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ABSTRACT

We study how individual political views shape firm behavior and labor market outcomes using new micro-data from Brazil. We first show that business owners are considerably more likely to employ copartisan workers. This phenomenon is in part driven by the overlapping of political and social networks. Multiple tests—a survey, an event study, analyses of wage premia and promotions within the firm, and a field experiment—further highlight how business owners' political preferences directly influence firms' employment decisions. A channel of political discrimination appears more relevant than one of political quid-pro-quo between firms and politicians.

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1 Introduction

It is well established that individual political identity drives hiring and career outcomes in bureaucracies and state-owned firms, where politicians might want to use jobs and the wages associated with them to reward their partisan supporters (Shleifer and Vishny, 1994; Besley et al., 2022). In contrast, private sector personnel decisions are typically considered insulated from political considerations, where the profit motive acts as a disciplining tool and "No politics at work" is seen as standard policy (Finan et al., 2017).

Yet, anecdotes abound about business owners making employment decisions guided by politics, and the potential implications of mixing politics and work are many. A dearth of comprehensive micro-data has made it challenging to study how individual political views shape firm behavior and labor market outcomes. In this paper, we address this gap using a combination of rich data sources and empirical approaches. We leverage new administrative data on the political affiliation of the universe of business owners and workers in the (formal) private sector of Brazil, a field experiment, and an original survey of both workers and owners. This allows us to (a) quantify the extent to which individual political views affect worker-firm sorting and within-firm careers, and (b) shed light on a number of economic mechanisms.

We study the complete Brazilian formal labor market from 2002 to 2019. Our first key contribution is to assemble a new dataset that combines three main sources of data. We start by augmenting the matched employer-employee data from the Ministry of Labor with data from the federal revenue service agency on the identity of all business owners. We then merge both workers and owners with the official records of all individuals affiliated with a political party over this period. We obtain information on the political affiliation of nearly 12 million individuals (11.4% and 7.8% of all private-sector owners and workers in the sample, respectively). This new worker-firm-owner-party matched dataset allows us to observe partisan affiliation for the entire formal economy over a long time period, to control for a wide set of observable characteristics in our analysis (such as workers' and owners' demographics, location, industry, and occupation), and to precisely benchmark our estimates of the role of politics to other well-established determinants of labor market outcomes, such as gender and race.

In the first part of the paper, we document the presence of a large degree of assortative matching along partisan lines between firms and workers: business owners are significantly more likely to employ workers who share their same partisan affiliation. We first establish this fact using the likelihood ratio index (Eika et al., 2019; Chiappori et al., 2020). We find that workers and employers belonging to the same party are about 50% more likely on average to match relative to random matching patterns within narrowly defined local labor markets.

To alleviate the concern that these findings might be driven by worker and owner characteristics correlated with both political affiliation and employment decisions, we then sharpen our analysis using a dyadic regression approach. This approach relies on billions of worker-owner dyads within all industry-municipality markets and allows us to control for an extensive set of worker, workplace, and owner characteristics that are likely to correlate with both political affiliation and labor market choices.[1] These estimates confirm the results established using the simpler likelihood ratio index: depending on the year, a politically affiliated worker is between 48% and 72% more likely to be employed by a copartisan owner than by an owner affiliated with a different party. We show that the results emerge both because of the higher likelihood of hiring workers who share the same party as the business owner, and because of a lower probability that these copartisan workers leave the firm after being hired.

Importantly, our estimates also show that political assortative matching is considerably larger than gender or racial assortative matching, patterns which we also document in the data. Given the major role gender and race play in labor markets, this is a significant finding speaking to the magnitude of the phenomenon that we document. Moreover, our analysis shows that while race and gender assortative matching have been steadily decreasing over the past two decades, political assortative matching has largely been increasing.

In the second part of the paper, we discuss several potential mechanisms behind our findings. We start by presenting results from an original survey of 891 business owners and 1,003 workers, which we sampled directly from the administrative data to be representative along several individual and firm dimensions. We ask respondents to express their views, independent of their own personal experience, about the results of a "recent study" (i.e., our findings), which shows that "business owners tend to hire workers with similar political views." Both business owners and workers believe that owners' discrimination in favor of copartisans, because of either taste-based (Becker, 1971) or belief-based (Phelps, 1972; Arrow, 1973) discrimination, is the primary driver of our findings. Respondents also argue that people of similar political views share the same social networks (Iyengar et al., 2019), which can explain the sorting of workers to firms as networks are important in the job-search process (Ioannides and Loury, 2004; Topa, 2011). Political quid-pro-quo exchanges between firms and politicians (Bertrand et al., 2018) gather lower credence from the respondents. Respondents also dismiss a mechanism whereby it is workers' choices of where to work that matter. Importantly, 29% of the surveyed business owners explicitly reveal that they do take into account the political views of the prospective employees when making hiring decisions.

We then present an extensive set of empirical tests for mechanisms. First, we evaluate the role of overlapping political and social networks. While isolating the importance of this mechanism is inherently challenging due to the impossibility of fully observing an individual's

[1] See Fafchamps and Gubert (2007) and Fafchamps and Jean-Louis (2012) for a discussion of dyadic regressions in the context of risk-sharing networks and participation in community-based organizations.

social network, we can probe its relevance by testing for a set of heterogeneous effects. Consistent with overlapping political and social networks being an important mechanism, we find a significantly stronger political assortative matching in smaller firms (which more commonly rely on networks for hiring), for workers at higher levels of the organizational hierarchy (who are more likely to belong to the same network as business owners), for workers in positions requiring strong interpersonal relationships (who are more likely to leverage networks in their job search process), and for workers who were already working in the same municipality before being hired (who are more likely to live locally and have a local network to rely on when searching for jobs). At the same time, we find the effects to be large and significant for *all* splits of the data. For example, we show that the results remain strong and large in magnitudes even when considering only workers who were working elsewhere—and far away from the firm's municipality—the year prior to being hired. On the one hand, these results together suggest that social and political networks strongly overlap, contributing to political assortative matching in the labor market. On the other hand, the pervasive effects and large magnitudes uncovered across a number of contexts where networks should matter little, if at all, suggest other explanations are likely to be at play.

We subsequently undertake a battery of tests aimed at isolating the direct role of political preferences in influencing business owners' employment decisions.

First, we leverage the fact that some business owners change party membership during our sample period to conduct an event-study analysis. We show that there is a sharp change in the political composition of the workforce when an owner switches party. We document a sudden increase in hiring probability for workers of the new party and a corresponding decrease for workers of the old party. To the extent that social networks that might overlap with political ones (e.g., the school someone went to, one's religion, or even the soccer team they support) are not suddenly erased at the time of party change, this is evidence in line with owners' political preferences playing a central role in employment decisions.

Second, we conduct a set of analyses that look at within-firm outcomes. We show that copartisans are more likely to rise in the organizational hierarchy through promotions, both from blue-collar to white-collar positions and from white-collar to managerial positions, and that they enjoy a substantial political wage premium, even within the same layer of the organizational hierarchy. Relative to their unaffiliated coworkers, copartisan managers earn 3.8% more, copartisan white-collar workers earn 3.4% more, and copartisan blue-collar workers earn 1.5% more. The strongest evidence consistent with a direct role of owners' political preferences as a driver of firm's decisions is that workers of a *different* party suffer substantial wage and promotion penalties relative to unaffiliated workers. These patterns hold true even within narrowly defined occupational groups within the same firm and controlling for a large set of socio-demographic characteristics.[2]

Taken together, the results point to a significant role played by business owners' political preferences in employment decisions. We then dig deeper into the specific mechanisms behind this result. One story is that business owners give favorable treatment to copartisans because they benefit from a *political quid-pro-quo*, either personally (e.g., because they are building local political support) or for their firm (e.g., because politicians may reciprocate with government contracts or other favors). Alternatively, the effects we observe may be due to a *political discrimination* mechanism whereby individuals have a taste-based preference for copartisans or believe copartisans would be more productive at work. Using individual- and firm-level data on political donors, candidates, and elected officials, on government contracts, and on local elections, we find no evidence pointing to a political quid-pro-quo mechanism. These findings are largely consistent with our earlier qualitative survey evidence.

We then provide direct evidence in support of a political discrimination channel using a field experiment akin to a correspondence audit study (Bertrand and Mullainathan, 2004). We partner with a leading job platform in Brazil and target a sample of 150 Brazilian business owners, following the nondeceptive incentivized resume rating (IRR) design (Kessler et al., 2019). We select business owners who are interested in hiring, and we ask them to rate a set of synthetic resumes of job seekers whose features—such as education, work experience, and other relevant activities—are realistic but fully randomized by our research team. Business owners are incentivized to truthfully rate resumes because upon survey completion, on the basis of a machine learning algorithm, they will receive resumes of real job seekers matching their revealed preferences. We vary the political party of the job seekers by introducing realistic, obfuscated cues that signal partisan affiliation in a number of ways and in different sections of a subset of the resumes (e.g., volunteering for the political campaign of a party). Importantly, our ability to sample respondents from the administrative data allows us to observe business owners' political affiliation without having to elicit this information in the survey, which significantly limits concerns of experimenter-demand effects. We find that owners rate significantly higher the resumes of copartisans relative to those of job seekers from opposing political parties. Analogously to the literature on correspondence audit studies identifying gender and race discrimination (Bertrand and Duflo, 2017), our experimental evidence isolates the presence of political discrimination in hiring decisions while muting alternative channels.

We conclude by discussing potential implications of these political preferences for firm productivity. We show that workers who are copartisans of the owner are negatively selected

[2]The presence of a wage premium for copartisans also indicates that workers' preferences to work in firms owned by copartisans play a secondary role. Indeed, compensating differentials would predict a negative wage premium if working for copartisan owners were seen as a valuable job amenity.

on education, especially if hired in a managerial role. Although it could be that copartisans of the owner are on average more productive along other dimensions, we show that firms with a higher share of workers who are owners' copartisans grow less relative to similar firms who employ fewer copartisans.

Our findings contribute to several strands of literature. First and foremost, we contribute to the body of work on the nexus between politics and the employment decisions of private and public organizations. A large political economy literature analyzes how individual political identity drives the hiring decisions of public sector organizations (see Finan et al., 2017 and Besley et al., 2022 for reviews). Examples include Colonnelli et al. (2020); Barbosa and Ferreira (2023); Brollo et al. (2017) in Brazil and Brassiolo et al. (2020) in Ecuador, among others. Recent complementary studies look at how political considerations affect the performance of public sector employees and bureaucrats (Xu, 2018; Akhtari et al., 2022; Spenkuch et al., 2023). Other studies focus on how political connections of firms affect employment outcomes. Carvalho (2014) and Bertrand et al. (2018) find that firms alter employment decisions due to political quid-pro-quo considerations between firms and politicians, while Cingano and Pinotti (2013) show that hiring individuals who are politically connected to local governments helps firms obtain several benefits.[3]

A rapidly growing, related but distinct literature analyzes the importance of partisanship in economic realms (see Iyengar et al. (2019) for a review, and Boxell et al. (2020) for cross-country evidence). Few studies focus on partisanship in labor markets.[4] Relying on a resume audit study in two U.S. counties, Gift and Gift (2015) find that the callback rate of fictitious resumes signaling job seekers' political affiliation depends on the political leaning of the county. McConnell et al. (2018) signal the partisan identification of the employer for an editing task on an online platform, and show that workers set lower reservation wages when the employer shares their political views. Lee et al. (2014), Hoang et al. (2020) and Fos et al. (2021) study the rising political polarization of top executives of U.S. listed firms, while

[3]See Fafchamps and Labonne (2017), Folke et al. (2017), and Gagliarducci and Manacorda (2020) for studies looking at the interaction between politics, family networks, and employment outcomes. A related literature in development economics studies how ethnic diversity and in-group bias affect resource allocation (Alesina and Ferrara, 2005; Anderson, 2011; Hjort, 2014; Fisman et al., 2017; Bazzi et al., 2019; Lowe, 2021; Marx et al., 2021; Ghosh, 2021; Oh, 2021). See also Fisman et al. (2017), Fisman et al. (2018), Hjort et al. (2019), Fisman et al. (2020b), and Fisman et al. (2020a) for work studying how social and ethnic ties affect economic outcomes.

[4]One strand of this literature has examined the link between political affiliation and consumers' spending, with mixed findings: while Gerber and Huber (2009) shows that individuals' alignment with the party of the President affects their spending, McGrath (2016) and Mian et al. (2021) find no evidence of this relationship. Other papers analyze how partisan alignment affects household financial (Bonaparte et al., 2017; Meeuwis et al., 2018) and real estate (McCartney and Zhang (2021)) decisions, credit analysts' rating actions (Kempf and Tsoutsoura (2021)), entrepreneurship (Engelberg et al., 2021), loan pricing (Dagostino et al. (2021)), and insurance marketplaces (Bursztyn et al., 2022).

Colonnelli et al. (2023) and Adrjan et al. (2023) study the impact of socially and politically polarizing corporate policies on job-seeker behavior.

Our paper connects the above strands of literature by bringing to the table extremely detailed micro-data combined with new firm-level experimental and survey evidence. This allows us to provide new comprehensive evidence that one's political identity is a major determinant of labor market outcomes and, crucially, to identify several important economic mechanisms. On the one hand, the literature on the political economy of firms has largely focused on the political quid-pro-quo aspect of employment decisions. On the other hand, the partisanship literature has focused on the Republican-Democrat ideological divide in the U.S. and on the measurement of sorting of individuals along political lines, but has abstracted away—largely due to lack of data—from the potentially relevant and competing motives based on political quid-pro-quo or social networks. To our knowledge, ours is the first paper matching administrative registries of workers, firms, owners, and party members, which is critical to estimate precise economic magnitudes and to show that these magnitudes are meaningful and pervasive in the economy, spanning the full range of sectors, firms, and employees. Moreover, our data and combination of empirical designs allow us to link the role of politics in firms' employment decisions to a number of economic channels, with correspondingly different implications for both firms and politicians.

Finally, our paper contributes to a vast literature on discrimination in labor markets, dating back to the theoretical contributions of Becker (1971) on employers' taste-based discrimination and Phelps (1972) and Arrow (1973) on statistical discrimination.[5] Our paper highlights political identity as a further, quantitatively important source of labor market discrimination and segregation.[6]

The paper is organized as follows. Section 2 describes the main data sources and summary statistics. Section 3 provides our estimates of political assortative matching and benchmarks them to similar estimates for both race and gender. Section 4 reports our analysis and discussion of mechanisms. Section 5 concludes.

2 New Administrative Data on Partisanship in the Private Sector

We assemble a new longitudinal worker-firm-owner-party dataset covering the entire Brazilian formal labor market by combining information from several administrative sources. We use administrative matched employer-employee data from the Relação Anual de Informações Sociais (RAIS). Data on the identity of business owners come from the Receita Federal do Brazil (RFB) and the Cadastro Nacional de Empresas (CNE). Finally, information on all

[5]See Gerard et al. (2021) and Morchio and Moser (2020) for studies of the role of race and gender in explaining wage gaps and sorting patterns in the Brazilian labor market. Hsu Rocha and Dias (2021) and Miller and Schmutte (2021) study worker-owner sorting based on race in Brazil.

[6]The role of politics in the workplace has also recently attracted attention in the psychology and organizational behavior literature, as illustrated in the review by Swigart et al. (2020).

individuals registered over time with a political party as well as voter registration records are drawn from the Tribunal Superior Eleitoral (TSE). In this section, we describe these data sources and present summary statistics about the role of political partisanship in the private sector. Full details on the various datasets and on their matching are provided in the Online Appendix.

2.1 Matched Employer-Employee Data Our employer-employee matched data is RAIS, a confidential administrative database managed by the Brazilian Ministry of Labor. RAIS provides information on the universe of workers in the formal private sector, and it is widely considered to be a high-quality census of employed workers (Dix-Carneiro, 2014). Unique individual and firm tax identifiers track individuals over time and across firms, as well as across establishments of the same firms.[7] Importantly, we focus only on firms operating in the private sector.

We construct a yearly panel of workers in the private sector for the 2002–2019 period.[8] RAIS contains rich information on the job (wage, specific occupation, hours worked, type of contract, among other details), the firm (sector, municipality), and the worker (gender, date of birth, education, race, nationality).[9]

The final panel dataset includes 87,015,166 unique workers and 7,562,262 unique firms.

2.2 Business Ownership An important contribution of our paper is matching the RAIS data to detailed administrative data on company registration and business ownership in Brazil. The primary dataset we use is the official federal registry of firms maintained by the Receita Federal do Brazil (RFB). All firms are required to register in the RFB in order to obtain their tax identifier, the Cadastro Nacional de Pessoas Juridicas (CNPJ). At the time of registration, firms are legally required to list all individual or corporate owners that have any equity stake in the company, together with the respective capital commitment of owners. Given our focus on political affiliation, we focus exclusively on individual owners and disregard corporate ones.

The RFB data contain information on all firm owners active in the formal sector as of 2019, as well as the date when they started owning the firm. Additionally, for firms that closed during the 2002–2019 period, we are able to observe the identity of all owners at the

[7] Our analysis focuses on the establishment to identify the employer, a choice that is inconsequential for our results but that allows us to pinpoint accurately the location and sector of each worker. As discussed later, since the ownership data refer to the firm, all establishments of a firm will be owned by the same business owners. For brevity, throughout the paper we'll use the term "firm" when referring to the employer.

[8] Following standard practices using RAIS (Colonnelli and Prem, 2022), we keep the highest paying job of the worker whenever a worker is employed by more than one firm in a given year.

[9] Workers' occupations are classified into 2,511 categories by the *Classificação Brasileira de Ocupações 2002* (CBO), while sectors follow the *Classificação Nacional de Atividades Economicas* (CNAE), which include 1,329 industries in its most granular breakdown. We categorize occupations into hierarchical layers of Managers, White-Collar, and Blue-Collar following Bernstein et al. (2022).

time the firm closed. In short, the one limitation of the data is that it does not allow us to identify owners who left a firm before 2019 for firms that are active in 2019, or before the firm closed for firms that became inactive before 2019. Given the extremely limited turnover among owners of a firm, this limitation is minor.

RFB classifies ownership structures as either a set of business associates (*socios*) or as "individual entrepreneurs" and "micro-entrepreneurs" when owned by a unique individual. There are 12,108,480 unique business associates (owning a total of 8,436,483 firms), 8,169,077 unique individual entrepreneurs (owning a total of 8,247,052 firms), and 13,522,653 unique individual micro-entrepeneurs (owning a total of 14,353,138 firms). For all individuals, we can observe either the individual tax identifier (CPF) or a combination of the full name and a subset of the tax identifier, which allow us to match individual owners to the other administrative datasets with a high degree of accuracy.

In addition to the above set of business owners, 6.8% of firms in RFB remain uncategorized and provide no individual owner identifiers. To address this issue, we complement the RFB dataset with an additional administrative data source on firm ownership, the *Cadastro Nacional de Empresas* (CNE). The CNE is managed by the Ministry of Development, Industry and Foreign Trade (MDIC), and we obtained access through a series of FOIA-like requests. The CNE aggregates all the ownership details required by each state at the time of company registration. In fact, all companies in Brazil are required to register both with the federal government (through RFB) and with the state government (through CNE), thus providing us with a way to ensure high-quality data on business ownership dynamics spanning all of Brazil, which helps to alleviate the issue of having only snapshots of the data in RFB. The data is recorded by each state annually and covers the period 2002–2017. The CNE data contain information on a total of 19,045,762 owners and 16,239,551 firms.[10]

2.3 Party Membership Data on all individuals registered as members of a Brazilian political party come from the Tribunal Superior Eleitoral (TSE).[11] The data contain the name of all current and past party members over the 2002–2019 period, including information on the date and municipality of registration, party affiliation, and voter registration number. We also observe the date of de-registration if individuals choose to de-register. We additionally match party members to the TSE Voter Registration Records to obtain information on their date of birth, which helps us achieve a high quality match between the TSE data and the other administrative datasets.

Registration with a party is open to all eligible voters. Every party has its own registration and membership rules, with some parties requiring registration fees and payments of monthly

[10]The CNE data has minor issues, due to imperfect reporting by some states in the earlier periods. Hence, we only rely on the CNE data to complement the main dataset by the RFB.

[11]Throughout the paper, we use the term "party member" interchangeably with "party affiliated."

dues, while other parties allow a simple online registration. Registered individuals can vote to choose party candidates and also at times participate in campaigning. Party affiliation can be interpreted as a signal of an individual's strong and visible political views, with unaffiliated individuals likely possessing milder views on politics.

There are 19,262,453 individuals who are members of a political party at some point over the 2002–2019 period, totaling 263,821,107 year-individual observations. While the political landscape in Brazil is quite fragmented and characterized by a large number of parties (35 over the period of our study), the top 7 parties account for almost 70% of all party members. Appendix Table A1 shows the distribution of members across parties.

2.4 Matching Workers, Firms, Owners, and Party Members We match data on workers, firms, owners, and party members using a combination of tax identifier, full name, date of birth, and municipality.

Our starting dataset is RAIS. We use firm tax identifiers to match the firms in RAIS to the ownership datasets RFB and CNE, thus creating a matched employer-employee-owner dataset. This allows us to observe, for each year, the links between individual employees and individual business owners in Brazil. We find at least one owner for 96.42% of the 41,461,244 firm-year observations in RAIS, corresponding to 92.51% of all worker-year observations. 5.03% of workers also appear as owners of a firm at some point over the sample period, while 45.06% of owners also appear as workers at some point over the sample period (either of their own firm or for a different firm). Crucially, for the subset of owners who also appear as workers, we observe the full set of their demographic characteristics collected in RAIS.[12]

After RAIS is augmented with the ownership information, we match all workers and owners appearing in RAIS to the party registration dataset.[13] We identify 11.39% of owners and 7.79% of workers as party members. We find that 32.84% of firm-years have at least one party-affiliated worker, and 15.48% of firm-years have at least one party-registered owner.[14] Importantly, changes of partisan affiliation over the sample period are rare for both workers and owners, with only 5.77% of workers and 7.96% of owners being affiliated with more than one party over the entire 2002–2019 period, suggesting that partisan affiliation can be interpreted as a measure of persistent political views.

[12]We consider owners who also appear as workers of their firm solely as owners.

[13]As mentioned earlier, the key to achieving a high matching quality is the addition of the date of birth (using the voter records) to the TSE data on party members, which contain the full names. In some of the matching steps, we also rely on the municipality of the firm associated to the owner or worker to improve accuracy. The unmatched set of party members may be workers of the public sector (which we drop from the analysis) or individuals in the informal sector.

[14]If a firm has multiple owners, we assign to the firm the partisan affiliation of the majority of its owners. We drop the very few cases in which there are multiple affiliated owners and where the majority is equally split among multiple parties.

2.5 Summary Statistics Table 1 presents summary statistics for the firms in our sample. The typical firm in RAIS is relatively small: the median number of workers and owners is 3 and 1, respectively, with an average of 16 workers and 1.6 owners. A minority of firms employ workers in managerial positions (on average, there are 0.87 managers per firm), and the median numbers of white-collar and blue-collar workers are 2 and 1, respectively. While the median Brazilian firm is quite small, the size distribution is significantly right skewed. The ownership of firms is quite concentrated, with the firm at the 75th percentile of the distribution having 2 owners. Relative to the population of workers in RAIS, business owners are on average older, more educated, and more likely to be male and white.

Figure 1, Panels A and B, compares affiliated and unaffiliated business owners and workers across a set of observable characteristics. On average, affiliated and unaffiliated owners manage similar firms in terms of size, and of workforce composition and pay. Affiliated and unaffiliated owners are also similar in terms of educational attainment, race, and age. The only notable difference between the two groups is that affiliated owners are more likely to be males. We observe similar patterns among workers: affiliated workers are not more likely to be employed by larger firms, to receive higher wages, or to differ in terms of education or race. They are however more likely to be male, and they are slightly older relative to unaffiliated workers.

In Figure 1, Panel C, we show how owners and workers differ in their political leaning across the Left/Center/Right spectrum. Perhaps not surprisingly, we find that owners are more likely to be members of conservative parties relative to workers (especially blue-collar and white-collar ones, rather than managers). Yet, workers seem to be quite evenly distributed across left-wing, right-wing, and centrist political parties.[15]

3 Measuring Political Assortative Matching

In this section, we show that business owners are more likely to employ copartisan workers, and we quantify the extent of this political assortative matching in the labor market by benchmarking it to similar matching patterns along racial and gender lines. First, in section 3.1 we present results using the likelihood ratio index (Eika et al., 2019). Second, in section 3.2 we rely on a dyadic regression approach to account for workers' and owners' characteristics that may be correlated with both political affiliation and employment decisions. Third, in section 3.3 we show that political assortative matching is driven both by owners' higher propensity to hire copartisans and by a lower probability that copartisans leave the firm after being hired.

[15]Appendix Figure A1 shows the share of affiliated workers (Panel A) and affiliated owners (Panel B) across Brazilian municipalities over the study period.

3.1 The Likelihood Ratio Index We start by measuring the extent of political assortative matching in the labor market using the likelihood ratio index. A version of this index has been recently employed by Eika et al. (2019) to measure the degree of educational assortative matching in the marriage market. Intuitively, we can assess the degree of political assortative matching in the labor market by comparing the contingency table for the worker's and owner's political affiliation to a contingency table generated by random matching (with respect to political affiliation) between workers and firms. That is, our measure captures whether workers and owners belonging to the same party match in the labor market more frequently than what we would expect under a random matching pattern.

Specifically, for each year in our data, we can define the observed probability that a worker of party p^w is employed by an owner of party p^o, relative to the probability under random matching. Defining by P^w the party of the worker, and by P^o the party of the owner, the ratio between these two probabilities is:

$$s(p^w, p^o) = \frac{Pr(P^w = p^w \ , \ P^o = p^o)}{Pr(P^w = p^w)Pr(P^o = p^o)} \tag{3.1}$$

The magnitude of $s(p^w, p^o)$ measures the probability of observing a match between workers of party p^w and owners of party p^o in the data, relative to what the probability of the match would be with random matching.[16] We can build a matrix of size P (the total number of parties p observed in the data for which we have at least one worker and at least one owner that is affiliated), with $s(p^w, p^o)$ as elements of the matrix. We are particularly interested in the diagonal elements of the matrix, which capture the probability that a worker is matched to an owner of her same party p, relative to the probability under random matching:

$$s(p, p) = \frac{Pr(P^w = P^o = p)}{Pr(P^w = p)Pr(P^o = p)} \tag{3.2}$$

To obtain a measure of overall political assortative matching we compute, for each year, the weighted sum of the elements along the diagonal, where the weights are the relative probability of observing workers and owners of the specific party p:

$$S = \sum_p \frac{Pr(P^w = p)Pr(P^o = p)}{\sum_p Pr(P^w = p)Pr(P^o = p)} s(p, p) = \frac{\sum_p Pr(P^w = P^o = p)}{\sum_p Pr(P^w = p)Pr(P^o = p)} \tag{3.3}$$

The index S is greater (lower) than 1 in presence of positive (negative) assortative matching: we are S times more (less) likely to observe in the data a worker of the same party as the owner than under random matching along party lines. Chiappori et al. (2020) prove that this weighted sum index satisfies two minimal intuitive criteria that any index of assortative matching should satisfy.

[16]Note that $Pr(P^o = p^o)$ is calculated as the share of owners of party p^o, and *not* as the share of workers in the data with owners of party p^o. With this approach, in the calculation of the random matching probability in the denominator, we are not forcing a firm to have the same number of workers as in the data.

We can also adjust the measure to take into account geographical sorting. For instance, if some parties are more popular in certain geographical areas, geographical sorting may increase the index, even though within municipality we could observe limited political assortative matching. To account for this, we can define an index for each party p and for each municipality m in the data. The diagonal element for party p in municipality m is:

$$s(p,p,m) = \frac{Pr(P^w = P^o = p|M = m)}{Pr(P^w = p|M = m)Pr(P^o = p|M = m)} \tag{3.4}$$

And the weighted average over all the (p,m) combinations is:

$$\begin{aligned} S^M &= \sum_{p,m} \frac{Pr(P^w = p|M = m)Pr(P^o = p|M = m)}{\sum_{p,m} Pr(P^w = p|M = m)Pr(P^o = p|M = m)} s(p,p,m) = \\ &= \frac{\sum_{p,m} Pr(P^w = P^o = p|M = m)}{\sum_{p,m} Pr(P^w = p|M = m)Pr(P^o = p|M = m)} \end{aligned} \tag{3.5}$$

In order to benchmark the magnitude of the political assortative matching, we compute the analogous versions of the index for gender (female versus male) and race (white versus non-white).

The estimated likelihood ratio indexes are presented in Figure 2. Panel A shows estimates of the simple version of the likelihood ratio index, without accounting for any geographical sorting. We find a large degree of positive political assortative matching between workers and owners: on average across the 2002–2019 period, workers and owners belonging to the same party are about twice as likely to match in the labor market relative to what we would expect under a random matching pattern along party lines. The index ranges from a minimum of 1.56 in 2002 to a maximum of 1.85 in 2016. In Appendix Figure A2, we show separate estimates for six of the largest Brazilian parties. We find large assortative matching across the political spectrum. For most of the years, left-wing (PT and PDT) and right-wing parties (PP and DEM) have higher values of the index than more moderate parties (PMDB and PSDB). Interestingly, we observe a sharp drop in the index for PT after 2015, in correspondence with the Lava Jato corruption scandal and the subsequent impeachment of President Dilma Roussef.

How do these estimates compare with other assortative matching criteria? We find a significant degree of positive assortative matching between owners and workers along gender and racial lines. The effects are large in magnitude, with an average of the gender index of about 1.2, and an average of the racial index of about 1.35. However, the relevance of partisan affiliation as an assortative matching criterion is considerably higher across all years in the sample period.

In Panel B, we present estimates of the indexes which account for geographical sorting across municipalities. While, unsurprisingly, the estimates are lower once we account for the fact that some parties are more popular in some areas of the country, the degree of political assortative matching is still substantial: on average over the sample period, workers and owners belonging to the same party are 55% more likely to match in the labor market relative to what we would expect under a random matching pattern *within a municipality.* While the estimates are also still significant for gender and race, the relevance of partisan affiliation as an assortative matching criterion is once again significantly higher throughout the sample period. Importantly, once we account for geographic sorting, we observe a clear increasing trend in the party index over time: the index averages 1.41 in the 2002–2006 period, 1.50 in the 2007–2011 period, 1.66 in the 2012–2015 period, and reaches a maximum of 1.67 in the 2016–2019 period. This is in contrast with what we observe for gender and racial assortative matching, whose indexes are, if anything, decreasing over the sample period.

3.2 Dyadic Regressions The likelihood ratio index has several attractive features and an intuitive interpretation. However, a shortcoming of the index is that it does not easily lend itself to a context, like ours, in which it is important to control for workers' and owners' characteristics that may be correlated with both political affiliation and employment decisions. For instance, if a party attracts more support from highly educated people, and highly educated owners have a preference for highly educated workers, failing to control for education would lead us to confound the role of partisan affiliation with that of education. Similarly, it is important to control for the industry of the firm to the extent that individuals working in the same industry are more likely to be members of the same political parties.

