POLITICS AT WORK

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Abstract. We study the role of politics in the labor market using new data on the political affiliation of the near-universe of private sector workers and business owners in Brazil over the 2002-2017 period. We establish three main facts. First, there is substantial political segregation in the workplace: workers of the same political party work together. Second, business owners of a given party are more likely to employ workers belonging to the same party. These results are mainly driven by owners' preferences for workers of their own party, rather than workers' preferences for co-partisan co-workers. Third, we uncover a large political wage premium: within a firm, workers of the same political party of the business owner are paid more. All these empirical facts are larger in magnitudes than analogous ones we establish along gender and racial lines. Our findings highlight the importance of individual political views in shaping firm behavior and labor market outcomes.

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1. Introduction

"No politics at work" has long been a standard policy among private sector corporations around the world. Yet times are changing, and firms and employees are becoming more and more open about their political views, often embracing politics as part of their culture. The majority of Americans report that they talk about politics at work (Global Strategy Group, 2020) and anecdotal evidence suggests that companies may take actions against employees because of their political views (Grind and Hagey, 2018). Indeed, partisan affiliation is considered an important element of an individual's social identity (Green et al., 2002), and can trigger feelings of animosity towards people with different political views (Iyengar et al., 2019).

Rather than being confined to the political arena, partisan animus could affect behavior in apolitical domains, and particularly in settings, like labor markets, which feature frequent personal interactions. For example, employers might prefer workers who share their political views, either because of taste-based discrimination (Becker, 1957), or because differences in political views within the firm may lead to lower productivity.[1] On the other hand, workers might view interacting with co-partisans as a valuable amenity, or they might similarly be averse to sharing the workplace with co-workers and business owners of different political views.

Empirical evidence on the role of politics in the labor market remains virtually non-existent, mainly due to the difficulty of linking data on individual political views to micro-data on firms and workers. As a result, several fundamental questions remain unanswered: does one's political views influence job choice and hiring decisions? Is politics a determinant of wages? How does politics shape firm choices and labor market outcomes?

In this paper, we aim to fill this gap by means of a new dataset we assembled linking millions of business owners and workers to information on their political affiliation. We study the full Brazilian formal labor market over the 2002-2017 period. Our first contribution is to bring together three main sources of data. We start by augmenting the RAIS 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 datasets. We then merge both workers and owners to the registry of individuals affiliated with a political party maintained by the Superior Electoral Court. Party affiliation can be considered as a signal of strong and visible political views, with unaffiliated individuals likely having somewhat milder views on politics. We find that 11.7% of owners and 8% of workers in the private sector are affiliated with a political party. Business owners are significantly more likely to belong to a right-wing or center party, while workers are equally split across the political spectrum.

The dataset we assemble has three key advantages. First, we can observe individual political views, as measured by partisan affiliation, for the entire set of workers and business owners in a major economy. Second, we are able to create a owner-firm-worker matched dataset, which allows us to study multiple types of labor market interactions. Third, we can observe an extremely rich set of individual- and job- level covariates, so that we can control for a wide set of observable characteristics in our analysis (such as workers' and owners' demographics, location, industry,

[1] See, for instance, Hjort (2014) for a study of how ethnic diversity affect productivity within the firm.

and occupation), and so that we can benchmark our politics estimates with those of well-established determinants of labor market outcomes, namely gender and race.

We start with motivating evidence in the spirit of a large literature on discrimination in hiring. We find that the larger the existing share of workers from a given political party in a firm, the more likely the firm is to hire workers from that party. Additionally, a firm with an owner of a given party is more likely to hire new workers from that party.

Building on this evidence, we exploit the granularity of our data and employ a dyadic regression approach where we construct billions of worker-worker and worker-owner dyads within all industry-municipality markets.[2] We use this approach to *(i)* estimate the level of political segregation in the workplace, studying whether and to what extent workers of the same party work in the same firm, and *(ii)* estimate the level of assortative political matching between workers and firms, studying whether and to what extent workers of a given party tend to work for business owners of the same party. The key advantage of our dyadic approach is that it allows us to address the concern that assortative criteria are often correlated, by controlling for an extensive set of workers', workplaces', and owners' characteristics that are likely to correlate with both an individuals' political affiliation and her labor market choices. In addition, this framework allows us to directly benchmark the role of politics with that of other demographics that are shared among workers and between workers and business owners.

We establish two main facts. First, there is a large degree of political segregation in the workplace: relative to the baseline sample probability of working in the same firm, a politically affiliated worker is between 6.3% and 10.8% more likely to work with a co-partisan rather than with someone from a different party. Second, we find a massive degree of assortative political matching between workers and business owners: politically affiliated workers are between 139% and 176% more likely be employed by a co-partisan owner than by one affiliated with a different party. Moreover, we find shared partisan affiliation to be a stronger driver of employment outcomes than shared gender or race, despite the large estimates we uncover in the same context.[3] While our results show that the degree of political segregation in the workplace is substantial, we do not observe significant time trends in the estimates during our study period.

We then investigate potential mechanisms that can explain these findings using a regression framework that jointly describes the worker-worker and worker-owner matching. We find no evidence that workers of the same party cluster together in firms whose owner is unaffiliated or affiliated with a different party. This result suggests that our results on workplace segregation are unlikely to be driven by workers' preferences for working with co-partisan co-workers. Similarly, it seems unlikely that business owners are hiring workers of the same party to increase cohesion among workers, and in turn productivity. If these were the primary mechanisms, we would expect to see political segregation among workers irrespective of the political affiliation of the business owners. Instead, we find large and significant political segregation estimates only for

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

[3] The role of shared gender and race in the workplace has recently been studied by Giuliano et al. (2009), Giuliano et al. (2011), Benson et al. (2019), and Morchio and Moser (2020).

workers employed by firms whose owner is affiliated with the party of the majority of the workers. In sum, our evidence suggests that the main driver of political segregation in the workplace is the owners' preference for workers of the same political party.

In the final part of the paper, we investigate how workers' and owners' political affiliation affect wages. We estimate highly saturated regressions that allow us to compare wages of observationally identical individuals working in the same occupation in the same firm at the same point in time. We uncover a substantial wage premium for workers who belong to the same political party of the business owner. Relative to their unaffiliated co-workers, these workers earn 3.6% higher wages. This "political wage premium" is significantly larger than the wage premium associated with sharing the same gender (1.6%) or race (1%) of the owner. We also find a significant, albeit smaller, 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. When we further restrict the comparison to co-workers employed in the same occupation, we continue to find a significant political wage premium, even if smaller in magnitude, suggesting that at least part of these wage differentials stems from the assignment of workers to different positions within the firm. The political wage premium is present across all main occupational categories of managers, white collar, and blue collar workers. Interestingly, politically affiliated workers suffer a 1.2% wage penalty in firms whose owner is unaffiliated, further pointing to the fact that the association between political affiliation and wages crucially depends on the type of owner the worker is matched to.

In interpreting these sets of results, it is important to emphasize that our current analysis is descriptive in nature. That is, it is interesting to dig deeper into *why* we observe these employment and wage patterns in the data. Our findings may be in line with a story according to which workers are more productive when matched to business owners with the same political views. Alternatively, an owner may use her political network to identify workers who are better, independently of observable characteristics. Additionally, the results may be explained by taste-based discrimination, with business owners discriminating in favor of workers who share their same partisan affiliation. In work in progress, we are collecting new data and performing additional tests to shed light on these important economic channels, which have different implications. Among the various next steps, a significant part of our focus is also on disentangling how much what we are capturing is about partisanship per se, or rather about broader views of the world, or differences in social identities, which happen to be well summarized by one's partisan affiliation.

Our paper contributes to several strands of literature. First, we speak to the recent growing literature on the importance of politics across apolitical realms, which focuses on the U.S. and that is recently reviewed by Iyengar et al. (2019). Individual political views seem to matter in product markets for both sellers (Michelitch, 2015) and buyers (Panagopoulos et al. (2016), McConnell et al. (2018)), as well as for friendship and dating choices (Huber and Malhotra, 2017). A recent stream of papers show that partisan affiliation also affects financial decisions (Kempf and Tsoutsoura (2018), Ke (2019), Evans et al. (2020), Dagostino et al. (2020)). Two experiments indicate that partisanship matters in labor markets. Gift and Gift (2015) use an audit design where CVs with partisan cues are randomly sent either to a highly conservative or a highly liberal U.S. county, finding that minority partisan affiliations are statistically less likely to obtain a callback than candidates without any partisan affiliation. McConnell et al. (2018) conduct an experiment with freelance editors on an online platform and show that study workers request systematically lower reservation wages when the employer shares their political stance. In addition to these studies, the role of politics in private organizations has recently attracted attention also in the psychology and organizational behavior literature, as illustrated in the review by Swigart et al. (2020). Our paper contributes to this body of work by identifying how individual politics shapes firm behavior and a range of labor market outcomes over a long time period and across all possible sectors and all managerial, white collar, and blue collar occupations. In fact, to our knowledge, ours is the first paper matching government registries of workers, business owners, and party members, likely because of the difficulty of accessing and linking these types of sensitive data in the U.S. and in most other countries. Using rich micro-data that combine multiple administrative sources is crucial to be able to disentangle different mechanisms and to estimate precise economic magnitudes, which can then be interpreted in light of and benchmarked with other well-established patterns in the labor market such as those of race and gender.

We also contribute to a vast literature on discrimination in labor markets, dating back to the theoretical contribution of Becker (1971) on employers' taste-based discrimination, and Phelps (1972) and Arrow (1973) on statistical discrimination. A large body of empirical work has investigated the role of employers' discrimination in hiring and compensation decisions (see for instance, Altonji and Pierret (2001), Bertrand and Mullainathan (2004), Black et al. (2006), Fryer et al. (2013), and Altonji and Blank (1999) for a review of an earlier literature), and its impact on performance (Glover et al., 2017). A number of recent papers focus specifically on the matching between managers' and workers' race or gender, showing their relevance for hiring and promotions (Giuliano et al. (2009), Giuliano et al. (2011), Kunze and Miller (2017), Benson et al. (2019), Cullen and Perez-Truglia (2019)). Besides confirming in our data the relevance of shared gender and race between employers and employees for employment and pay decisions, our paper highlights how the match/mismatch in partisan affiliation between employers and employees may represent an additional important source of labor market discrimination. In this sense, our paper is linked to the work studying how social and ethnic ties affect economic outcomes.[4] Relatedly, we speak to a large literature on labor market segregation (Bayard et al. (2003), Hellerstein and Neumark (2008), Åslund and Skans (2010), Hellerstein et al. (2011), Dustmann et al. (2016)). To our knowledge, ours is the first paper to identify the link between politics and workplace segregation.

We are not the first to explore the broad link between politics and labor outcomes. Most papers looking at individual politics focus on the the public sector (see Xu (2018) and Colonnelli

[4]Recent examples include Hjort (2014), Fisman et al. (2017), Fisman et al. (2018), Hjort et al. (2019), Fisman et al. (2020b), and Fisman et al. (2020a).

et al. (2020), for example, and the review by Finan et al. (2017)). There is also a smaller set of studies that connect politics to private labor markets. However, such studies focus on the careers of politicians or the connections of workers to politicians through family or corporate ties, such as the work by Cingano and Pinotti (2013), Fafchamps and Labonne (2017), Folke et al. (2017), and Bertrand et al. (2018). Our study takes a more comprehensive approach by studying the role of individual political views, as proxied by party registration, in driving labor market outcomes independently of direct connections to politicians in power.

Finally, we contribute to the literature on the importance of firms' employment and wage setting policies to explain pay differentials between socio-demographic groups. Card et al. (2018) provides a comprehensive summary of this strand of literature, which for the most part relies on matched employer-employee data structures similar to ours. In Brazil, Alvarez et al. (2018) provide a comprehensive picture of earnings inequality over most of our sample period, while Gerard et al. (2018) and Morchio and Moser (2020) study the role of race and gender in explaining wage gaps and sorting patterns in the labor market. Our results underline how employment and wage setting policies are at least in part driven by firms' owners' preferences for employees who share their same partisan affiliation, which may have important aggregate implications when considering that nearly 10% of the population is formally registered with a political party during our study period.

This paper is organized as follows. In Section 2 we describe the data creation. In Section 3 we provide a brief descriptive analysis of the data. Section 4 illustrates the findings on political segregation in the workplace. Section 5 presents the results on the political wage premium. Section 6 concludes.

2. Data

We assemble a new longitudinal dataset on the political affiliation of the near-universe of private sector workers and business owners across Brazil, combining information from four main 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, the Tribunal Superior Eleitoral (TSE) gives information all individuals registered with a political party. In this section we discuss these data sources in more details and how we match the datasets together. We subsequently present various descriptive facts about the role of political partisanship among workers and business owners.

2.1. **Workers: RAIS Dataset.** Our source of data for workers in the private sector is RAIS, an administrative matched employer-employee dataset managed by the Ministry of Labor (MTE). 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 individuals' (available starting in 2002) and employers' tax identifiers allow for tracking of individuals over time and across employers.[5] Importantly, we only keep firms operating in the private sector.

We construct a yearly panel of workers in the private sector for the period 2002-2017.[6] RAIS contains rich information on the jobs (wage, number of hours worked, specific occupation, type of contract, and length of the employment spell, among other details), the firm (sector, municipality), and the worker's demographics (gender, date of birth, education, race, nationality).[7]

After standard data cleaning steps, the panel dataset includes 82,472,322 unique workers, for a total of 584,741,033 year-worker observations, and 6,091,184 unique firms, for a total of 36,048,521 year-firm observations.

2.2. **Owners: RFB and CNE-MDIC Datasets.** An important contribution of our paper is to match the RAIS data to a new dataset on company registration and business ownership in Brazil. Specifically, we obtain two datasets for this purpose. The primary dataset 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, namely the Cadastro Nacional de Pessoas Juridicas. At the time of registration, it is a requirement to list all individual and corporate owners with any stake in the company, together with the total capital commitment. Given our focus on political affiliation, we focus on individual owners and disregard corporate ones.

