Occupational Donor Networks in Congressional Elections

Fred DeVeaux*

June 16, 2026

Abstract

Members of Congress are drawn from a narrow set of occupations whose members are also major sources of campaign money. How much do occupational donor networks shape fundraising in congressional elections? I assemble occupational histories for 9,100 candidates for U.S. Congress between 2010 and 2024, and classify the self-reported occupations of more than 14 million unique individual donors who contributed $14.4 billion to federal House and Senate campaigns. I find that candidates capture a larger share of contributions from donors who share their occupation than from other donors. These occupational donor networks operate in both general and primary elections, but are stronger in primaries. They vary both in the share of each occupation's donor pool that candidates capture and in the size of the donor pool itself. As a result, candidates from elite professional occupations gain tens of thousands of dollars from donors who share their occupation, while candidates from working-class occupations gain little. Occupational donor networks therefore provide the greatest fundraising advantages to candidates from occupations already overrepresented in Congress.

*Department of Political Science, University of California, Los Angeles

1 Introduction

Members of Congress come disproportionately from elite occupations (Carnes, 2013, 2018). Competitive campaigns require substantial fundraising (Thomsen, 2025), and the donors who supply that money are wealthier than the broader public (Bouton et al., 2022). Prior work documents donor affinity for candidates with shared characteristics such as age (Bonica and Grumbach, 2025), gender, race, and the intersection of race and gender (Grumbach, Sahn and Staszak, 2022). Existing evidence also suggests that occupational ties may matter: lawyer and physician candidates receive more support from donors in those same professions (Bonica, 2020). How much do occupational donor networks contribute to campaign fundraising in congressional elections?

This question is difficult to answer because there is no comprehensive dataset of congressional candidates' occupational backgrounds, especially for candidates who lose. Drawing on candidate occupational data assembled with Jared Abbott (Abbott and DeVeaux, 2026), I analyze the occupational histories of 9,100 House and Senate candidates who ran in primary elections between 2010 and 2024, using campaign websites archived by the Wayback Machine. I classify candidates' occupations and match them to the classified self-reported occupations of more than 14 million itemized individual donors.

I find descriptive evidence of occupational concentration at every stage of the campaign pipeline. The U.S. adult population is occupationally diverse, but candidates who run for Congress are disproportionately drawn from elite occupations. Donors are more occupationally concentrated still: business executives, lawyers, finance professionals, and medical professionals together contribute about a third of itemized individual dollars, while teachers and working-class donors each contribute less than 1%.

The central empirical challenge is that occupational donor networks are difficult to distinguish from other sources of fundraising advantage. The closest prior study, Bonica (2020), finds that lawyers raise more from lawyer-donors than comparable non-lawyers, but isolating this network remains an open challenge. Occupational donor pools are highly concentrated across districts and tend to expand when candidates from those occupations run, making it difficult to distinguish occupational affinity from differences in the fundraising environment (see details in Appendix A.7). Candidates from some occupations may also be stronger fundraisers overall, attracting more support from many kinds of donors rather than only from donors who share their occupation. Estimating a network premium therefore requires three design features: comparing matched and unmatched candidates within the same contest, so race-level factors do not drive the results; measuring each candidate's share of an occupational donor pool rather than raw dollars, so differences in pool size do not drive the estimate; and decomposing the matched-pool advantage to separate occupation-specific donor support from candidates' broader fundraising profiles.

I first estimate occupational donor networks in contested U.S. House and Senate general elections from 2010 to 2024. The design uses a panel of congressional districts over time to ask whether nominees capture a larger share of donations from their matched occupational donor pool than from other donor pools, relative to their broader fundraising advantage over the opposing nominee. Candidates receive an average network premium of about 3.2 percentage points: they capture about 3.2 percentage points more of their matched occupational donor pool than their performance in non-matched donor pools would predict. The largest premiums are for doctors, higher-education professionals, and lawyers. Broader fundraising advantages are more limited; lawyers are the main occupation whose candidates raise more from donors across the board.

I then turn to primary elections, where candidates share a party label and occupational ties may be more salient. The design uses a district-party panel to ask whether candidates capture a larger share of their matched occupational donor pool than of other donor pools. The average network premium rises to about 5.7 percentage points across U.S. House and Senate primaries from 2010 to 2024, and is somewhat larger in open-seat races, at about 6.8 percentage points. Nearly all occupational groups benefit from a network premium, but the effect sizes vary substantially. Doctors, candidates from agricultural occupations, and lawyers show the largest occupation-specific premiums.

How much do these network premiums contribute to fundraising disparities across candidates? The dollar value of an occupational network depends both on the network premium candidates receive and on the size of the donor pool to which that premium applies. In open-seat primaries, the premium is about \$41,000 for doctors, \$16,000 for lawyers, and \$14,000 for candidates from agricultural occupations, while the premium for working-class candidates is close to zero. Occupational networks operate in general elections as well, but there the premium is a small share of candidates' much larger total fundraising. The dollar advantage is concentrated in primaries, among candidates from occupations with large and active donor pools.

2 Data and Measurement

The analysis combines two sources of occupational information: candidates' occupational biographies and donors' self-reported occupations in campaign finance records.

2.1 Candidate Occupations

I collect occupational histories for major-party House and Senate candidates who ran in contested partisan primaries between 2010 and 2024 and received at least 5% of the primary vote. I use this threshold to focus on viable campaigns for which donor-network estimates are not driven by candidates who raise little money and do not seriously contest the race. I exclude California, Washington, and Louisiana because their top-two or nonpartisan primary systems do not generate comparable within-party contests. The resulting candidate universe contains 9,110 unique candidates and 12,176 candidate-years across 47 states.

Candidate occupations come from a joint data collection effort with Jared Abbott (Abbott and DeVeaux, 2026). With the help of research assistants, we used campaign websites scraped through the Wayback Machine to collect candidates' occupational biographies and classify all prior occupations mentioned in those biographies into an occupational schema based on Carnes (2013) (see Appendix A.2). I aggregate these categories into 13 substantive occupational groups. Coverage is high across the candidates I analyze: occupational information is missing for only 1.2% of primary winners, 2.6% of top-two primary finishers, and 7.1% of candidates receiving at least 5% of the primary vote. The median candidate lists four prior occupations. Collapsed to the 13 focal groups, just over half (53%) fall into a single group, 31% into two, and 17% into three or more.

2.2 Donor Occupations

The donor data come from itemized individual contributions to U.S. House and Senate candidates between 2010 and 2024, as filed with the Federal Election Commission and standardized through Adam Bonica's DIME dataset (Bonica, 2024). I exclude PAC contributions and analyze individual direct contributions only. The data cover $14.4 billion in cycle-level individual contributions to 10,999 candidates.[1] FEC records include two free-text fields relevant for occupation: the donor's position and employer. I use the position field as the primary signal and the employer field when the position alone is ambiguous. The raw data contain 775,349 distinct position strings and 7.2 million distinct position-employer combinations.

Using a language-model pipeline, I classify donors' self-reported occupation strings into a schema adapted from Carnes (2013), aggregated into 19 substantive occupational groups. Donor occupation strings are highly concentrated: the 20,579 most common strings account for about 95% of dollars from donors who report an occupation. Some titles are inherently ambiguous. A "president," for example, may be a banker, a corporate executive, a small-business owner, or a union official, depending on the employer. For these ambiguous strings, I classify the position together with the employer, covering roughly 776,000 position-employer combinations. Appendix A.3 lists the most common donor strings in each occupational pool.

Roughly 82% of itemized dollars ($11.8 billion of the $14.4 billion total) come from donors with a classifiable occupation string. The main analysis focuses on 13 occupational donor pools: lawyers, doctors and medical professionals, higher education, working class, agriculture, bankers and finance, business executives, consultants, STEM & technical professionals, small business and contractors, K–12 educators, real estate professionals, and corporate managers. These 13 pools account for $5.98 billion in contributions: 41.5% of all itemized individual dollars and 50.7% of classifiable dollars.

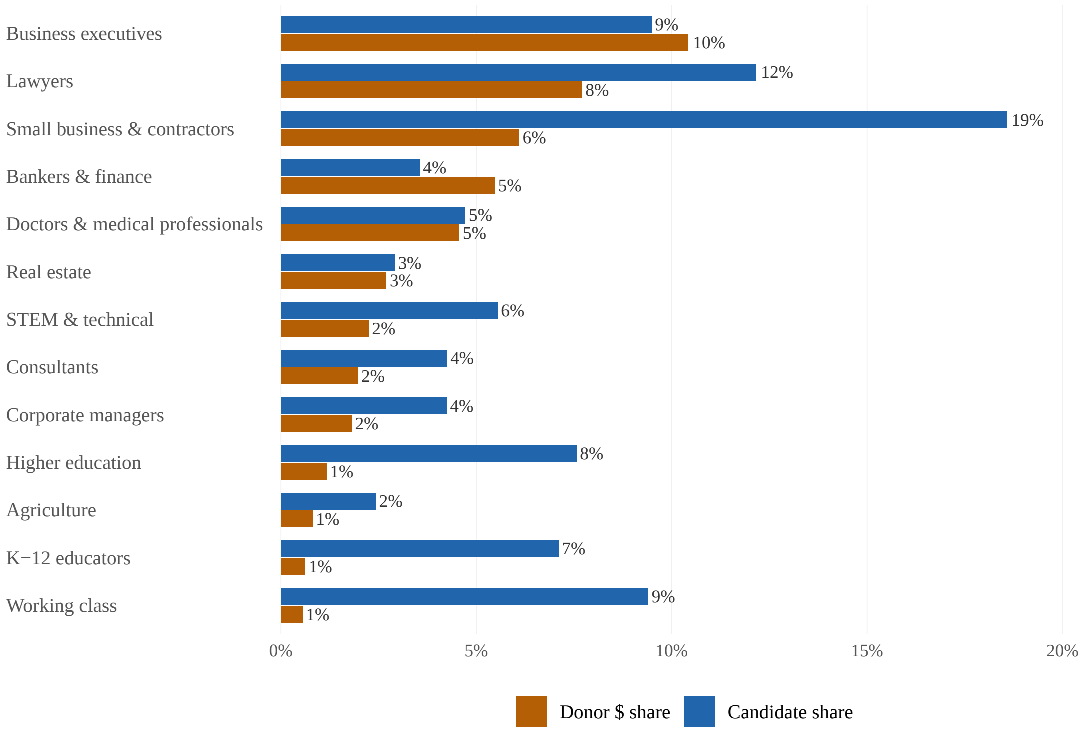
An additional 35% of itemized dollars comes from non-employment statuses, such as retired, unemployed, homemaker, student, or volunteer, which are classifiable but have no candidate-side analogue. The remaining 18% of itemized dollars are unclassifiable: blank, null, or too vague to pin to any occupation, such as "professional" or "business." Contributions from these statuses, from occupational groups outside the 13 focal pools, and from unclassifiable strings remain in the analysis as part of an "other occupation" pool. This preserves the broader donor environment used to estimate candidates' non-matched fundraising.

[1] Campaign committees are required to itemize donors only after they give more than $200 to that committee in a cycle, but conduit platforms such as ActBlue and WinRed report detailed contribution-level information for all contributions they process. By 2020, these conduit reports made contribution-level data observable for 92% of the total amounts received by candidates (Bouton et al., 2022).

3 Distribution of Candidate and Donor Occupations

I first describe the occupational composition of congressional candidates and donors. Figure 1 compares candidate and donor distributions across the 13 focal occupational groups. Candidate shares report the share of candidates with each occupational background; donor shares report the share of total itemized donor dollars from each occupational pool. Because candidate occupations are non-exclusive, candidate shares do not sum to 100. The full occupational distribution appears in Appendix A.1. Tables A.1 and A.2 report the occupations that comprise each candidate and donor category.

Figure 1: Donor and candidate occupational distributions, 13 occupational donor pools.



Notes: Contested major-party congressional primaries, 2010–2024, excluding CA, WA, and LA. Universe of 9,110 unique candidates / 12,176 candidate-years. Donor share denominator is total primary-stage itemized donor $ in the universe (including categories such as retired, unemployed, and uncategorized occupation strings). Candidate occupation shares are non-exclusive.

Figure 1 shows that candidates and donors are both occupationally concentrated, but in different ways. Lawyers and business executives are well represented among candidates and account for large shares of donor dollars. Small business owners are the largest candidate group, at about 24%, but account for about 6% of donor dollars. The divergence is sharpest for candidates from working-class backgrounds, who account for about 12% of candidates but only 0.6% of itemized donor dollars. Working-class candidates therefore have little same-occupation donor money to draw on, even when they run. The rest of the paper tests whether these unequal donor pools translate into unequal same-occupation fundraising advantages.

4 Occupational Networks in General Elections

I first estimate whether occupational donor networks operate in contested general elections, where party provides a powerful cue and may leave less room for occupational affinity.

The main empirical challenge is separating occupational donor networks from broader fundraising advantages. A lawyer-candidate, for example, may raise more from lawyer-donors because lawyers prefer candidates from their own profession. But the same candidate may also raise more from donors in other occupations because lawyers are stronger fundraisers more generally. I therefore distinguish three quantities: the non-matched effect, which captures whether candidates from an occupation receive more from donors outside that occupation; the matched-pool effect, which captures their total advantage among donors in their own occupational pool; and the network premium, which is the difference between the two.

