Supporting Information to "Workplace Networks And Political Selection"

Appendix

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A1 Data and code availability statement

The data material we use for our analysis in this research project consists of Swedish registry data that comes from Statistics Sweden. We have furthermore obtained permission from the Ethical Review board to analyze this kind data. There are various rules governing how this data must be handled and stored. All of the data sets we use are made available to our research group at a secured server which we have to log into in order to run our empirical analyses, meaning that there are no local versions of the data files. For this reason, we cannot make the data freely available online for replication purposes.

There are two pathways for other academics and scholars to replicate our empirical findings. The first is to order the exact same data that we have used from Statistics Sweden. Please follow this link for more information:https://www.scb.se/en/services/guidance-for-researchers-and-universities/). Before such an order can be processed, the researcher needs permission from the Ethical Review Board to process this kind of data. Statistics Sweden handles data requests on a case-by-case basis for a fee. The time and cost for ordering data are determined by the case officer at Statistics Sweden.

The second way to replicate our findings is to use the same secured remote desktop system that we have used. A researcher interested in this option needs to contact us, since we need permission from the Ethical Review Board to add a researcher to our research group on a temporary basis. Please note that there are geographical restrictions on where one can log into the remote desktop system in accordance with the the EU General Data Protection Regulation (GDPR).

We will make all do-files available upon request.

A2 Empirical details and descriptive figures

Some further details on the sample. For cases where information is missing with regard to workplace and/or occupation, we interpolate given existing values in the panel for a given individual. If the first row is missing, we make use of the second row. If the last row is missing, we make use of the second-to-last row. If there is a donut case, where indicators are missing in the middle of the panel, we make use of the value in t-1. For remaining missing values, we take the mode value for workplace and occupation indicators within the panel. If there are remaining missing values for any observation within the panel, we drop the individual from the analysis altogether.

The occupation codes originate from *Lönestrukturstatistiken*, whereas the workplace indicators come from *RAMS*. The occupational codes cover the entire population of public employees and of employees at large private workplaces; whereas employees at private workplaces with fewer than 500 workers are surveyed from a representative sample. This means that occupational codes are carried over to following years in LISA for some workers,

if they have not been surveyed in a specific year. Because of this structure in the registry data, we make use of the interpolations described in the paragraph above.

More on the empirical framework In the empirical framework section in the main text we argued for a linear probability model (LPM) with multiple fixed effects. Applied researchers usually prefer an LPM, since the estimated coefficients can more easily be interpreted as marginal effects. There are, however, some institutional issues that cast doubt on the suitability of an LPM for our particular setting, due to the problem of how to interpret the size of the estimated coefficients. First, the baseline probability of becoming a politician is very low. Second, focusing on marginal effects around the mean may be problematic, given that the probability of becoming a politician is so different for different parts of Sweden, on account of the varying ratio between the number of seats in the municipal council and the size of the local population. In general, it is easier to become a politician in a small municipality than in a big city. The marginal effect is therefore hard to interpret – even when municipality-fixed effects are included in an LPM model – in relation to the mean of the dependent variable. The effect may be driven by the smaller municipalities, where the baseline probability of running for office is higher. In a nutshell, relating the estimated LPM coefficients to the mean of the dependent variable becomes problematic for assessing the economic significance of the estimated coefficient.

These features argue for choosing a conditional logit model (e.g., Breslow et al. 1978), where we focus on odds ratios instead of on marginal effects. The problem is that a standard conditional logit model can only be run with one grouping variable. A conditional logit would also be computationally demanding, given the large number of observations we have.

However, we can run a conditional logit with the most important fixed effects W_{iwo} — that is, the grouped individual-, workplace-, and occupation-fixed effects — where we focus on the timing of a person's entry into politics. We can also include the non-binary covariates that are not included as fixed effects. In the analysis in the main text, therefore, we present results both for LPM estimations with all of the fixed effects, and for conditional logit models with a more limited set of fixed effects and covariates.

Moreover, we present results where we split the LPM estimations by different municipal population sizes, in order to see if our results are driven by the smaller municipalities. This analysis is presented in Figure A2 and further discussed in the next section of this Appendix.[1]

Lastly, the fact we are using fixed effects together with a lagged variable of interest connected to the dependent variable means we are risking a bias along the lines noted by Nickell (1981). This paper shows that, in a dynamic panel data model with fixed effects, there will be a bias in the estimates if the number of time periods does not go to infinity.

However, the set-up in our paper is not the equivalent of a dynamic panel data model

[1] We use a large set of fixed effects and we cluster the standard errors. This may be problematic, however, in connection with singletons within the fixed-effects groups. We therefore follow Correia (2015) and the reghdfe command, which drops singletons.

with a lag of Y. Instead, our variable of interest is the share of politicians at the workplace in $t-1$. Judson and Owen (1999), furthermore, have shown that the bias is above all present for estimated coefficients for lagged Y, whereas the biases for other included variables are small even when T is small.

Table A1 displays a simulation of the Nickell bias for our set-up. We generate 40,000 observations, and we assume a true causal effect equal to 0. We furthermore assume there are 2 % politicians in the population. Column 1 displays the expected null association between the share of politicians in t-1 and the probability of becoming a politician in t. The inclusion of individual-fixed effects does not substantially change this estimate (Column 2). The problems arise in Column 3–Column 6. Here we include fixed effects for workplace and occupation. The results in Column 3 – Column 6 suggest that, by including these fixed effects, we estimate a negative coefficient, even when the true causal effect is 0. However, this negative coefficient is estimated when only an interacted workplace- and occupation-fixed effects are included (Column 3); when an interacted workplace- and occupation-fixed effects together with individual-fixed effects are included separately (Column 4); and when an interacted workplace- and occupation-fixed effects, individual-fixed effects, and year-fixed effects are included (Column 5).