Relying on the granularity of our data, we employ a dyadic regression approach to estimate the extent of political segregation in the workplace.[17] For each year in the 2002–2019 period, we divide Brazil in M labor markets indexed by m. We define a labor market as a 2-digit CNAE industry code (out of a total of 87) within a municipality. In each labor market, we observe N_m workers and F_m firms. We create a matrix with all possible (i, f) worker-firm dyads within the market.[18] For each year, we obtain a dataset with $\sum_{m=1}^{M} N_m \times F_m$ dyads which we use to estimate the following specification:

$$y_{if} = \alpha_{m(f)} + \beta^{SP} SP_{if} + \beta^{DP} DP_{if} + \beta^{OW} OW_{if} + \beta^{OO} OO_{if} + SX'_{if}\gamma + \epsilon_{if} \tag{3.6}$$

The dependent variable y_{if} is an indicator taking value one if worker i is employed by firm f. The indicators SP_{if}, DP_{if}, OW_{if}, and OO_{if} turn to one, respectively, if i belongs to the same political party as the owner of firm f, if i belongs to a different party than the owner of f, if i is politically affiliated but f's owner is not, and if f's owner is politically affiliated

[17] This approach has been used to test for assortative matching in risk-sharing networks (Fafchamps and Gubert, 2007) and in community-based organizations (Fafchamps and Jean-Louis, 2012). More recently, Huber and Malhotra (2017) use a dyadic approach to study political homophily on an online dating site.

[18] In Appendix Figure A3, we show that we obtain qualitatively similar results if we define a labor market using municipality-occupation cells (using the first digit of the CBO code to define an occupational category).

but i is not. The case in which neither i nor f's owner are affiliated with a political party is the excluded category. We include market fixed effects ($\alpha_{m(f)}$), comparing only dyads within the same market, and we cluster standard errors at the market level to allow for arbitrary correlation of the residuals within a labor market.

Using the estimates from equation 3.6, we are interested in the linear combination $\Delta(SP, DP) = \beta^{SP} - \beta^{DP}$, which measures the differential probability that a politically affiliated worker is employed by a firm whose owner belongs to her same party, rather than by a firm whose owner belongs to a different party. This differential probability can be further decomposed as the sum of *(i)* $\Delta(SP, OO) = \beta^{SP} - \beta^{OO}$, namely the extent to which a politically affiliated owner employs workers of her same party rather than unaffiliated workers, and *(ii)* $\Delta(OO, DP) = \beta^{OO} - \beta^{DP}$, namely the extent to which a politically affiliated owner employs unaffiliated workers rather than workers of a party different from her own.

The key advantage of a dyadic approach is that it allows us to address the concern that assortative criteria are often correlated. In our context, we can control for an extensive set of worker, owner, and workplace characteristics that are likely to correlate with both an individual's political affiliation and with the choice of workplace. We include a set of indicators, SX'_{if}, which turn to one if worker i and f's owner share the same demographic characteristic. Specifically, we control for shared gender, race, age, and educational level.[19] By controlling for this wide set of covariates, we can investigate the role of copartisanship, net of any effect of these other shared demographic characteristics on the probability that a worker and an owner are matched in the labor market. Additionally, we leverage our measures of gender and racial segregation (the coefficients on "shared gender" and "shared race") as benchmarks to which we can compare the extent of political segregation in the labor market. Importantly, by exploiting only variation within a municipality-industry, we are also controlling for the geographic and industry clustering in partisan affiliation.[20]

Because of the massive size of the data, we estimate one regression for each year between 2002 and 2019. Additionally, computational constraints force us to use only a subset of the

[19]For gender and race we consider a "male"-"female" and "white"-"non-white" dychotomy. For age, we create seven age brackets (<25, (25-30], (30-35], (35-40], (40,45], (45,50], >50), and for education we create four educational levels (less than middle school, complete middle school, complete high school, more than high school). Each indicator c takes value one if the dyad (i, f) falls in the same group of that characteristic. We additionally include worker's occupation fixed effects, and we control for a continuous measure of a worker's experience.

[20]In the Appendix we present a version of the results without including the set of indicators SX'_{if} (Appendix Figure A4) and one where we include only the indicator for shared gender between worker and owner (Appendix Figure A5). Both these versions are estimated using the full sample of business owners, not only those for which we observe the full set of demographics. We find very similar estimates, indicating that the exclusion of business owners for which we cannot observe demographic characteristics is unlikely to bias our results. Additionally, in Appendix Figure A6 we present the results of the estimation of a version of equation 3.6 in the subsample of workers and owners that are affiliated with a party, thus excluding DP_{if}, OW_{if}, and OO_{if} from the estimating equation.

data available in each year for this specific analysis. In any given year, we restrict the sample used for estimation in two ways. First, we drop the top 1% of markets, based on the number of dyads. Second, we sample a random 25% of dyads in each market.[21]

We present the results graphically in Figure 3. The top panel shows estimates and 95% confidence intervals of $\Delta(SP, DP)$, $\Delta(SP, OO)$, and $\Delta(OO, DP)$, normalized by the sample probability that y_{if} equals one when $DP_{if} = 1$, when $OO_{if} = 1$, and when $DP_{if} = 1$, respectively. The bottom panel presents a comparison between $\Delta(SP, DP)$ and the effect of shared gender and shared race on the probability that worker i works in firm f. The full set of estimates of equation 3.6 are reported in Appendix Table A3.

The estimates of $\Delta(SP, DP)$ are shown in red in Panel A of Figure 3. We find a considerable degree of positive political assortative matching between workers and owners, even after directly accounting for the extensive set of additional assortative criteria that may be correlated with both political affiliation and employment decisions. Depending on the year, a politically affiliated worker is between 41% and 75% more likely to be employed by a copartisan owner than by an owner affiliated with a different party. This effect stems from a large estimate of $\Delta(SP, OO)$: conditional on firm f's owner being politically affiliated, the firm is more likely to employ workers belonging to the owner's same party, rather than unaffiliated workers. The likelihood of observing politically affiliated owners employing unaffiliated workers rather than workers who are affiliated with a different party is instead close to zero.

In Panel B of Figure 3, we benchmark the role of political affiliation with that of race and gender. The estimates show a significant degree of positive assortative matching between owners and workers along gender and racial lines. Even within the same municipality and industry, and after controlling for an extensive list of additional demographics, an owner and a worker sharing the same gender are 15%–31% more likely to match. The corresponding effect of shared race is on average 3.4%. In line with the estimates of the likelihood index described in the previous section, the relevance of partisan affiliation as assortative matching criterion is significantly higher than that of gender and race. Throughout the entire 2002–2019 period, sharing the same partisan affiliation as an owner increases the probability that a worker is employed by that owner's firm significantly more than sharing the same gender or race of the owner. Furthermore, while we do not observe significant time trends in political assortative matching over the 2002–2019 period, we observe a significant declining trend for both racial and gender assortative matching. As a consequence, relative to these other demographics, we observe an increase in the relevance of partisan affiliation as a driver of assortative matching in the labor market.

[21]In Appendix Table A2, we show that this restriction does not affect our results. We estimate our equations in the 75% of markets for which, given their size, we can use the full sample of dyads, and we show that we obtain nearly identical results to those obtained by drawing a random 25% sample.

3.3 Hiring and Tenure in the Firm The significant political assortative matching between workers and business owners that we document might be driven both by owners' higher propensity to hire copartisans and by a lower probability that copartisans leave the firm upon being hired. We now show that both of these forces are at play.

3.3.1 Preferential hiring We estimate a version of the dyadic regression 3.6 where we focus only on newly hired workers.[22] While the dyadic regression estimates of section 3.2 capture the effect of shared partisanship on both hiring and tenure decisions, the estimates from this new version of the regression focus only on the hiring margin. Appendix Figure A7 show that workers are significantly more likely to be hired by a firm whose owner is a copartisan than by a firm whose owner belongs to a different party. The magnitude of the effects range from a minimum of 32% to a maximum of 59%. Even when we focus only on the hiring margin, we continue to find a significantly higher presence of political assortative matching than assortative matching along gender and racial lines.

3.3.2 Longer tenure in the firm To investigate whether shared partisanship between workers and owners affects a worker's tenure in the firm, we again start with the sample of newly hired workers in each year. For each worker i who is hired in year t by firm f, we compute the variable $Tenure_{ift}$, that is the share of years in which the worker stays in the firm out of the total number of years between t and 2019 (the end of the sample period).[23] We then estimate the following specification:

$$Tenure_{ift} = \alpha_{tm(f)} + \beta^{SP} SP_{if} + \beta^{DP} DP_{if} + \beta^{OW} OW_{if} + \beta^{OO} OO_{if} + SX'_{if}\gamma + X'_i\delta + \epsilon_{ift} \tag{3.7}$$

where $SP_{if}, DP_{if}, OW_{if}, OO_{if}$ are defined as in equation 3.6, with affiliation status measured at the time of hire. $\alpha_{tm(f)}$ are fixed effects for the year-of-hire t and the municipality m where the firm is located. We include the same set of indicators SX'_{if} as in equation 3.6 to capture shared demographic characteristics between the worker and owner. The vector X'_i additionally includes a series of worker-level covariates, specifically an indicator turning to one if the worker is male, an indicator turning to one if the worker is white, education fixed effects, and year of birth fixed effects. We also estimate two more stringent specifications, where we include year-of-hire times market fixed effects, and year-of-hire times firm fixed effects.

Column 1 of Appendix Table A4 shows that workers who are affiliated with the same party of the owner stay in the firm about 10% longer than those who are affiliated with a different

[22]Newly hired workers are defined as workers who are employed in a firm in year t and who were not employed in that firm in year $t-1$.

[23]For instance, for a worker hired in 2010 who leaves the firm in 2017, $Tenure_{ift}$ will take value 0.7, as the worker stays in the firm for 7 out of the 10 years between 2010 and 2019. Note that if a worker is hired by a firm in 2010, leaves the firm in 2015, and then is hired back in 2018, the worker will enter the sample as two separate observations, corresponding to the 2 different hires.

party and are hired in the same municipality and year.[24] Once we include more stringent sets of fixed effects, comparing only workers in the same industry (column 2) or in the same firm (column 3), the magnitude of the effects decreases but remains statistically significant and large in magnitude.

4 Mechanisms

This section explores several potential mechanisms behind the large magnitudes of political assortative matching we uncover in the Brazilian labor market. We motivate our analysis by starting, in Section 4.1, with a qualitative discussion of relevant mechanisms based on a phone survey we conducted of both workers and owners in Brazil. We then focus on two broad sets of mechanisms.

One important mechanism relates to the overlapping of political and social networks: since networks are important in the job-search process (Ioannides and Loury, 2004; Topa, 2011), we might observe clustering of workers in firms owned by copartisans if people with the same political views also share the same social network.

A second set of mechanisms include explanations directly related to owners' political preferences in employment decisions. These preferences might in turn be driven by taste-based (Becker, 1971) or belief-based (Phelps, 1972; Arrow, 1973) *political discrimination*, or by *political quid-pro-quo* between firms and politicians (Bertrand et al., 2018).

We evaluate the importance of these different mechanisms using several different approaches. In Section 4.2 we study heterogeneous effects that inform a networks' channel, while simultaneously emphasizing the pervasive relevance of politics even in context where networks likely play a minimal role. In Sections 4.3 and 4.4, we provide several more direct tests underlining the relevance of owners' political preferences in employment decisions, using an event study and an analysis of within-firm promotion and wage premia and penalties. In Section 4.5, we show that these political preferences are unlikely to be driven by a political quid-pro-quo between firms and politicians. In Section 4.6, we provide experimental evidence for a mechanism of political discrimination. Finally, in section 4.7, we discuss the possible implications of our findings for firm productivity.[25]

4.1 A New Survey of Business Owners and Workers As a preliminary step to shed light on how politics may affect firms' employment decisions, we present results from a novel survey we conducted over the phone in the months of June–August 2021. The survey elicited

[24]This estimate is obtained by subtracting the coefficient on *Different party* from the coefficient on *Same party*, and dividing by the mean of the dependent variable in the sample of hires affiliated with a different party than the owner's party.

[25]While we focus only on owners' preferences, it could be that political assortative matching is driven by workers' preferences to work in a firm owned by a copartisan. As we show in the next sections, both our survey evidence and wage patterns indicate that this mechanism likely plays a minimal role in this specific context.

the beliefs of labor market participants about the most relevant drivers of our findings. It includes a representative random sample of 891 business owners and 1,003 workers drawn from our data. We sampled respondents so that approximately half of respondents in both groups were politically affiliated as of 2020, and to ensure broad representativeness along gender, age, education, geographical region, firm size, and sector.[26]

Respondents were asked to participate in a short survey to understand how hiring processes work in the Brazilian labor market. The final response rate was 26.84% (31.40% for workers and 21.82% for business owners). After agreeing to participate in the survey, respondents were told that: "A recent study reports that business owners tend to hire employees with similar political views," and they were asked for their opinion on the reasons behind this phenomenon. In order to make respondents directly evaluate different hypothesized mechanisms, we presented respondents with the following five statements (with the exception of the *italics* part at the end of each sentence, which is how we label the mechanisms internally), which they were asked to evaluate on a five-point scale ranging from "strongly disagree" to "strongly agree":[27]

(1) It is easier for a business owner and an employee to work productively together if they share the same political views (*belief-based discrimination*).
(2) Some business owners do not like to have people with different political views around, even if this does not hinder performance at work (*taste-based discrimination*).
(3) In general, business owners have more social interactions with people who have similar political views, so it is easier for them to know whether these people would be good hires for the company (*networks*).
(4) If business owners are affiliated with a party, the party will contact them with recommendations of affiliated people to be hired by their company (*political quid-pro-quo*).
(5) Workers do not want to work in companies where the business owner has different political views than their own (*workers' preferences*).

We present the results in Figure 4. In Panels A and B, we show the level of agreement with the different statements by owners and workers, respectively. The two mechanisms of employers' political discrimination attract the most support from respondents. Both groups of respondents agree that the *belief-based discrimination* mechanism is the most likely reason behind political assortative matching in the labor market: 47% of owners and 58% of workers either partially agree or strongly agree with the statement. This is followed by the *taste-based discrimination* mechanism (36% of owners and 52% of workers agree with the statement), and by the *networks* mechanism (39% of owners and 49% of workers agree with the statement).

[26]The text of the surveys for workers and owners can be found in Online Appendix A3 and Online Appendix A4, respectively.

[27]We randomized the order in which the statements were presented across different respondents.

Both groups of respondents show low levels of agreement with the other two mechanisms, namely *political quid-pro-quo* and *workers' preferences*.

In Panels C and D, we show the results in an alternative way. For each respondent, we code the statement with which she is most in agreement, and we plot the share of respondents who most agree with each of the statements.[28] Confirming the results of the previous two panels, respondents believe that employers' discrimination in favor of copartisans is likely the primary driver of our findings: 29% of owners and workers most strongly agree with the *belief-based discrimination* mechanism, and 25% of workers and 22% of owners most strongly agree with the *taste-based discrimination* mechanism. The *networks* mechanism attracts the most support of one out of five workers and owners. The *political quid-pro-quo* mechanism and especially the *workers' preferences* mechanism attract little support as the most likely mechanisms behind our findings.

Not only are the patterns very similar across business owners and workers but, as we show in Appendix Figures A8 and A9, they are largely independent of the political affiliation status of the respondent.

Importantly, at the end of the survey, we also directly ask business owners whether they consider the political views of potential employees when making hiring decisions. Specifically, the interviewer asks the business owner: "Finally, I would like to know about your experience as an entrepreneur. Do you think that the political views of a potential employee of your company can make any difference when hiring?" The question is open-ended, with the interviewer categorizing each answer into one of three categories: "No," "Yes," and "In some cases."[29] Naturally, many business owners are likely to feel uncomfortable discussing this issue in the context of their own hiring practices. Nevertheless, we find that almost one out of three business owners reveal that politics affects their hiring decisions. Specifically, 22% of the respondents answer "Yes," while 7% answer "In some cases." This qualitative evidence further confirms that employees' political views are an important element of consideration for employers when making their hiring decisions.

4.2 Social Networks and Heterogeneity When evaluating the importance of overlapping political and social networks as a mechanism behind our assortative matching patterns, it is important to note that our estimates in Section 3 are already obtained within extremely narrow labor markets featuring a large number of municipality-industry cells. Moreover, those estimates are obtained by also controlling for several standard assortative criteria—education, age, gender, race—that also likely proxy for a number of shared social networks. In

[28] If a respondent reports the same level of agreement on the 1–5 scale for more than one statement, we assign to the respondent two statements as the most agreed with.

[29] The category "In some cases" is used for cases in which business owners specify that they take into account individual political views only for specific positions within the firm, or only if the job seeker has extreme views.

short, we are already controlling for several characteristics that are likely to predict whether a worker and a business owner share the same network.

Nevertheless, it is impossible to capture all possible social networks in the data. Therefore, we probe the relevance of a social network mechanism in Figure 5 by reporting the estimates from our dyadic specification 3.6 for different subsamples of the data.[30]

Since personal interactions and social networks are likely more important in hiring decisions in smaller firms (Chandrasekhar et al., 2020), we start in Panel A of Figure 5 by investigating how the extent of political assortative matching differs across the distribution of firm size. We estimate our model separately in the subsample of small firms (up to 10 employees), medium firms (11–50 employees), and large firms (more than 50 employees). We find that political assortative matching decreases in firm size: while the effect is significant across the whole distribution, small firms have a degree of assortative matching along partisan lines that is more than twice that of medium firms, and more than six times that of large firms.

In Figure 5, Panel B, we estimate our model separately for workers employed in managerial occupations, in white-collar occupations, and in blue-collar occupations. We find that political assortative matching increases monotonically as we move up the layers of the hierarchy: the estimates are significantly larger for workers employed in managerial roles, and smaller, although still significant in magnitude, for white-collar and blue-collar workers. These results are consistent with overlapping political and social networks insofar as business owners and managers are more likely to belong to the same social circles (which is likely to the extent that income is an important driver of social networks).

To further characterize how our matching patterns depend on the relevance of social networks, we rely on the granular occupational data we observe in RAIS. The basic idea is that workers in jobs requiring strong interpersonal and social skills are likely to be workers for whom network-based hiring is more relevant. We match the occupation data from the CBO (Classificacao Brasileira de Ocupacoes) Brazilian classification to the O*NET data on occupational descriptions and categorizations.[31] The O*NET classification allows us to classify jobs based on the degree of *social skills* or *interpersonal relationships* required by the specific occupation.[32] In Figure 5, Panel C, we report the estimates of our model

[30] Appendix Tables A5-A18 provide the full set of dyadic estimates for these different subsamples.

[31] See `https://www.onetonline.org/`.

[32] More specifically, a job relies strongly on *social skills* whenever it scores highly on the following categories which involve "developed capacities used to work with people to achieve goals": Coordination, Social Perceptiveness, Service Orientation, Persuasion, Negotiation. By averaging across these dimensions, we can then classify jobs into those requiring social skills above or below median. Similarly, a job relies strongly on *interpersonal relationships* whenever it scores highly on the following dimensions: Contact With Others, Coordinate or Lead Others, Face-to-Face Discussions, Frequency of Conflict Situations, Responsibility for Outcomes and Results, Work With Group or Team. Analogous to social skills, we classify a job as above or below median in terms of interpersonal relationships required.

separately for these various subsamples. We find that the extent of political assortative matching is significantly higher—about double—the more the job requires social skills or involves interpersonal relationships.

In Figure 5, Panel D, we investigate to what extent assortative matching depends on the municipality of origin of the workers. To do so, we divide all workers who are hired in year t in a specific municipality among those that, in the year before, were (i) employed in the same municipality, (ii) employed in a different municipality, but in the same micro-region, (iii) employed in a different micro-region, and (iv) unemployed.[33] We then estimate our model for these different subsamples of workers. We find that assortative matching is considerably stronger when focusing on workers who were previously working in the same municipality ("Same Mun") or when focusing on those who were unemployed. Depending on the year, these effects can be twice as large as those obtained when focusing only on workers who were coming from a different municipality, in the same micro-region ("Diff Mun, Same Micro") or in a different micro-region ("Diff Mun, Diff Micro"). These results are consistent with a network channel, as those already working in the municipality are more likely to share a network with the local business owners relative to workers who were working (and likely living) in a different, far-away municipality.

Together, the results from Figure 5 speak to the relevance of overlapping political and social networks. At the same time, the effects are rather large in magnitudes for all splits of the data. In particular, results in Panel D are quite striking: business owners are more likely to hire workers who belong to the same party even when such workers come from an entirely different region, and who are therefore unlikely to be part of their same local networks prior to being hired.

All in all, the pervasive effects and large magnitudes uncovered across a number of contexts where networks should matter little suggest that other explanations are likely to be at play. We discuss more direct tests for the presence of a political preferences' channel next.

4.3 Event Study Around Owners' Change of Party In this section, we focus on a subset of owners who change partisan affiliation during the sample period, and we show that there are sharp changes in hiring patterns around the time of the switch in party. This test is important, since preexisting networks that might drive political assortative matching are unlikely to be suddenly erased when an individual changes party. Thus, by leveraging an event study design around the time of owners' party switching, we can provide evidence in favor of a mechanism of direct political preferences in employment decisions.

To implement this research design, we define a treated firm as the firm of an owner who switched affiliation at some point over the sample period. Each treated firm belongs to an

[33] We use the "micro-region" classification of Brazilian labor markets. There are approximately 550 micro-regions and 5,570 municipalities in Brazil.

"experiment," indexed by $m\tau AB$, which includes all firms located in market m whose owner switches in year τ from party A to party B. We then assign a set of control group firms to all treated firms in an experiment. Specifically, treated firms in the experiment $m\tau AB$ are matched to a control group of firms located in the same market m whose owners are always affiliated to party A in $t \in [\tau - 4, \tau + 4]$ (i.e., in the four years before and after the switch). We have a total of 14,613 "treated" firms whose owner switches partisan affiliation at some point during the sample period and that belong to a market with at least one "control" firm.[34] We then estimate the following specification:

$$y_{fmt\tau AB} = \alpha_{fm\tau AB} + \gamma_{mt\tau AB} + \sum_{s=\tau-4}^{\tau+4} \beta_s Switcher_f \mathbb{1}(s = t) + \epsilon_{fmt\tau AB} \tag{4.1}$$

where $\alpha_{fm\tau AB}$ are firm-experiment fixed effects, and $\gamma_{mt\tau AB}$ are time-experiment fixed effects. We are interested in the set of coefficients β_s, which trace the differential change in the outcome variable, relative to the year before the switch, between firms whose owners switch from party A to party B and firms in the same market whose owners remain affiliated to party A throughout the same period. We cluster standard errors by firm.

In Figure 6, we show the treatment effects on several employment outcomes. In Panel A, we focus on the hiring of new workers, considering their partisan affiliation at the time of hiring. We show estimates of equation 4.1 for four different dependent variables: the number of yearly hires who are affiliated with the new party of the switching owner (in red); who are affiliated with the old party of the switching owner (in green); who are affiliated with other parties (in blue); and who are unaffiliated (in orange). We normalize the estimates by the standard deviation of the respective dependent variable. We find large and sharp changes in hiring patterns in the year in which the owner changes party. These changes persist for the following four years. By the second year after the switch, the number of hires from the owner's new party increases by about 0.5 standard deviations, relative to firms in the control group. The effect remains large for the following three years of the event study window. This increase goes hand in hand with a drop in the number of hires from the owner's old party and, to a lesser extent, in the number of hires who are unaffiliated.

In the estimates of Panel B of Figure 6, the dependent variables are the shares of a firm's workforce of various partisan affiliations. In line with the estimates on hiring, we see sharp and persistent changes in the partisan composition of the workforce in firms where the owner changes party: the share of workers affiliated with the new party of the owner increases by about 2.5 percentage points, with symmetric decreases for unaffiliated workers and workers from the owner's old party.

[34] In order to have a sufficiently high number of switching firms with at least one control group firm in their market, we use a municipality as the relevant market. There is a total of 82,002 unique control firms.

While we do not claim that owners' changes of party are exogenous, to the extent that preexisting network links between an owner and perspective hires are unlikely to be suddenly erased when the owner switches partisan affiliation, the event-study results are consistent with politics directly influencing owners' employment decisions.

4.4 Evidence Within the Firm In this section, we investigate how the political affiliation of workers affects wages and promotions within the firm to provide additional evidence in support of a channel of political preferences in employment decisions.

We start by studying whether the political affiliation of workers affects their promotion chances relative to their coworkers. For each worker i who is hired in year t by firm f, we compute the variable $Promoted_{ift}$, that is an indicator taking value one if the worker will ever be promoted to a higher organizational layer during her tenure in the firm. We then estimate the following specification, where each worker appears only once for each employment spell:

$$Promoted_{ift} = \alpha_{tf} + \beta^{SP} SP_{if} + \beta^{DP} DP_{if} + \beta^{OW} OW_{if} + SX'_{if}\gamma + X'_i\delta + \epsilon_{ift} \tag{4.2}$$

where SP_{if}, DP_{if}, and OW_{if} are defined as in equation 3.6, with affiliation status measured at the time of hire, α_{tf} are fixed effects for the year-of-hire t times firm f, and all the other variables are defined as in equation 3.7. The coefficients β^{SP} and β^{DP} capture the differential promotion probability between workers of the same or different party of the owner, respectively, relative to unaffiliated workers who joined the same firm in the same year. The coefficient β^{OW} measures the differential promotion probability between affiliated workers and their unaffiliated coworkers in firms whose owner is unaffiliated

Table 2, columns 1 and 2, presents the results. In column 1, the sample includes workers who are hired in white-collar positions, and the dependent variable is an indicator for promotion to a managerial role. In column 2, the sample includes workers who are hired in blue-collar positions, and the dependent variable is an indicator for promotion to a white-collar position. Given the rare nature of promotion events, the respective coefficients are scaled by 100 to correspond to percentage points changes. In firms with politically affiliated owners, we find a substantial promotion premium for workers who are copartisans of the owner: relative to their unaffiliated coworkers who joined the firm in the same year, these workers are 0.563 percentage points more likely to be promoted from a white-collar to a managerial position (column 1), and 0.209 percentage points more likely to be promoted from a blue-collar to a white-collar position (column 2). The magnitude of these effects is significant considering that the average promotion probability for unaffiliated workers is 2.6% from white-collar to manager and 2.9% from blue-collar to white-collar. This "political promotion premium" is significantly larger than the promotion premium associated with sharing the same gender or race of the owner.

Importantly, for white-collar workers, we also find a significant promotion penalty associated with being affiliated with a party that is different from the owner's party: these workers are on average 0.104 percentage points less likely than their unaffiliated coworkers to be promoted to a managerial role. Interestingly, politically affiliated white-collar workers suffer a large promotion penalty in firms whose owner is unaffiliated, underlining the fact that their increased likelihood of promotion crucially depends on their matching to copartisan employers.

We next investigate whether the political affiliation of workers affects their wages by estimating the following wage equation:

$$\log w_{ift} = \alpha_{ft} + \beta^{SP} SP_{if} + \beta^{DP} DP_{if} + \beta^{OW} OW_{if} + SX'_{if}\gamma + X'_{i}\delta + \epsilon_{ift} \tag{4.3}$$

where $\log w_{ifmt}$ is the log wage paid to worker i employed in firm f at time t, α_{ft} are firm times year fixed effects, which restrict the comparison to workers of the same firm in the same year, and all other variables are defined as in equation 4.2 .

The results from estimating equation 4.3 are presented in column 3 of Table 2. In firms with politically affiliated owners, we find a substantial wage premium for workers who belong to the same political party of the owner. Relative to their unaffiliated coworkers, these workers earn 3.8% higher wages. Once again, the magnitude of the "political wage premium" is significantly larger than the gender (1.5%) or race (1%) wage premium.

We also find a significant wage penalty associated with being affiliated with a party that is different from the owner's party, with these workers earning on average 1.6% less than their unaffiliated coworkers. Moreover, politically affiliated workers suffer a 2.2% wage penalty in firms whose owner is unaffiliated.

In column 4 of the table we repeat the same analysis but substituting firm-year fixed effects with firm-year-occupation fixed effects, further restricting the comparison to coworkers employed in the same occupation within the same firm. While this decreases the size of the coefficients, in line with part of these wage differentials stemming from assignment of workers to different positions within the firm, their magnitude is still significant. We find a 2.8% political wage premium for copartisans and a 0.8% wage penalty for workers of different parties. Columns 5, 6, and 7 present the same analysis by occupational layer. The political wage premium and penalty is present across all main occupational categories of managers (column 5), white-collar workers (column 6), and blue-collar workers (column 7), with a relatively larger wage premium for white-collar employees, and a relatively larger wage penalty for managers belonging to a political party different than the owner's.

In Appendix Figure A10, we conduct a similar event study as in the previous section, but using as dependent variable the total wage bill for workers of different partisan affiliations. The wage bill for workers of the new party of the owner suddenly increases when the owner switches party, while the total wage bills for workers of the owners' old party and unaffiliated workers drop.

In sum, owner's copartisans are not only more likely to rise up in the organizational hierarchy through promotions, but they also earn more than their unaffiliated coworkers within the same hierarchical layer. Workers affiliated with a different party than the owner suffer instead promotion and wage penalties. On the one hand, these results indicate that the implications of politics for the private sector go beyond the matching between workers and firms. On the other hand, this analysis provides additional evidence consistent with a channel of political preferences in employment decisions, since a network mechanism is hard to reconcile with penalties for workers of opposing parties. The results in this section also indicate that workers' preferences to work in firms owned by copartisans play a minor role in explaining political assortative matching. Indeed, because of compensating differentials, we would expect opposite results—i.e., a negative wage premium—if working for copartisan owners was seen as a positive job amenity. This is perhaps also not surprising in a context characterized by high unemployment and highly valued formal jobs.

4.5 The (Limited) Role of Political Quid-Pro-Quo The results so far show that both shared networks and political preferences in employment decisions are important mechanisms. In this section, we shed more light on the specific driver of political preferences, and specifically on the role of *political quid-pro-quo* between firms and politicians (Bertrand et al., 2018).

The quid-pro-quo might favor owners who are interested in running for political office, and who may decide to provide employment to future political supporters as a way to build up local political support. If this is the case, we would expect our results to be especially strong when focusing on business owners who are directly involved in politics. Alternatively, the quid-pro-quo might benefit the firm: business owners may hire party members as a way to support local politicians, with the hope of obtaining a favorable exchange, for instance in the form of government contracts. If this is the case, we would expect results to be concentrated in sectors that are highly dependent on government contracts, and for parties with more political power.

Relying on a host of datasets that we constructed for previous studies (Colonnelli et al., 2020; Colonnelli and Prem, 2022), we find that none of these predictions has empirical support. We observe local electoral results as well as the identity of all individuals who ever run for politics (at either local or upper levels) and of those who donated to any political campaign over our entire sample period. We can also identify sectors that are more or less dependent on government contracts based on public procurement data for the state of Sao Paulo.