To estimate this premium, I construct a race-by-occupation panel of contested U.S. House and Senate general elections from 2010 to 2024. For each race and occupational donor pool, I create two observations. One records the Democratic nominee's share of contributions from donor pool g. The other records the Democratic nominee's share of all remaining donor dollars after excluding donor pool g. I estimate

$$Y_{igmot} = \beta_1 OccGap_{igot} + \beta_2 OccGap_{igot} \times Matched_m + X_{it}\theta + \gamma_{igmo} + \delta_{tgmo} + \epsilon_{igmot}.$$

Here, Y_{igmot} is the Democratic share of contributions in district i, donor pool g, row m, office o, and cycle t. $OccGap_{igot}$ equals one when the Democratic nominee, but not the Republican nominee, has occupation g, minus one when the Republican nominee, but not the Democratic nominee, has occupation g, and zero otherwise.[2] $Matched_m$

[2] Because the outcome is the Democratic share, a Republican nominee's occupation enters with the opposite sign, so the pooled coefficient is the average premium across Democratic and Republican nominees; I estimate the two separately in Appendix A.4. The zero category covers races where neither nominee has the occupation and the rarer races where both do; Appendix Table A.3 reports the composition by occupation, and excluding the both-occupation races leaves the premium unchanged.

indicates the donor-pool-g row, rather than the row containing all other donor dollars. The coefficient β_1 is the non-matched effect, $\beta_1 + \beta_2$ is the matched-pool effect, and β_2 is the network premium. The fixed effects γ_{igmo} and δ_{tgmo} absorb separate means for each district-by-pool-by-match-by-office cell and each cycle-by-chamber-by-pool-by-match cell. Identification comes from within-district variation across cycles in which a party's nominee holds occupation g, rather than from cross-sectional differences between districts. All models control for party incumbency, candidate gender and race, prior non-congressional political experience, and former federal incumbent status. Standard errors are clustered by district.

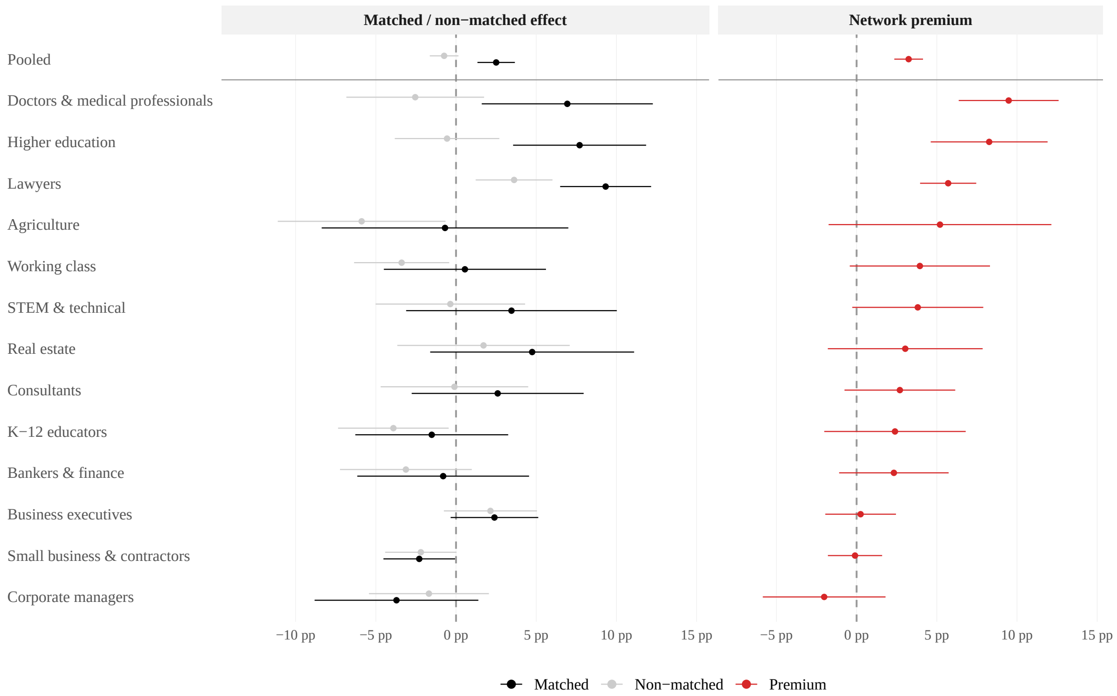
Figure 2 reports the pooled estimate across the 13 occupational donor pools and the occupation-specific premiums. In contested general elections, the matched-pool effect is larger than the non-matched effect, producing a network premium of about 3.2 percentage points. This is consistent with occupational networks operating even in partisan general-election contests.

The occupation-specific premiums vary in size and precision. The largest and most precisely estimated premiums are among doctors and medical professionals, at about 9 to 10 percentage points; higher-education professionals, at about 8 percentage points; and lawyers, at about 6 percentage points. Most other premiums are positive but smaller and less precisely estimated. Business executives, small business owners and contractors, and corporate managers have estimated premiums near zero or slightly negative.

By contrast, broader fundraising advantages across occupations are largely indistinguishable from zero. Lawyers are the only occupation with modest evidence of a broader fundraising advantage beyond their own occupational donor pool.

These results are robust to how the occupational pools are defined (combining the two education pools, or dropping the most loosely defined pools), to controls for candidate ideology, and to a correction for nominees who belong to more than one occupation. Across these specifications the average network premium ranges from about 3.0 to 4.1 percentage points. Pre-treatment leads of the occupation gap are small and statistically indistinguishable from zero. Full estimates and robustness checks appear in Appendix A.4.

Figure 2: Estimated effect of occupational match on donor-pool capture, general elections.



Notes: Contested major-party general elections, 2010–2024; 13 occupational donor pools. Left panel: matched-pool effect (black) and non-matched effect (light grey) for each pool. Right panel: network premium (red, matched − non-matched). 95% confidence intervals; standard errors clustered by redistricted district.

5 Occupational Networks in Primary Elections

Having estimated occupational donor networks in general elections, I next turn to contested primary elections. Three features of primaries may produce larger network premiums than in general elections. First, primary candidates share a party label, leaving occupational ties as a potentially more salient basis for donor differentiation. Second, primaries are lower-information environments, so donors may rely more heavily on existing professional networks and relationships. Third, early contributions are especially important in primaries, making occupational networks potentially more valuable at the start of the campaign.

I estimate the primary-election analogue of the general-election network premium. The sample includes contested major-party primaries for U.S. House and Senate between 2010 and 2024. I keep candidates who receive at least 5% of the primary vote and retain contests with at least two such candidates. I further restrict to primaries in "winnable seats," where the party's nominee received at least 30% of the two-party vote in the general election, and to candidates who reported positive itemized individual contributions over the cycle. These restrictions remove fringe candidates and nominees from districts where their party had little realistic chance of winning the general election. The more permissive sample, which uses only the 5% vote-share floor, is reported in Appendix A.5.

To estimate the primary-election network premium, I adapt the general-election design to the multi-candidate structure of primaries. Because several candidates in the same primary can share an occupation, I group candidates in each contest who share a given occupation into a *matched group*. For each contest c and donor pool g with at least one matched candidate, I construct two shares: the matched group's share of contributions from pool g, and its share of all other donor dollars in the contest. Stacking these as two rows per contest-pool, indexed by source $s \in \{\text{own}, \text{other}\}$, I estimate

$$Y_{cgs} = \beta\, \mathbf{1}[s = \text{own}] + \gamma_{q(c)g} + \delta_{a(c)g} + \varepsilon_{cgs},$$

Here, Y_{cgs} is the matched group's share of contributions on the own-pool row and its share of all other donor dollars on the other row. The fixed effects $\gamma_{q(c)g}$ and $\delta_{a(c)g}$ absorb district-party-by-pool and party-year-by-pool means. Standard errors are clustered by contest. The coefficient β is the network premium: the average amount by which the matched group's share of its own donor pool exceeds its share of all other donors in the same contest.[3]

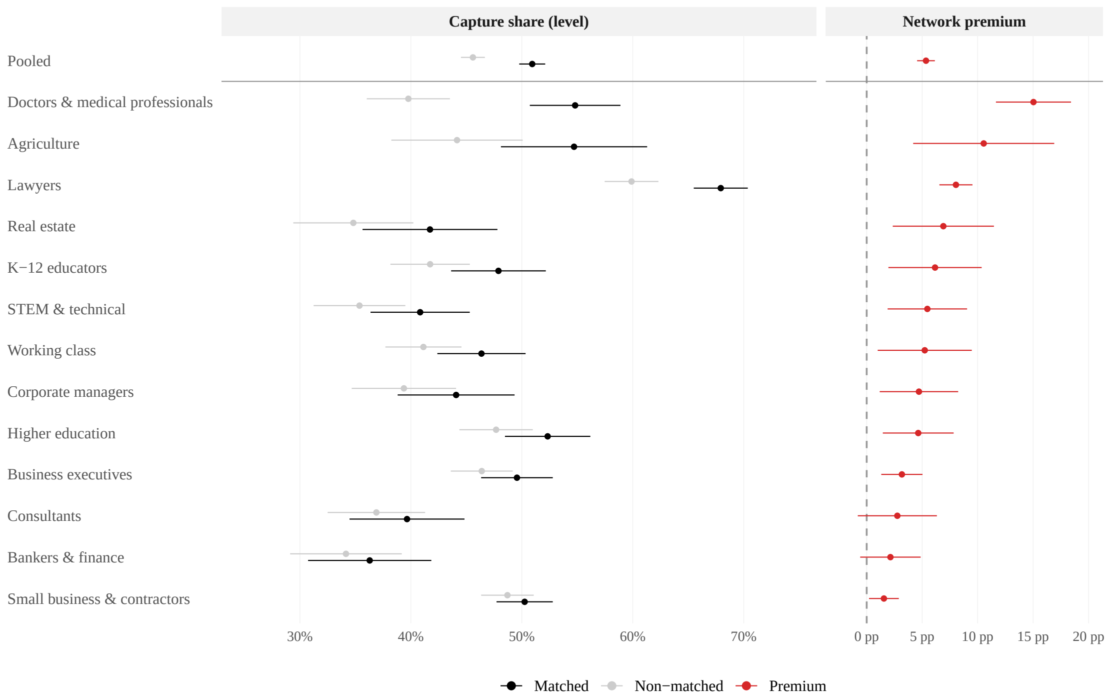
Figure 3 reports the pooled and per-pool estimates. In contested primaries, matched candidates capture a larger share of their own occupational donor pool than of all other donor dollars. Pooled across the 13 pools, they capture about 48% of their own pool's contributions, compared with about 43% of all other donor dollars in the same contest, a network premium of about 5.7 percentage points. The premium is already present in the first 90 days of the cycle, at about 7.0 percentage points, when early money is an especially important signal of candidate viability (Thomsen, 2025). The premium is somewhat larger in open-seat primaries, where no incumbent of either party is running, at about 6.8 percentage points. It is larger than the pooled general-election premium of about 3.2 percentage points, consistent with the possibility that occupational affinity

[3] The estimand conditions on contest-pool cells with at least one matched candidate, so it describes matched-group over-capture rather than the effect of a candidate's entry into the race. Grouping same-occupation candidates avoids the mechanical attenuation that would otherwise arise from dividing a single donor pool among several matched candidates. An alternative per-candidate specification reaches the same conclusion; see Appendix A.5.9.

matters more in primary donor decisions.

Figure 3 reports the premium separately by occupation. Nearly all occupational groups benefit from a network premium, but the effect sizes vary substantially. For example, matched lawyer-candidates capture about 66% of contributions from lawyer donors in their contests, compared with about 57% of all other donor dollars, a 9-percentage-point premium. The largest premiums are for doctors and medical professionals (about 16 percentage points), candidates from agricultural occupations (about 11 points), and lawyers (about 9 points). Real estate, K–12 educators, STEM professionals, working-class candidates, corporate managers, and higher-education professionals fall between about 4.5 and 7 points. The smallest premiums, among business executives, consultants, bankers, and small business owners, range from about 1.5 to 3 points and are not always distinguishable from zero.

Figure 3: Estimated network premium by occupation, primary elections.



Notes: Contested major-party congressional primaries, 2010–2024; candidates above the 5% vote-share floor, in primaries whose winner received at least 30% of the two-party vote in the general election, restricted to candidates with positive itemized individual contributions; 13 occupational donor pools. Each estimate is the matched-group network premium (β): matched candidates' share of their own occupational donor pool minus their share of all other donor dollars in the contest. The pooled estimate appears at the top. 95% confidence intervals; standard errors clustered by contest.

These results are robust to alternative estimating choices. The premium is unchanged whether I use cross-cycle or within-contest fixed effects. An alternative per-candidate specification, which measures each matched candidate's own-versus-other capture without grouping, yields a similar pooled premium of about 4.8 percentage points. The result also holds when I account for candidates with multiple occupations and when I exclude the small number of contest-pools in which several candidates share an occupation. Full estimates appear in Appendix A.5.