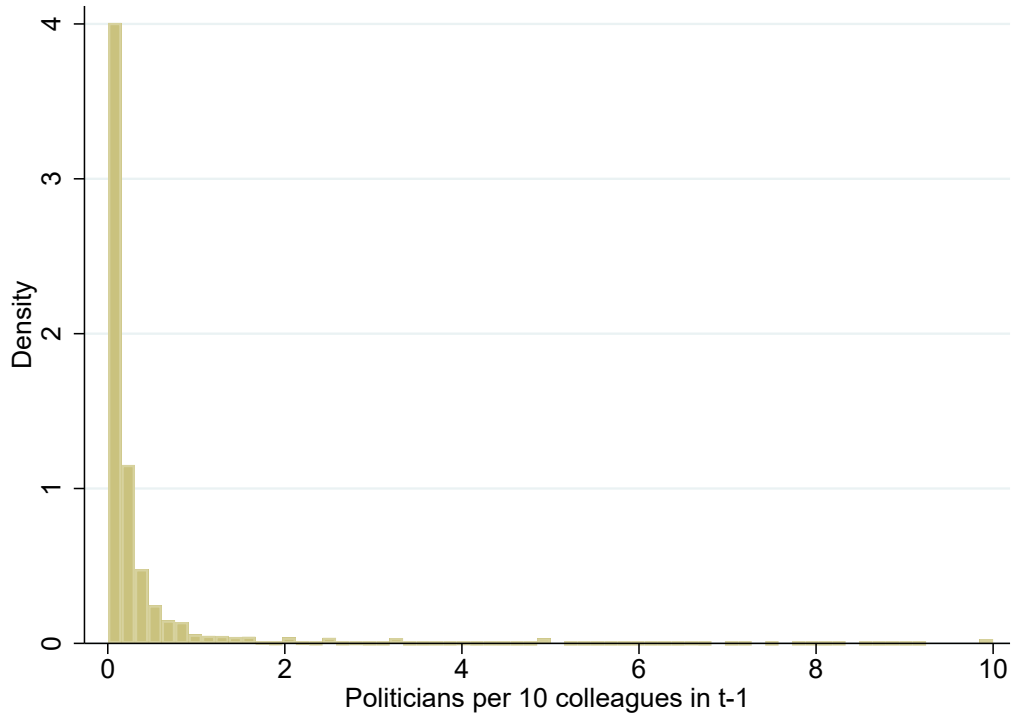
In Column 6 and Column 7, we interact workplace- and occupation-fixed effects together with individual-fixed effects. In essence, the only identifying variation we use is the timing of an individual's entry into politics. In this case, we find no evidence of any Nickell bias. This is also the strategy we use in our empirical analysis in the paper.

Table A1: Simulation of Nickell-bias

	(1) Nom.	(2) Nom.	(3) Nom.	(4) Nom.	(5) Nom.	(6) Nom.	(7) Nom.
L.share1	-0.0025	0.0001	-0.2489***	-0.2464***	-0.2591***	-0.0319	-0.0294
	(0.0515)	(0.0515)	(0.0592)	(0.0592)	(0.0602)	(0.0569)	(0.0578)
Individual FE	No	Yes	No	Yes	Yes	No	No
FirmOccupation FE	No	No	Yes	Yes	Yes	No	No
FirmOccupationFE*Ind	No	No	No	No	No	Yes	Yes
Year F.E.	No	No	No	No	Yes	No	Yes
R2	0.000	0.003	0.003	0.006	0.006	0.318	0.318
Observations	39211	39211	39211	39211	39211	39211	39211

Note: The table displays results from simulations. The true causal effects is assumed to be 0 and we simulate a 2 % share of politicians. We restrict the sample so that the individual cannot be a politician in $t-1$ *Standard errors in parentheses . *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

Figure A1: Distribution of treatment variable



Notes: Distribution of treatment variable (politicians per 10 colleagues), conditional on values > 0. The median value is 0.10.

A3 Robustness analysis for main results

In this section of the Appendix, we present and discuss various robustness checks for the main result presented in Table 2.

First, we run our most conservative LPM specification (column 4, Table 2) separately for five different groups of municipalities in Figure A2. This relates to our discussion regarding the choice of regression model between LPM and a conditonal logit model in the last section of the Appendix. The division is based on the population in the municipality, where for example <p20 represents the 20 % of observations (individuals and years) with the smallest population in their municipality of residence. It is clear from the figure that the effect diminishes almost proportionately with the average probability of being a politician in a given municipality and year. The conclusion is therefore that our main findings are driven by smaller municipalities where the ratio between seats and inhabitants is higher.

To continue, we run a sub-sample analysis where we have excluded occupations that are highly political in nature. We exclude full-time politicians, lobbyists, high civil servants, elected representatives (not politicians), and PR consultants. The results are presented in Table A2, and they are in line with our main findings in Table 2. We have also run a

sub-sample analysis where we exclude both the above-mentioned occupations and the five most common occupations among politicians. The results are presented in Table A3. The results are, yet again, in line with our main findings.

Next we have Table A4, where we have changed the treatment variable from the share of nominated politicians at the workplace to the share of elected politicians at the workplace. The results are in line with those of our main analysis. It is important here to remember that we end up with fewer politicians overall when we focus on elected instead of nominated politicians. The analyses are implemented using the stata command *reghdfe*, which drops singletons (Correia 2015). Consequently, the analysis cannot be run for the most conservative LPM specification in column 4 in Table A4, because there are so few elected politicians at workplaces.

In Table A5, we exclude large values in our treatment variable. If the treatment variable – i.e. the share of nominated politicians within a workplace-occupation cell – is larger than the 95 percentile, we drop the entire individual from the analysis. Important to remember is that the distribution of the share of politician-colleagues is skewed to the right with many values equal to 0 and a few workplace-occupation cells with larger values. For columns 1 and 2 in Table A5, we still estimate positive and statistically significant effects. In columns 3 and 4, the estimates are no longer statistically significant, small, and the sign has flipped. Our explanation for these results is that the main effect is foremost driven by those workplaces where the share of politicians within the workplace-occupation cell is relatively large where individuals are likely to socialize on a more daily basis. When excluding those individuals, the results becomes more sensitive to the choice of regression model. To further investigate this issue, we also present an analysis where we have changed the treatment variable to the number of politicians instead of using the share of politicians. The results are presented i Table A6 and they are in line with the discussion above, namely that the the *share* of politician colleagues is the crucial factor for our results. The estimated coefficients in Table A6 are only statistically significant in the the naive model in column 1 and for the conditional logit results in column 6 (and these coefficients are much smaller than the main effects presented in Table 2). In conclusion, the treatment effect is dependent on having a rather high share of politician (either a small network or a larger network with many politicians). We should also briefly comment on the somewhat puzzling estimated odds ratios in columns 5 and 6 in Table A5 which are larger than equivalent models in Table 2 in the main text. The fact that the coefficients are larger means that the S-shape logit function provides a better fit in the middle of the distribution when larger values in the tail of the treatment variable are dropped. However, it is difficult to compare the odds ratios to the linear models in column 1–4 especially when larger shares have been dropped which we expect to be important for socialization within workplace-occupation cells.

In the main analysis, we use cells of colleagues that work at the same workplace and occupation. The main reason is that many workplaces lack vertical integration. However, this

is not necessarily true at smaller workplaces. In Table A7, we run an analysis where the cells are defined as workplaces only. Furthermore, we restrict this analysis to workplaces with less than 50 workers and we include a workplace-individual fixed effect. In this case, we estimate statistically significant, large coefficients (compared to the ones presented in Table 2). One interpretation is that political recruitment actually does take place across occupation within a workplace. However, we should also acknowledge that there is likely more selection present in this specification, and that we run the analysis on a subset of all workplaces.

In Table A8 and Table A9, we assess whether our results in Table 2 are sensitive to the level of clustering of the standard errors. Throughout the paper, we have clustered the standard errors on the same level as the fixed effect: the combined individual*workplace*occupation fixed effect. The reason is that there might be serial correlation in the panel that we use for identification, given that we exploit the timing of becoming a politician. However, it is possible to argue that we should cluster the standard errors at a higher level. For instance, workers at the same workplace may experience correlated shocks. Similarly, individuals in the same municipality of residence may experience correlated shocks. We therefore run the same specification in Table A8 and Table A9 as in Table 2, but we cluster the standard errors on the workplace level and the municipality of residence level respectively. The estimated coefficients remain statistically significant in these two specifications.

