POLITICS AT WORK

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Abstract. We study how individual political views shape firm behavior and labor market outcomes. Using new micro-data on the political affiliation of business owners and private-sector workers in Brazil over the 2002–2019 period, we first document the presence of political assortative matching: business owners are significantly more likely to employ copartisan workers. Political assortative matching (which has been rising over time) is larger in magnitude than assortative matching along gender and racial lines (which have been decreasing over time). We then provide three sets of results consistent with the presence of employers' political discrimination. First, we conduct an incentivized resume rating field experiment showing that owners have a direct preference for copartisan workers opposed to workers from a different party. Second, several patterns in the micro-data and an event study are consistent with a discrimination channel. Third, we conduct representative large-scale surveys of owners and workers revealing that labor market participants view employers' discrimination as an important explanation behind our findings. We conclude by presenting evidence suggesting that political discrimination in the workplace has additional real implications: copartisan workers are paid more and are promoted faster within the firm, despite being less qualified; firms displaying stronger degrees of political assortative matching grow less than comparable firms.

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1 Introduction

Partisan affiliation is considered an important element of an individual's social identity (Green et al., 2002). While it is uncontroversial that partisanship drives personal policy preferences, the extent to which it has real effects in apolitical domains and upon market decisions remains an issue at the center of public and academic discourse (Iyengar et al., 2019). In this paper we study whether partisanship impacts a crucial institution, namely the labor market. While "no politics at work" has long been a standard policy among corporations around the world, there is a heated debate regarding whether firms discriminate along political lines, i.e., whether they consider individual political views when hiring or more broadly when managing their workforce.[1]

Despite the potential economic implications of mixing politics and work, a dearth of comprehensive micro-data has made it challenging to study how individual political views shape firm behavior and labor market outcomes, and specifically to identify the presence of political discrimination. 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 business owners and private-sector workers in Brazil, a field experiment, and an original representative large-scale survey of both workers and owners. This allows us to (a) quantify partisanship as a determinant in worker-firm sorting and within-firm careers, and (b) isolate the role of political discrimination.

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 on the identity of all business owners, which we obtain through a mix of public and confidential business registration records. We then merge both workers and owners with the registry of politically affiliated individuals maintained by the Superior Electoral Court. In the Brazilian system, party affiliation can be considered as a signal of strong and visible political views. 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

[1] See, for example, Managing a Polarized Workforce (Harvard Business Review, March-April 2022), and Why Did Facebook Fire a Top Executive? Hint: It Had Something to Do With Trump (The Wall Street Journal, November 2018).

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.[2] 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 politics is a considerably larger driver of assortative matching between workers and firms than gender or race, patterns which we also document in the data. Given the major role discrimination and segregation by 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 the mechanisms behind our findings. Our goal is to show that the new facts we document are at least in part driven by firms' political discrimination, an aspect at the center of the public and academic debate but that remains difficult to isolate empirically due to the presence of various confounders. We provide three sets of results that, taken together, point to the presence and relevant role of political discrimination in the labor market.

As our first and most direct step to isolate political discrimination in hiring, we conduct 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 that 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

[2]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.

are incentivized to truthfully rate resumes because, on the basis of a machine learning algorithm, we will send respondents resumes of real job seekers matching their revealed preferences upon survey completion. 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 identifies the presence of political discrimination while muting alternative channels.

As a second step, we leverage the richness of our administrative micro-data to probe the external validity of our experimental evidence. Indeed, while our experiment shows that political discrimination is at play, it is plausible that the large magnitudes of political assortative matching we documented earlier are attributable to other mechanisms, such as patronage or overlapping political and social networks. We therefore conduct a battery of empirical tests aimed at testing whether patterns in the full micro-data are consistent with a discrimination channel. First and consistent with discrimination being more relevant in settings with a higher degree of owner-worker personal interactions, we find a significantly stronger political assortative matching in smaller firms, for workers at higher levels of the organizational hierarchy, and for workers in highly social positions requiring strong interpersonal relationships. Second, political assortative matching is not stronger for parties in power at the local or state level, which is inconsistent with the patronage view that powerful parties push business owners to hire copartisans (Bertrand et al., 2018). Third, we find a sharp change in the political composition of the workforce when an owner switches party. In line with owners' change in political preferences, we document a sharp increase in hiring probability for workers of the new party and a corresponding sharp decrease for workers of the old party. To the extent that social networks that might overlap with political ones are not suddenly erased at the time of party change, this provides evidence of political discrimination playing a relevant role.

As a third and final step to shed light on the relevance of political discrimination compared to other potential mechanisms, we present 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. The survey asks respondents to evaluate potential mechanisms behind the findings in a "recent study" (i.e., our findings). Specifically, we state: "A recent study reports that business owners tend to hire workers with similar political views."

We then ask respondents to express their views, independently of their own personal experience. Both business owners and workers believe that employers' direct preferences for hiring copartisans—either because of taste-based discrimination or because of belief-based discrimination (as they believe that copartisans would be more productive workers)—are the primary drivers of our findings. While respondents also argue that social networks might play an important role, they largely dismiss alternative explanations. Interestingly, these patterns are similar across owners and workers, and seem largely independent of the political affiliation status of the respondent. Finally, 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.

Taken together, while we do not aim to rule out other likely important mechanisms, the evidence points to employers' political discrimination driving at least part of the pervasive political assortative matching that we document in the Brazilian labor market.

We conclude by providing evidence that political discrimination does not only affect the sorting of workers and firms, but has additional real economic implications. We first show that copartisans of the owner enjoy favorable treatment in the workplace. First, we find 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. Second, we document the presence of 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. Importantly, and again consistent with the presence of political discrimination in the workplace, workers of a different party suffer a substantial wage penalty. These patterns hold true even within narrowly defined occupational groups within the same firm and controlling for a large set of socio-demographic characteristics.[3] Despite their better within-firm outcomes, we show that copartisans are less qualified than other workers in the firm, as measured by their education level relative to what is required by their specific occupation. While we cannot observe whether copartisans are more productive along other dimensions, we provide suggestive evidence that firms displaying a larger degree of worker-owner matching along political lines grow less than other comparable firms. This is in line with a key theoretical prediction of Becker (1957)'s model of "taste-based" discrimination, and echoes recent evidence by Kline et al. (2021) that the extent of racial discrimination by U.S. firms is negatively correlated with profitability.

Our findings contribute to three broad strands of literature. First and foremost, we speak to the recent growing literature on the importance of politics in economic realms, which focuses almost exclusively on the Republican-Democrat divide in the U.S. (see Iyengar et al. (2019)

[3]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.

for a review and Boxell et al. (2020) for cross-country evidence). 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), and loan pricing (Dagostino et al. (2021)). A few studies focus on the role of partisanship in labor markets. 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 in 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 political polarization of top executives of U.S. listed firms.[4] Our paper contributes to this body of work by bringing to the table extremely detailed micro-data combined with new firm-level experimental and survey evidence. This allows us to provide comprehensive evidence that individuals' political views do affect real labor market outcomes and, crucially, to isolate political discrimination as a relevant mechanism. To our knowledge, ours is the first paper matching administrative registries of workers, firms, owners, and party members. An important advantage of these data is that they allow us to estimate precise economic magnitudes and to show that these magnitudes are economically meaningful by benchmarking them with well-established determinants of labor market outcomes, namely race and gender.

Second, 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. A large body of empirical work has relied on a combination of experimental and quasi-experimental evidence to investigate the role of employers' discrimination in hiring and compensation decisions.[5] A number of recent papers focus specifically on the matching between employers' and workers' race or gender,

[4]A separate literature analyzes the role of politics in the public sector labor market (see Finan et al. (2017) for a review, and Colonnelli et al. (2020), Spenkuch et al. (2021), and Akhtari et al. (2022) as recent examples). In addition, a number of studies focus on the careers of politicians or the connections of workers to politicians through family or corporate ties (e.g., Cingano and Pinotti (2013), Fafchamps and Labonne (2017), Folke et al. (2017), Bertrand et al. (2018), and Gagliarducci and Manacorda (2020)).

[5]See, among many others, Altonji and Pierret (2001), Bertrand and Mullainathan (2004), Black et al. (2006), Fryer et al. (2013), Glover et al. (2017), and Hoffman et al. (2018). Altonji and Blank (1999) provides an overview of earlier work, while Bertrand and Duflo (2017) and Baert (2018) discuss the experimental literature on discrimination. Kline and Walters (2021) and Kline et al. (2021) are two recent studies on labor market discrimination identified through correspondence field experiments.

showing their relevance for hiring and promotions.[6] While these papers mostly rely on data from specific large firms, our paper quantifies the relevance of shared gender and race between employers and employees using large-scale administrative owner-worker matched data, while highlighting how the partisanship of employers and employees may represent an additional distinct, quantitatively important source of labor market discrimination and segregation.

Third, we speak to the literature on the role of social incentives in the workplace (Ashraf and Bandiera, 2018). This literature investigates the role of social preferences among co-workers (Bandiera et al., 2005; Mas and Moretti, 2009; Alfridi et al., 2020), towards the employer (Gneezy and List, 2006; Della Vigna et al., 2022), or across the hierarchy (Bandiera et al., 2009) as drivers of effort and organizational performance.[7] 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). We contribute to this body of work by documenting how employers discriminate in favor of copartisan workers in hiring, promotion, and compensation decisions across the entire occupational hierarchy, finding evidence for both political in-group bias and out-group animosity. While we cannot directly observe whether political assortative matching results in higher productivity on the job, we show that copartisan workers are less likely to be qualified for their position, and that firms with more copartisan workers grow less than comparable firms.

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 of mechanisms. Section 5 discusses additional real costs associated with partisanship in the firm. Section 6 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 individuals registered over time with a political party as well as voter registration records are drawn from

[6] Examples of worker-manager matching include Giuliano et al. (2009), Giuliano et al. (2011), Kunze and Miller (2017), Benson et al. (2019), and Cullen and Perez-Truglia (2019). 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.

[7] 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).

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 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.[8] 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.[9] 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).[10]

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 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

[8]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.

[9]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.

[10]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).

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.[11]

2.3 Party Membership Data on all individuals registered as members of a Brazilian political party come from the Tribunal Superior Eleitoral (TSE).[12] 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 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

[11]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.

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

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.[13]

After RAIS is augmented with the ownership information, we match all workers and owners appearing in RAIS to the party registration dataset.[14] 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.[15] 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.

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 0.865 managers per firm), and the median

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

[14]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.

[15]If a firm has multiple owners we assign to the firm the partisan affiliation of the majority of its owners.

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 compares affiliated and unaffiliated workers and business owners 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 2 we show how owners and different types of 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.[16]

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 upon being hired.

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

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

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.[17] 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.

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:

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

[17]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.

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

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

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 3. 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.[18] 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. 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 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)* $\Delta(OO, DP) = \beta^{OO} - \beta^{DP}$,

[18] 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.

namely the extent to which a politically affiliated owner employs unaffiliated workers rather than workers of a party different from her own.[19]

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.[20] 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.[21]

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 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.[22]

We present the results graphically in Figure 4. The top panel shows estimates and 95% confidence intervals of $\Delta(SP, DP)$, $\Delta(SP, OO)$, and $\Delta(OO, DP)$, normalized by the sample

[19] Equivalently, $\Delta(SP, DP)$ can be decomposed as the sum of $\Delta(SP, OW)$ (the extent to which a politically affiliated worker is employed by an owner of her same party rather than by an unaffiliated owner) and $\Delta(OW, DP)$ (the extent to which a politically affiliated worker is employed by an unaffiliated owner rather than by an owner of a different party).

[20] 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.

[21] In the Appendix we present a version of the results without including the set of indicators SX'_{if} (Appendix Figure A3) and one where we include only the indicator for shared gender between worker and owner (Appendix Figure A4). 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 A5 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}.

[22] 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.

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 4. 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 4, 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.

3.3 Hiring, Tenure in the Firm, and Political Affiliation The significant political assortative matching between workers and business owners that we document above might be driven both by owners' higher propensity to hire copartisans and by a lower probability that copartisans leave the firm upon being hired.

To disentangle these effects, we first estimate a version of the dyadic regression 3.6 where we focus only on newly hired workers, defined as workers who are employed in a firm in year t and who were not employed in that firm in year $t-1$. 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. We present the results graphically in Appendix Figure A6. The estimates 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%. As shown in Panel B, 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.

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 characteristic 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.

We present the results in Table 2. The estimates in column 1 show that workers who are affiliated with the same party as the owner stay in the firm about 10% longer than those who are affiliated with a different 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: relative to co-workers who were hired in the same year and are affiliated with a different party than the owner, workers who are copartisans of the owner stay in the firm 5.5% longer.

[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.

[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.

In sum, we observe a large degree of political assortative matching in the market, driven both by a higher likelihood of copartisans being hired and by a longer duration of the match between copartisan owners and workers.

4 Identifying Political Discrimination

This section provides evidence that political discrimination is a relevant driver of political assortative matching in the labor market. Business owners might express a direct preference in favor of copartisans because of belief-based or taste-based discrimination. In the former case (Phelps, 1972; Arrow, 1973), employers hold the belief that copartisan workers are more productive, potentially because sharing partisan affiliation leads to better employee-employer collaboration and lower intra-firm conflict. In the latter case (Becker, 1971), employers have a personal taste in favor of employing copartisans in their firm, independent of productivity considerations.