6 Occupational Networks and Overall Fundraising

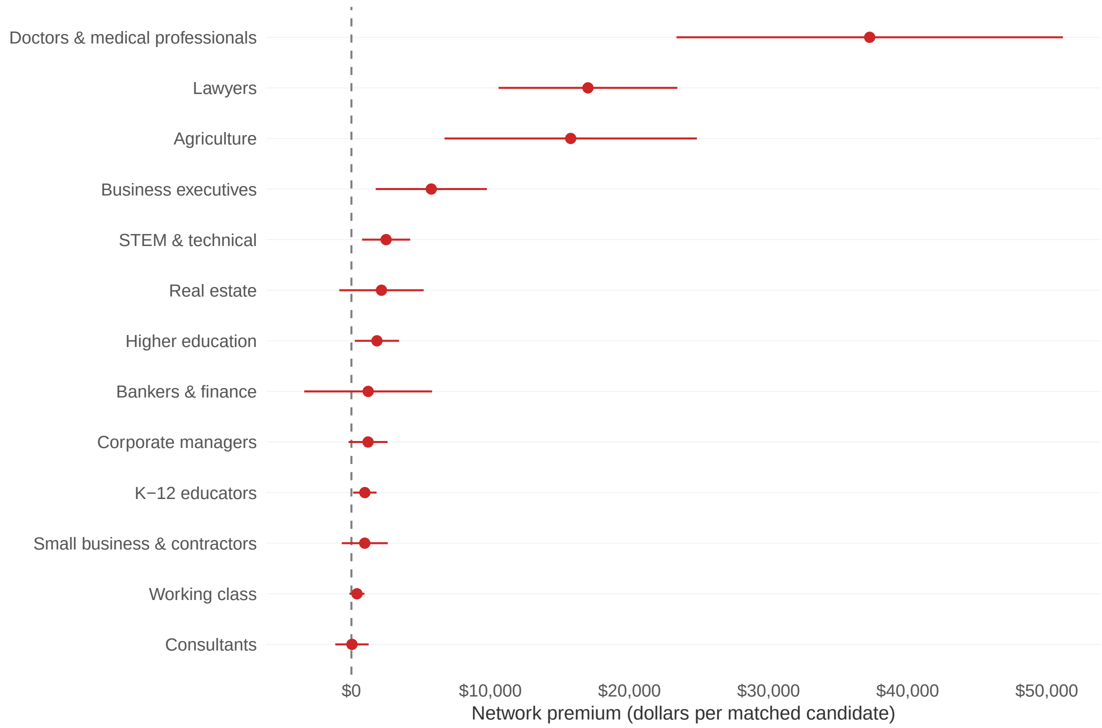
The estimates above show that candidates raise disproportionately more from donors who share their occupation. Whether this translates into a substantial fundraising advantage depends both on the size of the network premium and on the size of the donor pool to which it applies. How much do occupational donor networks contribute to fundraising in dollar terms, and how does this vary across occupations?

I restrict this section to open-seat primaries: contests in districts where no incumbent is running in either party. Incumbents raise more money for reasons unrelated to their occupation, and restricting to open seats removes this confound from the dollar estimates. The network premium for contests with same-party and opposite-party incumbents appears in Appendix A.6.

For each occupational donor pool, I estimate the dollar value of occupational donor networks directly from the contribution data. A matched candidate's dollar premium is the money they raise from their own occupational pool above what their general fundraising rate would predict: their actual own-pool receipts minus their share of all other donors applied to that pool. I compute this quantity for each matched candidate and average it within each occupational pool. To gauge substantive importance, I also express the premium relative to the total individual contributions raised by a typical candidate from that occupation.

Figure 4 reports the dollar premium by pool. It is largest for doctors and medical professionals (about $41,000), lawyers (about $16,000), and agriculture (about $14,000). Business executives are next, at about $4,500; for the remaining occupations it is under $3,500, and for working-class candidates it is near zero. Relative to total fundraising, the premium matters most for doctors, where it is about 8% of what a typical doctor-candidate raises; for lawyers it is about 2%, because lawyers raise so much overall that even a $16,000 premium is a small share of their total. The dollar premium reflects both the size of the share premium and the size of the donor pool. Occupations such as medicine combine large premiums with large donor pools, producing substantial dollar advantages, while occupations with smaller premiums, smaller pools, or both gain much less.

Figure 4: Dollar premium by occupation, open-seat primaries.



Notes: Per-pool dollar premium: each matched candidate's own-pool receipts minus their general-fundraising-rate counterfactual (their share of all non-pool donors applied to the pool), averaged across matched candidates. Open-seat primaries (no incumbent of either party running in the district), above the 5% vote-share floor, in contests whose winner received at least 30% of the two-party vote in the general election, restricted to candidates with positive itemized individual contributions; 13 occupational donor pools, 2010–2024 (476 open-seat contests). 95% confidence intervals; standard errors clustered by contest.

Applying the same dollar-premium construction to contested general elections yields far smaller premiums relative to candidates' total fundraising. The general-election dollar premium is largest for lawyers, at about $12,000, and smaller for every other occupation. Because general-election candidates raise much more than primary candidates, even the lawyer premium is only about 1.5% of a typical general-election lawyer-candidate's total individual fundraising; for every other occupation, it is below 1%. The per-occupation general-election figures appear in Appendix Figure A.16. In dollar terms, occupational networks matter far less in general elections than in primaries.

The dollar premium captures the matched candidate's own fundraising gain. A related question is how much occupational networks shift the fundraising balance within a primary. Because candidates compete for many of the same donors, occupational over-capture by matched candidates is accompanied by lower pool capture among their rivals. Measured as the gap between matched candidates' dollar premium and their rivals' corresponding shortfall, the within-primary balance shift is about $64,000 for doctors, $34,000 for lawyers, and $23,000 for candidates from agricultural occupations. The full construction appears in Appendix A.6.5.

Occupational networks thus deliver unequal fundraising advantages across occupations. Candidates from medicine, law, and agricultural occupations gain tens of thousands of dollars from same-occupation donors, while candidates from occupations with smaller donor pools gain little or nothing. The largest fundraising advantages accrue to candidates from a small set of high-donating occupations.

7 Conclusion

This paper asks whether occupational donor networks shape fundraising in congressional elections. Using new data on the occupational backgrounds of congressional candidates and the self-reported occupations of itemized donors, I show that candidates capture a larger share of contributions from donors who share their occupation than from other donors. This pattern appears in both general and primary elections.

The fundraising consequences of these networks vary across occupations. Occupational networks differ both in the share premium candidates receive from same-occupation donors and in the size of the donor pools to which those premiums apply. As a result, candidates from medicine, law, and agricultural occupations gain tens of thousands of dollars from same-occupation donors in open-seat primaries, while candidates from working-class occupations gain little.

As a share of a candidate's fundraising, these premiums are modest. Yet the fact that they appear at all is notable. Candidates often have multiple occupational backgrounds, occupational classifications are necessarily imperfect, and fundraising is shaped by many considerations besides occupational affinity, including party, viability, endorsements, and name recognition. Even in that environment, donors remain more likely to support candidates who share their occupational background.

These findings extend work on occupational inequality in candidate emergence (Carnes, 2013, 2018) and unequal access to campaign money (Bouton et al., 2022; Thomsen, 2025) by showing how the two are connected through occupational donor networks. Occupational background shapes access to donor networks, but those networks operate within a campaign finance system already structured by unequal capacity to give. The largest fundraising advantages accrue to candidates from a small set of high-donating occupations, many of which are already well represented among congressional candidates.

References

Abbott, Jared and Fred DeVeaux. 2026. "What Happens When Working-Class Candidates Run for Office?" Manuscript under review.

Bonica, Adam. 2020. "Why Are There So Many Lawyers in Congress?" *Legislative Studies Quarterly* 45(2):253–289.

Bonica, Adam. 2024. "Database on Ideology, Money in Politics, and Elections: Public version 4.0.". [Computer file].
URL: *https://data.stanford.edu/dime*

Bonica, Adam and Jacob M. Grumbach. 2025. "Old Money: Campaign Finance and Gerontocracy in the United States." *Journal of Public Economics* 249:105451.

Bouton, Laurent, Julia Cagé, Edgard Dewitte and Vincent Pons. 2022. Small Campaign Donors. Working Paper 30050 National Bureau of Economic Research.

Carnes, Nicholas. 2013. *White-Collar Government: The Hidden Role of Class in Economic Policy Making.* Chicago Studies in American Politics Chicago: The University of Chicago Press.

Carnes, Nicholas. 2018. *The Cash Ceiling: Why Only the Rich Run for Office–and What We Can Do about It.* Number 16 *in* "Princeton Studies in Political Behavior" Princeton, NJ: Princeton University Press.

Grumbach, Jacob M., Alexander Sahn and Sarah Staszak. 2022. "Gender, Race, and Intersectionality in Campaign Finance." *Political Behavior* 44(1):319–340.

Thomsen, Danielle M. 2025. "Early Money and Strategic Candidate Exit." *British Journal of Political Science* 55:e101.

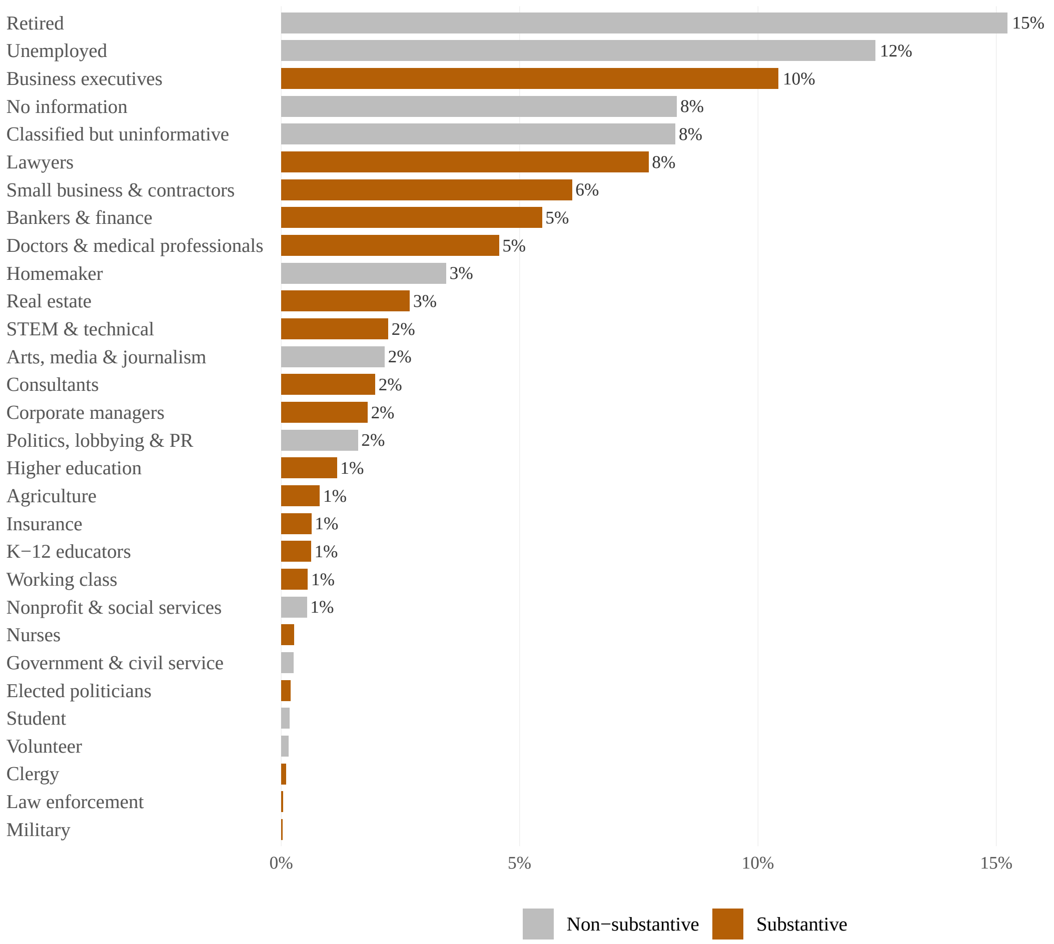
Online Appendix: Occupational Donor Networks in Congressional Elections

Appendix Contents

A.1 Full Occupational Distribution

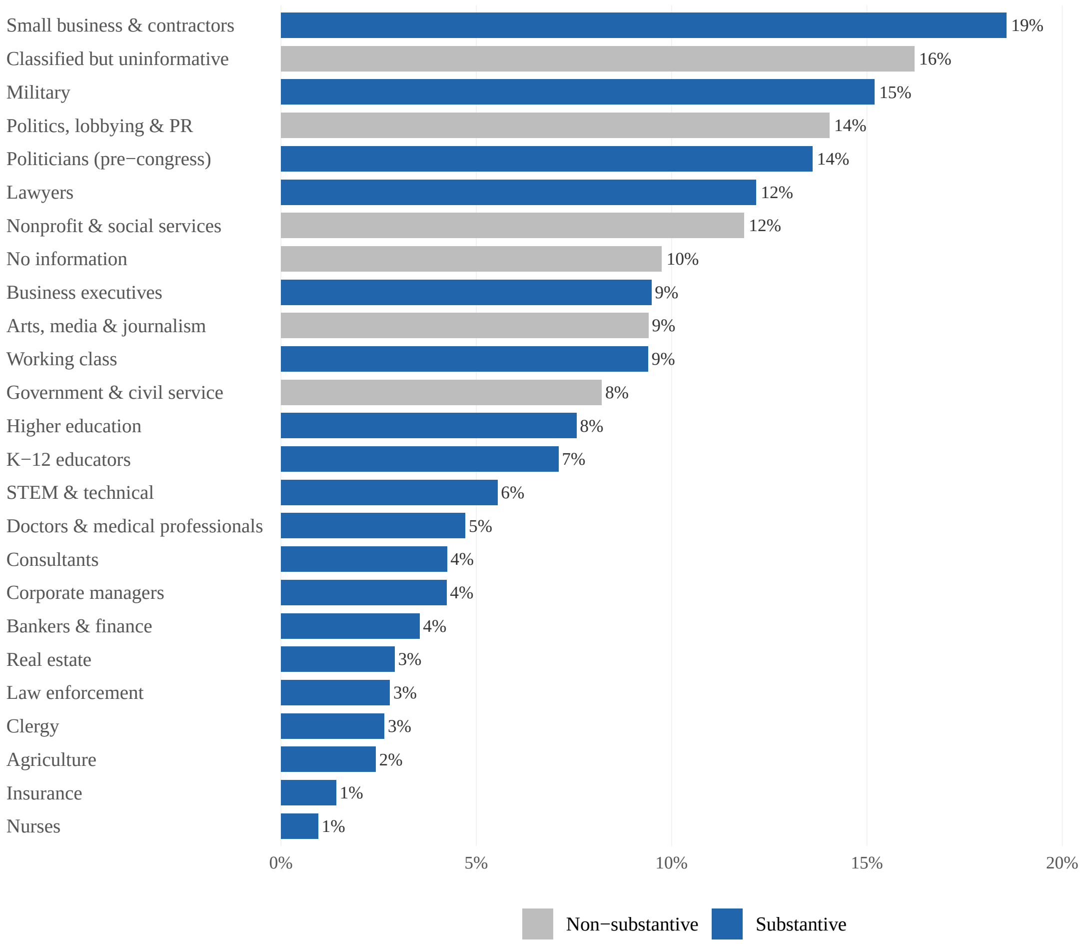
These two figures report the full occupational distribution of donors and of candidates. The first shows each occupation's share of itemized donor dollars; the second, each occupation's share of candidates. Both cover every occupational group, not only the 13 main pools in Figure 1. Two grey categories have no occupational pool: *No information* (a blank field) and *Classified but uninformative* (a string too vague to map, such as "business").