In Table A10, we have run a number of placebo checks. We have changed the outcome variable from becoming nominated in the next mandate period to six labor market outcomes: labor income, disposable income, parental leave income, unemployment benefits, years of education, and college enrollment in $t-1$. Because we study individuals with a workplace connection, we focus on the intensive margin for labor income, disposable income, unemployment benefits (which could be in the form of part time unemployment) and parental leave income. Hence, we focus on actual positive values where the outcome variable is above 1000 SEK (approximately $100) in order to not focus on cases with very low values for these variables which should be considered close to 0 in practice. To compensate for inflation over the years, we first take the residual from a regression where the income and benefit measures are run on a set of year dummies. These residual values are then logged to facilitate interpretation of the estimated coefficients. Years of education is expressed in levels and college enrolment is a dummy variable taking the value 0 or 1 in a given year in the panel. Looking at the estimated coefficients in Table A10, five of the six estimated coefficients are small and statistically insignificant. We estimate a statistically significant negative coefficient for college enrollment, but it is very small in magnitude. If the share of politicians at the workplace is increased by one per ten colleagues, the probability of being enrolled in college in t *falls* by approximately 0.081 percentage points. We consider this a null-effect in terms of practical significance. In the last column (7) we also add a lagged dependent variable as outcome. Since the explanatory variable is defined in $t-1$, we define being

nominated in t − 2. We restrict the analysis to new nominated, in other words we drop those who where politicians in previous periods (t − 3 – t − 5). Reassuringly, the estimated coefficient is small and statistically insignificant.

In Figure A3, we assess whether our main findings are sensitive to the number of employees at the workplace-occupation cell. The further to the right we go in the figure, the greater the number of individuals we allow for within a workplace and occupation category. The overall conclusion is that our main findings are stable across these specifications.

Figure A4 in turn splits the sample into similar sized cells. For example, in the case of 3–5 sized cells, we only include observations in which the number of workplace and occupation peers remains between 3–5 for the entire period. This will reduce the number of observations heavily. For this reason, we only include fixed effects for individual/occupation and workplace, but drop other regressors from the analyses.

In Figure A5, we have divided the labor market into 17 sectors based on a standard Swedish classifications. We then run the most conservative specification for each sector, and plot the results. Effects are sorted from least positive to most positive. Sectors from left to right: Communication; STEM/Law/Econ; Trade, Manufacturing; Culture, Public Administration; Finance; Water/Electricity/Gas; Education; Construction; Health; Transport; Service; Tourism; Real Estate.

Table A2: Robustness: Excluding politician occupations

	(1) Nom.	(2) Nom.	(3) Nom.	(4) Nom.	(5) Nom.	(6) Nom.
Politicians per 10 colleagues in t-1	0.00233***	0.00047***	0.00036***	0.00025***	1.10750***	1.07708***
	(0.00006)	(0.00007)	(0.00007)	(0.00008)	(0.01637)	(0.01640)
Mean dep. var.	0.0028	0.0017	0.0019	0.0018	0.3391	0.3674
Regression model	LPM	LPM	LPM	LPM	C.logit	C.logit
Individual*wp*occupation FE	No	Yes	Yes	Yes	Yes	Yes
WP occupation covs t-1.	No	No	Yes	Yes	No	Yes
Individual covs t.	No	No	Yes	Yes	No	Yes
Mandate period FE	No	No	Yes	Yes	No	No
Municipal FE	No	No	Yes	Yes	No	No
Occupation mandate trend	No	No	No	Yes	No	No
Workplace mandate trend	No	No	No	Yes	No	No
R2	0.000	0.382	0.407	0.478		
Pseudo-R2					0.001	0.132
Observations	30908730	22238755	17609544	15802598	108405	91474

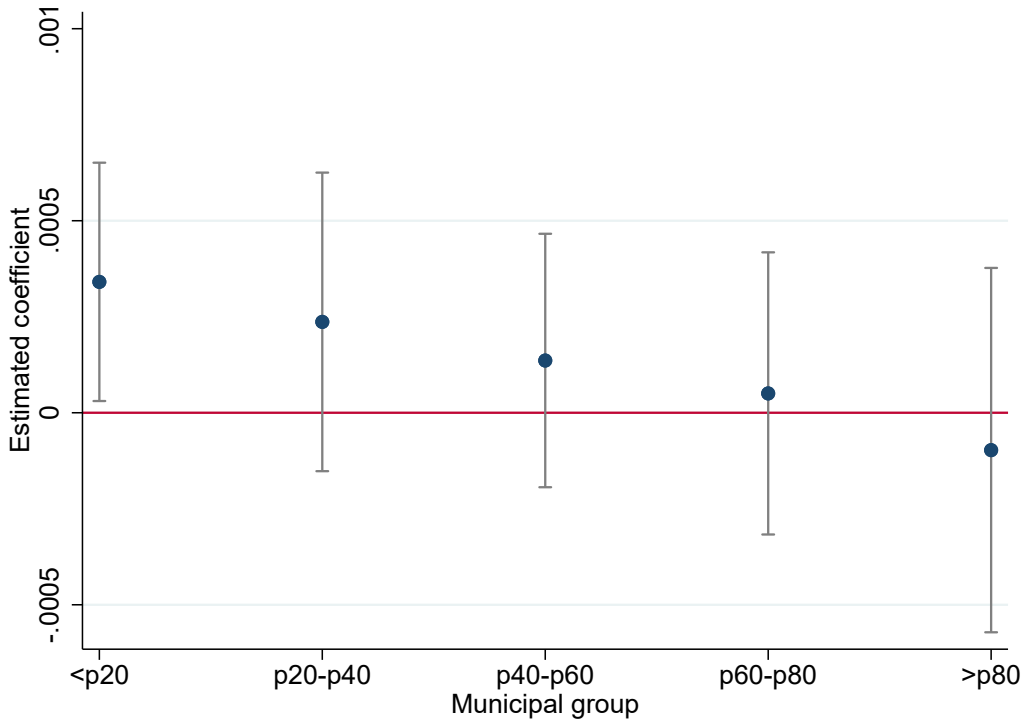
*Note: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Same as main results in Table 2, but full time politician, lobbyist, high civil servant, elected representative (not politician) and PR-consultants are excluded from the estimations. The dependent variable is binary and takes the values 0 or 1.*

Table A3: Robustness: Excluding politician occupations and 5 most common occupations

	(1) Nom.	(2) Nom.	(3) Nom.	(4) Nom.	(5) Nom.	(6) Nom.
Politicians per 10 colleagues in t-1	0.00212***	0.00041***	0.00029***	0.00016*	1.09607***	1.06217***
	(0.00007)	(0.00007)	(0.00008)	(0.00009)	(0.01780)	(0.01800)
Mean dep. var.	0.0026	0.0015	0.0018	0.0017	0.3377	0.3701
Regression model	LPM	LPM	LPM	LPM	C.logit	C.logit
Individual*wp*occupation FE	No	Yes	Yes	Yes	Yes	Yes
WP occupation covs t-1.	No	No	Yes	Yes	No	Yes
Individual covs t.	No	No	Yes	Yes	No	Yes
Mandate period FE	No	No	Yes	Yes	No	No
Municipal FE	No	No	Yes	Yes	No	No
Occupation mandate trend	No	No	No	Yes	No	No
Workplace mandate trend	No	No	No	Yes	No	No
R2	0.000	0.380	0.409	0.484		
Pseudo-R2					0.001	0.134
Observations	26777365	19179145	14902052	13228774	87659	72440