The RFB data contain information on all owners of firms that are active in the formal sector as of the year in which we obtained the data (i.e., 2019), together with the date in which each owner started having a stake in 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 other words, the limitation of the data is that it does not allow us to identify owners who left a firm before 2019 (for firms that are active in 2019), or before the firm closed (for firms that became inactive before 2019). Given the extremely limited turnover among owners of a firm, we do not think this limitation is too severe.

The ownership structure of a firm in RFB consists of a set of business associates (*socios*) or of a unique individual, the latter case being that of "individual entrepreneurs" and "micro-entrepreneurs." There are 11,234,541 unique business associates (owning a total of 7,540,882 firms), 7,782,961 unique individual entrepreneurs (owning a total of 7,851,679 firms), and 9,550,881

[5]RAIS allows to observe both the firm and the establishment an individual is associated with. In our analysis, we consider the establishment as the unit of comparison (for example, when defining coworkers or when measuring wage premia within the organization). As discussed later, the ownership data obviously always refer to the firm, and so all establishments of a firm are owned by the same business owners. In the text, for simplicity, we'll therefore use the term "firm" even if we refer to the "establishment."

[6]Following standard practices using RAIS, such as in Menezes-Filho et al. (2008) and Colonnelli and Prem (2020), we keep the highest paying job of the worker whenever a worker is employed by more than one firm in a given year.

[7]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.

unique individual micro-entrepeneurs (owning a total of 9,864,231 firms). For all these 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 individual datasets with a high degree of accuracy.

In addition to the above set of business owners, approximately 10% of firms in RFB remain uncategorized and provide no individual identifier for their owners. While a small issue, considering that these firms only make up a small percentage of employment once the data are matched to RAIS, we alleviate this issue by complementing the RFB dataset with an additional data source.

Specifically, we complement the RFB data with a second confidential source of ownership information, namely the *Cadastro Nacional de Empresas* (CNE), which is managed by the the *Ministério da Indústria, Comércio Exterior e Serviços* (MDIC) and is subject to regular checks over time by state officials. The CNE aggregates all the ownership details obtained by each state at a time of a company registration with their respective state. 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 that span the full Brazil, which helps to alleviate the issue of having only snapshots of the data in RFB.[8] The data is recorded by each state for every year, and cover the period 2002-2017. The CNE data contain information on a total of 19,045,762 owners and 16,239,551 firms.[9]

2.3. **Party Members: TSE Party Registration Dataset.** Data on all individuals registered as party members of a Brazilian political party come from the Tribunal Superior Eleitoral (TSE).[10] The data contain the name of all current and past party members over the 2002-2017 period, with information on the date of registration, municipality, party, and voter registration number. For individuals who end their registration with a party, we also observe the date of de-registration. We additionally match party members to the TSE Voter Registration Records using the voter registration numbers, to obtain information on their date of birth, which helps us achieve a high quality match between the TSE data and RAIS.

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 allowing a simple online registration. Registered individuals can typically participate in party activities and campaigning, and can vote to choose the party candidates. As of 2017, about 12% of the voting age population was affiliated with a party. Party affiliation can be interpreted as a signal of an individual's strong and visible political views, with unaffiliated individuals likely having somewhat milder views on politics.

[8]The data was obtained in October 2018 through a FOIA-like transparency request to the *Ministério da Indústria, Comércio Exterior e Serviços*.

[9]Unfortunately, the CNE data also has minor issues, due to imperfect reporting by some states in the earlier periods. Hence, we cross-check with each other and combine CNE and RFB to create what we deem to be the most reliable dataset on business ownership in Brazil.

[10]Throughout the paper, we use the terms "party registered" and "party affiliated" interchangeably.

There are 18,425,484 individuals who are members of a political party at some point over the 2002-2017 period, for a total of 225,452,560 year-individual observations. While politics in Brazil is quite fragmented, as it is 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. In parts of our analysis, we categorize specific parties into Left-Wing, Center, or Right-Wing. Appendix Table A1 shows the distribution of members across parties .

2.4. **Matching Workers, Owners, and Party Members.** We match data on workers, owners, and party members using a combination of tax identifiers, full name, date of birth, and municipality. Full details of the matching are reported in Appendix Table A2.

Our starting dataset is RAIS. We use firm tax identifiers to match the firms in RAIS to those in the ownership datasets RFB and CNE, thus creating a owner-firm-worker matched 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 96.3% of the 36,048,521 firm-year observations in RAIS, corresponding to 92.2% of all worker-year observations. 4.7% of workers also appear as owners of a firm at some point over the sample period, while 43.6% of owners also appear as workers at some point over the sample period (either of their own firm or of a different firm). Crucially, for the subset of owners who also appear as workers, we observe the full set of demographic characteristics collected in RAIS.[11]

After RAIS is augmented with ownership information, we match all workers and owners of firms appearing in RAIS to the party registration dataset.[12]

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 16.2 workers and 1.62 owners. A minority of firms employ workers in managerial positions (on average, there are 0.87 managers per firm), the median number of workers employed in a white collar position below managerial ones is 2, and the median number of blue collar workers is 1. While the median Brazilian firm is quite small, the size distribution is significantly right skewed, with a right tale of larger firms (the firm at the 90th percentile employs 21 workers). However, ownership is quite concentrated in all firms, with the firm at the 75th percentile of the distribution of number of owners having only 2 owners.

3. Descriptive Analysis

In this section we take a first look at the data we assembled to motivate the relevance of politics as a determinant of labor market outcomes.

[11]To avoid double counting, we consider owners who also appear as workers of their firm solely as owners.

[12]As mentioned earlier, key to achieve 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 operating in the informal sector.

3.1. **How Widespread is Partisan Affiliation in the Labor Market?** We match 11.7% of owners and 8% of workers to the party registration data. 34% of firm-years have at least one party registered worker, and 16% of firm-years have at least one party-registered owner. Out of the total number of years in which they appear in the data, the average worker is affiliated for 84% of the years, and the average owner is affiliated for 91% of the years. Importantly, changes of partisan affiliation over the sample period are rare for both workers and owners, with only 6% of workers and 8% of owners being affiliated with more than one party from 2002 to 2017. This suggests that partisan affiliation can be interpreted as a measure of persistent political views, at least over the 16 years period covered in our data.

Table 2 reports the results from regressions aimed at identifying how politically affiliated workers (columns 1 and 2) and owners (columns 3 and 4) differ from their respective counterparts in the economy. We find that both workers and owners that are politically affiliated are on average more likely to be highly educated, older, and male, but they are less likely to be white. Among workers, we also find that politically affiliated ones are more likely to occupy upper level positions in the firm (managers or white collar) rather then blue collar ones.[13]

As shown in Figure 1, there is substantial geographic variation in the degree of affiliation of workers and firm owners. The top panel of Figure 1 shows the geographical distribution of workers, while the bottom panel shows the distribution of owners. A quick glance at both figures suggests a higher concentration of politically affiliated workers in the poorer regions of Brazil. Notice that although we match 11.7% of owners and 8% of workers to the party registration data, the majority of the municipalities in our dataset (which we will use to define labor markets in our analysis) have a much larger share of workers and owners that are politically affiliated.

In Figure 2, we report the distribution of politically affiliated workers and business owners by sector and political orientation.[14] In the top panel, we can see that certain sectors are characterized by a higher concentration of politically affiliated individuals. Indeed, heavily regulated sectors like Transport/Utilities/Communication and Construction have higher shares of both workers and owners who are registered party members, relative to other sectors, such as the non-tradable ones of Services and Trade. In the bottom panel of Figure 2 we instead 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.

3.2. **Preliminary evidence on political segregation.** To motivate the study of politics in the labor market, we start by investigating whether the political affiliation of a firm's new hires is associated to the political affiliation of the firm's current workforce, and to the political affiliation of the firm's owner.

[13]Notice that, while we observe them for all workers, we can only observe socioeconomic and demographic characteristics for the owners that are also matched to RAIS at any point in the 2002-2017 period.

[14]The classification in sectors follows the 7-digit split adopted by Dix-Carneiro (2014).

We start by showing whether a worker is more likely to be hired by a firm that employs a higher share of workers belonging to her same party. We focus on the sample of firms that hire at least one worker in a given year, and we estimate the following equation:

$$y_{fpt} = \alpha_{pt} + \beta S_{f,p,t-1} + \gamma D_{f,p,t-1} + X'_{ft}\delta + \epsilon_{fpt} \tag{3.1}$$

where y_{fptm} is the share of workers from party p among all new hires in firm f in year t, and $S_{f,p,t-1}$ is the share of workers from party p employed in the firm in year $t-1$.[15] The parameter of interest β identifies the impact of having a higher share of workers from a given party on the probability that the firm hires a larger share of workers from that specific party. We also control for the share of workers from a party other than p employed in the firm in year $t-1$ ($D_{f,p,t-1}$), so as to capture the degree to which the firm employs affiliated workers, irrespective of their political party. The matrix X_{ft} includes controls for the share of new hires that belong to a specific gender, racial, age, and educational group. Finally, we include party-year fixed effects (α_{pt}) to control for overall party popularity in a given year.

The results are shown in Panel A of Table 3. The specification in column 1 indicates that a 10 percentage points increase in the share of workers from a given party in the firm is associated with a 60 percent increase in the share of new hires that are from that party, relative to the sample mean of the dependent variable. In columns 2 and 3, we show that the estimates are robust to estimating a more stringent specifications which include party-year-municipality fixed effects, or party-year-municipality-industry fixed effects, exploiting only variation within a municipality, or within an industry in a municipality.

We find a similar pattern when studying how the probability of being hired depends on the partisan affiliation of the business owner, as illustrated in Panel B of Table 3.[16]

To sum up, we uncover two facts. First, the larger the existing share of workers from a given party in a firm, the more likely the firm is to hire new workers from that party. Second, a firm with an owner of a given party is more likely to hire new workers from that party.

While this type of analysis is typical of studies of discrimination in the labor market (see, for example, Benson et al. (2019)), it suffers from a few shortcomings. First, it does not allow us to adequately 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 women, and women cluster in specific workplaces, failing to control for gender may lead us to confound the role of partisan affiliation with that of gender. Second, this firm-level analysis describes only the relevance of partisan affiliation for hiring patterns, and cannot provide a complete picture of the extent of political segregation in the workplace. Third, we would like to understand whether the extent of political segregation in the labor market stands out relative to the extent of workplace segregation along other shared demographic characteristics, such as gender and race. The framework used in this section does not allow us to directly benchmark

[15]Note that each firm-year observation is multiplied by the number of parties in Brazil.

[16]Throughout the paper, for the minority of firms with more than one owner and with owners who are affiliated with different parties, we define the firm's owners' partisan affiliation as the partisan affiliation of the majority of the owners.

the role of politics with that of other demographics that are shared between workers, or between workers and owners. Fourth, the analysis does not allow us to pin down the main reasons why politics matters in the workplace. For instance, the results in Panel A Table 3 may merely stem from the findings in Panel B of Table 3: in other words, the fact that workers tend to be politically segregated may be entirely be driven by employers' preferences for employing workers who share their political affiliation.

In the next section, in order to paint a more detailed picture of the role of politics as a driver of workers' and employers' choices, we employ an empirical framework that allows us to a large extent to address these shortcomings.

4. Political Segregation in the Workplace: a Dyadic Regression Approach

In this section we exploit the granularity of our data and employ a dyadic regression approach to estimate the extent of political segregation in the workplace.[17] We start by describing whether and to what extent a worker is more likely to be employed by a firm that employs a large share of workers with her same political affiliation. We then investigate the extent of assortative political matching between workers and firms, namely we ask whether a worker belonging to a given political party is more likely to work for a firm whose owner is from her same party. Finally, we combine both analyses to disentangle whether the patterns of political segregation in the workplace that we observe are primarily driven by workers' or owners' preferences.

4.1. **Political Segregation Among Workers.** We describe the extent of political segregation among workers with the following series of dyadic regressions. For each year between 2002 and 2017, we divide Brazil in M labor markets indexed by m. We define a labor market as a 2-digit CNAE industry code within a municipality.[18] In each labor market, we observe N_m workers. We create a matrix with all possible (i, j) worker-worker dyads within the market. For each year, we obtain a dataset with $\sum_{m=1}^{M} N_m \times (N_m - 1)/2$ dyads, which we use for the estimation of the following equation:

$$y_{ijm} = \alpha_m + \beta^{SP} SP_{ij} + \beta^{DP} DP_{ij} + \beta^{O} O_{ij} + \sum_{c} \gamma^c SX_{ij}^c + \epsilon_{ijm} \tag{4.1}$$

where y_{ijm} is an indicator taking value one if i and j work in the same firm, SP_{ij} is an indicator taking value one if i and j belong to the same party, DP_{ij} is an indicator taking value one if i and j belong to a different party, O_{ij} is an indicator taking value one if only one between i and j is affiliated to a party. The case in which neither i nor j are affiliated with a political party is the excluded category. We include market fixed effects (α_m), effectively comparing only dyads within the same market. In all regressions, we cluster standard errors at the market level, to allow for arbitrary correlation of the residuals within a labor market.

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

[18] There are 99 2-digit CNAE industry codes.

The estimates from equation 4.1 allow us to measure the extent of political segregation among workers. The linear combination $\Delta(SP, DP) = \beta^{SP} - \beta^{DP}$ measures the differential probability that a politically affiliated employee works with someone from the same party rather than with someone from a different party.