Figure A.1: Donor occupational distribution, all donor groups.



Notes: Share of total primary-stage itemized donor $ in the universe of major-party congressional primaries 2010–2024 (excl. CA, WA, LA). The 13 occupational donor pools (orange) account for 46% of total primary-stage itemized donor $; all other categories (grey), which include substantive occupations outside the 13 focal pools, non-employment statuses such as retired or unemployed, and blank or uninformative strings, account for the remaining 54%.

Figure A.2: Candidate occupational distribution, all candidate groups.



Notes: Share of candidates with each occupation, over all major-party candidates who ran in primaries 2010–2024; general-election nominees are a subset. Non-exclusive. Occupational groups in blue; categories without an occupational mapping in grey.

A.2 Candidate Occupation Mapping

The 13 occupations analyzed in the paper appear first; the remaining categories are grouped under "Other" and are not modeled separately, because their donor pools are too small, too coarse, or not coherent enough to estimate as occupational networks.

Table A.1: Detailed candidate occupations grouped by main category (2010–2024).

Main group	Detailed occupation	N candidates
Headline analytical pools		
Agriculture	Farmer; rancher; farm owner; ranch owner	214
	Farm manager	16
Bankers & finance	Bank manager/investment banker/stock broker	161
	Accountant	112
	Bank owner/banker	59
	Economist (nonacademic)	24
Business executives	Executive of a medium- or large-sized business	604
	Owner of a medium- or large-sized business	238
	Media executive; publisher; or media owner	105
Consultants	Other consultant	265
	Leadership or management consultant	139
Corporate managers	Manager in a medium- or large-sized business	388
Doctors & medical professionals	Medical doctor	237
	Hospital/medical services administrator	103
	Scientific or health care consultant	85
	Psychiatrist/psychologist	27
	Dentist	19
	Pharmacist	15
	Veterinarian	11
Higher education	College professor (except law schools)	491
	College administrator	189
	Law school professor	64
K-12 educators	Elementary or secondary school teacher	590
	Elementary or secondary school administrator	105
Lawyers	Lawyer; private practice	503
	Government attorney	440
	Lawyer; unspecified	430
	Lawyer; other	187
	Lawyer; corporate	97
Real estate	Real estate agent or broker	190
	Real estate developer	99
STEM & technical	Engineer/scientist (nonacademic)	379
	Other technical professional	138
	Architect or urban planner	15
Small business & contractors	Owner of a small/local business	1,554
	Manager of a small/ local business	159
	Contractor	72
Working class	Service industry worker	468
	Manual laborer	414
	Union employee/official	83
	Other working-class	27
Other		
Elected politicians	Officeholder: state government	998
	Officeholder: local government	884
Clergy	Rabbi; minister; priest; reverend; or other clergy	241
Law enforcement	Law enforcement officer or patrolman	189
	Law enforcement manager/director	81
	Law enforcement analyst	44
Military	Military service member	1,384
Nurses	Nurse	87
Arts, media & journalism	Author/public speaker	367
	Journalist	249
	Musician/entertainer	156
	Coach; fitness instructor; or referee	121
	Actor/director	71
	Athlete	69
	Artist/director	1

continued on next page

Table A.1 continued

Main group	Detailed occupation	N candidates
Classified but uninformative	Business employee	850
	Business person (no other information given)	291
	Provider of other local public services	266
	Other occupation	196
	Chamber of Commerce or Jaycees leader	87
Government & civil service	Government Employee / Civil Servant	749
Nonprofit & social services	Nonprofit service group director or executive	807
	Nonprofit service group worker	286
	Social worker	84
	Advocate for the elderly	23
	Librarian	10
Politics, lobbying & PR	Political staffer	586
	Interest group director; executive; founder	502
	Politics; government; or public relations consultant	217
	Interest group worker	207
	Interest group lobbyist	56

Notes to Table A.1: Detailed occupational categories are an expanded version of the 67-category occupational scheme in Carnes (2013), grouped by main occupational pool. *N candidates* counts unique candidates in the universe (9,110 candidates / 12,176 candidate-years; major-party congressional primaries 2010–2024, excluding CA, WA, and LA) with each category listed in their occupational history. A single candidate can appear in multiple categories. The 13 occupational donor pools used in the main analysis appear first; remaining categories are grouped under "Other".

A.3 Donor Occupation Mapping

Each donor pool is built by classifying the free-text occupation and employer strings donors report on their contributions.

Table A.2: Top contributing donor occupation strings per main group (DIME, 2010–2024).

Main group	Donor occupation string	$ contributed	% of group $
Business executives	ceo [employer]	$259.1M	20%
	executive [employer]	$211.8M	17%
	president [employer]	$203.3M	16%
	chairman [employer]	$115.9M	9%
	owner [employer]	$62.9M	5%
Lawyers	attorney	$741.0M	77%
	lawyer	$132.3M	14%
	partner [employer]	$21.6M	2%
	general counsel	$6.5M	1%
	attorney at law	$4.3M	0%
Small business & contractors	owner [employer]	$162.2M	22%
	president [employer]	$115.2M	15%
	ceo [employer]	$101.0M	13%
	contractor	$28.4M	4%
	business owner [employer]	$27.2M	4%
Bankers & finance	investor	$159.4M	23%
	finance	$67.9M	10%
	banker	$37.6M	5%
	investments	$35.9M	5%
	cpa	$34.6M	5%
Doctors & medical professionals	physician	$262.0M	44%
	dentist	$23.9M	4%
	psychologist	$22.7M	4%
	doctor	$19.4M	3%
	md	$17.6M	3%
STEM & technical	engineer	$95.9M	26%
	software engineer	$35.2M	10%
	architect	$23.9M	7%
	scientist	$18.8M	5%
	software developer	$8.5M	2%
Real estate	real estate	$133.9M	39%
	realtor	$44.1M	13%
	real estate developer	$30.4M	9%
	real estate broker	$23.8M	7%
	real estate investor	$16.1M	5%
Consultants	consultant [employer]	$123.2M	48%
	consulting	$8.0M	3%
	principal [employer]	$7.2M	3%
	management consultant	$6.5M	3%
	partner [employer]	$5.4M	2%
Corporate managers	manager [employer]	$64.2M	27%
	vice president [employer]	$14.3M	6%
	management [employer]	$12.6M	5%
	general manager	$10.1M	4%
	business manager	$5.9M	2%
Higher education	professor	$95.1M	54%
	president [employer]	$4.5M	3%
	law professor	$4.2M	2%
	instructor	$3.8M	2%
	administrator [employer]	$3.3M	2%
Agriculture	farmer	$52.7M	46%
	rancher	$16.1M	14%
	owner [employer]	$7.6M	7%
	agriculture	$3.4M	3%
	farming	$2.8M	2%
K-12 educators	teacher	$60.5M	64%
	educator	$18.0M	19%
	retired teacher	$3.3M	4%
	substitute teacher	$1.7M	2%
	music teacher	$1.0M	1%

continued on next page

Table A.2 continued

Main group	Donor occupation string	$ contributed	% of group $
Working class	truck driver	$4.5M	5%
	driver	$3.9M	4%
	electrician	$3.7M	4%
	carpenter	$2.3M	3%
	caregiver	$2.3M	3%

Notes to Table A.2: Top five donor occupation strings by total contribution dollars within each of the 13 occupational donor pools, pooled across the 2010–2024 cycles. Strings with the suffix "[employer]" are ambiguous positions (e.g., president, CEO) whose pool assignment depends on the donor's employer; the dollar amount shown is the portion of that position's giving routed to this pool. Pools are ordered by total donor dollars descending; within each pool, strings are ordered by their contribution to that pool's total.

A.4 General Election Network Premium: Robustness

This appendix documents the composition of the estimation sample, reports the regression tables behind Figure 2, and presents heterogeneity, robustness, and identification checks.

A.4.1 Treatment composition

Table A.3 reports how estimation-sample races distribute across the four categories of the candidate-occupation gap. For each donor pool, a race is coded +1 when only the Democratic nominee has the occupation, −1 when only the Republican does, and 0 when both or neither do. The +1 and −1 races identify the network premium; both- and neither-occupation races enter the baseline.

Table A.3: Treatment composition by occupation.

Occupation	Dem only (+1)	Rep only (−1)	Both (0)	Neither (0)	Total
Lawyers	700	361	150	1,645	2,856
Small business & contractors	340	718	168	1,606	2,832
Business executives	310	382	67	2,081	2,840
Higher education	415	186	37	1,985	2,623
Working class	294	193	38	1,942	2,467
K-12 educators	340	101	22	2,040	2,503
Doctors & medical professionals	131	230	14	2,470	2,845
STEM & technical	171	137	9	2,429	2,746
Consultants	139	133	12	2,480	2,764
Corporate managers	112	149	4	2,473	2,738
Bankers & finance	76	132	8	2,596	2,812
Real estate	76	110	2	2,555	2,743
Agriculture	59	112	9	2,041	2,221

Notes to Table A.3: Counts of estimation-sample races (those in which the donor pool has positive contributions) by treatment type, for each of the 13 occupational donor pools. Dem only (+1): only the Democratic nominee has the occupation; Rep only (−1): only the Republican does; Both and Neither (0): both or neither nominee has the occupation. Contested major-party general elections, 2010–2024.

A.4.2 Pooled and per-pool regression tables

Table A.4 reports the coefficients behind the pooled estimate in Figure 2: the matched effect on the candidate's own donor pool, the non-matched effect on all other donor dollars in the race, and the network premium (matched minus non-matched). Table A.5 reports the same three quantities estimated separately for each of the 13 occupational donor pools.

Table A.4: Estimated effect of occupational match, pooled.

Quantity	$\hat{\beta}$ (SE)	95% CI	N
Matched	0.025*** (0.006)	[0.013, 0.037]	—
Non-matched	-0.007 (0.005)	[-0.016, 0.002]	—
Premium	0.032*** (0.005)	[0.023, 0.041]	—

Notes to Table A.4: Matched = the candidate's share of contributions from their own occupational donor pool; non-matched = their share of all other donor dollars in the race; premium = matched − non-matched. Contested major-party general elections, 2010–2024; 13 occupational donor pools. 95% confidence intervals; standard errors clustered by redistricted district. * $p < .05$, ** $p < .01$, *** $p < .001$.

Table A.5: Estimated effect of occupational match, by donor pool (general elections).

Donor pool / Quantity	$\hat{\beta}$ (SE)	95% CI	p-value
Doctors & medical professionals			
Matched	0.069* (0.027)	[0.016, 0.123]	0.011
Non-matched	-0.025 (0.022)	[-0.068, 0.017]	0.245
Premium	0.095*** (0.016)	[0.064, 0.126]	0.000
Higher education			
Matched	0.077*** (0.021)	[0.036, 0.119]	0.000
Non-matched	-0.006 (0.017)	[-0.038, 0.027]	0.736
Premium	0.083*** (0.019)	[0.046, 0.119]	0.000
Lawyers			
Matched	0.093*** (0.014)	[0.065, 0.122]	0.000
Non-matched	0.036** (0.012)	[0.012, 0.060]	0.003
Premium	0.057*** (0.009)	[0.040, 0.075]	0.000
Agriculture			
Matched	-0.007 (0.039)	[-0.084, 0.070]	0.861
Non-matched	-0.059* (0.027)	[-0.111, -0.007]	0.027
Premium	0.052 (0.035)	[-0.017, 0.121]	0.142
Working class			
Matched	0.006 (0.026)	[-0.045, 0.056]	0.830
Non-matched	-0.034* (0.015)	[-0.064, -0.004]	0.025

