

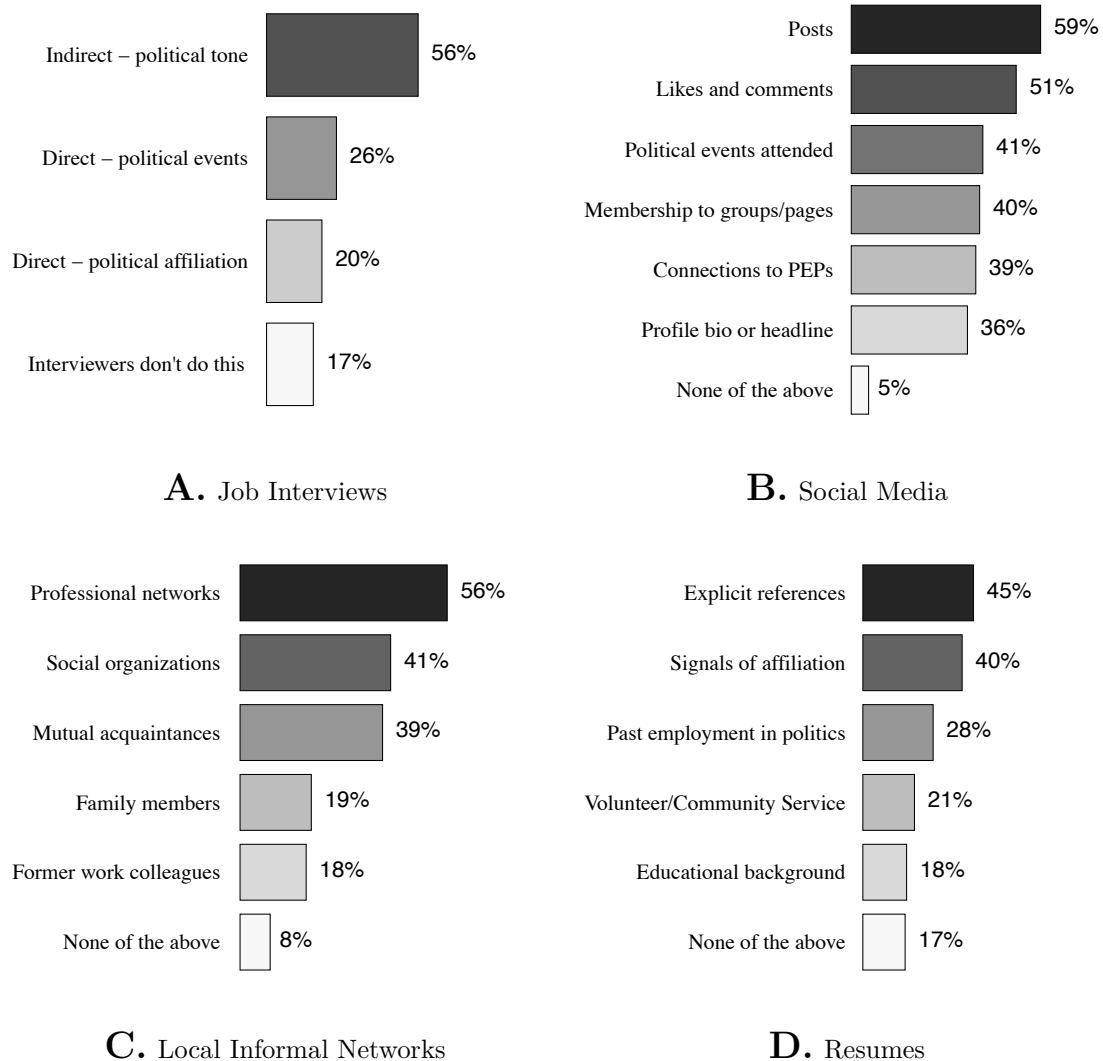
ONLINE APPENDIX

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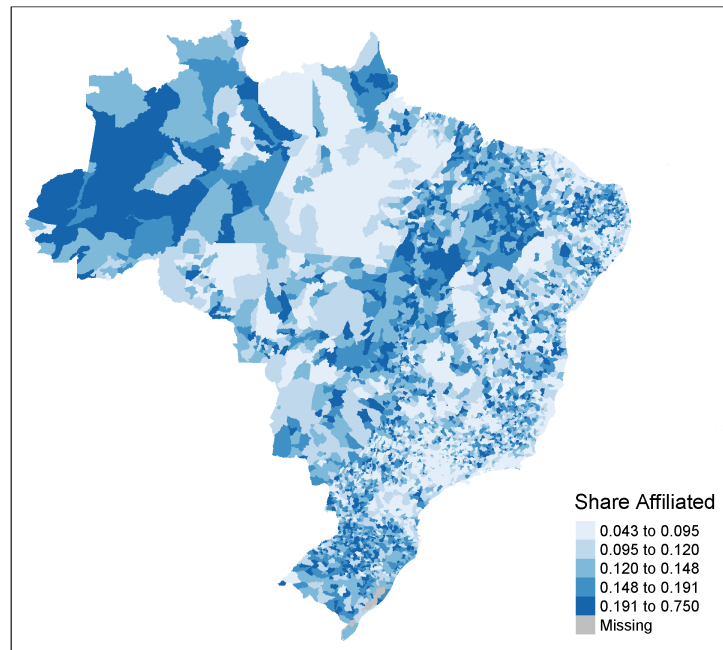
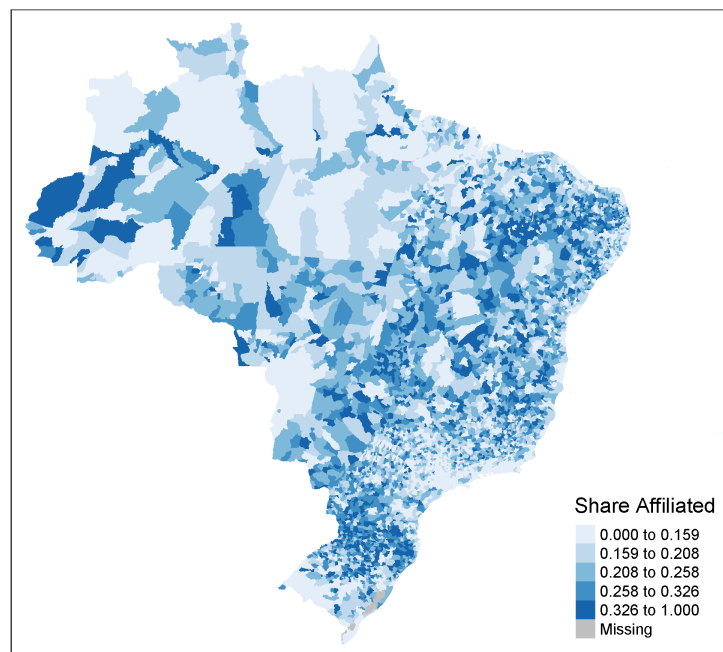
ONLINE APPENDIX A1: ADDITIONAL RESULTS

FIGURE A1. How Are Job-seekers Political Views Known?



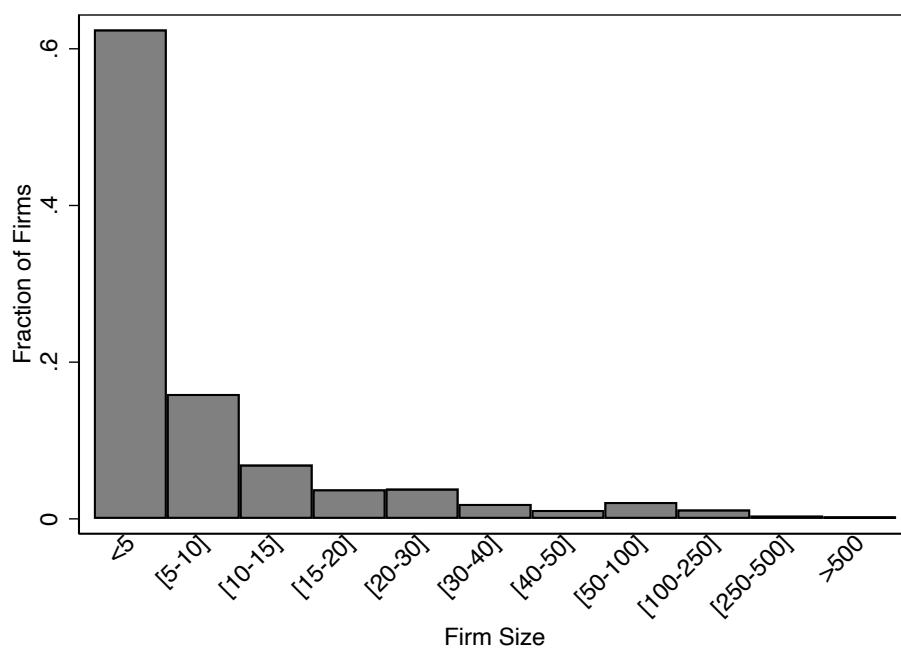
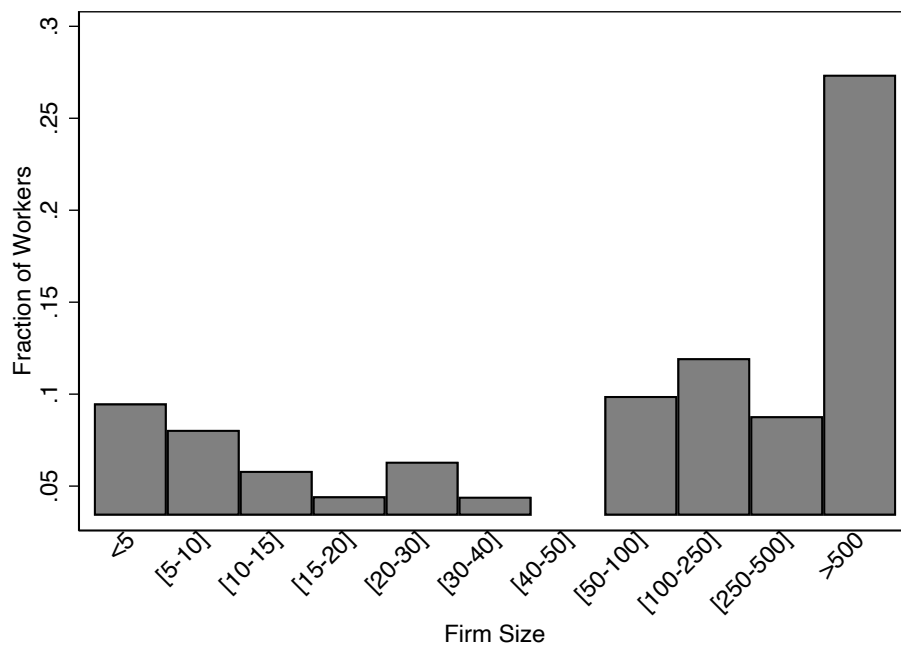
Notes: The figure presents results from our survey of Brazilian business owners and workers described in section IA. Panel A shows responses to the following question: “During interviews, how do you think interviewers making hiring decisions usually try to learn about the political views of the job applicant?”. Panel B shows responses to the following question: “When looking at job candidates’ social media (e.g., LinkedIn, Facebook, Instagram), which specific indicators do you think companies look into to infer the job candidates’ political views? (Please select all that apply)”. Panel C shows responses to the following question: “Within these local personal and business communities, who do business owners and managers rely on to gather information about a candidate’s political views? (Please select all that apply)”. Panel D shows responses to the following question: “What clues or information do you think companies use to infer a candidate’s political views from their CV or cover letter? (Please select all that apply)”.

FIGURE A2. The Geography of Political Affiliation

**A.** Share of affiliated workers**B.** Share of affiliated owners

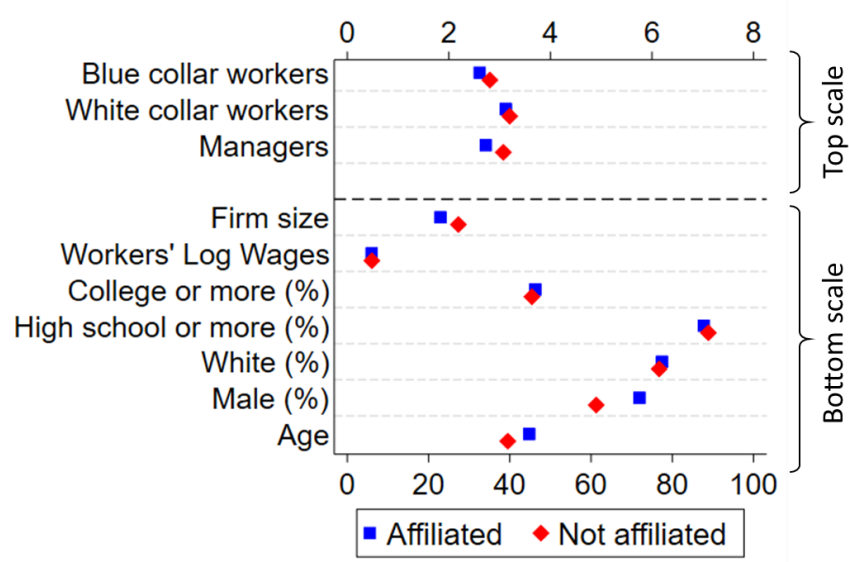
Notes: The figure shows the share of affiliated workers (Panel A) and affiliated owners (Panel B) across Brazilian municipalities over the period 2002–2019.

FIGURE A3. Distribution of Firms and Workers by Firm Size

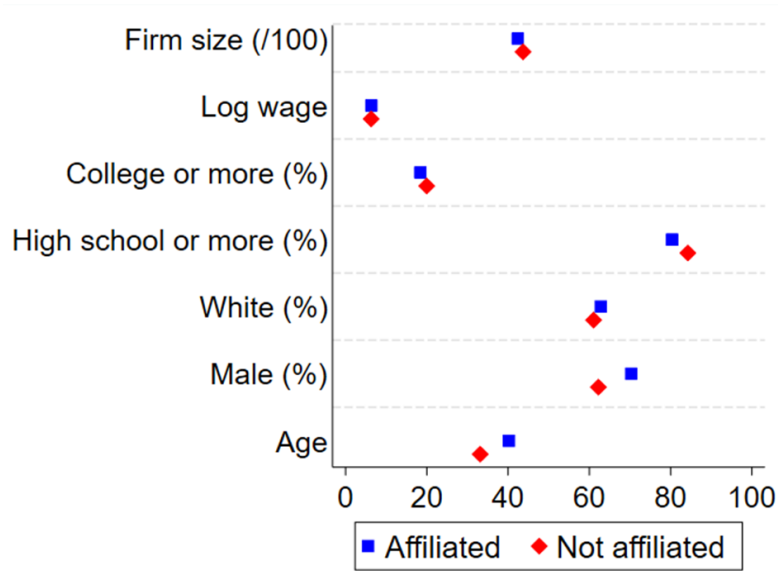
**A.** Distribution of firms by number of workers**B.** Distribution of workers by size of their firm

Notes: Panel A shows the distribution of firms by number of workers, while Panel B shows the distribution of workers by size of their firm.