The extent to which we observe segregation along party lines among politically affiliated workers can be further decomposed as the sum of two components: the extent to which politically affiliated workers work with co-partisan rather than with unaffiliated workers ($\Delta(SP, O) = \beta^{SP} - \beta^{O}$), and the extent to which politically affiliated workers work with unaffiliated workers rather than with workers of different parties ($\Delta(O, DP) = \beta^{O} - \beta^{DP}$). Since $\Delta(SP, DP) = \Delta(SP, O) + \Delta(O, DP)$, political segregation will be higher when *(i)* a worker who is party affiliated is more likely to work with a worker from the same party than with an unaffiliated worker, and *(ii)* a worker who is party affiliated is more likely to work with a worker who is not affiliated than with a worker from a different party.

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 workers' and workplaces' 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^{c}_{ij} which turn to one if i and j share the same demographic characteristic c. Specifically, we control for shared gender, race, age, educational level, experience, and occupation.[19] By controlling for this wide set of covariates, we can investigate the role of co-partisanship, net of any effect of these other shared demographic characteristics on the probability of working together. 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.

Because of the massive size of the data, we estimate one regression for each year between 2002 and 2017. Additionally, computational constraints force us to use only a subset of the data available in each year for this specific analysis.[20] 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 workers. Second, we sample a random 5% of dyads in each market.[21]

[19]While for gender and race we consider a "male"-"female" and "white"-"non-white" dychotomy, for the other variables we create groupings of values: specifically, we create 7 age brackets (<25, (25-30], (30-35], (35-40], (40,45], (45,50], >50), 4 educational levels (less than middle school, complete middle school, complete high school, more than high school), 5 brackets of experience, and 10 occupation groups (using the first digit of the the *Classificação Brasileira de Ocupações 2002* code). Each indicator c takes value one if the dyad (i, j) falls in the same group of that characteristic.

[20]The full set of observations for 2002 and 2014 (the years with the lowest and highest number of dyads) would be approximately 5.4 trillions and 19.6 trillions, respectively.

[21]In Appendix Table A3 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 the same results as those obtained by drawing a random 5% sample. This is not surprising given that a 5% sample of dyads still involves between 376,251,912 and 860,299,968 observations, depending on the year, as the basis of our estimation.

We present the results graphically in Figure 3. The top panel shows the point estimates and 95% confidence intervals of $\Delta(SP, DP)$, $\Delta(SP, O)$, and $\Delta(O, DP)$. The bottom panel shows a comparison between $\Delta(SP, DP)$ and the effect of shared gender and shared race on the probability that employees (i, j) work in the same firm. All estimates are normalized by the baseline sample probability that a dyad works in the same firm. The full set of estimates of equation 4.1 are reported in Appendix Table A4.

The estimates of $\Delta(SP, DP)$ are shown in red in panel A of Figure 3. The estimates show a significant degree of political segregation in the Brazilian workforce: relative to the baseline probability of working in the same firm observed in the sample, depending on the year, a politically affiliated worker is between 6.3% and 10.8% more likely to work with a co-partisan rather than with someone from a different party. The grey estimates of $\Delta(SP, O)$ show that the probability of observing two co-workers of the same party is 10-15% higher than the probability of observing a match between an affiliated and an unaffiliated worker. Interestingly, as shown in the black estimates of $\Delta(O, DP)$, it is slightly more likely to observe a match between two workers of different parties than between one affiliated and one unaffiliated worker.

In sum, the estimates show that, conditional on two workers being politically affiliated, the likelihood of observing them in the same firm is significantly higher if they belong to the same party. The extent of political segregation among workers is only marginally reduced by the fact that an affiliated worker is somewhat more likely to work in a firm with other affiliated workers, irrespective of which party they belong to. Finally, while the degree of political segregation in the workplace is substantial, we do not observe significant trends in the estimates over the 2002-2017 period.

In panel B of Figure 3, we benchmark the role of politics with that of race and gender. This exercise allows us to gauge the relevance of politics as a determinant of labor market sorting. The point estimates show a significant degree of segregation along gender and racial lines. Even within the same municipality and industry, and after controlling for an extensive list of additional demographics, two workers sharing the same gender are 5.7-7.4% more likely to work in the same firm. The corresponding effect of shared race is of 3.5-6%. Perhaps strikingly given the well-established importance of racial and gender segregation in various labor markets, the relevance of politics as a driver of segregation appears even higher than that of gender and race: in eleven of the sixteen years in the period under study, sharing the same partisan affiliation increases the probability of working together by significantly more than sharing the same gender or race.

4.2. **Assortative Political Matching Between Workers and Owners.** We now move to describe the extent of assortative political matching between workers and owners. We use a similar dyadic regression approach as the one used in the previous subsection. For each year between 2002 and 2017, and for each municipality-industry labor market m, we create a matrix with all possible worker-firm (i, f) dyads. Defining N_m and F_m as the number of workers and firms observed in market m, 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:

$$y_{ifm} = \alpha_m + \beta^{SP} SP_{if} + \beta^{DP} DP_{if} + \beta^{OW} OW_{if} + \beta^{OO} OO_{if} + \sum_c \gamma^c SX^c_{if} + \epsilon_{ifm} \tag{4.2}$$

The dependent variable y_{ifm} 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, 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 (α_m), comparing only dyads within the same market, and we cluster standard errors at the market level.

Using the estimates from equation 4.2, we are interested in the linear combination $\Delta(SP, DP) = \beta^{SP} - \beta^{DP}$, which measures the differential probability that a politically affiliated worker is employed by a firm whose owner belongs to her same party, rather than by a firm whose owner belongs to a different party. This differential probability can be further decomposed as the sum of *(i)* $\Delta(SP, OO) = \beta^{SP} - \beta^{OO}$, namely the extent to which a politically affiliated owner employs workers of her same party rather than unaffiliated workers, and *(ii)* $\Delta(OO, DP) = \beta^{OO} - \beta^{DP}$, namely the extent to which a politically affiliated owner employs unaffiliated workers rather than workers of a party different from her own.[22]

Similarly to our analysis in section 4.1, we include the set of indicators SX^c_{if}, which turn to one if worker i and f's owner share the same demographic characteristic c. We do not control for experience and occupation, as these variables cannot be defined for firm owners, but we additionally include worker's occupation fixed effects and we control for a continuous measure of a worker's experience.[23]

Once again, given the dimensionality of the data, we need to focus only on a subset of the data for computational reasons, even though the restrictions are milder considering that there are significantly fewer owners than workers. Specifically, we drop the top 1% of markets, based on the number of dyads, and we sample a random 25% of dyads in each market.[24]

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 $\Delta(OO, DP)$, while the bottom panel presents a comparison between $\Delta(SP, DP)$ and the effect of shared gender and shared race on the probability that i works in firm f. All estimates are normalized by the baseline sample probability

[22]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).

[23]Importantly, we include in the estimation only firms owned by the 43.6% of owners who also appear as workers in RAIS at some point over the sample period (either employed in their own firm or in a different firm), since only for these owners we have information on race, education and age. We also estimated our results using the full set of owners, and only controlling for an indicator for shared gender (which we have for all the owners), finding largely the same results.

[24]In Appendix Table A5 we show that this restriction does not affect our results.

that y_{ifm} equals one. The full set of estimates of equation 4.2 are reported in Appendix Table A6.

The estimates of $\Delta(SP, DP)$ are shown in red in panel A of Figure 4. We find a considerable degree of assortative political matching between workers and firms' owners. Relative to the baseline probability in the sample, depending on the year, a politically affiliated worker is between 139% and 176% more likely be employed by a co-partisan 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 workers who are affiliated with a different party is instead limited. As was the case for the results in the previous subsection, we again do not observe significant trends in the estimates over the 2002-2017 period.

In panel B of Figure 4, we benchmark the role of politics with that of race and gender. There is a significant degree of positive assortative matching between owners and workers along gender and racial lines, which is consistent with the studies of Giuliano et al. (2009), Giuliano et al. (2011), and Benson et al. (2019). While the effects are large in magnitude (a 13.7-25.4% effect for gender, and a 5.6-8.2% effect for race), the relevance of partisan affiliation as assortative matching criterion is significantly higher.

In sum, the results from this and the previous subsection indicate the presence of a previously unexplored important channel of segregation in the the labor market, namely individual political preferences.

4.3. **Disentangling Workers' and Owners' Preferences.** In this subsection, we combine the results of the previous two dyadic analyses to shed light on the relative importance of workers' and owners' preferences in determining the political segregation in the workplace we just established. There are three main mechanisms that may explain the findings of the previous sections.

First, irrespective of the owner's political affiliation, a worker may have a preference for working in a firm that employs many workers of her same party. This preference for co-partisan co-workers would be consistent with the findings of Figure 3. We call this the *workers' preference for co-partisan co-workers* mechanism.

Second, irrespective of her own partisan affiliation, an owner may prefer to employ several workers of a given party, if she believes it would increase team cohesion and productivity. This would be consistent with the findings of Figure 3. We call this the *owners' preference for political team cohesion* mechanism.

Third, an owner of a given partisan affiliation may have a preference to hire workers of her same partisan affiliation, either because of bias, or because she believes the ideological matching between employers and employees would increase productivity. This would be consistent not only with the findings of Figure 4, but also with those of Figure 3: if an owner is more likely to hire a worker of her same party, there will be more and more firms with a politically homogeneous workforce. We call this the *owners' preference for co-partisan workers* mechanism.

In order to investigate these mechanisms, we need a framework that allows for the simultaneous analysis of the matching among workers as well as between workers and firms. To do so, we combine the frameworks of the previous two sections. Specifically, for each year between 2002 and 2017, and for each industry-municipality labor market m, we create a matrix with all possible worker-worker-firm (i, j, f) triads. For computational reasons, while we consider all firms in a market, we focus only on workers who are affiliated with a party. Defining N_m and F_m as the number of affiliated workers and the number of firms observed in market m, respectively, for each year we obtain a dataset with $\sum_{m=1}^{M} N_m \times (N_m - 1)/2 \times F_m$ triads. We then estimate the following specification:

$$\begin{aligned} y_{ijfm} = \alpha_m &+ \beta_1 \mathbb{1}(\text{worker}_i = \text{worker}_j = \text{owner}_f = p_A) + \\ &+ \beta_2 \mathbb{1}(\text{worker}_i = \text{worker}_j = p_A \text{ , owner}_f = p_B) + \\ &+ \beta_3 \mathbb{1}(\text{worker}_i = \text{worker}_j = p_A \text{ , owner}_f = \varnothing) + \\ &+ \beta_4 \mathbb{1}(\text{worker}_i = \text{owner}_f = p_A \text{ , worker}_j = p_B) + \\ &+ \beta_5 \mathbb{1}(\text{worker}_i = p_A \text{ , worker}_j = p_B \text{ , owner}_f = \varnothing) + \\ &+ \gamma^c SX^c_{ij} + \epsilon_{ijfm} \end{aligned} \tag{4.3}$$

where y_{ijfm} is an indicator taking value one if both worker i and worker j are employed in firm f. The model includes a full set of dummies for each of the possible combination of i, j, and owner of firm f's political affiliation. For instance, the first dummy in the model takes value one if workers i and j and the owner of firm f all belong to the same party (party A). Similarly, the fifth dummy in the model takes value one if i and j belong to two different parties (parties A and B), while the owner of firm f is unaffiliated. The excluded category captures the case in which i and j belong to two different parties (parties A and B), and the owner of firm f belongs to a third, different party (party C).[25]

In Figure 5 we plot five sets of point estimates, normalized by the baseline mean of y_{ijfm}, which can help us shed light on the underlying mechanisms.[26] Specifically, we plot the estimates of β_1 in red, which show that in a firm whose owner belongs to party A there is a 57-63% higher probability of observing two workers of party A than one worker of party B and one worker of party C. The estimates in green are the estimated linear combinations of $\beta_1 - \beta_4$, and they show that, in a firm whose owner belongs to party A, there is 47-61% higher probability of observing two workers of party A than one worker of party A and one worker of party B.

These results are in line with all three of the mechanisms described above: all mechanisms predict that we are more likely to observe co-partisan workers being employed in the same firm. However, both the *workers' preference for co-partisan co-workers* and the *owners' preference for political team cohesion* mechanisms predict that this should be true irrespective of an owner's

[25]As in the previous results, we include a set of indicators SX^c_{ij}, which turn to one if i and j share the same demographic characteristic c, and we cluster standard errors by market m. For computational reasons, for each year, we drop the same top 1% of markets of the dyadic analysis in section 4.1 and we sample a random 5% of triads in each market.

[26]Appendix Table A7 presents the full set of estimated coefficients.

political affiliation, while the *owners' preference for co-partisan workers* mechanism predicts that we should observe a higher likelihood of observing co-partisan workers only in firms whose owner also belongs to that same party. To test these predictions, we plot two additional sets of point estimates. The gray series shows the estimates of β_2, which capture the extent to which, in a firm whose owner belongs to party A, we are more likely to see two workers of party B rather than one worker of party B and one worker of party C. The black series shows the estimated linear combinations of $\beta_3 - \beta_5$, which captures whether in a firm whose owner is unaffiliated we are more likely to see co-partisan workers than workers of different parties. These estimated effects are almost always small in magnitude and statistically insignificant.[27]

In sum, consistent with the *owners' preference for co-partisan workers* mechanism, the significant political segregation among workers described in Figure 3 is found only in firms whose owner is affiliated with the party of a majority of her workers. That is, we do not find much evidence that workers sort to firms with other co-partisans because of their preferences for specific co-workers, or because of owners' preference for political team cohesion.

5. The Political Wage Premium

In this section, we ask how workers' and owners' partisan affiliations affect wage setting.

5.1. **Political Owners and Workers.** We start by examining average wage differentials for affiliated versus unaffiliated workers, and in firms with affiliated versus unaffiliated owners, irrespective of any ideological matching between workers and firm owners. We measure wages as the total yearly wages earned by the worker in the given job, which are obtained multiplying the average monthly wage reported in RAIS by the total number of months the individual worked in the firm in that given year.