continued on next page

Table A.5 continued

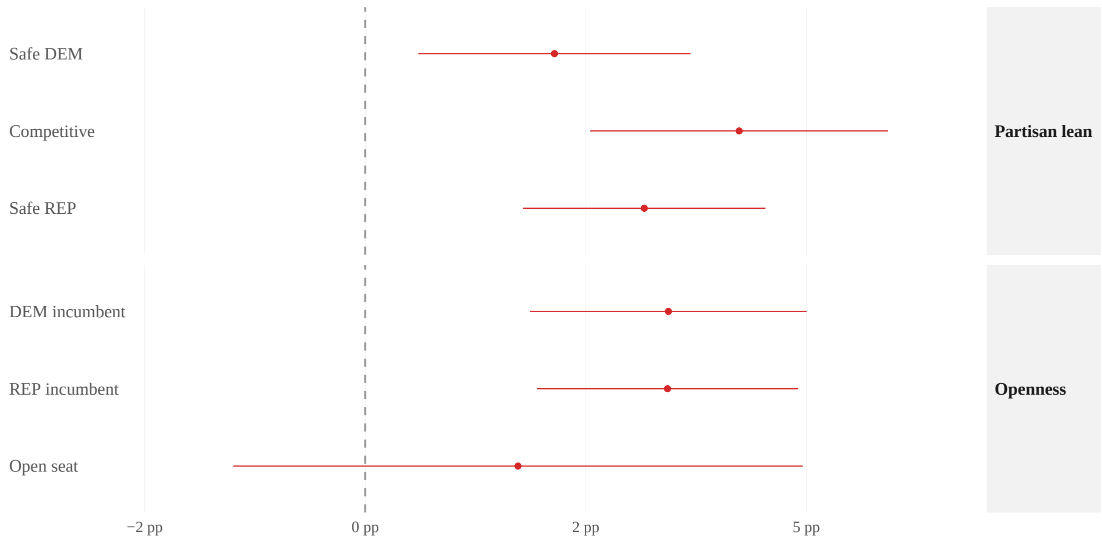
Donor pool / Quantity	$\hat{\beta}$ (SE)	95% CI	p-value
Premium	0.039 (0.022)	[-0.004, 0.083]	0.077
STEM & technical			
Matched	0.035 (0.034)	[-0.031, 0.100]	0.302
Non-matched	-0.004 (0.024)	[-0.050, 0.043]	0.881
Premium	0.038 (0.021)	[-0.003, 0.079]	0.067
Real estate			
Matched	0.047 (0.032)	[-0.016, 0.111]	0.143
Non-matched	0.017 (0.027)	[-0.037, 0.071]	0.532
Premium	0.030 (0.025)	[-0.018, 0.079]	0.218
Consultants			
Matched	0.026 (0.027)	[-0.028, 0.080]	0.342
Non-matched	-0.001 (0.023)	[-0.047, 0.045]	0.966
Premium	0.027 (0.018)	[-0.008, 0.061]	0.126
K-12 educators			
Matched	-0.015 (0.024)	[-0.063, 0.033]	0.534
Non-matched	-0.039* (0.018)	[-0.074, -0.005]	0.026
Premium	0.024 (0.023)	[-0.020, 0.068]	0.288
Bankers & finance			
Matched	-0.008 (0.027)	[-0.062, 0.046]	0.769
Non-matched	-0.031 (0.021)	[-0.072, 0.010]	0.136
Premium	0.023 (0.017)	[-0.011, 0.057]	0.182
Business executives			
Matched	0.024 (0.014)	[-0.003, 0.051]	0.086
Non-matched	0.021 (0.015)	[-0.008, 0.050]	0.147
Premium	0.002 (0.011)	[-0.020, 0.025]	0.824
Small business & contractors			
Matched	-0.023* (0.011)	[-0.045, -0.001]	0.044
Non-matched	-0.022 (0.011)	[-0.044, 0.000]	0.053
Premium	-0.001 (0.009)	[-0.018, 0.016]	0.908
Corporate managers			
Matched	-0.037 (0.026)	[-0.088, 0.014]	0.154
Non-matched	-0.017 (0.019)	[-0.054, 0.020]	0.376
Premium	-0.020 (0.020)	[-0.058, 0.018]	0.300

Notes to Table A.5: Same regression as Table A.4, estimated separately for each of the 13 occupational donor pools. Same fixed effects and clustering as Table A.4. $^{*}\, p < .05$, $^{**}\, p < .01$, $^{***}\, p < .001$.

A.4.3 Heterogeneity: partisan lean and openness

Figure A.3 re-estimates the network premium on subsets of races defined by district partisan lean (the district's average Democratic presidential voteshare over the redistricting period) and by openness (whether the seat had an incumbent). The premium is positive and statistically significant in every subset except open seats: it ranges from 2.1 to 4.2 percentage points across the partisan-lean bins and is 3.4 points in incumbent-held races, against 1.7 points in open seats.

Figure A.3: Network premium by district partisan lean and openness.

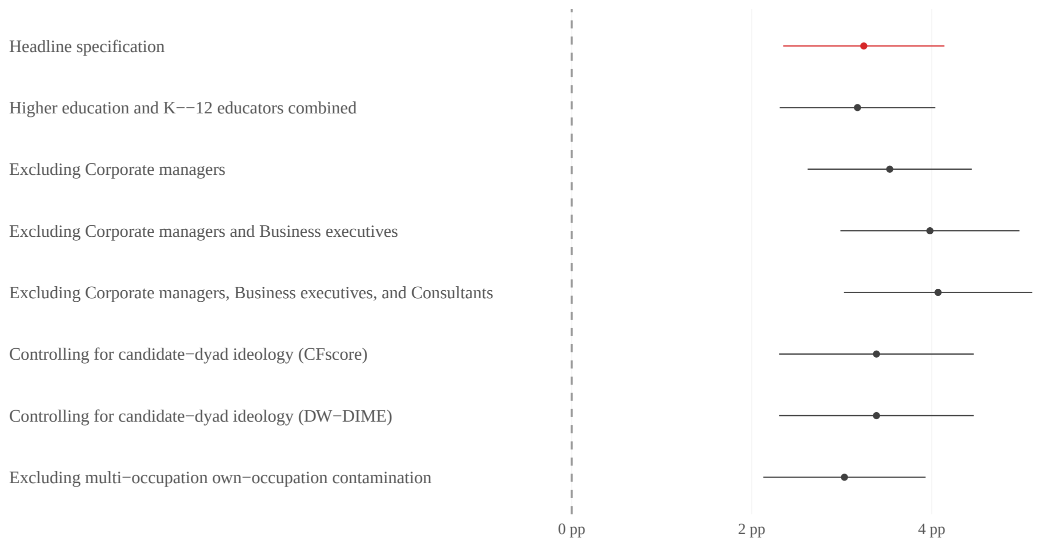


Notes: Network premium (matched − non-matched) re-estimated on subsets of races. Top: by district partisan lean, the district's average Democratic two-party presidential voteshare over the redistricting period (Safe Democratic > 55%; Competitive 45–55%; Safe Republican < 45%). Bottom: by whether the seat had a Democratic incumbent, a Republican incumbent, or no incumbent. 95% confidence intervals; standard errors clustered by redistricted district. Same fixed-effect structure as the main pooled specification.

A.4.4 Robustness across alternative specifications

Figure A.4 re-estimates the pooled network premium under four alternative specifications. The first two test whether the result is sensitive to how the occupational groups are constructed. Collapsing the two education pools (Higher education and K–12 educators) into one leaves the premium unchanged at 3.2 percentage points. Progressively dropping the three broad business and managerial pools (Corporate managers, then also Business executives, then also Consultants), which aggregate heterogeneous roles rather than a single profession and are the least likely to form a coherent occupational network, raises the premium to between 3.5 and 4.1 points; the headline, which retains these pools, is if anything conservative. The third adds controls for the ideological midpoint and distance between the two nominees (CFscore or DW-DIME), testing whether co-occupational giving merely reflects ideological proximity; the premium holds at 3.4 points. The fourth strips each nominee's other matched-occupation pools out of the non-matched baseline, so a candidate with several occupations does not have their other networks inflate the comparison; the premium is 3.0 points, against 3.2 in the headline.

Figure A.4: Estimated effect of occupational match, across robustness specifications.

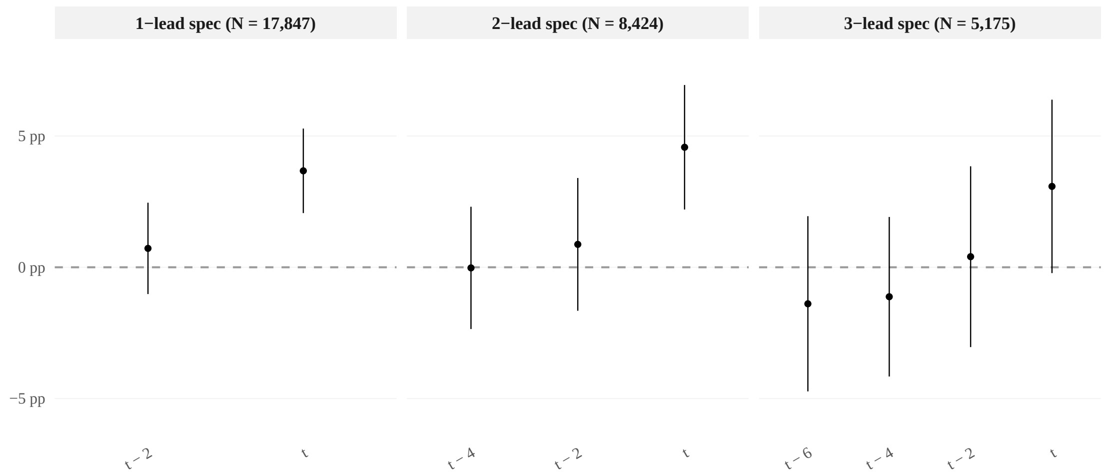


Notes: Pooled network premium (matched − non-matched) re-estimated under alternative specifications. Main specification in red. Subsequent rows: combining the two education pools into one; dropping Corporate managers, then also Business executives, then also Consultants from the pool list; adding controls for the candidate-dyad midpoint and ideological distance, using either the CFscore or DW-DIME measure of candidate ideology; and excluding each nominee's other matched-occupation donor pools from the non-matched baseline (multi-occupation correction). 95% confidence intervals; standard errors clustered by redistricted district.

A.4.5 Parallel-trends test

I test the parallel-trends assumption by adding leads of the candidate-occupation match indicator to the main specification, following Grumbach, Sahn and Staszak (2022). If district-pool cells about to be treated were already on different donation trajectories, the lead coefficients would be non-zero. Figure A.5 reports the contemporaneous match alongside leads at two, four, and six cycles before treatment. The contemporaneous match is significant, while the leads are all small and statistically indistinguishable from zero, consistent with parallel pre-treatment trends.

Figure A.5: Parallel-trends test: contemporaneous match and pre-treatment leads.

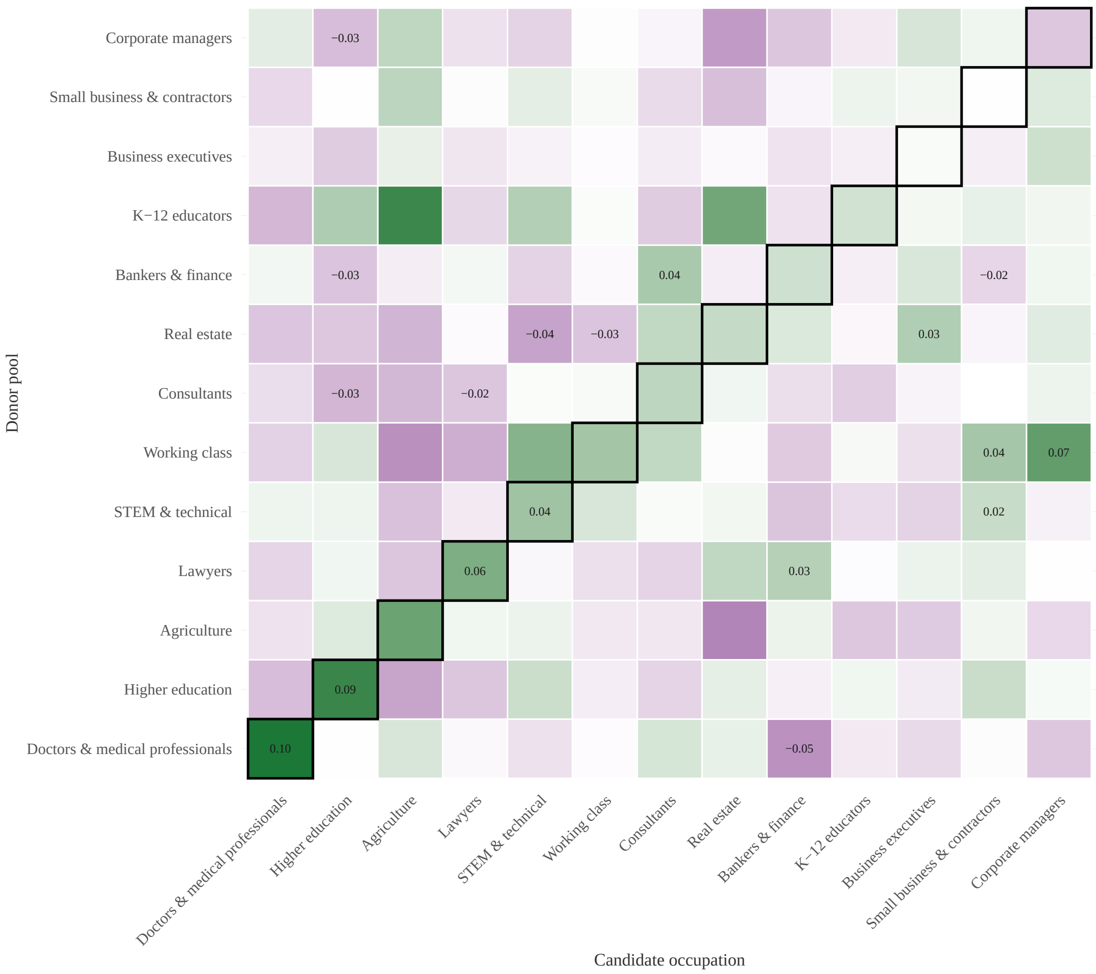


Notes: The main specification with one, two, or three future-cycle leads of the candidate-occupation match indicator added, each estimated as a separate regression. Each additional lead requires the next future cycle's candidate composition to be observed, so sample sizes shrink (1-lead spec $N = 17{,}847$; 2-lead $N = 8{,}424$; 3-lead $N = 5{,}175$). X-axis labels follow standard event-study convention: $t - k$ indicates a donation made k cycles before the matched candidate appears. Same fixed effects and clustering as the main specification. 95% confidence intervals; standard errors clustered by redistricted district.

A.4.6 Cross-pool effects

In Figure A.6 I estimate the network premium of each of the 13 candidate occupations on every donor pool, not only the candidate's own. For each donor pool, the premium is the candidate's share of that pool minus their share of all donors outside it, so general fundraising advantage is differenced out, and each cell reports how a given candidate occupation shifts that premium. The diagonal, where the candidate's occupation matches the donor pool, dominates, while off-diagonal premiums are mostly small or zero: the advantage is occupation-specific rather than a broad elite-occupation network.