FIGURE A4. Differences in Observables Between Affiliated and Unaffiliated Owners and Workers



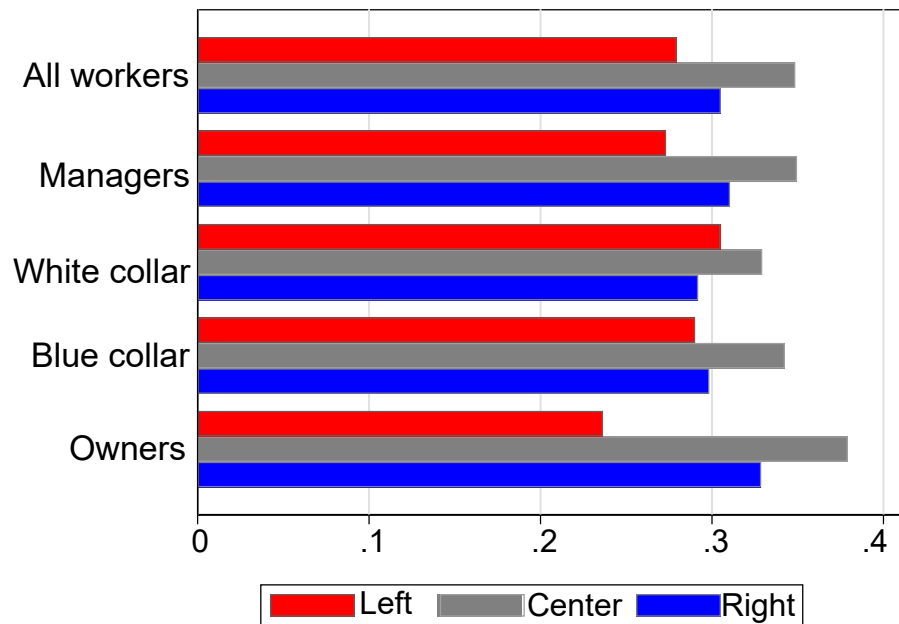
A. Owners



B. Workers

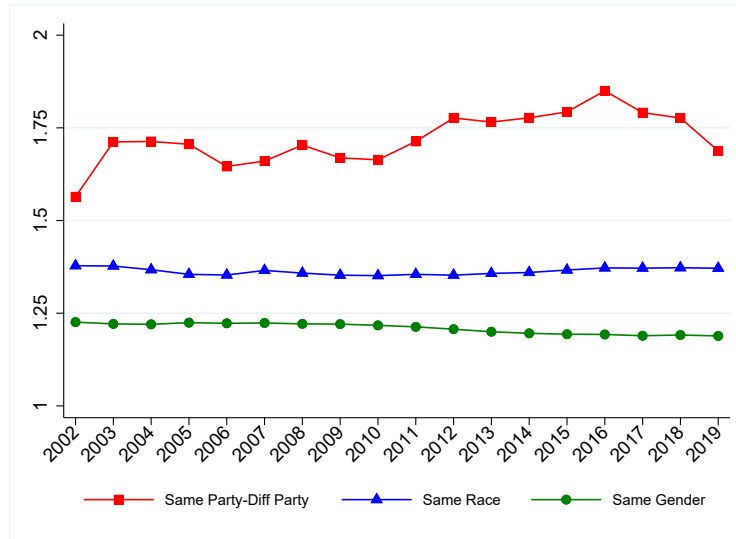
Notes: Panels A and B show average differences between affiliated (in blue) and unaffiliated (in red) owners and workers for each variable listed on the y-axis. The unit of observation in all panels is a worker/owner-year. *Blue-collar workers* / *White-collar workers* / *Managers* are the number of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

FIGURE A5. Political Orientation of Owners and Workers

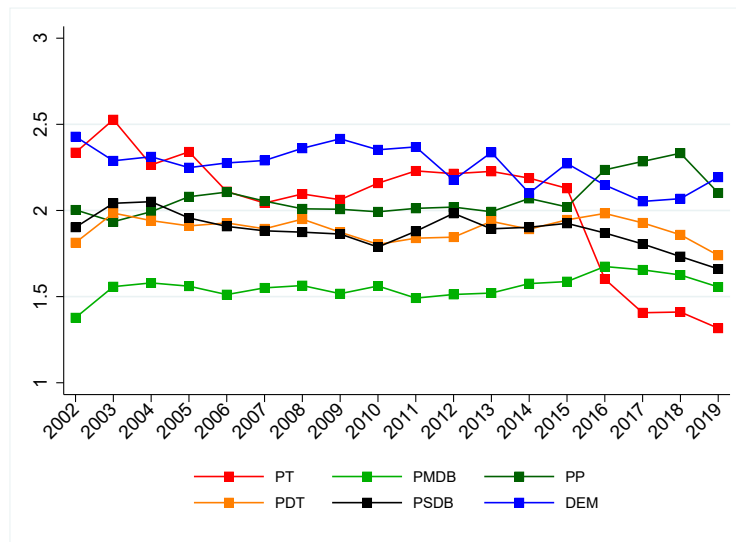


Notes: The figure shows the distribution of workers' and owners' political orientation. The unit of observation is a worker/owner-year. See Appendix Table A1 for the categorization of Brazilian parties as Left/Center/Right.

FIGURE A6. The Likelihood Ratio Index by Party



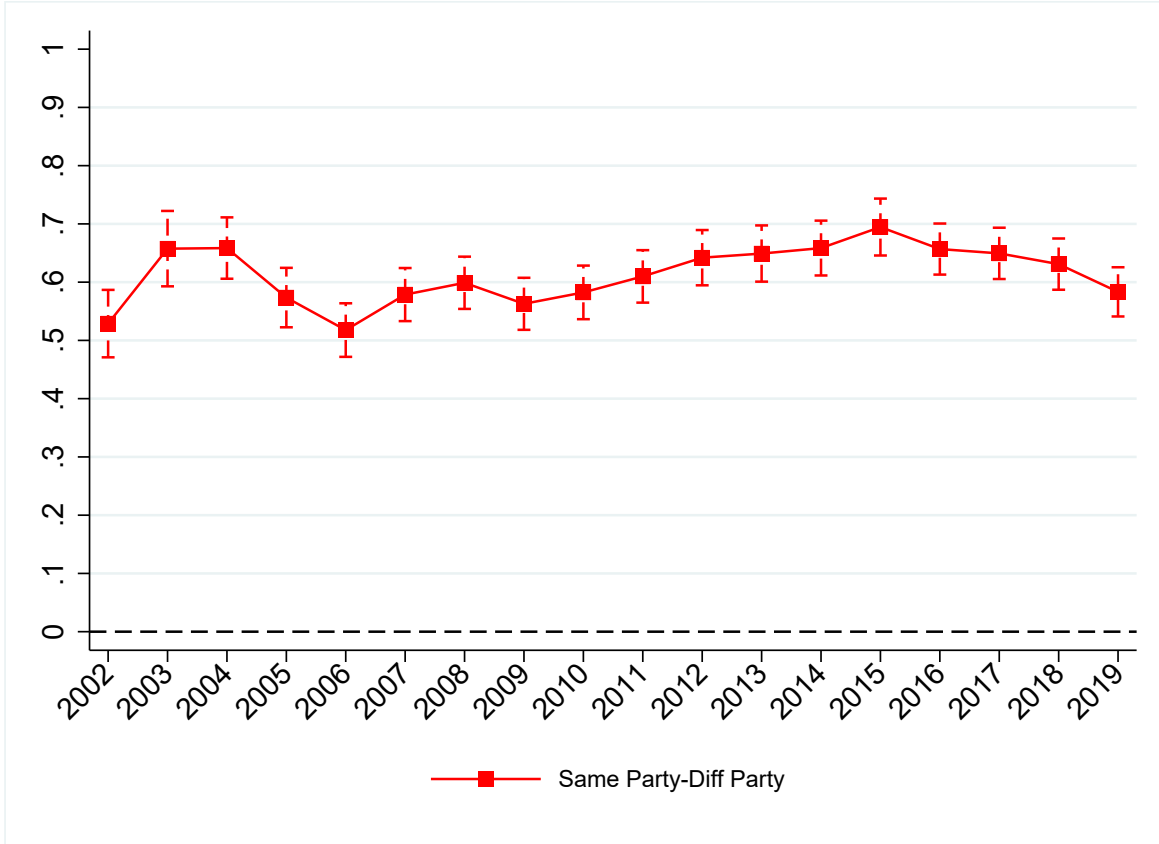
A. Basic Index



B. Basic Index by Party

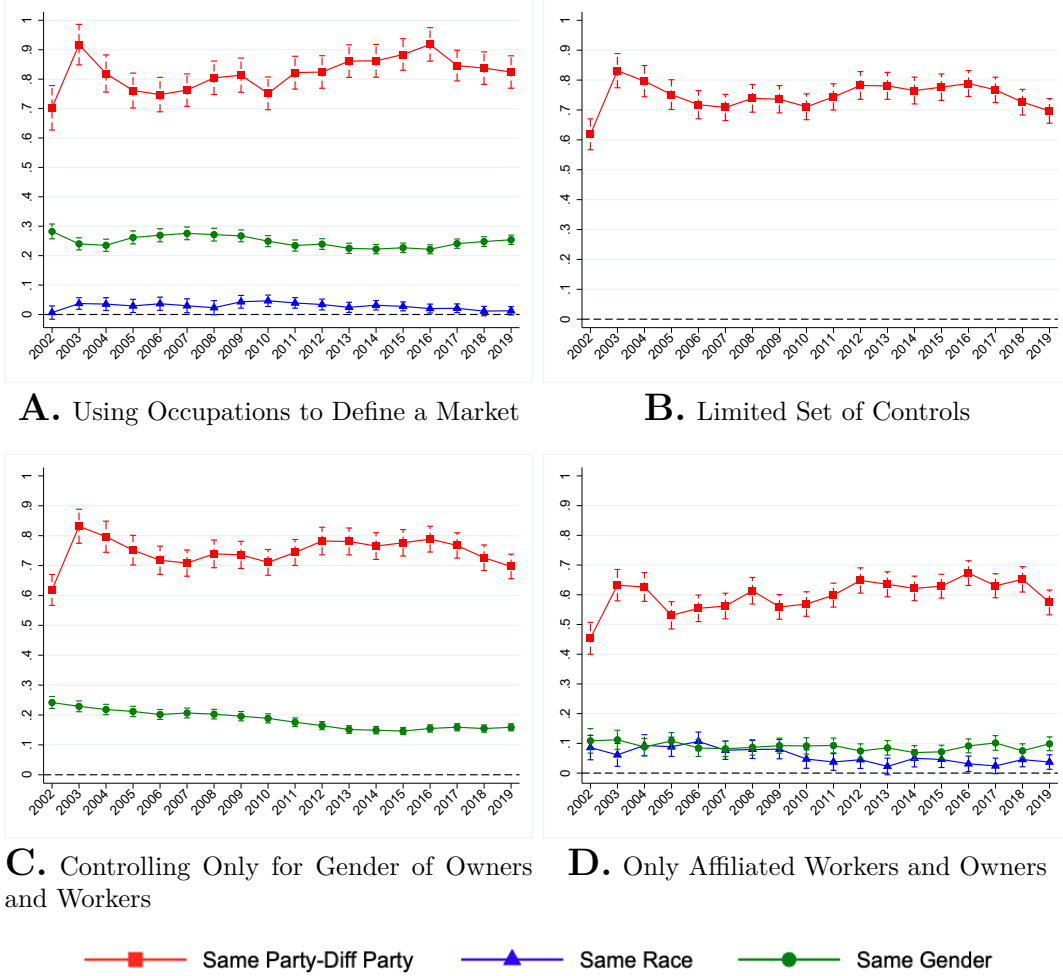
Notes: Panel A shows estimates of the likelihood Ratio Index without adjusting for geographical sorting. Panel B shows estimates of the likelihood ratio index for each of the top 6 parties by number of affiliates. See section IIIA and Online Appendix A3 for additional details.

FIGURE A7. **Political Assortative Matching: Dyadic Regression Estimates Controlling for Same Last Name**



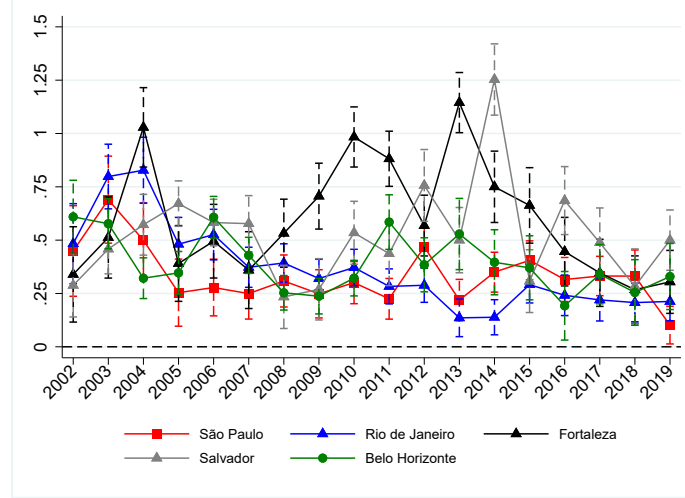
Notes: The figure shows the point estimates and 95% confidence intervals of $\Delta(SP, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$, our measure of Political Assortative Matching. The estimates are from a version of equation (1) in which we additionally control for an indicator equal to one if the owner and the worker have the same last name. Confidence intervals are based on standard errors clustered at the market level. See section IIIB and equation (1) for details on the estimation.

FIGURE A8. Political Assortative Matching: Dyadic Regression Estimates and Robustness

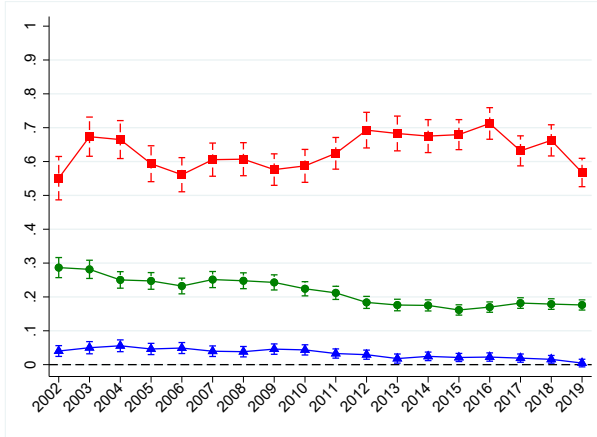


Notes: Panel A shows the point estimates and 95% confidence intervals of $\Delta(SP, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in red), our measure of Political Assortative Matching, and the effect of shared gender (in green) and shared race (in blue) on the probability that i works in firm f , normalized by the sample probability that y_{if} equals one if the worker and the owner have a different gender or race, respectively. In this figure, the markets are defined as a municipality-occupation cell (using the first digit of the CBO code to define an occupational category). Panel B shows the point estimates and 95% confidence intervals of $\Delta(SP, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in red), our measure of Political Assortative Matching, from a version of equation (1) without including the set of indicators SX'_{if} , Z'_i , and W'_f , and estimated on the sample of all business owners. Panel C shows point estimates and 95% confidence intervals of $\Delta(SP, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in red), and $SameGender_{if}$ divided by the sample probability that y_{if} equals one if $SameGender_{if} = 0$ (in green), from a version of equation (1) without including the set of indicators SX'_{if} , Z'_i , and W'_f (except indicators for gender), and estimated on the sample of all business owners. Panel D shows the point estimates and 95% confidence intervals of $SameParty_{y_{if}}$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in red), our measure of Political Assortative Matching, and the effect of shared gender (in green) and shared race (in blue) on the probability that i works in firm f , normalized by the sample probability that y_{if} equals one if the worker and the owner have a different gender or race, respectively. The estimates are from a version of equation (1) estimated on the subsample of affiliated workers and owners. Confidence intervals are based on standard errors clustered at the market level. See section IIIB and equation (1) for details on the estimation.

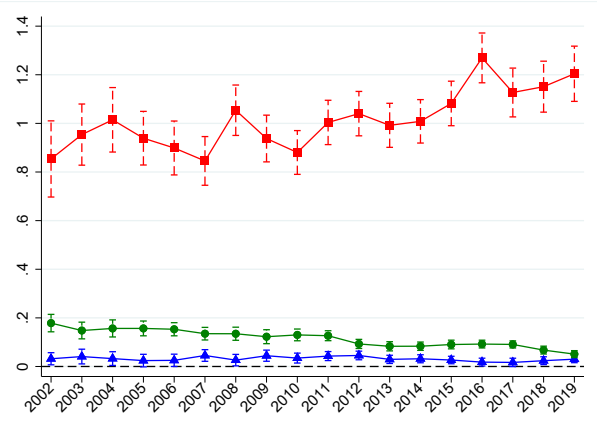
FIGURE A9. **Political Assortative Matching: Dyadic Regression Estimates - Robustness to Alternative Samples**