*Note: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Same as main results in Table 2, but five most common occupations and full time politician, lobbyist, high civil servant, elected representative (not elected politician) and PR-consultants are excluded from the estimations. The dependent variable is binary and takes the values 0 or 1.*

Figure A2: Marginal effects, using LPM, stratified for municipality population size



*Notes:*The figure display the estimated coefficient and 95% confidence interval corresponding to the specification in column 4 in Table 2, i.e. the most conservative LPM-specification in the main analysis. Municipality size in quintiles by individuals and time: in other words the <p20 coefficient shows the analysis for the 20 % of individuals and years living in the population-wise smallest municipalities.

Table A4: Robustness: Elected politician instead of nominated as treatment variable

	(1) Nom.	(2) Nom.	(3) Nom.	(4) Nom.	(5) Nom.	(6) Nom.
Elected per 10 colleagues in t-1	0.00387***	0.00060***	0.00049***		1.09888***	1.10173***
	(0.00015)	(0.00015)	(0.00016)		(0.02695)	(0.02855)
Mean dep. var.	0.0029	0.0017	0.0019	0.0018	0.3385	0.3677
Regression model	LPM	LPM	LPM	LPM	C.logit	C.logit
Individual*wp*occupation FE	No	Yes	Yes	Yes	Yes	Yes
WP occupation covs t-1.	No	No	Yes	Yes	No	Yes
Individual covs t.	No	No	Yes	Yes	No	Yes
Mandate period FE	No	No	Yes	Yes	No	No
Municipal FE	No	No	Yes	Yes	No	No
Occupation mandate trend	No	No	No	Yes	No	No
Workplace mandate trend	No	No	No	Yes	No	No
R2	0.000	0.381	0.408	0.477		
Pseudo-R2					0.000	0.133
Observations	31995947	22917601	18162465	16337407	113189	94903

*Note: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is binary and takes the values 0 or 1. The regression model cannot be run for column 4, becasue there are too many singletons.*

Table A5: Robustness: Excluding large values in treatment variable

	(1) Nom.	(2) Nom.	(3) Nom.	(4) Nom.	(5) Nom.	(6) Nom.
Politicians per 10 colleagues in t-1	0.00294***	0.00226***	-0.00060	-0.00013	4.88020***	2.27409**
	(0.00039)	(0.00054)	(0.00060)	(0.00082)	(1.85243)	(0.92476)
Mean dep. var.	0.0024	0.0015	0.0017	0.0015	0.3331	0.3654
Regression model	LPM	LPM	LPM	LPM	C.logit	C.logit
Individual*wp*occupation FE	No	Yes	Yes	Yes	Yes	Yes
WP occupation covs t-1.	No	No	Yes	Yes	No	Yes
Individual covs t.	No	No	Yes	Yes	No	Yes
Mandate period FE	No	No	Yes	Yes	No	No
Municipal FE	No	No	Yes	Yes	No	No
Occupation mandate trend	No	No	No	Yes	No	No
Workplace mandate trend	No	No	No	Yes	No	No
R2	0.000	0.374	0.404	0.495		
Pseudo-R2					0.000	0.145
Observations	27063416	19579942	15156795	13356086	86060	70120

*Note: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

Table A6: Robustness: Number of politicians as treatment variable

	(1) Nom.	(2) Nom.	(3) Nom.	(4) Nom.	(5) Nom.	(6) Nom.
N. politicians in t-1	0.00026***	0.00002	-0.00001	-0.00003	1.00106	1.00856***
	(0.00002)	(0.00004)	(0.00004)	(0.00006)	(0.00239)	(0.00251)
Mean dep. var.	0.0029	0.0017	0.0019	0.0018	0.3385	0.3677
Regression model	LPM	LPM	LPM	LPM	C.logit	C.logit
Individual*wp*occupation FE	No	Yes	Yes	Yes	Yes	Yes
WP occupation covs t-1.	No	No	Yes	Yes	No	Yes
Individual covs t.	No	No	Yes	Yes	No	Yes
Mandate period FE	No	No	Yes	Yes	No	No
Municipal FE	No	No	Yes	Yes	No	No
Occupation mandate trend	No	No	No	Yes	No	No
Workplace mandate trend	No	No	No	Yes	No	No
R2	0.000	0.381	0.408	0.477		
Pseudo-R2					0.000	0.133
Observations	31995947	22917601	18162465	16337407	113189	94903

*Note: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

Table A7: Fixed effects at the workplace level. 50 or fewer workers

	(1) Nom.	(2) Nom.	(3) Nom.	(4) Nom.	(5) Nom.	(6) Nom.
Politicians per 10 colleagues in t-1	0.00402***	0.00083***	0.00071***	0.00172***	1.13127***	1.09375***
	(0.00020)	(0.00020)	(0.00020)	(0.00029)	(0.03676)	(0.03322)
Mean dep. var.	0.0030	0.0019	0.0022	0.0020	0.3253	0.3496
Regression model	LPM	LPM	LPM	LPM	C.logit	C.logit
Individual*wp* FE	No	Yes	Yes	Yes	Yes	Yes
WP occupation covs t-1.	No	No	Yes	Yes	No	Yes
Individual covs t.	No	No	Yes	Yes	No	Yes
Mandate period FE	No	No	Yes	Yes	No	No
Municipal FE	No	No	Yes	Yes	No	No
Workplace mandate trend	No	No	No	Yes	No	No
R2	0.000	0.362	0.387	0.500		
Pseudo-R2					0.000	0.138
Observations	15655990	12351940	9653443	7802291	72522	60480

*Note: Clustered standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

Table A8: Standard errors clustered at the workplace level

	(1) Nom.	(2) Nom.	(3) Nom.	(4) Nom.	(5) Nom.	(6) Nom.
Politicians per 10 colleagues in t-1	0.00251***	0.00049***	0.00037***	0.00022**	1.10244***	1.07729***
	(0.00012)	(0.00009)	(0.00009)	(0.00010)	(0.01642)	(0.01591)
Mean dep. var.	0.0029	0.0017	0.0019	0.0018	0.3385	0.3677
Regression model	LPM	LPM	LPM	LPM	C.logit	C.logit
Individual*wp*occupation FE	No	Yes	Yes	Yes	Yes	Yes
WP occupation covs t-1.	No	No	Yes	Yes	No	Yes
Individual covs t.	No	No	Yes	Yes	No	Yes
Mandate period FE	No	No	Yes	Yes	No	No
Municipal FE	No	No	Yes	Yes	No	No
Occupation mandate trend	No	No	No	Yes	No	No
Workplace mandate trend	No	No	No	Yes	No	No
R2	0.000	0.381	0.408	0.477		
Pseudo-R2					0.001	0.134
Observations	31995947	22917601	18162465	16337407	113189	94903