Figure A.6: Network premium of each candidate occupation on each donor pool.

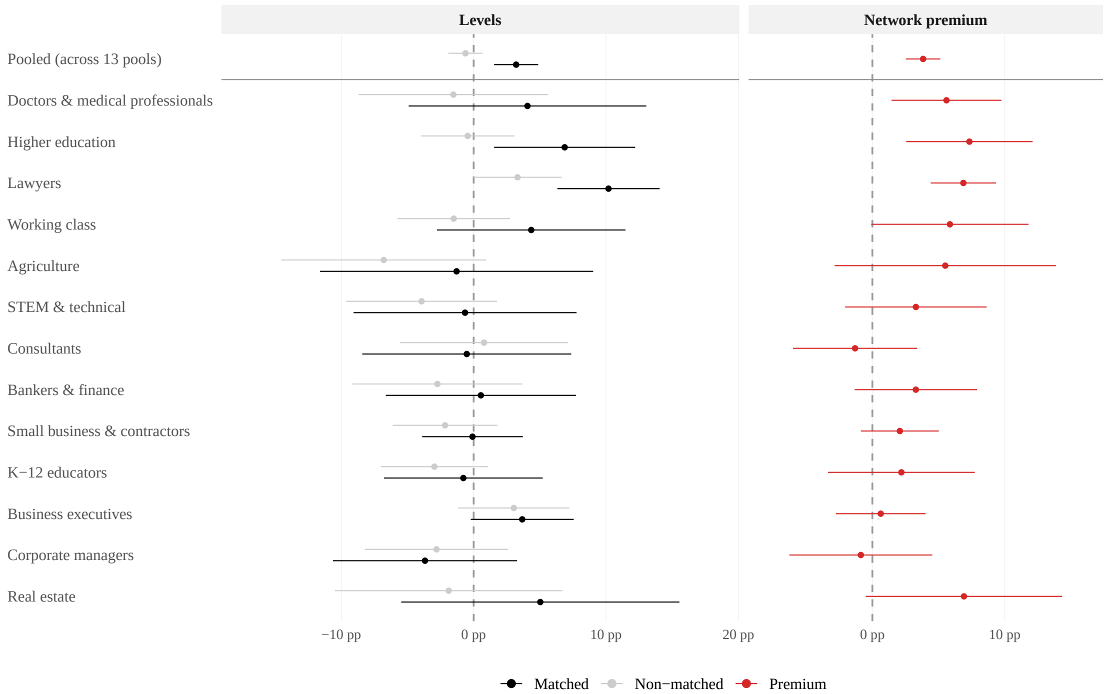


Notes: Rows are donor pools; columns are candidate occupations. For each donor pool, I regress its network premium (the Democratic share of that pool minus the Democratic share of all donors outside it) on indicators for all 13 candidate-occupation matches (coded +1 when only the Democratic nominee has the occupation, −1 when only the Republican does). Each cell is the coefficient on the column occupation; the diagonal is each occupation's premium on its own pool, off-diagonal cells its premium on other pools. Coefficients are shown only for cells significant at the 5% level. Fixed effects: district × chamber + cycle × chamber. Standard errors clustered by redistricted district.

A.4.7 By-party heterogeneity

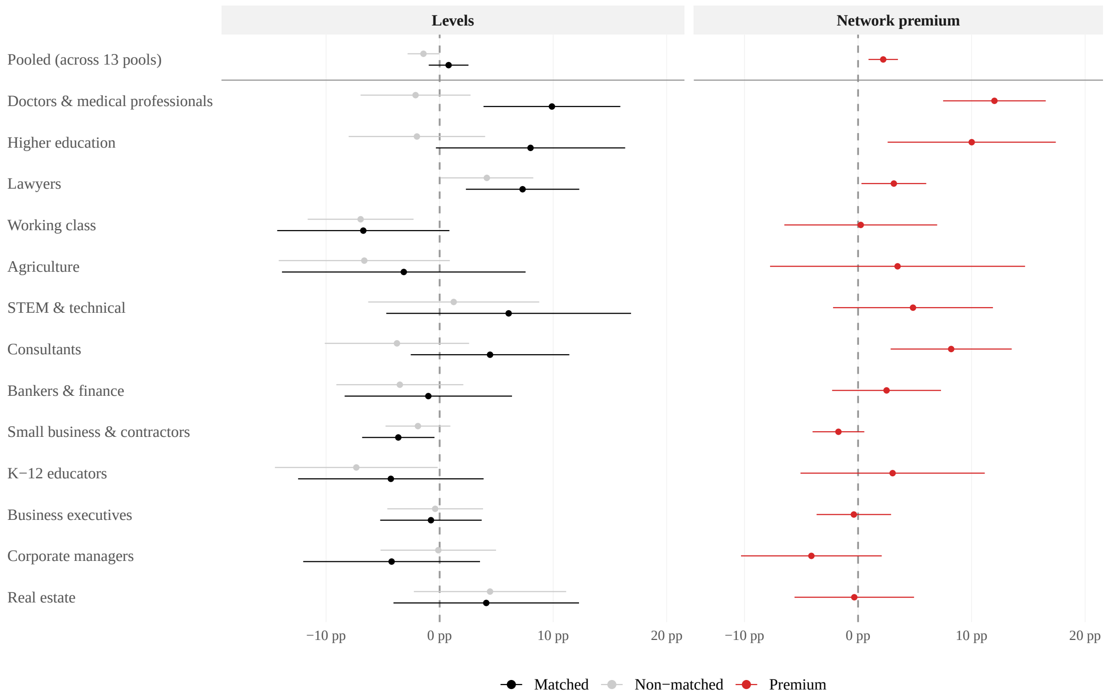
Figures A.7 and A.8 re-estimate the per-pool premium separately on the Democratic-nominee and Republican-nominee samples. Because the pooled specification enters a Republican nominee's occupation with the opposite sign, this separates the two parties; the premium holds for nominees of both, at about 3.8 percentage points for Democratic nominees and 2.2 points for Republican nominees.

Figure A.7: Effect of occupational match on donor-pool capture, Democratic nominees.



Notes: Same regression as Figure 2, estimated on the Democratic-nominee sample (races where the Democratic nominee has the occupation and the Republican does not, plus races where neither nominee does). Matched (black) = share of own-pool dollars; non-matched (light grey) = share of all other donor dollars; premium (red) = matched − non-matched. Pooled estimate is the bottom row, separated by a thin horizontal line. 95% confidence intervals; standard errors clustered by redistricted district.

Figure A.8: Effect of occupational match on donor-pool capture, Republican nominees.



Notes: Same regression as Figure 2, estimated on the Republican-nominee sample (races where the Republican nominee has the occupation and the Democratic does not, plus races where neither does; outcomes computed as the Republican nominee's shares). 95% confidence intervals; standard errors clustered by redistricted district.

A.5 Primary Election Network Premium: Robustness

This appendix documents the composition of the estimation sample, reports the regression tables behind Figure 3, and presents the within-contest specification, heterogeneity, and robustness checks.

A.5.1 Treatment composition

Table A.6 reports how the primary contests in the main analysis sample distribute by the number of candidates holding each occupation. The premium for a pool is identified within the contests where at least one candidate holds that occupation; the matched-group design groups several same-occupation candidates (the final column), avoiding the mechanical attenuation of dividing a pool among them.

Table A.6: Treatment composition by occupation, primaries.

Occupation	No matched candidate	One matched	Two or more matched	Total contests
Small business & contractors	1,021	763	226	2,010
Lawyers	1,234	641	135	2,010
Business executives	1,391	547	72	2,010
Higher education	1,536	433	41	2,010
Working class	1,556	410	44	2,010
K-12 educators	1,617	357	36	2,010
Doctors & medical professionals	1,680	316	14	2,010
STEM & technical	1,720	266	24	2,010
Consultants	1,757	244	9	2,010
Corporate managers	1,774	229	7	2,010
Bankers & finance	1,811	191	8	2,010
Agriculture	1,842	155	13	2,010
Real estate	1,843	159	8	2,010

Notes to Table A.6: Counts of primary contests in the main analysis sample by the number of candidates holding each occupation: none, exactly one, or two or more. The estimation sample is contested major-party primaries above the 5% vote-share floor, whose winner received at least 30% of the two-party vote in the general election, restricted to candidates with positive itemized individual contributions, 2010–2024 (2,010 contests). Candidate occupations are non-exclusive, so a candidate can appear under several occupations.

A.5.2 Pooled and per-pool regression tables

Tables A.7 and A.8 report the coefficients behind Figure 3, pooled and separately for each of the 13 occupational donor pools.

Table A.7: Estimated effect of occupational match, pooled (primaries).

Quantity	$\hat{\beta}$ (SE)		95% CI	N
Matched	0.509***	(0.006)	[0.498, 0.521]	—
Non-matched	0.456***	(0.006)	[0.445, 0.467]	—
Premium	0.053***	(0.004)	[0.045, 0.061]	—

Notes to Table A.7: Matched = candidate's share of contributions from their own occupational donor pool; non-matched = their share of all other donor dollars in the contest; premium = matched − non-matched. Contested major-party primaries above the 5% vote-share floor, where the winner received at least 30% of the two-party vote in the general election, restricted to candidates with positive itemized individual contributions, 2010–2024; 13 occupational donor pools. Specification: cross-cycle within district-party. 95% confidence intervals; standard errors clustered by contest. * $p < .05$, ** $p < .01$, *** $p < .001$.

Table A.8: Estimated effect of occupational match, by donor pool (primary elections).

Donor pool / Quantity	$\hat{\beta}$ (SE)		95% CI	p-value
Doctors & medical professionals				
Matched	0.548***	(0.021)	[0.507, 0.589]	0.000
Non-matched	0.398***	(0.019)	[0.360, 0.435]	0.000
Premium	0.150***	(0.017)	[0.116, 0.184]	0.000
Agriculture				
Matched	0.547***	(0.033)	[0.481, 0.613]	0.000
Non-matched	0.442***	(0.030)	[0.382, 0.501]	0.000
Premium	0.105**	(0.032)	[0.042, 0.169]	0.001
Lawyers				
Matched	0.679***	(0.012)	[0.655, 0.704]	0.000
Non-matched	0.599***	(0.012)	[0.575, 0.623]	0.000
Premium	0.080***	(0.008)	[0.066, 0.095]	0.000
Real estate				
Matched	0.417***	(0.031)	[0.356, 0.478]	0.000
Non-matched	0.348***	(0.027)	[0.294, 0.402]	0.000
Premium	0.069**	(0.023)	[0.023, 0.115]	0.003
K-12 educators				
Matched	0.479***	(0.022)	[0.436, 0.522]	0.000
Non-matched	0.417***	(0.018)	[0.382, 0.453]	0.000
Premium	0.062**	(0.021)	[0.020, 0.104]	0.004
STEM & technical				
Matched	0.408***	(0.023)	[0.364, 0.453]	0.000

continued on next page

Table A.8 continued

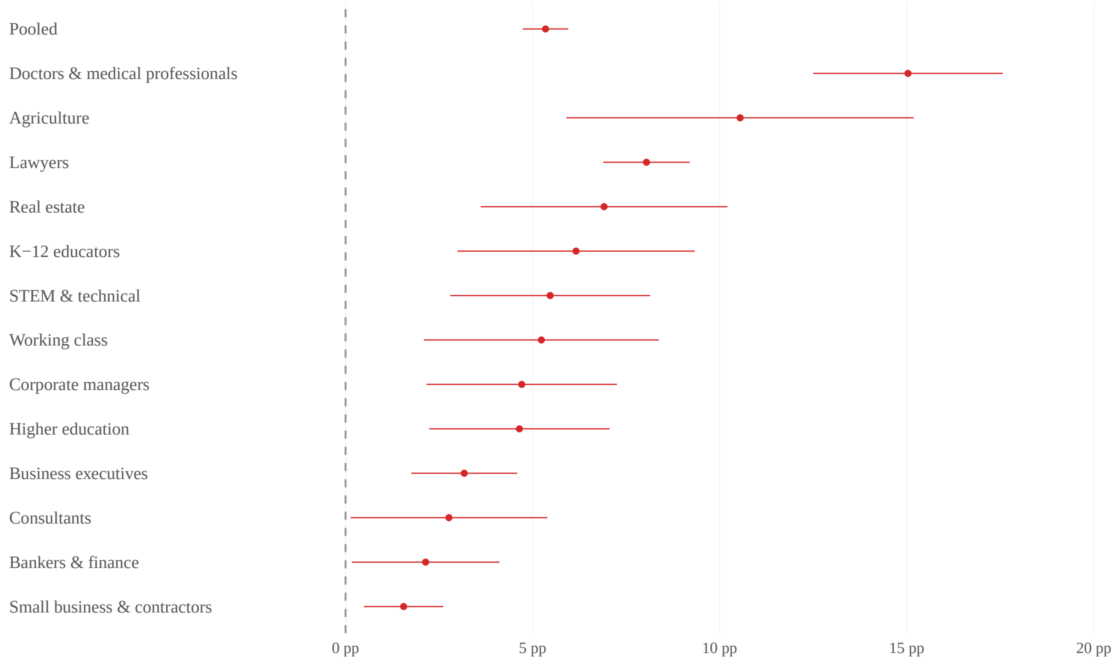
Donor pool / Quantity	$\hat{\beta}$ (SE)		95% CI	p-value
Non-matched	0.354***	(0.021)	[0.312, 0.395]	0.000
Premium	0.055**	(0.018)	[0.019, 0.090]	0.003
Working class				
Matched	0.464***	(0.020)	[0.424, 0.503]	0.000
Non-matched	0.411***	(0.017)	[0.377, 0.446]	0.000
Premium	0.052*	(0.022)	[0.010, 0.095]	0.016
Corporate managers				
Matched	0.441***	(0.027)	[0.388, 0.493]	0.000
Non-matched	0.394***	(0.024)	[0.347, 0.441]	0.000
Premium	0.047**	(0.018)	[0.012, 0.082]	0.009
Higher education				
Matched	0.523***	(0.020)	[0.485, 0.562]	0.000
Non-matched	0.477***	(0.017)	[0.444, 0.510]	0.000
Premium	0.046**	(0.016)	[0.015, 0.078]	0.004
Business executives				
Matched	0.496***	(0.016)	[0.463, 0.528]	0.000
Non-matched	0.464***	(0.014)	[0.436, 0.492]	0.000
Premium	0.032***	(0.009)	[0.013, 0.050]	0.001
Consultants				
Matched	0.397***	(0.026)	[0.345, 0.448]	0.000
Non-matched	0.369***	(0.022)	[0.325, 0.413]	0.000
Premium	0.028	(0.018)	[-0.008, 0.063]	0.128
Bankers & finance				
Matched	0.363***	(0.028)	[0.307, 0.418]	0.000
Non-matched	0.341***	(0.026)	[0.291, 0.392]	0.000
Premium	0.021	(0.014)	[-0.006, 0.049]	0.123
Small business & contractors				
Matched	0.503***	(0.013)	[0.477, 0.528]	0.000
Non-matched	0.487***	(0.012)	[0.463, 0.511]	0.000
Premium	0.016*	(0.007)	[0.002, 0.029]	0.024

Notes to Table A.8: Same regression as Table A.7, estimated separately for each of the 13 occupational donor pools. Same fixed effects and clustering as Table A.7. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

A.5.3 Within-contest specification

Figure A.9 replaces the cross-cycle fixed effects with a single contest-by-pool fixed effect, so the premium is identified entirely within each primary. It is unchanged, at about 5.7 percentage points.