There are two main alternative explanations that might, at least in part, drive the political assortative matching patterns we document in the previous section. One is a political patronage mechanism: political parties might leverage their connections to business owners to push them to hire party members. According to this mechanism, business owners do not exhibit direct preferences in favor of copartisans, but they are more likely to employ them in order to please powerful politicians (Bertrand et al., 2018). A second, 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 who share the same social network (e.g., copartisans also support the same soccer team and therefore interact in the same social circle).[25]

Our goal in this section is not to disprove that political patronage and overlapping social and political networks play a role in driving political assortative matching. Instead, we aim to provide evidence that employers' political discrimination is one of the relevant mechanisms driving employers' choices. We do so in three ways.

Our most direct test of political discrimination is presented in section 4.1. We partner with a leading job platform in Brazil to conduct a field experiment in which business owners evaluate synthetic resumes containing political signals. In this context where all else is held fixed, we find that owners express a preference for copartisan workers opposed to workers from a different party.

Second, in section 4.2, we exploit the richness of our micro-data to show several patterns consistent with political discrimination. Specifically, we show that: (i) assortative matching

[25]Notice however that several standard networks channels are shut down by the fact that our estimates in Section 3 are obtained within extremely narrow labor markets featuring a large number of municipality-industry cells, and by controlling (in the dyadic regression analysis) for several standard assortative criteria—education, age, gender, race—that also likely proxy for a number of shared social networks.

is higher the higher the on-the-job personal interactions, by showing how our main estimates vary across the firm size distribution and across occupations; (ii) assortative matching does not depend on the political strength of the party at the local or state level; (iii) in an event study framework, owners' change of party is accompanied by a sharp change in the hiring patterns of their firms.

Third, in section 4.3, we present results from an original representative survey where we directly ask business owners and workers to evaluate the plausibility of various mechanisms behind our findings.

4.1 Incentivized Resume Rating Field Experiment We provide direct evidence that business owners discriminate in favor of copartisan workers in employment decisions using a field experiment conducted in collaboration with a leading job platform in Brazil (whose identity we agreed to keep anonymous). The key advantage of this approach is that it allows us to isolate the role of political discrimination by shutting down alternative forces that might contribute to political assortative matching.

4.1.1 ***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 recent methodology by (Kessler et al., 2019), recently adopted in a number of other matching contexts.[26] The experimental design features employers' ratings of job-seekers' resumes while avoiding deceiving respondents. Specifically, business owners who are recruited 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 and trusted Brazilian employee-employer match-making platform to send our subjects resumes of real job seekers 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.[27] 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.

4.1.2 ***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

[26]See, for example, Colonnelli et al. (2022) in the context of assortative matching among investors.
[27]Respondents are also provided a standard compensation for time spent on the survey that is regularly provided by our survey company.

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.[28] 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 the Appendix.

4.1.3 ***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 A14 describes in detail the set of characteristics that we randomly vary across resumes.

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.[29]

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

[28]Both this survey and the one described in Section 4.3 were conducted by the Brazilian survey company OPUS Institute (`https://www.opuspesquisa.com/`).

[29]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.

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.[30] 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."[31] 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 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.

[30]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).

[31]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."

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

$$V_{ij} = \alpha_i + \beta SameParty_{ij} + X_j\theta + \epsilon_{ij} \tag{4.1}$$

where V_{ij} is employer i's interest in resume j on the discrete 1-to-7 Likert scale. Our regressor of interest, $SameParty_j$, 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.[32]

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, the results from our experiment identify a direct preference of business owners for workers who belong to their same party, while shutting down any channel that might link the employment decision to either a shared nonpolitical network or a political patronage explanation.

4.2 Evidence from the Administrative Micro-data We leverage the richness of our administrative micro-data to probe the external validity of our experimental evidence. Indeed, while our experiment shows that political discrimination is at play, it is plausible that the large magnitudes of political assortative matching we documented in Section 3 are attributable to other mechanisms, such as patronage or social networks. We therefore conduct a battery of empirical tests aimed at testing whether patterns in the full micro-data are consistent with a discrimination channel.

[32] The 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.

4.2.1 ***Political Assortative Matching is Stronger the Higher the On-the-job Personal Interaction*** A key prediction of political discrimination is that assortative matching would be stronger in settings where owners and workers interact more directly. This prediction follows both from taste-based discrimination, as owners' preferences should play a larger role the more they expect to be in contact with the worker, and from belief-based discrimination, as in settings with higher personal interactions we expect partisan homogeneity to have a stronger effect on firm productivity. To investigate this hypothesis, we report in Figure 5 the estimates from our dyadic specification 3.6 for different subsamples of the data.

Since personal interactions between owner and worker are likely more frequent in smaller firms, 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 equation 3.6 separately for the sample of workers employed in managerial occupations, in white-collar occupations, and as blue-collar workers. We find that political assortative matching increases monotonically in the hierarchical layers of the organization, with the effects being significantly larger for workers employed in managerial roles, and smaller, although still large, for white-collar and blue-collar workers. These results are consistent with partisanship being more important for workers who work more closely with the firm's owner.

To further characterize how our matching patterns depend on the degree of personal interaction, we rely on the granular occupational data we observe in RAIS. We match the occupation data from the CBO (Classificacao Brasileira de Ocupacoes) Brazilian classification to the O*NET data on occupational descriptions and categorizations.[33] The O*NET classification allows us to classify jobs based on the degree of *social skills* or *interpersonal relationships* involved and/or required by the specific occupation. 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.

[33]See https://www.onetonline.org/.

Analogous to social skills, we classify a job as above or below median in terms of interpersonal relationships required. In Figure 5, Panel C and D, we report the estimates of our dyadic equation 3.6 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.

4.2.2 ***Political Assortative Matching is Not Stronger for More Powerful Parties***

A prediction of a mechanism of political discrimination is that employers, not political parties, are the driving force of political assortative matching. In light of this, the political leverage that a party has on firms should not influence the extent of political matching. On the other hand, if political patronage were the dominant force, we would expect political assortative matching to be stronger for more powerful parties, since these parties have more power over connected business owners, and because owners should have a higher incentive to please powerful politicians.

To investigate this, we estimate an alternative version of the dyadic regression 3.6, where we differentiate between the parties in the coalition of the ruling mayor in the municipality and the opposing parties. We focus on the subsample of politically affiliated workers and owners, and we estimate the following specification:

$$
\begin{aligned}
y_{if} = &\alpha_m(f) + \beta^1 SP, Power_{if} + \beta^2 SP, NotPower_{if} + \\
&+ \beta^3 DP, OwnerPower + \beta^4 DP, WorkerPower + SX'_{if}\gamma + \epsilon_{if}
\end{aligned}
\tag{4.2}
$$

where $SP, Power_{if}$ is an indicator equal to one if worker and owner are from the same party, and that party is in power in the municipality; $SP, NotPower_{if}$ is an indicator equal to one if worker and owner are from the same party, and that party is *not* in power in the municipality; $DP, OwnerPower$ and $DP, WorkerPower$ are indicators equal to one if worker and owner are from different parties, and the party of the owner, or of the worker, is in power, respectively. The excluded category captures the case in which worker and owner are from different parties, neither of which is in power. All the other variables are defined as before. We also estimate a similar regression, but differentiate between parties in the coalition of the state governor and opposing parties.

In Appendix Figure A7 we plot the linear combination of $\beta^1 - \beta^3$ (in red), normalized by the sample probability that y_{if} equals one when worker and owner are form different parties, and the party of the owner is in power. In blue, we plot the coefficient β^2, normalized by the sample probability that y_{if} equals one if worker and owner are from different parties, neither of which is in power. Panel A focuses on the power of the party at the municipal level, while Panel B focuses on the power of the party at the state level. Both panels show that, if anything, there is a larger degree of political assortative matching when owner and worker belong to parties not in power locally or in the firm's state, and thus have less ability to convince business owners to hire copartisans (Bertrand et al., 2018).

4.2.3 ***Event Study Around Owners' Change of Party*** A mechanism of political discrimination implies that we should observe sharp changes in hiring patterns in firms whose owner changes partisan affiliation. We test this prediction by focusing on the set of 5,262 owners who switch partisan affiliation at some point during the sample period. These owners provide us with a set of event studies to investigate how the partisan affiliation of their workforce shifts around the time of the change in partisan affiliation.

An additional advantage of this design is that it allows us to further control for assortative criteria that could be correlated with both political affiliation and employment decisions. In particular, while the dyadic regression approach allows us to control for many relevant observable assortative criteria, we cannot directly observe all network links between business owners and workers. Given the importance of networks in the job-search process, employers might be more likely to hire copartisans simply because they are more likely to belong to the same social network. This might be the case if copartisans go to the same church, went to the same school, live in the same local neighborhood, support the same soccer team, and more generally belong to the same network of friends. However, many of these network links are unlikely to change suddenly when an individual changes party. Thus, our event study design allows us to control to a large extent for nonpolitical network links between employers and potential workers.

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 "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 then estimate the following specification:

$$y_{fmt\tau AB} = \alpha_{fm\tau AB} + \gamma_{mt\tau AB} + \sum_{s=\tau-4}^{\tau+4} \beta_s Switcher_f \mathbb{1}(s = t) + \epsilon_{fmt\tau AB} \tag{4.3}$$

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 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 show estimates of equation 4.3 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. At the time in which an owner changes party, we observe a sizable (about 0.2 standard deviation) and sharp increase in the number of hires from the owner's new party, relative to firms in the control group. 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 affiliated with other parties or unaffiliated. In Panel B, 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 five percentage points.

In sum, in line with a mechanism of political discrimination, the event study results are consistent with a change in political preferences driving a change in hiring patterns.

4.3 A New Survey of Business Owners and Workers We conclude our discussion of mechanisms by presenting the results from a novel survey we conducted over the phone in the months of June-August 2021, which directly elicits the beliefs of labor market participants about the most relevant drivers of our findings. The survey 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.

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:"[34]

(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*).

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

(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 (*patronage*).
(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 7. 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' 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). Both groups of respondents show low levels of agreement with the other two mechanisms, namely *patronage* 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.[35] 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 *patronage* 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, we finally 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

[35] 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.

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."[36] 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.

5 Discussion: Additional Real Implications of Politics in the Workplace

In this section, we document that political discrimination in the labor market is not limited to the sorting of workers and firms. We show that workers who are copartisan with the owner are more likely to be promoted within the firm and enjoy a significant wage premium. We observe opposite, negative patterns for workers affiliated with a different political party than owners. We then document that copartisans are less qualified for their job. Finally, we show that a higher share of owner copartisans in the workplace negatively correlates with firm growth.

5.1 The Political Promotion and Wage Premia In addition to playing a role in hiring decisions, political discrimination might affect other personnel decisions within a firm. To shed light on this, we compare how the career trajectories of otherwise similar workers shift depending on their partisan alignment with their firm's owner.

Specifically, 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 within the firm. We estimate the following specification, where each worker appears only once for each employment spell:

$$Promoted_{ift} = \alpha_{tm(f)} + \beta^{SP} SP_{if} + \beta^{DP} DP_{if} + \beta^{OW} OW_{if} + \beta^{OO} OO_{if} + SX'_{if}\gamma + X'_{i}\delta + \epsilon_{ift} \quad (5.1)$$

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 times the market m of firm f, and all the other variables are defined as in equation 3.7. We also estimate a more stringent specification with year-of-hire times firm fixed effects, comparing workers who were hired in the same year by the same firm.

The coefficients β^{SP} and β^{WP} capture the differential promotion probability between workers of the same or different party of the owner, respectively, and unaffiliated workers. The coefficient β^{OW} measures the average difference between affiliated and unaffiliated workers in promotion probability in firms whose owner is unaffiliated. Finally, the coefficient β^{OO} measures the

[36]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 perspective employee has extreme views.

average difference in the promotion probability of unaffiliated workers between firms whose owner is affiliated and those whose owner is unaffiliated.

Table 4 presents the results. In columns 1 and 2, 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 columns 3 and 4, 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 point 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 co-workers, these workers are 0.448 percentage points more likely to be promoted from a white-collar to a managerial position (column 1), and 0.44 percentage points more likely to be promoted from a blue-collar to a white-collar position (column 3). The magnitude of these effects is significant considering that the average promotion probability across layers is 2.58% from white-collar to manager and 2.98% from blue-collar to white-collar. These results are robust to the inclusion of year-of-hire times firm fixed effects (columns 2 and 4), which restricts the comparison to co-workers hired in the same year. 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 0.104-0.180 percentage points less likely than their unaffiliated co-workers to be promoted to a managerial role. Interestingly, politically affiliated white-collar workers suffer a 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 political discrimination affects workers' wages by estimating the following wage equation:

$$\log w_{ift} = \alpha_{ft} + \beta^{SP} SP_{if} + \beta^{DP} DP_{if} + \beta^{OW} OW_{if} + SX'_{if}\gamma + X'_i\delta + \epsilon_{ift} \tag{5.2}$$

where $\log w_{ifmt}$ is the log wage paid to worker i employed in firm f at time t, α_{ft} are firm-year fixed effects, which restricts the comparison to workers of the same firm in the same year, and all other variables are defined as in equation 5.1 .