A. Five Largest Capitals in Brazil



B. Dropping firms with owners of different party

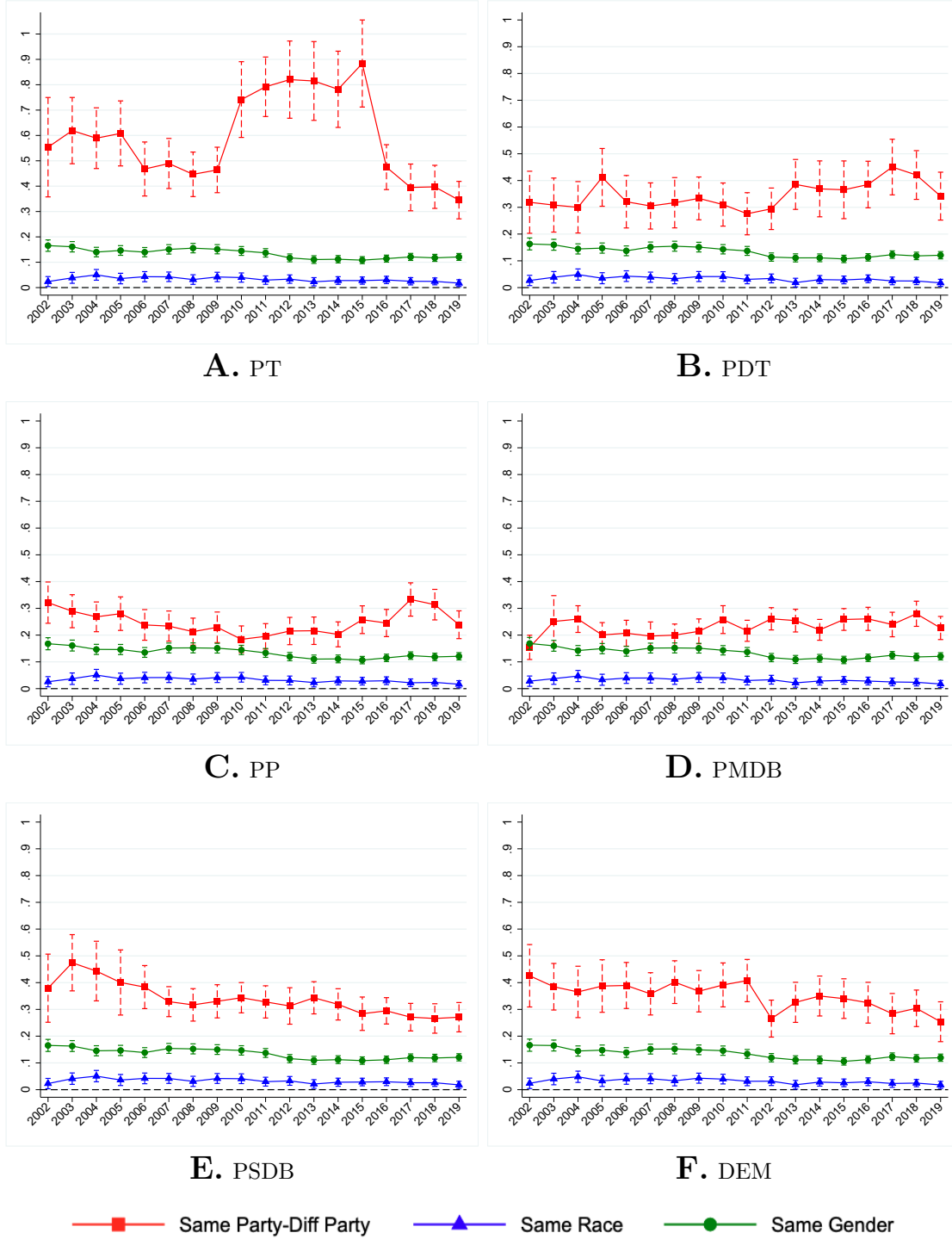


C. Dropping firms with multiple owners

—■— Same Party-Diff Party —▲— Same Race —●— Same Gender

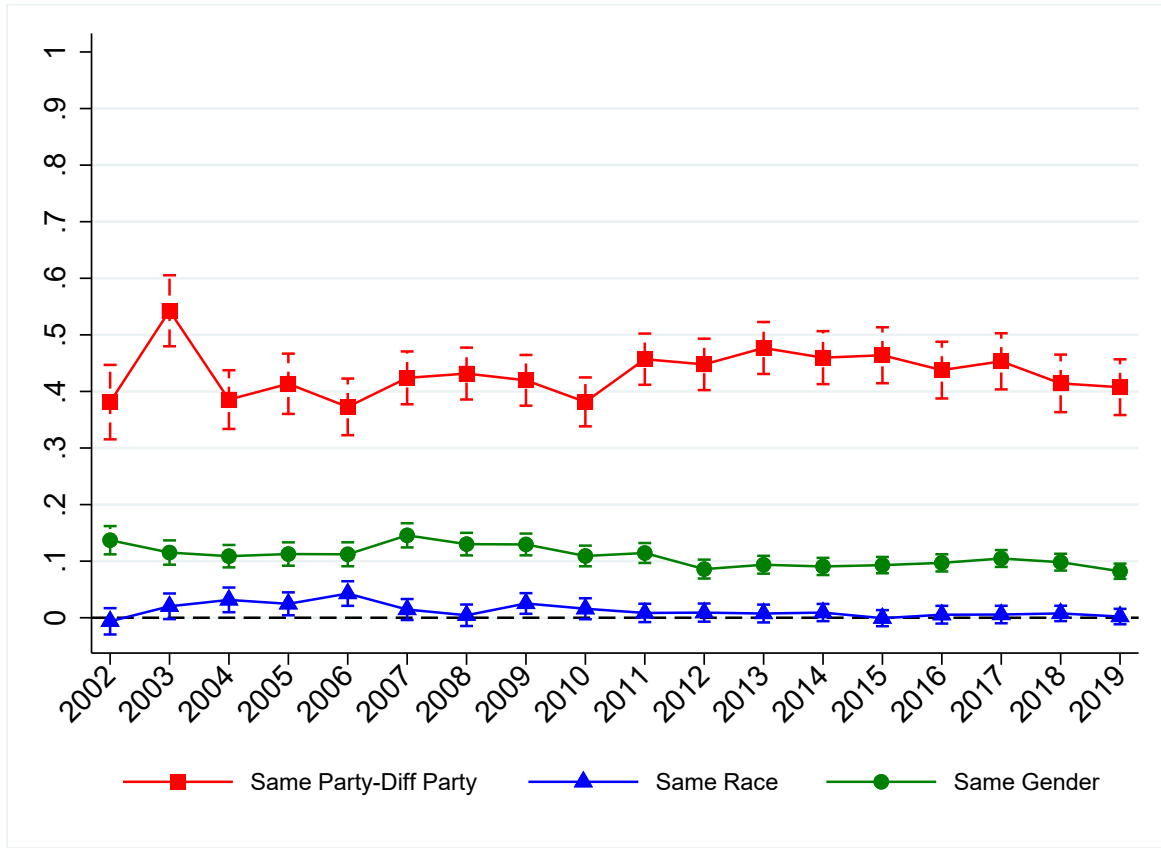
Notes: Panel A and Panel B show the point estimates and 95% confidence intervals of $\Delta(SP, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in red), our measure of Political Assortative Matching, and the effect of shared gender (in green) and shared race (in blue) on the probability that i works in firm f , normalized by the sample probability that y_{if} equals one if the worker and the owner have a different gender or race, respectively. The estimates are from a version of equation (1) estimated for the five largest state capitals (Panel A), on a subsample where we drop firms with owners from different parties (panel B) and where we drop firms with multiple owners altogether (panel C). Confidence intervals are based on standard errors clustered at the market level. See section IIIB and equation (1) for details on the estimation.

FIGURE A10. Political Assortative Matching by Party, considering 2 Groups (Members of a Specific Party *versus* Other Individuals)



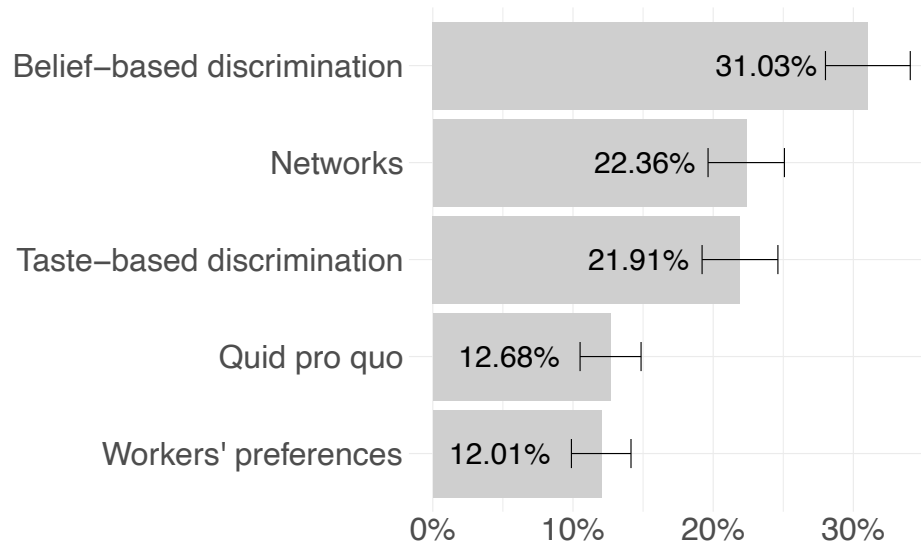
Notes: The figure shows estimates of political (in red), gender (in green) and race (in blue) assortative matching based on a version of the dyadic regression equation (1) in which partisanship is specified in a dichotomous way. Specifically, we assigned workers and owners to only two groups: affiliated to party P , or not affiliated to party P , and we run these regressions for each of the top 6 parties in Brazil. Each panel presents estimates for a specific party P , focusing on the top 6 parties for number of affiliates. Confidence intervals are based on standard errors clustered at the market level. See section IIIB and equation (1) for details on the estimation.

FIGURE A11. Political Assortative Matching: Hiring Margin

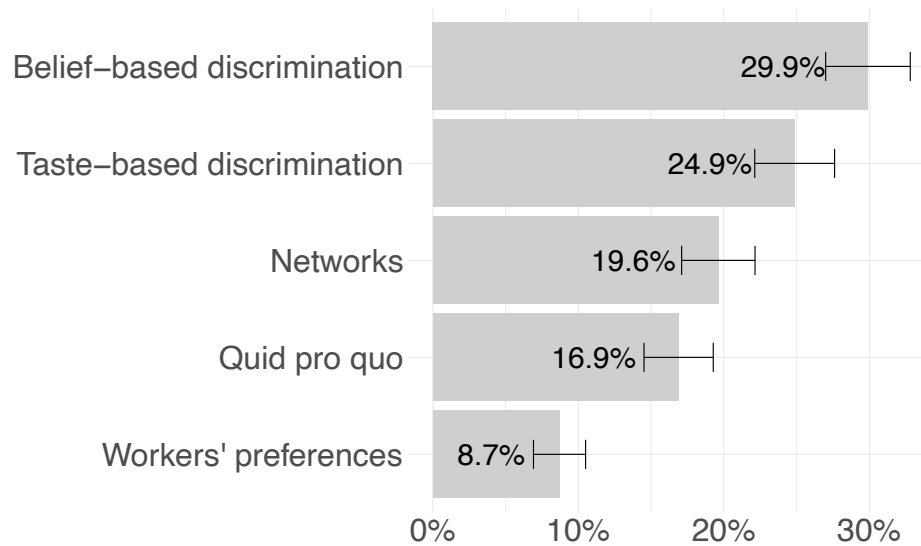


Notes: The figure presents results from dyadic regressions estimated in a sample including only workers who were hired in the specific year. The figure shows the point estimates and 95% confidence intervals of $\Delta(SP, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in red), our measure of Political Assortative Matching, and the effect of shared gender (in green) and shared race (in blue) on the probability that i works in firm f , normalized by the sample probability that y_{if} equals one if the worker and the owner have a different gender or race, respectively. Confidence intervals are based on standard errors clustered at the market level. See section IIIC and equation (1) for details on the estimation.

FIGURE A12. Survey Evidence on Most Relevant Mechanisms – Affiliated Respondents



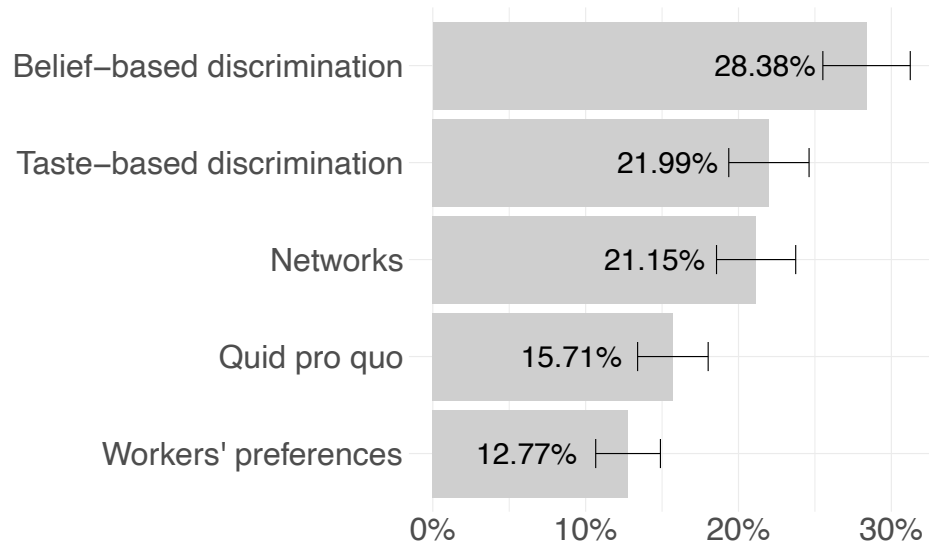
A. Owners' most relevant mechanism



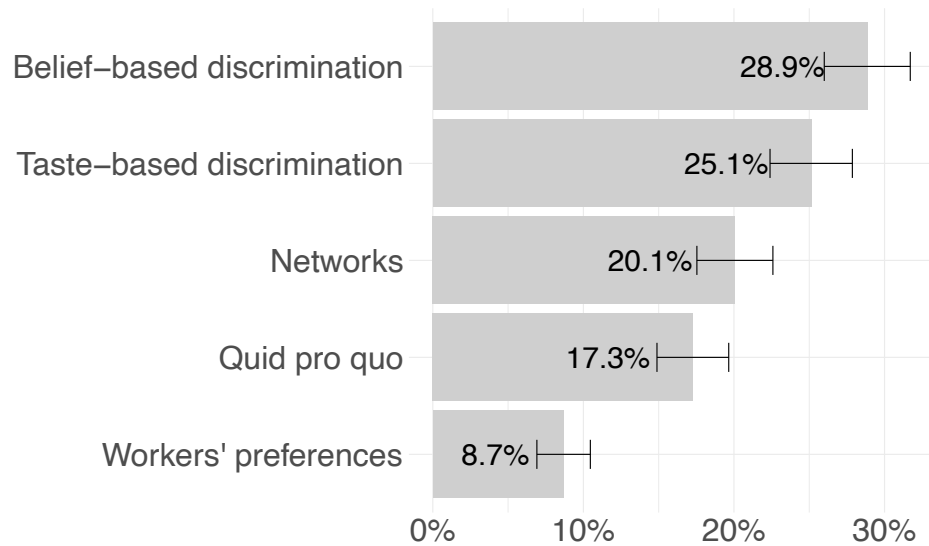
B. Workers' most relevant mechanism

Notes: The figure presents results from our survey of Brazilian business owners and workers, described in section IVA. Panels A and B plot, for each statement, the share of owners and workers, respectively, who agree the most with that statement as mechanism behind our finding of political assortative matching. The sample is restricted to politically affiliated business owners and workers.

FIGURE A13. Survey Evidence on Most Relevant Mechanisms – Un-affiliated Respondents



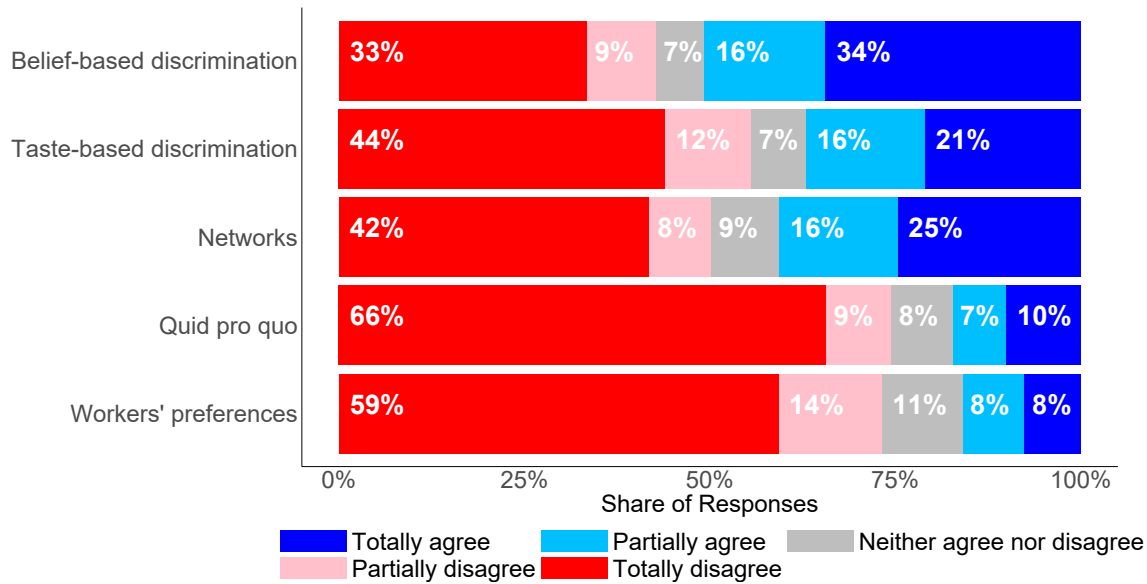
A. Owners' most relevant mechanism



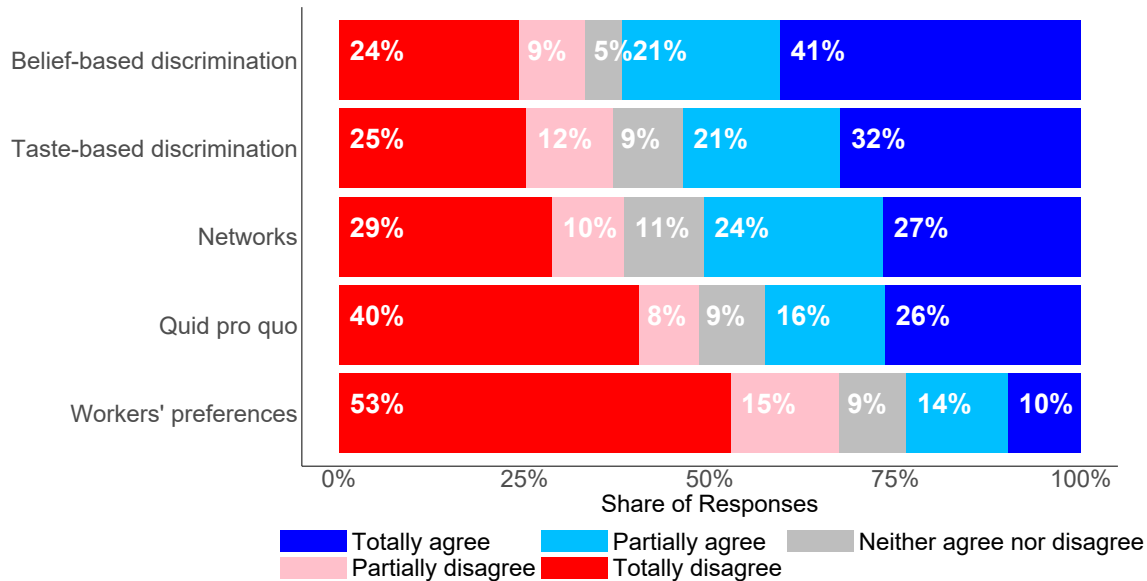
B. Workers' most relevant mechanism

Notes: The figure presents results from our survey of Brazilian business owners and workers, described in section [IVA](#). Panels A and B plot, for each statement, the share of owners and workers, respectively, who agree the most with that statement as mechanism behind our finding of political assortative matching. The sample is restricted to unaffiliated business owners and workers.