In Figure 7, Panel A, we show that our estimates of political assortative matching are unchanged if we drop from the sample the 16.2 % owners and 5.57 % workers who ever run for political office or donated to a political campaign during our sample period. This suggests that our results are not driven by individuals who are more politically active, and thus more likely to be interested in using employment as a tool to build up personal political support.

In Panel B, we show that the estimates are rather similar between sectors that are more or less dependent on government contracts. We calculate two industry-level measures of government dependency. First, we classify a sector as having high government dependency if the share of firms in that sector that ever obtained a government contract is above the median in the distribution across all sectors. Second, we classify a sector as having high government dependency if the average contract values for contracts won by firms in that sector is above the median in the distribution across all sectors. While some of the early years in our sample period display larger political assortative matching in sectors that are more government dependent, the estimates are similar in magnitude and statistically indistinguishable in most of the years.

In Panel C, we show estimates of political assortative matching for different parties, characterized by different degrees of political power. Specifically, we focus on the top two parties for each election (the one of the elected mayor and the one of the runner-up candidate), and we divide parties in twenty groups, depending on the performance of their candidate for mayor in the most recent local election. The x-axis indicates the decile of margin of victory (positive numbers) or loss (negative numbers) of the party, based on the distribution of margins of victory across all elections. The y-axis reports the estimates of political assortative matching in these different subsamples of parties.[35] Neither whether the political party won the election or not, nor the margin of victory over the opponent, affect the extent to which business owners of that party engage in political hiring. This is inconsistent with a political quid-pro-quo explanation of the political assortative matching. Consistent with this analysis, Appendix Table A19 shows that, while firms win more procurement contracts when the owner belongs to the same party of the mayor, such effect is not stronger when the owner employs more copartisans.[36]

We conduct an additional test to show that quid-pro-quo considerations by the owners do not seem the be a dominant mechanism. In a small subset of (larger) firms in our data, hiring decisions are delegated to Human Resource (HR) managers. Some of these employees

[35] To focus only on business owners' employment decisions taken following the election results, in this figure we focus on political assortative matching among new hires.

[36] These results are based on a panel regression at the firm-year-election level. For each local election, a firm active in the municipality appears for 3 periods before and for 4 periods after the election year. We include Firm-Election fixed effects and Period-Election fixed effects, restricting the comparison to firms active in the same municipality in the same year.

have a different partisan affiliation than the owner. If hiring is driven by quid-pro-quo considerations, we expect copartisans of the *owner*—not of the *HR manager*—to be favored. Focusing on the sample of firms with an HR manager who is from a different party of the owner, we estimate political assortative matching by including in our dyadic regressions both an indicator turning to one if the worker shares the same party of the owner, and an indicator turning to one if the worker shares the same party of the HR manager.[37] Appendix Figure A11, Panel A shows that partisan alignment between workers and HR managers matter nearly as much as partisan alignment between workers and owners, with the relative effects varying depending on the time period.[38] Panel B of the figure shows that in firms in which only the HR manager (and not the owner) is affiliated, we find large political assortative matching driven by the HR manager's partisan affiliation.

In sum, we find little evidence pointing to *political quid-pro-quo* between firms and politicians being the relevant driver of political preferences in employment decisions. The above results seem more consistent with a mechanism of *political discrimination*. We provide more direct evidence for a political discrimination channel in the next section.

4.6 Identifying Political Discrimination: An Incentivized Resume Rating Field Experiment We provide direct evidence that business owners discriminate in favor of copartisans using a field experiment conducted in collaboration with a leading job platform in Brazil (whose identity we agreed to keep anonymous) and inspired by the classical "resume audit studies" adopted to identify the presence of gender and racial discrimination (Bertrand and Mullainathan, 2004; Bertrand and Duflo, 2017).

4.6.1 ***Experimental Design*** We implement an incentivized resume rating (IRR) experiment with a sample of Brazilian business owners who report interest in hiring. We follow closely the methodology of Kessler et al. (2019), recently adopted in a number of other matching contexts (Low, 2021; Macchi, 2023; Colonnelli et al., 2024). The experimental design features employers' ratings of job-seekers' resumes while avoiding deception. Specifically, business owners who are invited to participate in the study are asked to report their interest in the resumes of synthetic job seekers, whose features—such as education, work experience, and other relevant activities—are realistic but fully randomized by our research team. There is no deception because respondents know the resumes are hypothetical. The incentives to report truthfully are strong because we partner with a leading Brazilian job

[37]We use the full CBO Brazilian occupational classification in our matched employer-employee dataset to identify HR Department of each firm. In particular, HR Department are identified by the codes 252405 (Analista de recursos humanos), 142205 (Gerente de recursos humanos) and 123205 (Diretor de recursos humanos). If there are more than one worker at the HR Department, we pick the highest paid worker to identify the *HR manager*.

[38]Note that these firms are clearly not representative of the universe of firms, as firms with an HR manager are much larger than the average firm, which explains the lower magnitude of the assortative matching estimates in this figure.

platform to send our subjects resumes of real job seekers (in their location) selected from the platform's database based on their preferences. Specifically, we explain to respondents that their ratings of the synthetic resumes will be used to select the real resumes on the basis of a machine learning algorithm. Thus, respondents know that the accurate and truthful rating of synthetic resumes will maximize the value of the real resumes that they will receive. Since our key objective is to elicit owners' preferences for hiring copartisans, we introduced cues of the job seeker's partisan leaning for a subset of the fictitious resumes.

4.6.2 ***Recruitment of Business Owners*** We recruit participants through direct sampling from our administrative data. We focus on owners of firms in the *Receita Federal do Brasil*, which contains firms' contact information. We focus on owners who are affiliated with one of Brazil's six major political parties. We select three left-wing parties ("PT," "PDT," "PCdoB") and four center-right wing parties ("PSDB," "PMDB," "DEM," "PP"). We further restrict the sampling frame to owners whose firm had at least one employee. We ensure broad representativeness along gender, age, and education of the owner and along geographical region, size, and sector of the firm.

We contact owners by phone and explain the incentivized resume rating procedure and the details of the incentive. If owners express interest in participating in the study, they are sent a link to continue to the experimental portion of the survey on their computer or phone.[39] The survey was conducted over the months of March–May 2022. We targeted a sample of 150 respondents, which we obtained with a response rate of 11%.

One key advantage of this recruitment strategy is that we know business owners' political affiliation from the administrative data. This allows us to avoid asking respondents about their political preferences before they take the experimental portion of the survey, which avoids priming them to think about politics when rating the resumes. The full text of the survey is provided in Online Appendix A5.

4.6.3 ***Resume Creation and Rating*** The experiment asks individuals to rate a set of synthetic resumes. We construct these resumes by first creating realistic sets of elements for each resume section and then randomly selecting elements from these sets. We randomize several components of the resumes, namely gender, education, work experience, on-the-job training, technical skills, locations of education and employment, and hobbies. In order to increase the realism of the resumes, reduce strain among participants, and motivate engagement, we randomize the formatting of the resumes, using one of eight different templates. Each section title (i.e., Work Experience, Education, etc.) within the resume is also uniformly drawn from a list of multiple options. Appendix Table A20 describes in detail the set of characteristics that we randomly vary across resumes.

[39]Both this survey and the one described in Section 4.1 were conducted by the Brazilian survey company OPUS Institute (https://www.opuspesquisa.com/).

In order to show only resumes of candidates who are potentially interesting for the owners, we first require participants to select the region of their firm and the required education level, so that only synthetic resumes that fit these basic criteria are shown to the respondent.[40]

Since partisan affiliation is typically not reported in real resumes, we introduce cues to a candidate's partisan leaning through two resume components: work experiences, and training or leadership activities. We have a total of 35 unique cues (20 for work experiences and 15 for other activities), which are short bullets in the resume. As an example, "Political campaign analyst for PT" and "Sticker distributor for the Jair Bolsonaro 2018 campaign" in the "work experiences" section of the resume would be cues of partisan leanings towards PT and President Bolsonaro, respectively. Similarly, "DEM state youth representative" is an example appearing in the "leadership positions" section of the resume, and it is meant to signal that the job seeker is politically close to the DEM party. Importantly, to ensure realism, we select cues by drawing real examples found in resumes available on the online portal of our partner job platform.

Since it would not be realistic to show only resumes containing partisan cues, which are typically a minority, we show to each owner the following set of resumes, in random order: sixteen resumes without any cue to partisan leaning, two resumes with a cue that the worker is of the same party as the owner, and two resumes with a cue that the worker is of a party from the opposite side of the political spectrum.[41] The sixteen resumes without any political information, while not used in our analysis, are included to infer owners' preferences and to personalize the real resumes that respondents will receive from our partner.

For each resume, we ask employers to answer two questions. The first question is: "How interested would you be in hiring this candidate?" We use the answers to this question to construct our main dependent variable. Respondents provide an answer on a Likert scale from 1 to 7. In order to provide concrete meaning to each point in the scale, we assign short descriptions to each point, with 1 corresponding to "I would never hire the candidate" and 7 corresponding to "I would certainly hire the candidate."[42] Importantly, we also specify: "Imagine that there was a guarantee that the applicant would accept your job offer, and just think about your interest in the candidate." This ensures that we are capturing only an

[40]If a participant requests resumes where high school is the highest attained education, then only resumes with high school graduation are shown. Otherwise, if a participant requests college educated candidates, they must select one of four fields of study: (a) "Economics, business or accounting", (b) "Engineering, computer science, mathematics or statistics", (c) "Law", (d) "Others (humanities, other social sciences and natural sciences)," and only resumes with college education in the specific field are shown.

[41]Specifically, if the owner belongs to a left wing party, "opposite party" resumes include one resume linked to one of the three most popular center-right wing parties (PMDB, PSDB or DEM) and one resume linked directly to the far-right president Jair Bolsonaro, who traditionally does not belong to a specific party; if the owner belongs to a right wing party, "opposite party" resumes include two resumes linked to three of the most popular left-wing parties (PCdoB, PDT or PT).

[42]The full scale is: 1 - "I would never hire the candidate," 2 - "Very low interest," 3 - "Low interest," 4 - "Average interest," 5 - "High interest," 6 - "Very high interest," 7 - I would certainly hire the candidate."

employer's interest in the resume, which is independent of the perceived likelihood that the candidate will accept an offer.

Our second question asks: "How interested do you think this candidate would be in the job?," with instructions to think only about a situation in which they had offered a job to the candidate. As for the first question, respondents provide an answer on a Likert scale from 1 to 7, and we provide a short description of the meaning of each point on the scale, ranging from "The candidate would never accept" to "The candidate would certainly accept." As in Kessler et al. (2019), the primary purpose of this question is to ensure that respondents focus only on their preference for the candidate when answering the first question. In addition, this question also allows us to see whether the partisan leaning of job seekers has any impact on the business owner's perception of the likelihood that they would accept a job offer.

4.6.4 ***Results*** To study whether business owners express a preference for copartisan job seekers, we estimate the following equation:

$$V_{ij} = \alpha_i + \beta SameParty_{ij} + X_j\theta + \epsilon_{ij} \tag{4.4}$$

where V_{ij} is employer i's interest in resume j on the discrete 1-to-7 Likert scale. Our regressor of interest, $SameParty_{ij}$, is an indicator equal to one if resume j contains a cue that the job seeker is from the same party as employer i. Thus, the coefficient β captures the average difference in employers' rating of resumes from their same party versus resumes with a cue that the job seeker is from a party on the other side of the political spectrum. Respondent fixed effects, α_i, account for different average ratings across respondents. The vector of resume-level controls, X_j, is included in a robustness specification.

Table 3 shows the results. The coefficient in column 1 shows that employers on average rate resumes from their same party 0.213 higher on the 1–7 Likert scale. Relative to the average rating for resumes from a different party, this represents a 7.4% increase. In column 2, we show that the estimate is similar when we add a series of resume-level controls, in line with the randomization of resume characteristics.

Columns 3 and 4 of the table show results when we use as dependent variable the respondent's perception of the likelihood that the candidate would accept a job offer. We find little evidence in line with employers' perceptions that copartisans would be more likely to accept a job offer, if one was made: the estimated effect is statistically insignificant and also considerably smaller than the effect in columns 1 and 2.

In short, experimentally shutting down alternative explanations, the results from this section isolate a channel of political discrimination whereby owners discriminate in favor of copartisans at the hiring stage.

4.7 Discussion We conclude this paper by discussing the possible implications of our findings for firm outcomes, which are themselves informative of the underlying drivers of political assortative matching.

Our analysis cannot provide a causal estimate of the impact of political assortative matching on firm outcomes, since we lack exogenous variation in the extent to which political assortative matching varies across firms or across markets. However, we can provide some evidence to start shedding some initial light on these issues. First, as discussed earlier and showed in Appendix Table A19, firms engaging in more political assortative matching do not seem to benefit by obtaining more government contracts. Second, we provide evidence pointing to a potentially sizable cost of political assortative matching, namely a worse selection of workers in terms of education. Specifically, we construct a measure of educational mismatch at the worker-job pair level. We create the variable $Qualified_{ift}$, which is equal to one if worker i in firm f is qualified, in terms of education, for the occupation in which she is employed in year t.[43] We then estimate a version of equation 4.3, where we replace a worker's wage with the variable $Qualified_{ift}$ as the dependent variable. The results are presented in column 1 of Table 4. Copartisans of the owners are significantly less likely to be qualified for the job. Relative to their coworkers who are unaffiliated, workers who share the same party of the owner are 2.1 percentage points less likely to be qualified, or 2.3% relative to the mean probability of being qualified. The economic magnitude of all the other coefficients is very small, suggesting that only being a copartisan of the owner represents a relevant trait which substitutes for educational qualifications. In columns 2–4, we analyze the results for different occupational categories, finding a particularly strong effect for managers.

Since we cannot observe all dimensions of individuals' competence and productivity on the job, it could still be that copartisans of the owner are on average more productive along dimensions we do not observe. Yet, Figure 8 (and Appendix Table A21) shows that firms with a higher share of owner's copartisans grow less, not more, than similar firms who employ fewer copartisans. These "similar" firms have the same number of workers and the same number of affiliated workers in the same year, and are active in the same municipality and in the same sector. A higher share of copartisan workers is strongly associated with significantly lower firm growth (in the subsequent year), with an estimated β coefficient of -0.076 in the most stringent specification. To gauge the magnitude of this effect, two firms that are one standard deviation apart in Share Copartisan$_{f,t-1}$ have a growth rate gap of approximately 1%.

[43] To do so, following Colonnelli et al. (2020), we combine information on a worker's education with information on the level of education required to perform each of the 2,511 occupations appearing in the data. The latter information was manually collected from the *Classificação Brasileira de Ocupações 2002*, which describes the educational level typically required to perform a specific occupation. By combining this information we know if a worker's educational level is the same or higher than the one required to adequately perform the occupation.

Although we emphasize that these results are only suggestive, the negative associations between political assortative matching and firm outcomes seem not only inconsistent with a quid-pro-quo exchange between firms and politicians, but also with belief-based political discrimination—whereby owners would correctly believe that copartisans are more productive at work (possibly because partisan conflicts between owners and employees might decrease team performance). Instead, the combined evidence points towards a “taste-based” nature of political discrimination.[44]

5 Conclusion

This paper uses new micro-data to provide detailed evidence that individual political views spill over from political to apolitical domains, focusing on the Brazilian labor market over the past two decades.

We make two primary contributions. First, we document a considerable degree of assortative matching along political lines between firm owners and their workers. The magnitude of these effects is striking: shared partisan affiliation is a stronger driver of assortative matching between firms and workers than shared gender or race.

Second, we rely on a number of empirical approaches to shed light on the mechanisms behind our findings. While we show evidence consistent with overlapping social and political networks being an important driver of political assortative matching, we provide a series of tests—a survey, an event study, analyses of wage premia and promotions within the firm, and a field experiment—that reveal that business owners’ political preferences directly influence employment decisions. Additionally, the results suggest that these preferences are driven by discrimination in favor of copartisans, rather than by political quid-pro-quo exchanges between firms and politicians.

An important contribution of our work is to provide a bridge between two related strands of literature that have largely kept a distinct focus. On the one hand, the literature on the political economy of firms has primarily focused on quid-pro-quo mechanisms benefiting politically connected firms and corrupt politicians, with little attention paid to individual political biases of firms’ owners. On the other hand, a more recent literature, focused on the Republican-Democrat ideological divide in the U.S., highlights the possible role of partisanship in affecting individuals’ decisions in apolitical realms. Thanks to our detailed administrative micro-data, and leveraging experimental and survey evidence, we can estimate precise economic magnitudes and show that a number of economic channels are at play in explaining political assortative matching in the labor market.

[44]Alternatively, employers might have inaccurate beliefs that copartisans are more productive, as discussed by Bohren et al. (2019) in a general context. Disentangling taste-based discrimination from inaccurate belief-based discrimination remains extremely challenging and beyond the scope of our paper.

Another direct implication of our work is that trends in political polarization may reshape the way we think about organizational structures and firm behavior. In addition, the substantial degree of segregation along political lines in the labor market might have important implications for political polarization itself. Fears about the presence of echo chambers have been primarily associated with online interactions, with both online news consumption and interactions on social media deemed more likely to expose people to a homogeneous set of political views (Sunstein, 2017). We provide evidence that workplaces may well contribute to the emergence of echo chambers if workers and owners with similar political views cluster in the same firms.

Our study naturally leaves many open questions. First and foremost, future work should leverage natural and field experiments to quantify the causal effects of political assortative matching on firm growth and productivity. Our final results raise the possibility that business owners might be willing to trade-off firm growth to have a workforce of individuals with similar political views, but our evidence remains suggestive. Additionally, a key objective of the paper is to highlight the importance of multiple mechanisms contributing to the large magnitudes of the political assortative matching that we observe. We believe that precisely quantifying the relative importance of various channels, and how these vary across different contexts, remains an important next step.

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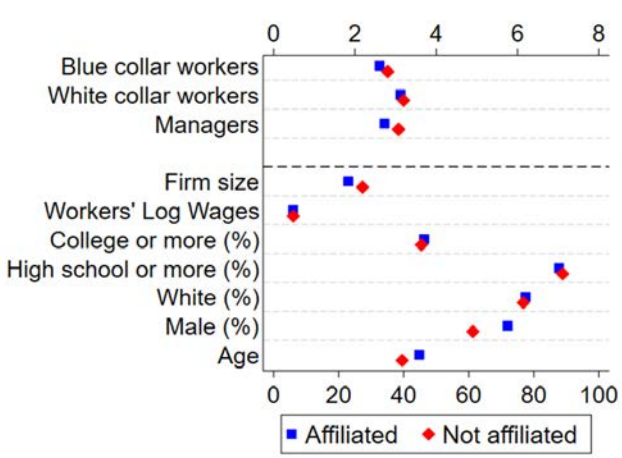
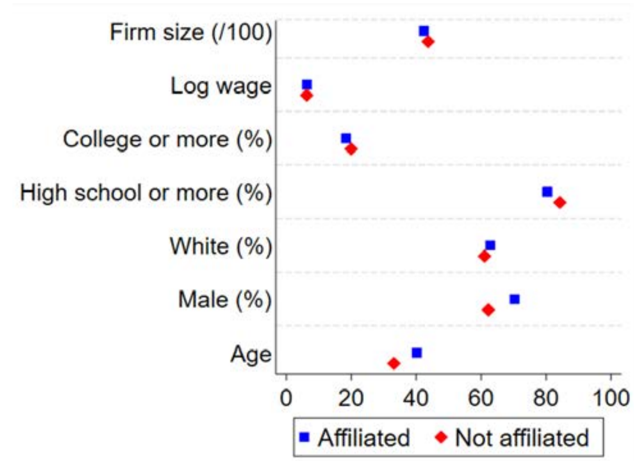
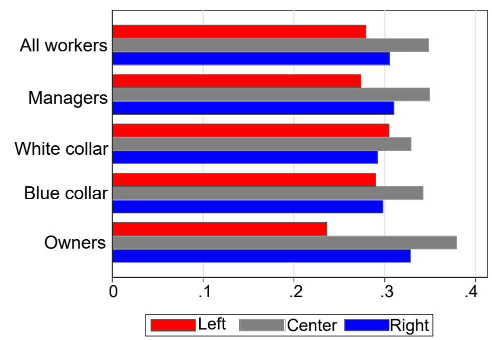
Figure 1. **Comparing Affiliated and Unaffiliated Owners and Workers**



A. Owners



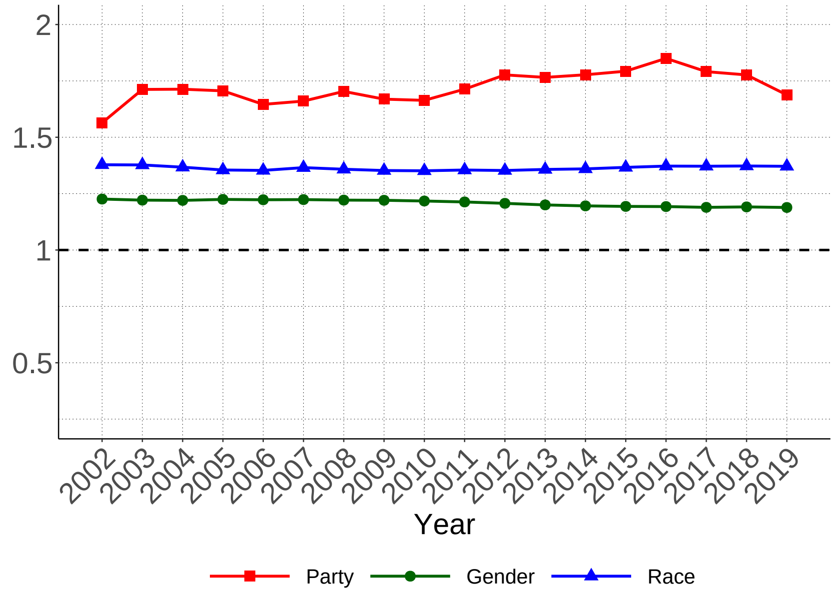
B. Workers



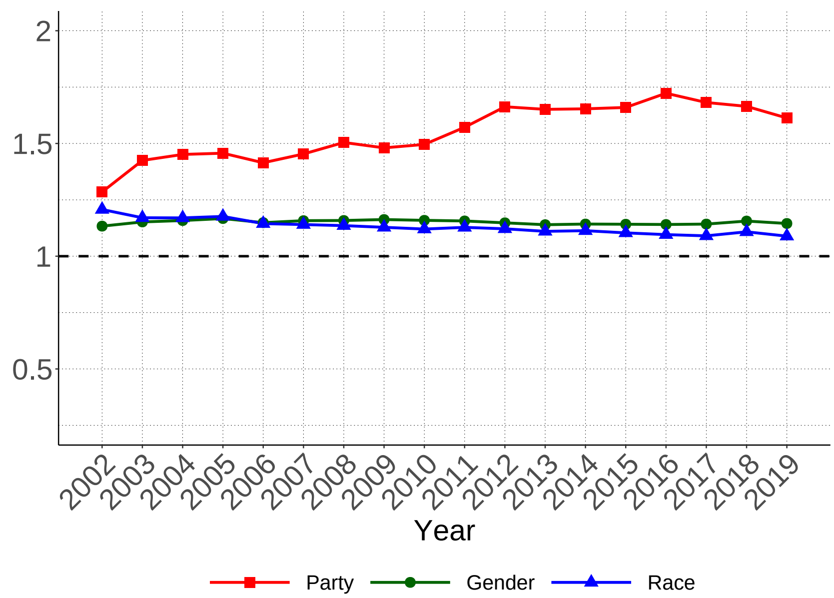
C. Political Orientation of Owners and Workers

Notes: Panels A and B show average differences between affiliated (in blue) and unaffiliated (in red) owners and workers for each variable listed on the y-axis. Panel C shows the distribution of workers' and owners' political orientation. The unit of observation in all panels is a worker/owner-year. *Blue-collar workers / White-collar workers / Managers* are the number of workers in the firm that are employed in blue-collar/white-collar/managerial occupations. *Firm size* and *Firm size (/100)* are the number of workers in each firm-year, with the latter being divided by 100 for scaling purposes. *Workers' Log wages* is the average of the natural log of wages for the workers in the firm, deflated to 2002 BRL. *Log wages* is the natural log wages of the worker, deflated to 2002 BRL. *College or more (%)* and *High school or more (%)* are the share of owners/workers that hold at least a college degree and at least a high school degree, respectively. *White (%)* is the share of owners/workers who are white. *Male (%)* is the share of owners/workers who are male. *Age* is the age of owners/workers. See Appendix Table A1 for the categorization of Brazilian parties as Left/Center/Right.

FIGURE 2. **Political Assortative Matching: Likelihood Ratio Index**



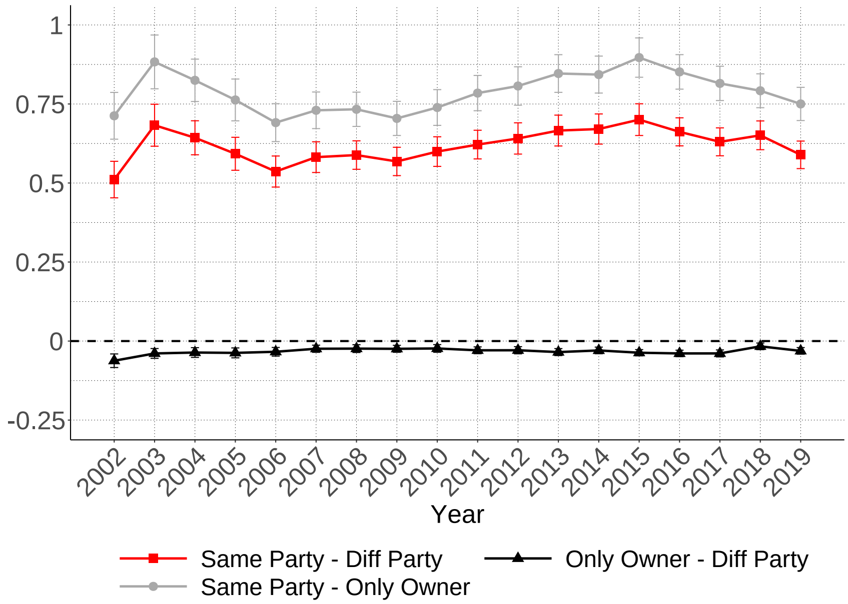
A. Basic Index



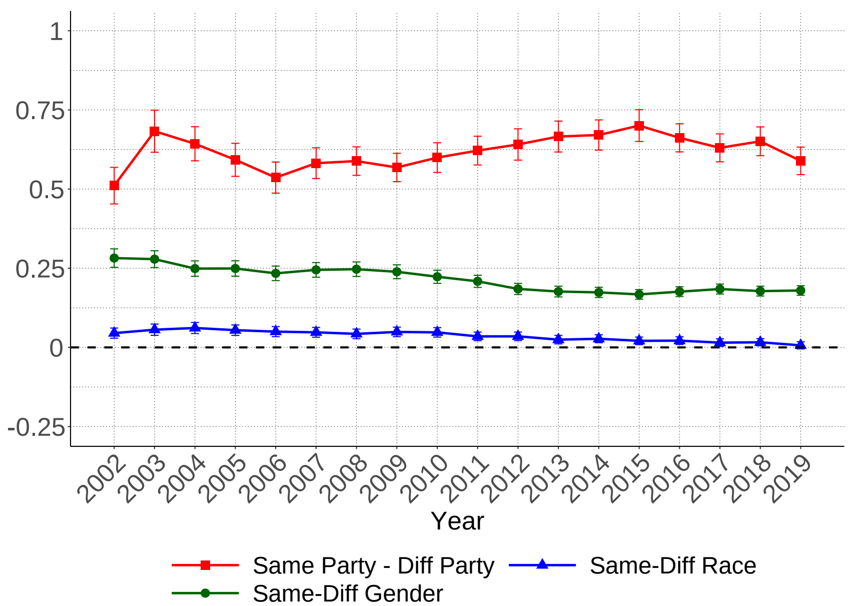
B. Accounting for Geographical Sorting

Notes: The top panel shows estimates of the likelihood ratio index (calculated as in equation 3.3), while the bottom panel shows estimates of the index which accounts for geographical sorting (calculated as in equation 3.5). The estimates in red are for political assortative matching, the estimates in green are for assortative matching along gender lines, and the estimates in blue are for assortative matching along racial lines. See section 3.1 for additional details.

FIGURE 3. **Political Assortative Matching: Dyadic Regression Estimates**



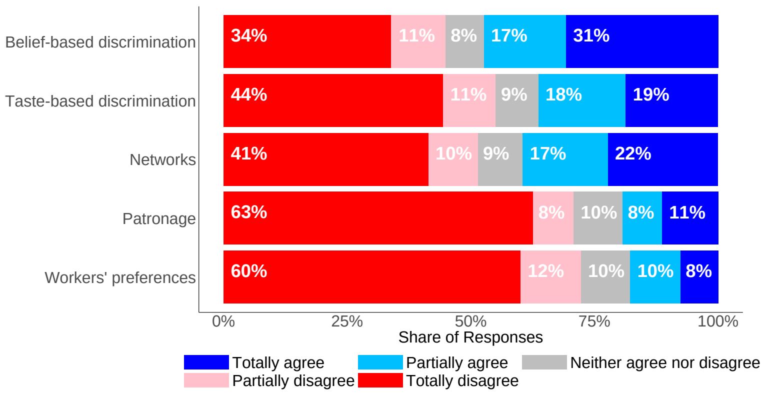
A.



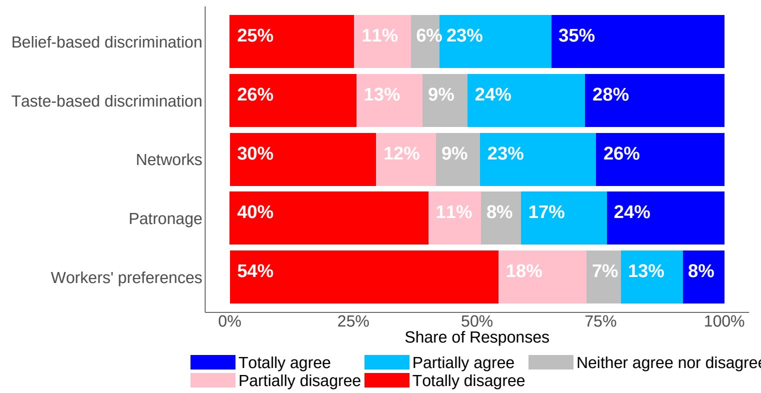
B.

Notes: The top panel shows the point estimates and 95% confidence intervals of $\Delta(SP, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in red), $\Delta(SP, OO)$ divided by the sample probability that y_{if} equals one if $OO_{if} = 1$ (in gray), and $\Delta(OO, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in black), from equation 3.6. The bottom panel shows a comparison between $\Delta(SP, DP)$ and the effect of shared gender and shared race on the probability that i works in firm f, normalized by the sample probability that y_{if} equals one if the worker and the owner have a different gender or race, respectively. Confidence intervals are based on standard errors clustered at the market level. See section 3.2 and equation 3.6 for details on the estimation.