The results from estimating equation 5.2 are presented in column 1 of Table 5. 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 co-workers, these workers earn 3.9% higher wages. Once again, the role of partisan affiliation is larger than that of gender and race: 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 co-workers. Moreover, we notice that politically affiliated workers suffer a 2.2% wage penalty in firms whose owner is unaffiliated.

We repeat the analysis in column 2 of Table 5 by substituting firm-year fixed effects with firm-year-occupation fixed effects, further restricting the comparison to co-workers 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.

Finally, we conduct the analysis focusing on different categories of workers, depending on their position in the organizational hierarchy of the firm. We report the results in columns 3, 4, and 5 of Table 5. Importantly, we find that the political wage premium is present across all main occupational categories of managers (column 3), white-collar workers (column 4), and blue-collar workers (column 5), 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 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 co-workers within the same hierarchical layer. In addition to being consistent with the presence of political discrimination in the workplace, this evidence indicates that workers' preferences to work in firms owned by copartisans play a minor role. Indeed, we would expect opposite results—i.e., a negative wage premium—if working for copartisan owners were seen as a positive job amenity. This is perhaps also not surprising in a context largely characterized by high unemployment and highly valued formal jobs.

5.2 Copartisan Workers are Less Qualified Political discrimination in hiring might affect the quality of the workforce to the extent that partisan alignment substitutes for competence in hiring decisions.

While we cannot observe all dimensions of competence, we test this hypothesis by focusing on a standard and important dimension of individual competence: education. Specifically, following Colonnelli et al. (2020), we construct a measure of educational mismatch at the worker-job pair level. To do so, 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. We create the variable $Qualified_{ift}$ to be 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; that is, if her educational level is the same or higher than the required educational level or the occupation.

We then estimate a version of equation 5.2, 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 6. Copartisans of the owners are significantly less likely to be qualified for the job. Relative to their co-workers 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.

In sum, while owner's copartisans are more likely to be promoted within the firm and earn more than their co-workers, they are less qualified for the job, based on education. While the lack of on-the-job productivity data makes it difficult to make conclusive statements about efficiency, these findings are consistent with a political discrimination channel and with taste-based discrimination in particular.

5.3 Political Discrimination and Firm Growth The evidence so far shows that political discrimination is an important mechanism behind political assortative matching, and that there are additional spillovers on promotion and compensation decisions at the firm. A natural question is whether political assortative matching has implications for firm productivity and growth. While we showed that political affiliation substitutes for educational qualification, we cannot exclude that workers are more productive along other dimensions when matched to copartisan owners, leading to a net positive impact on firm performance.

Theoretically, the answer to this question depends on the source of employers' political discrimination. On the one hand, employers might have a "taste for discrimination," if they consider employing copartisans as an amenity and employing workers of different parties as a disamenity. In this case, in line with the prediction of Becker (1957), firms that discriminate should be less productive. On the other hand, employers' discrimination might be "belief-based," if employers perceive copartisans to be more productive (Phelps, 1972; Arrow, 1973). If these beliefs are accurate, employing a higher share of workers who are copartisans of the owner should make a firm more productive. However, as emphasized by Bohren et al. (2019) among others, these beliefs might be inaccurate, leading employers to make suboptimal personnel choices instead of productivity-enhancing ones.

Since we lack a source of exogenous variation in the extent of political discrimination, we cannot pinpoint the causal effect of political discrimination on firm productivity. Nevertheless, we can use our data to provide some initial, suggestive evidence in this regard. Specifically, we compare the employment growth of similar firms that differ in their share of workers who are copartisan of the owner. To do so, we estimate the following specification, restricting the sample to firms whose owner is politically affiliated:

$$\text{Growth}_{ft} = \alpha_{t-1,n(f,t-1),a(f,t-1)} + \beta \text{Share Copartisan}_{f,t-1} + \epsilon_{ft} \tag{5.3}$$

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 Share $\text{Copartisan}_{f,t-1}$ 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 the year $t-1$, times the total number of workers n of firm f in year $t-1$, times the number of politically affiliated workers a of firm f in year $t-1$. The coefficient β measures how a firm's growth between year $t-1$ and year t is related to the share of workers who are copartisan of the owner, restricting the comparison to firms of the *same size* and with the *same number of affiliated workers* in year $t-1$.

Figure 8 shows a graphical representation of the results, while details of the estimation are presented in Appendix Table A15.[37] A higher share of copartisan workers is associated with significantly lower firm growth, with an estimated β coefficient of -0.071. To gauge the magnitude of this effect, two firms that are one standard deviation apart in Share $\text{Copartisan}_{f,t-1}$ have a growth rate gap of approximately 1%, which is substantial when compared to an average annual firm growth rate of 10%. In columns 2 and 3 of Appendix Table A15 we show that this result is robust to including increasingly stringent sets of fixed effects, which further restrict the comparison to firms in the same municipality or in the same municipality-industry.

Although we emphasize that these results are only suggestive, the negative association between the extent of political assortative matching and firm growth point towards a "taste-based" nature of political discrimination, and this is less consistent with accurate owner beliefs about higher productivity in politically homogeneous workplaces.

6 Conclusion

This paper uses new micro-data to provide detailed evidence that individual political views spill over from political to apolitical domains. We focus on Brazil over the past two decades and show that individual political views have large, real implications for hiring and management practices of private-sector firms.

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.

[37] We winsorize firm growth at the 1% of the distribution to minimize the impact of outliers. Results are similar when using the non-winsorized variable.

Second, we rely on a number of empirical approaches to isolate the relevant role played by political discrimination in hiring, whereby business owners have a preference to hire copartisan workers. First, in our most direct test, we partner with a leading job platform in Brazil to conduct a field experiment in which owners evaluate synthetic resumes containing political signals and uncover that owners have a preference for copartisan workers over workers from a different party—all else equal. Second, we use our micro-data to show several patterns consistent with a discrimination channel: (i) assortative matching is higher the higher the on-the-job personal interactions; (ii) assortative matching does not depend on the political strength of the party in power at the local level; (iii) in an event study framework, the share of copartisan workers goes up sharply when the owner changes party. Third, we survey both sides of the labor market, finding a consensus among business owners and workers that political discrimination does play an important role in firms' hiring decisions.

Our paper highlights the importance of politics in shaping labor market outcomes, a topic that is becoming more salient in recent years with a large increase in political polarization around the world (Boxell et al., 2020). One direct implication of our work is that trends in political polarization may reshape the way we think about organizational structures and firm behavior. On the other hand, 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 isolate the importance of political discrimination. However, other mechanisms, such as overlapping political and nonpolitical networks, likely contribute to the magnitudes we establish about the relevance of partisanship in driving the sorting of workers across firms. We believe that precisely quantifying the relative importance of various channels remain important next steps.

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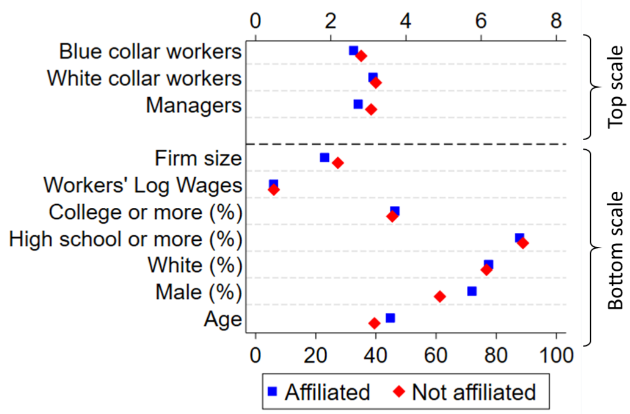
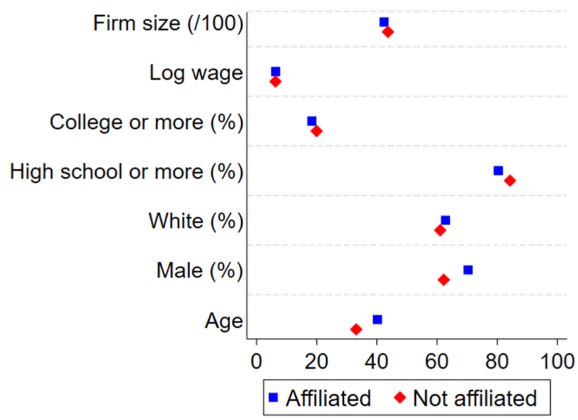
FIGURE 1. **Comparing Affiliated and Unaffiliated Workers and Owners**



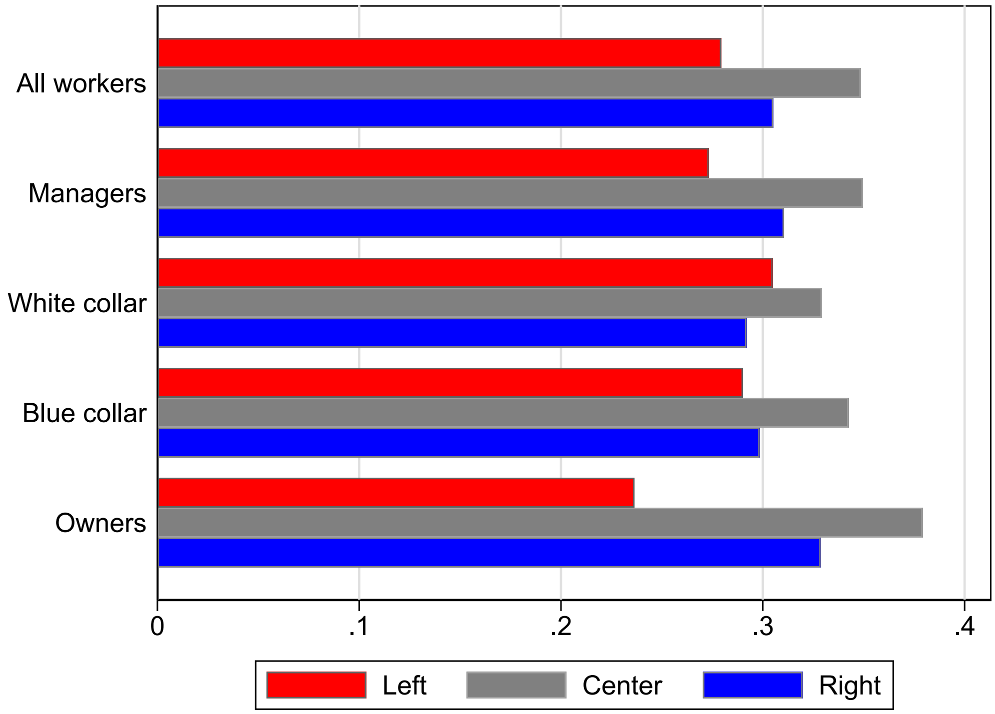
A. Owners



B. Workers

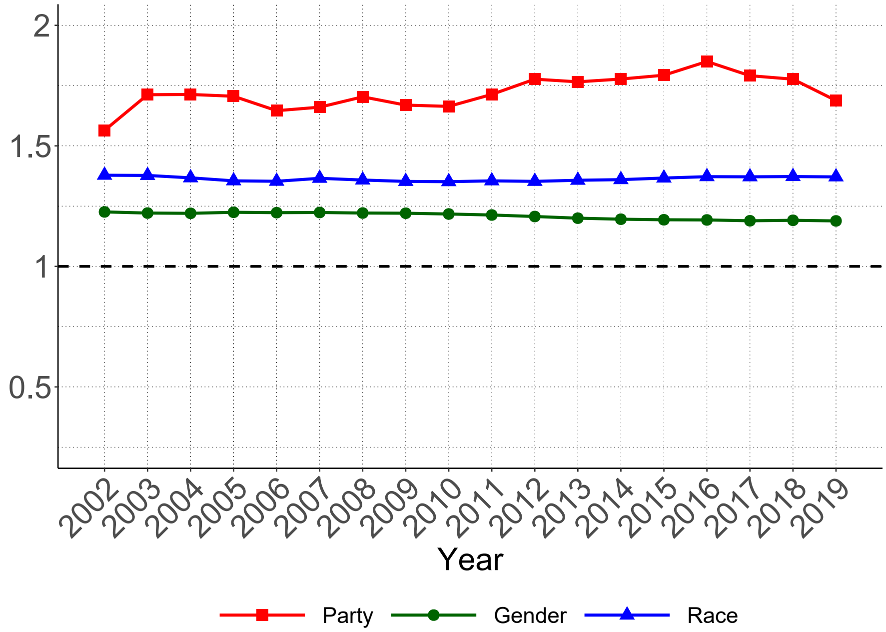
Notes: The figure shows average differences between affiliated (in blue) and unaffiliated (in red) workers and owners for each variable listed on the y-axis. Panel A presents estimates for each owner-firm-year in the data. Panel B presents estimates for each worker-year in the data. *Blue-collar workers / 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 workers who are male. *Age* is the age of owners/workers.