To investigate whether firms whose owner is politically affiliated exhibit a wage premium relative to other firms, we estimate the following model:

$$\log w_{ifmt} = \alpha_{mt} + \beta^P P_{ft} + X'_{imt}\gamma + \epsilon_{ifmt} \tag{5.1}$$

where $\log w_{ifmt}$ is the log wage for individual i working in firm f in market m and year t, P_{ft} is an indicator equal to one if the owner of firm f is politically affiliated in year t, α_{mt} are market-year fixed effects, and worker-level demographic controls X'_{imt} include age fixed effects, gender, race, education, and tenure in the firm (in months).

The first two columns of Table 4 show that there is essentially no wage premia paid by firms owned by politically affiliated owners. In the first column, we include industry by year by municipality fixed effects, while in the second column we also interact these dummies with occupation fixed effects. While in the first case, the 0.006 coefficient is marginally significant, the statistical significance disappears in the latter case. This first look at the data indicates that

[27] The estimates of $\beta_3 - \beta_5$ are insignificant in all years, while the estimates of β_2 are insignificant in 2002, 2007 and 2012, while they are significant in 2017, which may suggest that these channels may have become somewhat more relevant in recent years.

worker wages do not differ on average depending on whether firm owners are registered party members or not.

Another interesting question is whether politically affiliated workers earn different wages than unaffiliated ones. For this purpose, we estimate a wage equation similar to 5.1, where we substitute P_{ft} with P_{it}, where the latter is an indicator equal to one if worker i is politically affiliated in year t. We report the results in columns 3-6 of Table 4. When controlling only for industry by year by municipality fixed effects (column 3), we uncover a wage penalty for affiliated workers of 1.6%. This estimate remains statistically significant even when adding finer sets of fixed effects to the estimation. The more stringent specification is in column 6, where we compare workers within a firm-occupation cell. In this case, we find a wage penalty of 0.7% relative to unaffiliated workers.

5.2. **Estimating the Political Wage Premium for Co-partisans.** The central question of our wage analysis is whether the political matching between workers and firm owners affects wage premia within the firm. To this end we specify and estimate the following wage equation:

$$\log w_{ifmt} = \alpha_{ft} + \beta^{SP} SP_{if} + \beta^{DP} DP_{if} + \beta^{OW} OW_{if} + \sum_{c} \gamma^{c} SX^{c}_{if} + X^{'}_{imt}\gamma + \epsilon_{ifm} \tag{5.2}$$

where we add separate indicators SP_{if}, DP_{if}, and OW_{if}, which are defined in Section 4. We include firm-year fixed effects α_{ft}, restricting the comparison to workers of the same firm, and absorbing any time-series variation in wages. We additionally control for the same set of indicators SX^{c}_{if} included in equation 4.2, which turn to one if worker i and f's owner share the same demographic characteristic c. Finally, we include the worker-level version of the demographic controls ($X^{'}_{imt}$). Standard errors are clustered at the firm level.

The coefficients β^{SP} and β^{WP} capture wage differentials in firms whose owner is politically affiliated. Specifically, β^{SP} measures the average wage difference between workers of the same party of the owner and their unaffiliated co-workers in the same year. Similarly, β^{DP} measures the average wage difference between workers of a different party than the owner and their unaffiliated co-workers in the same year. The coefficient β^{OW} measures any wage differential in firms whose owner is unaffiliated, between affiliated and unaffiliated workers.

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 3.6% higher wages. This "political wage premium" is significantly larger than the wage premium associated with sharing the same gender (1.6%) or race (1%) of the owner.

We also find a significant, albeit smaller, 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. Interestingly, politically affiliated workers suffer a 2.1% wage penalty in firms whose owner is unaffiliated, further pointing to the fact that the association between political affiliation and wages crucially depends on the type of owner the worker is matched to.

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. While the estimated coefficients shrink by about one third, suggesting that part of these wage differentials stem from assignment of workers to different positions within the firm, their magnitude is still significant. That is, we find a political wage premium of 2.4% for co-partisan workers. We find a similar pattern of results with respect to the other coefficients in the regression, highlighting the robustness of our findings.

Finally, to further investigate the source of the political wage premia we observe, 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. What stands out is the significantly larger wage penalty for managers belonging to a political party different than the owner's.

6. Conclusion

In this paper, we document a new set of stylized facts about the role of politics in the labor market. We use labor market data on the near-universe of private sector workers and business owners in Brazil over the 2002-2017 period, matched to information on individual political affiliation. Using a dyadic regression approach, which allows to control for an extensive set of workers', workplaces', and owners' characteristics that are likely to correlate with both an individuals' political affiliation and with employment decisions, we document that workplaces are politically homogeneous: workers of the same party work together, and business owners of a given party are more likely to employ workers of the same party. We show that these patterns are mainly driven by business owners' preferences for workers of their own party, rather than by workers' preferences for co-partisan co-workers. We also document the existence of a political wage premium, as workers of the same party of their business owner are paid significantly more than other workers.

In interpreting these sets of results, it is important to emphasize that our current analysis is descriptive in nature. That is, it is interesting to dig deeper into *why* we observe these employment and wage patterns in the data. Our findings may be in line with a story according to which workers are more productive when matched to business owners with the same political views. Alternatively, an owner may use her political network to identify workers who are better, independently of observable characteristics. Additionally, the results may be explained by taste-based discrimination, with business owners discriminating in favor of workers who share their same partisan affiliation. In work in progress, we are collecting new data and performing additional tests to shed light on these important economic channels, which have different implications. Among the various next steps, a significant part of our focus is also on disentangling how much what we are capturing is about partisanship per se, or rather about broader views of the world, or differences in social identities, which happen to be well summarized by one's partisan affiliation.

In sum, our paper highlights the importance of politics in shaping labor market outcomes, a topic that is becoming more and more salient in recent years, which saw a large increase in political polarization around the world (Boxell et al., 2020). Moreover, 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 (2001), Sunstein (2017)). Sunstein (2001) draws a distinction between online interactions and traditional face-to-face interactions, like those in workplaces. 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.

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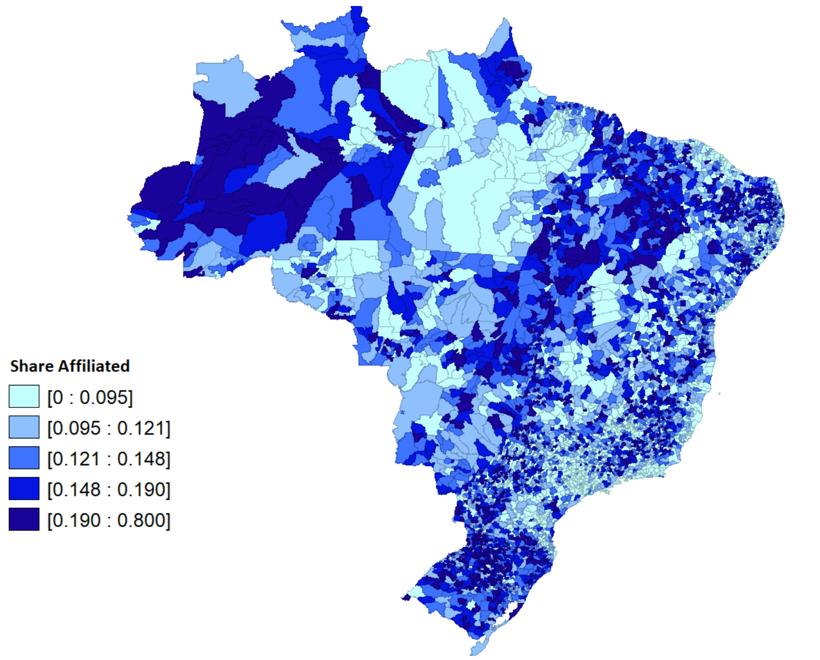
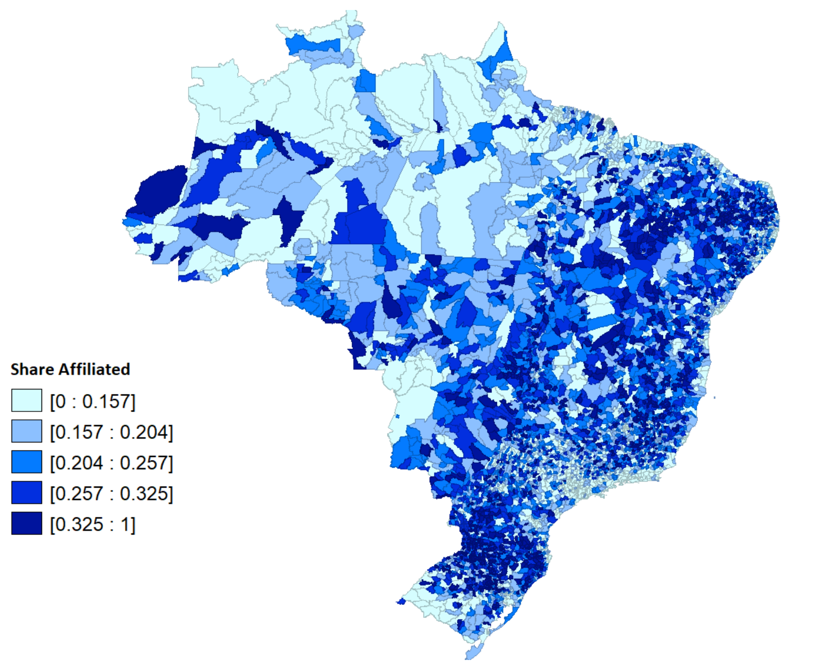
Figure 1. **The Geography of Political Affiliation**



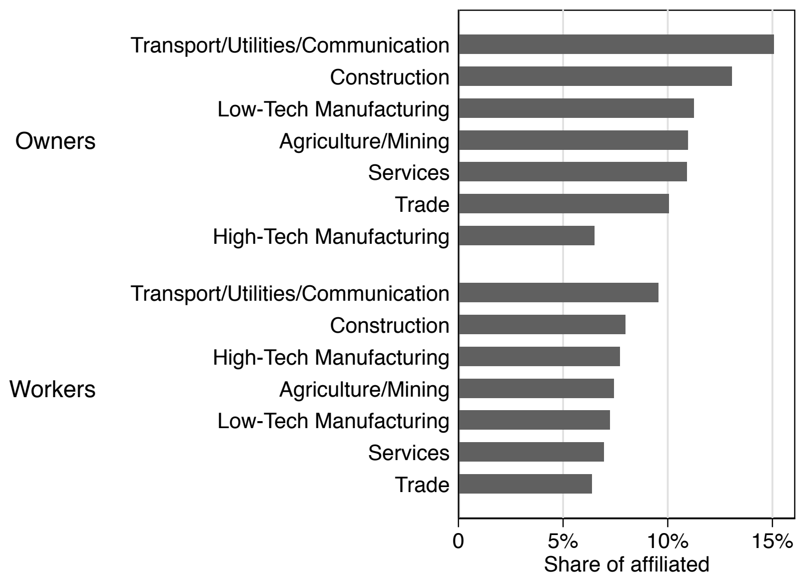
A. Share of workers affiliated



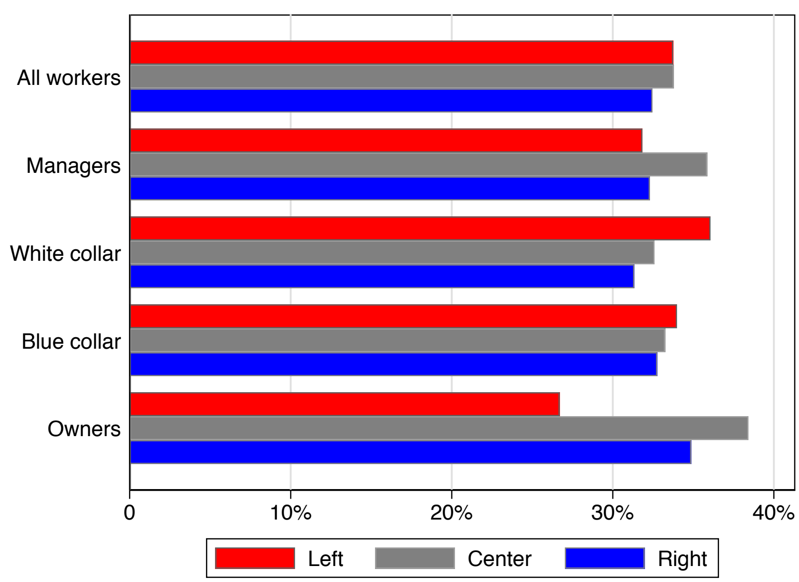
B. Share of owners affiliated

Notes: The figure shows the share of affiliated workers (Panel A) and affiliated owners (Panel B) across Brazilian municipalities over the period 2002-2017.