FIGURE A14. Survey Evidence on Most Relevant Mechanisms – Affiliated Respondents



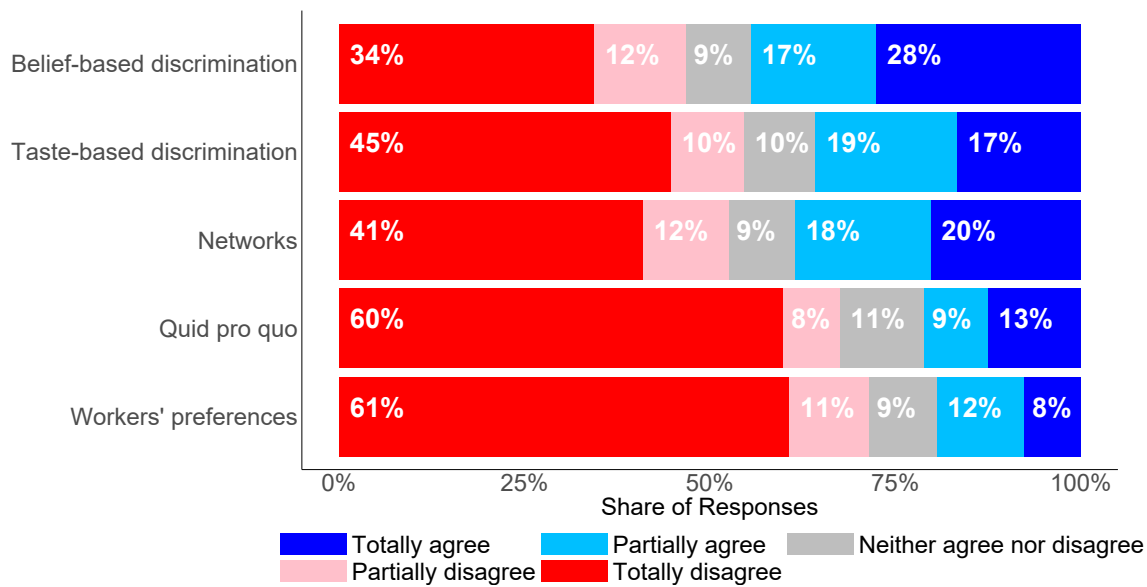
A. Owners' agreement with the five statements



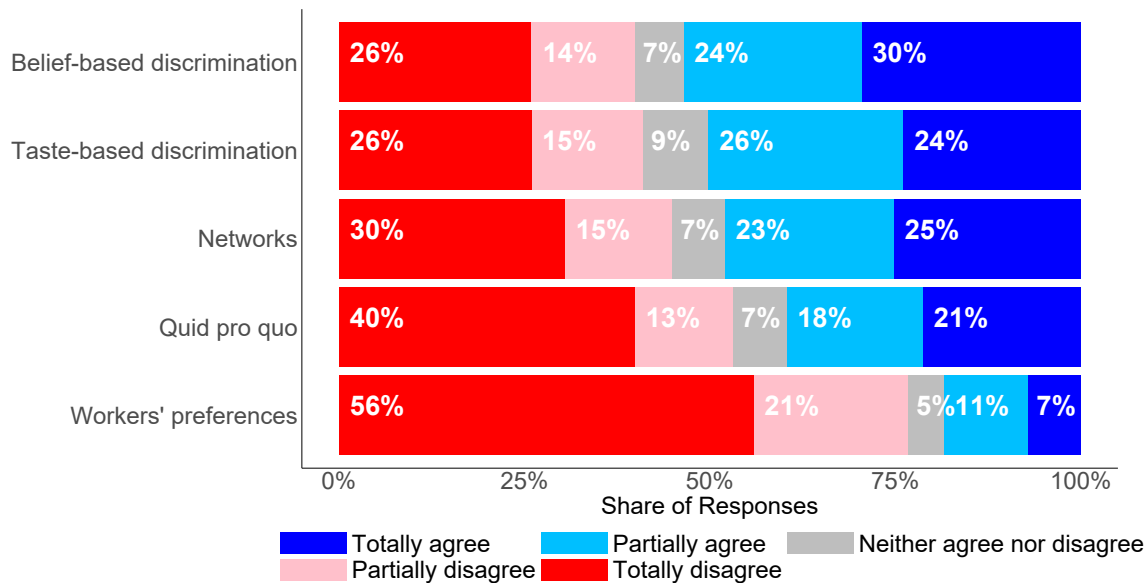
B. Workers' agreement with the five statements

Notes: The figure presents results from our survey of Brazilian business owners and workers, described in section IVA. The sample is restricted to politically affiliated business owners and workers. Panels A and B plot the level of agreement (on a scale from 1 “Totally disagree” to 5 “Totally agree”) with the different statements by owners and workers, respectively.

FIGURE A15. Survey Evidence on Most Relevant Mechanisms – Un-affiliated Respondents



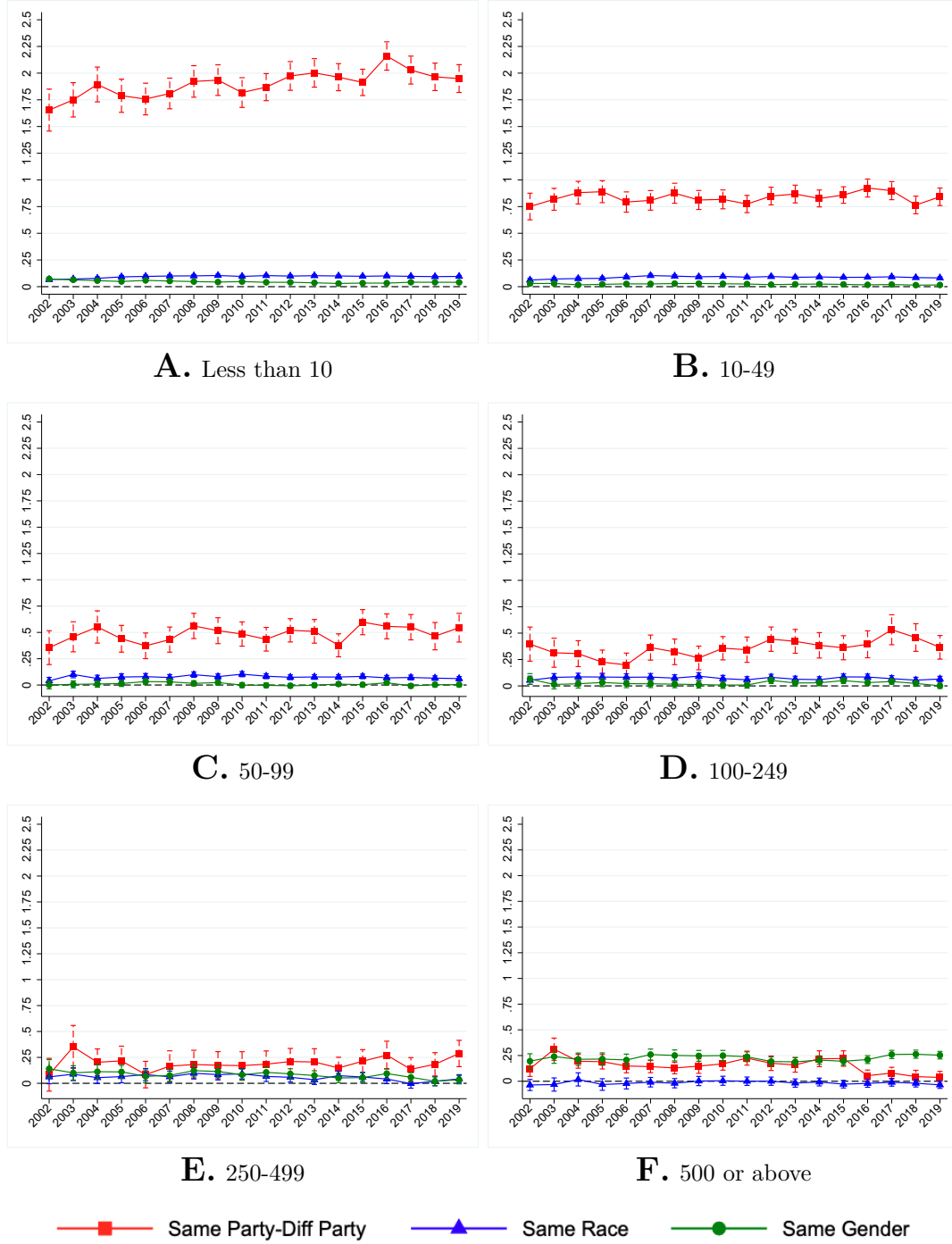
A. Owners' agreement with the five statements



B. Workers' agreement with the five statements

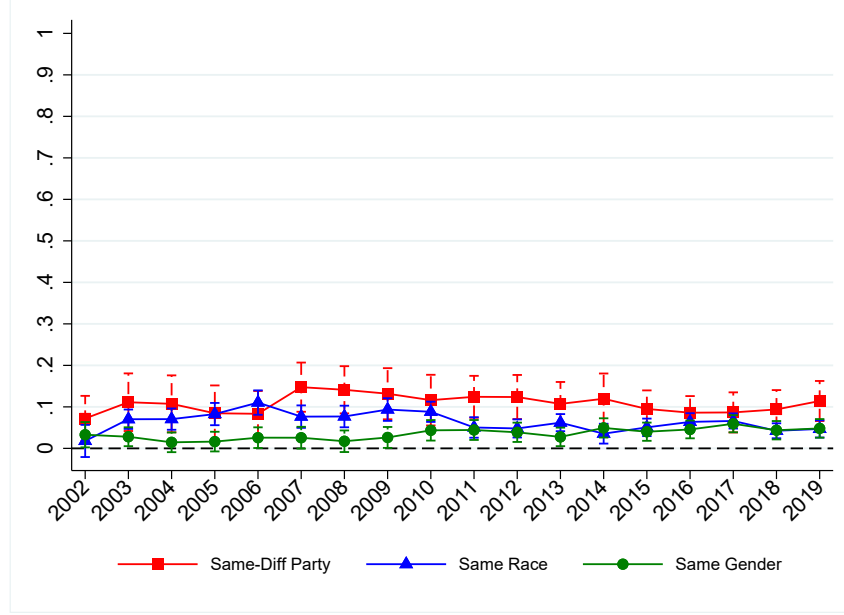
Notes: The figure presents results from our survey of Brazilian business owners and workers, described in section IVA. The sample is restricted to unaffiliated business owners and workers. Panels A and B plot the level of agreement (on a scale from 1 “Totally disagree” to 5 “Totally agree”) with the different statements by owners and workers, respectively.

FIGURE A16. Political Assortative Matching by Firm Size

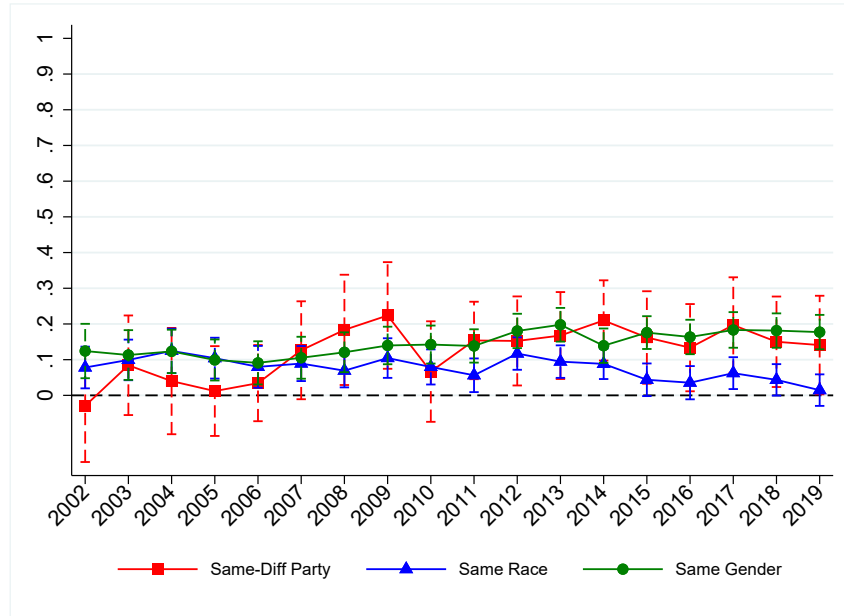


Notes: The figures show the point estimates and 95% confidence intervals of $\Delta(SP, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in red), our measure of Political Assortative Matching, and the effect of shared gender (in green) and shared race (in blue) on the probability that i works in firm f , normalized by the sample probability that y_{if} equals one if the worker and the owner have a different gender or race, respectively. The different panels plot estimates in different samples based on firm size categories (less than 10 employees, 10-49, 50-99, 100-249, 250-499, and 500 or more employees). Confidence intervals are based on standard errors clustered at the market level. See section IIIB and equation (1) for details on the estimation.

FIGURE A17. Political Assortative Matching Among Workers and Human Resources Manager and Top Manager



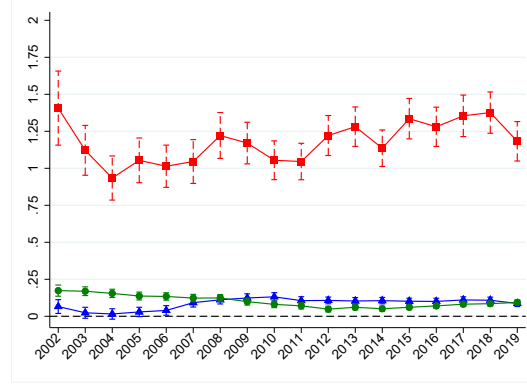
A. HR Manager



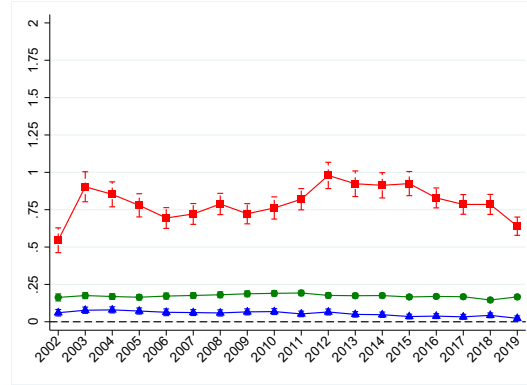
B. Top Manager (Firms above 500)

Notes: The figures show the point estimates and 95% confidence intervals of $\Delta(SP, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in red), our measure of Political Assortative Matching, and the effect of shared gender (in green) and shared race (in blue) on the probability that i works in firm f , normalized by the sample probability that y_{if} equals one if the worker and the owner have a different gender or race, respectively. Panel A focuses on the sample of firms with a HR manager, considering the matching between the party of the worker and that of the HR manager. Panel B focuses on firms with more than 500 employees, considering the matching between the party of the worker and that of the top manager of the firm. Confidence intervals are based on standard errors clustered at the market level. See section IIIB and equation (1) for details on the estimation.