FIGURE 2. **Political Orientation of Workers and Owners**

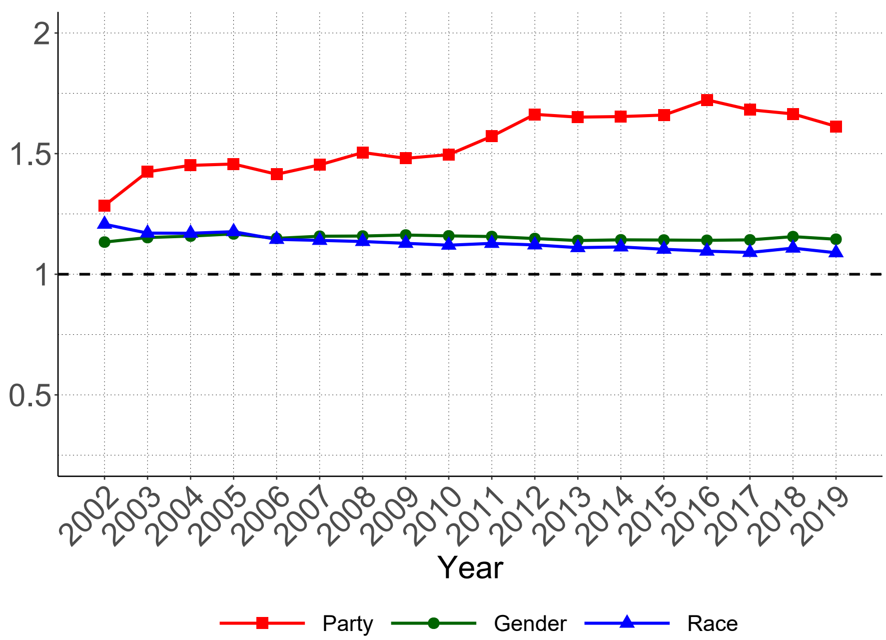


Notes: The figure shows the distribution of workers' and owners' political orientation. See Appendix Table A1 for the categorization of Brazilian parties as Left/Center/Right.

FIGURE 3. **Political Assortative Matching: The Likelihood Ratio Index**



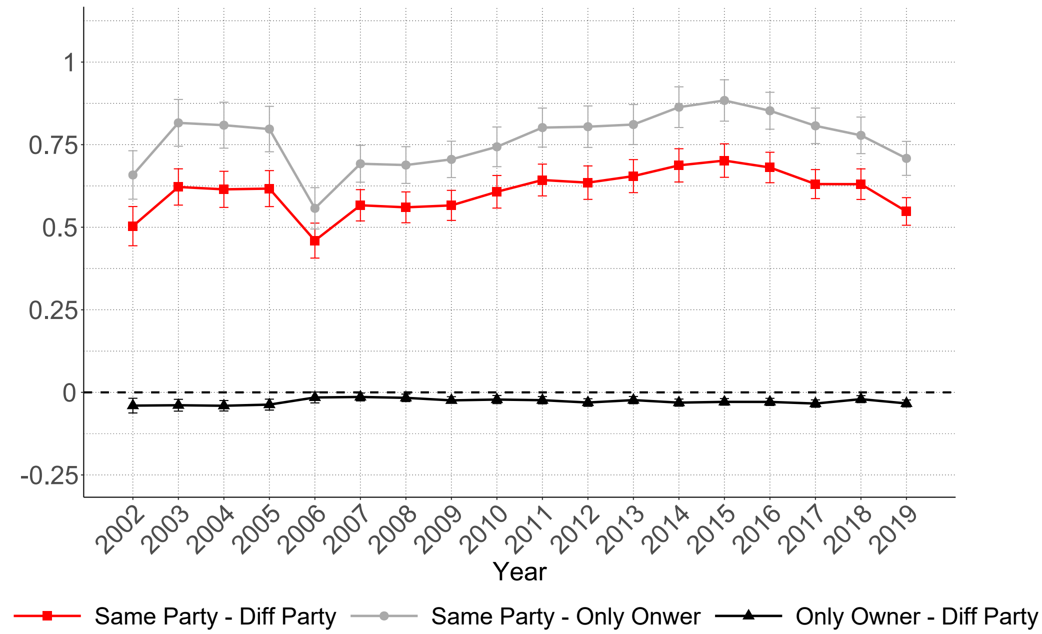
A. Basic Index



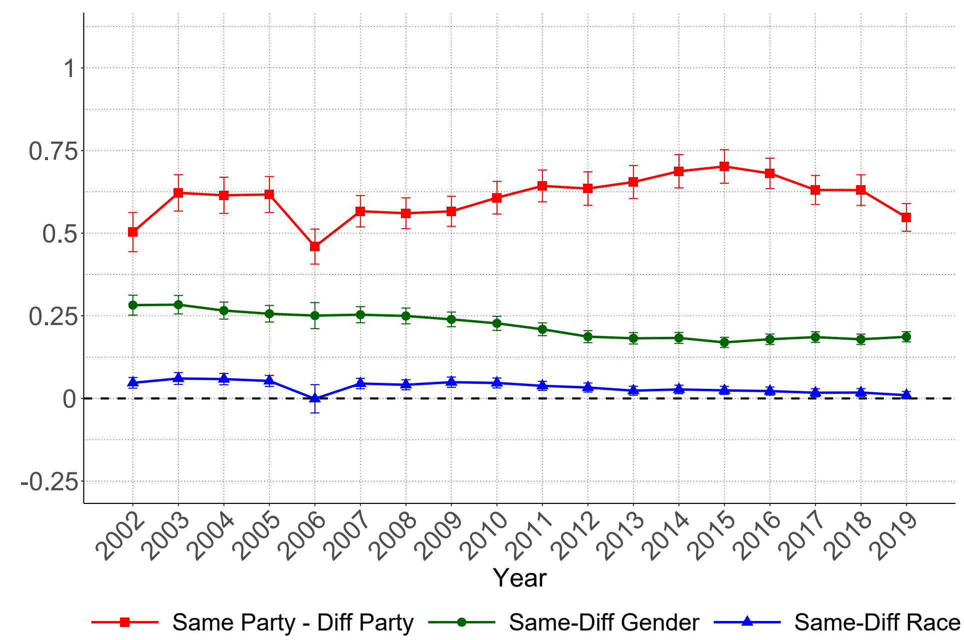
B. Accounting for Geographical Sorting

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 4. **Political Assortative Matching: Dyadic Regression Estimates**



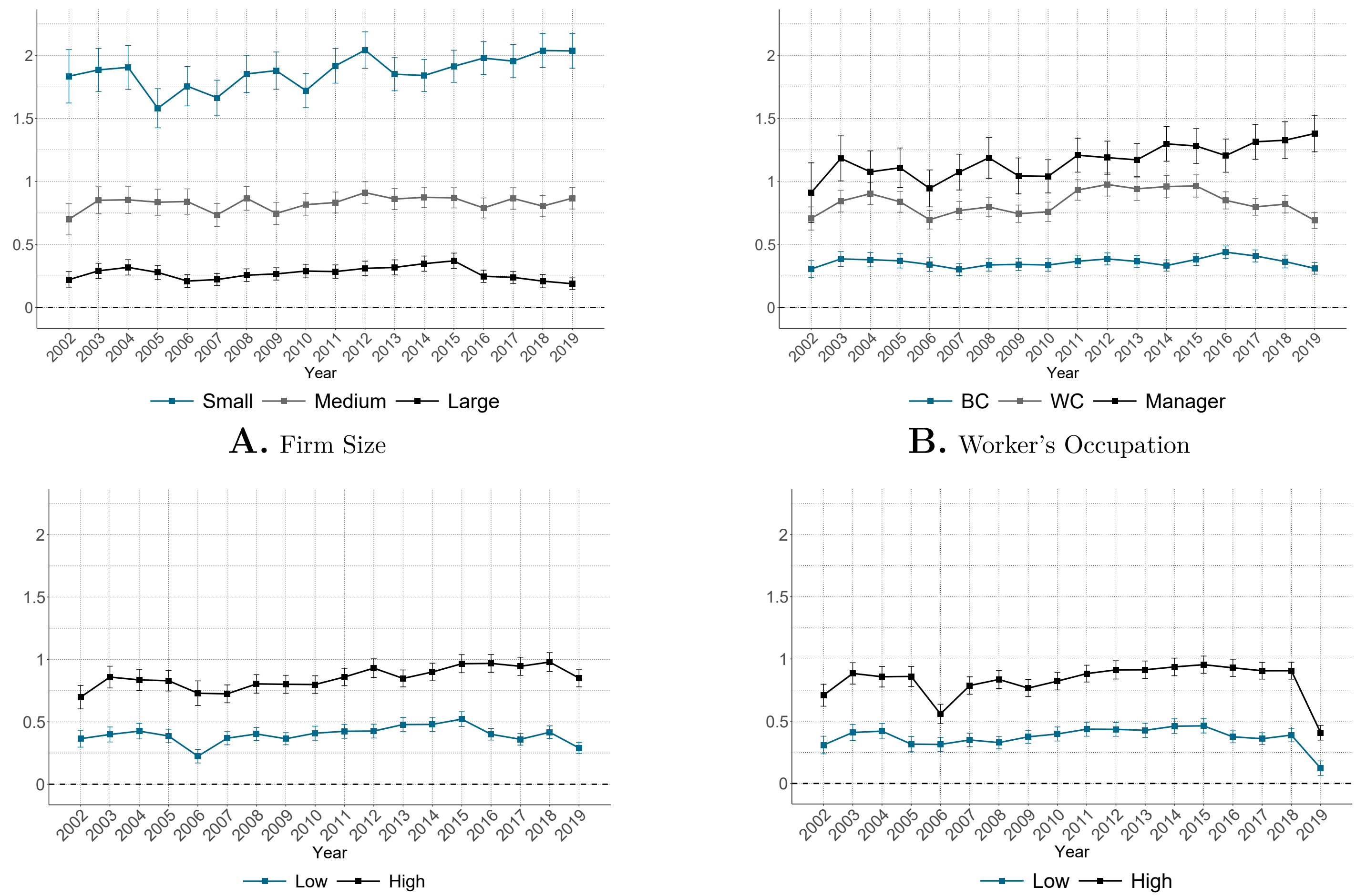
A.



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 5. **Political Assortative Matching: Heterogeneity by Firm Size and Occupation**



A. Firm Size

B. Worker's Occupation

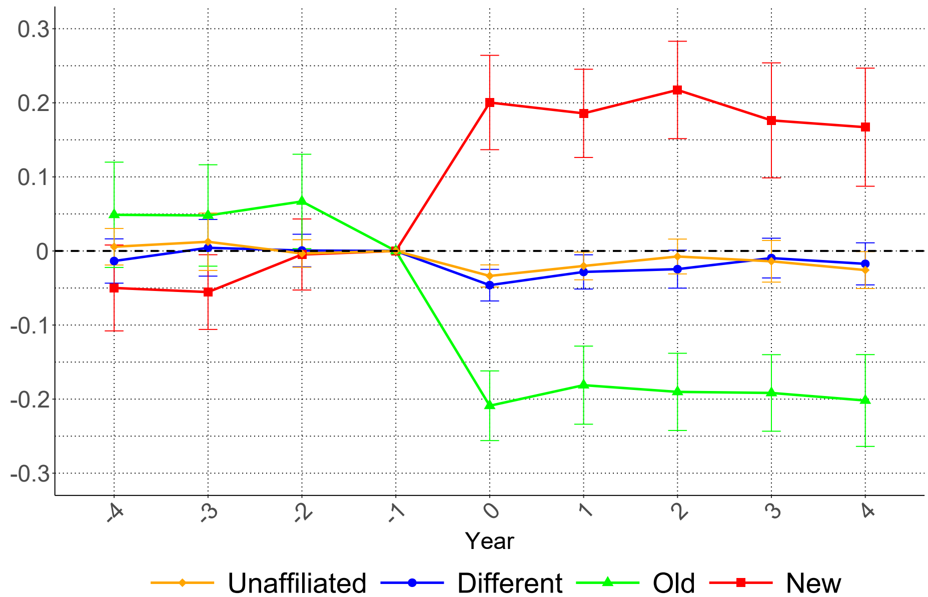
C. Social Skills of Job

D. Interpersonal Relationships of Job

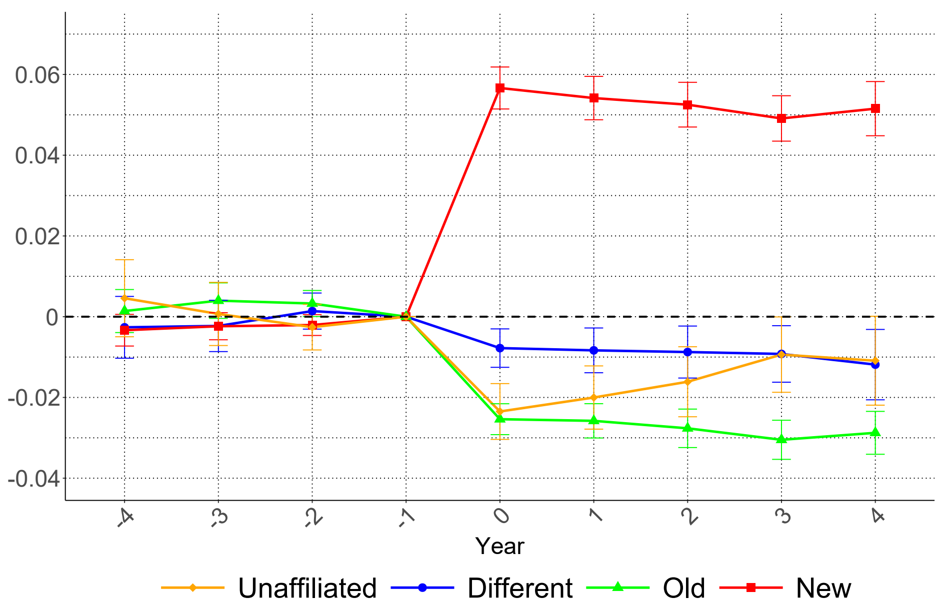
S

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, the equation is separately estimated restricting the sample to small (less than 10 employees), medium (10–50 employees), and large (more than 50 employees) firms. In panel B, the equation is separately estimated restricting the sample to workers employed in managerial occupations, in other white-collar occupations (WC), and in blue-collar occupations (BC). In Panel C and D, the equation is separately estimated restricting the sample to 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 (following the O*NET categorization of occupations, see Section 4.2.1 for details).