FIGURE 2. **Politics in the Labor Market - Distribution by sector and political orientation**



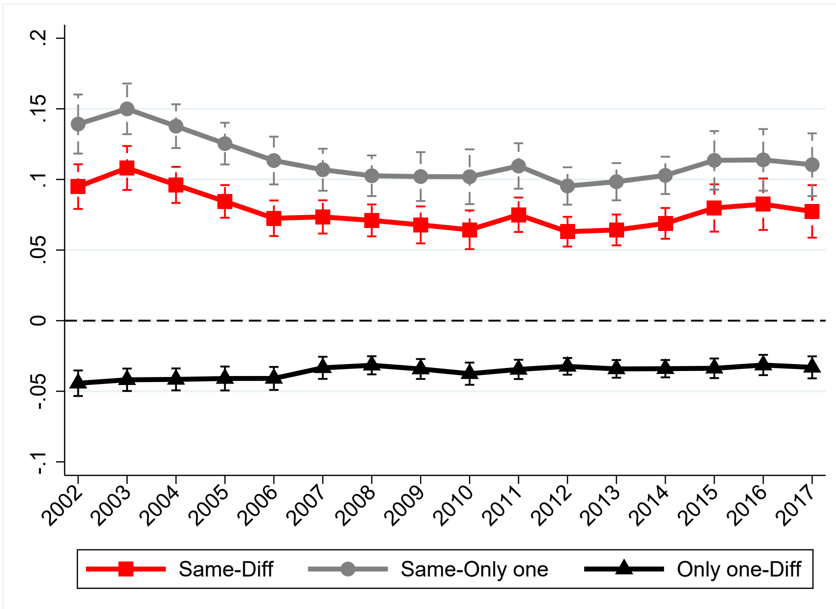
A. Share of affiliated workers and owners by sector



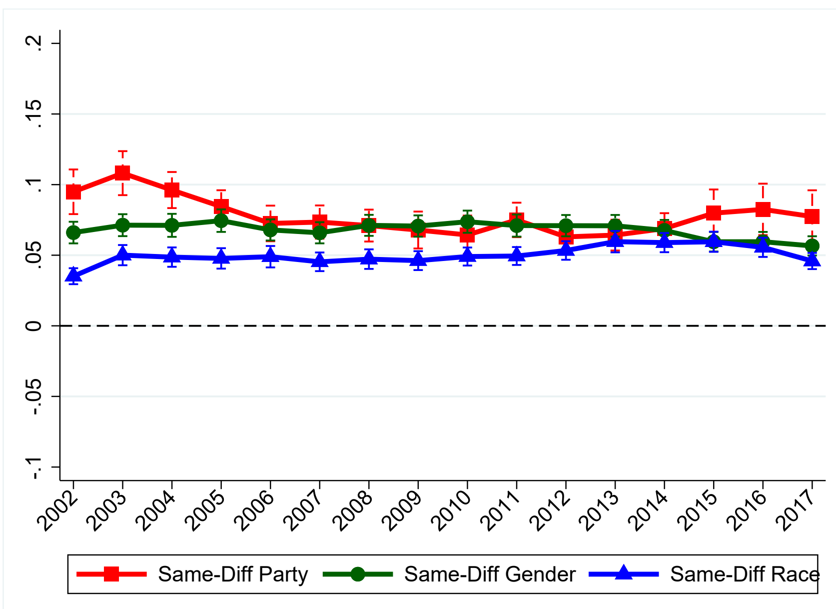
B. Political orientation of affiliated workers and owners

Notes: Panel A shows he share of politically affiliated workers and owners by sector of their firm. Panel B shows the distribution of workers and owners' political orientation. Statistics calculated over the 2002-2017 period. See Appendix Table A1 for the categorization of Brazilian parties as Left/Center/Right.

FIGURE 3. **Political Segregation in the Workplace**



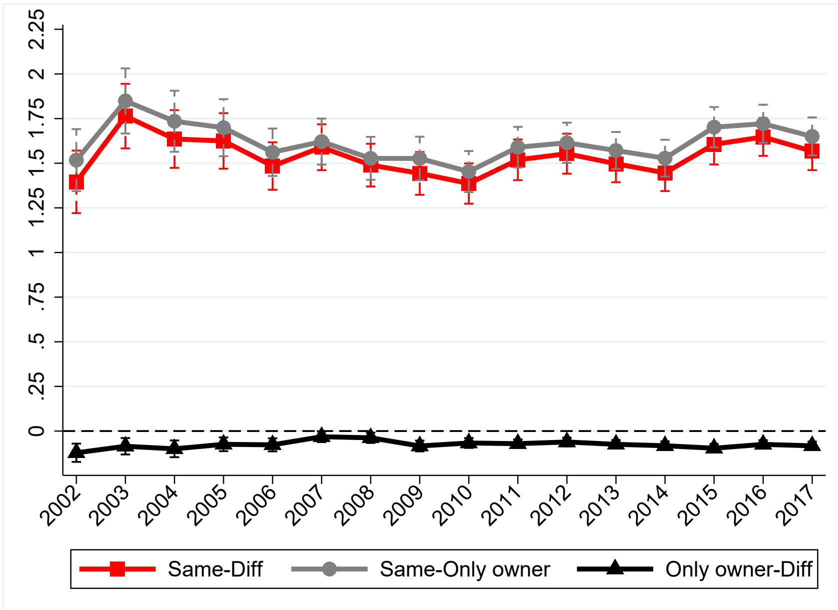
A.



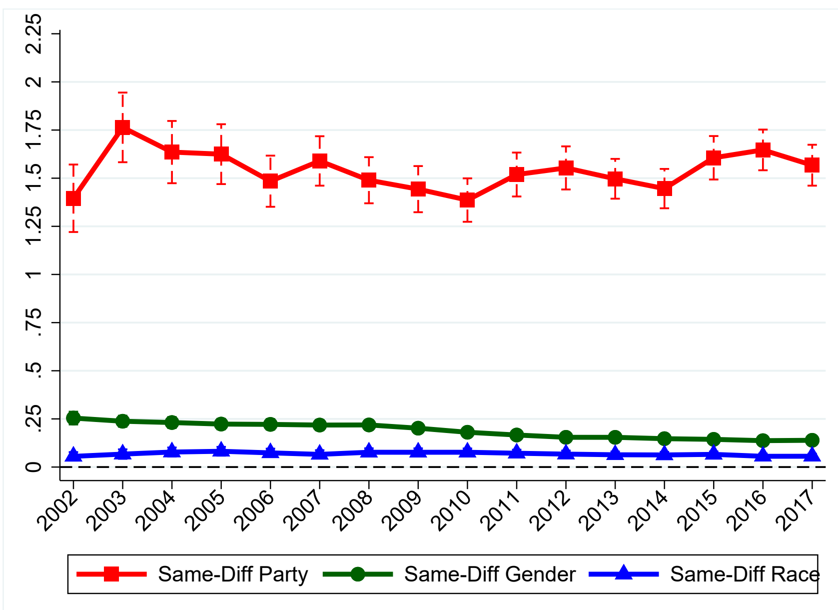
B.

Notes: The top panel shows the point estimates and 95% confidence intervals of $\Delta(SP, DP)$, $\Delta(SP, O)$, and $\Delta(O, DP)$. The bottom panel shows and a comparison between $\Delta(SP, DP)$ and the effect of shared gender and shared race on the probability that employees (i, j) work in the same firm. All estimates are normalized by the baseline sample probability that a dyad works in the same firm. Confidence intervals are based on standard errors clustered at the market level. See section 4.1 and equation 4.1 for details of the estimation.

FIGURE 4. **Assortative Political Matching Between Workers and Owners**



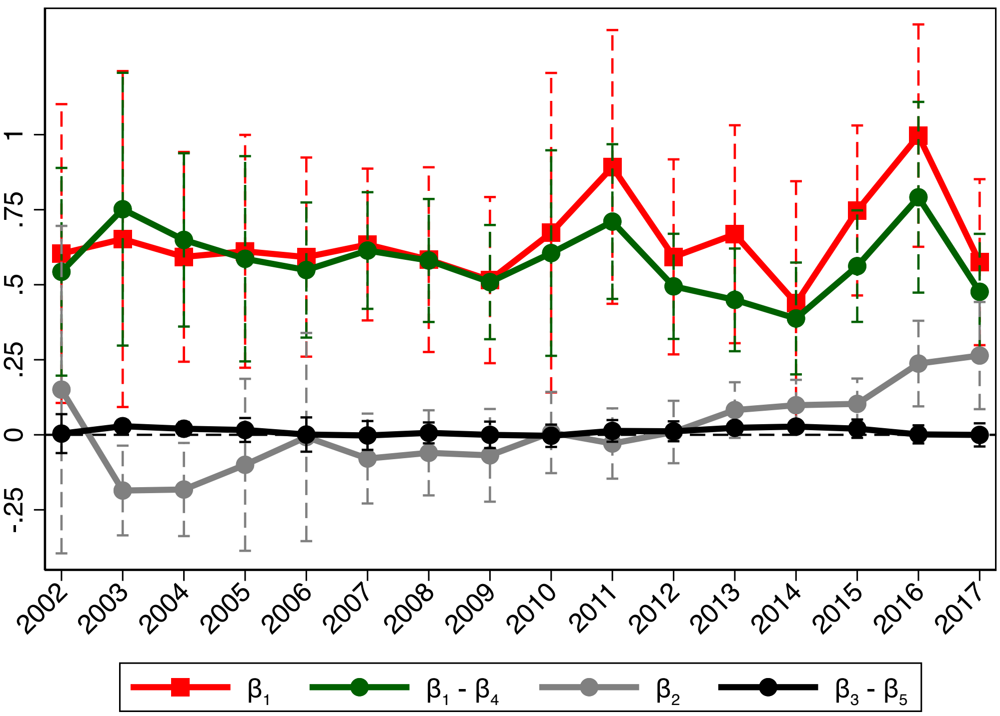
A.



B.

Notes: The top panel shows the point estimates and 95% confidence intervals of $\Delta(SP, DP)$, $\Delta(SP, OO)$, and $\Delta(OO, DP)$. 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. All estimates are normalized by the baseline sample probability that i works in firm f. Confidence intervals are based on standard errors clustered at the market level. See section 4.2 and equation 4.2 for details of the estimation.

FIGURE 5. **Disentangling Workers' and Owners' Preferences**



Notes: The figure shows the point estimates and 95% confidence intervals of β_2, $\beta_1 - \beta_4$, β_2, and $\beta_3 - \beta_5$ from equation 4.3. All estimates are normalized by the baseline sample probability that i works with j in firm f. Confidence intervals are based on standard errors clustered at the market level. See section 4.3 and equation 4.3 for details of the estimation.

Table 1. **Summary Statistics on Workers and Owners**

	(1) Mean	(2) Std. dev.	(3) p25	(4) Median	(5) p75	(6) Firm-Years
Num. Workers	16.20	263.18	2	3	9	36,048,521
Num. Owners	1.62	1	1	1	2	34,712,023
Num. Managers	0.87	41.82	0	0	0	36,048,521
Num. White Collar	7.35	188.89	1	2	4	36,048,521
Num. Blue Collar	7.86	114.81	0	1	3	36,048,521
Avg. Pay	473.92	2433.54	316.50	396.00	515.00	36,046,375
% Workers College (or higher)	0.18	0.26	0.00	0.03	0.29	36,048,060
% Workers High School	0.66	0.31	0.50	0.67	1.00	36,048,060
% Workers Less than HS	0.17	0.25	0.00	0.00	0.27	36,048,060
% Workers Male	0.56	0.35	0.29	0.60	0.91	36,048,521
% Workers White	0.69	0.35	0.50	0.83	1.00	35,974,998
Avg. Workers' Age	34.07	7.73	28.77	33.26	38.46	36,048,521

Notes: The table presents summary statistics for the 36,048,521 firm-years in our sample, covering the period 2002-2017. *Num. Workers* is the total number of workers in the firm. *Num. Owners* is the number of owners in the firm, for the firm-years in which we find at least one owner. *Num. Managers/Num. White Collar/Num. Blue Collar* is the total number of workers in the firm that are employed in managerial/white collar/blue collar occupations. *Avg. Pay* is the average pay of the firm's workers. *% Workers College (or higher)/% Workers High School/% Workers Less than HS* is the share of workers in the firm whose highest level of education is college or higher / high school / less than high school. *% Workers Male* is the share of workers in the firm who are male. *% Workers White* is the share of workers in the firm who are white. *Avg. Workers' Age* is the average age of the workers in the firm.

TABLE 2. **Who Are the Party Members?**

	Dep Var: =1 if party registered			
	(1)	(2)	(3)	(4)
	Workers	Workers	Owners	Owners
College (or more)	0.015***	0.014***	0.019***	0.015***
	(0.000)	(0.000)	(0.000)	(0.000)
High School	0.016***	0.014***	0.017***	0.015***
	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.004***	0.004***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.019***	0.018***	0.054***	0.053***
	(0.000)	(0.000)	(0.000)	(0.000)
White	-0.003***	-0.002***	-0.009***	-0.008***
	(0.000)	(0.000)	(0.000)	(0.000)
Manager	0.007***	0.008***		
	(0.000)	(0.000)		
White Collar	0.009***	0.007***		
	(0.000)	(0.000)		
Pay (in log)	-0.006***	-0.006***		
	(0.000)	(0.000)		
Observations	575,089,635	574,658,654	22,396,544	21,996,953
Mean D.V	0.0803	0.0803	0.135	0.133
Municipality-Year FEs	Yes	No	Yes	No
MunicipalityYear-Industry FEs	No	Yes	No	Yes

Notes: Column 1 and 2 present the results from a regression of an indicator equal to one if a worker is registered with a party in that year on an indicator equal to one if the worker's highest level of education is college or more than college, an indicator equal to one if the worker's highest level of education is high school, the worker's age, an indicator equal to one if the worker is male, an indicator equal to one if the worker is white, an indicator equal to one if the worker is employed in a managerial occupation, an indicator equal to one if the worker is employed in a white collar occupation, the worker's pay per hour. Each observation is a worker-year. Column 3 and 4 present the results from a regression of an indicator equal to one if an owner is registered with a party in that year on a set of variables for the owner's education, age, gender, race, defined as in columns 1 and 2. Each observation is an owner-year, only for the subset of owners for which we have demographic characteristics. Results in columns 1 and 3 include municipality-year fixed effects, while results in columns 2 and 4 include municipality-year-industry fixed effects. Standard errors in parentheses clustered by individual. $^{***}p < 0.001$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3. **Co-partisan Workers and Owners and Hiring Probability**