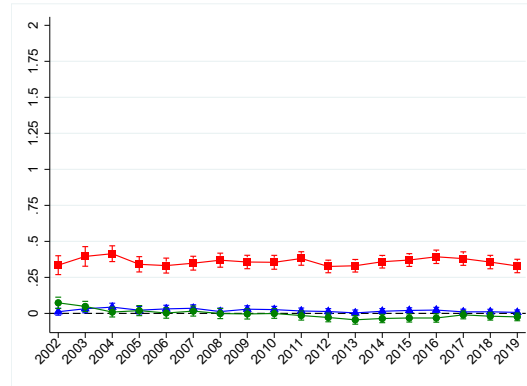
FIGURE A18. **Political Assortative Matching by Occupational Layers in the Firm**



A. Manager



B. White Collar

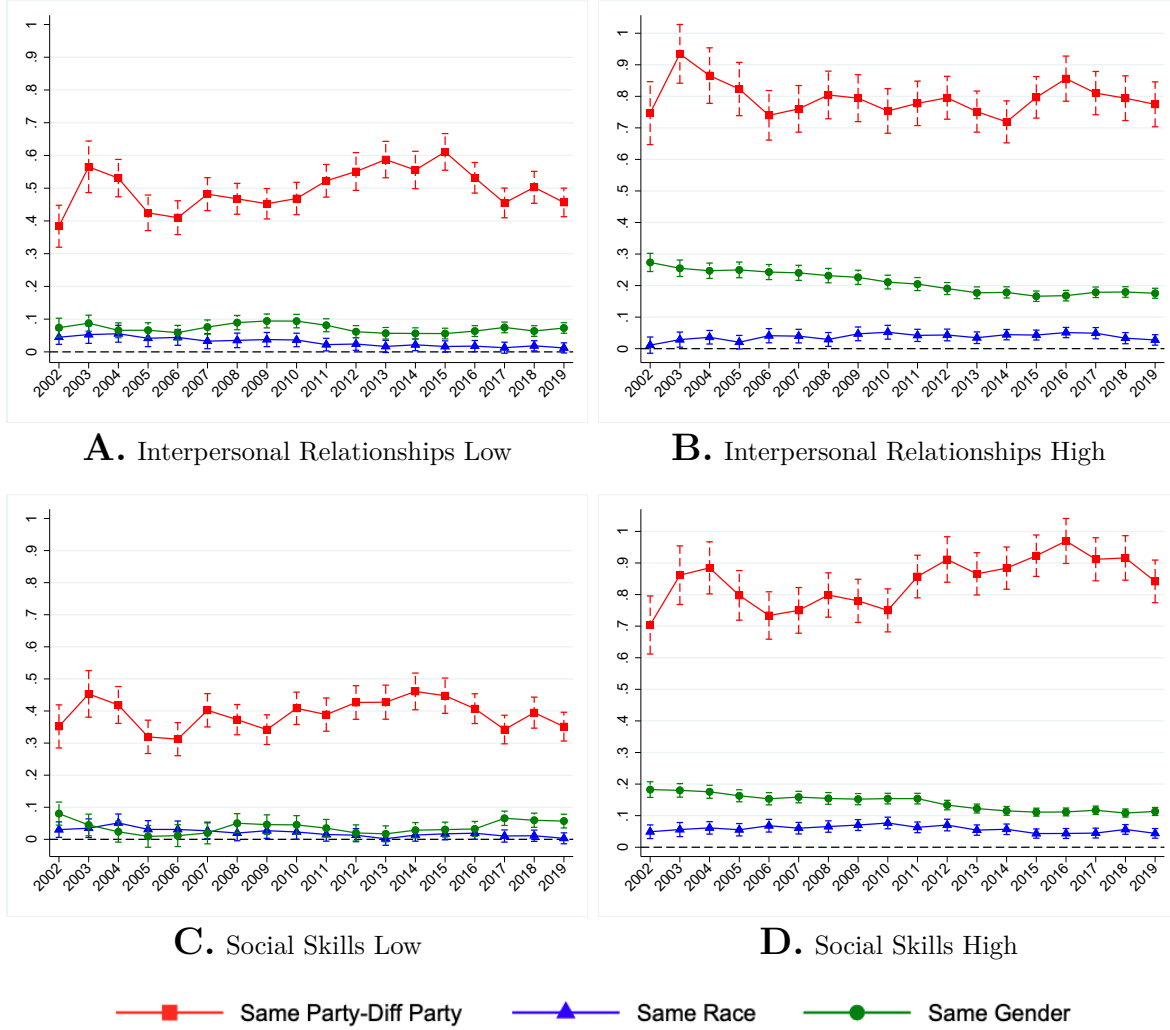


C. Blue Collar

—■— Same Party-Diff Party —▲— Same Race —●— Same Gender

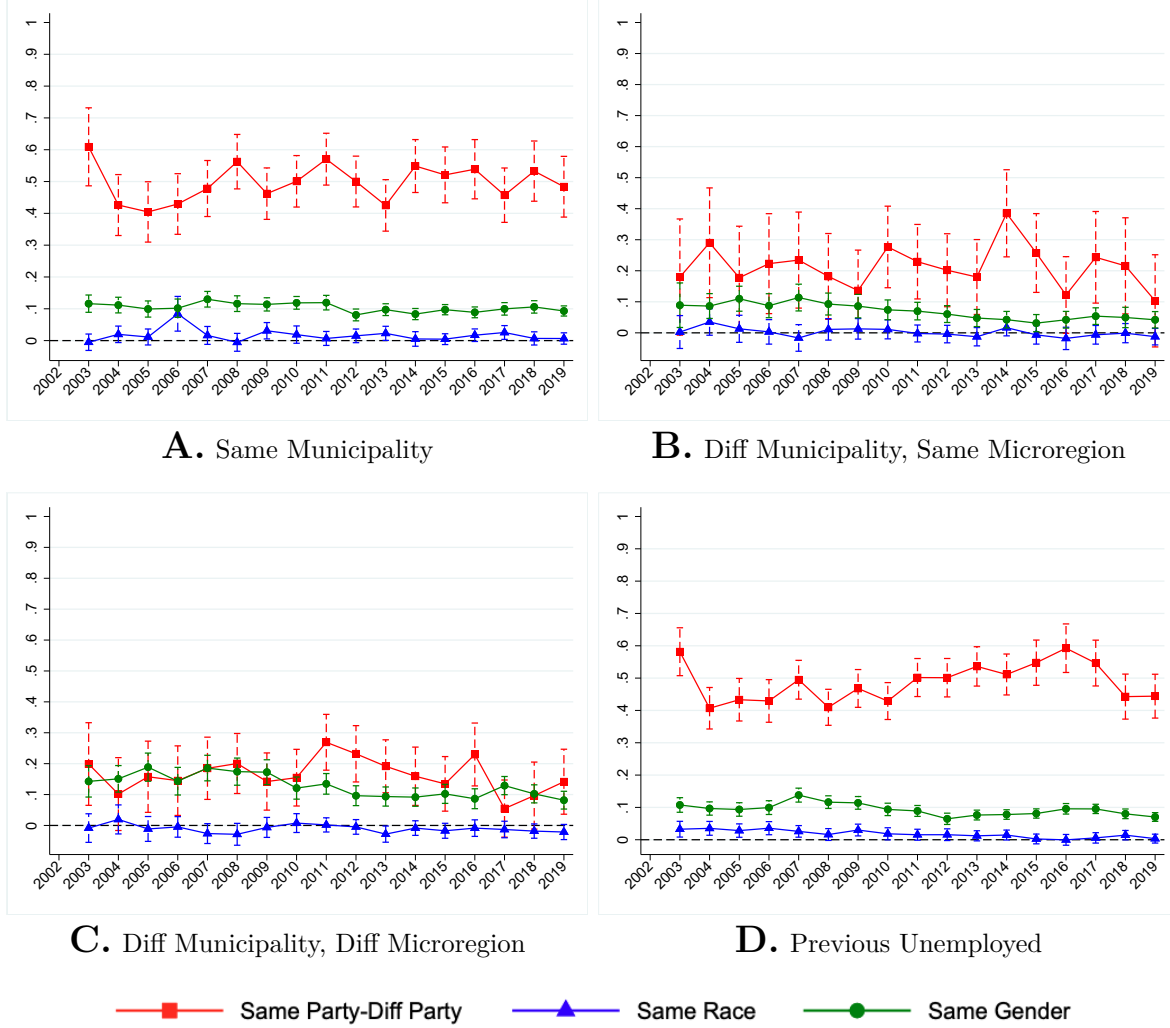
Notes: The figures show the point estimates and 95% confidence intervals of $\Delta(SP, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in red), our measure of Political Assortative Matching, and the effect of shared gender (in green) and shared race (in blue) on the probability that i works in firm f , normalized by the sample probability that y_{if} equals one if the worker and the owner have a different gender or race, respectively. The different panels plot estimates for workers employed in managerial, other white-collar, and blue-collar occupations. Confidence intervals are based on standard errors clustered at the market level. See section IIIB and equation (1) for details on the estimation.

FIGURE A19. Political Assortative Matching by Levels of Social and Interpersonal Skills Required in the Occupation



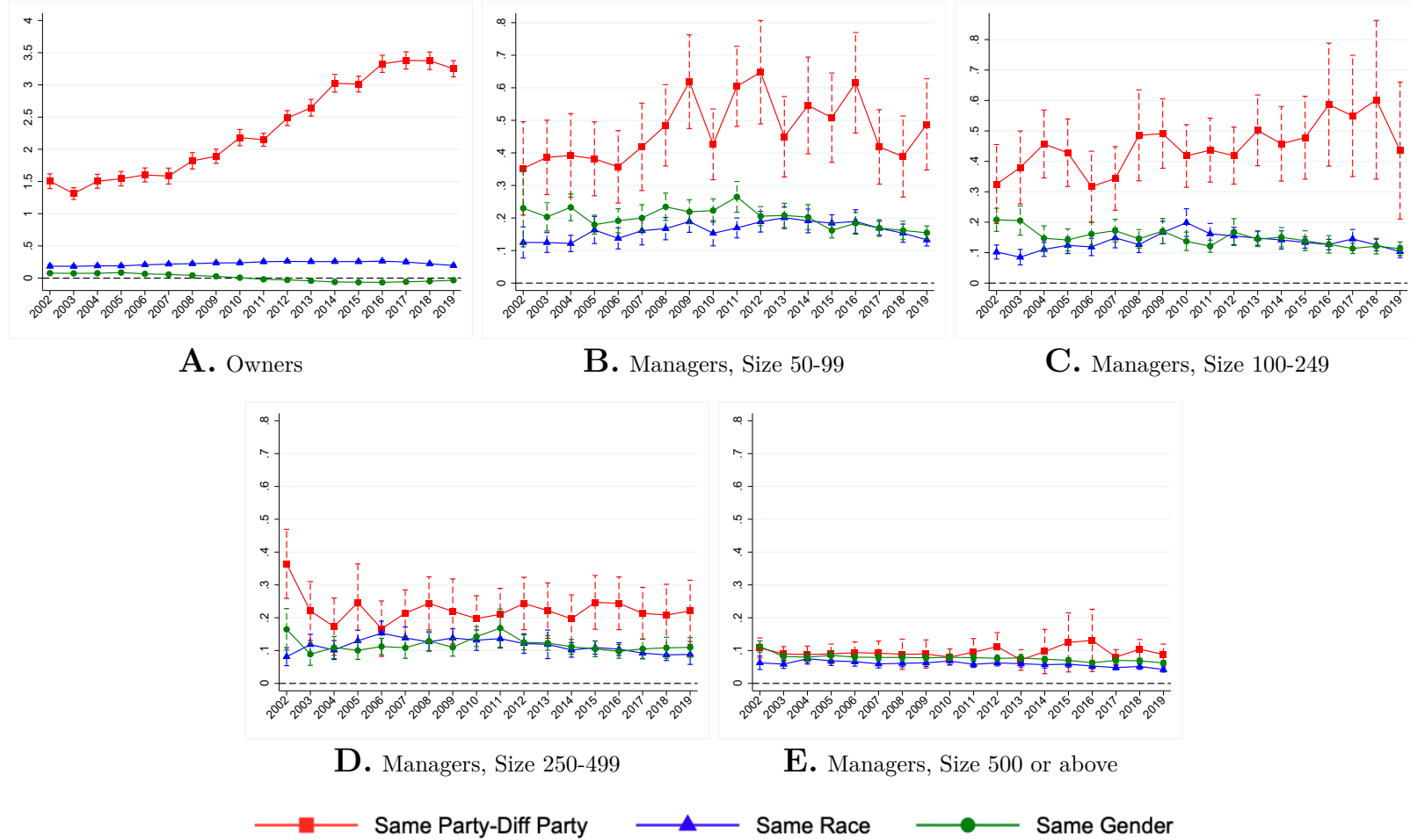
Notes: The figures show the point estimates and 95% confidence intervals of $\Delta(SP, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in red), our measure of Political Assortative Matching, and the effect of shared gender (in green) and shared race (in blue) on the probability that i works in firm f , normalized by the sample probability that y_{if} equals one if the worker and the owner have a different gender or race, respectively. The different panels focus on occupations with required interpersonal relationships below (panel A) or above median (Panel B), and on occupations with required social skills below (Panel C) or above median (Panel D). Confidence intervals are based on standard errors clustered at the market level. See section IIIB and equation (1) for details on the estimation.

FIGURE A20. Political Assortative Matching by Location of Previous Employment

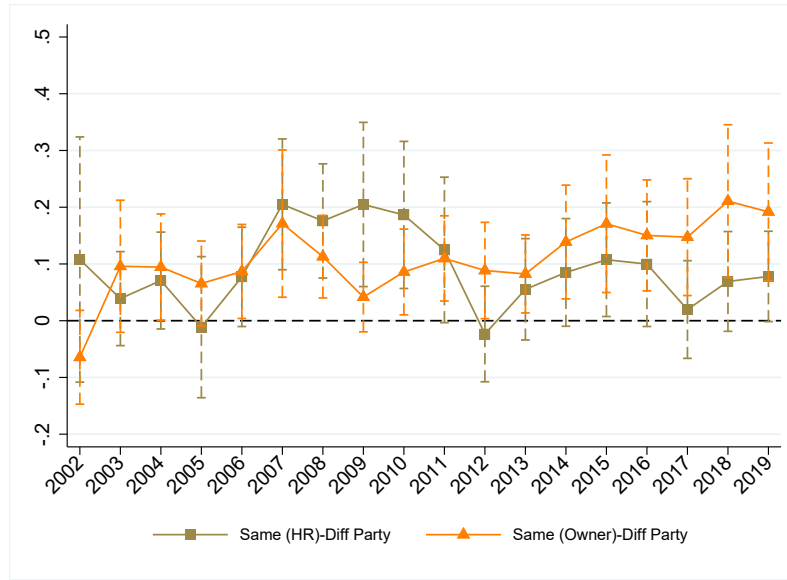
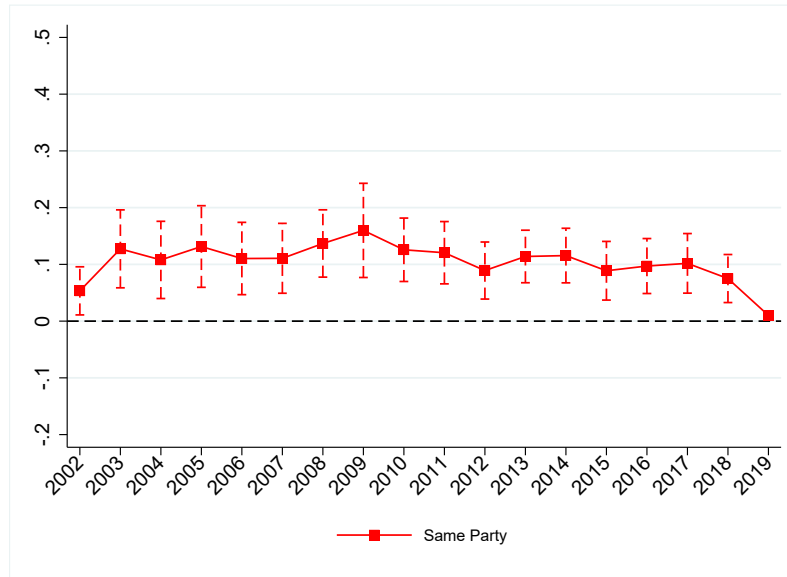


Notes: The figures show the point estimates and 95% confidence intervals of $\Delta(SP, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in red), our measure of Political Assortative Matching, and the effect of shared gender (in green) and shared race (in blue) on the probability that i works in firm f , normalized by the sample probability that y_{if} equals one if the worker and the owner have a different gender or race, respectively. The different panels focus on different subsample of newly hired workers based on the employment status in the previous year, distinguishing between workers who (a) were employed in the same municipality as their current job, (b) worked in a different municipality within the same micro-region, (c) were employed in a different municipality outside the micro-region, or (d) were unemployed. Confidence intervals are based on standard errors clustered at the market level. See section IIIB and equation (1) for details on the estimation.