Figure 6. **Event Study Around Owners' Change of Party**



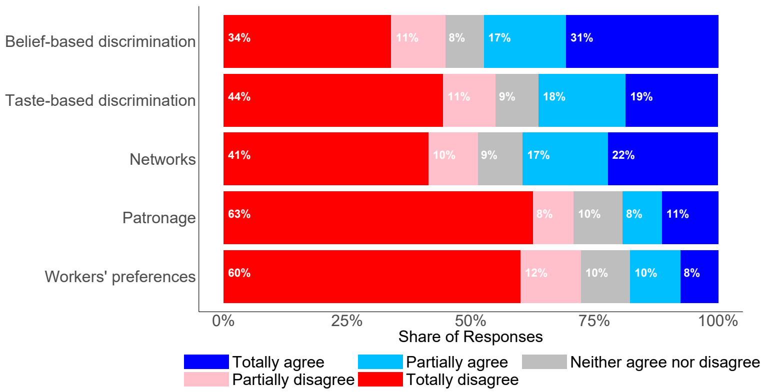
A. Number of hires of different partisan affiliations



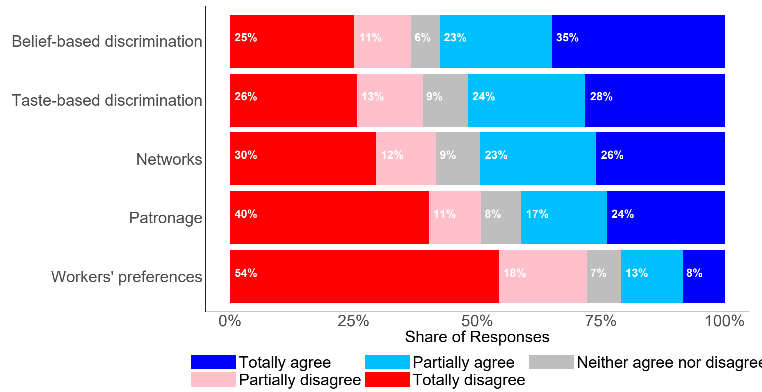
B. Share of workers of different partisan affiliations

Notes: The figure shows estimates of the coefficients β_s from equation 4.3, 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 4.2.3 for details on the estimation.

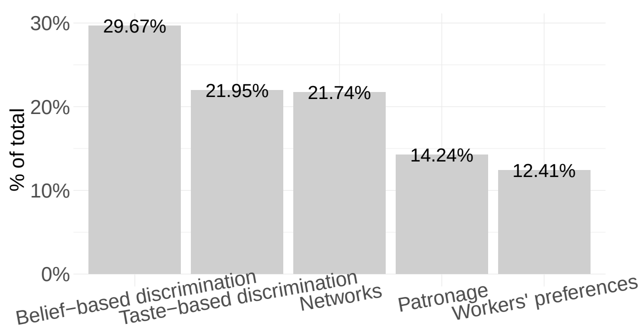
Figure 7. **Survey Evidence on Most Relevant Mechanisms**



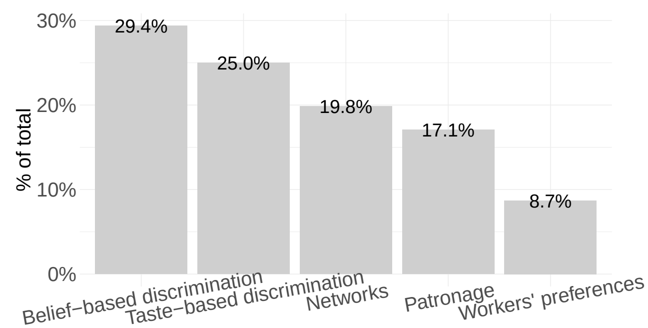
A. Owners' agreement with the five statements



B. Workers' agreement with the five statements



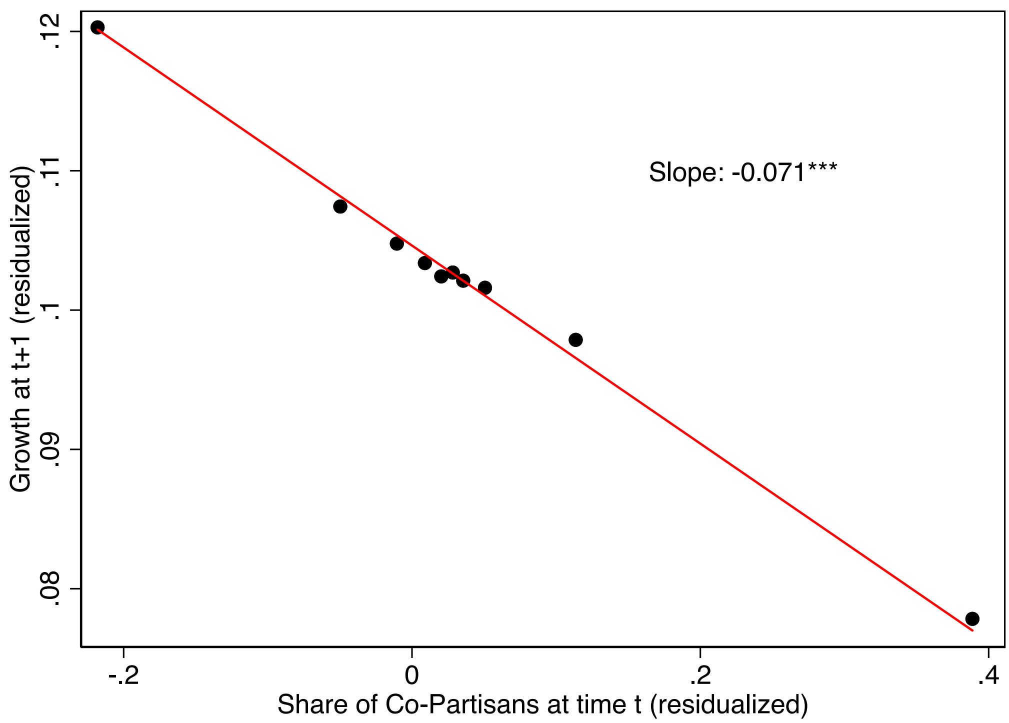
C. Owners' most relevant mechanism



D. Workers' most relevant mechanism

Notes: The figure plots responses from our survey of Brazilian business owners and workers, described in section 4.3. 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 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.

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. **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
R-squared	0.300	0.314	0.366	0.392	0.503	0.516
Mean DV Diff Party	0.392	0.416	0.409	0.416	0.389	0.397
Worker Controls	Yes	Yes	Yes	Yes	Yes	Yes
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. Standard errors in parentheses clustered by firm. ***$p < 0.001$, **$p < 0.05$, *$p < 0.1$:

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
R-squared	0.531	0.556	0.615	0.641
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 4.1. 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. ***$p < 0.001$, **$p < 0.05$, *$p < 0.1$

Table 4. **The Political Promotion Premium**

	(1)	(2)	(3)	(4)
	Promotion from WC to Manager		Promotion from BC to WC	
Same Party	0.448***	0.563***	0.440***	0.209***
	(0.135)	(0.078)	(0.086)	(0.056)
Different Party	-0.180**	-0.104***	0.242***	0.035
	(0.072)	(0.030)	(0.067)	(0.022)
Only Worker	-0.081***	-0.094***	0.040***	0.030***
	(0.024)	(0.014)	(0.012)	(0.011)
Only Owner	-0.079		0.176**	
	(0.074)		(0.074)	
Same Gender	-0.011	0.097***	0.339***	-0.085*
	(0.020)	(0.018)	(0.040)	(0.050)
Same Race	0.053	0.084***	0.005	0.103***
	(0.042)	(0.017)	(0.040)	(0.018)
Same Education	0.192***	0.399***	-0.187***	0.461***
	(0.036)	(0.039)	(0.052)	(0.040)
Same Age	-0.117***	-0.057***	-0.121***	-0.013
	(0.025)	(0.014)	(0.023)	(0.010)
Observations	49,249,076	45,511,727	56,611,040	54,093,318
Number of Firms	2,581,271	1,525,400	1,971,079	1,242,185
Number of Workers	31,728,658	29,805,723	32,764,045	31,543,165
R-squared	0.070	0.212	0.075	0.219
Mean DV Control	2.582	2.608	2.977	2.908
Worker Controls	Yes	Yes	Yes	Yes
Year-Mun-Industry FE	Yes	No	Yes	No
Year-Firm FE	No	Yes	No	Yes

Notes: The table presents estimates from equation 5.1. The outcome variable is an indicator equal to one if the worker will ever be promoted within the firm to a position higher than the one at the time of hiring. The dependent variable is scaled by 100. Promotions are classified as movements from a white-collar to a managerial position (columns 1-2) or from a blue-collar to a white-collar position (columns 3-4). The unit of observation is a hire. "Mean DV Control" is the mean of the dependent variable for the excluded category. Standard errors in parentheses clustered by firm. ***$p < 0.001$, **$p < 0.05$, *$p < 0.1$

TABLE 5. **The Political Wage Premium**

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Log Wages				
	Sample: All workers	Sample: All workers	Sample: Manager	Sample: White collar	Sample: Blue collar
Same party	0.038***	0.028***	0.016***	0.034***	0.015***
	(0.003)	(0.005)	(0.006)	(0.010)	(0.001)
Different party	-0.016***	-0.008***	-0.038***	-0.006	-0.004***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.001)
Only worker	-0.022***	-0.014***	-0.046***	-0.017***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Same gender	0.015***	0.014***	0.017***	0.014***	0.011***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Same race	0.010***	0.005***	0.011***	0.005***	0.002***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Same education	0.062***	0.024***	0.034***	0.026***	0.004***
	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
Same age	-0.012***	-0.008***	0.006***	-0.004	-0.015***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)
Observations	346,677,291	330,938,933	15,693,479	147,542,138	159,687,329
Number of Firms	2,849,093	2,647,370	419,329	1,925,362	1,569,792
Number of Workers	66,954,626	65,784,191	4,594,503	37,897,399	37,990,945
R-squared	0.667	0.769	0.828	0.791	0.703
Mean DV Control	6.392	6.397	7.366	6.466	6.224
Worker Controls	Yes	Yes	Yes	Yes	Yes
Year-Firm FE	Yes	No	No	No	No
Year-Firm-Occup FE	No	Yes	Yes	Yes	Yes

Notes: The table presents estimates from equation 5.2. The dependent variable in all columns is the log wage paid to the worker in a given year. In columns 1 and 2, the sample includes all workers. Columns 3-5 restrict the sample to workers employed in a managerial, white-collar, and blue-collar occupation. 'Mean DV Control" is the mean of the dependent variable for the excluded category. Standard errors in parentheses clustered by firm. ***$p < 0.001$, **$p < 0.05$, *$p < 0.1$

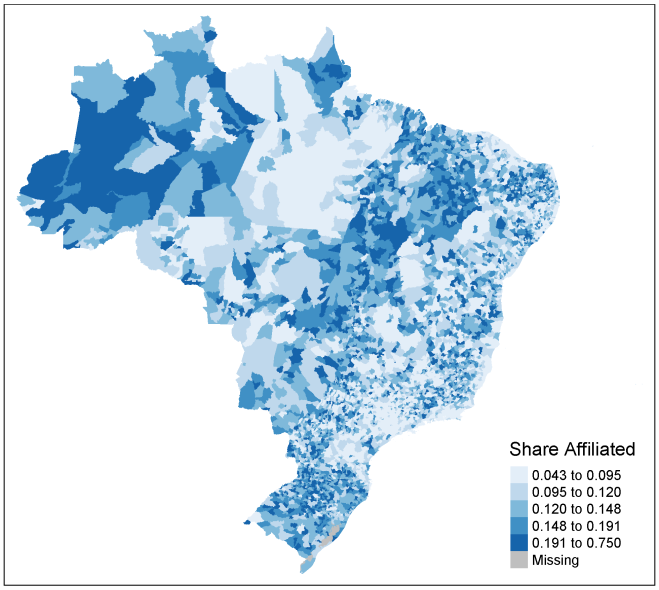
Table 6. **Copartisan Workers Are Less Qualified**