Dep. var: Share of hires from party p at t	(1)	(2)	(3)
Panel A: Share of Co-partisan Workers			
Share employees party p at $t-1$	0.038***	0.026***	0.023***
	(0.000)	(0.000)	(0.000)
Observations	127,162,805	127,140,363	123,368,231
R-squared	0.007	0.023	0.078
Mean Dep. Var.	0.0064	0.0064	0.0063
Panel B: Co-partisan Owner			
Owner from party p at t	0.017***	0.013***	0.012***
	(0.000)	(0.000)	(0.000)
Observations	190,539,671	190,526,896	185,828,384
R-squared	0.006	0.021	0.072
Mean Dep. Var.	0.0065	0.0065	0.0064
Party*Year FEs	Yes	No	No
Party*Year*Mun FEs	No	Yes	No
Party*Year*Mun-Industry FEs	No	No	Yes

Notes: Panel A presents estimates from equation 3.1. Panel B presents estimates from a version of equation 3.1. in which the variable *Share employees party p at* $t-1$ (the share of employees of party p employed in the firm in the previous year) is replaced with *Owner from party p at t* (an indicator taking value one if the firm's owner is from party p). Standard errors in parentheses clustered by firm. ***$p < 0.001$, **$p < 0.05$, *$p < 0.1$

Table 4. **Wage Premia for Politically Affiliated Workers and Owners**

	(1)	(2)	(3)	(4)	(5)	(6)
	Affiliated Owner Premium		***Affiliated Worker Premium***			
Affiliated	0.006*	0.006	-0.016***	-0.010***	-0.013***	-0.007***
	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)	(0.000)
Observations	534,321,209	528,414,499	534,321,209	528,414,499	525,754,903	497,819,599
R-squared	0.522	0.606	0.522	0.606	0.658	0.759
Number of Workers	79,007,264	78,866,162	79,007,264	78,866,162	78,533,546	77,380,648
Number of Firms	5,891,692	5,841,368	5,891,692	5,841,368	4,482,035	4,164,304
Industry*Mun*Year FE	Yes	No	Yes	No	No	No
Industry*Mun*Year*Occ FE	No	Yes	No	Yes	No	No
Mun*Year*Firm FE	No	No	No	No	Yes	No
Mun*Year*Firm*Occ FE	No	No	No	No	No	Yes

Notes: Columns 1 and 2 of the table present estimates from equation 5.1, with *Affiliated* being an indicator equal to one if the firm's owner is politically affiliated. Columns 3, 4 and 5 of the table present estimates from a version equation 5.1, with *Affiliated* being an indicator equal to one if the firm's owner is politically affiliated. 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)
	All Workers		Managers	White Collar	Blue Collar
Same party	0.036***	0.024***	0.012**	0.023***	0.015***
	(0.003)	(0.002)	(0.006)	(0.003)	(0.002)
Different party	-0.016***	-0.009***	-0.039***	-0.009***	-0.003***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Only worker	-0.021***	-0.012***	-0.048***	-0.015***	-0.004***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)
Same gender	0.016***	0.015***	0.019***	0.015***	0.012***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Same race	0.010***	0.005***	0.012***	0.005***	0.002***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)
Same educ	0.061***	0.024***	0.034***	0.027***	0.005***
	(0.002)	(0.001)	(0.005)	(0.002)	(0.001)
Same age	-0.006***	-0.004***	0.012***	-0.001	-0.012***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Observations	292,613,319	279,023,490	13,105,174	123,379,577	136,834,366
R-squared	0.677	0.775	0.832	0.799	0.711
Number of Workers	61,713,097	60,557,279	4,014,681	34,025,393	35,071,000
Number of Firms	2,553,492	2,368,963	367,066	1,722,004	1,407,767
Mun*Year*Firm FE	Yes	No	No	No	No
Mun*Year*Firm*Occ FE	No	Yes	Yes	Yes	Yes

Notes: The table presents estimates from equation 5.2. Columns 1 and 2 estimates the equation on the sample of all workers. Columns 3-5 restrict the sample to workers employed in a managerial, white collar, and blue collar occupation. Standard errors in parentheses clustered by firm. ***$p < 0.001$, **$p < 0.05$, *$p < 0.1$:

APPENDIX

Appendix A.1. Additional Results

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

Party Name	Acronym	% of members
Panel A: Left		
Workers Party	PT	9.90
Democratic Labor Party	PDT	8.01
Brazilian Socialist Party	PSB	3.57
Popular Socialist Party	PPS	3.15
Communist Party of Brazil	PCdoB	2.09
Green Party	PV	1.97
National Mobilization Party	PMN	1.39
Socialism and Freedom Party	PSOL	0.41
Solidarity	SD	0.26
Republican Social Order Party	PROS	0.13
Brazilian Communist Party	PCB	0.11
Unified Socialist Workers Party	PSTU	0.10
Free Homeland Party	PPL	0.08
Brazilian Women's Party	PMB	0.04
Party of the Workers' Cause	PCO	0.02
Sustainability Network	REDE	0.02
Panel B: Center		
Brazilian Democratic Movement	MDB	16.24
Brazilian Social Democracy Party	PSDB	9.21
Brazilian Labor Party	PTB	8.05
Forward	AVANTE	1.02
Social Democratic Party	PSD	0.76
Panel C: Right		
Progressive Party	PP	9.75
Democrats	DEM	7.67
Liberal Party	PL	5.07
Christian Social Party	PSC	2.22
Progressive Republican Party	PRP	1.44
Brazilian Republican Party	PRB	1.44
Liberal Social Party	PSL	1.25
Christian Labor Party	PTC	1.11
Christian Democracy	DC	1.01
Humanist Solidarity Party	PHS	0.92
We can	PODE	0.78
Brazilian Labor Renewal Party	PRTB	0.70
Patriot	PATRI	0.10
New Party	NOVO	0.01

Table A2. **Matching of Workers and Owners to Party Registration Data: Matching Steps**

Matching Steps	**Matched (total)**	**Matched (%)**
Step 1: perfect by name - DOB - municipality	5,736,086	49.14
Step 2: perfect by name - DOB - state	2,551,645	21.86
Step 3: perfect by name - DOB	628,524	5.38
Step 4: perfect by name - year_birth - month birth - municipality	62,211	0.53
Step 5: perfect by name - year_birth - day birth - municipality	47,332	0.41
Step 6: perfect by name - month_birth - day birth - municipality	45,243	0.39
Step 7: perfect by name - year_birth - month birth - state	72,556	0.62
Step 8: perfect by name - year_birth - day birth - state	39,212	0.34
Step 9: perfect by name - month_birth - day birth - state	77,673	0.67
Step 10: perfect by name - year_birth - municipality	112,651	0.97
Step 11: perfect by name - year_birth - state	179,829	1.54
Step 12: perfect by name - municipality	572,574	4.91
Step 13: perfect by name - state	479,858	4.11
Step 14: fuzzy by name, blocking on DOB - municipality	715,539	6.13
Step 15: fuzzy by name, blocking on DOB - state	352,064	3.02
All matched (unique individuals)	11,672,997	100

Table A3. **Dyadic Worker-Worker Regressions – 5% versus full sample**

	sample	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Same Party	All dyads	.0800042	.0958271	.088952	.0786745	.0703601	.0797938	.0804714	.0716493	.0633833	.0722369	.0651924	.0645078	.0583033	.0632481	.0691976	.0626982
		(.0028786)	(.0043044)	(.0041227)	(.0036364)	(.0031159)	(.0026507)	(.0035958)	(.0028613)	(.0026542)	(.002345)	(.0019644)	(.0023806)	(.002279)	(.0019895)	(.0023483)	(.0025025)
	5pct	.0802436	.0901579	.0855647	.073813	.0739096	.0828101	.0840314	.0683236	.0654047	.0716805	.0674685	.0637957	.0583208	.0581202	.0667058	.0621474
		(.0048449)	(.0055164)	(.0052173)	(.004722)	(.0044775)	(.0039226)	(.0049083)	(.0041098)	(.0042109)	(.0036887)	(.0035308)	(.0037335)	(.0037194)	(.0036332)	(.0040884)	(.0040187)
Different Party	All dyads	.0136963	.0094841	.0093557	.0081259	.0087256	.0054528	.0052012	.0046968	.0052054	.0046372	.0031158	.0051875	.004478	.0038494	.0030867	.0026339
		(.0012513)	(.001266)	(.001172)	(.0011224)	(.0010735)	(.0010517)	(.0010466)	(.0009647)	(.0009068)	(.0008733)	(.0008439)	(.0008822)	(.0008838)	(.0008452)	(.000854)	(.0009106)
	5pct	.0131014	.0115678	.0093144	.0083715	.0062327	.0068396	.0056502	.0044372	.004952	.0064353	.0018083	.0036958	.0048118	.0042323	.0037913	.0022621
		(.0019627)	(.0018276)	(.0017264)	(.0016866)	(.001612)	(.0014838)	(.0014901)	(.0014792)	(.0014068)	(.0013254)	(.001331)	(.0013536)	(.0013528)	(.0013318)	(.0013567)	(.0014346)
Only one	All dyads	.0025062	.0000286	-.0001491	-.0003819	.0001399	-.0017236	-.0015355	-.0010794	-.0008767	-.0016773	-.0019551	-.0013668	-.0017174	-.0020043	-.0024484	-.0029138
		(.000523)	(.0005127)	(.0004913)	(.000496)	(.0004728)	(.0004813)	(.0004578)	(.0004407)	(.0004204)	(.000413)	(.0003975)	(.000402)	(.0004056)	(.0003906)	(.0003957)	(.000401)
	5pct	.0023665	-.0007077	-.0001999	-.0011375	-.0005083	-.0008931	-.0015936	-.0009872	-.0008803	-.0014136	-.0015588	-.0010521	-.0015567	-.0022002	-.0022363	-.0030683
		(.0006447)	(.0006387)	(.0006162)	(.00061)	(.0005812)	(.0005848)	(.0005606)	(.0005428)	(.0005153)	(.0005087)	(.0004947)	(.0004912)	(.0004945)	(.0004848)	(.0005005)	(.0005034)
Same Gender	All dyads	.0243439	.0228419	.0232638	.0245672	.0228759	.0228879	.0226554	.0236759	.0233435	.0222316	.022261	.0215322	.0214943	.0218355	.0205766	.0208545
		(.0008461)	(.0008307)	(.0008128)	(.0008121)	(.0007569)	(.0007303)	(.0007067)	(.0007036)	(.0006714)	(.0006347)	(.0006066)	(.0005994)	(.0005828)	(.0006)	(.0005613)	(.000547)
	5pct	.0237827	.0229013	.0234586	.0245288	.0226722	.0235167	.0226292	.0233022	.0236194	.0221994	.0220591	.0214287	.021374	.0219219	.0203158	.0206832
		(.0008988)	(.0008939)	(.0008729)	(.0008688)	(.0008089)	(.0007949)	(.0007597)	(.0007504)	(.0007179)	(.0006848)	(.000658)	(.0006459)	(.0006272)	(.0006462)	(.000621)	(.0006015)
Same Race	All dyads	.0117172	.0164849	.0184268	.0192998	.0194337	.0211716	.0206657	.0217453	.0220649	.0232782	.0231906	.0241498	.023343	.0232621	.0212864	.0188202
		(.0005439)	(.0006777)	(.0006723)	(.0006757)	(.0006544)	(.0007)	(.0006547)	(.0006221)	(.0006298)	(.0006145)	(.0005954)	(.0005985)	(.00055)	(.0005418)	(.0005033)	(.0004729)
	5pct	.0120145	.0160603	.0184342	.0197015	.0194411	.0212387	.0208791	.0218611	.0219337	.0230576	.0231875	.0238952	.0236613	.0234077	.021096	.0188028
		(.0006428)	(.0007696)	(.0007533)	(.0007606)	(.000731)	(.0007689)	(.0007186)	(.0006886)	(.0006859)	(.0006743)	(.000647)	(.0006535)	(.0006048)	(.0005984)	(.0005745)	(.0005397)
Same Occupation	All dyads	.1375081	.113801	.1079146	.1067315	.1038859	.1047119	.1004675	.0987151	.0986477	.0966448	.0919558	.0913174	.0881989	.0866679	.08465	.0851464
		(.0016947)	(.0016228)	(.0015011)	(.0015075)	(.0014388)	(.0013858)	(.001333)	(.0013219)	(.001305)	(.0012125)	(.0011741)	(.0011878)	(.0011089)	(.0010922)	(.0010619)	(.0010928)
	5pct	.1371782	.1137002	.1071939	.1064249	.1036948	.104633	.100042	.0983119	.0983657	.0966719	.0921962	.090917	.0881441	.0861272	.0847894	.0853274
		(.0017292)	(.00166)	(.0015423)	(.0015441)	(.0014698)	(.0014226)	(.0013632)	(.0013519)	(.0013285)	(.0012457)	(.0012034)	(.0012172)	(.0011373)	(.0011193)	(.001093)	(.0011251)
Same Education	All dyads	.0139532	.0163236	.0163723	.016874	.01655	.0172703	.0167237	.0171957	.0168701	.0168127	.017426	.0168034	.0174234	.0159998	.0160628	.0150077
		(.0004691)	(.0005388)	(.0004792)	(.0004796)	(.0004677)	(.000498)	(.0004874)	(.0005018)	(.0004971)	(.0004849)	(.0005229)	(.0005179)	(.0005611)	(.0005007)	(.0005417)	(.0004877)
	5pct	.013685	.0157937	.0163847	.016991	.0168355	.0175351	.0171944	.0173128	.016882	.0167047	.0173931	.0166863	.0173372	.015927	.0157316	.0149111
		(.0005495)	(.0006222)	(.0005549)	(.0005575)	(.0005395)	(.0005688)	(.0005513)	(.0005626)	(.0005502)	(.0005401)	(.0005717)	(.0005645)	(.0006004)	(.0005492)	(.0005957)	(.0005438)
Same Experience	All dyads	.0810199	.0846434	.0822698	.0789404	.0782498	.0751898	.0706957	.0730404	.070648	.0643933	.0655956	.0638802	.0634884	.0715687	.0817831	.0859114
		(.0011881)	(.0012313)	(.0011704)	(.00111)	(.0010853)	(.0010293)	(.0010132)	(.0009959)	(.0009865)	(.0009052)	(.0009034)	(.0008705)	(.0008304)	(.0008765)	(.0009062)	(.0009271)
	5pct	.0809222	.0843262	.0826836	.0791459	.0781009	.0755091	.0708525	.0733651	.0712195	.0640759	.0651645	.0639231	.063346	.0714389	.0820541	.0857254
		(.0012268)	(.0012832)	(.0012157)	(.001153)	(.0011263)	(.0010703)	(.0010563)	(.0010399)	(.0010269)	(.0009443)	(.0009406)	(.0009071)	(.0008677)	(.0009149)	(.0009512)	(.0009695)
Same Age	All dyads	.0094419	.012021	.0129962	.0128671	.0142803	.0144215	.0146666	.01402	.0143488	.0145949	.0147052	.0142986	.0144335	.0142742	.0149036	.0156366
	5pct	.0096234	.0119891	.0126764	.0126028	.014477	.0145406	.0142657	.0139927	.0144899	.0141531	.0152713	.0144845	.014393	.0141746	.0148382	.0154894
		(.0004534)	(.0004517)	(.0004806)	(.0004261)	(.000439)	(.0004008)	(.0003677)	(.0003576)	(.0003578)	(.0003553)	(.0003543)	(.000358)	(.0003535)	(.0003164)	(.0003243)	(.0003145)
		(.0005652)	(.0005783)	(.0006041)	(.0005515)	(.0005496)	(.0005231)	(.0004886)	(.0004741)	(.0004639)	(.0004551)	(.0004563)	(.000452)	(.0004482)	(.000428)	(.0004412)	(.0004401)

Notes: The table presents estimates from the estimation of equation 4.1. 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 5% sample of dyads. Standard errors in parentheses are clustered by market. See section 4.1 for details of the estimation.