*Note: Clustered standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

Table A9: Standard errors clustered at the municipality of residence

	(1) Nom.	(2) Nom.	(3) Nom.	(4) Nom.	(5) Nom.	(6) Nom.
Politicians per 10 colleagues in t-1	0.00257***	0.00050***	0.00037***	0.00022**	1.09661***	1.07729***
	(0.00010)	(0.00009)	(0.00009)	(0.00010)	(0.01714)	(0.01713)
Mean dep. var.	0.0030	0.0018	0.0019	0.0018	0.3461	0.3677
Regression model	LPM	LPM	LPM	LPM	C.logit	C.logit
Individual*wp*occupation FE	No	Yes	Yes	Yes	Yes	Yes
WP occupation covs t-1.	No	No	Yes	Yes	No	Yes
Individual covs t.	No	No	Yes	Yes	No	Yes
Mandate period FE	No	No	Yes	Yes	No	No
Municipal FE	No	No	Yes	Yes	No	No
Occupation mandate trend	No	No	No	Yes	No	No
Workplace mandate trend	No	No	No	Yes	No	No
R2	0.000	0.387	0.408	0.477		
Pseudo-R2					0.001	0.134
Observations	30262678	20999948	18162465	16337407	109191	94903

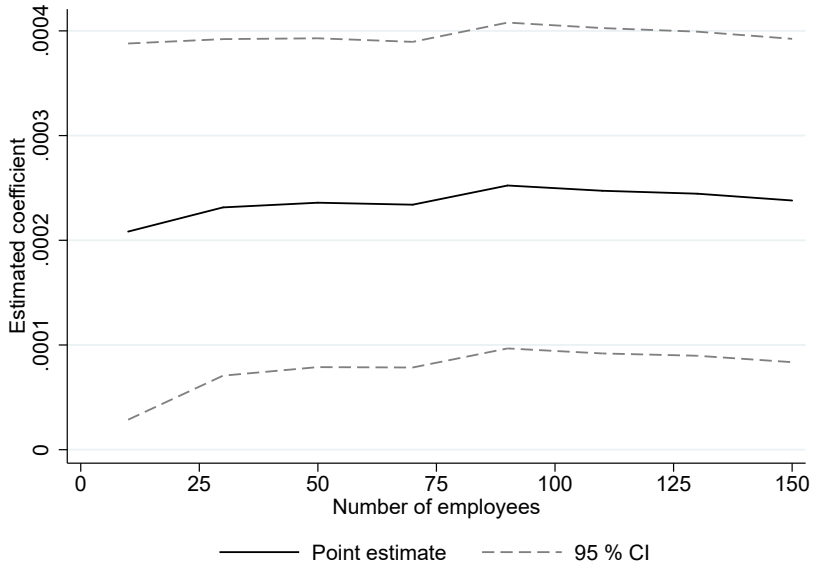
*Note: Clustered standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

Table A10: Placebo analyses

	(1) Lab.Inc	(2) Disp.Inc	(3) Par.Leave	(4) UnemBen	(5) Y.educ	(6) College.P	(7) l2.Nom
Politicians per 10 colleagues in t-1	-0.00000	0.00000	-0.00000	-0.00000	-0.00029	-0.00081***	0.00004
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00084)	(0.00023)	(0.00013)
Mean dep. var.	12.206	12.098	8.385	8.224	12.496	0.055	0.002
Individual*wp*occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
WP occupation covs t-1.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual covs t.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mandate period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation mandate trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Workplace mandate trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	1.000	1.000	1.000	1.000	0.958	0.604	0.499
Observations	12279936	15047200	1498207	297207	15188957	15188957	13126272

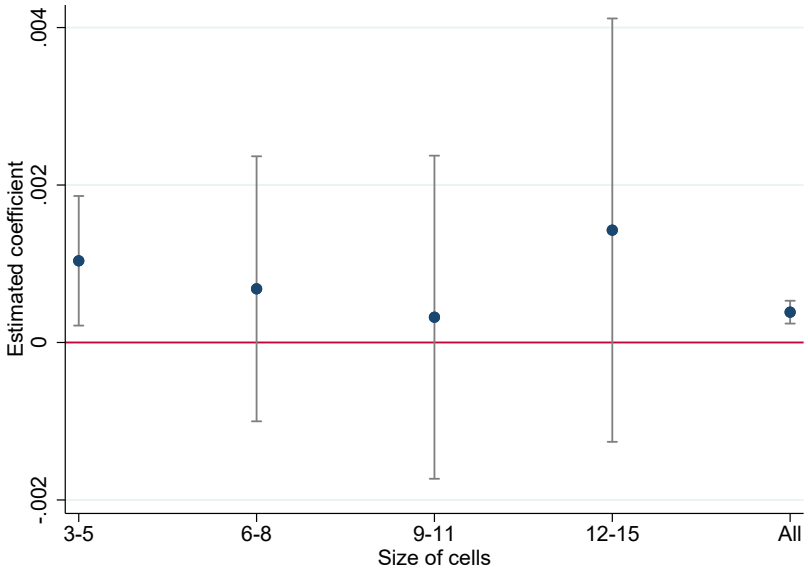
*Note: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

Figure A3: Robustness: Main results for different number of employees



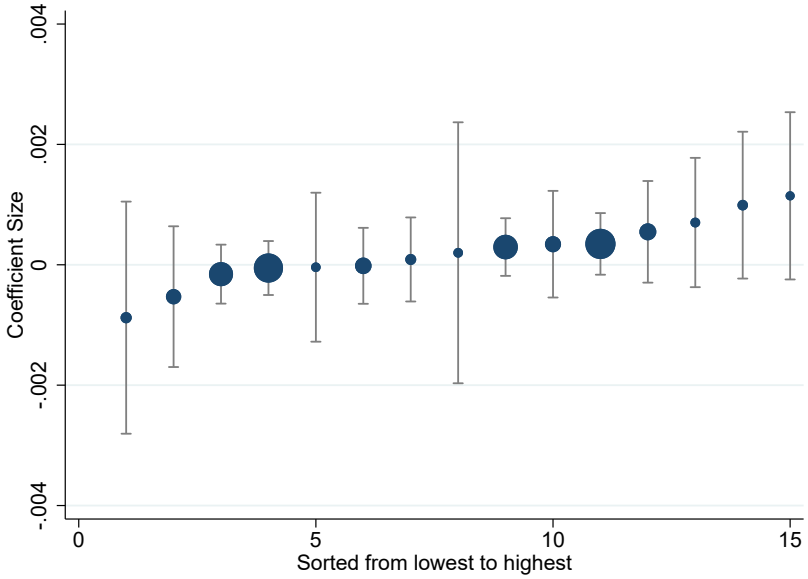
*Notes:*The figure displays the estimated coefficient, together with a 95% confidence interval corresponding to the specification in column 4 in Table 2, i.e. the most conservative LPM-specification in the main analysis.