	(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
R-squared	0.367	0.660	0.485	0.465
Mean DV Control	0.932	0.845	0.946	0.935
Worker Controls	Yes	Yes	Yes	Yes
Year-Firm FE	Yes	Yes	Yes	Yes

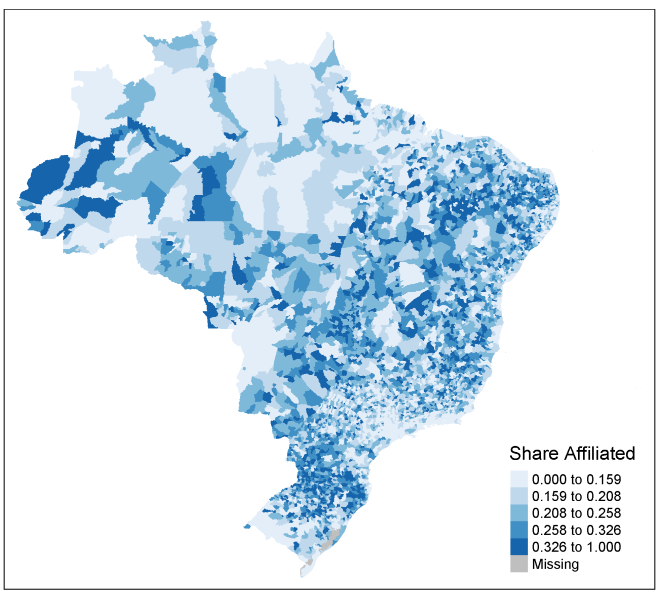
Notes: The table presents estimates from a version of equation 5.2, where the dependent variable is an indicator equal to one if the worker is qualified, in terms of education, for the occupation in which she is employed. In column 1, the sample includes all workers.. Columns 2-4 restrict the sample to workers employed in a managerial, white-collar, and blue-collar occupation. "Mean DV Control" is the mean of the dependent variable for the excluded category. Standard errors in parentheses clustered by firm. ***$p < 0.001$, **$p < 0.05$, *$p < 0.1$

ONLINE APPENDIX: ADDITIONAL RESULTS

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



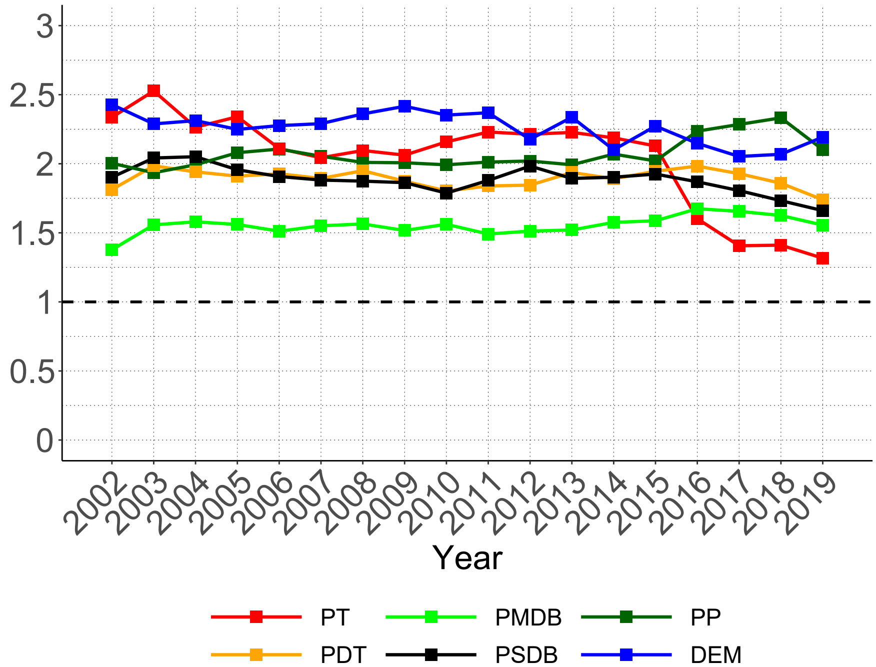
A. Share of affiliated workers



B. Share of affiliated owners

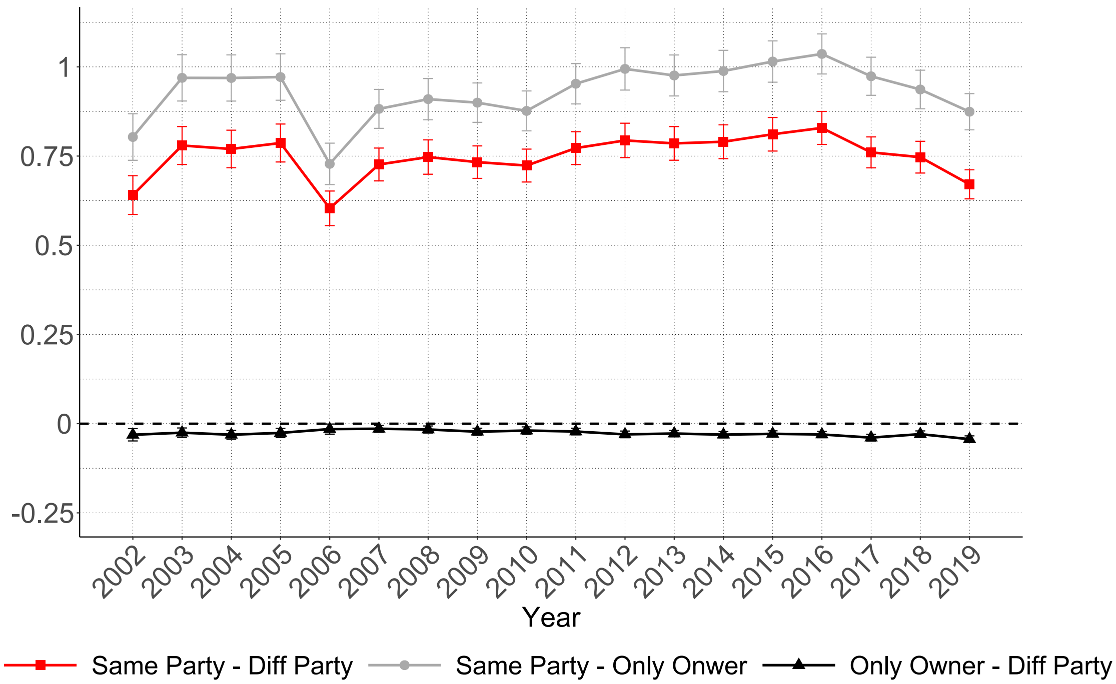
Notes: The figure shows the share of affiliated workers (Panel A) and affiliated owners (Panel B) across Brazilian municipalities over the period 2002–2019.

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



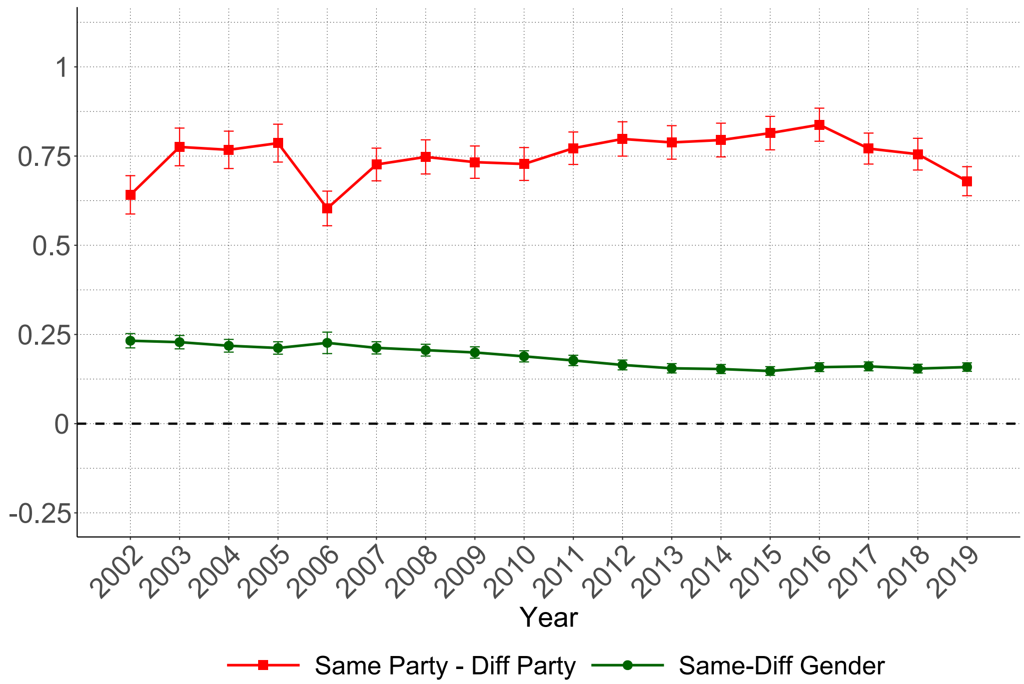
Notes: The figure shows estimates of the likelihood ratio index (calculated as in equation 3.3) for each party. See section 3.1 for additional details.

FIGURE A3. **Political Assortative Matching: Dyadic Regression Estimates - Limited Set of Controls**



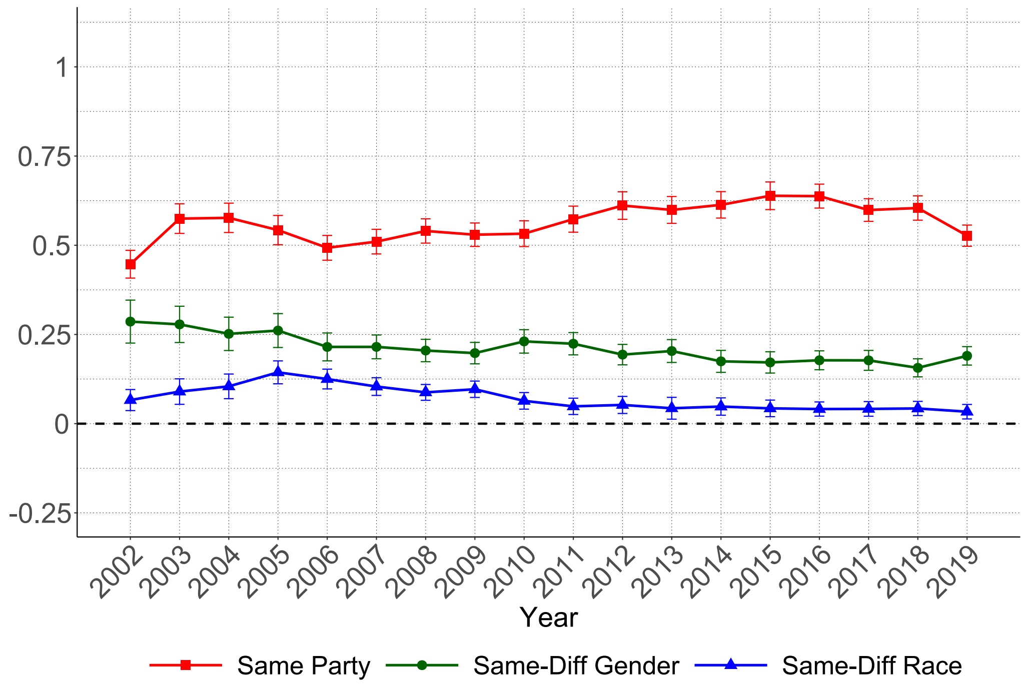
Notes: The figure shows point estimates and 95% confidence intervals of $\Delta(SP, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in red), $\Delta(SP, OO)$ divided by the sample probability that y_{if} equals one if $OO_{if} = 1$ (in gray), and $\Delta(OO, DP)$ divided 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 for 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 A4. **Political Assortative Matching: Dyadic Regression Estimates - Controlling Only for Shared Gender**