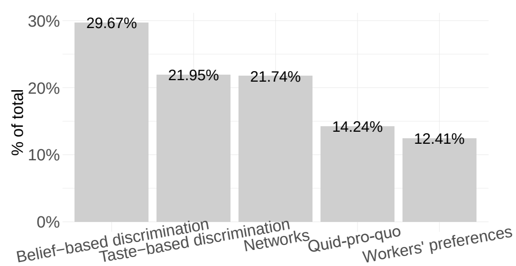
Figure 4. **Survey Evidence on Most Relevant Mechanisms**



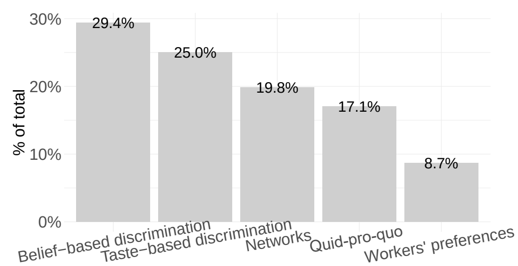
A. Owners' agreement with the five statements



B. Workers' agreement with the five statements



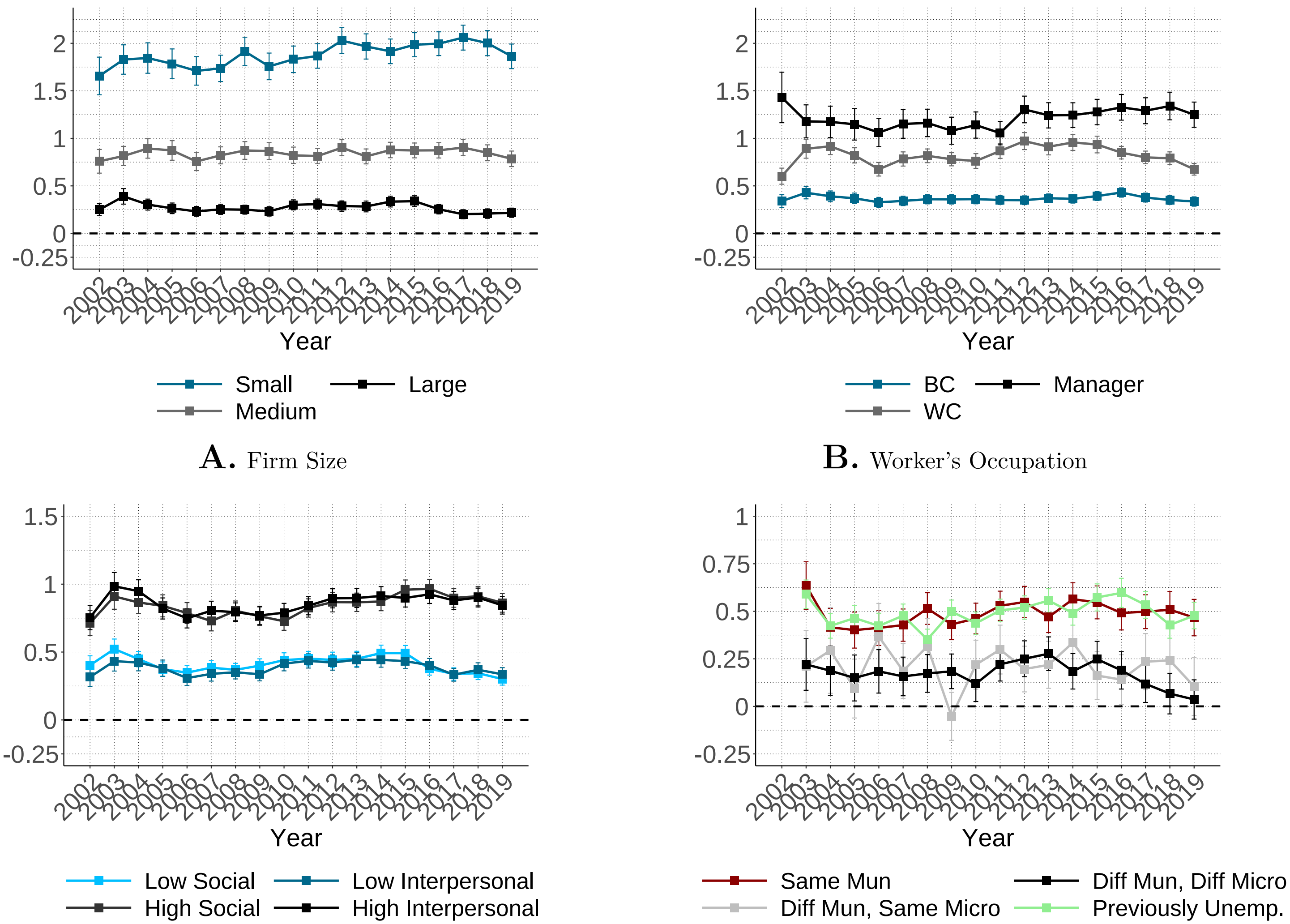
C. Owners' most relevant mechanism



D. Workers' most relevant mechanism

Notes: The figure plots responses from our survey of Brazilian business owners and workers, described in section 4.1. Panels A and B plot the level of agreement (on a scale from 1 "Totally disagree" to 5 "Totally agree") with the different statements by owners and workers, respectively. Panels C and D plot, for each statement, the share of respondents who agree the most with that statement.

FIGURE 5. **Social Networks and Heterogeneity**



A. Firm Size

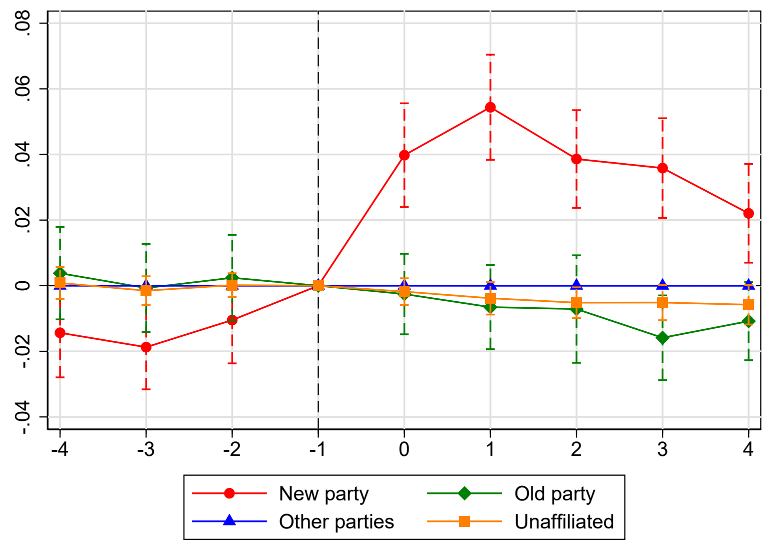
B. Worker's Occupation

C. Social and Interpersonal Skills of Job

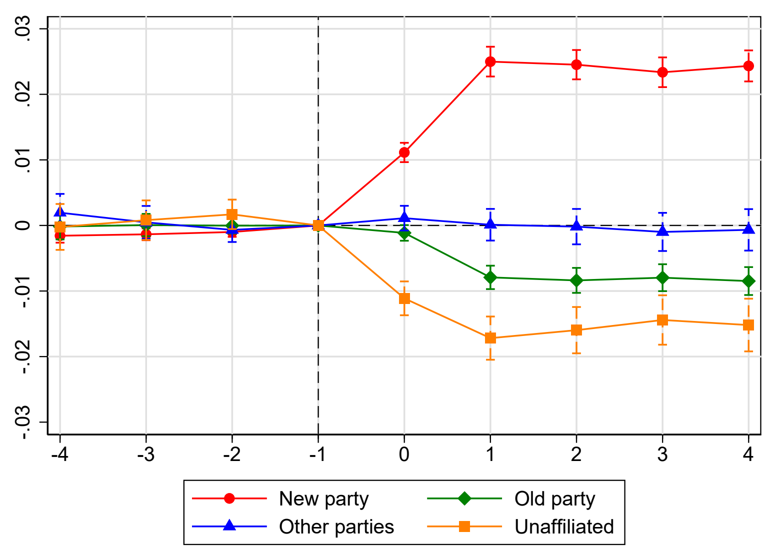
D. Previous Location of Worker

Notes: The figure shows the point estimates and 95% confidence intervals of $\Delta(SP, DP)$ from equation 3.6, divided by the sample probability that y_{if} equals one if $DP_{if} = 1$, estimated for different samples of firms and workers. In panel A, samples are small (less than 10 employees), medium (10–50 employees), and large (more than 50 employees) firms. In panel B, the samples include workers employed in managerial occupations, in other white-collar occupations (WC), and in blue-collar occupations (BC). In Panel C, the samples include workers employed in occupations which require above or below median social skills, and in occupations above or below median in terms of the interpersonal relationships required. In Panel D, the samples include newly hired workers who in the previous year (a) were employed in the same municipality as their current job; (b) were employed in a different municipality within the same micro-region; (c) were employed in a different municipality outside the micro-region; (d) were unemployed. See section 4.2 for additional details.

FIGURE 6. **Event Study Around Owners' Change of Party: Hiring and Composition of the Workforce**



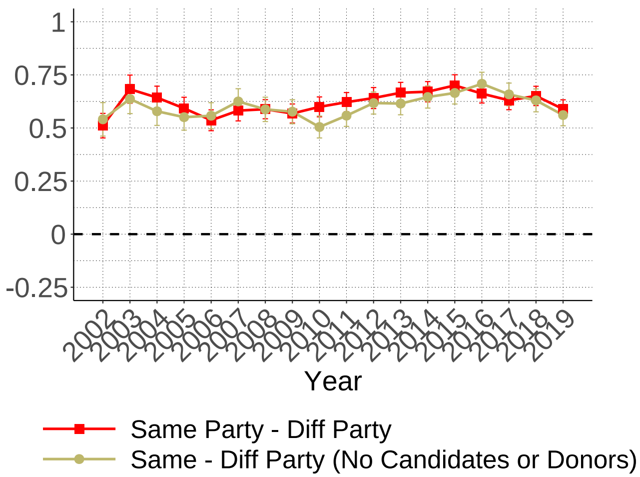
A. Number of hires from different groups



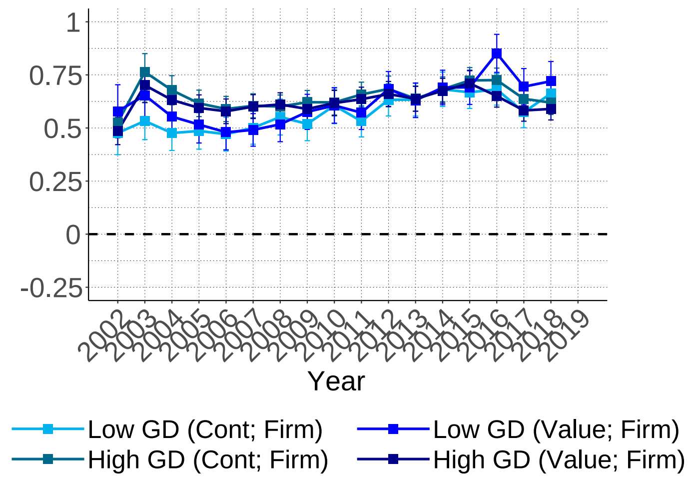
B. Share of workers from different groups

Notes: The figure shows estimates of the coefficients β_s from equation 4.1, together with 95% confidence intervals based on standard errors clustered at the firm level. In total, each panel presents the coefficients for four estimations. The dependent variables are the number of new hires (Panel A) and the shares of workers employed in the firm (Panel B), who are affiliated with the new party of the switching owner (in red), with the old party of the switching owner (in green), with other parties (in blue), and unaffiliated (in orange). The estimates in panel A are normalized by the standard deviation of the outcome variable. See section 4.3 for additional details on the estimation.

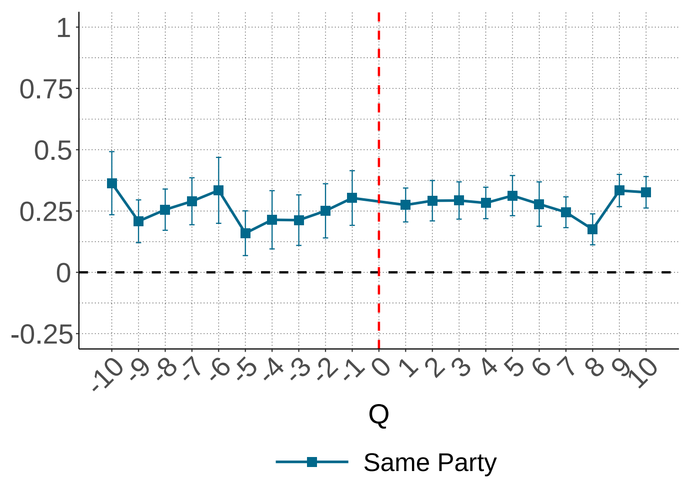
Figure 7. **The (Limited) Role of Political Quid-pro-quo**



A. Excluding Donors or Candidates



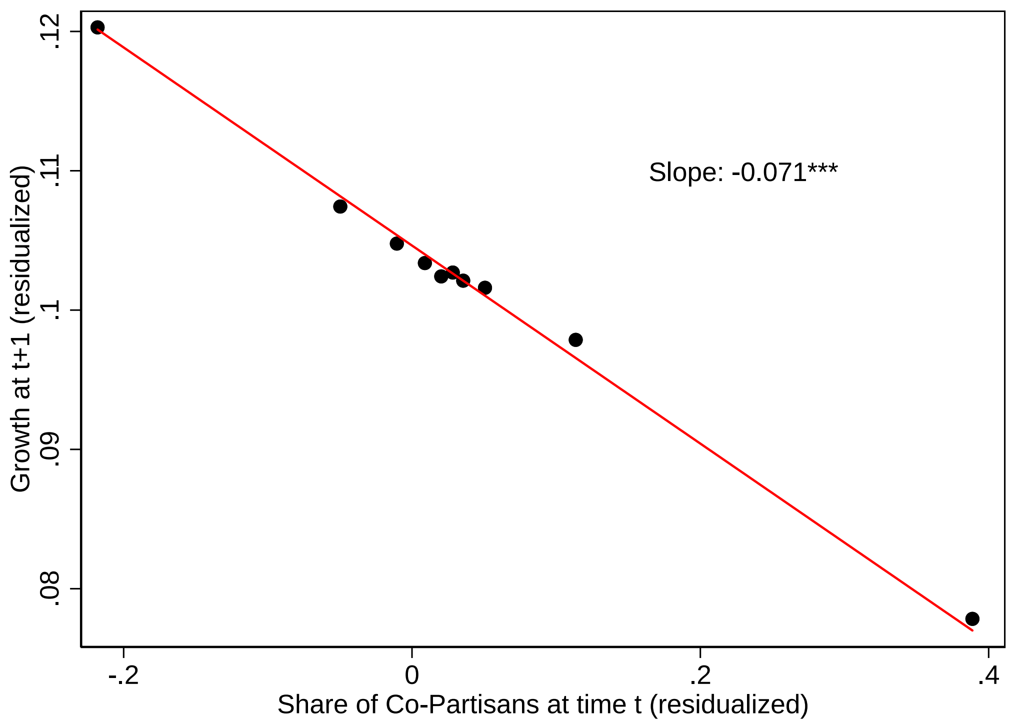
B. Government Dependence



C. Heterogeneity by the political power of the party

Notes: Panel A presents our baseline dyadic regression estimates, as well as dyadic regression estimates after excluding from the sample all individuals (owners and workers) who have ever been political candidates or campaign donors. Panel B presents dyadic regression estimates in subsamples of firms with low (below median) v.s. high (above median) government dependency. We calculate two industry-level measures of government dependency using data on firms' contracts with municipal governments for the state of São Paulo, based on the share of firms with local government contracts in each sector and average contract values. Panel C presents dyadic regression estimates, restricting to newly hired workers, for parties with different degrees of political power, defined based on the of margin of victory/loss of the party in the most recent local election (the x-axis shows the decile of the party in the distribution of margins of victory/loss across all elections in the data). See section 4.5 for additional details.

Figure 8. **Politically Homogeneous Firms Grow Less**



Notes: The figure shows the correlation between the share of a firm's workers who are copartisan of the owner in year t and firm's employment growth between year t and year $t+1$, after partialling out fixed effects for the firm's total number of workers times the firm's number of affiliated workers times year. The slope and the best fit line are calculated on the underlying data. See section 4.7 for additional details.

Table 1. **Summary Statistics**

	(1) Firm-Year	(2) Mean	(3) Std. Dev.	(4) p25	(5) p50	(6) p75
Panel A: Workers' Characteristics						
Num. Workers	41,364,038	16.02	263.87	2.00	3.00	9.00
Num. Managers	41,364,038	0.87	42.55	0.00	0.00	0.00
Num. White Collar Workers	41,364,038	7.32	188.47	1.00	2.00	4.00
Num. Blue Collar Workers	41,364,038	7.64	113.93	0.00	1.00	3.00
Avg. Pay	41,357,975	478.92	2269.34	323.00	405.00	523.80
% College (or higher)	41,363,232	0.15	0.27	0.00	0.00	0.20
% High School	41,363,232	0.70	0.33	0.50	0.79	1.00
% Less than High School	41,363,232	0.15	0.26	0.00	0.00	0.20
% Male	41,364,038	0.54	0.40	0.06	0.58	1.00
% White	41,193,503	0.67	0.38	0.40	0.83	1.00
Avg. Age	41,364,035	33.52	8.50	27.57	32.50	38.07
Panel B: Owners' Characteristics						
Num. Owners	39,959,687	1.60	1.17	1.00	1.00	2.00
% College (or higher)	21,020,059	0.43	0.47	0.00	0.00	1.00
% High School	21,020,059	0.45	0.47	0.00	0.33	1.00
% Less than High School	21,020,059	0.12	0.31	0.00	0.00	0.00
% Male	37,002,209	0.61	0.41	0.00	0.50	1.00
% White	19,793,102	0.77	0.40	0.50	1.00	1.00
Avg. Age	21,031,478	39.88	11.06	32.00	39.00	47.00

Notes: The table presents summary statistics for workers and owners, for each firm-year in our sample, over the period 2002–2019. *Num. Workers* is the total number of workers in the firm. *Num. Owners* is the total number of owners in the firm. *Num. Managers/Num. White Collar/Num. Blue Collar* is the total number of workers in the firm employed in managerial/white-collar/blue-collar occupations. *Avg. Pay* is the average pay of the firm's workers. *% College (or higher)/% High School/% Less than HS* is the share of workers/owners in the firm whose highest level of education is college or higher / high school / less than high school. *% Male* is the share of workers/owners in the firm who are male. *% White* is the share of workers/owners in the firm who are white. *Avg. Age* is the average age of the workers/owners in the firm.

TABLE 2. **The Political Promotion and Wage Premium**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Promotion		Log Wages				
	WC to Manager	BC to WC	All workers	All workers	Manager	WC	BC
Same Party	0.563***	0.209***	0.038***	0.028***	0.016***	0.034***	0.015***
	(0.078)	(0.056)	(0.003)	(0.005)	(0.006)	(0.010)	(0.001)
Different Party	-0.104***	0.035	-0.016***	-0.008***	-0.038***	-0.006	-0.004***
	(0.030)	(0.022)	(0.002)	(0.002)	(0.002)	(0.004)	(0.001)
Only Worker	-0.094***	0.030***	-0.022***	-0.014***	-0.046***	-0.017***	-0.005***
	(0.014)	(0.011)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Same Gender	0.097***	-0.085*	0.015***	0.014***	0.017***	0.014***	0.011***
	(0.018)	(0.050)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Same Race	0.084***	0.103***	0.010***	0.005***	0.011***	0.005***	0.002***
	(0.017)	(0.018)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Same Education	0.399***	0.461***	0.062***	0.024***	0.034***	0.026***	0.004***
	(0.039)	(0.040)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
Same Age	-0.057***	-0.013	-0.012***	-0.008***	0.006***	-0.004	-0.015***
	(0.014)	(0.010)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)
Observations	45,511,727	54,093,318	346,677,291	330,938,933	15,693,479	147,542,138	159,687,329
Number of Firms	1,525,400	1,242,185	2,849,093	2,647,370	419.329	1,925,362	1,569,792
Number of Workers	29,805,723	31,543,165	66,954,626	65,784,191	4,594,503	37,897,399	37,990,945
Mean DV Control	2.608	2.908	6.392	6.397	7.366	6.466	6.224
Year-Mun-Industry FE	No	No	Yes	No	No	No	No
Year-Firm FE	Yes	Yes	Yes	No	No	No	No
Year-Firm-Occup FE	No	No	No	Yes	Yes	Yes	Yes

Notes: The table presents estimates from equations 4.2 and 4.3. The dependent variable in columns 1 and 2 is an indicator equal to 1 if the worker is ever promoted from a white-collar to a managerial position, or from a blue-collar to a white-collar position, respectively. The dependent variable is multiplied by 100. The dependent variable in columns 3-7 is the worker's log wages. The sample in columns 1-2 is at the worker-firm level, with each worker entering the sample once for every firm in which they were employed over the sample period. The sample in columns 3 and 4 is at the worker-year level and it includes all workers. Columns 5-7 restrict the sample to workers employed in a managerial, white-collar, and blue-collar occupation, respectively. All specifications include the worker-level controls included in equation 3.7. "Mean DV Control" is the mean of the dependent variable for workers who are unaffiliated. Standard errors in parentheses clustered by firm. ***$p < 0.001$, **$p < 0.05$, *$p < 0.1$. See section 4.4 for additional details.

Table 3. **Identifying Political Discrimination: Experimental Evidence**

	(1) Interest	(2) Interest	(3) Accept	(4) Accept
Same party	0.213**	0.254**	0.150	0.158
	(0.104)	(0.101)	(0.099)	(0.097)
Observations	600	600	600	600
Respondents	150	150	150	150
Mean DV Diff Party	2.950	2.950	3.340	3.340
Respondent FE	Yes	Yes	Yes	Yes
CV Characteristics	No	Yes	No	Yes

Notes: The table presents estimates from equation 4.4. The dependent variable in columns 1-2 is the respondent's interest in the candidate on a discrete 1-to-7 Likert scale. The dependent variable in columns 3-4 is the respondent's perception of the likelihood that the candidate will accept the job offer on a discrete 1-to-7 Likert scale. Respondent FE are fixed effects for the respondent. CV Characteristics included as controls are: an indicator equal to one if the job seeker is a female, an indicator equal to one if the job seeker has the same gender as the business owner, an indicator equal to one if the resume contains at least one "high skill" work experience, the job seeker's years of work experience, the number of programming and Microsoft Office skills listed in the resume, and the number of training experiences listed in the resume. "Mean DV Diff Party" is the mean of the dependent variable for resumes from a different party. Robust standard errors in parentheses. ***$p < 0.001$, **$p < 0.05$, *$p < 0.1$. See section 4.6 for additional details.

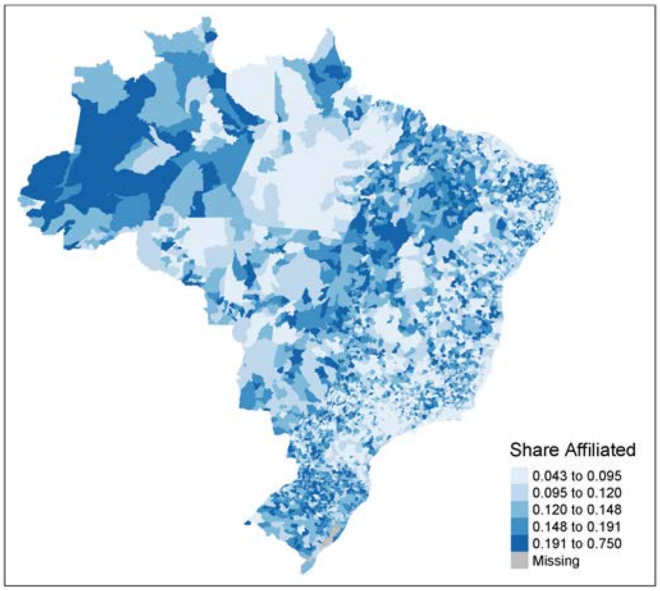
Table 4. **Copartisan Workers Are Less Qualified**

	(1)	(2)	(3)	(4)
	Dependent Variable: Qualified for the occupation			
	Sample: All workers	Sample: Manager	Sample: White collar	Sample: Blue collar
Same party	-0.021***	-0.021***	-0.003***	-0.002**
	(0.001)	(0.003)	(0.001)	(0.001)
Different party	-0.003***	-0.001	0.001***	-0.000
	(0.000)	(0.001)	(0.000)	(0.000)
Only worker	-0.002***	0.002**	0.000	-0.001***
	(0.000)	(0.001)	(0.000)	(0.000)
Same gender	0.001***	0.002***	-0.001***	-0.000
	(0.000)	(0.001)	(0.000)	(0.001)
Same race	-0.000	-0.001	-0.000**	-0.000
	(0.000)	(0.001)	(0.000)	(0.000)
Same education	-0.001	-0.042***	-0.003***	0.002
	(0.001)	(0.005)	(0.001)	(0.002)
Same age	0.001*	0.001	-0.001***	-0.001*
	(0.000)	(0.001)	(0.000)	(0.000)
Observations	342,865,778	17,007,788	152,797,381	162,838,069
Number of Firms	2,826,854	467,294	2,048,779	1,628,667
Number of Workers	66,639,486	4,862,131	38,573,831	38,403,682
Mean DV Control	0.932	0.845	0.946	0.935
Year-Firm FE	Yes	Yes	Yes	Yes

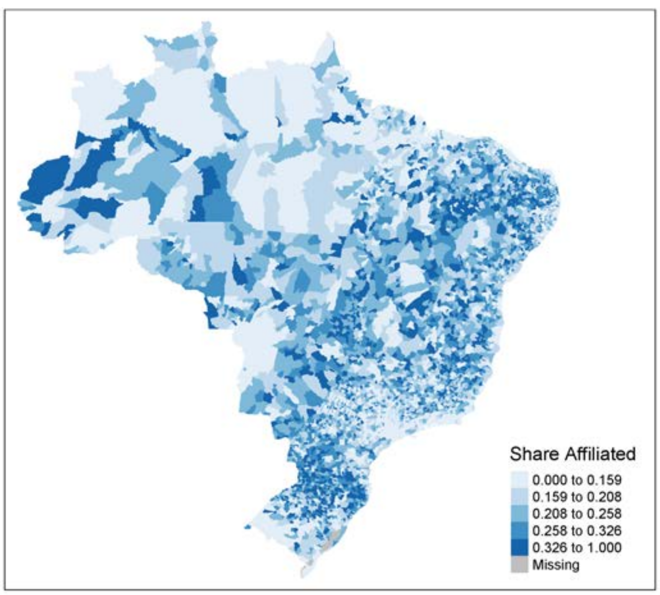
Notes: The table presents estimates from a version of equation 4.3, where the dependent variable is an indicator equal to one if the worker is qualified, in terms of education, for the occupation in which she is employed. In column 1, the sample includes all workers.. Columns 2-4 restrict the sample to workers employed in a managerial, white-collar, and blue-collar occupation, respectively. All specifications include the worker-level controls included in equation 3.7. "Mean DV Control" is the mean of the dependent variable among unaffiliated workers. Standard errors in parentheses clustered by firm. ***$p < 0.001$, **$p < 0.05$, *$p < 0.1$. See section 4.7 for additional details.

ONLINE APPENDIX A1: ADDITIONAL RESULTS

Figure A1. **The Geography of Political Affiliation**



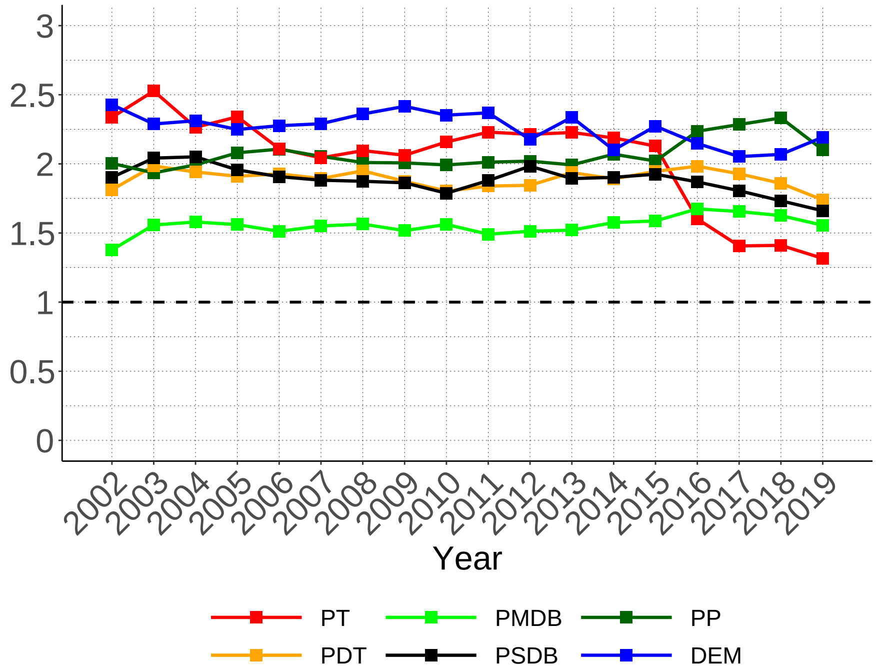
A. Share of affiliated workers



B. Share of affiliated owners

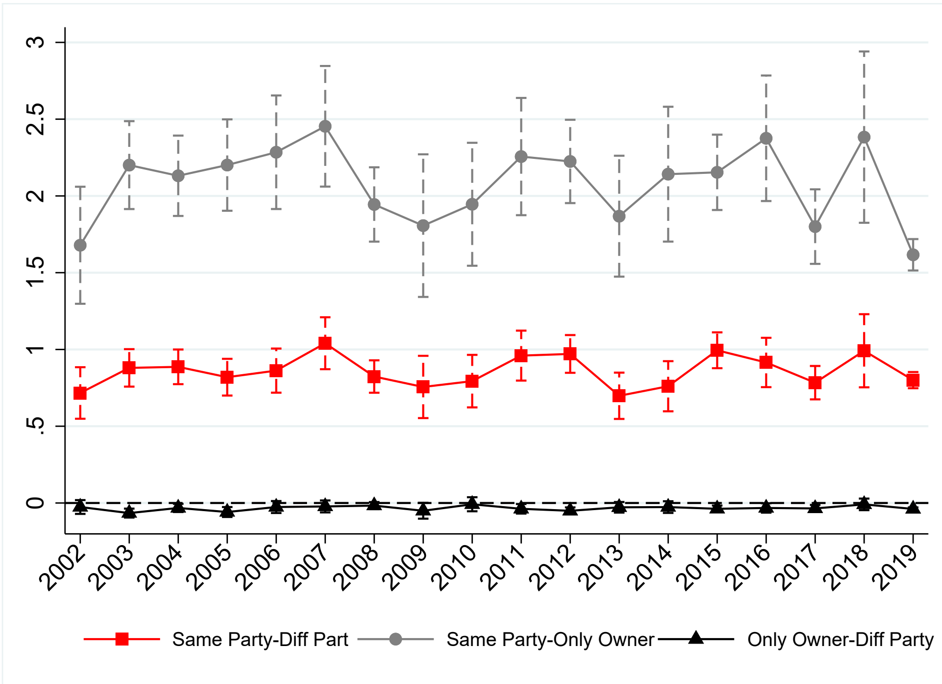
Notes: The figure shows the share of affiliated workers (Panel A) and affiliated owners (Panel B) across Brazilian municipalities over the period 2002–2019.