Figure A4: Robustness: Main results for similar sized cells



*Notes:*The figure displays the estimated coefficient, together with a 95% confidence interval. All regressions are run with fixed effects for individual*wp*occupation. Similar sized cells refers to the individual, workplace and occupation cells being the relevant value for all periods. The final point estimate "All", includes all individual/occupation/workplace cells.

Figure A5: Effects per labor market sector



*Notes:*The figure displays the estimated coefficient, together with a 95% confidence interval corresponding to the specification in column 4 in Table 2, but with one regression separate for each sector. Size of point scaled with size of sector.

B1 Intensive margin

Up until this point, we have focused on the probability of becoming a nominated politician conditional on having politician-colleagues at the workplace. We now continue to an analysis where we investigate the effect of having politician-colleagues in t-1 on the party list-position in t. Here we follow Buisseret et al. (2022), who divide each party nomination list in Sweden into six different categories: top, safe, advantaged, highly contested, disadvantaged, and certain loss. Essentially, the party putting the list together may have a good prior understanding, based on earlier election results, of which slots on the list are electable and which are not. We then use these list categories as dependent variables and apply the most conservative LPM specification (column (4), Table 2 in the main text). The results are presented in Table B1.

We find that the main effect shown in Table 2 is driven by nominations in the "certain loss" category on the party lists in time period t. In other words, the person nominated is not likely to be elected. This makes a lot of sense, given that we analyze first-time nominated politicians only. That said, these people are nonetheless substitutes, and it is not uncommon for them to serve on municipal subcommittees. In conclusion, we find that workplace networks increase the probability of running for office; however, the main effect may be explained by lower list nominations in the next mandate period.

Let us move on to time periods $t+1$ and $t+2$. The results can also be seen in Table B1, but in panel B and panel C. For these two analyses, we modify the sample restriction such that the candidate can be a nominated candidate in t (dependent variable measured in $t+1$) and a candidate in both t and $t+1$ (dependent variable measured in $t+2$). The treatment variable remains the share of politician-colleagues in $t-1$. Interestingly, we now find effects further up on the party lists. In $t+1$, we estimate statistically significant effects for both the safe slot and the disadvantaged slot, together with a prevailing effect on the certain loss category. In $t+2$, we estimate a statistically significant effect in the safe category, the highly competitive category, and the certain loss category, although most of these coefficients are only significant on the 10% level.

Corresponding results from conditional logit models are presented in Table B2. For time period t in panel A, the results are in line with the LPM coefficients in Table B1, where the effect manifests itself in the certain loss category. However, for time periods $t+1$ and $t+2$, the estimated coefficients (here expressed as odds ratios) are no longer statistically significant. The likely explanation is that the conditional logit models are more data demanding. Furthermore, we cannot run the conditional logit models with all fixed effects that were included in Table B1, meaning that the results are not entirely comparable.

In Table B3, we change the outcome variable to becoming an elected politician in t. The conclusion is that the estimated coefficients are generally positive, but they are smaller and less precisely estimated in comparison to the one in Table 2. This is in line with the

conclusion in Table B1, where we demonstrated that the results where driven by the certain loss list position category in t. This result is hence not surprising, given that we focus on first-time nominated politicians in t in Table B3.

Table B1: List position categories as the dependent variable in t, t + 1, and t + 2

Panel A: t	(1) Top	(2) Safe	(3) Advantage	(4) Highly	(5) Disad.	(6) Cert.Loss.
Politicians per 10 colleagues in t-1	0.00001	0.00002	0.00001	0.00000	0.00001	0.00017***
	(0.00000)	(0.00002)	(0.00001)	(0.00002)	(0.00002)	(0.00006)
Mean dep. var.	0.0000	0.0001	0.0001	0.0001	0.0001	0.0011
Panel B: t + 1	TopL1	SafeL1	AdvantageL1	HighlyL1	DisadL1.	Cert.LossL1
Politicians per 10 colleagues in t-1	0.00003	0.00019***	0.00005	0.00001	0.00017***	0.00076***
	(0.00003)	(0.00006)	(0.00005)	(0.00005)	(0.00005)	(0.00012)
Mean dep. var.	0.0001	0.0006	0.0002	0.0003	0.0004	0.0027
Panel C: t + 2	TopL2	SafeL2	AdvantageL2	HighlyL2	DisadL2.	Cert.LossL2
Politicians per 10 colleagues in t-1	-0.00000	0.00019*	0.00011*	0.00016**	-0.00008	0.00032*
	(0.00006)	(0.00010)	(0.00006)	(0.00007)	(0.00007)	(0.00017)
Mean dep. var.	0.0002	0.0011	0.0003	0.0005	0.0005	0.0040
Regression model	LPM	LPM	LPM	LPM	LPM	LPM
Individual*wp*occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
WP occupation covs t-1.	Yes	Yes	Yes	Yes	Yes	Yes
Individual covs t.	Yes	Yes	Yes	Yes	Yes	Yes
Mandate period FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipal FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation mandate trend	Yes	Yes	Yes	Yes	Yes	Yes
Workplace mandate trend	Yes	Yes	Yes	Yes	Yes	Yes
R2 panel A	0.464	0.490	0.479	0.481	0.481	0.473
Observations panel A	16337407	16337407	16337407	16337407	16337407	16337407
R2 panel B	0.582	0.648	0.530	0.514	0.522	0.615
Observations panel B	11230370	11230370	11230370	11230370	11230370	11230370
R2 panel C	0.707	0.721	0.563	0.547	0.545	0.673
Observations panel C	8390981	8390981	8390981	8390981	8390981	8390981

*Note: Standard errors in parentheses are clustered at the individual/workplace/occupation level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is binary and takes the value of 0 or 1. Columns 1–6 display LPM estimated coefficients.*

Table B2: Robustness: Conditional logit estimates for list position in t, t + 1 and t + 2

Panel A: t	(1) Top	(2) Safe	(3) Advantage	(4) Highly	(5) Disad	(6) Cert.Loss
Politicians per 10 colleagues in t-1	1.17836	1.03525	1.10281	1.07146	1.06621	1.08977***
	(0.21802)	(0.05933)	(0.08212)	(0.06921)	(0.05502)	(0.02008)
Mean dep. var.	0.3517	0.3862	0.3639	0.3762	0.3761	0.3656
Panel B: t+1	TopL1	SafeL1	AdvantageL1	HighlyL1	DisadL1.	Cert.LossL1
Politicians per 10 colleagues in t-1	1.15398	1.02016	1.03100	1.01367	0.95916	1.01340
	(0.11735)	(0.03911)	(0.05965)	(0.04855)	(0.04592)	(0.01899)
Mean dep. var.	0.3864	0.4180	0.3921	0.3918	0.3960	0.4081
Panel C: t+2	TopL2	SafeL2	AdvantageL2	HighlyL2	DisadL2.	Cert.LossL2
Politicians per 10 colleagues in t-1	0.81123*	1.02620	1.03410	1.00691	0.92445	0.99671
	(0.10300)	(0.06194)	(0.05214)	(0.05489)	(0.04611)	(0.02110)
Mean dep. var.	0.4359	0.4483	0.4218	0.4170	0.4187	0.4385
Regression model	C.logit	C.logit	C.logit	C.logit	C.logit	C.logit
Individual*wp*occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
WP occupation covs t-1.	Yes	Yes	Yes	Yes	Yes	Yes
Individual covs t.	Yes	Yes	Yes	Yes	Yes	Yes
Mandate period FE	No	No	No	No	No	No
Municipal FE	No	No	No	No	No	No
Occupation mandate trend	No	No	No	No	No	No
Workplace mandate trend	No	No	No	No	No	No
Observations panel A	1086	5894	3190	4872	6649	56289
Observations panel B	1677	8100	4397	6560	8006	52960
Observations panel C	1693	7751	4111	5964	7227	43856