Figure A.9: Network premium, within-contest specification.



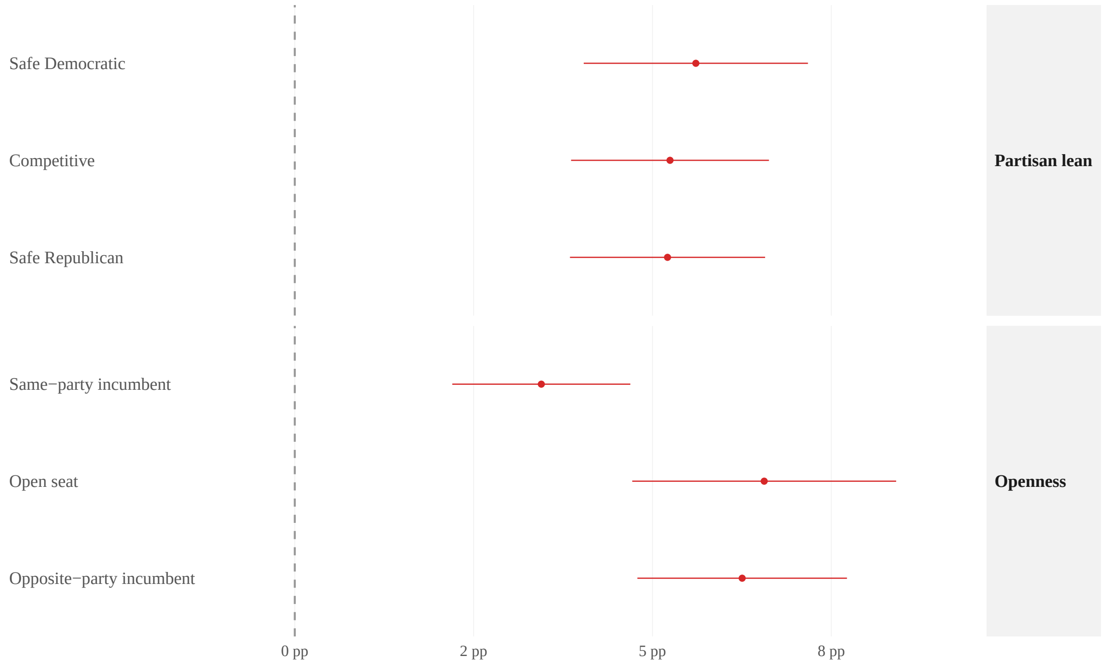
Notes: Same construction as Figure 3, with the cross-cycle district-party-by-pool and party-year-by-pool fixed effects replaced by a single contest-by-pool fixed effect. 95% confidence intervals; standard errors clustered by contest.

A.5.4 Heterogeneity: partisan lean and openness

Figure A.10 re-estimates the network premium on subsets of contests defined by district partisan lean and by openness. The premium is significant in every subset: it is flat across partisan lean (5.5 to 5.7 percentage points) and larger in open-seat contests (6.8 points) than in same-party-incumbent contests (3.6 points).

Following Bonica (2020), I also test whether the network operates where the seat is unwinnable, which a strategic, win-seeking motive cannot explain. Because the main sample screens out the least winnable districts, I use the broader sample above the 5% vote-share floor: the premium is 3.9 percentage points (95% confidence interval [1.5, 6.2]) in districts the party will lose, indistinguishable from 4.4 where the seat is competitive. The persistence of the premium where the general election is out of reach is consistent with affinity rather than an instrumental bet.

Figure A.10: Network premium by district partisan lean and openness, primaries.

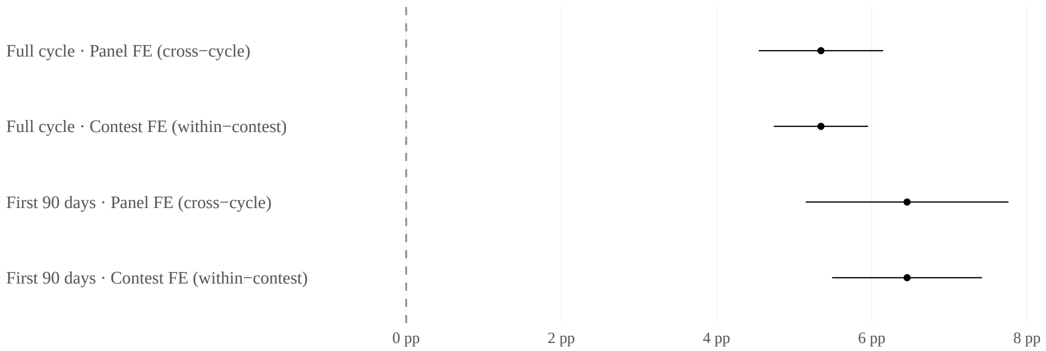


Notes: Network premium (matched − non-matched) re-estimated on subsets of contests. Top: by district partisan lean, the district's average Democratic two-party presidential voteshare over the redistricting period (Safe Democratic > 55%; Competitive 45–55%; Safe Republican < 45%). Bottom: by whether the seat had a same-party incumbent, an opposite-party incumbent, or was open (no incumbent in this contest). 95% confidence intervals; standard errors clustered by contest. Same specification as Figure 3.

A.5.5 First-90-days estimates

Figure A.11 re-estimates the pooled network premium using only contributions made in the first 90 days of the primary cycle, alongside the main full-cycle estimate, under both specifications. The first-90 premium is about 7.0 percentage points, larger than the full-cycle estimate and identical under the cross-cycle and within-contest specifications.

Figure A.11: Network premium, full cycle vs. first 90 days.

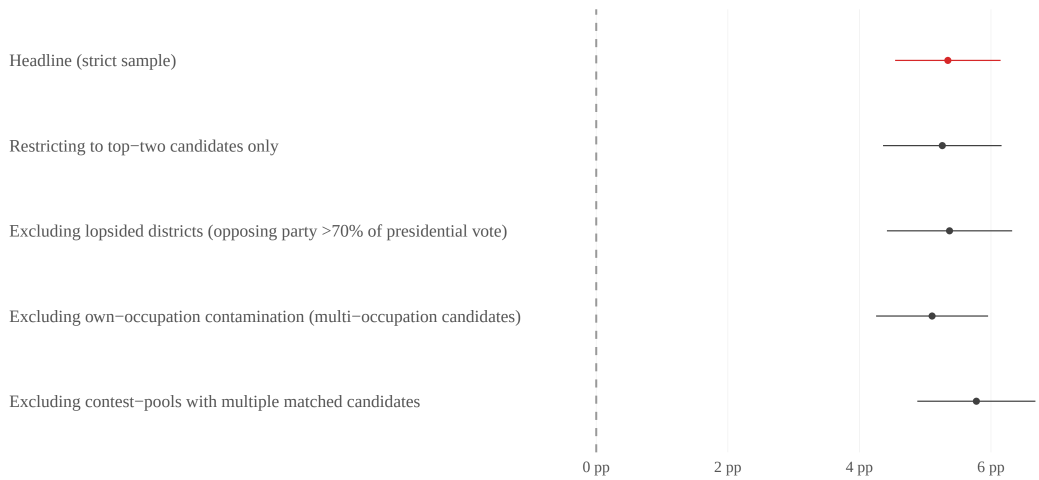


Notes: Pooled network premium re-estimated using two definitions of the donor-dollar outcome: full primary cycle (the main analysis) and contributions during the first 90 days only. Each definition uses its own sample: the full-cycle estimate requires positive itemized contributions over the full cycle; the first-90 estimate requires positive itemized contributions in the first 90 days. Both impose the 5% vote-share floor and competitive-contest restriction. Each estimated under both the cross-cycle and within-contest specifications. 95% confidence intervals; standard errors clustered by contest.

A.5.6 Robustness across alternative specifications

Figure A.12 re-estimates the pooled premium under four alternative specifications: restricting to the top two candidates in each primary (guarding against fringe candidates); excluding districts where the opposing party won more than 70% of the two-party presidential vote (dropping primaries with little realistic chance in the general); stripping each candidate's other matched-occupation pools out of the other-donor baseline (so a multi-occupation candidate's other networks do not inflate the comparison); and excluding contest-pools in which several candidates share an occupation (testing sensitivity to the matched-group collapse). The premium is stable across all of them, between 5.2 and 6.0 percentage points.

Figure A.12: Estimated effect of occupational match, across robustness specifications (primaries).

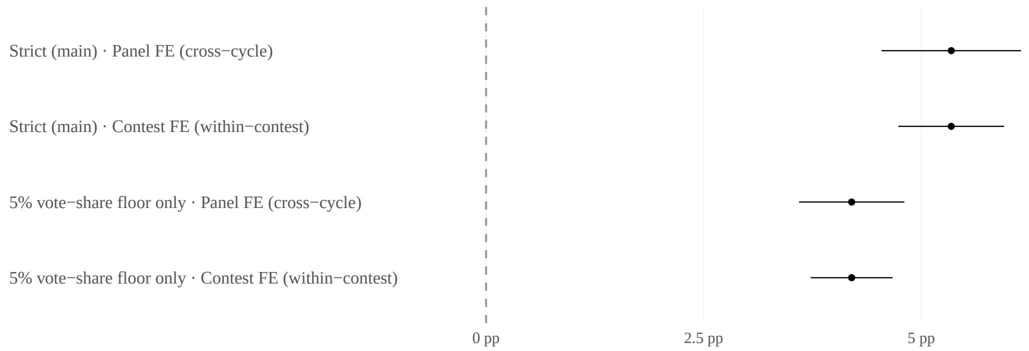


Notes: Pooled network premium under alternative specifications. Main specification in red. Subsequent rows: restricting to the top two candidates per primary; excluding districts where the opposing party received more than 70% of the two-party presidential vote share; excluding multi-occupation candidates' own-occupation contamination from the other-pool baseline; and excluding contest-pools with multiple matched candidates. All specifications use the matched-group cross-cycle design. The more permissive sample appears in Figure A.13; ideology-controlled estimates appear in Appendix A.5.9. 95% confidence intervals; standard errors clustered by contest.

A.5.7 Relaxing the sample restrictions

Figure A.13 reports the pooled network premium when the only sample restriction is the 5% vote-share floor, dropping the further requirements (general-election winner $\geq$ 30% of the two-party vote; candidate reported positive itemized individual contributions over the cycle) that define the main sample. Dropping these restrictions lowers the pooled premium to about 4.4 percentage points, from 5.7 in the main sample.

Figure A.13: Pooled network premium, main sample vs. more permissive sample.