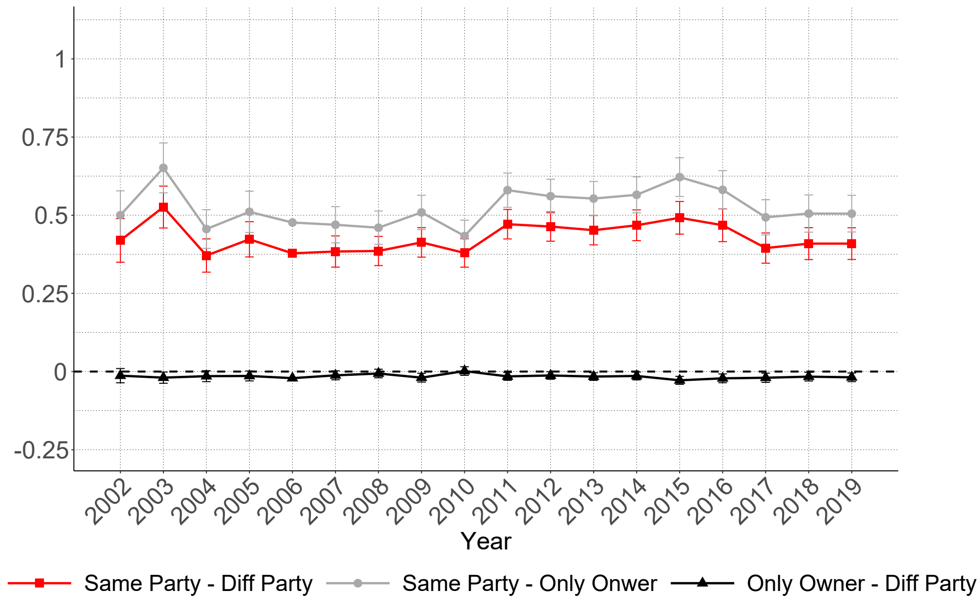
Notes: The figure shows point estimates and 95% confidence intervals of $\Delta(SP, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in red), and $\textit{Same Gender}_{if}$ divided by the sample probability that y_{if} equals one if $\textit{Same Gender}_{if} = 0$ (in green), from a version of equation 3.6 without including the set of indicators SX'_{if} (except same gender), and estimated for 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 - Only Affiliated Workers and Owners**

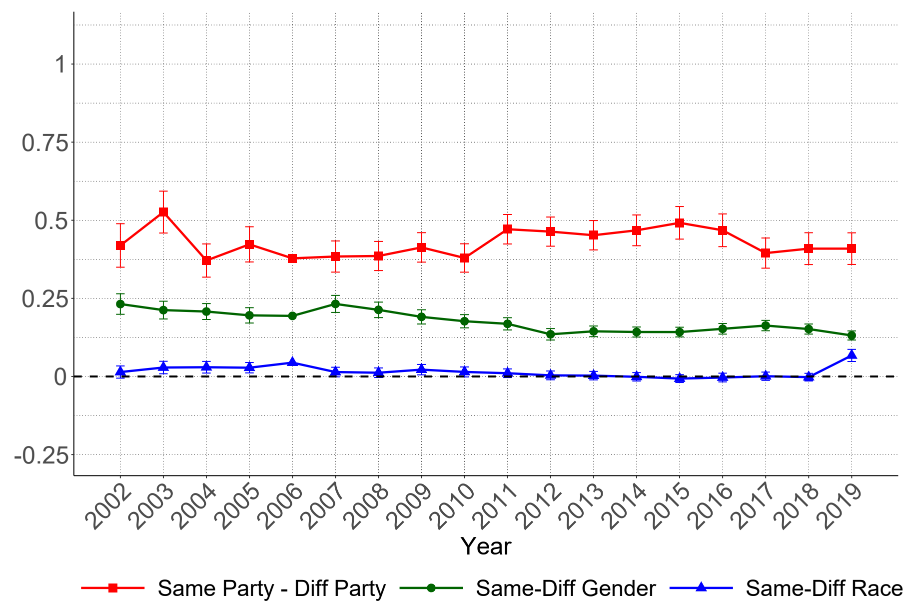


Notes: The figure shows the point estimates and 95% confidence intervals of SP_{if} divided by the sample probability that y_{if} equals one if the worker is from a different party than the owner (in red), $\mathit{Same\ Gender}_{if}$ divided by the sample probability that y_{if} equals one if $\mathit{Same\ Gender}_{if} = 0$ (in green) and $\mathit{Same\ Race}_{if}$ divided by the sample probability that y_{if} equals one if $\mathit{Same\ Race}_{if} = 0$ (in blue), from a version of equation 3.6 which excludes DP_{if}, OW_{if} and OO_{if} and is estimated on the sample 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 A6. **Political Assortative Matching: Hiring Margin**



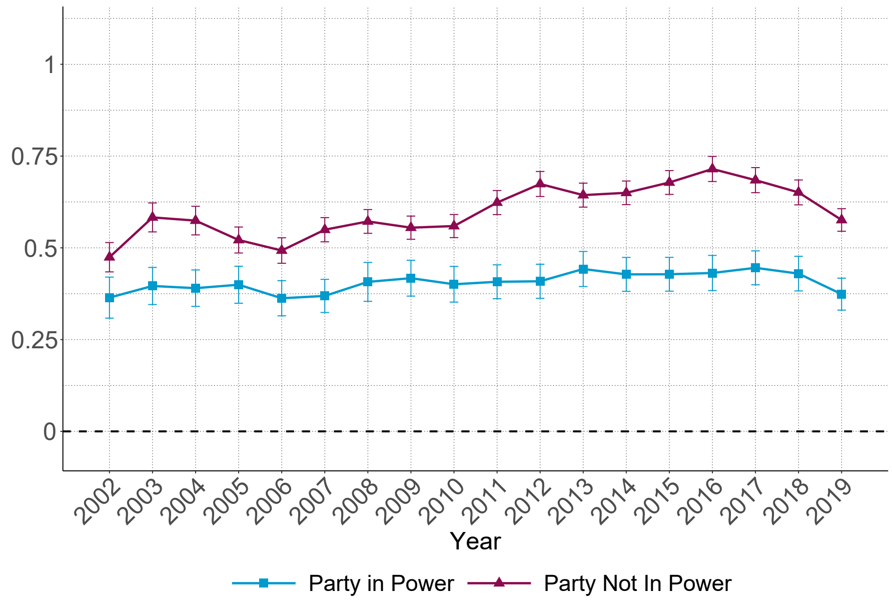
A.



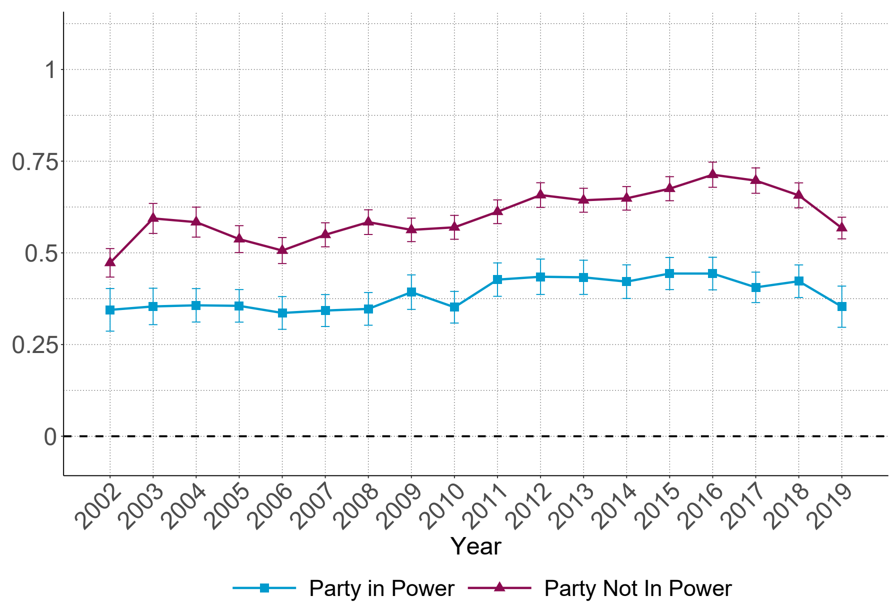
B.

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, for the samples of workers who were hired in a specific year. 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 a version of equation 3.6 and estimated for the sample of affiliated workers and owners. Confidence intervals are based on standard errors clustered at the market level. See section 3.3 and equation 3.6 for details on the estimation.

FIGURE A7. **Heterogeneity by Power of the Party at Local and State Levels**



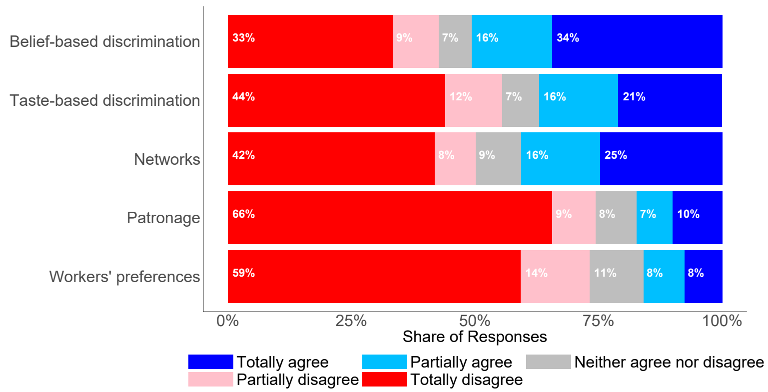
A. Power at the local level



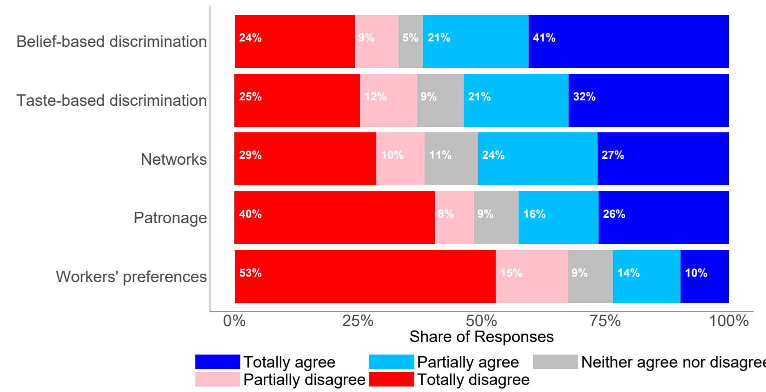
B. Power at the state level

Notes: The figure shows the point estimates and 95% confidence intervals of $\beta_1 - \beta_3$ normalized by the sample probability that y_{if} equals one when worker and owner are form different parties, and the party of the owner is in power, and of β_2, normalized by the sample probability that y_{if} equals one if worker and owner are from different parties, neither of which is in power. Confidence intervals are based on standard errors clustered at the market level. See section 4.2.2 and equation 4.2 for details of the estimation. Panel A and B differ in terms of the scope of the party in power: panel A focuses on the power of the parties at the municipal level (if the party supports the mayor) and panel B focuses on the power of the parties at the state level (if the party supports the state governor).

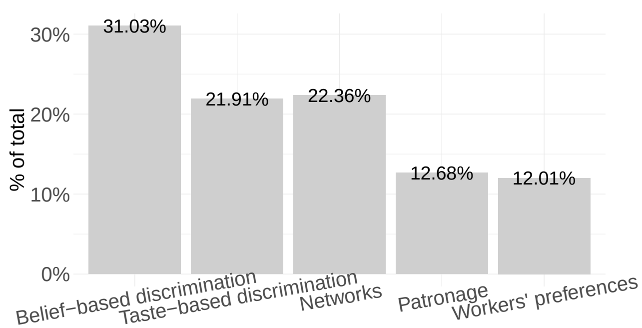
FIGURE A8. **Survey Evidence on Most Relevant Mechanisms – Affiliated Respondents**



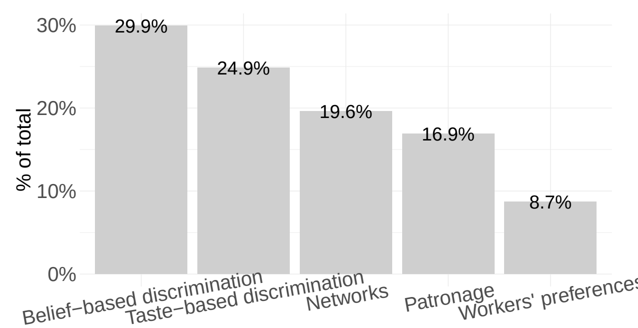
A. Owners' agreement with the five statements



B. Workers' agreement with the five statements



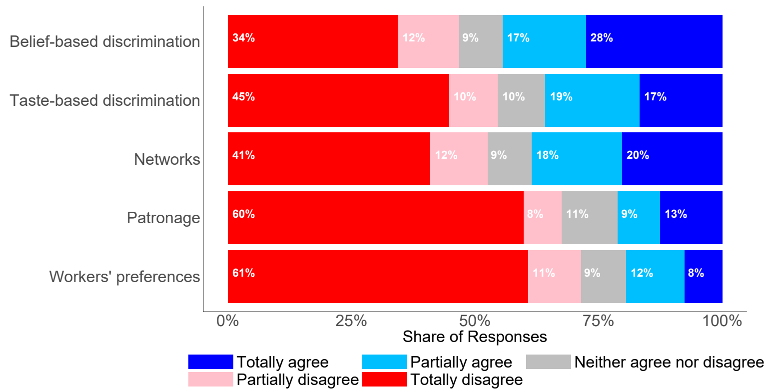
C. Owners' most relevant mechanism



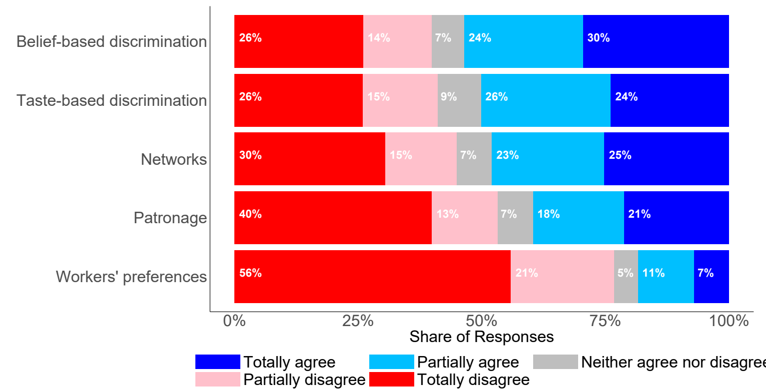
D. Workers' most relevant mechanism

Notes: The figure plots responses from our survey of Brazilian business owners and workers, described in section 4.3. 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.