Figure A2. **The Likelihood Ratio Index by Party**



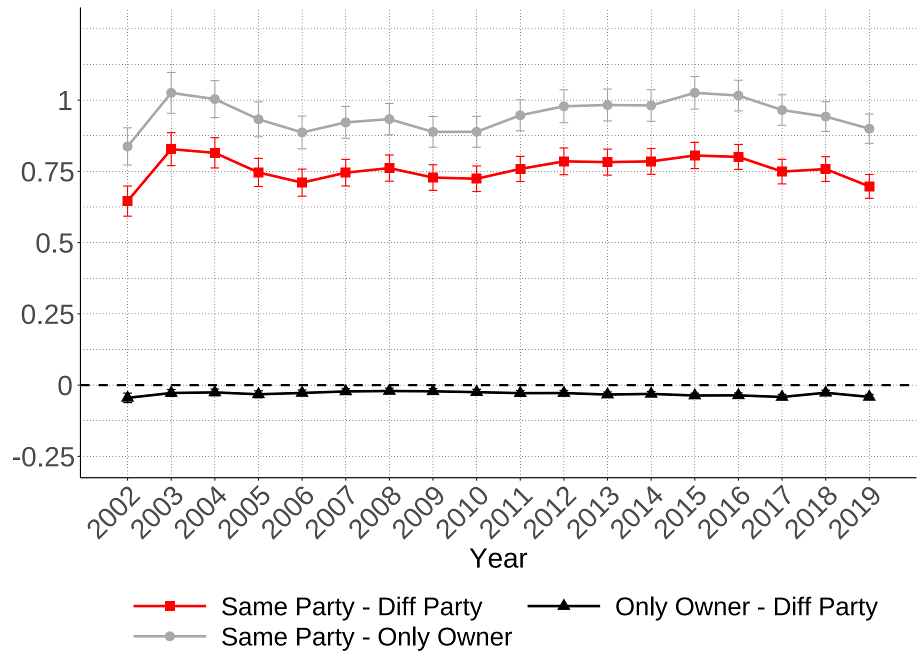
Notes: The figure shows estimates of the likelihood ratio index (calculated as in equation 3.3) for each party. See section 3.1 for additional details.

FIGURE A3. **Political Assortative Matching: Dyadic Regression Estimates – Using occupations to define a market**



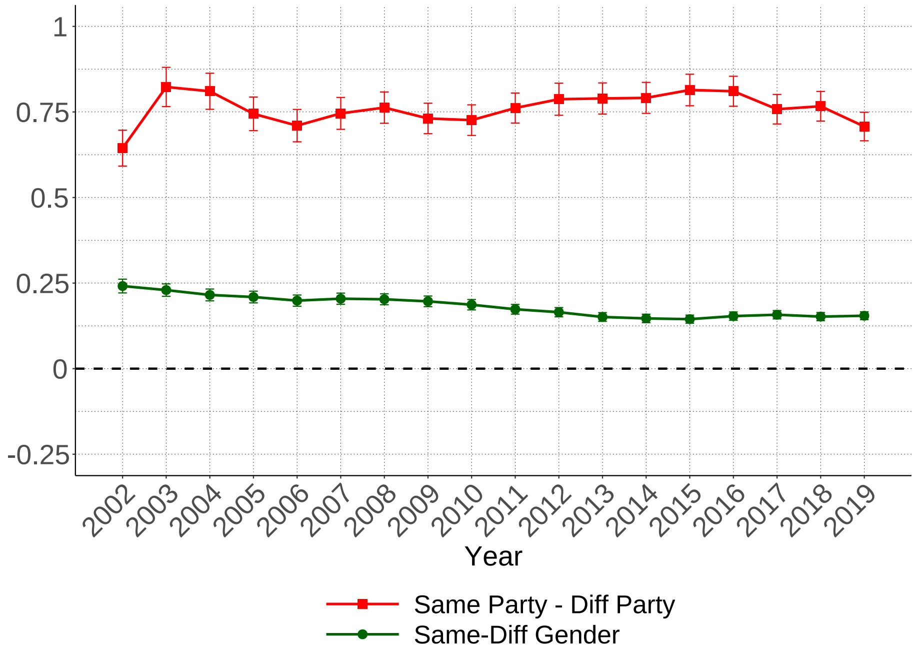
Notes: The figure shows the point estimates and 95% confidence intervals of $\Delta(SP, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in red), $\Delta(SP, OO)$ divided by the sample probability that y_{if} equals one if $OO_{if} = 1$ (in gray), and $\Delta(OO, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in black), from equation 3.6. In this figure, the markets are defined as a municipality-occupation cell (using the first digit of the CBO code to define an occupational category). Confidence intervals are based on standard errors clustered at the market level. See section 3.2 and equation 3.6 for details on the estimation.

FIGURE A4. **Political Assortative Matching: Dyadic Regression Estimates - Limited Set of Controls**



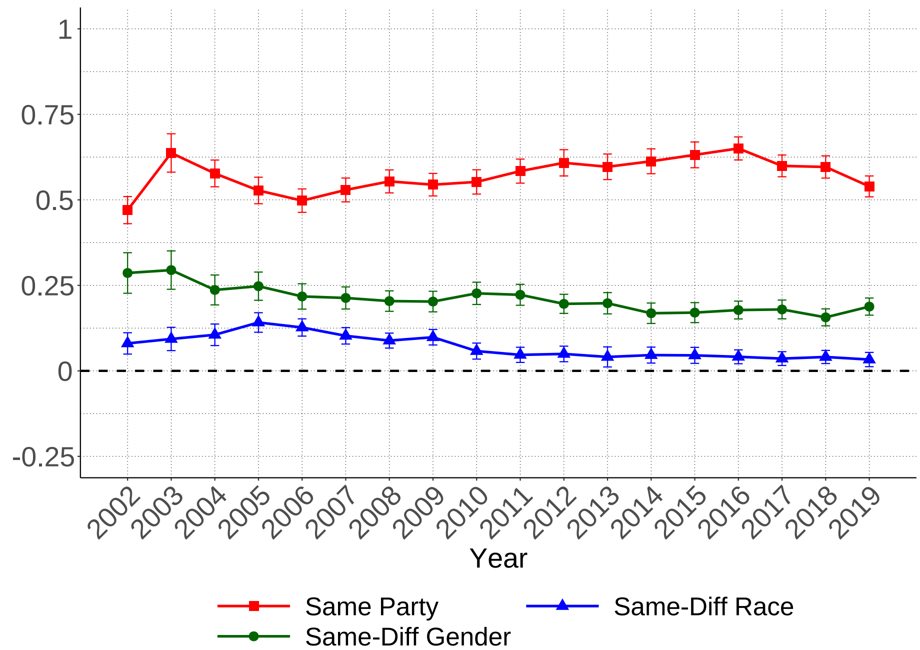
Notes: The figure shows point estimates and 95% confidence intervals of $\Delta(SP, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in red), $\Delta(SP, OO)$ divided by the sample probability that y_{if} equals one if $OO_{if} = 1$ (in gray), and $\Delta(OO, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in black), from a version of equation 3.6 without including the set of indicators SX'_{if}, and estimated on the sample of all business owners. Confidence intervals are based on standard errors clustered at the market level. See section 3.2 and equation 3.6 for details on the estimation.

FIGURE A5. **Political Assortative Matching: Dyadic Regression Estimates - Controlling Only for Shared Gender**



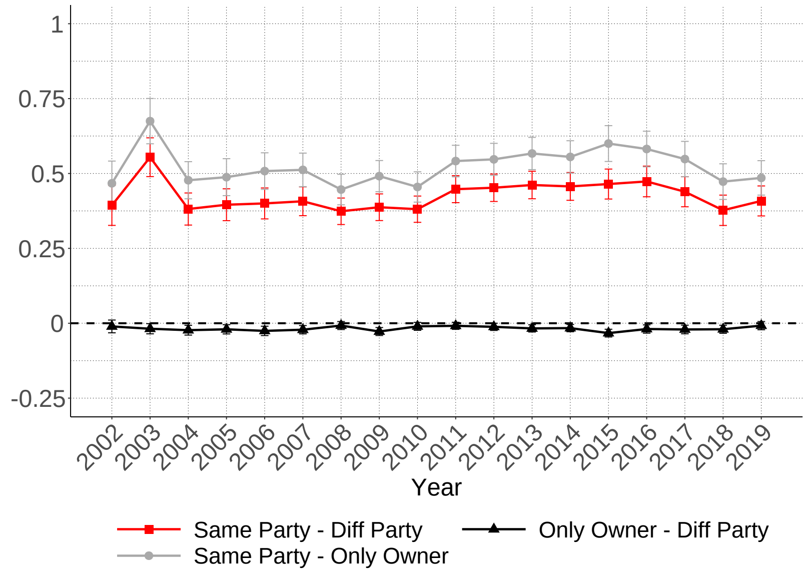
Notes: The figure shows point estimates and 95% confidence intervals of $\Delta(SP, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in red), and $\textit{Same Gender}_{if}$ divided by the sample probability that y_{if} equals one if $\textit{Same Gender}_{if} = 0$ (in green), from a version of equation 3.6 without including the set of indicators SX'_{if} (except same gender), and estimated on the sample of all business owners. Confidence intervals are based on standard errors clustered at the market level. See section 3.2 and equation 3.6 for details on the estimation.

FIGURE A6. **Political Assortative Matching: Dyadic Regression Estimates - Only Affiliated Workers and Owners**

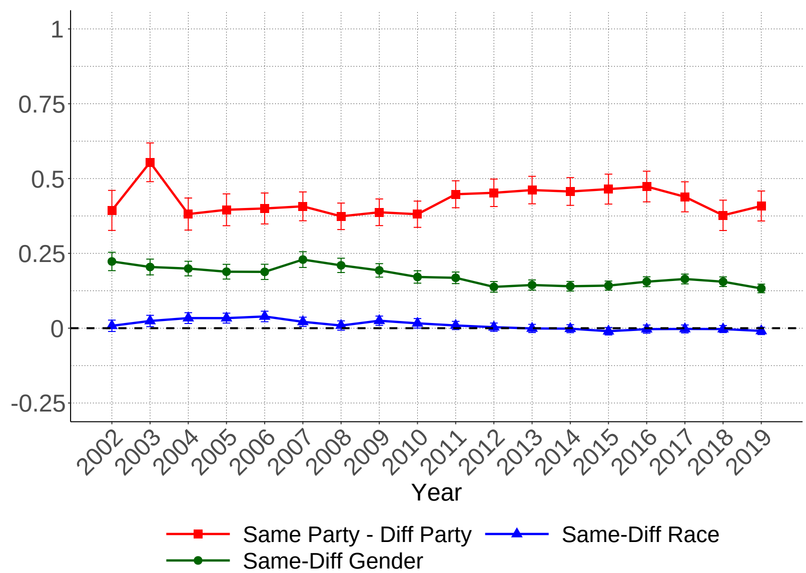


Notes: The figure shows the point estimates and 95% confidence intervals of SP_{if} divided by the sample probability that y_{if} equals one if the worker is from a different party than the owner (in red), $Same\ Gender_{if}$ divided by the sample probability that y_{if} equals one if $Same\ Gender_{if} = 0$ (in green) and $Same\ Race_{if}$ divided by the sample probability that y_{if} equals one if $Same\ Race_{if} = 0$ (in blue), from a version of equation 3.6 which excludes DP_{if}, OW_{if} and OO_{if} and is estimated on the subsample of affiliated workers and owners. Confidence intervals are based on standard errors clustered at the market level. See section 3.2 and equation 3.6 for details on the estimation.

FIGURE A7. **Political Assortative Matching: Hiring Margin**



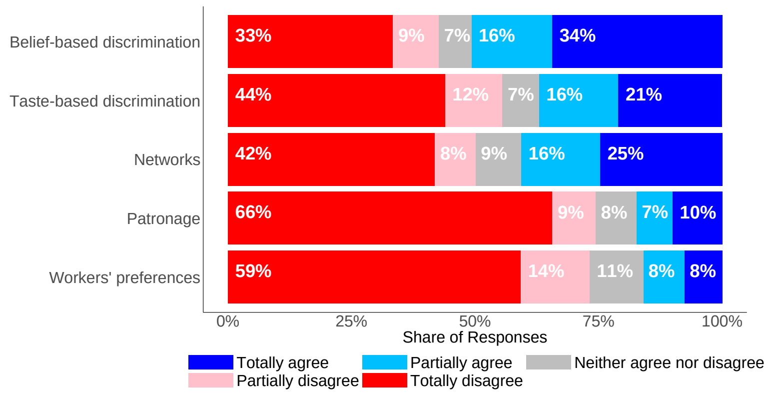
A.



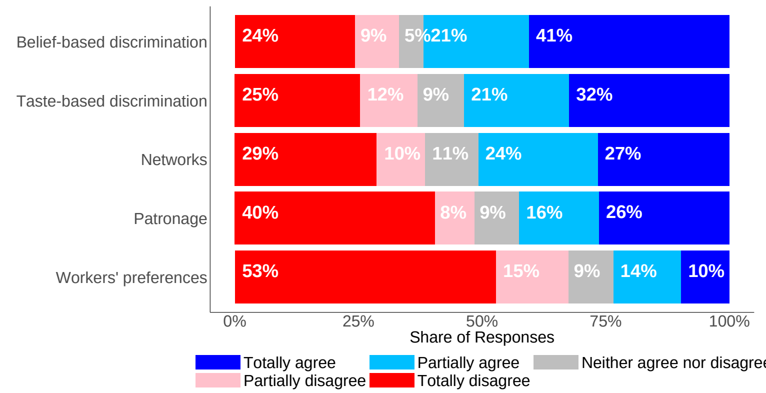
B.

Notes: The figure presents results from dyadic regressions estimated in a sample including only workers who were hired in the specific year. The top panel shows the point estimates and 95% confidence intervals of $\Delta(SP, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in red), $\Delta(SP, OO)$ divided by the sample probability that y_{if} equals one if $OO_{if} = 1$ (in gray), and $\Delta(OO, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in black), from equation 3.6. The bottom panel shows the point estimates and 95% confidence intervals of $\Delta(SP, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in red), *Same* $Gender_{if}$ divided by the sample probability that y_{if} equals one if *Same* $Gender_{if} = 0$ (in green) and *Same* $Race_{if}$ divided by the sample probability that y_{if} equals one if *Same* $Race_{if} = 0$ (in blue), from equation 3.6. Confidence intervals are based on standard errors clustered at the market level. See section 3.3.2 and equation 3.6 for details on the estimation.

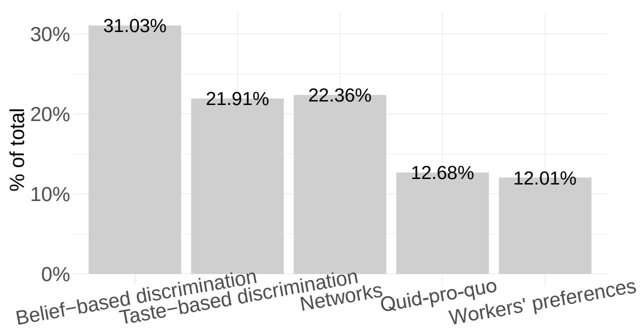
Figure A8. **Survey Evidence on Most Relevant Mechanisms – Affiliated Respondents**



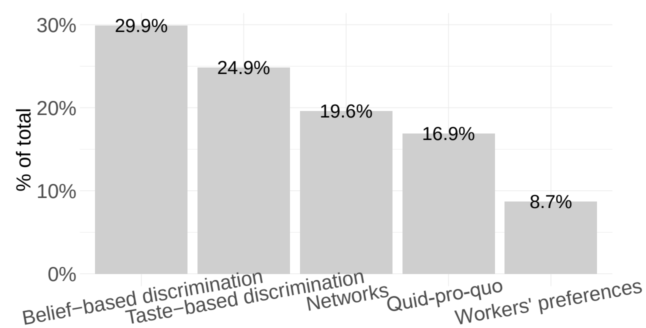
A. Owners' agreement with the five statements



B. Workers' agreement with the five statements



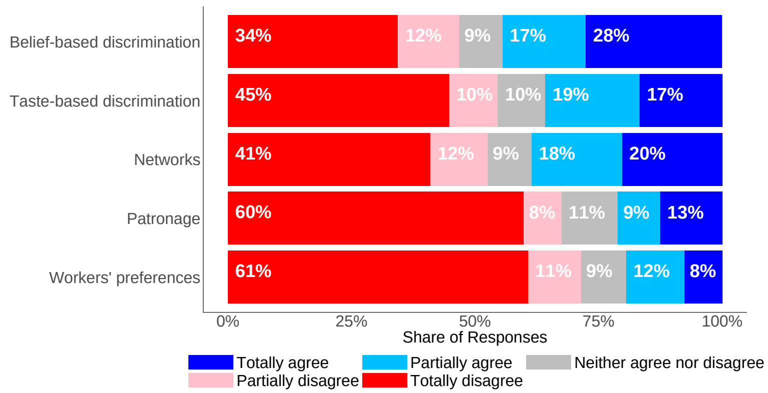
C. Owners' most relevant mechanism



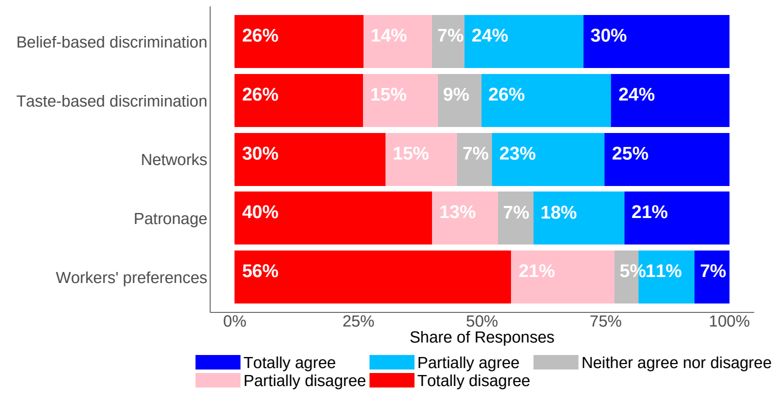
D. Workers' most relevant mechanism

Notes: The figure plots responses from our survey of Brazilian business owners and workers, described in section 4.1. The sample is restricted to politically affiliated business owners and workers. Panels A and B plot the level of agreement (on a scale from 1 "Totally disagree" to 5 "Totally agree") with the different statements by owners and workers, respectively. Panels C and D plot, for each statement, the share of respondents who agree the most with that statement.

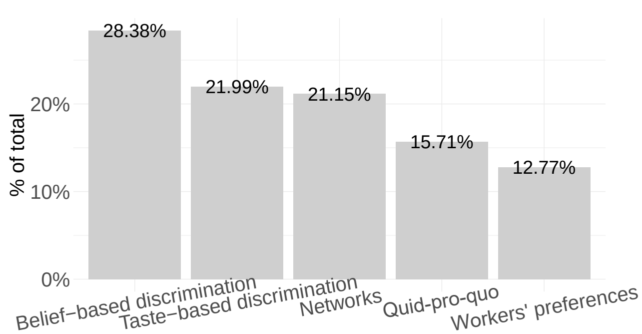
FIGURE A9. **Survey Evidence on Most Relevant Mechanisms – Unaffiliated Respondents**



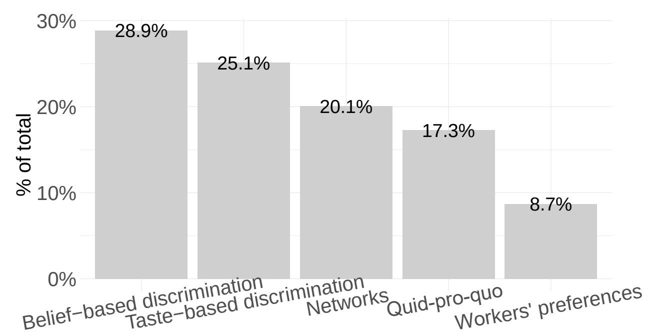
A. Owners' agreement with the five statements



B. Workers' agreement with the five statements



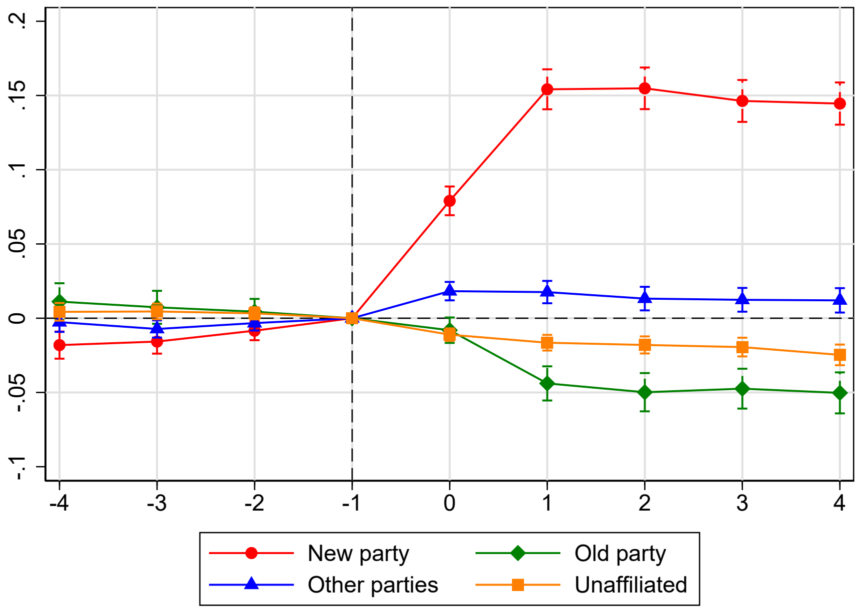
C. Owners' most relevant mechanism



D. Workers' most relevant mechanism

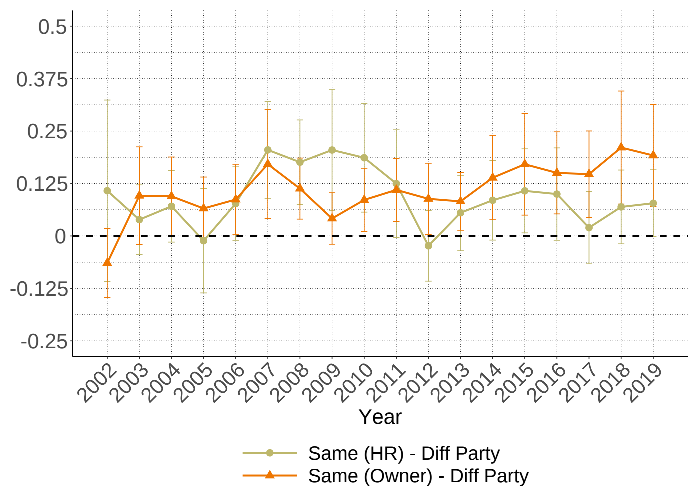
Notes: The figure plots responses from our survey of Brazilian business owners and workers, described in section 4.1. The sample is restricted to politically unaffiliated business owners and workers. Panels A and B plot the level of agreement (on a scale from 1 "Totally disagree" to 5 "Totally agree") with the different statements by owners and workers, respectively. Panels C and D plot, for each statement, the share of respondents who agree the most with that statement.

Figure A10. **Event Study Around Owners' Change of Party: Total Wage Bill**

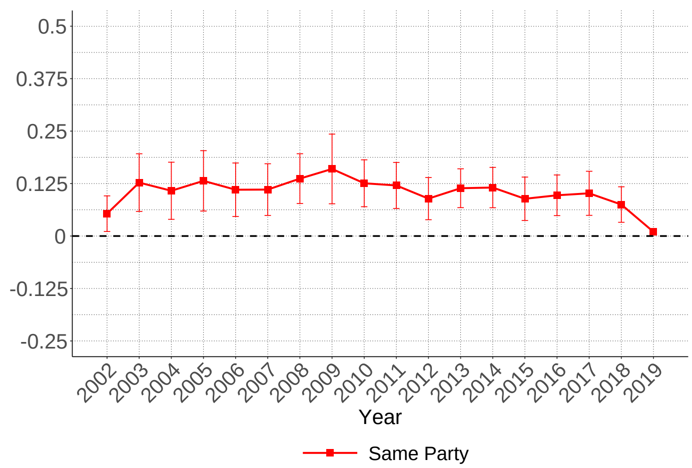


Notes: The figure presents estimates of the coefficients β_s from equation 4.1 together with 95% confidence intervals based on standard errors clustered at the firm level. The dependent variable is the log of the firm's wage bill for employees affiliated with the new party of the switching owner (in red), with the old party of the switching owner (in green), with other parties (in blue), and unaffiliated (in orange). See section 4.3 for additional details on the estimation.

FIGURE A11. **Political Assortative Matching: HR Managers**



A. Both Owners and HR affiliated



B. Only HR affiliated

Notes: The figure presents dyadic regression estimates for firms with Human Resources departments. In panel A, we restrict the sample to firms in which the owner and the HR top manager are both affiliated, but with different parties. In panel B, we restrict the sample to observations where firm owners are unaffiliated and both the HR top manager and workers are affiliated. In panel A, we plot assortative matching estimates for the owner's party (i.e. the worker belongs to same party as the owner vs a different party) and for the HR manager (i.e. the worker belongs to same party as the HR manager vs a different party) . In panel B, we plot assortative matching estimates based on the party of the HR manager.

Table A1. **Distribution of Party Members, and Left/Center/Right Party Categorization**

Party Name	Acronym	% of Members
Panel A: Left		
Workers' Party	PT	11.21
Democratic Labour Party	PDT	7.84
Brazilian Socialist Party	PSB	3.82
Communist Party of Brazil	PCdoB	2.44
Green Party	PV	2.31
National Mobilization Party	PMN	1.41
Socialism and Freedom Party	PSOL	0.58
Solidarity	SD	0.46
Republican Party of The Social Order	PROS	0.20
Unified Workers' Socialist Party	PSTU	0.12
Brazilian Communist Party	PCB	0.10
Sustainability Network	REDE	0.04
Workers' Cause Party	PCO	0.03
Popular Union	UP	0.00
Free Homeland Party	PPL	0.00
Panel B: Center		
Brazilian Democratic Movement	(P)MDB	14.14
Brazilian Social Democracy Party	PSDB	9.59
Brazilian Labor Party	PTB	7.67
Forward	AVANTE	1.08
Social Democratic Party	PSD	1.00
Panel C: Right		
Progressives	PP	8.40
Democrats	DEM	6.81
Liberal Party	PL	4.97
Socialist People's Party	PPS	3.34
Christian Social Party	PSC	2.33
We can	PODE	2.01
Brazilian Republican Party	PRB	1.86
Patriot	PATRI	1.63
Social Liberal Party	PSL	1.45
Christian Democracy	DC	1.16
Christian Labor Party	PTC	1.08
Brazilian Labor Renewal Party	PRTB	0.77
New Party	NOVO	0.11
Brazilian Women's Party	PMB	0.07
Progressive Republican Party"	PRP	0.00
Humanist Solidarity Party	PHS	0.00

Notes: The table presents the list of all Brazilian parties over the 2002–2019 period, categorized by party ideology (Left/Center/Right). *% of Members* is computed as the number of affiliated observations per party divided by the total number of affiliated observations for the full panel.