TABLE A4. **Dyadic Worker-Worker Regressions – Full Set of Estimates**

Year:	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Same Party	.0338301	.0353569	.0327526	.0302723	.0273199	.0255083	.0247828	.0244503	.0246186	.0260094	.022042	.0220309	.0222119	.0240525	.0232934	.022597
	(.0025695)	(.0021625)	(.0019152)	(.0018801)	(.0021231)	(.001931)	(.0018555)	(.0022121)	(.0024362)	(.0020447)	(.0016503)	(.0016166)	(.0015586)	(.0023727)	(.0023807)	(.0025349)
Different Party	.0129668	.0117483	.0116767	.0117505	.0114352	.0088475	.0087189	.009348	.0103673	.0094375	.0084492	.0085483	.0083383	.0078909	.0067207	.0067064
	(.0013673)	(.0011931)	(.0011623)	(.0012712)	(.0012312)	(.0012031)	(.0010261)	(.0011215)	(.0012016)	(.0010666)	(.0009251)	(.000955)	(.0009155)	(.0010273)	(.0010033)	(.0011303)
Only One	.0032282	.0026054	.0025618	.0027666	.0024752	.0012743	.0015673	.0017276	.0020521	.0018096	.0014655	.0013808	.0014902	.0010571	.0004082	-.0000816
	(.0004461)	(.0004126)	(.0003884)	(.0004026)	(.0004066)	(.0003944)	(.0003716)	(.0003963)	(.0003934)	(.0003715)	(.00034)	(.0003445)	(.0003405)	(.0003685)	(.0003383)	(.0003784)
Same Gender	.0145148	.0155662	.0155969	.0163374	.0148793	.014944	.0161	.0157348	.0163251	.0156873	.0153042	.0148673	.0136096	.012059	.0119747	.0116246
	(.0008575)	(.000866)	(.0009115)	(.000892)	(.0008345)	(.0008663)	(.000858)	(.0008579)	(.0008875)	(.0008842)	(.0008309)	(.0008205)	(.0007638)	(.0007152)	(.0007071)	(.0007132)
Same Race	.0077253	.0109304	.0106668	.0104726	.0107251	.0102793	.0106872	.0102818	.0108642	.0109246	.0115113	.0125094	.0118711	.0120559	.0111677	.0094249
	(.0006348)	(.0007961)	(.0007673)	(.0008095)	(.0008474)	(.0007633)	(.0008003)	(.0007607)	(.0007201)	(.0007152)	(.0007245)	(.000812)	(.0006986)	(.0007388)	(.000696)	(.0006002)
Same Occupation	.0915697	.068134	.0663842	.0660912	.0633176	.0657587	.0623188	.0624232	.060832	.0610807	.0594608	.0576362	.0554554	.0544044	.0518871	.0533926
	(.0026695)	(.0021991)	(.0022316)	(.0022648)	(.0021385)	(.0022267)	(.002079)	(.0021316)	(.0020283)	(.0020175)	(.0020418)	(.0019055)	(.0018067)	(.0018397)	(.00171)	(.0018057)
Same Education	.0074233	.0076771	.0071063	.0064454	.0062653	.005421	.0051084	.0049979	.0046415	.004123	.0044237	.0053549	.006112	.0074699	.009769	.0073642
	(.0006081)	(.0006054)	(.0006013)	(.0006131)	(.0005838)	(.0005888)	(.0005654)	(.0005923)	(.0006328)	(.0006134)	(.0007106)	(.0007377)	(.000845)	(.0009025)	(.0012046)	(.0009488)
Same Experience	.0557323	.0562186	.0548844	.050112	.0498257	.0465681	.0423041	.0431506	.037699	.0363768	.0376301	.036748	.0364244	.0416536	.0471974	.0505337
	(.0021621)	(.0019874)	(.0021463)	(.0017211)	(.0017272)	(.0015085)	(.0015096)	(.0014738)	(.0012313)	(.0013773)	(.0015474)	(.0013147)	(.0011793)	(.0013204)	(.0014335)	(.0016311)
Same Age	.0067112	.0088074	.009177	.0092212	.0084462	.0098447	.0090832	.0092731	.0090942	.0089344	.0081513	.0087679	.0086212	.0096494	.0099012	.0111196
	(.0004459)	(.0006081)	(.0005754)	(.0005852)	(.0004956)	(.0006357)	(.0004993)	(.0005988)	(.0005156)	(.0004842)	(.0004323)	(.0004005)	(.0003485)	(.0004507)	(.0004214)	(.0005728)
Same-Diff	0.095	0.108	0.096	0.084	0.073	0.073	0.071	0.068	0.064	0.075	0.063	0.064	0.069	0.080	0.082	0.077
Same-Only One	0.139	0.150	0.138	0.125	0.113	0.107	0.103	0.102	0.102	0.110	0.095	0.098	0.103	0.114	0.114	0.110
Diff-Only One	0.044	0.042	0.042	0.041	0.041	0.033	0.032	0.034	0.038	0.035	0.032	0.034	0.034	0.034	0.031	0.033
Same-Diff Gender	0.066	0.071	0.071	0.074	0.068	0.066	0.071	0.071	0.074	0.071	0.071	0.071	0.068	0.060	0.060	0.057
Same-Diff Race	0.035	0.050	0.049	0.048	0.049	0.045	0.047	0.046	0.049	0.049	0.053	0.060	0.059	0.060	0.056	0.046
Observations	376,251,912	387,972,827	427,330,878	470,279,355	510,380,413	554,611,725	634,282,467	652,558,391	737,563,935	779,234,513	831,694,079	858,181,598	860,299,968	787,483,608	686,718,380	656,346,375
Num Workers	10,604,934	11,139,612	11,873,756	12,610,512	13,356,990	14,159,547	15,393,078	15,721,192	16,993,455	17,950,877	18,650,501	19,245,625	19,500,506	18,837,453	17,639,586	17,239,182
Num Firms	787,030	825,766	865,121	908,105	954,446	989,298	1,042,876	1,093,258	1,167,834	1,237,896	1,290,918	1,355,022	1,406,061	1,419,216	1,402,615	1,395,247
Num Markets	40,037	44,794	46,010	47,510	48,729	51,569	53,503	54,692	56,620	60,968	61,640	63,099	64,178	65,613	65,500	64,800

Notes: The table presents estimates from the estimation of equation 4.1. Standard errors in parentheses are clustered by market. See section 4.1 for details of the estimation.

TABLE A5. **Dyadic Owner-Worker Regressions – 25% versus full sample**

	sample	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Same Party	full	.0512456	.0595304	.0579615	.0553647	.0531032	.0584198	.0562311	.0552773	.0535657	.0591557	.0579137	.0570043	.0559247	.0613604	.0652367	.0624327
		(.0020332)	(.0018553)	(.0018159)	(.0017082)	(.0016125)	(.0015449)	(.0015614)	(.0015218)	(.00147)	(.0014177)	(.0013919)	(.0013476)	(.0012927)	(.0013554)	(.0014346)	(.0014057)
	25pct	.0494616	.0574182	.0581587	.0552357	.0503466	.0583672	.0572336	.0564531	.0533885	.0571419	.0571015	.0575325	.055071	.0608244	.0638503	.0618778
		(.0030936)	(.0026646)	(.0026998)	(.002456)	(.0023593)	(.0022074)	(.0023031)	(.0022463)	(.0021107)	(.0020072)	(.0020337)	(.00195)	(.0019531)	(.0019971)	(.0020439)	(.0020839)
Different Party	All dyads	.0054545	.0057657	.0056098	.0058281	.0065547	.0065649	.0059389	.0057502	.0052081	.0056216	.0052442	.0054933	.0062689	.0055794	.0053091	.0050745
		(.0009228)	(.0008202)	(.0007949)	(.000787)	(.0007514)	(.0006895)	(.0006933)	(.0006417)	(.0006205)	(.000584)	(.0005335)	(.0005174)	(.0005094)	(.0005029)	(.0004903)	(.0005008)
	25pct	.0044707	.0064226	.0060893	.0063658	.0067131	.006613	.0055713	.0060188	.0054984	.0057766	.0052542	.0058652	.0067892	.0055699	.0051883	.0060847
		(.0011397)	(.0010078)	(.000976)	(.0009579)	(.0009194)	(.0008269)	(.0008309)	(.0007924)	(.0007624)	(.0007161)	(.0006731)	(.0006501)	(.0006391)	(.0006428)	(.0006258)	(.0006413)
Only Worker	full	-.0012756	-.0021005	-.0020141	-.0021295	-.0018584	-.0022223	-.0021922	-.0021895	-.0021828	-.0026017	-.002392	-.0024867	-.0024678	-.0028233	-.0031154	-.0030945
		(.0002313)	(.0002306)	(.0002174)	(.0002079)	(.0001927)	(.0001905)	(.0001806)	(.0001711)	(.0001578)	(.0001605)	(.0001438)	(.0001366)	(.000131)	(.0001349)	(.0001365)	(.0001357)
	25pct	-.0015745	-.0024229	-.0017786	-.0016734	-.0015651	-.0012899	-.0017969	-.0021149	-.0022448	-.0028466	-.0023498	-.0023473	-.0024094	-.002708	-.003309	-.0031184
		(.000442)	(.000417)	(.0003944)	(.0003794)	(.0003519)	(.0003486)	(.0003229)	(.0003156)	(.0002973)	(.0002942)	(.0002735)	(.0002607)	(.0002492)	(.0002616)	(.0002655)	(.0002668)
Only Owner	full	.0061246	.0057911	.0054158	.0054085	.0059991	.0063615	.0054917	.0052184	.0048208	.0050269	.0050081	.0048533	.0056583	.0049132	.0045887	.0045948
		(.0008152)	(.0007666)	(.0007361)	(.0007196)	(.0006867)	(.0006578)	(.0006491)	(.0006063)	(.0005725)	(.0005418)	(.0005014)	(.000479)	(.0004654)	(.0004624)	(.0004531)	(.0004602)
	25pct	.0058828	.0060858	.0055674	.0052223	.0061494	.0066869	.0055441	.0054851	.0049668	.0050228	.0047105	.0050363	.0056508	.0051092	.0047397	.0046475
		(.0008397)	(.0008019)	(.0007726)	(.0007446)	(.0007253)	(.0006912)	(.0006741)	(.0006336)	(.0005953)	(.0005695)	(.0005212)	(.000501)	(.000485)	(.0004902)	(.0004779)	(.0004805)
Same Gender	full	.0037667	.00296	.0026538	.0029385	.002569	.0020921	.0023303	.0018289	.001582	.0016578	.00105	.0011379	.001369	.0012112	.0013412	.0013214
		(.0004039)	(.0004011)	(.0003924)	(.0003715)	(.0003492)	(.0003505)	(.0003441)	(.0003153)	(.0002922)	(.0002833)	(.0002659)	(.0002573)	(.000237)	(.0002452)	(.0002423)	(.0002396)
	25pct	.0037458	.0027089	.0025015	.0029509	.0025945	.001927	.0020488	.0019156	.0016707	.0015662	.0011975	.0012263	.0013265	.0011564	.0013327	.0012581
		(.0004432)	(.0004427)	(.0004341)	(.0004076)	(.0003845)	(.0003857)	(.0003723)	(.0003474)	(.0003233)	(.0003165)	(.0002952)	(.0002824)	(.0002639)	(.0002727)	(.0002737)	(.0002688)
Same Race	full	.0015695	.0022309	.0024551	.0025949	.0025448	.0024096	.0023623	.0026452	.0025811	.0029843	.0028528	.0024387	.0026958	.0028128	.0025093	.00221
		(.00034)	(.0003636)	(.0003533)	(.0003409)	(.0003292)	(.0003423)	(.0003238)	(.0003154)	(.0002871)	(.0002725)	(.0002525)	(.0002482)	(.0002307)	(.0002212)	(.0002178)	(.0002171)
	25pct	.0014026	.0022803	.0023628	.0026863	.0023774	.002247	.0026244	.0023184	.0024201	.0029827	.0029186	.002355	.0025774	.0028788	.002623	.001978
		(.0004174)	(.000444)	(.0004252)	(.0003974)	(.0003888)	(.0004006)	(.0003779)	(.000367)	(.0003355)	(.0003211)	(.0002941)	(.000289)	(.0002708)	(.0002657)	(.0002631)	(.0002594)
Same Educ	full	.0002526	.0003458	.0008792	.001211	.0010301	.0004211	.0004392	.0004059	.000176	.0005652	.0000501	-.0002749	-.0003899	-.0004365	-.0004854	-.0005995
		(.0003058)	(.0003082)	(.0002927)	(.0002987)	(.0002837)	(.000292)	(.000282)	(.000271)	(.000262)	(.0002607)	(.0002419)	(.0002345)	(.0002273)	(.0002339)	(.0002322)	(.0002337)
	25pct	.0002026	.0000318	.000832	.001099	.0011258	.0002998	.0001078	.0005182	-.0000348	.0002532	.0001009	-.0002639	-.0004712	-.0003858	-.0003785	-.0005841
		(.0003634)	(.000369)	(.0003433)	(.000351)	(.0003307)	(.0003353)	(.0003239)	(.0003118)	(.0002949)	(.0002952)	(.0002736)	(.0002655)	(.0002548)	(.0002649)	(.0002631)	(.0002647)
Same Age	full	-.0004916	.0003371	.0001117	-.0002198	.0000482	.0008639	.0003547	.0006401	.0006248	.0010997	.0011953	.0012262	.001413	.0017987	.0020744	.0024089
		(.0002716)	(.0002728)	(.0002493)	(.0002373)	(.0002279)	(.0002344)	(.0002136)	(.0001991)	(.0001843)	(.0001806)	(.0001721)	(.0001602)	(.0001504)	(.0001495)	(.0001488)	(.0001477)
	25pct	-.0000771	.0001837	-.0003659	-.0000799	-.0002776	.0008954	.0000453	.00058	.000702	.0011718	.0010354	.001226	.0009627	.0019966	.0021774	.0024884
		(.0003872)	(.0003841)	(.0003532)	(.0003423)	(.0003211)	(.0003315)	(.0003058)	(.0002908)	(.0002678)	(.0002689)	(.0002496)	(.0002399)	(.0002282)	(.0002359)	(.0002388)	(.0002372)