*Note: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

Table B3: Robustness: Elected as the dependent variable

	(1) Elect.	(2) Elect.	(3) Elect.	(4) Elect.	(5) Elect.	(6) Elect.
Politicians per 10 colleagues in t-1	0.00051***	0.00005*	0.00002	0.00000	1.06256*	1.05121
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.03740)	(0.04246)
Mean dep. var.	0.0004	0.0002	0.0003	0.0003	0.3413	0.3724
Regression model	LPM	LPM	LPM	LPM	C.logit	C.logit
Individual*wp*occupation FE	No	Yes	Yes	Yes	Yes	Yes
WP occupation covs t-1.	No	No	Yes	Yes	No	Yes
Individual covs t.	No	No	Yes	Yes	No	Yes
Mandate period FE	No	No	Yes	Yes	No	No
Municipal FE	No	No	Yes	Yes	No	No
Occupation mandate trend	No	No	No	Yes	No	No
Workplace mandate trend	No	No	No	Yes	No	No
R2	0.000	0.385	0.412	0.483		
Pseudo-R2					0.000	0.132
Observations	31995947	22917601	18162465	16337407	15454	12906

*Note: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

C1 Robustness analysis mechanism section

In the mechanism analysis in the main text, we ran an analysis where we investigated whether our reduced form effects could be explained by a partisan channel. The results were presented in Table 3. For that analysis, we did not include the Sweden Democrats in any of the two blocs. In Table C1, we include the Sweden Democrats into the right-wing bloc. The results are similar to those in the main text. The share of right-wing-politicians (including the Sweden Democrats) increases the probability of becoming nominated for any of the right-wing parties (including the Sweden Democrats). The share of left-wing politicians does not have an impact (although the point estimate in the naive specification in column 1 is statistically significant).

In Tables C2 and C3, we further analyse the effects specifically for the (traditionally) two largest parties in the country. In case of the Social democrats, we see both an effect of increased tendency to enter politics if colleagues from other parties as well as from their own party enters. This suggests that recruitment is unlikely to be the only channel through which our effect operates. In the case of the Moderate party, we see a much clearer effect when new colleagues belong to the same prospective party.

Table C1: Robustness: Right-wing bloc + Sweden Democrats

	(1) Nom. R + SD	(2) Nom. R + SD	(3) Nom. R + SD	(4) Nom. R + SD	(5) Nom. R + SD	(6) Nom. R + SD
RW + SD per 10 colleagues in t-1	0.00146***	0.00026***	0.00018**	0.00004	1.08373***	1.04897*
	(0.00007)	(0.00008)	(0.00008)	(0.00009)	(0.02569)	(0.02688)
LW per 10 colleagues in t-1	0.00055***	0.00002	-0.00002	0.00003	1.00704	0.97711
	(0.00005)	(0.00006)	(0.00006)	(0.00007)	(0.03518)	(0.03771)
Mean dep. var.	0.0014	0.0008	0.0010	0.0009	0.3378	0.3663
Regression model	LPM	LPM	LPM	LPM	C. logit	C. logit
Individual*wp*occupation FE	No	Yes	Yes	Yes	Yes	Yes
WP occupation covs t-1.	No	No	Yes	Yes	No	Yes
Individual covs t.	No	No	Yes	Yes	No	Yes
Mandate period FE	No	No	Yes	Yes	No	No
Municipal FE	No	No	Yes	Yes	No	No
Occupation mandate trend	No	No	No	Yes	No	No
Workplace mandate trend	No	No	No	Yes	No	No
R2	0.000	0.382	0.407	0.483		
Pseudo-R2					0.000	0.142
Observations	31995947	22917601	18162465	16337407	56680	47567

*Note: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is binary and takes the values 0 or 1.*

Table C2: Only the Moderate party

	(1) Nom. M	(2) Nom. M	(3) Nom. M	(4) Nom. M	(5) Nom. M	(6) Nom. M
RW per 10 colleagues (not M)	0.00025***	0.00003	0.00003	0.00000	1.05411	1.05471
	(0.00004)	(0.00004)	(0.00004)	(0.00005)	(0.06556)	(0.08062)
M per 10 colleagues in t-1	0.00105***	0.00037***	0.00033***	0.00011	1.23653***	1.23304***
	(0.00011)	(0.00012)	(0.00013)	(0.00013)	(0.07226)	(0.09596)
CL per 10 colleagues in t-1	0.00015***	0.00002	0.00003	0.00003	1.03798	1.04305
	(0.00003)	(0.00003)	(0.00004)	(0.00004)	(0.06639)	(0.06881)
Mean dep. var.	0.0004	0.0002	0.0003	0.0002	0.3433	0.3772
Regression model	LPM	LPM	LPM	LPM	C. logit	C. logit
Individual*wp*occupation FE	No	Yes	Yes	Yes	Yes	Yes
WP occupation covs t-1.	No	No	Yes	Yes	No	Yes
Individual covs t.	No	No	Yes	Yes	No	Yes
Mandate period FE	No	No	Yes	Yes	No	No
Municipal FE	No	No	Yes	Yes	No	No
Occupation mandate trend	No	No	No	Yes	No	No
Workplace mandate trend	No	No	No	Yes	No	No
R2	0.000	0.385	0.414	0.489		
Pseudo-R2					0.001	0.169
Observations	31995947	22917601	18162465	16337407	16189	13082

*Note: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is binary and takes the values 0 or 1.*

Table C3: Only Socialdemocratic party

	(1) Nom. S	(2) Nom. S	(3) Nom. S	(4) Nom. S	(5) Nom. S	(6) Nom. S
LW per 10 colleagues (not S)	0.00064***	0.00029***	0.00027***	0.00026**	1.37528***	1.24587**
	(0.00008)	(0.00010)	(0.00010)	(0.00012)	(0.14819)	(0.11338)
S per 10 colleagues in t-1	0.00270***	0.00039***	0.00036***	0.00018	1.10587***	1.09060***
	(0.00012)	(0.00012)	(0.00012)	(0.00011)	(0.03326)	(0.03164)
CR per 10 colleagues in t-1	0.00029***	0.00008**	0.00006*	0.00007	1.13147**	1.08059
	(0.00003)	(0.00003)	(0.00004)	(0.00004)	(0.06077)	(0.05853)
Mean dep. var.	0.0007	0.0004	0.0005	0.0005	0.3447	0.3751
Regression model	LPM	LPM	LPM	LPM	C. logit	C. logit
Individual*wp*occupation FE	No	Yes	Yes	Yes	Yes	Yes
WP occupation covs t-1.	No	No	Yes	Yes	No	Yes
Individual covs t.	No	No	Yes	Yes	No	Yes
Mandate period FE	No	No	Yes	Yes	No	No
Municipal FE	No	No	Yes	Yes	No	No
Occupation mandate trend	No	No	No	Yes	No	No
Workplace mandate trend	No	No	No	Yes	No	No
R2	0.000	0.389	0.414	0.470		
Pseudo-R2					0.002	0.095
Observations	31995947	22917601	18162465	16337407	25962	22022

*Note: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is binary and takes the values 0 or 1.*

D1 Heterogeneity analysis: Political support

The question we ask in this section is whether the effects that we found in the main text display some heterogeneity. We focus on the question if the partisan effect is larger if the politician-colleague represents the bloc which has the upper hand in terms of mandates on the municipal level.