FIGURE A21. Political Assortative Matching Among Owners and Among Managers of Big Firms (by Firm Size)

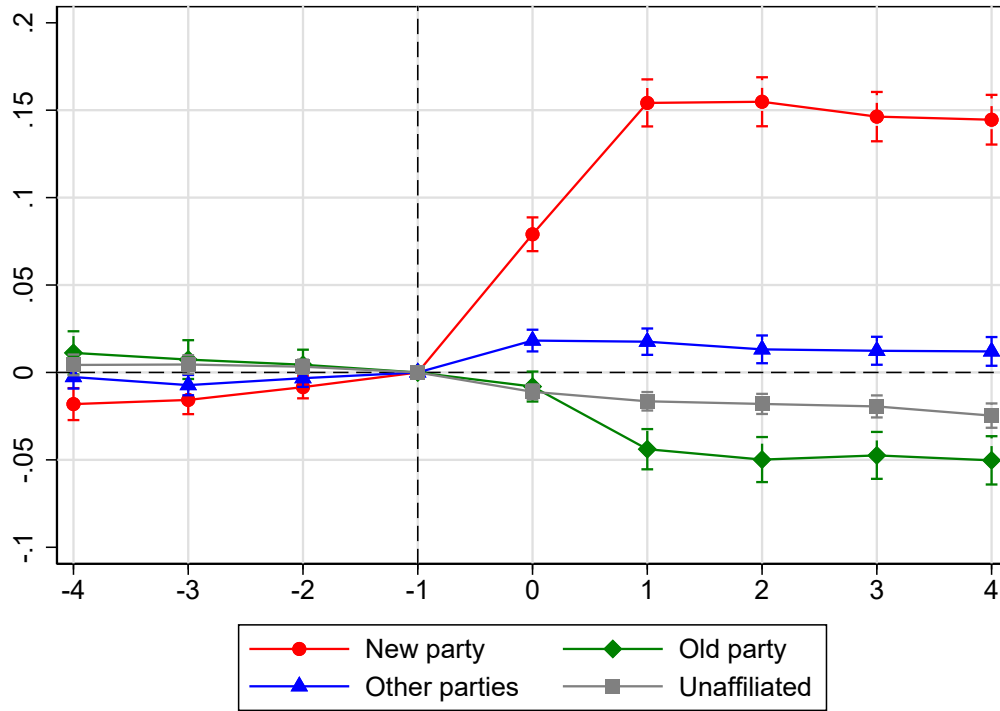


Notes: The figures show the point estimates and 95% confidence intervals of $\Delta(SP, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in red), our measure of Political Assortative Matching, and the effect of shared gender (in green) and shared race (in blue) on the probability that i works in firm f , normalized by the sample probability that y_{if} equals one if the worker and the owner have a different gender or race, respectively. Panel A shows assortative matching estimates for owners and Panels B, C, D, and E show assortative matching estimates for managers of big firms (size 50-100, 100-250, 250-500 and above 500 employees). Confidence intervals are based on standard errors clustered at the market level. See section III B and equation (1) for details on the estimation.

FIGURE A22. **Political Assortative Matching: HR Managers****A.** Both Owners and HR affiliated**B.** Only HR affiliated

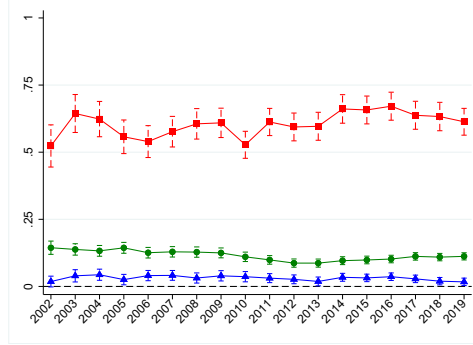
Notes: The figure presents dyadic regression estimates for firms with Human Resources departments. In panel A, we restrict the sample to firms in which the owner and the HR top manager are both affiliated, but with different parties. In panel B, we restrict the sample to observations where firm owners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

FIGURE A23. **Event Study Around Owners' Change of Party: Total Wage Bill**

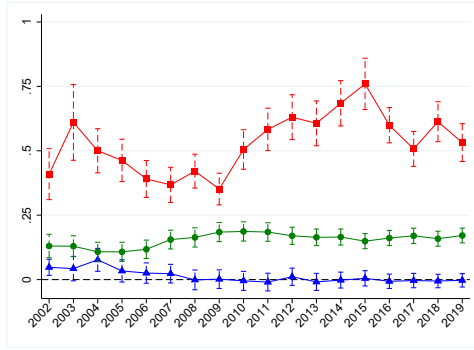


Notes: The figure presents estimates of the coefficients β_s from equation (1) together with 95% confidence intervals based on standard errors clustered at the firm level. The dependent variable is the log of the firm's wage bill for employees affiliated with the new party of the switching owner (in red), with the old party of the switching owner (in green), with other parties (in blue), and unaffiliated (in orange). See section IVC for additional details on the estimation.

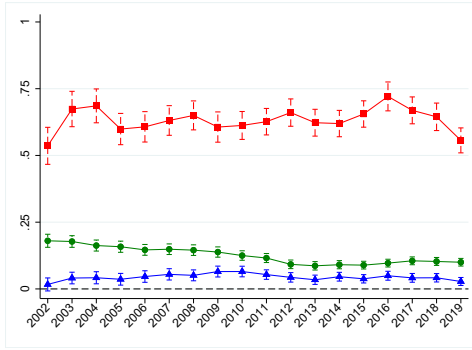
FIGURE A24. Political Assortative Matching - Quid-Pro-Quo



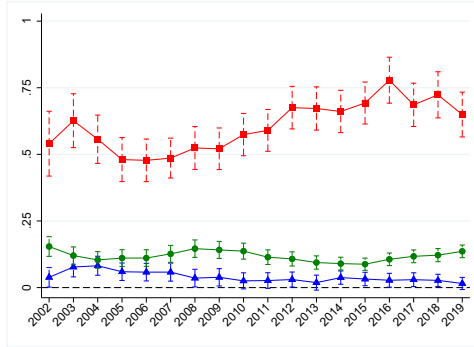
A. Without Donors and Candidates



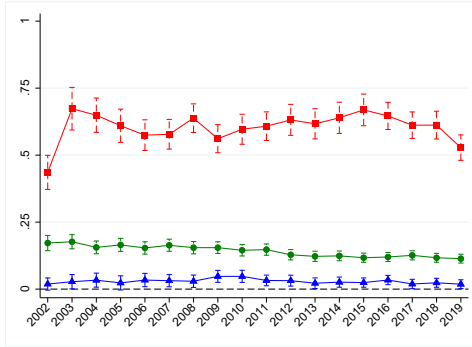
B. Low GD - Corruption



C. High GD - Corruption



D. Low GD - Procurement

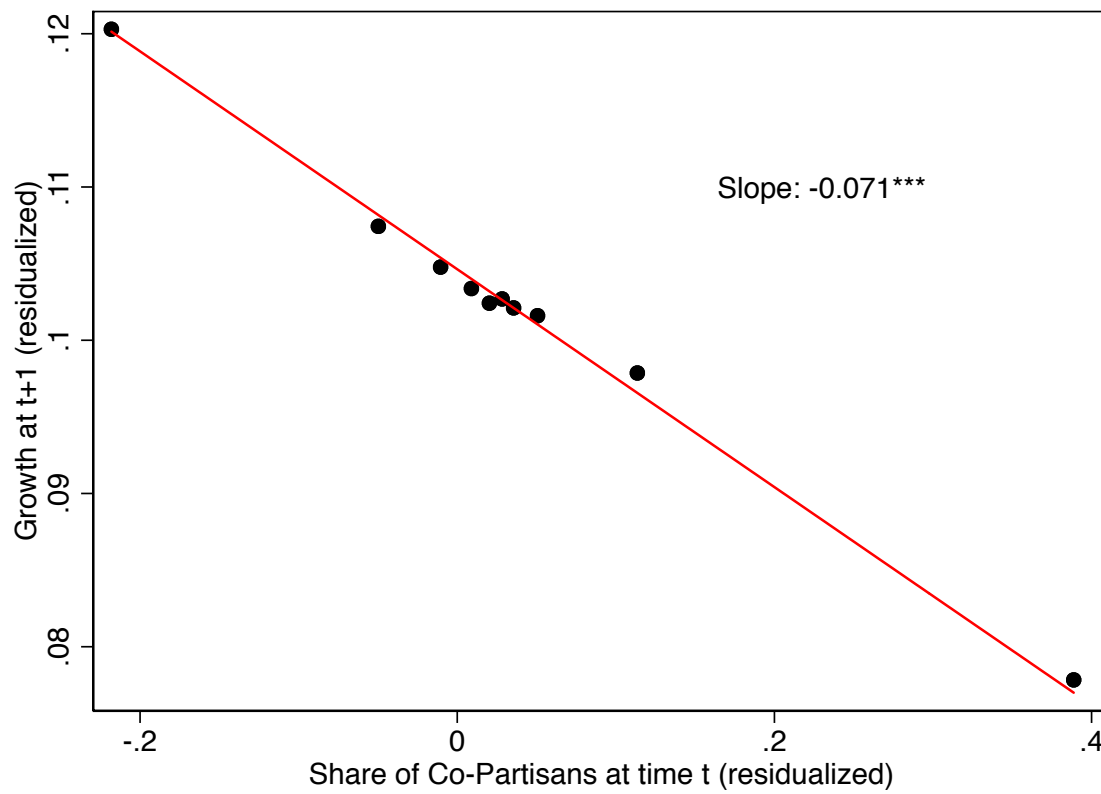


E. High GD - Procurement

—■— Same Party-Diff Party —▲— Same Race —●— Same Gender

Notes: The figures show the point estimates and 95% confidence intervals of $\Delta(SP, DP)$ divided by the sample probability that y_{if} equals one if $DP_{if} = 1$ (in red), our measure of Political Assortative Matching, and the effect of shared gender (in green) and shared race (in blue) on the probability that i works in firm f , normalized by the sample probability that y_{if} equals one if the worker and the owner have a different gender or race, respectively. Panel A presents estimates excluding individuals (owners and workers) who have been political candidates or campaign donors. Panels B, C, D, and E show estimates for subsamples of firms with low (below median) vs. high (above median) government dependency, based on exposure to corruption, or based on reliance on public procurement. Confidence intervals are based on standard errors clustered at the market level. See section IIIB and equation (1) for details on the estimation.

FIGURE A25. Politically Homogeneous Firms Grow Less



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

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

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

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

TABLE A2. Dyadic Regression Estimates – 25% versus Full Sample

	Sample	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Same Party	Full	0.057046 (0.002163)	0.071873 (0.001952)	0.067151 (0.001807)	0.062146 (0.001727)	0.057664 (0.001575)	0.061514 (0.001501)	0.061861 (0.001522)	0.059116 (0.001453)	0.061413 (0.001465)	0.064106 (0.001413)	0.066346 (0.001443)	0.064340 (0.001369)	0.062505 (0.001354)	0.065655 (0.001334)	0.069905 (0.001476)	0.066327 (0.001405)	0.063010 (0.001399)	0.064089 (0.001390)
	25pct	0.054240 (0.003440)	0.075693 (0.002957)	0.061861 (0.002719)	0.062363 (0.002652)	0.056438 (0.002492)	0.060574 (0.002370)	0.061409 (0.002351)	0.059458 (0.002272)	0.059116 (0.002218)	0.063594 (0.002161)	0.066580 (0.002188)	0.059817 (0.002081)	0.059637 (0.002112)	0.063470 (0.002083)	0.068513 (0.002209)	0.062797 (0.002179)	0.060825 (0.002199)	0.062230 (0.002214)
Different Party	Full	0.002916 (0.000773)	0.003127 (0.000705)	0.003382 (0.000655)	0.003998 (0.000620)	0.003582 (0.000584)	0.004397 (0.000554)	0.004519 (0.000530)	0.004005 (0.000500)	0.003928 (0.000481)	0.004677 (0.000459)	0.003258 (0.000437)	0.003484 (0.000420)	0.003310 (0.000403)	0.004968 (0.000401)	0.005640 (0.000409)	0.004984 (0.000420)	0.003927 (0.000407)	0.005565 (0.000423)
	25pct	0.003563 (0.001326)	0.003976 (0.001098)	0.003182 (0.001051)	0.004539 (0.001013)	0.004778 (0.000957)	0.003515 (0.000891)	0.004290 (0.000849)	0.003780 (0.000822)	0.004710 (0.000790)	0.003822 (0.000737)	0.002799 (0.000701)	0.003871 (0.000688)	0.002484 (0.000663)	0.004850 (0.000666)	0.005505 (0.000676)	0.004576 (0.000686)	0.003272 (0.000672)	0.005918 (0.000682)
Same Gender	Full	0.004472 (0.000446)	0.004567 (0.000455)	0.003172 (0.000424)	0.004022 (0.000407)	0.003768 (0.000391)	0.003416 (0.000380)	0.003331 (0.000369)	0.003464 (0.000347)	0.003392 (0.000327)	0.003080 (0.000321)	0.002832 (0.000294)	0.002554 (0.000283)	0.002819 (0.000267)	0.002548 (0.000271)	0.002568 (0.000265)	0.002954 (0.000255)	0.002365 (0.000252)	0.002654 (0.000254)
	25pct	0.004784 (0.000518)	0.004764 (0.000524)	0.003664 (0.000490)	0.003898 (0.000467)	0.003568 (0.000446)	0.003257 (0.000434)	0.003323 (0.000417)	0.003503 (0.000391)	0.003539 (0.000369)	0.002937 (0.000360)	0.002960 (0.000332)	0.002578 (0.000318)	0.002863 (0.000303)	0.002402 (0.000307)	0.002400 (0.000302)	0.002898 (0.000294)	0.002400 (0.000289)	0.002685 (0.000287)
Same Race	Full	0.002221 (0.000526)	0.003274 (0.000556)	0.003933 (0.000542)	0.004495 (0.000499)	0.003990 (0.000494)	0.003377 (0.000507)	0.003589 (0.000461)	0.003777 (0.000446)	0.003709 (0.000426)	0.003610 (0.000398)	0.003833 (0.000375)	0.002931 (0.000358)	0.003482 (0.000338)	0.003343 (0.000323)	0.002753 (0.000325)	0.002606 (0.000306)	0.002900 (0.000296)	0.002781 (0.000286)
	25pct	0.002204 (0.000629)	0.003052 (0.000647)	0.003932 (0.000630)	0.004152 (0.000571)	0.003809 (0.000562)	0.003226 (0.000580)	0.003941 (0.000527)	0.003706 (0.000514)	0.003741 (0.000480)	0.003845 (0.000455)	0.003693 (0.000426)	0.002945 (0.000409)	0.003664 (0.000379)	0.003353 (0.000375)	0.002791 (0.000373)	0.002745 (0.000353)	0.002807 (0.000344)	0.002583 (0.000334)
Same-Diff/E[y—DP=1]	Full	0.5595 (0.000629)	0.7090 (0.000647)	0.6816 (0.000630)	0.6187 (0.000571)	0.5952 (0.000562)	0.6323 (0.000580)	0.6460 (0.000527)	0.6348 (0.000514)	0.6671 (0.000480)	0.6875 (0.000455)	0.7584 (0.000426)	0.7519 (0.000409)	0.7363 (0.000379)	0.7235 (0.000375)	0.7655 (0.000373)	0.7341 (0.000353)	0.7378 (0.000344)	0.6763 (0.000334)
	25pct	0.5189 (0.000629)	0.7361 (0.000647)	0.6319 (0.000630)	0.6136 (0.000571)	0.5613 (0.000562)	0.6344 (0.000580)	0.6437 (0.000527)	0.6439 (0.000514)	0.6275 (0.000480)	0.6962 (0.000455)	0.7687 (0.000426)	0.6859 (0.000409)	0.7150 (0.000379)	0.6968 (0.000375)	0.7491 (0.000373)	0.6987 (0.000353)	0.7273 (0.000344)	0.6494 (0.000334)
Same Gender/E[y—SG=0]	Full	0.0773 (0.000629)	0.0691 (0.000647)	0.0490 (0.000630)	0.0633 (0.000571)	0.0616 (0.000562)	0.0536 (0.000580)	0.0540 (0.000527)	0.0570 (0.000514)	0.0572 (0.000480)	0.0500 (0.000455)	0.0477 (0.000426)	0.0443 (0.000409)	0.0504 (0.000379)	0.0443 (0.000375)	0.0443 (0.000373)	0.0514 (0.000353)	0.0418 (0.000344)	0.0461 (0.000334)
	25pct	0.0827 (0.000629)	0.0720 (0.000647)	0.0568 (0.000630)	0.0613 (0.000571)	0.0582 (0.000562)	0.0511 (0.000580)	0.0539 (0.000527)	0.0578 (0.000514)	0.0599 (0.000480)	0.0476 (0.000455)	0.0499 (0.000426)	0.0449 (0.000409)	0.0512 (0.000379)	0.0416 (0.000375)	0.0414 (0.000373)	0.0504 (0.000353)	0.0426 (0.000344)	0.0469 (0.000334)
Same Race/E[y—SR=0]	Full	0.0335 (0.000629)	0.0438 (0.000647)	0.0543 (0.000630)	0.0632 (0.000571)	0.0577 (0.000562)	0.0473 (0.000580)	0.0521 (0.000527)	0.0558 (0.000514)	0.0567 (0.000480)	0.0538 (0.000455)	0.0593 (0.000426)	0.0471 (0.000409)	0.0579 (0.000379)	0.0542 (0.000375)	0.0444 (0.000373)	0.0426 (0.000353)	0.0487 (0.000344)	0.0456 (0.000334)
	25pct	0.0332 (0.000629)	0.0407 (0.000647)	0.0542 (0.000630)	0.0580 (0.000571)	0.0551 (0.000562)	0.0452 (0.000580)	0.0452 (0.000527)	0.0549 (0.000514)	0.0574 (0.000480)	0.0573 (0.000455)	0.0571 (0.000426)	0.0475 (0.000409)	0.0571 (0.000379)	0.0475 (0.000375)	0.0611 (0.000373)	0.0544 (0.000353)	0.0449 (0.000344)	0.0422 (0.000334)

Notes: The table presents estimates from equation (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 using only a random 25% sample of dyads. Standard errors in parentheses are clustered by market. See section IIIB and equation (1) for details on the estimation.