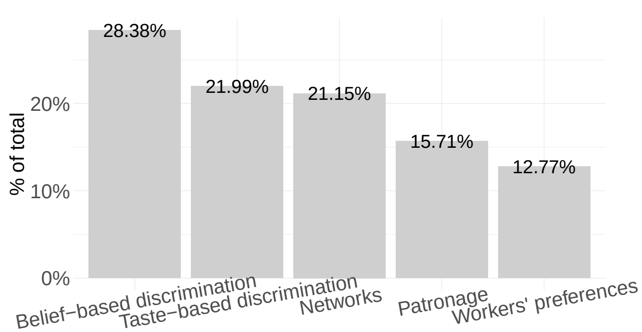
Figure A9. **Survey Evidence on Most Relevant Mechanisms – Unaffiliated Respondents**



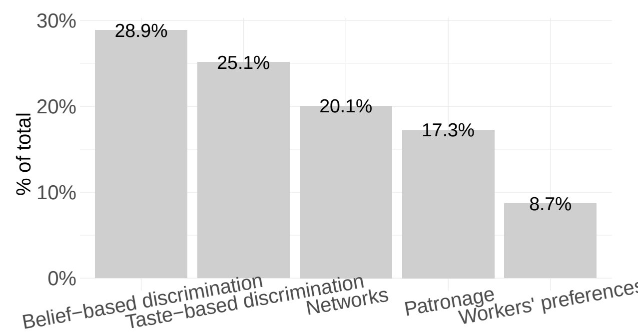
A. Owners' agreement with the five statements



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 4.3. 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.

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	0.0686	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)
	25pct	0.0151	0.0187	0.0175	0.0173	0.0153	0.0143	0.0135	0.0135	0.0148	0.0153	0.0149	0.0147	0.0146	0.0147	0.0147	0.0143	0.0134	0.0132
		(0.0008)	(0.0008)	(0.0008)	(0.0007)	(0.0009)	(0.0006)	(0.0005)	(0.0005)	(0.0006)	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0004)
Different Party	Full	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)
	25pct	0.0038	0.0038	0.0035	0.0037	0.0040	0.0026	0.0023	0.0027	0.0032	0.0032	0.0033	0.0031	0.0030	0.0028	0.0029	0.0030	0.0026	0.0032
		(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(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)
Only Worker	Full	-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)
	25pct	-0.0005	-0.0006	-0.0004	-0.0005	0.0000	-0.0003	-0.0003	-0.0003	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0005	-0.0004	-0.0004	-0.0004
		(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)	(0.0000)
Only Owner	Full	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)
	25pct	0.0029	0.0029	0.0025	0.0029	0.0036	0.0023	0.0020	0.0022	0.0028	0.0028	0.0027	0.0027	0.0025	0.0023	0.0024	0.0024	0.0022	0.0026
		(0.0003)	(0.0003)	(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)
Same Gender	Full	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)
	25pct	0.0028	0.0031	0.0028	0.0025	0.0029	0.0025	0.0024	0.0022	0.0021	0.0019	0.0017	0.0016	0.0015	0.0015	0.0016	0.0016	0.0016	0.0017
		(0.0002)	(0.0002)	(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	Full	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)
	25pct	0.0006	0.0008	0.0007	0.0006	0.0000	0.0006	0.0005	0.0006	0.0005	0.0004	0.0003	0.0002	0.0003	0.0002	0.0002	0.0002	0.0002	0.0001
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Educ	Full	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)
	25pct	-0.0009	-0.0006	-0.0007	-0.0006	0.0009	-0.0009	-0.0011	-0.0010	-0.0012	-0.0012	-0.0013	-0.0013	-0.0013	-0.0013	-0.0013	-0.0013	-0.0014	-0.0014
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0004)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Age	Full	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)
	25pct	-0.0011	-0.0007	-0.0009	-0.0010	-0.0005	-0.0010	-0.0010	-0.0006	-0.0007	-0.0005	-0.0004	-0.0003	-0.0002	-0.0001	0.0000	0.0001	0.0001	0.0002
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

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. **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 A5. **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 A6. **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 A7. **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 for details of the estimation.

Table A8. **Dyadic Regression Estimates – White-Collar Workers**

	2002	2003	2004	2005	2006	2007	2008	2009	2010
Same Party	0.0193	0.0202	0.0193	0.0191	0.0157	0.0157	0.0153	0.0143	0.0155
	(0.0011)	(0.0010)	(0.0009)	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0007)
Different Party	0.0053	0.0041	0.0034	0.0043	0.0037	0.0030	0.0027	0.0029	0.0035
	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Only Worker	-0.0007	-0.0006	-0.0006	-0.0007	-0.0004	-0.0005	-0.0004	-0.0004	-0.0005
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(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
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Same Gender	0.0009	0.0011	0.0010	0.0008	0.0008	0.0008	0.0008	0.0008	0.0007
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Race	0.0008	0.0010	0.0009	0.0008	0.0008	0.0006	0.0007	0.0007	0.0006
	(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)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(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
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same-Diff	0.014	0.016	0.015	0.014	0.012	0.012	0.012	0.011	0.012
Same-Only Worker	0.020	0.020	0.019	0.019	0.016	0.016	0.015	0.014	0.016
Same-Only Owner	0.015	0.017	0.016	0.016	0.013	0.013	0.013	0.012	0.012
Diff-Only Worker	0.006	0.004	0.004	0.005	0.004	0.003	0.003	0.003	0.004
Only Owner-Diff	0.001	0.000	0.000	0.001	0.001	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
Observations	35260925	44462775	50259273	58806887	66263984	71055823	82429485	91696133	103613506
Num Workers	2433138	3253156	3477133	3812717	4115318	4388406	4864504	5157565	5586379
Num Firms	448213	521375	555463	597289	637922	667965	716242	760444	813701
Num Markets	22819	26391	27475	28666	29968	32290	34021	35325	37352

	2011	2012	2013	2014	2015	2016	2017	2018	2019
Same Party	0.0174	0.0175	0.0168	0.0167	0.0176	0.0159	0.0153	0.0133	0.0139
	(0.0007)	(0.0008)	(0.0008)	(0.0007)	(0.0008)	(0.0006)	(0.0006)	(0.0005)	(0.0005)
Different Party	0.0032	0.0030	0.0032	0.0030	0.0033	0.0031	0.0031	0.0021	0.0032
	(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	-0.0004	-0.0005	-0.0005	-0.0005	-0.0004	-0.0004
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Only Owner	0.0025	0.0024	0.0025	0.0023	0.0026	0.0023	0.0023	0.0019	0.0024
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Same Gender	0.0007	0.0006	0.0005	0.0005	0.0005	0.0006	0.0006	0.0004	0.0005
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0001)
Same Race	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)
Same Educ	0.0001	0.0000	0.0000	-0.0002	-0.0002	-0.0003	-0.0003	-0.0004	-0.0004
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same Age	-0.0005	-0.0004	-0.0003	-0.0002	-0.0002	-0.0002	0.0000	-0.0002	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Same-Diff	0.014	0.014	0.013	0.013	0.014	0.012	0.012	0.011	0.010
Same-Only Worker	0.017	0.018	0.017	0.017	0.018	0.016	0.015	0.013	0.014
Same-Only Owner	0.014	0.015	0.014	0.014	0.015	0.013	0.013	0.011	0.011
Diff-Only Worker	0.003	0.003	0.003	0.003	0.003	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
Only Owner-Only Worker	0.003	0.003	0.003	0.002	0.003	0.002	0.002	0.002	0.002
Observations	113028394	123692697	134671457	144660502	142312463	135400587	134646745	136041096	145081396
Num Workers	5971705	6319888	6662718	6957129	6902007	6654855	6597202	6508020	6827768
Num Firms	869361	906374	953214	994202	1006926	995323	989556	979387	995441
Num Markets	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 for details of the estimation.

Table A9. **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 for details of the estimation.

Table A10. **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 for details of the estimation.

Table A11. **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 for details of the estimation.

Table A12. **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 with a below median level of interpersonal interactions. Standard errors in parentheses are clustered by market. See section 3 for details of the estimation.

Table A13. **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 with an above median level of interpersonal interactions. Standard errors in parentheses are clustered by market. See section 3 for details of the estimation.

Table A14. **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 A15. **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
R-squared	0.068	0.094	0.293
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 equation 5.3. *SYA* correspond to *worker-year-number of affiliated workers* fixed effects. *SYAI* adds *two-digit industry* fixed effects. SYAIM adds *municipality* fixed effects. *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.

ONLINE APPENDIX: 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)[38], *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 A10 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,[39] gender, date of birth, race, level of education, nationality, municipality, firm's sector of activity, worker's occupation, pay,[40] and the number of weekly hours in the contract. Unique workers' and employers' tax identifiers allow to follow individuals over time and across firms.

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

[39]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.

[40]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.[41] 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*).[42] 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 owner of a firm in all

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

[42]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.

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.[43] 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.[44] 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 to retrieve information on date of birth and gender for all individuals who are registered to a party.

[43]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.

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

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.[45]

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.[46] 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.

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.

[45]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.

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

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:[47]

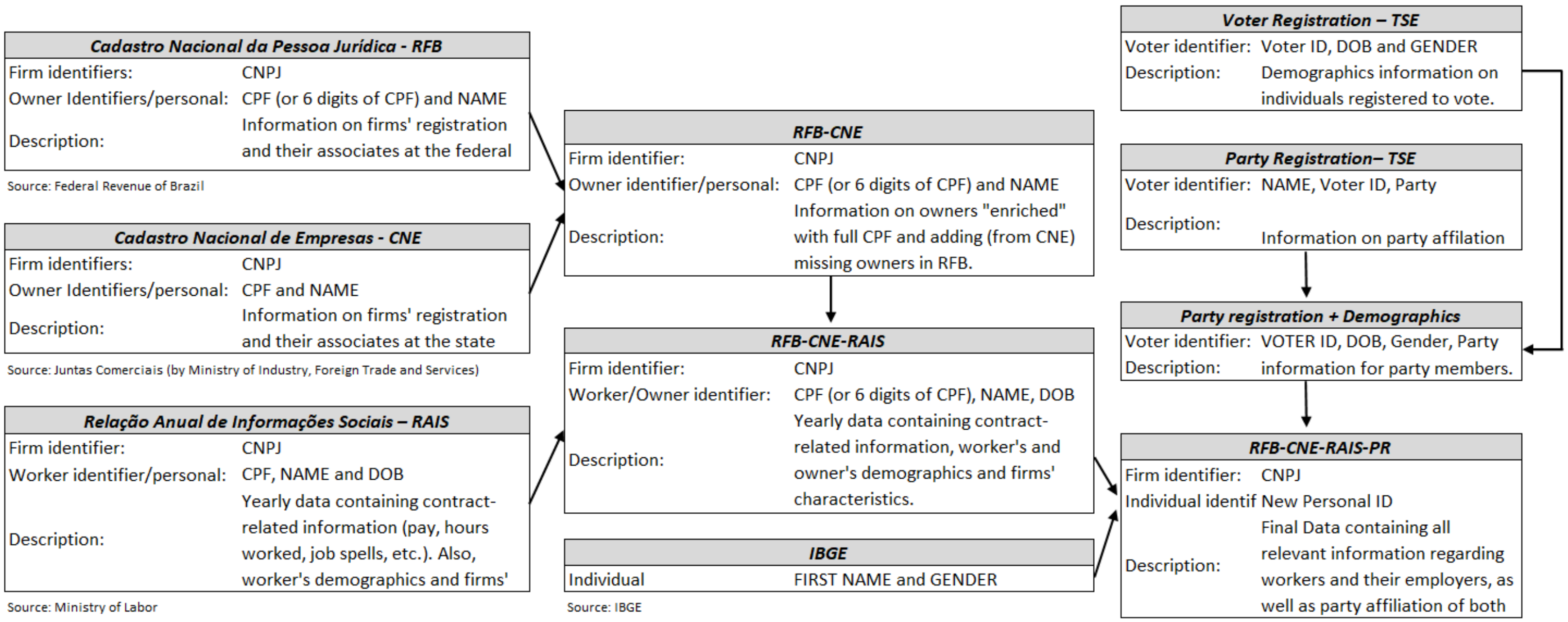
- Step 1: perfect by name - year of birth - month of birth - day of birth - municipality (matching rate: 50.05%)
- Step 2: perfect by name - year of birth - month of birth - day of birth - state (matching rate: 22.18%)

[47]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 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 A10. Visual representation of the linkage structure



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.

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 co-workers? 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

APPENDIX A4.2: 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