(0.0033)	(0.0033)	(0.0033)	(0.0033)
P-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	4,705,671	5,142,642	5,642,647	6,053,083	6,214,259	6,510,831	6,907,431	6,995,669	5,812,073	6,982,664	6,803,318	5,388,960	4,144,315
Occ+Ind+Census Tract FE Model													
Coefficient	0.0546***	0.0546***	0.0549***	0.0546***	0.0551***	0.0554***	0.0563***	0.0567***	0.0581***	0.0572***	0.0569***	0.0576***	0.0564***
Std. Error	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0029)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0029)
P-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	4,660,840	5,096,787	5,594,862	6,005,650	6,168,079	6,462,511	6,860,125	6,952,611	5,775,592	6,952,263	6,772,426	5,363,177	4,123,063

NOTES: This table presents regression coefficients from a longitudinal analysis of workplace segregation from 2012–2024. Each model reports coefficients, standard errors (in parentheses), and the number of annual observations. The dependent variable is the percentage of Republican coworkers. The independent variable is an indicator for Republican partisanship. Standard errors are clustered by MSA. Panel A shows results for the full sample. Panel B shows results for workers in their first year at a position. For each model, the degrees of freedom are over 4mm and in most cases much larger than this. Significance levels: *** $p<0.001$, ** $p<0.01$, * $p<0.05$.

Table A6: Details of O*NET codes

O*NET Zone	Details
Zone One	
Education	High school diploma or GED may be required
Related Experience	Little or no previous work-related skill, knowledge, or experience
Job Training	A few days to a few months
Examples	Food prep workers, dishwashers, landscaping workers, baristas
Zone Two	
Education	Usually require a high school diploma
Related Experience	Some previous work-related skill, knowledge, or experience
Job Training	A few months to one year working with experienced employees
Examples	Orderlies, counter clerks, customer service representatives
Zone Three	
Education	Vocational skills, on-the-job experience, or associate's degree
Related Experience	Previous work-related skill, knowledge, or experience
Job Training	1–2 years of training; both on-the-job and informal training
Examples	Electricians, agricultural technicians, barbers, medical assistants
Zone Four	
Education	Most occupations require a four-year bachelor's degree
Related Experience	Considerable work-related skill, knoweldge, or experience
Job Training	Several years of work-related experience and/or training
Examples	Real estate broker, sales manager, graphic designer, cost estimator
Zone Five	
Education	Most require graduate school
Related Experience	Extensive skill, knowledge, and experience
Job Training	Typically assume that person has required skills and knowledge
Examples	Pharmacists, lawyers, clergy, veterinarians

Table A7: Sensitivity of segregation coefficient to firm size/industry restrictions

	Raw	Occ + Ind + Tract FE
Baseline	0.117***	0.027***
Std. Error	(0.006)	(0.001)
P-value	[0.000]	[0.000]
Observations	37,200,614	37,200,614
Professional services Only	0.110***	0.030***
Std. Error	(0.006)	(0.001)
P-value	[0.000]	[0.000]
Observations	3,734,624	3,734,624
Exclude firms $\geq$ 500	0.126***	0.032***
Std. Error	(0.006)	(0.001)
P-value	[0.000]	[0.000]
Observations	28,123,580	28,123,580
Exclude firms $\geq$ 250	0.129***	0.033***
Std. Error	(0.006)	(0.001)
P-value	[0.000]	[0.000]
Observations	25,220,461	25,220,461
Exclude firms $\geq$ 100	0.133***	0.036***
Std. Error	(0.006)	(0.001)
P-value	[0.000]	[0.000]
Observations	20,937,670	20,937,670
Exclude firms $\geq$ 50	0.137***	0.039***
Std. Error	(0.006)	(0.001)
P-value	[0.000]	[0.000]
Observations	17,510,603	17,510,603

NOTES: Standard errors in parentheses; clustered by MSA. Each row shows results for the same sample restriction across two models: Raw and Occupation+Industry+Tract fixed effects. For each model, the degrees of freedom are over 17mm and in many cases much larger than this. *** p<0.001, ** p<0.01, * p<0.05.