TABLE A3. Dyadic Regression Estimates – Full Set of Estimates

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Same Party	0.0119 (0.0007)	0.0156 (0.0008)	0.0143 (0.0006)	0.0127 (0.0006)	0.0114 (0.0005)	0.0116 (0.0005)	0.0113 (0.0004)	0.0110 (0.0004)	0.0115 (0.0005)	0.0119 (0.0004)	0.0123 (0.0005)	0.0117 (0.0004)	0.0112 (0.0004)	0.0121 (0.0004)	0.0124 (0.0004)	0.0119 (0.0004)	0.0114 (0.0004)	0.0120 (0.0004)
Different Party	0.0017 (0.0003)	0.0012 (0.0002)	0.0013 (0.0002)	0.0011 (0.0002)	0.0009 (0.0002)	0.0007 (0.0001)	0.0006 (0.0001)	0.0008 (0.0001)	0.0008 (0.0001)	0.0010 (0.0001)	0.0009 (0.0001)	0.0008 (0.0001)	0.0009 (0.0001)	0.0009 (0.0001)	0.0010 (0.0001)	0.0009 (0.0001)	0.0007 (0.0001)	0.0010 (0.0001)
Same Gender	0.0015 (0.0001)	0.0016 (0.0001)	0.0014 (0.0001)	0.0014 (0.0001)	0.0013 (0.0001)	0.0014 (0.0001)	0.0014 (0.0001)	0.0014 (0.0001)	0.0013 (0.0001)	0.0012 (0.0001)	0.0010 (0.0001)	0.0009 (0.0001)	0.0009 (0.0001)	0.0009 (0.0001)	0.0010 (0.0001)	0.0011 (0.0001)	0.0010 (0.0001)	0.0011 (0.0001)
Same Race	0.0003 (0.0001)	0.0005 (0.0001)	0.0006 (0.0001)	0.0004 (0.0001)	0.0005 (0.0001)	0.0005 (0.0001)	0.0003 (0.0001)	0.0005 (0.0001)	0.0004 (0.0001)	0.0003 (0.0001)	0.0003 (0.0001)	0.0002 (0.0001)	0.0003 (0.0001)	0.0003 (0.0001)	0.0003 (0.0001)	0.0002 (0.0001)	0.0002 (0.0001)	0.0002 (0.0001)
Same Educ	0.0009 (0.0001)	0.0012 (0.0001)	0.0011 (0.0001)	0.0013 (0.0001)	0.0015 (0.0001)	0.0014 (0.0001)	0.0014 (0.0001)	0.0015 (0.0001)	0.0014 (0.0001)	0.0015 (0.0001)	0.0016 (0.0001)	0.0016 (0.0001)	0.0016 (0.0001)	0.0016 (0.0001)	0.0018 (0.0001)	0.0019 (0.0001)	0.0021 (0.0001)	0.0018 (0.0001)
Same Age	0.0004 (0.0001)	0.0009 (0.0001)	0.0007 (0.0001)	0.0005 (0.0001)	0.0005 (0.0000)	0.0005 (0.0000)	0.0004 (0.0000)	0.0005 (0.0000)	0.0005 (0.0000)	0.0005 (0.0000)	0.0005 (0.0000)	0.0005 (0.0000)	0.0005 (0.0000)	0.0005 (0.0000)	0.0005 (0.0000)	0.0006 (0.0000)	0.0005 (0.0000)	0.0006 (0.0000)
Same-Diff	0.0101 (0.0006)	0.0144 (0.0007)	0.0130 (0.0006)	0.0116 (0.0005)	0.0105 (0.0005)	0.0109 (0.0005)	0.0107 (0.0004)	0.0102 (0.0004)	0.0107 (0.0004)	0.0109 (0.0004)	0.0114 (0.0004)	0.0108 (0.0004)	0.0103 (0.0004)	0.0112 (0.0004)	0.0113 (0.0004)	0.0110 (0.0004)	0.0107 (0.0004)	0.0110 (0.0004)
Observations	79,003,966	99,666,125	112,054,890	127,051,524	141,554,165	149,826,055	171,790,536	185,772,179	212,840,738	231,584,012	256,025,095	276,679,434	298,639,684	292,332,537	276,382,069	272,790,805	274,826,284	288,426,847
Num Markets	27,292	31,803	32,791	34,030	35,185	38,015	39,531	40,850	42,869	47,097	47,964	49,241	50,147	52,114	52,433	51,928	50,757	52,257
Num Firms	683,994	785,436	828,648	877,102	929,106	963,071	1,019,145	1,070,952	1,148,165	1,223,690	1,281,435	1,345,095	1,405,588	1,426,846	1,415,846	1,409,084	1,394,937	1,413,175
Num Workers	6,465,204	8,802,119	9,465,712	10,226,392	10,980,092	11,761,369	12,886,417	13,330,159	14,632,824	15,621,270	16,409,387	17,161,657	17,707,782	17,354,834	16,448,225	16,146,192	15,990,805	16,611,783

Notes: The table presents estimates from equation (1). Standard errors in parentheses are clustered by market. See section IIIB and equation (1) for details on the estimation.

TABLE A4. Oster Delta

Year	Oster Delta for Same Party coefficient
2002	2.8826
2003	3.7213
2004	3.7016
2005	3.4072
2006	3.1785
2007	3.2522
2008	3.5548
2009	3.3509
2010	3.7483
2011	3.7899
2012	4.0035
2013	4.1544
2014	4.0139
2015	4.2099
2016	4.2423
2017	4.4048
2018	4.0962
2019	3.8361

Notes: The table presents estimates of [Oster \(2019\)](#)'s δ for each year between 2002 and 2019. We compare the estimates of β^{SP} in equation (1) from a regression where we control only for market fixed effects to those from a regression with our full set of controls. We compute δ under the assumption that R_{max}^2 , namely the R^2 from a hypothetical regression of the outcome on *SameParty_{if}* and all covariates, observed and unobserved ones, equals $1.3R^2$, where R^2 is from our estimation with the full set of controls.

TABLE A5. Differences in Observables Between Treated (Switching Owner) and Control (Non-Switching Owner) Firms: Firms/Owners Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	Treated Firms		Control Firms		Treated-Control	
	Mean	Standard Devia- tion	Mean	Standard Devia- tion	Standardized Difference	p-value Equiv- alence test
Firm of size <10	0.668	0.471	0.641	0.467	0.0584	0.0000
Firm of size 10-49	0.273	0.445	0.291	0.437	-0.0413	0.0000
Firm of size 50-99	0.033	0.179	0.037	0.177	-0.0195	0.0000
Firm of size 100-249	0.017	0.128	0.020	0.132	-0.0225	0.0000
Firm of size 250-499	0.005	0.071	0.007	0.077	-0.0231	0.0000
Firm of size >500	0.004	0.063	0.005	0.068	-0.0146	0.0000
Agriculture/Mining	0.018	0.133	0.009	0.093	0.0897	0.1256
Low-Tech Manufacturing	0.138	0.344	0.125	0.328	0.0375	0.0000
High-Tech Manufacturing	0.014	0.119	0.022	0.143	-0.0518	0.0000
Construction	0.027	0.162	0.035	0.183	-0.0464	0.0000
Trade	0.522	0.500	0.452	0.495	0.1421	1.0000
Transp./Utilities/Communic. Services	0.045	0.208	0.048	0.213	-0.0137	0.0000
	0.235	0.424	0.309	0.460	-0.1612	1.0000
% of owners who are White	0.790	0.387	0.799	0.374	-0.0237	0.0000
% of owners who are Female	0.272	0.339	0.339	0.354	-0.1905	1.0000
% of owners middle school	0.084	0.261	0.086	0.259	-0.0094	0.0000
% of owners high school	0.366	0.452	0.368	0.446	-0.0051	0.0000
% of owners >HS	0.520	0.472	0.515	0.468	0.0113	0.0000
% of owners <=25 years old	0.049	0.193	0.053	0.195	-0.0233	0.0000
% of owners (25-30] years old	0.075	0.240	0.073	0.221	0.0080	0.0000
% of owners (30-35] years old	0.124	0.305	0.113	0.270	0.0403	0.0000
% of owners (35-40] years old	0.151	0.334	0.131	0.287	0.0685	0.0038
% of owners (40,45] years old	0.164	0.344	0.153	0.306	0.0349	0.0000
% of owners (45,50] years old	0.159	0.341	0.157	0.307	0.0064	0.0000
% of owners >50 years old	0.278	0.418	0.319	0.417	-0.0991	0.4666
Observations	14,611		81,896		96,507	

Notes: The table compares switching (treated) and non-switching (control) owners in terms of observable firm and owner's characteristics. Columns 1 and 3 report the mean of each characteristic among treated and control firms, respectively, and columns 2 and 4 report the standard deviations in both samples. Column 5 reports the standardized difference in means between the two groups. Column 6 reports the p-value from tests for the equivalence of means using a two one-sided t-tests approach; the reported p-value is the largest of the two p-values from two one-sided t-tests, under the null hypothesis that the difference is larger than 0.1 standard deviation, or smaller than 0.1 standard deviation, respectively.

TABLE A6. Differences in Observables Between Treated (Switching Owner) and Control (Non-Switching Owner) Firms: Workers Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	Treated Firms		Control Firms		Treated-Control	
	Mean	Standard Deviation	Mean	Standard Deviation	Standardized Difference	p-value Equivalence test
% of workers who are White	0.7034	0.3494	0.7326	0.3210	-0.0897	0.1213
% of workers who are Female	0.4293	0.3577	0.4499	0.3600	-0.0573	0.0000
Average tenure (in months)	38.6306	31.2716	41.3555	33.5903	-0.0821	0.0221
% of Managers	0.0445	0.1148	0.0495	0.1156	-0.0434	0.0000
% of White-Collar	0.5341	0.3759	0.5542	0.3688	-0.0543	0.0000
% of Blue-Collar	0.4214	0.3744	0.3963	0.3692	0.0678	0.0002
Average Pay per hour worked	2.6663	2.9042	3.0063	2.5236	-0.1314	0.9998
% of workers with middle school	0.1389	0.2079	0.1316	0.1991	0.0364	0.0000
% of workers with high school	0.6630	0.2869	0.6629	0.2792	0.0004	0.0000
% of workers with > HS	0.1496	0.2255	0.1693	0.2364	-0.0839	0.0392
% of workers <=25 years old	0.2907	0.2634	0.2677	0.2434	0.0932	0.2271
% of workers (25-30] years old	0.1834	0.2071	0.1750	0.1831	0.0449	0.0000
% of workers (30-35] years old	0.1507	0.1893	0.1493	0.1716	0.0080	0.0000
% of workers (35-40] years old	0.1201	0.1759	0.1195	0.1575	0.0037	0.0000
% of workers (40,45] years old	0.0942	0.1576	0.0993	0.1502	-0.0336	0.0000
% of workers (45,50] years old	0.0722	0.1416	0.0805	0.1399	-0.0591	0.0000
% of workers >50 years old	0.0886	0.1658	0.1087	0.1768	-0.1147	0.9454
Observations	14,611		81,896		96,507	

Notes: The table compares switching (treated) and non-switching (control) owners in terms of observable characteristics of the workforce. Columns 1 and 3 report the mean of each characteristic among treated and control firms, respectively, and columns 2 and 4 report the standard deviations in both samples. Column 5 reports the standardized difference in means between the two groups. Column 6 reports the p-value from tests for the equivalence of means using a two one-sided t-tests approach; the reported p-value is the largest of the two p-values from two one-sided t-tests, under the null hypothesis that the difference is larger than 0.1 standard deviation, or smaller than 0.1 standard deviation, respectively.

TABLE A7. Political Assortative Matching and Public Procurement Contracts with Local Governments

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

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

TABLE A8. Political Assortative Matching, Local Connections and Firm Outcomes (Employment and Wages per Employee)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			<i>Mayor</i>				<i>Governor</i>	
Variables	ln(emp)	ln(emp)	ln(pay/emp)	ln(pay/emp)	ln(emp)	ln(emp)	ln(pay/emp)	ln(pay/emp)
Connected	0.534*	0.520*	-0.285**	-0.344***	0.053	0.057	0.024	0.029
	(0.307)	(0.290)	(0.111)	(0.112)	(0.078)	(0.078)	(0.081)	(0.081)
Same		-0.063		0.053		-0.034**		0.027
		(0.055)		(0.049)		(0.014)		(0.018)
Connected X Same		0.010		-0.020		0.063**		0.020
		(0.095)		(0.095)		(0.026)		(0.029)
Diff		-0.059		-0.063		-0.059***		-0.028
		(0.068)		(0.087)		(0.015)		(0.017)
Connected X Diff		0.042		0.115		0.065***		0.050*
		(0.083)		(0.107)		(0.022)		(0.027)
Observations	607,632	607,632	607,632	607,632	3,415,320	3,415,320	3,415,320	3,415,320
Firm-Year Election FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period-Election FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table shows estimates of the relationship between owners' affiliation with the party in power at the local (columns 1-4) level or at the state level (columns 5-8), the share of the firm's workers from the same or different party of the owner, and log number of employees of the firm (columns 1, 2, 5, 6) or log pay per employee (columns 3, 4, 7, 8). Results in columns 1-4 are restricted to close elections with a margin of 5 percentage points or less between winner and runner up, and include only firms whose owner is affiliated with the party of the mayor or of the runner-up. All regressions include firm times election fixed effects and period (since the election) times election fixed effects. Standard errors in parentheses, clustered at the firm level *** p<0.01, ** p<0.05, * p<0.1.

TABLE A9. Randomization of Resume Components

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

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

ONLINE APPENDIX A2: DATA CONSTRUCTION

A.1 DATA DESCRIPTION

In this paper, we combine data from the following sources: *Relação Anual de Informações Sociais-RAIS* from the former Ministry of Labor (MTE), *Cadastro Nacional de Pessoa Jurídica-CNPJ* from the *Receita Federal do Brasil* (RFB), *Cadastro Nacional de Empresas-CNE* from the former Ministry of Industry, Foreign Trade and Services (MDIC)⁶³, *Party Membership System-PR* and *Voter Registration* data from the Superior Electoral Court (TSE), and the dataset *Nomes do Brasil* provided by the *Brazilian Institute for Geography and Statistics (IBGE)*. In the following sections, we provide details on each of these datasets, and on how we match them to create our final dataset at the firm-owner-worker-year level, containing information on the political affiliation of owners and workers in the formal private sector labor market. The reader is encouraged to see Figure A26 for a visual representation of how the various data sources are linked.

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

We construct a yearly panel dataset of workers for the period 2002–2019. The variable *natureza juridica* can be used to identify private sector employers. As workers can work for multiple firms in the same year, we select the highest paying job of an individual in a given year to create a panel at the worker-firm-year level, with one observation for each worker-year. This panel includes data on the following variables: year, CPF (the unique personal *Taxpayer Identification Number*), workers' names, firm and plant identifiers,⁶⁴ gender, date of birth, race, level of education, nationality, municipality, firm's sector of activity, worker's occupation, pay,⁶⁵ and the number of weekly hours in the contract. Unique workers' and employers' tax identifiers allow us to follow individuals over time and across firms.

⁶³Currently, all these three entities are under the Ministry of Economy.

⁶⁴The variables *firmid* and *plantid* are created based on the unique establishment taxpayer identifier, *CNPJ*. The first 8 digits of the *CNPJ* are used to identify the firm (*firmid*), while the additional 4 digits are used to identify the plant of a given firm (*plantid*). Clearly, only a subset of the firms have multiple plants.

⁶⁵We use the average monthly pay over all the months in which the individual was employed in the firm over the course of the year.

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

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

RFB Data

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

Owners in RFB belong to one of three categories: Business Associates, Individual Microentrepreneurs, and Individual Entrepreneurs.⁶⁶ We observe 12,108,480 unique business associates (owning a total of 8,436,483 firms), 8,169,077 unique individual entrepreneurs (owning a total of 8,247,052 firms), and 13,522,653 unique individual micro-entrepreneurs (owning a total of 14,353,138 firms). Business Associates are owners of companies with multiple owners (known as *sociedades*).⁶⁷ Owners of smaller and single owned firms are categorized as Individual Microentrepreneurs or as Individual Entrepreneurs. The data contain different identifying information for the three categories of owners. Specifically, for Business Associates we observe the 6 central digits of the CPF and the full name; for Individual Microentrepreneurs we observe both the full CPF and the full name; for Individual Entrepreneurs we observe only the full name.

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

⁶⁶The data also contains information on corporate owners. Given the focus of the paper, we disregard these owners.