We run two heterogeneity analyses: One for the right-wing bloc and one for the left-wing bloc. The focus is on partisan effects, which we know from Table 3 in the main text is present. To do this, we focus on one treatment variable so that the independent variable and the dependent variable concerns the same political bloc. The analysis take the form of an interacted regression model for each bloc separately, where three variables are included in each case.[2] First we have the partisan treatment variable, which is the number of left-wing/right-wing politicians among 10 colleagues in a workplace–occupation cell. We then include a dummy variable taking the value 1 if the left-wing/right-wing bloc is the largest political bloc in the municipal council and 0 otherwise.[3] Lastly, we include an interaction variable between the other two. The results are presented in Table D1 and Table D2. It bears noting that these interacted models are data demanding given that we also include many fixed effects.

Beginning with Table D1 and the analysis for left-wing nominations, we find that the share of left-wing politicians in the workplace-occupation cell is statistically significant and positive, but the interaction term is close to zero and insignificant. Continuing with Table D2, we find the opposite: the probability of becoming nominated for the right-wing bloc is not increased when having politician-colleagues if the right-wing bloc is smaller than the left-wing bloc ($\texttt{CRplur.} = 0$). However, when the right-wing bloc is the larger bloc ($\texttt{CRplur.} = 1$), then the interaction effect is positive and statistically significant for the less conservative regression models. This would mean that the main partisan effect found in Table 3 is driven by those cases where the right-wing bloc has the majority in the municipal council. We do not want to overstate these findings given that the interaction terms in general are not statistically significant. However, the findings provide some (suggestive)

[2] It bears noting that it is not an exogenous event whether a political bloc has a majority in the municipal council. A solution to this endogeneity problem could be to run a regression discontinuity design (RDD) in line with Lee and Lemieux (2010) using the seats shares as a running variable. There are however several obstacles involved in order to run such an analysis in relation to the heterogeneity analysis we have in mind. We have a discrete running variable with few mass points and we find unbalance in observables when implementing the local randomization approach discussed in Cattaneo et al. (2020). We therefore choose to implement a simpler interaction analysis and acknowledge that our results in this section could not be interpreted as the causal effect estimates, but rather whether the partisan effect is stronger or weaker depending on whether a political bloc has the plurality of the seats.

[3] Fiva et al. (2018) argue that a given vote share in a municipal election could result is different seat share pluralities depending on the relative support of the different political parties and how mandates in municipal councils are allocated (a modified Sainte-Laguë-method is applied in Sweden). This may then result is different probabilities that the left-wing bloc or the right-wing bloc end up having an actual majority of the seats. We therefore choose to focus on seat shares for this analysis.

evidence that right-wing politicians are more prone to be politically engaged when it yields more political power.

Table D1: Heterogeneity analysis left-wing bloc

	(1) Nom. CL	(2) Nom. CL	(3) Nom. CL	(4) Nom. CL	(5) Nom. CL	(6) Nom. CL
CL per 10 colleagues in t-1	0.00275***	0.00071***	0.00056***	0.00038**	1.21839***	1.15771***
	(0.00017)	(0.00016)	(0.00016)	(0.00016)	(0.06282)	(0.06015)
CL plur.	0.00007***	-0.00009***	-0.00002	-0.00004	0.82791***	0.91403**
	(0.00001)	(0.00002)	(0.00002)	(0.00004)	(0.03183)	(0.03930)
CL per 10 colleagues. in t-1 * CL plur.	0.00002	-0.00016	-0.00009	-0.00016	0.94071	0.98991
	(0.00021)	(0.00021)	(0.00021)	(0.00021)	(0.05113)	(0.05631)
Mean dep. var.	0.0011	0.0006	0.0007	0.0007	0.3511	0.3743
Regression model	LPM	LPM	LPM	LPM	C. logit	C. logit
Individual*wp*occupation FE	No	Yes	Yes	Yes	Yes	Yes
WP occupation covs t-1.	No	No	Yes	Yes	No	Yes
Individual covs t.	No	No	Yes	Yes	No	Yes
Mandate period FE	No	No	Yes	Yes	No	No
Municipal FE	No	No	Yes	Yes	No	No
Occupation mandate trend	No	No	No	Yes	No	No
Workplace mandate trend	No	No	No	Yes	No	No
R2	0.000	0.392	0.412	0.470		
Pseudo-R2					0.003	0.136
Observations	29460594	20440954	17431864	15633068	37731	32858

*Note: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is binary and takes the values 0 or 1.*

Table D2: Heterogeneity analysis right-wing bloc

	(1) Nom. CR	(2) Nom. CR	(3) Nom. CR	(4) Nom. CR	(5) Nom. CR	(6) Nom. CR
CR per 10 colleagues in t-1	0.00139***	0.00007	-0.00000	-0.00011	1.03057	1.00700
	(0.00010)	(0.00011)	(0.00011)	(0.00011)	(0.03623)	(0.03319)
CR plur.	0.00040***	0.00006***	0.00014***	0.00015***	1.11996***	1.06246
	(0.00001)	(0.00002)	(0.00002)	(0.00004)	(0.03904)	(0.04197)
CR per 10 colleagues. in t-1 * CR plur.	0.00023	0.00032**	0.00036**	0.00032*	1.07741	1.07294
	(0.00015)	(0.00016)	(0.00016)	(0.00018)	(0.05074)	(0.05142)
Mean dep. var.	0.0013	0.0007	0.0008	0.0007	0.3548	0.3792
Regression model	LPM	LPM	LPM	LPM	C. logit	C. logit
Individual*wp*occupation FE	No	Yes	Yes	Yes	Yes	Yes
WP occupation covs t-1.	No	No	Yes	Yes	No	Yes
Individual covs t.	No	No	Yes	Yes	No	Yes
Mandate period FE	No	No	Yes	Yes	No	No
Municipal FE	No	No	Yes	Yes	No	No
Occupation mandate trend	No	No	No	Yes	No	No
Workplace mandate trend	No	No	No	Yes	No	No
R2	0.000	0.396	0.417	0.492		
Pseudo-R2					0.001	0.153
Observations	29460594	20440954	17431864	15633068	40920	35239

*Note: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is binary and takes the values 0 or 1.*

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