Table A2. **Dyadic Regression Estimates – 25% versus Full Sample**

	Sample	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Same Party	Full	0.0661	0.0762	0.0727	0.0683	0.0642	0.0669	0.0690	0.0660	0.0671	0.0702	0.0733	0.0710	0.0702	0.0723	0.0770	0.0747	0.0709	0.0723
		(0.0016)	(0.0015)	(0.0014)	(0.0013)	(0.0013)	(0.0012)	(0.0013)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0011)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
	25pct	0.0638	0.0764	0.0729	0.0687	0.0665	0.0694	0.0688	0.0652	0.0664	0.0703	0.0718	0.0698	0.0681	0.0696	0.0758	0.0757	0.0710	0.0732
		(0.0024)	(0.0021)	(0.0020)	(0.0019)	(0.0019)	(0.0018)	(0.0018)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Different Party	Full	0.0077	0.0059	0.0050	0.0059	0.0045	0.0049	0.0045	0.0050	0.0061	0.0064	0.0063	0.0067	0.0072	0.0081	0.0078	0.0079	0.0069	0.0098
		(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0005)
	25pct	0.0083	0.0052	0.0055	0.0061	0.0051	0.0050	0.0050	0.0057	0.0066	0.0068	0.0058	0.0065	0.0067	0.0081	0.0073	0.0074	0.0068	0.0098
		(0.0009)	(0.0008)	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Only Worker	Full	-0.0029	-0.0039	-0.0037	-0.0035	-0.0032	-0.0036	-0.0035	-0.0033	-0.0031	-0.0034	-0.0032	-0.0030	-0.0029	-0.0033	-0.0035	-0.0032	-0.0028	-0.0031
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
	25pct	-0.0028	-0.0044	-0.0037	-0.0034	-0.0038	-0.0039	-0.0034	-0.0036	-0.0032	-0.0035	-0.0032	-0.0030	-0.0028	-0.0036	-0.0034	-0.0030	-0.0030	-0.0030
		(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Only Owner	Full	0.0083	0.0069	0.0058	0.0062	0.0046	0.0050	0.0047	0.0051	0.0061	0.0060	0.0063	0.0065	0.0068	0.0071	0.0065	0.0066	0.0059	0.0078
		(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
	25pct	0.0081	0.0065	0.0057	0.0062	0.0043	0.0049	0.0050	0.0050	0.0060	0.0062	0.0062	0.0064	0.0070	0.0070	0.0066	0.0066	0.0060	0.0078
		(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Same-Diff/E[y|DP=1]	Full	0.7348	0.8664	0.8609	0.7861	0.7728	0.7972	0.8381	0.7969	0.8017	0.8248	0.8857	0.8643	0.8488	0.8349	0.8948	0.8631	0.8488	0.7828
		(0.0197)	(0.0174)	(0.0171)	(0.0160)	(0.0158)	(0.0150)	(0.0156)	(0.0149)	(0.0147)	(0.0145)	(0.0154)	(0.0150)	(0.0148)	(0.0141)	(0.0152)	(0.0150)	(0.0154)	(0.0145)
	25pct	0.6917	0.8819	0.8578	0.7886	0.7898	0.8248	0.8281	0.7733	0.7841	0.8176	0.8818	0.8545	0.8342	0.7980	0.8890	0.8908	0.8583	0.7912
		(0.0298)	(0.0257)	(0.0254)	(0.0238)	(0.0239)	(0.0226)	(0.0230)	(0.0222)	(0.0226)	(0.0217)	(0.0230)	(0.0225)	(0.0227)	(0.0217)	(0.0232)	(0.0238)	(0.0246)	(0.0230)
Same Gender/E[y|SG=0]	Full	0.1324	0.1157	0.0903	0.1046	0.1009	0.0892	0.0871	0.0875	0.0846	0.0730	0.0664	0.0612	0.0669	0.0580	0.0600	0.0649	0.0529	0.0610
		(0.0089)	(0.0080)	(0.0075)	(0.0074)	(0.0074)	(0.0068)	(0.0068)	(0.0065)	(0.0062)	(0.0058)	(0.0055)	(0.0054)	(0.0053)	(0.0051)	(0.0050)	(0.0049)	(0.0049)	(0.0049)
	25pct	0.1321	0.1114	0.0938	0.1036	0.1021	0.0944	0.0881	0.0849	0.0859	0.0682	0.0711	0.0644	0.0646	0.0543	0.0628	0.0649	0.0546	0.0606
		(0.0100)	(0.0088)	(0.0084)	(0.0082)	(0.0081)	(0.0076)	(0.0075)	(0.0071)	(0.0068)	(0.0064)	(0.0061)	(0.0060)	(0.0058)	(0.0057)	(0.0056)	(0.0055)	(0.0055)	(0.0054)
Same Race/E[y|SR=0]	Full	0.0455	0.0573	0.0601	0.0655	0.0581	0.0426	0.0502	0.0578	0.0535	0.0513	0.0558	0.0467	0.0532	0.0486	0.0386	0.0371	0.0418	0.0375
		(0.0067)	(0.0063)	(0.0063)	(0.0060)	(0.0060)	(0.0061)	(0.0056)	(0.0056)	(0.0056)	(0.0051)	(0.0050)	(0.0049)	(0.0048)	(0.0045)	(0.0045)	(0.0043)	(0.0043)	(0.0040)
	25pct	0.0476	0.0580	0.0630	0.0605	0.0585	0.0400	0.0535	0.0596	0.0507	0.0533	0.0513	0.0432	0.0538	0.0476	0.0402	0.0362	0.0426	0.0364
		(0.0082)	(0.0075)	(0.0074)	(0.0070)	(0.0071)	(0.0071)	(0.0066)	(0.0065)	(0.0064)	(0.0060)	(0.0057)	(0.0057)	(0.0055)	(0.0053)	(0.0053)	(0.0051)	(0.0052)	(0.0049)

Notes: The table presents estimates from equation 3.6. For each year, the sample excludes the 25% largest municipality-industry markets in terms of number of dyads. We compare estimates using the full set of dyads in these markets with those on a random 25% sample of dyads. Standard errors in parentheses are clustered by market. See section 3.2 and equation 3.6 for details on the estimation.

Table A3. **Dyadic Regression Estimates – Full Set of Estimates**

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Same Party	0.0686	0.0783	0.0739	0.0712	0.0591	0.0661	0.0650	0.0630	0.0650	0.0679	0.0709	0.0684	0.0668	0.0704	0.0735	0.0687	0.0665	0.0677
	(0.0024)	(0.0022)	(0.0020)	(0.0019)	(0.0017)	(0.0018)	(0.0017)	(0.0016)	(0.0017)	(0.0018)	(0.0016)	(0.0016)	(0.0016)	(0.0015)	(0.0016)	(0.0015)	(0.0015)	(0.0015)
Different Party	0.0126	0.0111	0.0098	0.0102	0.0063	0.0075	0.0068	0.0071	0.0082	0.0076	0.0066	0.0072	0.0071	0.0077	0.0073	0.0070	0.0049	0.0087
	(0.0012)	(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Only Worker	-0.0036	-0.0044	-0.0039	-0.0035	-0.0027	-0.0039	-0.0038	-0.0034	-0.0037	-0.0040	-0.0036	-0.0036	-0.0034	-0.0041	-0.0043	-0.0041	-0.0036	-0.0040
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Only Owner	0.0123	0.0111	0.0098	0.0102	0.0060	0.0068	0.0060	0.0062	0.0073	0.0064	0.0063	0.0069	0.0070	0.0067	0.0060	0.0061	0.0045	0.0070
	(0.0011)	(0.0010)	(0.0010)	(0.0009)	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0007)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0006)
Same Gender	0.0083	0.0082	0.0065	0.0072	0.0075	0.0063	0.0059	0.0055	0.0053	0.0047	0.0040	0.0036	0.0036	0.0034	0.0034	0.0037	0.0030	0.0037
	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Same Race	0.0029	0.0043	0.0045	0.0047	0.0037	0.0030	0.0039	0.0040	0.0036	0.0035	0.0036	0.0030	0.0031	0.0028	0.0024	0.0021	0.0024	0.0025
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Same Educ	0.0018	0.0023	0.0026	0.0029	0.0040	0.0030	0.0022	0.0021	0.0014	0.0015	0.0009	0.0006	0.0002	-0.0003	-0.0002	-0.0002	-0.0004	-0.0005
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Same Age	0.0005	0.0033	0.0022	-0.0004	0.0000	-0.0005	-0.0008	0.0009	0.0003	0.0011	0.0012	0.0015	0.0017	0.0026	0.0027	0.0030	0.0026	0.0033
	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Same-Diff	0.056	0.067	0.064	0.061	0.052	0.058	0.058	0.055	0.056	0.060	0.064	0.061	0.059	0.062	0.066	0.061	0.061	0.059
Same-Only Worker	0.072	0.082	0.077	0.074	0.061	0.070	0.068	0.066	0.068	0.071	0.074	0.072	0.070	0.074	0.077	0.072	0.070	0.071
Same-Only Owner	0.056	0.067	0.064	0.060	0.053	0.059	0.058	0.056	0.057	0.061	0.064	0.061	0.059	0.063	0.067	0.062	0.062	0.060
Diff-Only Worker	0.016	0.015	0.013	0.013	0.009	0.011	0.010	0.010	0.011	0.011	0.010	0.010	0.010	0.011	0.011	0.011	0.008	0.012
Only Owner-Diff	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.001	0.001	0.000	0.000	0.001
Only Owner-Only Worker	0.015	0.015	0.013	0.013	0.008	0.010	0.009	0.009	0.011	0.010	0.009	0.010	0.010	0.010	0.010	0.010	0.008	0.011
Observations	9129837	10347983	11509382	13137010	16553569	15255644	17513003	19017438	21978293	22893268	25497858	28263383	30652094	29584381	28855091	29513356	30474985	31803076
Num Workers	1372265	1725762	1832437	1973070	2257284	2181805	2382239	2469476	2699008	2824308	2966920	3111721	3223946	3155002	3044004	3045125	3040992	3162535
Num Firms	197670	218676	230636	246253	284604	273014	291040	307579	332798	352449	370733	394177	413095	416721	416585	419710	421801	427087
Num Markets	19451	22096	22928	23933	26277	27018	28248	29338	31002	34217	34990	35988	36714	38174	38495	38172	37416	38574

Notes: The table presents estimates from equation 3.6. Standard errors in parentheses are clustered by market. See section 3.2 and equation 3.6 for details on the estimation.

TABLE A4. **Tenure in the Firm and Political Assortative Matching**

	(1)	(2)	(3)	(4)	(5)	(6)
	Share of tenure (years) in the firm					
Same party	0.056***	0.056***	0.047***	0.040***	0.024***	0.020***
	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)
Different party	0.010***	0.013***	0.004***	0.005***	-0.002***	-0.002***
	(0.002)	(0.004)	(0.001)	(0.002)	(0.000)	(0.000)
Only worker	-0.005***	-0.007***	-0.007***	-0.006***	-0.004***	-0.004***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Only owner	0.014***	0.017***	0.008***	0.009***		
	(0.003)	(0.004)	(0.001)	(0.002)		
Same gender		0.005***		0.001**	-0.001***	-0.001***
		(0.001)		(0.000)	(0.000)	(0.000)
Same race		0.002**		0.002***		0.004***
		(0.001)		(0.001)		(0.000)
Same education		-0.005***		-0.003***		0.007***
		(0.002)		(0.001)		(0.001)
Same age		-0.008***		-0.004***		-0.000
		(0.001)		(0.000)		(0.000)
Observations	207,274,731	121,635,349	210,979,987	121,402,068	198,211,975	114,769,176
Number of Firms	5,895,952	3,373,694	5,823,205	3,330,573	4,025,449	2,317,368
Number of Workers	76,988,504	60,150,270	77,112,392	60,061,553	75,035,681	58,499,210
Mean DV Diff Party	0.392	0.416	0.409	0.416	0.389	0.397
Year-Mun FE	Yes	Yes	No	No	No	No
Year-Mun-Industry FE	No	No	Yes	Yes	No	No
Year-Firm FE	No	No	No	No	Yes	Yes

Notes: The table presents estimates from equation 3.7. The unit of observation is a hire. In all specifications, the dependent variable is the share of years in which the worker stays in the firm out of the total number of years between the year of hire and the end of the sample period. "Mean DV Diff Party" is the mean of the dependent variable for hires affiliated with a different party than the owner's party. See section 3.3.2 for the full list of the controls included. Standard errors in parentheses clustered by firm. ***$p < 0.001$, **$p < 0.05$, *$p < 0.1$.

Table A5. **Dyadic Regression Estimates – Small Firms**

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Same Party	0.0164	0.0191	0.0192	0.0155	0.0166	0.0166	0.0172	0.0167	0.0159	0.0181	0.0192	0.0176	0.0167	0.0187	0.0199	0.0195	0.0204	0.0193
	(0.0010)	(0.0009)	(0.0009)	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0007)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Different Party	-0.0004	-0.0004	-0.0002	0.0000	0.0000	0.0001	-0.0001	-0.0002	0.0001	-0.0001	0.0000	0.0001	-0.0001	0.0001	0.0001	0.0001	0.0002	-0.0001
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Only Worker	-0.0003	-0.0004	-0.0004	-0.0004	-0.0003	-0.0005	-0.0003	-0.0004	-0.0003	-0.0004	-0.0005	-0.0005	-0.0005	-0.0006	-0.0006	-0.0006	-0.0006	-0.0005
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Only Owner	-0.0003	-0.0003	-0.0003	-0.0003	-0.0002	-0.0003	-0.0003	-0.0002	-0.0002	-0.0003	-0.0002	-0.0002	-0.0002	-0.0001	-0.0002	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Same Gender	0.0004	0.0004	0.0004	0.0003	0.0002	0.0003	0.0003	0.0003	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0003
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Same Race	0.0004	0.0004	0.0005	0.0005	0.0004	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0006	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Same Educ	0.0006	0.0008	0.0007	0.0007	0.0007	0.0008	0.0008	0.0008	0.0008	0.0008	0.0008	0.0007	0.0007	0.0007	0.0008	0.0007	0.0007	0.0007
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Same Age	0.0004	0.0005	0.0006	0.0005	0.0005	0.0006	0.0005	0.0006	0.0007	0.0007	0.0007	0.0006	0.0007	0.0007	0.0008	0.0008	0.0007	0.0008
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Same-Diff	0.016	0.019	0.019	0.015	0.016	0.016	0.017	0.017	0.015	0.018	0.019	0.017	0.016	0.018	0.019	0.019	0.020	0.019
Same-Only Worker	0.016	0.019	0.019	0.015	0.016	0.017	0.017	0.017	0.016	0.018	0.019	0.018	0.017	0.019	0.020	0.020	0.021	0.019
Same-Only Owner	0.016	0.019	0.019	0.015	0.016	0.016	0.017	0.017	0.016	0.018	0.019	0.017	0.016	0.018	0.020	0.019	0.020	0.019
Diff-Only Worker	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	0.000	0.000	0.000	0.000	0.000
Only Owner-Diff	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	0.000	0.000	0.000	0.000	0.000
Only Owner-Only Worker	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	0.000	0.000	0.000	0.000	0.000
Observations	19305886	23091336	25872543	29733986	33634681	35423304	39692299	43814821	49383365	53070205	57461824	62440037	67161781	68005797	67227357	67740613	67449251	69946541
Num Workers	1234415	1572427	1674935	1804621	1930397	2022214	2156278	2301132	2475218	2652332	2787210	2942484	3084342	3137313	3131620	3122793	3083835	3109369
Num Firms	465232	531776	565053	605938	648054	678117	720974	768266	826856	885593	929835	986252	1036229	1060172	1063430	1067111	1057335	1068596
Num Markets	21413	24960	25948	27131	28217	30539	32037	33433	35424	39018	40001	41379	42555	44030	44345	44182	43369	44471

Notes: The table presents estimates from equation 3.6 for the sample of small firms. Standard errors in parentheses are clustered by market. See section 3.2 and equation 3.6 for details on the estimation.

Table A6. **Dyadic Regression Estimates – Medium Firms**

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Same Party	0.0104	0.0138	0.0136	0.0125	0.0123	0.0104	0.0117	0.0102	0.0107	0.0116	0.0120	0.0110	0.0113	0.0116	0.0113	0.0119	0.0112	0.0118
	(0.0009)	(0.0008)	(0.0008)	(0.0007)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Different Party	0.0009	0.0011	0.0013	0.0012	0.0012	0.0009	0.0009	0.0010	0.0010	0.0012	0.0011	0.0010	0.0012	0.0012	0.0014	0.0013	0.0013	0.0013
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Only Worker	-0.0003	-0.0004	-0.0003	-0.0004	-0.0004	-0.0002	-0.0003	-0.0002	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0004	-0.0004	-0.0004	-0.0004
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Only Owner	0.0007	0.0007	0.0007	0.0006	0.0006	0.0005	0.0005	0.0005	0.0006	0.0006	0.0006	0.0007	0.0008	0.0007	0.0007	0.0008	0.0008	0.0008
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Gender	0.0004	0.0005	0.0003	0.0004	0.0003	0.0003	0.0003	0.0003	0.0002	0.0002	0.0002	0.0001	0.0002	0.0002	0.0001	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Same Race	0.0005	0.0005	0.0006	0.0006	0.0006	0.0007	0.0007	0.0007	0.0007	0.0006	0.0006	0.0006	0.0006	0.0005	0.0005	0.0005	0.0005	0.0005
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Same Educ	0.0004	0.0004	0.0005	0.0005	0.0004	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003	0.0002	0.0002	0.0002	0.0002	0.0002	0.0001	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Same Age	0.0000	0.0002	0.0000	0.0001	0.0001	0.0002	0.0002	0.0002	0.0002	0.0003	0.0003	0.0002	0.0003	0.0003	0.0004	0.0004	0.0004	0.0004
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Same-Diff	0.009	0.012	0.012	0.011	0.011	0.009	0.010	0.009	0.009	0.010	0.010	0.010	0.010	0.010	0.009	0.010	0.009	0.010
Same-Only Worker	0.010	0.014	0.013	0.012	0.012	0.010	0.011	0.010	0.011	0.011	0.012	0.011	0.011	0.011	0.011	0.012	0.011	0.012
Same-Only Owner	0.009	0.013	0.012	0.011	0.011	0.010	0.011	0.009	0.010	0.011	0.011	0.010	0.010	0.010	0.010	0.011	0.010	0.011
Diff-Only Worker	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Only Owner-Diff	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	0.000	0.000	0.000	0.000	0.000
Only Owner-Only Worker	0.001	0.001	0.001	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Observations	21572170	26990062	30542548	34972516	39189400	41961871	48197958	53606138	60886370	67519427	74359840	81324059	87551287	86778270	82090140	81846727	82759299	88200801
Num Workers	1656238	2208065	2361098	2541098	2712633	2877127	3113670	3297922	3581931	3891621	4116890	4319208	4499437	4478737	4270437	4196681	4183316	4338765
Num Firms	122296	130286	138487	147885	156716	165563	178023	188120	203671	220456	232260	243049	252546	253444	244004	240880	240756	250742
Num Markets	19724	22430	23232	24402	25309	27245	28637	29826	31736	34537	35494	36904	37804	38836	38640	38322	37984	39230

Notes: The table presents estimates from equation 3.6 for the sample of medium firms. Standard errors in parentheses are clustered by market. See section 3.2 and equation 3.6 for details on the estimation.

Table A7. **Dyadic Regression Estimates – Large Firms**

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Same Party	0.0173	0.0201	0.0193	0.0184	0.0152	0.0133	0.0131	0.0133	0.0155	0.0154	0.0152	0.0151	0.0147	0.0150	0.0125	0.0125	0.0107	0.0118
	(0.0016)	(0.0016)	(0.0015)	(0.0014)	(0.0012)	(0.0010)	(0.0010)	(0.0009)	(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0009)	(0.0010)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Different Party	0.0088	0.0084	0.0073	0.0082	0.0077	0.0058	0.0050	0.0053	0.0068	0.0070	0.0065	0.0066	0.0060	0.0057	0.0060	0.0061	0.0054	0.0067
	(0.0011)	(0.0010)	(0.0008)	(0.0008)	(0.0007)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0005)	(0.0005)	(0.0004)	(0.0005)
Only Worker	-0.0008	-0.0008	-0.0008	-0.0006	-0.0005	-0.0003	-0.0004	-0.0004	-0.0004	-0.0004	-0.0005	-0.0004	-0.0003	-0.0004	-0.0003	-0.0003	-0.0002	-0.0003
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Only Owner	0.0070	0.0069	0.0062	0.0070	0.0068	0.0055	0.0046	0.0050	0.0062	0.0062	0.0058	0.0059	0.0052	0.0049	0.0051	0.0053	0.0048	0.0056
	(0.0008)	(0.0008)	(0.0007)	(0.0007)	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Same Gender	0.0064	0.0070	0.0063	0.0058	0.0052	0.0056	0.0052	0.0048	0.0045	0.0041	0.0035	0.0033	0.0032	0.0031	0.0035	0.0037	0.0035	0.0037
	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Same Race	0.0008	0.0013	0.0013	0.0008	0.0008	0.0006	0.0005	0.0006	0.0005	0.0003	0.0002	0.0000	0.0000	-0.0001	-0.0001	-0.0002	-0.0002	-0.0003
	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Educ	-0.0032	-0.0029	-0.0029	-0.0027	-0.0026	-0.0032	-0.0034	-0.0032	-0.0036	-0.0037	-0.0038	-0.0037	-0.0037	-0.0038	-0.0039	-0.0038	-0.0040	-0.0041
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Same Age	-0.0032	-0.0023	-0.0029	-0.0029	-0.0029	-0.0030	-0.0028	-0.0021	-0.0021	-0.0017	-0.0015	-0.0012	-0.0010	-0.0009	-0.0007	-0.0005	-0.0006	-0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same-Diff	0.008	0.011	0.012	0.010	0.007	0.007	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.009	0.006	0.006	0.005	0.005
Same-Only Worker	0.018	0.020	0.020	0.019	0.015	0.013	0.013	0.013	0.016	0.015	0.015	0.015	0.015	0.015	0.012	0.012	0.010	0.012
Same-Only Owner	0.010	0.013	0.013	0.011	0.008	0.007	0.008	0.008	0.009	0.009	0.009	0.009	0.009	0.010	0.007	0.007	0.005	0.006
Diff-Only Worker	0.009	0.009	0.008	0.008	0.008	0.006	0.005	0.005	0.007	0.007	0.007	0.007	0.006	0.006	0.006	0.006	0.005	0.007
Only Owner-Diff	0.001	0.001	0.001	0.001	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	0.001
Only Owner-Only Worker	0.007	0.007	0.007	0.007	0.007	0.005	0.005	0.005	0.006	0.006	0.006	0.006	0.005	0.005	0.005	0.005	0.004	0.005
Observations	26508620	33655787	38151572	44501560	49774959	55742821	65908074	71974850	84282019	93258737	104277407	115139768	123910354	119224480	109170231	108672036	110745606	118652525
Num Workers	3147506	4243311	4599601	5026908	5457434	5966085	6719928	6878294	7653804	8145933	8596179	9011224	9254954	8906316	8271439	8127725	8051265	8510949
Num Firms	27155	28760	30473	32571	34412	36951	40598	41386	44993	48472	50337	52286	53406	51693	48034	47140	46958	49351
Num Markets	14682	16273	16838	17896	18888	20239	21688	22098	23463	25291	26020	26656	27173	27757	27392	27224	26513	28150

Notes: The table presents estimates from equation 3.6 for the sample of large firms. Standard errors in parentheses are clustered by market. See section 3.2 and equation 3.6 for details on the estimation.

Table A8. **Dyadic Regression Estimates – Managers**

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Same Party	0.0163	0.0265	0.0248	0.0254	0.0232	0.0234	0.0207	0.0190	0.0231	0.0248	0.0239	0.0226	0.0228	0.0218	0.0231	0.0255	0.0246	0.0272
	(0.0023)	(0.0020)	(0.0019)	(0.0017)	(0.0016)	(0.0015)	(0.0015)	(0.0013)	(0.0013)	(0.0012)	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0012)	(0.0013)	(0.0013)
Different Party	-0.0012	-0.0001	0.0009	0.0015	0.0023	0.0013	-0.0004	0.0005	0.0034	0.0034	0.0033	0.0030	0.0025	0.0018	0.0029	0.0029	0.0021	0.0032
	(0.0008)	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Only Worker	-0.0002	-0.0009	-0.0006	-0.0008	-0.0005	-0.0008	-0.0007	-0.0007	-0.0005	-0.0006	-0.0003	-0.0006	-0.0006	-0.0007	-0.0004	-0.0006	-0.0006	-0.0006
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Only Owner	-0.0020	0.0008	0.0013	0.0015	0.0029	0.0011	-0.0003	-0.0004	0.0034	0.0034	0.0033	0.0033	0.0028	0.0018	0.0029	0.0031	0.0024	0.0040
	(0.0006)	(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0003)
Same Gender	0.0044	0.0045	0.0045	0.0035	0.0031	0.0030	0.0027	0.0022	0.0019	0.0017	0.0014	0.0013	0.0013	0.0012	0.0014	0.0013	0.0014	0.0015
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Race	0.0007	0.0008	0.0007	0.0006	0.0004	0.0016	0.0018	0.0020	0.0018	0.0016	0.0016	0.0014	0.0012	0.0012	0.0012	0.0013	0.0012	0.0011
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Educ	0.0008	0.0021	0.0022	0.0032	0.0029	0.0027	0.0024	0.0029	0.0026	0.0026	0.0024	0.0023	0.0022	0.0023	0.0024	0.0026	0.0025	0.0024
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Age	0.0003	0.0015	0.0012	0.0010	0.0007	0.0009	0.0007	0.0004	0.0004	0.0004	0.0004	0.0005	0.0005	0.0007	0.0005	0.0006	0.0006	0.0005
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same-Diff	0.017	0.026	0.024	0.023	0.020	0.022	0.021	0.018	0.019	0.021	0.020	0.019	0.020	0.020	0.020	0.022	0.022	0.024
Same-Only Worker	0.016	0.027	0.025	0.026	0.023	0.024	0.021	0.019	0.023	0.025	0.024	0.023	0.023	0.022	0.023	0.026	0.025	0.027
Same-Only Owner	0.018	0.025	0.023	0.023	0.020	0.022	0.021	0.019	0.019	0.021	0.020	0.019	0.019	0.020	0.020	0.022	0.022	0.023
Diff-Only Worker	0.001	0.000	0.001	0.002	0.002	0.002	0.000	0.001	0.003	0.003	0.003	0.003	0.003	0.002	0.003	0.003	0.002	0.003
Only Owner-Diff	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	0.000	0.000	0.000	0.000	0.000
Only Owner-Only Worker	0.001	0.001	0.001	0.002	0.003	0.001	0.000	0.000	0.004	0.004	0.003	0.003	0.003	0.002	0.003	0.003	0.003	0.004
Observations	2635741	3836563	4307863	4997088	5667755	6283933	7471773	8582172	10056617	11418081	12934520	14388396	15554489	15850288	15256085	15293663	15412309	16330427
Num Workers	232829	378413	399934	431931	471711	506417	565725	616995	682270	752420	817470	870013	911425	921487	896755	889499	889267	911037
Num Firms	84768	117627	127278	140377	154667	167725	186742	205357	228822	251803	271490	290849	307472	312489	306162	303122	298580	304050
Num Markets	14374	17852	18698	19845	21162	22547	24017	25386	27150	29504	30998	32454	33420	34639	34735	34888	34570	35359

Notes: The table presents estimates from equation 3.6 for the sample of workers employed in managerial occupations. Standard errors in parentheses are clustered by market. See section 3.2 and equation 3.6 for details on the estimation.

Table A9. **Dyadic Regression Estimates – White-Collar Workers**

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Same Party	0.0193	0.0202	0.0193	0.0191	0.0157	0.0157	0.0153	0.0143	0.0155	0.0174	0.0175	0.0168	0.0167	0.0176	0.0159	0.0153	0.0133	0.0139
	(0.0011)	(0.0010)	(0.0009)	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0007)	(0.0007)	(0.0008)	(0.0008)	(0.0007)	(0.0008)	(0.0006)	(0.0006)	(0.0005)	(0.0005)
Different Party	0.0053	0.0041	0.0034	0.0043	0.0037	0.0030	0.0027	0.0029	0.0035	0.0032	0.0030	0.0032	0.0030	0.0033	0.0031	0.0031	0.0021	0.0032
	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Only Worker	-0.0007	-0.0006	-0.0006	-0.0007	-0.0004	-0.0005	-0.0004	-0.0004	-0.0005	-0.0005	-0.0005	-0.0005	-0.0004	-0.0005	-0.0005	-0.0005	-0.0004	-0.0004
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Only Owner	0.0038	0.0032	0.0027	0.0031	0.0026	0.0025	0.0022	0.0024	0.0027	0.0025	0.0024	0.0025	0.0023	0.0026	0.0023	0.0023	0.0019	0.0024
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Same Gender	0.0009	0.0011	0.0010	0.0008	0.0008	0.0008	0.0008	0.0008	0.0007	0.0007	0.0006	0.0005	0.0005	0.0005	0.0006	0.0006	0.0004	0.0005
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0001)
Same Race	0.0008	0.0010	0.0009	0.0008	0.0008	0.0006	0.0007	0.0007	0.0006	0.0006	0.0005	0.0004	0.0004	0.0003	0.0003	0.0003	0.0003	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Educ	0.0005	0.0006	0.0007	0.0007	0.0007	0.0007	0.0005	0.0004	0.0003	0.0001	0.0000	0.0000	-0.0002	-0.0002	-0.0003	-0.0003	-0.0004	-0.0004
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Age	-0.0008	-0.0003	-0.0004	-0.0006	-0.0006	-0.0008	-0.0007	-0.0004	-0.0005	-0.0005	-0.0004	-0.0003	-0.0002	-0.0002	-0.0002	0.0000	-0.0002	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Same-Diff	0.014	0.016	0.015	0.014	0.012	0.012	0.012	0.011	0.012	0.014	0.014	0.013	0.013	0.014	0.012	0.012	0.011	0.010
Same-Only Worker	0.020	0.020	0.019	0.019	0.016	0.016	0.015	0.014	0.016	0.017	0.018	0.017	0.017	0.018	0.016	0.015	0.013	0.014
Same-Only Owner	0.015	0.017	0.016	0.016	0.013	0.013	0.013	0.012	0.012	0.014	0.015	0.014	0.014	0.015	0.013	0.013	0.011	0.011
Diff-Only Worker	0.006	0.004	0.004	0.005	0.004	0.003	0.003	0.003	0.004	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.002	0.003
Only Owner-Diff	0.001	0.000	0.000	0.001	0.001	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
Only Owner-Only Worker	0.004	0.003	0.003	0.003	0.003	0.002	0.002	0.002	0.003	0.003	0.003	0.003	0.002	0.003	0.002	0.002	0.002	0.002
Observations	35260925	44462775	50259273	58806887	66263984	71055823	82429485	91696133	103613506	113028394	123692697	134671457	144660502	142312463	135400587	134646745	136041096	145081396
Num Workers	2433138	3253156	3477133	3812717	4115318	4388406	4864504	5157565	5586379	5971705	6319888	6662718	6957129	6902007	6654855	6597202	6508020	6827768
Num Firms	448213	521375	555463	597289	637922	667965	716242	760444	813701	869361	906374	953214	994202	1006926	995323	989556	979387	995441
Num Markets	22819	26391	27475	28666	29968	32290	34021	35325	37352	41006	42159	43400	44535	46249	46512	46120	45235	46725

Notes: The table presents estimates from equation 3.6 for the sample of workers employed in white-collar occupations other than managerial ones. Standard errors in parentheses are clustered by market. See section 3.2 and equation 3.6 for details on the estimation.