Notes: The table presents estimates from the estimation of equation 4.2. 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 5% sample of dyads. Standard errors in parentheses are clustered by market. See section 4.2 for details of the estimation.

TABLE A6. **Dyadic Owner-Worker Regressions – Full Set of Estimates**

Year:	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Same Party	.0105765	.0137689	.0130012	.0124395	.011759	.0123207	.0115837	.0116536	.010837	.0118126	.0116276	.0112517	.0109365	.0121697	.0126724	.0125898
	(.0005822)	(.0006748)	(.0006374)	(.0005837)	(.0004942)	(.000497)	(.0004509)	(.0004491)	(.0004182)	(.0004153)	(.0003969)	(.0003647)	(.0003612)	(.0003969)	(.0003834)	(.0003928)
Different Party	.0022543	.0023093	.0024713	.0023526	.0025518	.0020302	.0020331	.0025205	.0021936	.00216	.0020997	.0020796	.0021336	.0021435	.0021239	.0023249
	(.0002703)	(.0002796)	(.0002775)	(.0002417)	(.0002345)	(.0002186)	(.0002061)	(.0002043)	(.000184)	(.0001671)	(.0001702)	(.0001612)	(.0001564)	(.0001531)	(.000151)	(.000155)
Only Worker	-.0002111	-.0002974	-.00036	-.0002803	-.0002497	-.0002349	-.0002529	-.0002849	-.0002502	-.0002612	-.0003018	-.0002531	-.0003129	-.000283	-.0003343	-.0003018
	(.0000431)	(.0000477)	(.000049)	(.0000388)	(.0000351)	(.0000338)	(.0000323)	(.0000305)	(.000028)	(.0000254)	(.0000249)	(.000024)	(.0000232)	(.0000239)	(.0000252)	(.0000252)
Only Owner	.0015292	.0017563	.0018311	.0018921	.0020739	.0018257	.0017904	.001992	.0017773	.0017118	.0017249	.001625	.0016333	.0015449	.0016472	.0017838
	(.0001837)	(.0002056)	(.0002003)	(.0001864)	(.0001908)	(.0001861)	(.0001771)	(.0001655)	(.0001527)	(.00014)	(.0001417)	(.0001324)	(.0001245)	(.0001196)	(.0001192)	(.0001237)
Same Gender	.0015162	.0015455	.0014884	.001386	.0013747	.0014119	.0014021	.001277	.0011262	.0010572	.0009477	.000946	.0008974	.0008981	.0008781	.0009101
	(.0001014)	(.0000955)	(.0000936)	(.0000861)	(.0000874)	(.0000887)	(.0000826)	(.0000771)	(.000068)	(.0000651)	(.0000594)	(.0000572)	(.0000533)	(.0000537)	(.0000529)	(.0000521)
Same Race	.0003316	.0004372	.0005022	.0005084	.0004574	.0004264	.0004931	.0004859	.0004793	.0004566	.0004125	.0003915	.0003839	.0004111	.0003581	.0003677
	(.0000675)	(.0000819)	(.000077)	(.0000724)	(.000069)	(.0000718)	(.0000669)	(.0000661)	(.000063)	(.0000591)	(.0000573)	(.0000522)	(.0000486)	(.0000473)	(.0000462)	(.0000432)
Same Educ	-.0005366	-.0004238	-.0004025	-.0003777	-.000514	-.0006568	-.0006804	-.0006602	-.0007553	-.0008178	-.0008278	-.0008838	-.0009117	-.0008815	-.0008464	-.0008207
	(.0000604)	(.0000582)	(.0000567)	(.0000536)	(.0000591)	(.0000606)	(.0000587)	(.0000567)	(.0000554)	(.0000543)	(.0000515)	(.0000496)	(.0000492)	(.0000483)	(.0000478)	(.000048)
Same Age	-.0005024	-.0003538	-.0003931	-.0004031	-.0004372	-.0003734	-.0003564	-.000289	-.0002143	-.0001832	-.0000865	-.0000211	.0000544	.0000678	.0001942	.0002952
	(.0000563)	(.000052)	(.0000523)	(.0000476)	(.000046)	(.0000457)	(.0000428)	(.0000408)	(.0000362)	(.0000333)	(.0000337)	(.000031)	(.0000289)	(.0000283)	(.0000274)	(.0000295)
Same-Diff	1.396	1.764	1.636	1.625	1.484	1.590	1.489	1.443	1.386	1.519	1.553	1.497	1.446	1.606	1.647	1.567
Same-Only Worker	1.809	2.165	2.075	2.049	1.936	1.939	1.846	1.886	1.778	1.900	1.945	1.878	1.848	1.995	2.031	1.968
Diff-Only Worker	0.413	0.401	0.440	0.424	0.452	0.350	0.356	0.443	0.392	0.381	0.392	0.381	0.402	0.389	0.384	0.401
Same-Only Owner	1.517	1.849	1.735	1.699	1.561	1.621	1.527	1.527	1.453	1.590	1.614	1.571	1.528	1.702	1.721	1.650
Diff-Only Owner	0.122	0.085	0.099	0.074	0.077	0.032	0.038	0.084	0.067	0.071	0.061	0.074	0.082	0.096	0.074	0.083
Same-Diff Gender	0.254	0.238	0.231	0.223	0.222	0.218	0.219	0.202	0.181	0.166	0.155	0.154	0.147	0.144	0.137	0.139
Same-Diff Race	0.056	0.067	0.078	0.082	0.074	0.066	0.077	0.077	0.077	0.072	0.067	0.064	0.063	0.066	0.056	0.056
Observations	76,980,492	98,063,599	109,382,753	124,867,265	139,619,661	148,325,070	168,230,794	182,320,695	210,833,032	230,647,714	257,946,023	278,918,292	297,307,902	293,426,001	278,470,836	275,724,046
Num Workers	6,314,970	8,556,216	9,251,569	9,986,394	10,785,682	11,590,163	12,688,875	13,192,879	14,473,149	15,516,999	16,409,494	17,134,281	17,682,617	17,300,435	16,369,649	16,067,220
Num Firms	683,360	786,930	828,186	879,684	931,045	969,932	1,023,816	1,078,505	1,156,421	1,234,246	1,296,092	1,359,887	1,415,313	1,440,514	1,430,133	1,424,785
Num Markets	24,538	28,653	29,618	30,743	31,724	34,538	36,025	37,413	39,118	43,030	43,857	45,175	46,037	47,815	48,076	47,748

Notes: The table presents estimates from the estimation of equation 4.2. Standard errors in parentheses are clustered by market. the See section 4.2 for details of the estimation.

Table A7. **Disentangling Workers' and Owners' Preferences – Full Set of Estimates**

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
β_1	.0043778	.0041403	.0036181	.0034379	.003361	.0036066	.0031269	.0026983	.0034524	.0046859	.002972	.0032164	.0019881	.0035229	.0046901	.0028801
	(.001841)	(.0018125)	(.0010881)	(.0011128)	(.0009606)	(.0007338)	(.0008414)	(.0007393)	(.0013926)	(.0012216)	(.0008309)	(.0008915)	(.0009406)	(.0006809)	(.0008892)	(.0007064)
β_2	.0010911	-.0011782	-.0011123	-.000562	-.0000425	-.0004499	-.0003219	-.0003583	.0000389	-.0001524	.0000467	.0003967	.0004477	.0004859	.0011166	.0013221
	(.0020174)	(.0004838)	(.000483)	(.0008219)	(.0010043)	(.0004345)	(.0003876)	(.0004125)	(.000354)	(.0003138)	(.000266)	(.0002276)	(.0001954)	(.0002027)	(.0003421)	(.0004562)
β_4	.0004405	-.0006317	-.0003449	.0001402	.000245	.0001136	.0000152	.0000347	.0003475	.0009558	.0004924	.0010525	.0002303	.0008739	.0009667	.0004937
	(.0012351)	(.0005801)	(.0005736)	(.0005645)	(.0008133)	(.0004504)	(.0004928)	(.0004499)	(.0005711)	(.0006688)	(.0004888)	(.0005702)	(.0006012)	(.0003038)	(.0002964)	(.0003203)
β_5	-.0053346	-.0034901	-.0030537	-.0037788	-.0021134	-.0017927	-.0014401	-.0017231	-.0013872	-.0018848	-.0014243	-.0010098	-.0012993	-.0005845	-.0009382	-.0015754
	(.00135)	(.0006032)	(.0006209)	(.0009045)	(.0005008)	(.0006219)	(.0005724)	(.0006041)	(.0006049)	(.0006404)	(.0005284)	(.00043)	(.0004803)	(.0003824)	(.0003934)	(.0004595)
Same Gender	.0004033	.0003764	.0003599	.0003584	.000321	.0003308	.0003147	.0003223	.0003389	.0003192	.0002948	.0002797	.0002729	.0002347	.000273	.0002803
	(.0000338)	(.0000307)	(.0000266)	(.0000286)	(.0000265)	(.000027)	(.0000241)	(.0000246)	(.0000261)	(.0000253)	(.0000241)	(.0000244)	(.0000242)	(.0000203)	(.000022)	(.0000246)
Same Race	.000312	.0003578	.000352	.0003324	.0003828	.0003455	.0003392	.000329	.0003065	.0003032	.0002819	.0003234	.000291	.0002486	.0002562	.0002015
	(.0000366)	(.000036)	(.0000378)	(.0000333)	(.0000502)	(.0000409)	(.0000402)	(.0000376)	(.0000367)	(.0000341)	(.0000345)	(.0000346)	(.0000312)	(.0000284)	(.0000314)	(.0000267)
Same Occupation	.002187	.0014091	.0013278	.0012436	.0012445	.0012871	.0011702	.0011899	.0011618	.0011893	.0011381	.0010756	.0010308	.001102	.0010661	.0011571
	(.0001163)	(.0000762)	(.0000731)	(.0000702)	(.0000734)	(.0000752)	(.0000638)	(.0000682)	(.0000639)	(.0000632)	(.0000593)	(.0000606)	(.0000521)	(.0000593)	(.0000577)	(.0000656)
Same Education	.0002586	.0002332	.0002247	.0001716	.0001714	.0001343	.0001427	.0001452	.0001501	.0001151	.0001176	.0001313	.0001648	.0001821	.0002195	.0002028
	(.0000399)	(.0000322)	(.0000288)	(.0000242)	(.0000245)	(.0000211)	(.0000199)	(.0000232)	(.000033)	(.0000197)	(.0000201)	(.0000204)	(.0000218)	(.0000243)	(.0000302)	(.0000289)
Same Experience	.0023283	.0019571	.0019092	.0016839	.0016421	.0014895	.0012998	.0013212	.00124	.001179	.0011703	.0011405	.0011603	.0012569	.0013847	.001504
	(.0001576)	(.0000981)	(.0001058)	(.0000915)	(.0000848)	(.0000751)	(.00007)	(.0000695)	(.0000701)	(.0000611)	(.0000614)	(.0000648)	(.0000633)	(.0000553)	(.0000628)	(.0000658)
Same Age	.0002895	.0002526	.0002253	.0002307	.0002216	.0002351	.0002127	.0002165	.0002151	.0001917	.0001694	.0002198	.0002096	.000216	.0002123	.0002179
	(.0000335)	(.0000239)	(.0000208)	(.0000205)	(.000025)	(.0000186)	(.0000177)	(.0000195)	(.0000213)	(.0000177)	(.0000171)	(.0000188)	(.0000185)	(.0000202)	(.0000203)	(.0000251)

Notes: The table presents estimates from the estimation of equation 4.3. Standard errors in parentheses are clustered by markets. the See section 4.3 and equation 4.3 for details of the estimation.