⁶⁷See the list of *naturezas jurídicas* of these firms at https://www38.receita.fazenda.gov.br/cadsincnac/jsp/coleita/ajuda/topicos/Tabela_IV_-_Natureza_Juridica_Quadro_de_Socios_e_Administradores.htm.

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

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

CNE Data

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

A1.3 Data on Party and Voter Registration - TSE Data TSE Party Registration data provide us information on the universe of individuals who have ever been affiliated with any political party in Brazil over the 2002-2020 period.⁶⁸ For each record, we know the name of the affiliated individual, the voter registration number (which is the TSE's unique personal identifier), the municipality of affiliation, and the party to which the individual is affiliated. The data also records the specific dates of registration/de-registration of each individual, which we use to expand the data to obtain a panel at the individual-year level, where each individual appears as registered with a specific party in all years between registration and de-registration with that party over the 2002-2020 period.

We complement the party registration data with a second dataset from TSE, which contains information on the universe of individuals registered to vote in Brazil.⁶⁹ The dataset includes the voter registration number, and the individual's date of birth, and gender. We match this data to the party registration data using the voter registration number in order

⁶⁸We downloaded the data from the TSE website (<https://english.tse.jus.br/>) in Feb of 2021. As of March 2022, the data is no longer publicly available.

⁶⁹We obtained access to this data via FOIA-like request to TSE.

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

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

A.2 MATCHING RFB-CNE-RAIS-PR DATA

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

A1.1 Matching RFB and CNE As a first step, we combine the RFB and CNE panels. We consider RFB as the primary source of owners' information, since the CNE data contain a smaller number of firms, presumably due to imperfect data maintenance by *Juntas Comerciais*. Nevertheless, data from CNE is useful to complement RFB for multiple reasons. First, since RFB contains only a snapshot of the data as of 2019, we can use CNE to obtain information on owners who left a firm before 2019 (or before the firm closed). Second, we can use CNE to look for the owners of the 9.65% of firms without owners' identifying information in RFB. Third, since we observe both CPF and full name for all owners in CNE, we can assign the full CPF to the owners in RFB for which we do not observe the CPF, or for which we observe only its 6 central digits.⁷⁰

We combine the two datasets by first implementing a fuzzy matching by owner's name (with a precision cutoff of 0.95), while requiring the CNPJ firm identifier to match perfectly.⁷¹ Since we require a perfect match by CNPJ, this works essentially as a perfect matching, dealing only with slight differences in owners' name reporting across the two datasets. If a firm in CNE is not found in RFB in a given year (so that there is no owner associated with that firm in RFB for that year), we append the CNE observations to the RFB panel. We refer to the final panel as the RFB-CNE panel.

⁷⁰In addition, in some cases the names in RFB are reported in abbreviated form, while CNE reports the full, unabbreviated name. For these cases, we also update owners' information with their most accurate version of the full name.

⁷¹We implement this fuzzy matching, as well as all the fuzzy matching steps described in the next sections, using the Stata command *reclink*.

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

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

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

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

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

A1.3 Matching owners and workers to party registration data Finally, we match workers and owners to the party registration data (which, after having been matched to the TSE data on voters’ registration, also contain information on gender and date of birth of party affiliates). We perform the following 15 steps of matching, with each individual entering a matching step only if not already matched in previous steps:⁷²

⁷²While all steps can potentially be performed for all workers, the same is true only for owners with information on date of birth (i.e., the 58.96% of owners who have been matched to RAIS), while the remaining ones can be matched only in steps 12 and 13.

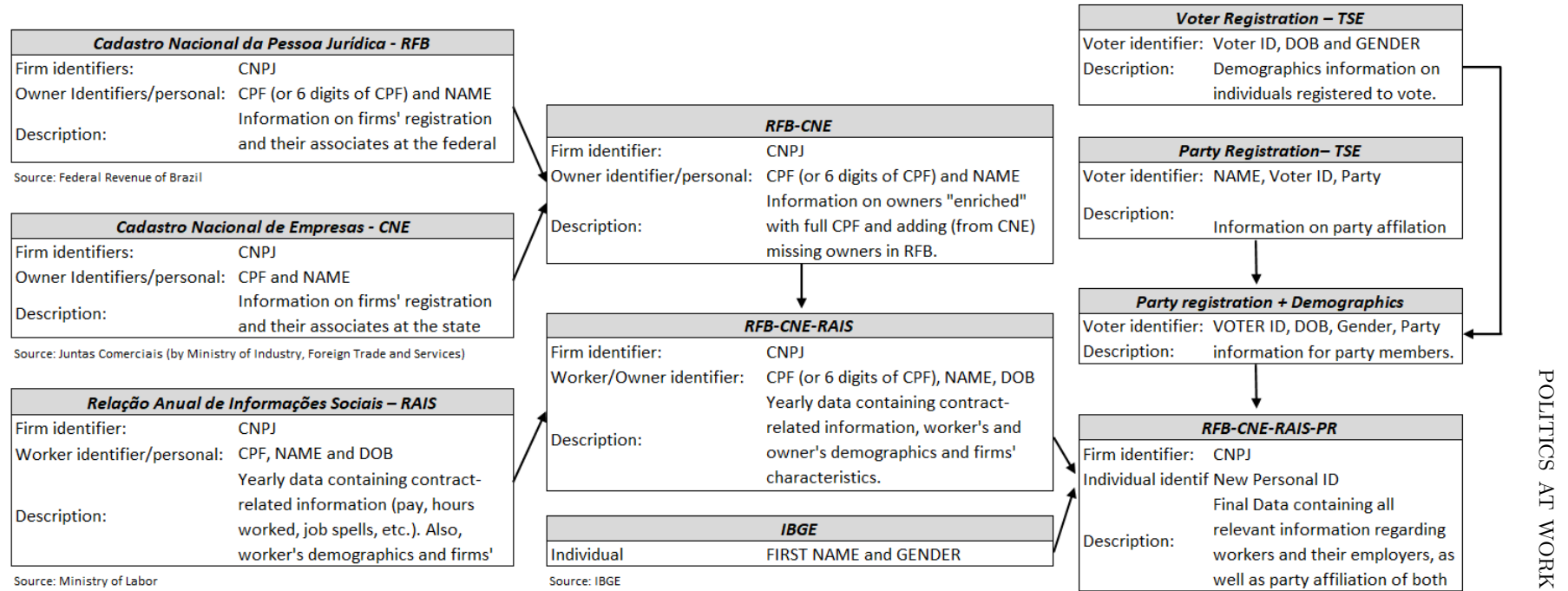
- Step 1: perfect by name - year of birth - month of birth - day of birth - municipality (matching rate: 50.05%)
- Step 2: perfect by name - year of birth - month of birth - day of birth - state (matching rate: 22.18%)
- Step 3: perfect by name - year of birth - month of birth - day of birth (matching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

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

In the paper, we use the political affiliation of the majority of the firm's owners to define the political affiliation of the firm. This is, of course, straightforward if the firm has only one owner. If the firm has multiple owners, and they are all affiliated and they all have the same partisan affiliation, this is also straightforward (this happens for 1.61 percent of the firms with multiple owners). The more tricky case is if the firm has multiple owners, and they do not all have the same partisan affiliation. This might be the case if: 1) they are all affiliated but not all with the same party (this happens for 1.13 percent of the firms with multiple owners), or 2) some of them are affiliated, all with the same party, while some are not affiliated (this happens for 85.24 percent of the firms with multiple owners), or 3) some of them are affiliated, not all with the same party, while some are not affiliated (this happens

for 12.02 percent of the firms with multiple owners). In case 1), we impute the partisan affiliation of the majority of the owners. In case 2), we impute the partisan affiliation of the affiliated owners (who are all from the same party). In case 3), we impute the partisan affiliation of the majority of the affiliated owners.

FIGURE A26. Visual Representation of the Linkage Structure



ONLINE APPENDIX A3: CONSTRUCTION OF THE LIKELIHOOD RATIO INDEX

In this section, we provide additional details on the construction of the likelihood ratio indexes that we use in section IIIA.

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

$$(A1) \quad s(p^w, p^o) = \frac{Pr(P^w = p^w, P^o = p^o)}{Pr(P^w = p^w)Pr(P^o = p^o)}$$

The magnitude of $s(p^w, p^o)$ measures the probability of observing a match between workers of party p^w and owners of party p^o in the data, relative to what the probability of the match would be with random matching.⁷³ We can build a matrix of size P (the total number of parties p observed in the data for which we have at least one worker and at least one owner that is affiliated), with $s(p^w, p^o)$ as elements of the matrix. We are particularly interested in the diagonal elements of the matrix, which capture the probability that a worker is matched to an owner of her same party p , relative to the probability under random matching:

$$(A2) \quad s(p, p) = \frac{Pr(P^w = P^o = p)}{Pr(P^w = p)Pr(P^o = p)}$$

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

$$(A3) \quad S = \sum_p \frac{Pr(P^w = p)Pr(P^o = p)}{\sum_p Pr(P^w = p)Pr(P^o = p)} s(p, p) = \frac{\sum_p Pr(P^w = P^o = p)}{\sum_p Pr(P^w = p)Pr(P^o = p)}$$

To adjust the measure to take into account geographical sorting, we define an index for each party p and for each municipality m in the data. The diagonal element for party p in municipality m is:

$$(A4) \quad s(p, p, m) = \frac{Pr(P^w = P^o = p | M = m)}{Pr(P^w = p | M = m)Pr(P^o = p | M = m)}$$

⁷³Note that $Pr(P^o = p^o)$ is calculated as the share of owners of party p^o , and *not* as the share of workers in the data with owners of party p^o . With this approach, in the calculation of the random matching probability in the denominator, we are not forcing a firm to have the same number of workers as in the data.

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

$$\begin{aligned}
 (A5) \quad S^M &= \sum_{p,m} \frac{Pr(P^w = p|M = m)Pr(P^o = p|M = m)}{\sum_{p,m} Pr(P^w = p|M = m)Pr(P^o = p|M = m)} s(p, p, m) = \\
 &= \frac{\sum_{p,m} Pr(P^w = P^o = p|M = m)}{\sum_{p,m} Pr(P^w = p|M = m)Pr(P^o = p|M = m)}
 \end{aligned}$$

ONLINE APPENDIX A4: WORKER'S PHONE SURVEY

- (1) Are you currently employed?
 - Yes
 - No
- (2) We are interested in finding out how Brazilian workers generally find their jobs. Think about the last job you got. Could you describe how you found the job?
 - *Open ended*
- (3) A recent study states that business owners tend to hire employees with similar political views. What do you think this might be happening?
 - *Open ended*
- (4) It is easier for employer and employee to work well together if they share the same political views.
 - Totally disagree
 - Partially disagree
 - Neither agree nor disagree
 - Partially agree
 - Totally agree
- (5) Why do you think this?
 - *Open ended*
- (6) Some bosses don't like to have people with different political views around, even if it doesn't hinder performance at work.
 - Totally disagree
 - Partially disagree
 - Neither agree nor disagree
 - Partially agree
 - Totally agree
- (7) Why do you think this?
 - *Open ended*
- (8) Business owners generally interact more with people of similar political views, so it's easier to know if they would be better suited to work at the company.
- (9) Why do you think this?
 - *Open ended*
- (10) If an owner is part of a political party, the party will contact them to indicate affiliates to work in his company.
 - Totally disagree
 - Partially disagree

- Neither agree nor disagree
 - Partially agree
 - Totally agree
- (11) Why do you think this?
- *Open ended*
- (12) Workers do not want to work in companies where the owners have different political views than their own.
- Totally disagree
 - Partially disagree
 - Neither agree nor disagree
 - Partially agree
 - Totally agree
- (13) Why do you think this?
- *Open ended*
- (14) I would like to know about your experience as a worker. Have you ever gone through any situation where the political vision of an entrepreneur influenced your daily work?
- Yes, situation has occurred.
 - No, situation has never occurred.
- (15) When you need to accept or decline a job offer, do you consider the business owner's political views?
- Yes, considers owner affiliation important
 - No, does not consider owner affiliation important
- (16) And about the political views of your future coworkers? Do you take this into account before accepting or rejecting a job offer?
- Yes, considers future coworker affiliation important
 - No, does not consider future coworker affiliation important
- (17) What is the field of activity of the company you work for (last company you worked for)?
- Agriculture/ Mining/ Manufacturing/ Construction
 - Transport/ Communications/ Services
 - Commerce
- (18) How many employees does the company you work (last worked) for have (had)?
- *Open ended - numeric*
- (19) What gender do you identify as?
- Female
 - Male
- (20) How old are you?

- *Open ended*
- (21) What is your schooling background?
- Elementary school incomplete
 - Elementary school complete
 - High school incomplete
 - High school complete
 - Higher education complete
 - Post-graduate complete
- (22) In which city is your main residence?
- *Open ended*
- (23) In which state is your main residence?
- *Open ended from list of Brazilian states*
- (24) In which region is your main residence?
- North
 - North-east
 - Central-west
 - South-east
 - South

ONLINE APPENDIX A5: OWNER'S PHONE SURVEY

- (1) Do you work in a private company, in the public sector, on your own or are you a businessman?
 - Private firm
 - Public sector
 - Business owner
- (2) We are interested in finding out how Brazilian entrepreneurs manage to hire new employees. Thinking about the last three employees hired by your company, what was the method used for selection?
 - *Open ended*
- (3) A recent study states that business owners tend to hire employees with similar political views. Why do you think this might be happening?
 - *Open ended*
- (4) It is easier for employer and employee to work well together if they share the same political views.
 - Totally disagree
 - Partially disagree
 - Neither agree nor disagree
 - Partially agree
 - Totally agree
- (5) Why do you think this?
 - *Open ended*
- (6) Some bosses don't like to have people with different political views around, even if it doesn't hinder performance at work.
 - Totally disagree
 - Partially disagree
 - Neither agree nor disagree
 - Partially agree
 - Totally agree
- (7) Why do you think this?
 - *Open ended*
- (8) Business owners generally interact more with people of similar political views, so it's easier to know if they would be better suited to work at the company.
 - Totally disagree
 - Partially disagree
 - Neither agree nor disagree

- Partially agree
 - Totally agree
- (9) Why do you think this?
- *Open ended*
- (10) If an owner is part of a political party, the party will contact them to indicate affiliates to work in his company.
- Totally disagree
 - Partially disagree
 - Neither agree nor disagree
 - Partially agree
 - Totally agree
- (11) Why do you think this?
- *Open ended*
- (12) Workers do not want to work in companies where the owners have different political views than their own.
- Totally disagree
 - Partially disagree
 - Neither agree nor disagree
 - Partially agree
 - Totally agree
- (13) Why do you think this?
- *Open ended*
- (14) Finally, I would like to know about your experience as an entrepreneur. Do you think that the political views of a potential employee of your company can make any difference in your decision to hire?
- *Open ended*
- (15) What is your field of work?
- Agriculture/ Mining/ Manufacturing/ Construction
 - Transport/ Communications/ Services
 - Commerce
- (16) How many employees does your company currently have?
- *Open ended - numeric*
- (17) Their oldest company is how many years in the market?
- *Open ended - numeric*
- (18) What gender do you identify as?
- Female
 - Male

- (19) How old are you?
- *Open ended*
- (20) What is your schooling background?
- Elementary school incomplete
 - Elementary school complete
 - High school incomplete
 - High school complete
 - Higher education complete
 - Post-graduate complete
- (21) In which city is your main residence?
- *Open ended*
- (22) In which state is your main residence?
- *Open ended from list of Brazilian states*
- (23) In which region is your main residence?
- North
 - North-east
 - Central-west
 - South-east
 - South

ONLINE APPENDIX A6: EXPERIMENTAL SURVEY

INTRODUCTION

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

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

We ask that you evaluate the resumes on two axes:

1. Given that the candidate wants to work in the position you have in mind, how interested would you be in hiring?
2. Given that you want to hire the candidate for the position, how interested do you think the candidate would be in being hired?

By clicking NEXT, you can start.

The survey will take approximately 15 minutes to complete.

All your responses will be kept strictly confidential in accordance with LGPD standards.

If you are interested, the aggregate results and implications of this study can be shared with you!

FILTERING QUESTIONS

Filtering question 1:

To sort for relevant CVs, we will also need to know geographic information about your firm.

In case your firm is spread across Brazil, please identify the most relevant location.

What region is your firm located in?

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

Filtering question 2A:

You may not be hiring right now but you may well need to hire someone soon. For the

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

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

- Complete high school
- Complete higher education

Filtering question 2B:

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

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

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

RESUME RATINGS

Now come the 20 hypothetical resumes!

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

How to evaluate the resumes:

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

Note that:

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

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

How interested would you be in hiring this candidate?

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

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

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

Additional question:

Please provide the best email below to receive the resumes from the algorithm.

*Given the nature of the algorithm and the state of the search, we will contact you when (1) there are enough responses for the algorithm to work well or (2) by April 30, 2022.

Additional question:

Thank you for completing our survey!

We are always looking to improve our surveys and would love to receive some feedback. Feel free to make whatever comments, criticisms, etc. you may have in the box below.