TABLE A10. **Dyadic Regression Estimates – Blue-Collar Workers**

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Same Party	0.0112	0.0144	0.0134	0.0132	0.0122	0.0103	0.0104	0.0103	0.0106	0.0114	0.0117	0.0106	0.0094	0.0100	0.0118	0.0114	0.0107	0.0100
	(0.0010)	(0.0010)	(0.0010)	(0.0009)	(0.0009)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Different Party	0.0035	0.0033	0.0030	0.0034	0.0035	0.0027	0.0022	0.0023	0.0029	0.0031	0.0033	0.0030	0.0029	0.0025	0.0028	0.0029	0.0030	0.0033
	(0.0007)	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Only Worker	-0.0005	-0.0004	-0.0004	-0.0004	-0.0003	-0.0002	-0.0002	-0.0002	-0.0002	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Only Owner	0.0024	0.0024	0.0025	0.0026	0.0030	0.0023	0.0019	0.0021	0.0027	0.0029	0.0029	0.0028	0.0025	0.0019	0.0024	0.0026	0.0027	0.0028
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Same Gender	0.0052	0.0054	0.0049	0.0047	0.0044	0.0046	0.0045	0.0043	0.0039	0.0036	0.0031	0.0030	0.0030	0.0028	0.0031	0.0031	0.0033	0.0034
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Race	0.0003	0.0006	0.0006	0.0004	0.0005	0.0004	0.0002	0.0002	0.0002	0.0001	0.0000	-0.0001	0.0000	0.0000	0.0001	0.0000	-0.0002	-0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Educ	-0.0032	-0.0031	-0.0032	-0.0032	-0.0032	-0.0037	-0.0039	-0.0038	-0.0038	-0.0037	-0.0038	-0.0037	-0.0035	-0.0035	-0.0036	-0.0035	-0.0036	-0.0038
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Age	-0.0015	-0.0016	-0.0017	-0.0016	-0.0015	-0.0015	-0.0014	-0.0011	-0.0010	-0.0008	-0.0006	-0.0004	-0.0003	-0.0001	0.0000	0.0002	0.0002	0.0004
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same-Diff	0.007	0.011	0.010	0.009	0.008	0.007	0.008	0.007	0.007	0.008	0.008	0.007	0.006	0.007	0.009	0.008	0.007	0.006
Same-Only Worker	0.011	0.014	0.013	0.013	0.012	0.010	0.010	0.010	0.010	0.011	0.012	0.010	0.009	0.010	0.012	0.011	0.011	0.010
Same-Only Owner	0.008	0.012	0.010	0.010	0.009	0.008	0.008	0.008	0.007	0.008	0.008	0.007	0.006	0.008	0.009	0.008	0.008	0.007
Diff-Only Worker	0.004	0.003	0.003	0.003	0.003	0.002	0.002	0.002	0.003	0.003	0.003	0.003	0.003	0.002	0.003	0.003	0.003	0.003
Only Owner-Diff	0.001	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	0.000	0.000	0.000	0.000
Only Owner-Only Worker	0.003	0.002	0.002	0.002	0.003	0.002	0.002	0.002	0.002	0.003	0.003	0.003	0.002	0.002	0.002	0.002	0.003	0.003
Observations	35121148	35509994	40050164	45508564	50737068	55818072	63976619	69143078	80895029	89243724	99149380	108996841	117054572	113086328	104257802	103087383	102213531	105959272
Num Workers	3642381	4391890	4759183	5124643	5510848	5964347	6558261	6692844	7426262	7940051	8328422	8672246	8877489	8554988	7946591	7707113	7583944	7799565
Num Firms	396575	409837	437414	469148	500296	528018	556271	589625	643196	694190	734866	778984	815601	826681	815838	810679	799801	811176
Num Markets	24103	26209	27189	28463	29642	32044	33438	34666	36940	40287	41453	42870	43942	45411	45547	45291	44611	45866

Notes: The table presents estimates from equation 3.6 for the sample of workers employed in blue-collar occupations. Standard errors in parentheses are clustered by market. See section 3.2 and equation 3.6 for details on the estimation.

Table A11. **Dyadic Regression Estimates – Low Social Skills Jobs**

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Same Party	0.0158	0.0168	0.0166	0.0161	0.0133	0.0137	0.0133	0.0122	0.0140	0.0147	0.0142	0.0151	0.0141	0.0154	0.0128	0.0122	0.0122	0.0112
	(0.0012)	(0.0011)	(0.0011)	(0.0010)	(0.0012)	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Different Party	0.0049	0.0041	0.0037	0.0046	0.0058	0.0032	0.0027	0.0029	0.0038	0.0041	0.0040	0.0040	0.0036	0.0038	0.0036	0.0038	0.0031	0.0041
	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0010)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0004)
Only Worker	-0.0005	-0.0005	-0.0004	-0.0005	0.0006	-0.0001	-0.0003	-0.0003	-0.0003	-0.0005	-0.0004	-0.0004	-0.0004	-0.0005	-0.0004	-0.0004	-0.0003	-0.0004
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0004)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Only Owner	0.0040	0.0032	0.0034	0.0039	0.0056	0.0031	0.0025	0.0027	0.0034	0.0036	0.0035	0.0035	0.0031	0.0030	0.0029	0.0031	0.0029	0.0033
	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0009)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Same Gender	0.0048	0.0055	0.0049	0.0047	0.0058	0.0050	0.0045	0.0041	0.0037	0.0035	0.0030	0.0029	0.0029	0.0028	0.0031	0.0031	0.0030	0.0033
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0005)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Race	0.0005	0.0009	0.0008	0.0005	-0.0003	0.0003	0.0002	0.0003	0.0002	0.0001	0.0000	-0.0001	0.0000	0.0000	0.0000	-0.0001	-0.0001	-0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0008)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Educ	-0.0022	-0.0025	-0.0025	-0.0027	-0.0002	-0.0032	-0.0032	-0.0032	-0.0033	-0.0033	-0.0034	-0.0033	-0.0032	-0.0032	-0.0033	-0.0032	-0.0034	-0.0036
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0006)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Age	-0.0016	-0.0014	-0.0018	-0.0018	-0.0009	-0.0018	-0.0016	-0.0010	-0.0011	-0.0009	-0.0007	-0.0005	-0.0004	-0.0002	0.0000	0.0002	0.0001	0.0004
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same-Diff	0.010	0.012	0.012	0.011	0.007	0.010	0.010	0.009	0.010	0.010	0.010	0.011	0.010	0.011	0.009	0.008	0.009	0.007
Same-Only Worker	0.016	0.017	0.017	0.016	0.012	0.013	0.013	0.012	0.014	0.015	0.014	0.015	0.014	0.015	0.013	0.012	0.012	0.011
Same-Only Owner	0.011	0.013	0.013	0.012	0.007	0.010	0.010	0.009	0.010	0.011	0.010	0.011	0.011	0.012	0.010	0.009	0.009	0.007
Diff-Only Worker	0.005	0.004	0.004	0.005	0.005	0.003	0.002	0.003	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.003	0.004
Only Owner-Diff	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	0.000	0.000	0.000	0.000	0.000
Only Owner-Only Worker	0.004	0.003	0.003	0.004	0.005	0.003	0.002	0.003	0.003	0.004	0.003	0.004	0.003	0.003	0.003	0.003	0.003	0.003
Observations	26113162	31455484	35530451	40400073	53442967	49168614	61729938	66311689	77801059	85385711	94948100	103821607	111720747	108804267	101360966	99928785	99337190	104652989
Num Workers	3030685	3947748	4287633	4622052	5444918	5393071	6338233	6456109	7175058	7654275	8039155	8372351	8586000	8318965	7785831	7563537	7385993	7711307
Num Firms	344117	384528	410353	438592	513645	489142	556044	589425	644285	693905	737273	781644	819182	831893	823239	818164	808789	822540
Num Markets	23864	27020	28014	29355	32357	33072	35131	36385	38812	42324	43596	45026	46085	47745	47919	47531	46554	48200

Notes: The table presents estimates from equation 3.6 for the sample of workers employed in occupations requiring a below median level of social skills. Standard errors in parentheses are clustered by market. See section 3.2 and equation 3.6 for details on the estimation.

Table A12. **Dyadic Regression Estimates – High Social Skills Jobs**

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Same Party	0.0158	0.0189	0.0168	0.0167	0.0170	0.0137	0.0142	0.0139	0.0143	0.0149	0.0155	0.0142	0.0143	0.0148	0.0155	0.0153	0.0149	0.0142
	(0.0010)	(0.0010)	(0.0009)	(0.0008)	(0.0012)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Different Party	0.0034	0.0032	0.0025	0.0030	0.0029	0.0023	0.0021	0.0022	0.0027	0.0026	0.0025	0.0026	0.0024	0.0021	0.0024	0.0024	0.0019	0.0025
	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Only Worker	-0.0005	-0.0005	-0.0005	-0.0005	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0005	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Only Owner	0.0020	0.0023	0.0018	0.0021	0.0024	0.0019	0.0017	0.0017	0.0022	0.0021	0.0020	0.0021	0.0020	0.0017	0.0019	0.0020	0.0018	0.0021
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Gender	0.0013	0.0015	0.0013	0.0011	0.0009	0.0009	0.0008	0.0007	0.0007	0.0007	0.0005	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Same Race	0.0006	0.0008	0.0008	0.0007	0.0002	0.0007	0.0007	0.0007	0.0008	0.0006	0.0006	0.0005	0.0005	0.0004	0.0004	0.0004	0.0004	0.0004
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0000)
Same Educ	0.0002	0.0005	0.0005	0.0008	0.0016	0.0006	0.0004	0.0004	0.0003	0.0002	0.0002	0.0001	0.0000	0.0000	0.0000	0.0000	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0000)
Same Age	-0.0008	-0.0003	-0.0004	-0.0004	-0.0003	-0.0005	-0.0005	-0.0004	-0.0003	-0.0003	-0.0003	-0.0002	-0.0002	-0.0001	-0.0001	0.0000	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Same-Diff	0.012	0.015	0.014	0.013	0.014	0.011	0.012	0.011	0.011	0.012	0.013	0.011	0.011	0.012	0.013	0.013	0.013	0.011
Same-Only Worker	0.016	0.019	0.017	0.017	0.017	0.014	0.014	0.014	0.014	0.015	0.016	0.014	0.014	0.015	0.015	0.015	0.015	0.014
Same-Only Owner	0.013	0.016	0.015	0.014	0.014	0.011	0.012	0.012	0.012	0.012	0.013	0.012	0.012	0.013	0.013	0.013	0.013	0.012
Diff-Only Worker	0.003	0.003	0.003	0.003	0.003	0.002	0.002	0.002	0.003	0.003	0.003	0.003	0.002	0.002	0.002	0.002	0.002	0.002
Only Owner-Diff	0.001	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	0.000	0.000	0.000	0.000
Only Owner-Only Worker	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
Observations	32368749	41629613	46816631	54519346	72426648	66406776	76965479	85906272	97979004	107149274	117784024	129241076	138952628	137444748	130963464	131623007	134223060	142436081
Num Workers	2322965	3151737	3347137	3646484	4234663	4192304	4652833	4943937	5405463	5793087	6144467	6512474	6793847	6750419	6498805	6463304	6496729	6719793
Num Firms	442178	520582	554473	596127	701713	669140	717703	763443	823335	881998	923295	973404	1017098	1033608	1023383	1021799	1016950	1035922
Num Markets	23134	26708	27761	29048	31978	32580	34297	35662	37601	41367	42574	43832	45033	46641	46979	46585	45931	47256

Notes: The table presents estimates from equation 3.6 for the sample of workers employed in occupations requiring an above median level of social skills. Standard errors in parentheses are clustered by market. See section 3.2 and equation 3.6 for details on the estimation.

Table A13. **Dyadic Regression Estimates – Low Interpersonal Skills Jobs**

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Same Party	0.0128	0.0165	0.0158	0.0134	0.0116	0.0120	0.0105	0.0113	0.0136	0.0152	0.0151	0.0144	0.0142	0.0136	0.0125	0.0127	0.0117	0.0157
	(0.0012)	(0.0013)	(0.0012)	(0.0011)	(0.0012)	(0.0009)	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0014)
Different Party	0.0036	0.0032	0.0029	0.0039	0.0024	0.0021	0.0018	0.0017	0.0034	0.0039	0.0043	0.0042	0.0038	0.0033	0.0037	0.0040	0.0028	0.0112
	(0.0008)	(0.0008)	(0.0007)	(0.0007)	(0.0008)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0020)
Only Worker	-0.0005	-0.0006	-0.0004	-0.0005	0.0002	-0.0001	-0.0002	-0.0002	-0.0004	-0.0003	-0.0004	-0.0004	-0.0004	-0.0004	-0.0005	-0.0004	-0.0003	-0.0012
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Only Owner	0.0025	0.0025	0.0026	0.0030	0.0026	0.0021	0.0017	0.0019	0.0033	0.0036	0.0037	0.0037	0.0032	0.0026	0.0030	0.0031	0.0027	0.0071
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0011)
Same Gender	0.0053	0.0060	0.0055	0.0051	0.0066	0.0054	0.0047	0.0045	0.0042	0.0039	0.0034	0.0033	0.0032	0.0031	0.0034	0.0036	0.0034	0.0050
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0006)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0003)
Same Race	0.0003	0.0007	0.0008	0.0006	-0.0004	0.0004	0.0004	0.0003	0.0003	0.0002	0.0001	-0.0001	0.0000	0.0000	0.0001	-0.0001	-0.0001	-0.0008
	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0007)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0003)
Same Educ	-0.0031	-0.0027	-0.0029	-0.0027	-0.0016	-0.0035	-0.0037	-0.0035	-0.0036	-0.0035	-0.0035	-0.0034	-0.0033	-0.0032	-0.0032	-0.0032	-0.0033	-0.0032
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0002)
Same Age	-0.0017	-0.0019	-0.0020	-0.0019	-0.0018	-0.0017	-0.0015	-0.0011	-0.0011	-0.0008	-0.0006	-0.0004	-0.0003	-0.0001	0.0001	0.0003	0.0002	0.0015
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0004)
Same-Diff	0.009	0.013	0.012	0.009	0.009	0.010	0.008	0.009	0.010	0.011	0.010	0.010	0.010	0.010	0.008	0.008	0.008	0.004
Same-Only Worker	0.013	0.017	0.016	0.013	0.011	0.012	0.010	0.011	0.013	0.015	0.015	0.014	0.014	0.014	0.013	0.013	0.012	0.017
Same-Only Owner	0.010	0.014	0.013	0.010	0.009	0.009	0.008	0.009	0.010	0.011	0.011	0.010	0.010	0.011	0.009	0.009	0.009	0.008
Diff-Only Worker	0.004	0.003	0.003	0.004	0.002	0.002	0.002	0.002	0.003	0.004	0.004	0.004	0.004	0.003	0.004	0.004	0.003	0.012
Only Owner-Diff	0.001	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	0.000	0.000	0.000	0.004
Only Owner-Only Worker	0.003	0.003	0.003	0.003	0.002	0.002	0.001	0.002	0.003	0.003	0.004	0.004	0.003	0.003	0.003	0.003	0.003	0.008
Observations	22969784	28162127	31575923	35751748	47055722	43767796	55536370	59743334	69940233	76821537	85451712	93735336	100720683	97386365	89662048	88444032	87560377	97235765
Num Workers	2802640	3711636	4020247	4316945	5116295	5063798	6007691	6107226	6791784	7236188	7585642	7905727	8092162	7789647	7241864	7028113	6889677	7434992
Num Firms	310476	352682	375834	401219	470603	447915	514613	544819	594120	641918	680250	720936	753950	763373	751656	745168	735055	771640
Num Markets	22643	25553	26484	27766	30748	31240	33370	34626	36921	40332	41480	42949	44081	45629	45693	45311	44576	47148

Notes: The table presents estimates from equation 3.6 for the sample of workers employed in occupations requiring a below median level of interpersonal relationships. Standard errors in parentheses are clustered by market. See section 3.2 and equation 3.6 for details on the estimation.

Table A14. **Dyadic Regression Estimates – High Interpersonal Skills Jobs**

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Same Party	0.0178	0.0195	0.0181	0.0180	0.0178	0.0159	0.0157	0.0145	0.0146	0.0153	0.0150	0.0148	0.0144	0.0157	0.0149	0.0150	0.0144	0.0151
	(0.0010)	(0.0009)	(0.0008)	(0.0008)	(0.0013)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0007)
Different Party	0.0043	0.0034	0.0031	0.0034	0.0051	0.0030	0.0027	0.0029	0.0027	0.0027	0.0024	0.0025	0.0023	0.0025	0.0022	0.0024	0.0021	0.0057
	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0006)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0007)
Only Worker	-0.0005	-0.0007	-0.0005	-0.0006	-0.0002	-0.0005	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0003	-0.0004	-0.0004	-0.0004	-0.0004	-0.0007
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Only Owner	0.0031	0.0027	0.0023	0.0027	0.0043	0.0025	0.0023	0.0023	0.0023	0.0022	0.0020	0.0021	0.0020	0.0021	0.0019	0.0020	0.0019	0.0046
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0006)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0004)
Same Gender	0.0014	0.0014	0.0013	0.0011	0.0009	0.0010	0.0009	0.0008	0.0007	0.0006	0.0005	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Same Race	0.0007	0.0008	0.0008	0.0006	0.0003	0.0006	0.0006	0.0007	0.0007	0.0006	0.0005	0.0004	0.0004	0.0003	0.0004	0.0003	0.0004	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0001)
Same Educ	0.0004	0.0004	0.0004	0.0006	0.0023	0.0005	0.0004	0.0004	0.0002	0.0001	0.0000	-0.0001	-0.0002	-0.0002	-0.0002	-0.0003	-0.0004	0.0005
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0004)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)
Same Age	-0.0008	-0.0001	-0.0003	-0.0005	0.0003	-0.0006	-0.0006	-0.0004	-0.0004	-0.0003	-0.0003	-0.0002	-0.0002	-0.0001	-0.0001	0.0000	0.0000	0.0008
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0003)
Same-Diff	0.013	0.016	0.015	0.014	0.012	0.012	0.013	0.011	0.012	0.012	0.012	0.012	0.012	0.013	0.012	0.012	0.012	0.009
Same-Only Worker	0.018	0.020	0.018	0.018	0.018	0.016	0.016	0.014	0.015	0.015	0.015	0.015	0.014	0.016	0.015	0.015	0.014	0.015
Same-Only Owner	0.014	0.016	0.015	0.015	0.013	0.013	0.013	0.012	0.012	0.013	0.013	0.012	0.012	0.013	0.013	0.013	0.012	0.010
Diff-Only Worker	0.004	0.004	0.003	0.004	0.005	0.003	0.003	0.003	0.003	0.003	0.002	0.002	0.002	0.003	0.002	0.002	0.002	0.006
Only Owner-Diff	0.001	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	0.000	0.000	0.000	0.001
Only Owner-Only Worker	0.003	0.003	0.002	0.003	0.004	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.005
Observations	35512068	44920746	50778268	59165197	78813919	71804752	83153194	92481088	105839127	115743147	127276737	139324339	149952535	148870423	142651729	143098027	146004286	166881800
Num Workers	2550951	3388029	3614510	3951671	4563312	4522255	4983913	5292685	5787840	6210600	6598588	6979194	7286344	7279489	7043072	6997581	6993702	7561098
Num Firms	459898	533940	568372	610559	717977	684358	733238	779480	841046	898734	941557	992251	1037461	1055101	1047025	1046657	1041206	1093884
Num Markets	23452	26857	27839	29116	32059	32769	34459	35728	37960	41585	42758	44042	45178	46954	47223	46877	46025	48574

Notes: The table presents estimates from equation 3.6 for the sample of workers employed in occupations requiring an above median level of interpersonal relationships. Standard errors in parentheses are clustered by market. See section 3.2 and equation 3.6 for details on the estimation.

Table A15. **Dyadic Regression Estimates – Same Municipality**

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Same Party	0.0105	0.0081	0.0085	0.0084	0.0075	0.0080	0.0073	0.0074	0.0091	0.0093	0.0082	0.0079	0.0083	0.0078	0.0080	0.0078	0.0068
	(0.0011)	(0.0008)	(0.0008)	(0.0008)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Different Party	0.0009	0.0016	0.0023	0.0021	0.0012	0.0007	0.0012	0.0013	0.0019	0.0020	0.0021	0.0013	0.0015	0.0015	0.0014	0.0013	0.0012
	(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Only Worker	-0.0003	-0.0002	-0.0001	-0.0003	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002	-0.0003	-0.0001	-0.0002	-0.0002	-0.0002	-0.0002	-0.0003	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Only Owner	0.0010	0.0012	0.0019	0.0015	0.0010	0.0008	0.0011	0.0014	0.0015	0.0018	0.0019	0.0012	0.0011	0.0013	0.0011	0.0011	0.0010
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Same Gender	0.0020	0.0019	0.0016	0.0016	0.0019	0.0017	0.0016	0.0014	0.0014	0.0010	0.0011	0.0009	0.0009	0.0009	0.0011	0.0011	0.0009
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Race	0.0001	0.0003	0.0004	0.0008	0.0003	0.0001	0.0004	0.0002	0.0001	0.0001	0.0002	0.0000	0.0000	0.0001	0.0001	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Educ	-0.0007	-0.0009	-0.0004	-0.0007	-0.0010	-0.0010	-0.0009	-0.0011	-0.0010	-0.0011	-0.0012	-0.0011	-0.0010	-0.0010	-0.0010	-0.0010	-0.0009
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Age	-0.0008	-0.0009	-0.0010	-0.0011	-0.0010	-0.0010	-0.0008	-0.0008	-0.0007	-0.0007	-0.0006	-0.0004	-0.0004	-0.0002	-0.0003	-0.0002	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Same-Only Worker	0.010	0.008	0.008	0.008	0.007	0.008	0.007	0.007	0.009	0.009	0.008	0.008	0.008	0.008	0.008	0.008	0.007
Same-Only Owner	0.009	0.006	0.006	0.007	0.006	0.007	0.006	0.006	0.007	0.007	0.006	0.006	0.007	0.006	0.006	0.006	0.005
Diff-Only Worker	0.001	0.001	0.002	0.002	0.001	0.000	0.001	0.001	0.002	0.002	0.002	0.001	0.001	0.001	0.001	0.001	0.001
Only Owner-Diff	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	0.000	0.000	0.000	0.000
Only Owner-Only Worker	0.001	0.001	0.002	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.002	0.001	0.001	0.001	0.001	0.001	0.001
Num Workers	758905	859921	917641	1024781	1115062	1298021	1364946	1546629	1669206	1790528	1835758	1847382	1653473	1472695	1403333	1381215	1318527
Num Firms	231192	252370	272137	292425	312860	351719	374542	412320	445352	473948	485846	507045	478262	432820	413831	414690	426255
Num Markets	22175	23656	24864	26124	27858	30021	31437	33375	36059	37370	38430	39395	39915	39460	39062	38700	39517

Notes: The table presents estimates from equation 3.6 for the sample of hired workers who are from the same municipality as the firm. Standard errors in parentheses are clustered by market. See section 3.2 and equation 3.6 for details on the estimation.

Table A16. **Dyadic Regression Estimates – Different Municipality, Same Microregion**

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Same Party	0.0052	0.0056	0.0048	0.0084	0.0044	0.0053	-0.0003	0.0048	0.0062	0.0044	0.0048	0.0059	0.0040	0.0037	0.0054	0.0060	0.0035
	(0.0022)	(0.0023)	(0.0018)	(0.0018)	(0.0016)	(0.0014)	(0.0011)	(0.0013)	(0.0012)	(0.0010)	(0.0011)	(0.0011)	(0.0010)	(0.0011)	(0.0013)	(0.0014)	(0.0013)
Different Party	0.0005	-0.0002	0.0027	0.0013	0.0007	-0.0006	0.0007	0.0008	0.0009	0.0011	0.0011	0.0007	0.0014	0.0013	0.0014	0.0019	0.0018
	(0.0013)	(0.0008)	(0.0009)	(0.0007)	(0.0008)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0006)	(0.0005)
Only Worker	-0.0001	0.0000	-0.0001	-0.0004	0.0001	0.0000	0.0000	0.0002	-0.0002	-0.0001	-0.0002	-0.0001	-0.0002	-0.0002	-0.0001	-0.0001	-0.0002
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Only Owner	0.0017	0.0002	0.0013	0.0013	0.0004	0.0002	0.0003	0.0004	0.0007	0.0007	0.0006	0.0003	0.0006	0.0011	0.0013	0.0016	0.0013
	(0.0017)	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)
Same Gender	0.0035	0.0030	0.0031	0.0027	0.0034	0.0030	0.0024	0.0025	0.0024	0.0020	0.0018	0.0017	0.0016	0.0017	0.0019	0.0017	0.0013
	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)
Same Race	0.0002	0.0006	0.0004	0.0003	-0.0002	0.0003	0.0001	0.0000	-0.0001	-0.0002	-0.0003	-0.0001	-0.0003	-0.0002	-0.0002	-0.0002	-0.0002
	(0.0004)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Same Educ	-0.0019	-0.0019	-0.0018	-0.0017	-0.0022	-0.0019	-0.0019	-0.0022	-0.0022	-0.0021	-0.0022	-0.0020	-0.0020	-0.0019	-0.0020	-0.0018	-0.0018
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Same Age	-0.0018	-0.0020	-0.0015	-0.0020	-0.0020	-0.0020	-0.0016	-0.0016	-0.0016	-0.0014	-0.0012	-0.0011	-0.0008	-0.0008	-0.0008	-0.0006	-0.0007
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same-Only Worker	0.005	0.005	0.004	0.008	0.004	0.005	0.000	0.004	0.006	0.004	0.005	0.006	0.004	0.003	0.005	0.006	0.003
Same-Only Owner	0.003	0.005	0.003	0.007	0.004	0.005	0.000	0.004	0.005	0.003	0.004	0.005	0.003	0.002	0.004	0.004	0.002
Diff-Only Worker	0.000	0.000	0.002	0.001	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.000	0.001	0.001	0.001	0.002	0.002
Only Owner-Diff	0.001	0.000	0.001	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	0.000
Only Owner-Only Worker	0.001	0.000	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.001
Num Workers	176949	199045	215844	243870	278221	330085	344767	414862	465467	500196	539303	536330	470525	399713	366769	363714	359052
Num Firms	57009	63910	70359	76673	83923	97652	104661	119207	133209	142443	151881	156306	145076	127621	119862	118836	124978
Num Markets	12886	14211	15133	16170	17507	19298	20260	22141	24293	25508	26627	27148	27071	25939	25610	25240	25465

Notes: The table presents estimates from equation 3.6 for the sample of hired workers who are from a different municipality within the same microregion as the firm. Standard errors in parentheses are clustered by market. See section 3.2 and equation 3.6 for details on the estimation.

Table A17. **Dyadic Regression Estimates – Different Municipality, Different Microregion**

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Same Party	0.0054	0.0048	0.0061	0.0054	0.0052	0.0033	0.0049	0.0020	0.0049	0.0056	0.0070	0.0041	0.0055	0.0047	0.0036	0.0021	0.0025
	(0.0018)	(0.0017)	(0.0016)	(0.0015)	(0.0014)	(0.0012)	(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0010)	(0.0010)	(0.0010)
Different Party	-0.0002	0.0003	0.0024	0.0009	0.0012	-0.0006	0.0009	-0.0004	0.0005	0.0007	0.0018	0.0009	0.0010	0.0012	0.0013	0.0009	0.0019
	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0007)	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)
Only Worker	0.0000	-0.0002	-0.0001	0.0001	-0.0002	0.0000	-0.0002	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	0.0000	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Only Owner	-0.0002	0.0009	0.0018	0.0011	0.0004	-0.0008	0.0002	-0.0003	0.0006	0.0004	0.0011	0.0005	0.0006	0.0009	0.0009	0.0007	0.0010
	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)
Same Gender	0.0054	0.0053	0.0051	0.0048	0.0055	0.0049	0.0044	0.0039	0.0041	0.0032	0.0032	0.0030	0.0029	0.0030	0.0033	0.0031	0.0027
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Same Race	0.0003	0.0006	0.0003	0.0004	-0.0001	0.0000	0.0003	0.0002	0.0001	-0.0002	-0.0004	-0.0002	-0.0003	-0.0001	-0.0002	-0.0002	-0.0003
	(0.0004)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Same Educ	-0.0019	-0.0016	-0.0015	-0.0016	-0.0023	-0.0022	-0.0021	-0.0024	-0.0024	-0.0023	-0.0025	-0.0023	-0.0019	-0.0019	-0.0020	-0.0018	-0.0021
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Same Age	-0.0018	-0.0024	-0.0021	-0.0021	-0.0025	-0.0024	-0.0017	-0.0019	-0.0017	-0.0016	-0.0014	-0.0013	-0.0010	-0.0010	-0.0009	-0.0007	-0.0007
	(0.0004)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same-Only Worker	0.005	0.005	0.006	0.005	0.005	0.003	0.005	0.002	0.005	0.005	0.007	0.004	0.005	0.004	0.003	0.002	0.002
Same-Only Owner	0.005	0.003	0.004	0.004	0.004	0.004	0.004	0.002	0.004	0.005	0.005	0.003	0.004	0.003	0.002	0.001	0.001
Diff-Only Worker	0.000	0.000	0.002	0.000	0.001	0.000	0.001	0.000	0.000	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.002
Only Owner-Diff	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	0.000	0.000	0.000	0.000
Only Owner-Only Worker	0.000	0.001	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.001
Num Workers	313435	354555	386279	433828	509940	616416	648191	757029	859462	925416	988308	988400	886592	758372	707194	684340	696025
Num Firms	85455	93675	102443	109933	122332	140994	152026	172356	194525	207862	224548	230754	215197	192013	180908	176029	186332
Num Markets	19086	20238	21346	22575	24701	26511	27871	30120	33060	34346	35832	36645	36889	35706	35155	34425	34570

Notes: The table presents estimates from equation 3.6 for the sample of hired workers who are from a different microregion as the firm. Standard errors in parentheses are clustered by market. See section 3.2 and equation 3.6 for details on the estimation.

Table A18. **Dyadic Regression Estimates – Previously Unemployed**

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Same Party	0.0124	0.0094	0.0103	0.0092	0.0105	0.0069	0.0096	0.0085	0.0101	0.0095	0.0106	0.0093	0.0099	0.0113	0.0102	0.0077	0.0087
	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0005)
Different Party	0.0009	0.0013	0.0016	0.0014	0.0011	0.0007	0.0012	0.0011	0.0014	0.0013	0.0018	0.0018	0.0013	0.0018	0.0016	0.0012	0.0014
	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Only Worker	-0.0001	-0.0002	-0.0001	-0.0002	-0.0001	-0.0001	-0.0002	-0.0001	-0.0002	-0.0001	-0.0002	-0.0002	-0.0002	-0.0003	-0.0002	-0.0002	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Only Owner	0.0004	0.0008	0.0013	0.0010	0.0009	0.0003	0.0009	0.0010	0.0012	0.0013	0.0014	0.0014	0.0010	0.0014	0.0012	0.0009	0.0013
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Same Gender	0.0018	0.0015	0.0015	0.0014	0.0018	0.0015	0.0013	0.0011	0.0010	0.0007	0.0008	0.0008	0.0008	0.0011	0.0011	0.0010	0.0009
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Race	0.0004	0.0004	0.0004	0.0004	0.0003	0.0002	0.0003	0.0002	0.0001	0.0001	0.0000	0.0001	-0.0001	-0.0001	0.0000	0.0000	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Educ	-0.0003	-0.0005	-0.0004	-0.0004	-0.0009	-0.0008	-0.0008	-0.0010	-0.0011	-0.0010	-0.0011	-0.0012	-0.0011	-0.0011	-0.0012	-0.0012	-0.0013
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Age	-0.0008	-0.0009	-0.0008	-0.0008	-0.0011	-0.0010	-0.0007	-0.0009	-0.0008	-0.0007	-0.0006	-0.0005	-0.0004	-0.0003	-0.0002	-0.0002	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same-Only Worker	0.012	0.009	0.010	0.009	0.010	0.007	0.009	0.008	0.010	0.009	0.010	0.009	0.010	0.011	0.010	0.007	0.008
Same-Only Owner	0.012	0.008	0.009	0.008	0.009	0.006	0.008	0.007	0.008	0.008	0.009	0.007	0.008	0.009	0.008	0.006	0.007
Diff-Only Worker	0.001	0.001	0.001	0.001	0.001	0.000	0.001	0.001	0.001	0.001	0.002	0.002	0.001	0.002	0.001	0.001	0.001
Only Owner-Diff	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	0.000	0.000	0.000	0.000
Only Owner-Only Worker	0.000	0.001	0.001	0.001	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Num Workers	2076216	2344139	2446142	2505394	2777793	3074697	2734200	3361080	3375327	3193917	3256952	3110763	2482910	2180122	2419944	2563893	2700136
Num Firms	436937	470418	503131	514826	537869	582632	583614	653528	687471	682195	709209	707576	632637	580037	605758	622181	642573
Num Markets	29262	30443	31673	32635	35234	36853	37792	40199	43882	44296	45721	46316	47038	46360	46475	46059	47326

Notes: The table presents estimates from equation 3.6 for the sample of hired workers who were unemployed prior to joining the firm. Standard errors in parentheses are clustered by market. See section 3.2 and equation 3.6 for details on the estimation.

Table A19. Political Assortative Matching and Public Procurement Contracts with Local Governments

	(1) Contract	(2) Contract	(3) Value (in log)	(4) Value (in log)
Mayor	0.029**	0.032**	0.336***	0.353***
	(0.011)	(0.012)	(0.111)	(0.121)
Share Same Party		-0.006		-0.014
		(0.010)		(0.101)
Mayor X Share Same Party		0.022		0.173
		(0.023)		(0.242)
Share Diff. Party		-0.001		-0.001
		(0.005)		(0.048)
Mayor X Share Diff. Party		-0.009		-0.095
		(0.010)		(0.093)
Observations	1,720,048	1,720,048	1,720,048	1,720,048
Firm-Election FE	Yes	Yes	Yes	Yes
Period-Election FE	Yes	Yes	Yes	Yes

Notes: The table shows estimates of the relationship between owners' affiliation with the party in power at the local level, the share of the firm's workers from the same or different party of the owner, and procurement outcomes. We use data on business contracts with the local public sector for the 645 municipalities in the state of São Paulo between 2008 and 2018. We focus on the three years before and the four years after the three elections of 2008, 2012, and 2016. The variable *Mayor* is an indicator equal to one if the firm's owner is affiliated with the same party of the winning mayor. The variable *Share Same Party* is the share of the firm's workers who are affiliated with the same party of the owner. The variable *Share Diff. Party* is the share of the firm's workers who are affiliated with a different party than the one of the owner. The dependent variable is an indicator equal to one if the firm has won at least a contract in the year (columns 1 and 2) or the log value of the contracts obtained (columns 3 and 4). All regressions include firm times election fixed effects and period (since the election) times election fixed effects. Standard errors in parentheses, clustered at the firm level *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A20. **Randomization of Resume Components**

Resume Component	**Description**
Formatting	
Layout	Drawn uniformly from a set of eight formats
Personal Information	
Gender	50% male, 50% female
First name	Conditional on gender, drawn uniformly from set of 32 most popular first names in our administrative data for 2019.
Last name	Conditional on gender, drawn uniformly from set of 32 most popular last names in our administrative data for 2019.
Education	
Highest degree	Specified by participant.
High school name	State drawn uniformly from the respondent's region, school drawn uniformly from a set of five schools in the state.
College name	State drawn uniformly from the respondent's region, school drawn uniformly from top four institutions in the state.
Highest degree graduation date	Drawn from multinomial distribution, with P(2016 OR 2021) = 1/12; P(2017 OR 2020) = 1/6; P(2018 OR 2019) = 1/4.
College GPA	Randomly appears in 25% of resumes with college education; drawn from continuous *Uniform(6,10)*.
Political signal	16/20 resumes without political signal. 2/20 resumes have a work experience related to the respondent's party. 2/20 resumes have a work experience uniformly drawn from the set of opposition parties.
Work Experience	
Quantity of experiences	Drawn from discrete *Uniform(1,4)*.
Quality of experiences	3/4 (1/4) of college (high school) educated profiles are assigned high quality jobs.
Title and employer	Low quality jobs uniformly drawn from 20 job titles. High quality jobs uniformly drawn from 20 job titles.
Description of role	Number of bullet points drawn from discrete *Uniform(2,4)*.
Location	State drawn uniformly from states in the respondent's region, city drawn uniformly from three largest cities in the state.
Dates	Conditional on graduation date and number of work experiences.
Additional Experiences and Skills	
Leadership positions	One position randomly appears in 30% of resumes. Sampled uniformly from list of 11 (if political signal=0) or 6 (if political signal=1) experiences.
Complementary training	Section randomly appears in 60% of resumes (one or two experiences, with equal chance). Sampled uniformly from list of 25 (if political signal=0) or 6 (if political signal=1) experiences.
Design skills	Section randomly appears in 30% of resumes (one or two skills, with equal chance). Sampled uniformly from list of 6 skills.
Programming skills	Section randomly appears in 30% of resumes (two or three skills, with equal chance). Sampled uniformly from list of 12 skills.
Microsoft Office skills	Section randomly appears in 30% of resumes. Number of skills drawn from discrete *Uniform(2,5)*.
Language skills	Section randomly appears in 40% of resumes (one or two languages, with equal chance). English selected with 60% chance; one of four other languages selected with 10% chance. Proficiency level drawn randomly from basic/intermediate/advanced.
Hobbies	Section randomly appears in 30% of resumes. One hobby sampled uniformly from list of 11 hobbies.

Notes: The table describes the series of resume components, and how we randomize them across resumes.

Table A21. **Firm Growth**

	(1) Growth	(2) Growth	(3) Growth
Same Party	-0.071***	-0.063***	-0.076***
	(0.002)	(0.002)	(0.005)
Observations	5,452,517	5,226,092	2,399,837
FEs	SYA	SYAI	SYAIM
Mean DV	0.103	0.108	0.148
SD Same Party	0.138	0.140	0.129

Notes: The table presents estimates from estimating the equation $\text{Growth}_{ft} = \alpha_{t-1,n(f,t-1),a(f,t-1)} + \beta\text{Share Copartisan}_{f,t-1} + \epsilon_{ft}$, where Growth_{ft} is the employment growth rate of firm f in year t, defined as the difference in number of workers between year t and year $t-1$, divided by the number of workers in year $t-1$. The variable $\text{Share Copartisan}_{f,t-1}$ measures the share of workers who are copartisan of the owner of firm f in year $t-1$. We restrict the comparison to similar firms by including the vector $\alpha_{t-1,n(f,t-1),a(f,t-1)}$, which are fixed effects for firms characteristics measured in year $t-1$. Specifically, SYA (column 1) correspond to *worker-year-number of affiliated workers* fixed effects. SYAI (column 2) adds *two-digit industry* fixed effects. SYAIM (column 3) adds *municipality* fixed effects. We winsorize firm growth at the 1% of the distribution to minimize the impact of outliers. *Mean DV* and *SD Same Party* correspond to the mean of the dependent variable and to the standard deviation of the Same Party variable, respectively. Standard errors in parentheses, clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

ONLINE APPENDIX A2: DATA CONSTRUCTION

A.1 Data Description

In this paper, we combine data from the following sources: *Relação Anual de Informações Sociais-RAIS* from the former Ministry of Labor (MTE), *Cadastro Nacional de Pessoa Jurídica-CNPJ* from the *Receita Federal do Brazil* (RFB), *Cadastro Nacional de Empresas-CNE* from the former Ministry of Industry, Foreign Trade and Services (MDIC)[45], *Party Membership System-PR* and *Voter Registration* data from the Superior Electoral Court (TSE), and the dataset *Nomes do Brasil* provided by the *Brazilian Institute for Geography and Statistics (IBGE)*. In the following sections, we provide details on each of these datasets, and on how we match them to create our final dataset at the firm-owner-worker-year level, containing information on the political affiliation of owners and workers in the formal private sector labor market. The reader is encouraged to see Figure A12 for a visual representation of how the various data sources are linked.

A1.1 Data on Workers - *RAIS*. RAIS is the Brazilian linked employer-employee administrative data, which contains records from a mandatory survey filled annually by all registered firms in Brazil with at least one formal employee in the reference year. RAIS contains demographic characteristics of workers, several attributes of the employment contract (e.g., type of contract, pay, job spells, hours worked per week, etc.), characteristics of the firms (e.g., sector, location, firm identifier, etc.) and employee's occupation and education.

We construct a yearly panel dataset of workers for the period 2002–2019. The variable *natureza juridica* can be used to identify private sector employers. As workers can work for multiple firms in the same year, we select the highest paying job of an individual in a given year to create a panel at the worker-firm-year level, with one observation for each worker-year. This panel includes data on the following variables: year, CPF (the unique personal *Taxpayer Identification Number*), workers' names, firm and plant identifiers,[46] gender, date of birth, race, level of education, nationality, municipality, firm's sector of activity, worker's occupation, pay,[47] and the number of weekly hours in the contract. Unique workers' and employers' tax identifiers allow us to follow individuals over time and across firms.

[45]Currently all these three entities are under the Ministry of Economy.

[46]The variables *firmid* and *plantid* are created based on the unique establishment taxpayer identifier, *CNPJ*. The first 8 digits of the *CNPJ* are used to identify the firm (*firmid*), while the additional 4 digits are used to identify the plant of a given firm (*plantid*). Clearly, only a subset of the firms have multiple plants.

[47]We use the average monthly pay over all the months in which the individual was employed in the firm over the course of the year.

While RAIS is a rich data source covering all employees in the Brazilian formal labor market, it does not provide information on the owners of the firms. We obtain this information from the firms' registration records at the federal and state level, as discussed below.

A1.2 Data on Owners - *RFB* and *CNE*. We use two sources of data in order to gather information on business ownership in Brazil: *Cadastro Nacional de Pessoa Jurídica-CNPJ* and *Cadastro Nacional de Empresas-CNE*.

RFB Data

All firms in Brazil are required to be legally registered in the *Cadastro Nacional de Pessoa Jurídica-CNPJ* mantained by RFB to obtain the tax identifier number *CNPJ*. The raw data contain cumulative information on all the owners of currently active firms in the formal sector as of the year that we obtained the data (2019), together with the date on which firms entered/updated their information. For firms that closed before 2019, we have information on the set of owners when the firm closed (i.e., the last update). Therefore, RFB data does not allow us to identify owners who left the firm before 2019 (for firms that are active in 2019), or before the firm closed (for firms that became inactive before 2019).

Owners in RFB belong to one of three categories: Business Associates, Individual Microentrepreneurs, and Individual Entrepreneurs.[48] We observe 12,108,480 unique business associates (owning a total of 8,436,483 firms), 8,169,077 unique individual entrepreneurs (owning a total of 8,247,052 firms), and 13,522,653 unique individual micro-entrepeneurs (owning a total of 14,353,138 firms). Business Associates are owners of companies with multiple owners (known as *sociedades*).[49] Owners of smaller and single owned firms are categorized as Individual Microentrepreneurs or as Individual Entrepreneurs. The data contain different identifying information for the three categories of owners. Specifically, for Business Associates we observe the 6 central digits of the CPF and the full name; for Individual Microentrepreneurs we observe both the full CPF and the full name; for Individual Entrepreneurs we observe only the full name.

To produce a panel at the owner-firm-year level, we use information on the year of entry of each company (for Individual Microentrepreneurs, and Individual Entrepreneurs) or the year in which an owner joins the firm as a Business Associate. In addition, for firms that have closed before 2019, we infer the year of exit based on the year in which the firm changes its status to "closed." Based on these years of entry/exit for each owner-firm, we expand the data to obtain a panel at the owner-firm-year level, where each individual appears as

[48]The data also contains information on corporate owners. Given the focus of the paper, we disregard these owners.

[49]See the list of *naturezas juridicas* of these firms at https://www38.receita.fazenda.gov.br/cadsincnac/jsp/coleta/ajuda/topicos/Tabela_IV_-_Natureza_Juridica_Quadro_de_Socios_e_Administradores.htm.

owner of a firm in all years between entry and exit over the 2002–2019 period. Each firm is identified by its *CNPJ*, and each owner is identified by a combination of CPF and/or full name.

The RFB contains an additional residual group of firms for which we have no identifying information on their owners. This residual group comprises a small share (8.87%) of observations, and its relevance decreases over time (from 19.66% of all owners in 2002 to 4.21% of all owners in 2019). The data from the Cadastro Nacional de Empresas-CNE described in the next section can be used to obtain information also on this set of owners.

CNE Data

On top of being legally registered at the federal level (in RFB), all companies in Brazil are also required to obtain permission to operate at the state level through their local *Juntas Comerciais*. Our second source of data on owners come from *Cadastro Nacional de Empresas* (CNE), and includes ownership information collected from each Brazilian state. The data contains information on firm identifiers (CNPJ), their owners' identifier (CPF) and full name, and dates of entry/exit of the firms and their owners. We use this information to construct a second panel at the owner-firm-year level between 2002 and 2017 (i.e., the year in which we obtained the data). We use this source to complement the panel from RFB for cases in which owners' information is missing in RFB, as well as to retrieve information on owners' full CPF when this is not fully reported in RFB.

A1.3 Data on Party and Voter Registration - *TSE* Data TSE Party Registration data provide us information on the universe of individuals who have ever been affiliated with any political party in Brazil over the 2002-2020 period.[50] For each record, we know the name of the affiliated individual, the voter registration number (which is the TSE's unique personal identifier), the municipality of affiliation, and the party to which the individual is affiliated. The data also records the specific dates of registration/de-registration of each individual, which we use to expand the data to obtain a panel at the individual-year level, where each individual appears as registered with a specific party in all years between registration and de-registration with that party over the 2002-2020 period.

We complement the party registration data with a second dataset from TSE, which contains information on the universe of individuals registered to vote in Brazil.[51] The dataset includes the voter registration number, and the individual's date of birth and gender. We match this data to the party registration data using the voter registration number in order

[50]We downloaded the data from the TSE website (https://english.tse.jus.br/ in Feb of 2021. As of March 2022, the data is no longer publicly available.

[51]We obtained access to this data via FOIA-like request to TSE.

to retrieve information on date of birth and gender for all individuals who are registered to a party.

A1.4 Data on Gender - *IBGE* Data Finally, we use auxiliary data to assign a gender to first names. We do this for all owners who do not appear in RAIS or in the party registration data (as described below). We use the *Nomes do Brasil* dataset from IBGE, which includes the list of all first names appearing in the Brazilian 2010 census, with the indication of how many males and females have each name. We classify a first name as male (female) in all cases in which at least 95% of Brazilians with that first name in *Nomes do Brasil* are males (females). Since first names in Brazil are usually single-gender, this list can be used to assign a gender to a first name in the almost totality of cases.

A.2 Matching RFB-CNE-RAIS-PR Data

This section details all the steps implemented to combine the datasets described in the previous section.

A1.1 Matching RFB and CNE As a first step, we combine the RFB and CNE panels. We consider RFB as the primary source of owners' information, since the CNE data contain a smaller number of firms, presumably due to imperfect data maintenance by *Juntas Comerciais*. Nevertheless, data from CNE is useful to complement RFB for multiple reasons. First, since RFB contains only a snapshot of the data as of 2019, we can use CNE to obtain information on owners who left a firm before 2019 (or before the firm closed). Second, we can use CNE to look for the owners of the 9.65% of firms without owners' identifying information in RFB. Third, since we observe both CPF and full name for all owners in CNE, we can assign the full CPF to the owners in RFB for which we do not observe the CPF, or for which we observe only its 6 central digits.[52]

We combine the two datasets by first implementing a fuzzy matching by owner's name (with a precision cutoff of 0.95), while requiring the CNPJ firm identifier to match perfectly.[53] Since we require a perfect match by CNPJ, this works essentially as a perfect matching, dealing only with slight differences in owners' name reporting across the two datasets. If a firm in CNE is not found in RFB in a given year (so that there is no owner associated with that firm in RFB for that year), we append the CNE observations to the RFB panel. We refer to the final panel as the RFB-CNE panel.

[52]In addition, in some cases the names in RFB are reported in abbreviated form, while CNE reports the full, unabbreviated name. For these cases, we also update owners' information with their most accurate version of the full name.

[53]We implement this fuzzy matching, as well as all the fuzzy matching steps described in the next sections, using the Stata command *reclink*.

A1.2 Matching RFB-CNE to RAIS We first match firms in the RFB-CNE panel to firms in RAIS by CNPJ. We find at least one owner for 96.42% of firms in RAIS. We discard all the firms in RFB-CNE which do not appear in RAIS, and thus have never employed a worker over the entire 2002–2019 period.

Next, we match individuals in the RFB-CNE panel to individuals in RAIS. This step identifies owners who also appear as workers (either of their own firm or of another firm) at some point over the 2002–2019 period. We implement the following five rounds of matching, with each individual entering a matching step only if not already matched in previous steps:

- Step 1: perfect matching by full CPF (for the owners with full CPF)
- Step 2: perfect matching by name and six digits of the CPF (for the owners with at least 6 digits of the CPF)
- Step 3: fuzzy matching by name (with a precision cutoff of 0.995), requiring a perfect match by six digits of the CPF (for the owners with at least 6 digits of the CPF)
- Step 4: perfect matching by name and municipality
- Step 5: fuzzy matching by name, requiring a perfect match by municipality and by the first letter of the name (with a precision cutoff of 0.995)

We obtain a final matching rate of 58.96%. Out of matched owners, we match 59.11% of owners in step 1, 20.59% of owners in step 2, 2.87% of owners in step 3, 2.91% of owners in step 4, and 14.53% of owners in step 5, For these owners, we can recover all the demographic information contained in RAIS (e.g., gender, date of birth, race, education). In particular, information on date of birth will be useful to match owners to the party registration data, as described in the next section.

Our final RFB-CNE-RAIS dataset is a panel at the firm-owner-worker-year level for the 2002–2019 period. For each firm (identified by a CNPJ) and year, we have information on its workers (identified by CPF and full name) and its owners (identified by full or partial CPF and/or full name). Owners without a full CPF are assigned a unique personal identifier on the basis of six-digits CPF and full name (this is the case for 13.35% of owners in the data), or, when no information on CPF is available, on the basis of full name and municipality (this is the case for 5.4% of owners in the data).

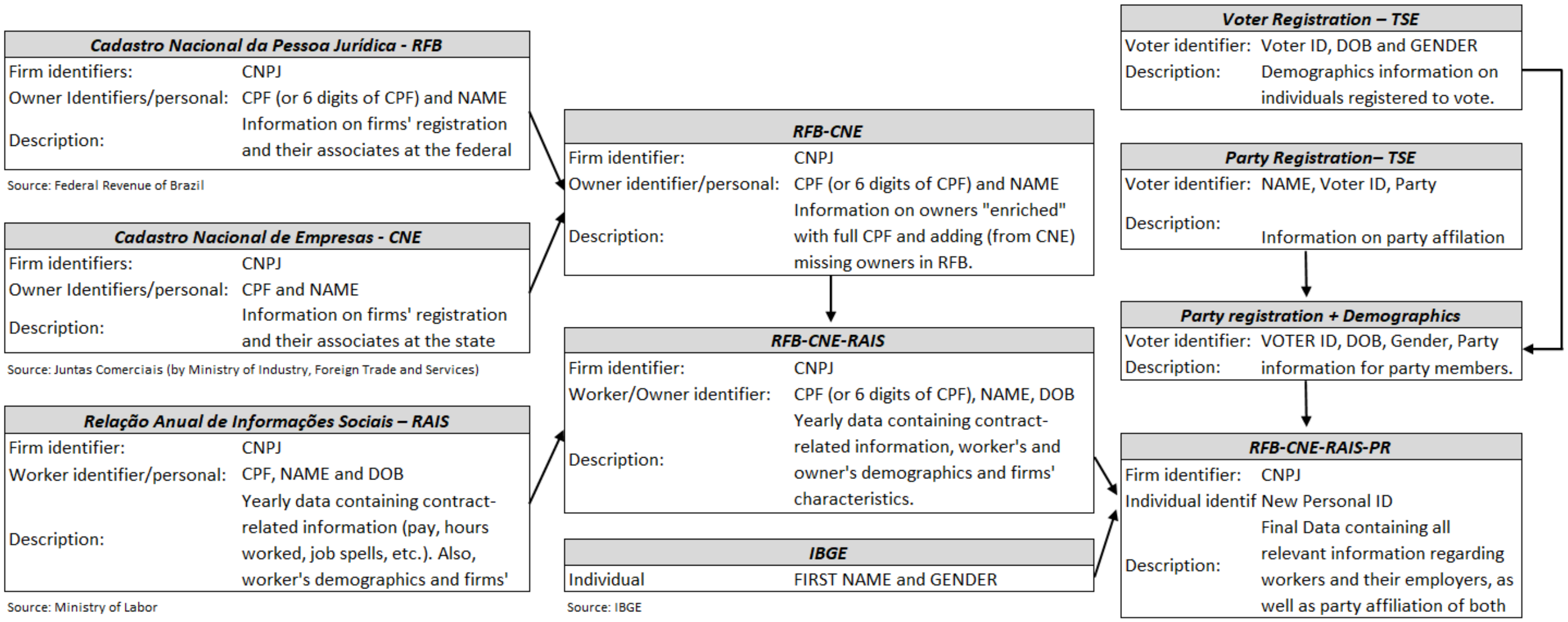
A1.3 Matching owners and workers to party registration data Finally, we match workers and owners to the party registration data (which, after having been matched to the TSE data on voters' registration, contain also information on gender and date of birth of party affiliates). We perform the following 15 steps of matching, with each individual entering a matching step only if not already matched in previous steps:[54]

[54]While all steps can potentially be performed for all workers, the same is true only for owners with information on date of birth (i.e., the 58.96% of owners who have been matched to RAIS), while the remaining ones can be matched only in steps 12 and 13.

- Step 1: perfect by name - year of birth - month of birth - day of birth - municipality (matching rate: 50.05%)
- Step 2: perfect by name - year of birth - month of birth - day of birth - state (matching rate: 22.18%)
- Step 3: perfect by name - year of birth - month of birth - day of birth (matching rate: 5.50%)
- Step 4: perfect by name - year of birth - month birth - municipality (matching rate: 0.51%)
- Step 5: perfect by name - year of birth - day birth - municipality (matching rate: 0.39%)
- Step 6: perfect by name - month of birth - day birth - municipality (matching rate: 0.37%)
- Step 7: perfect by name - year of birth - month birth - state (matching rate: 0.57%)
- Step 8: perfect by name - year of birth - day birth - state (matching rate: 0.31%)
- Step 9: perfect by name - month of birth - day birth - state (matching rate: 0.62%)
- Step 10: perfect by name - year of birth - municipality (matching rate: 0.86%)
- Step 11: perfect by name - year of birth - state (matching rate: 1.39%)
- Step 12: perfect by name - municipality (matching rate: 4.96%)
- Step 13: perfect by name - state (matching rate: 3.95%)
- Step 14: fuzzy by name (with a precision cutoff of 0.995), requiring a perfect match by year of birth - month of birth - day of birth - municipality (matching rate: 5.54%)
- Step 15: fuzzy by name (with a precision cutoff of 0.995), requiring a perfect match by year of birth - month of birth - day of birth - state (matching rate: 2.78%)

Our final matching rate is 11.49%. For owners who have not been matched to RAIS, we recover information on gender from the party registration data; for the subset of owners who have not been matched to RAIS and have not been matched to party registration data, we recover information on gender from *Nomes do Brasil*.

FIGURE A12. Visual representation of the linkage structure



ONLINE APPENDIX A3: WORKER'S PHONE SURVEY

(1) Are you currently employed?
- Yes
- No

(2) We are interested in finding out how Brazilian workers generally find their jobs. Think about the last job you got. Could you describe how you found the job?
- *Open ended*

(3) A recent study states that business owners tend to hire employees with similar political views. What do you think this might be happening?
- *Open ended*

(4) It is easier for employer and employee to work well together if they share the same political views.
- Totally disagree
- Partially disagree
- Neither agree nor disagree
- Partially agree
- Totally agree

(5) Why do you think this?
- *Open ended*

(6) Some bosses don't like to have people with different political views around, even if it doesn't hinder performance at work.
- Totally disagree
- Partially disagree
- Neither agree nor disagree
- Partially agree
- Totally agree

(7) Why do you think this?
- *Open ended*

(8) Business owners generally interact more with people of similar political views, so it's easier to know if they would be better suited to work at the company.

(9) Why do you think this?
- *Open ended*

(10) If an owner is part of a political party, the party will contact them to indicate affiliates to work in his company.
- Totally disagree
- Partially disagree

- Neither agree nor disagree
- Partially agree
- Totally agree

(11) Why do you think this?
- *Open ended*

(12) Workers do not want to work in companies where the owners have different political views than their own.
- Totally disagree
- Partially disagree
- Neither agree nor disagree
- Partially agree
- Totally agree

(13) Why do you think this?
- *Open ended*

(14) I would like to know about your experience as a worker. Have you ever gone through any situation where the political vision of an entrepreneur influenced your daily work?
- Yes, situation has occured.
- No, situation has never occured.

(15) When you need to accept or decline a job offer, do you consider the business owner's political views?
- Yes, considers owner affiliation important
- No, does not consider owner affiliation important

(16) And about the political views of your future coworkers? Do you take this into account before accepting or rejecting a job offer?
- Yes, considers future coworker affiliation important
- No, does not consider future coworker affiliation important

(17) What is the field of activity of the company you work for (last company you worked for)?
- Agriculture/ Mining/ Manufacturing/ Construction
- Transport/ Communications/ Services
- Commerce

(18) How many employees does the company you work (last worked) for have (had)?
- *Open ended - numeric*

(19) What gender do you identify as?
- Female
- Male

(20) How old are you?

- *Open ended*

(21) What is your schooling background?
- Elementary school incomplete
- Elementary school complete
- High school incomplete
- High school complete
- Higher education complete
- Post-graduate complete

(22) In which city is your main residence?
- *Open ended*

(23) In which state is your main residence?
- *Open ended from list of Brazilian states*

(24) In which region is your main residence?
- North
- North-east
- Central-west
- South-east
- South

ONLINE APPENDIX A4: OWNER'S PHONE SURVEY

(1) Do you work in a private company, in the public sector, on your own or are you a businessman?
- Private firm
- Public sector
- Business owner

(2) We are interested in finding out how Brazilian entrepreneurs manage to hire new employees. Thinking about the last three employees hired by your company, what was the method used for selection?
- *Open ended*

(3) A recent study states that business owners tend to hire employees with similar political views. Why do you think this might be happening?
- *Open ended*

(4) It is easier for employer and employee to work well together if they share the same political views.
- Totally disagree
- Partially disagree
- Neither agree nor disagree
- Partially agree
- Totally agree

(5) Why do you think this?
- *Open ended*

(6) Some bosses don't like to have people with different political views around, even if it doesn't hinder performance at work.
- Totally disagree
- Partially disagree
- Neither agree nor disagree
- Partially agree
- Totally agree

(7) Why do you think this?
- *Open ended*

(8) Business owners generally interact more with people of similar political views, so it's easier to know if they would be better suited to work at the company.
- Totally disagree
- Partially disagree
- Neither agree nor disagree

- Partially agree
- Totally agree

(9) Why do you think this?
- *Open ended*

(10) If an owner is part of a political party, the party will contact them to indicate affiliates to work in his company.
- Totally disagree
- Partially disagree
- Neither agree nor disagree
- Partially agree
- Totally agree

(11) Why do you think this?
- *Open ended*

(12) Workers do not want to work in companies where the owners have different political views than their own.
- Totally disagree
- Partially disagree
- Neither agree nor disagree
- Partially agree
- Totally agree

(13) Why do you think this?
- *Open ended*

(14) Finally, I would like to know about your experience as an entrepreneur. Do you think that the political views of a potential employee of your company can make any difference in your decision to hire?
- *Open ended*

(15) What is your field of work?
- Agriculture/ Mining/ Manufacturing/ Construction
- Transport/ Communications/ Services
- Commerce

(16) How many employees does your company currently have?
- *Open ended - numeric*

(17) Their oldest company is how many years in the market?
- *Open ended - numeric*

(18) What gender do you identify as?
- Female
- Male

(19) How old are you?
- *Open ended*

(20) What is your schooling background?
- Elementary school incomplete
- Elementary school complete
- High school incomplete
- High school complete
- Higher education complete
- Post-graduate complete

(21) In which city is your main residence?
- *Open ended*

(22) In which state is your main residence?
- *Open ended from list of Brazilian states*

(23) In which region is your main residence?
- North
- North-east
- Central-west
- South-east
- South

ONLINE APPENDIX A5: EXPERIMENTAL SURVEY

Introduction

Following up on our call, welcome to the questionnaire that offers 10 resumes of young talented individuals in your area in exchange for your participation!

The questionnaire asks you to think about the vacancy you want to fill and evaluate 20 hypothetical resumes, so our platform can suggest the best resumes for you!

We ask that you evaluate the resumes on two axes:
1. Given that the candidate wants to work in the position you have in mind, how interested would you be in hiring?
2. Given that you want to hire the candidate for the position, how interested do you think the candidate would be in being hired?

By clicking NEXT, you can start.

The survey will take approximately 15 minutes to complete.
All your responses will be kept strictly confidential in accordance with LGPD standards.
If you are interested, the aggregate results and implications of this study can be shared with you!

Filtering Questions

Filtering question 1:
To sort for relevant CVs, we will also need to know geographic information about your firm. In case your firm is spread across Brazil, please identify the most relevant location.
What region is your firm located in?

- North
- North-east
- Mid-west
- South-east
- South

Filtering question 2A:
You may not be hiring right now but you may well need to hire someone soon. For the

questionnaire, it is important you have a position (or a set of positions) in mind when evaluating resumes.

What level of education would you be looking for in the candidate?

- Complete high school
- Complete higher education

Filtering question 2B:

(Shown only for participants who selected Complete Higher Education in Filtering question 2A)

What undergraduate courses education would you be looking for in the candidate?

- Business, economics, and accounting
- Engineering, computer science, mathematics, and statistics
- Law
- Others (humanities, other social sciences, and natural sciences)

Resume Ratings

Now come the 20 hypothetical resumes!

When evaluating the resumes, we will ask that you think not just like an owner but also like a job candidate. We want to know your interest in each candidate and the candidate's interest in your firm. This is very important, since it will help us find the best matches for your firm.

How to evaluate the resumes:

1. Your interest in the applicant: imagine that there was a guarantee that the applicant would accept your job offer, and just think about your interest in the candidate.
2. The candidate's interest in employment: imagine that the candidate knew that you would hire him or her, and just think about your perception of the candidate's interest.

Note that:

1. The progress tab will not change until you complete this step.
2. There are 20 resumes, so this session will take about 10 minutes!

(20 resumes shown. After seeing each resume, the respondent answers the following two questions)

How interested would you be in hiring this candidate?

- I would never hire the candidate
- Very low interest
- Low interest
- Average interest
- High interest
- Very high interest
- I would certainly hire the candidate

How interested do you think this candidate would be in the job?

- The candidate would never accept
- Very low interest
- Low interest
- Average interest
- High interest
- Very high interest
- The candidate would certainly accept

Additional question:
Please provide the best email below to receive the resumes from the algorithm.
*Given the nature of the algorithm and the state of the search, we will contact you when (1) there are enough responses for the algorithm to work well or (2) by April 30, 2022.

Additional question:
Thank you for completing our survey!
We are always looking to improve our surveys and would love to receive some feedback. Feel free to make whatever comments, criticisms, etc. you may have in the box below.