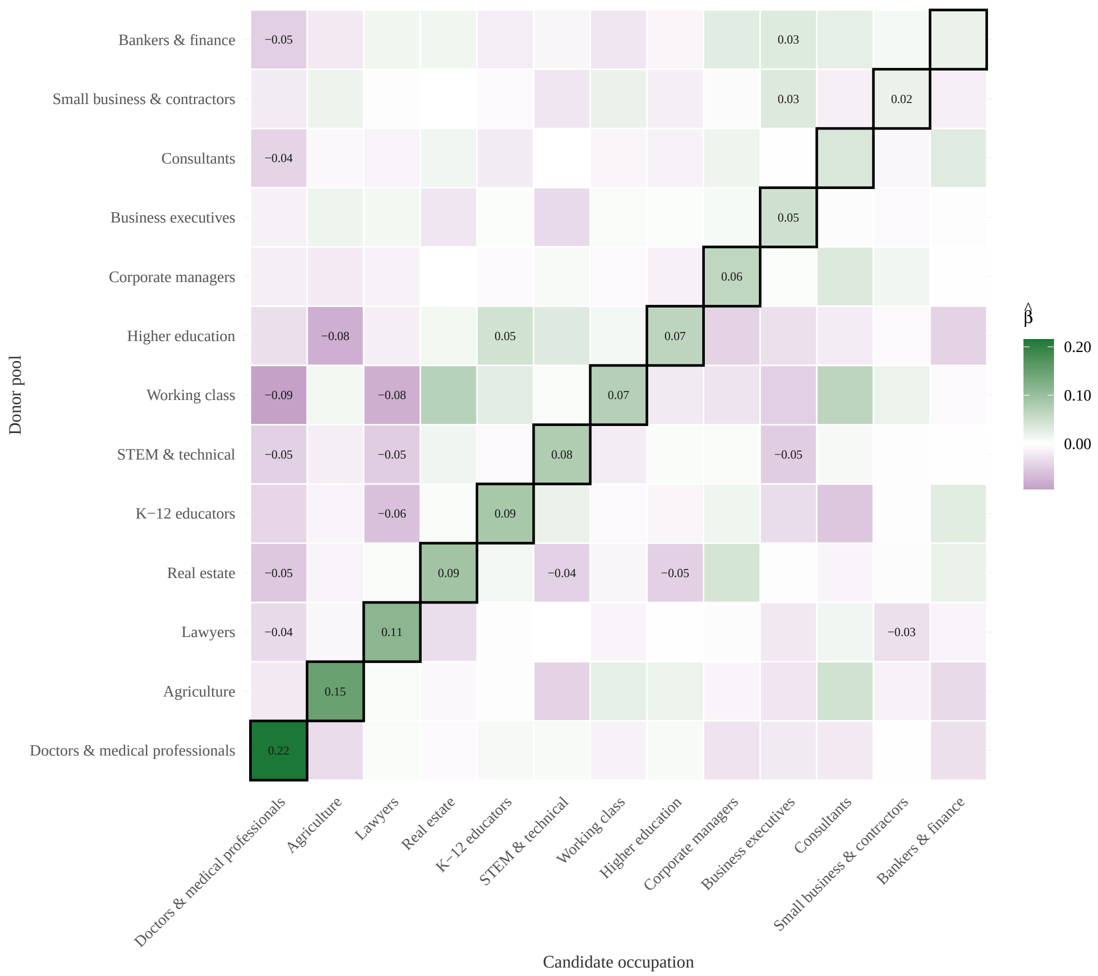


Notes: Pooled network premium by sample and specification. The main sample (red): candidates above the 5% vote-share floor, in contests whose winner received at least 30% of the two-party vote in the general election, who reported positive itemized contributions. The more permissive sample (grey) keeps only the 5% floor. 95% confidence intervals; standard errors clustered by contest.

A.5.8 Cross-pool effects

Figure A.14 repeats the cross-pool analysis for primaries. For each donor pool, I regress the within-contest network premium (a candidate's share of that pool minus their share of all other donors in the contest) on indicators for all 13 candidate occupations. As in general elections, the diagonal dominates: the premium concentrates where the candidate's occupation matches the donor pool.

Figure A.14: Network premium of each candidate occupation on each donor pool, primaries.



Notes: Rows are donor pools; columns are candidate occupations. For each donor pool, I regress the within-contest network premium (a candidate's share of that pool minus their share of all other donors in the contest) on binary indicators for all 13 candidate occupations (non-exclusive). Each cell is the coefficient on the column occupation; the diagonal is each occupation's premium on its own pool, off-diagonal cells its premium on other pools. Coefficients are shown only for cells significant at the 5% level. Fixed effects: district × party + party × cycle. Standard errors clustered by contest.

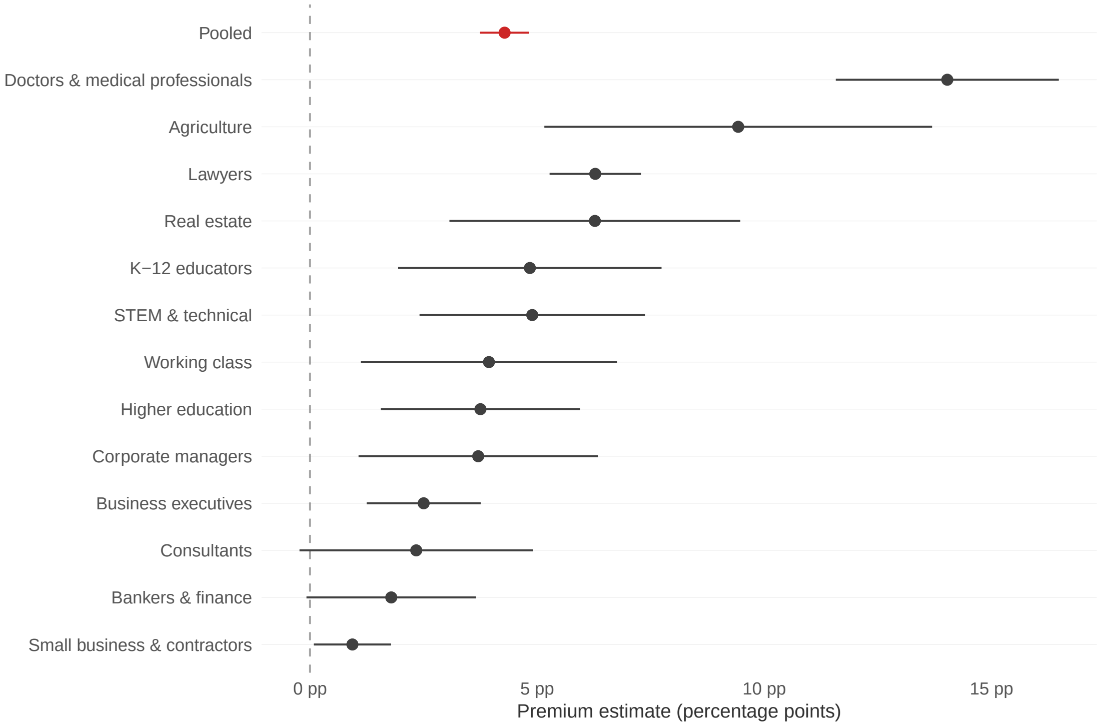
A.5.9 Per-candidate specification

The headline specification groups same-occupation candidates within a contest into one matched group. To check that the premium does not depend on this grouping, and to allow a control for candidate ideology that the grouped design cannot accommodate, I re-estimate it candidate by candidate: for candidate i and pool g, their share of pool g's contributions minus their share of all other donor dollars in the contest, averaged over matched candidates.[4] The premium is 4.8 percentage points, close to the matched-group estimate of 5.7, with the same per-pool ordering (Figure A.15). Adding a candidate-level control for ideology (CFscore or DW-DIME) leaves it at 5.0 points. Controls for the candidate's gender, race, prior political experience, and incumbency, paralleling those in the general-election specification, leave it at 4.7. The gap from the matched-group estimate is the attenuation from pool-splitting: restricting to the contest-pools where only one candidate holds the occupation, so no pool is divided, raises the per-candidate premium to 6.0 percentage points, matching the matched-group design.

I keep the matched-group specification as the headline because it parallels the general-election design in stacking own- and other-source rows within a unit, and avoids the attenuation that arises when several same-occupation candidates split one pool.

[4]Differencing matched against non-matched candidates instead would return a larger number, but mechanically: pool shares sum to one within a contest, so non-matched candidates under-capture the pool, and subtracting their negative average inflates the estimate. The within-candidate difference avoids this.

Figure A.15: Network premium, per-candidate specification (primaries).



Notes: Per-pool and pooled premium under the per-candidate specification: each matched candidate's share of their own pool minus their share of all other donors in the contest, averaged. Main analysis sample, 2010–2024. 95% confidence intervals; standard errors clustered by contest.

A.6 Network Premium in Dollars

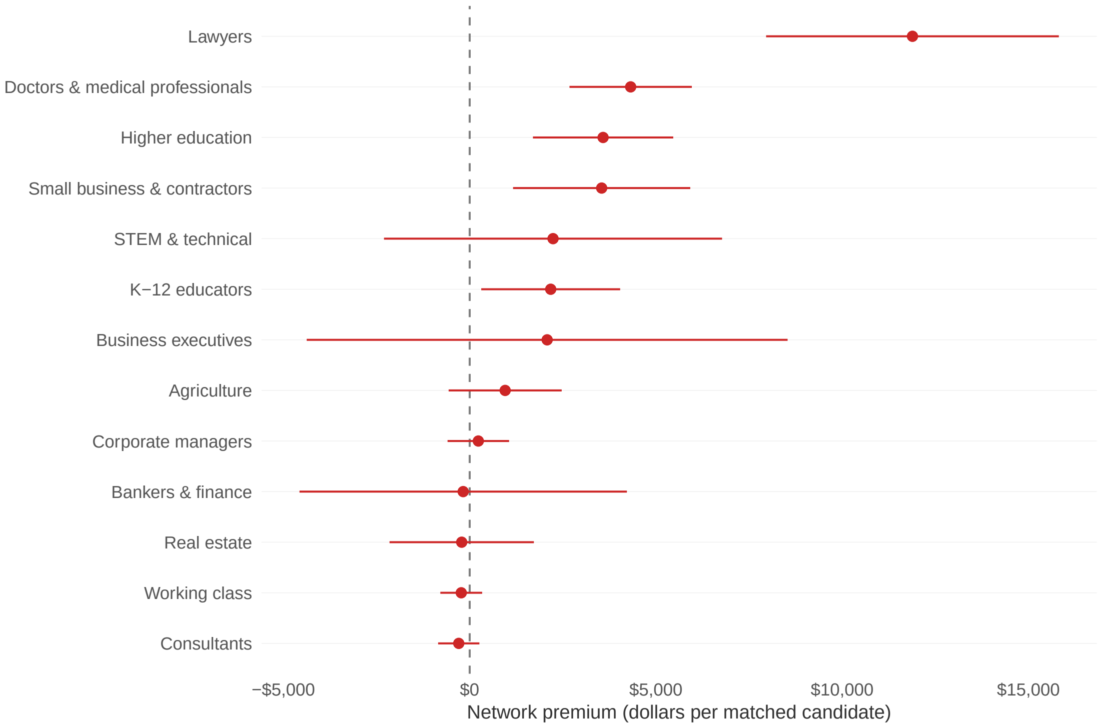
I report the network premium in dollars rather than as a share. For a matched candidate i in their occupational pool g, the dollar premium is their actual receipts from pool g minus what they would have raised from it at their general (non-g) fundraising rate:

$$\pi_{ig} \;=\; r_{ig} \;-\; \frac{r_{i,-g}}{R_{-g}}\, R_g,$$

where r_{ig} and $r_{i,-g}$ are i's receipts from pool g and from all other donors, and R_g and R_{-g} are the contest's total contributions from pool g and from all other donors. Each per-pool estimate averages π_{ig} over matched candidates. The estimates cover general elections and primaries; because the main-text dollar premium (Section 6) uses only open-seat primaries, I re-estimate it for the other primary contest types (all primaries pooled, same-party incumbent, opposite-party incumbent). The final subsection reports the competitive advantage this premium creates over rivals.

A.6.1 General elections

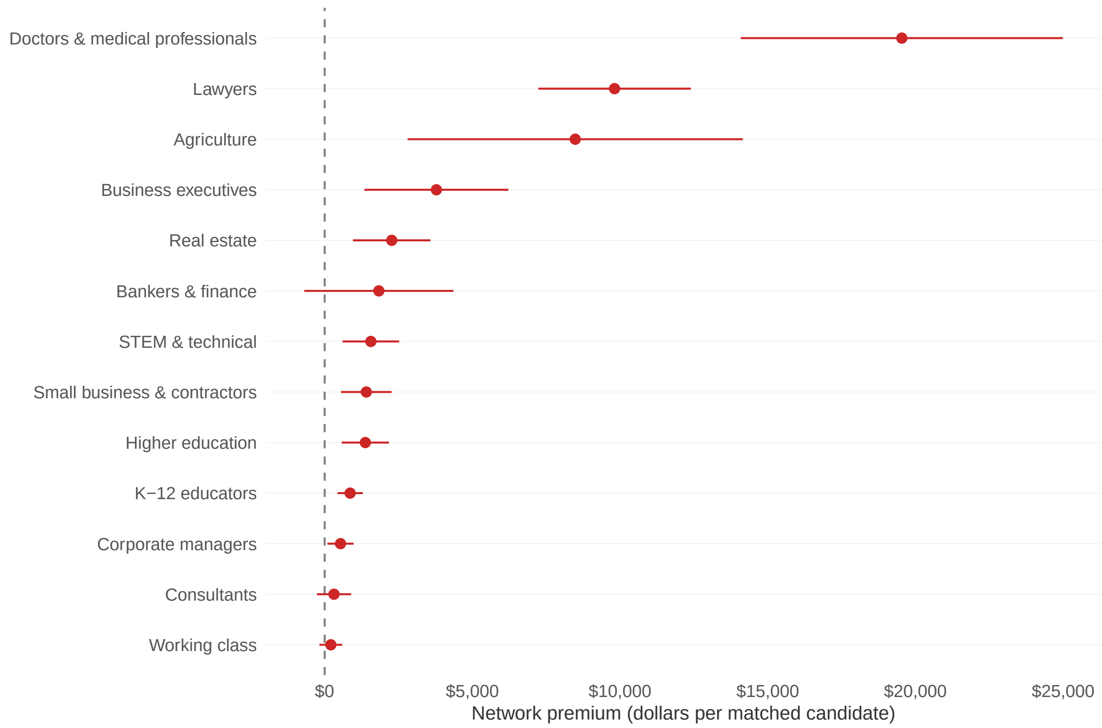
Figure A.16: General-election network premium in dollars by occupation.



Notes: Per-pool general-election network premium in dollars: the matched nominee's actual own-pool receipts minus the receipts predicted by their capture rate among all other donors in the race, averaged across matched races. All contested major-party general elections, 2010–2024; 13 occupational donor pools; individual contributions only. 95% confidence intervals; standard errors clustered by redistricted district.

A.6.2 All primary contests

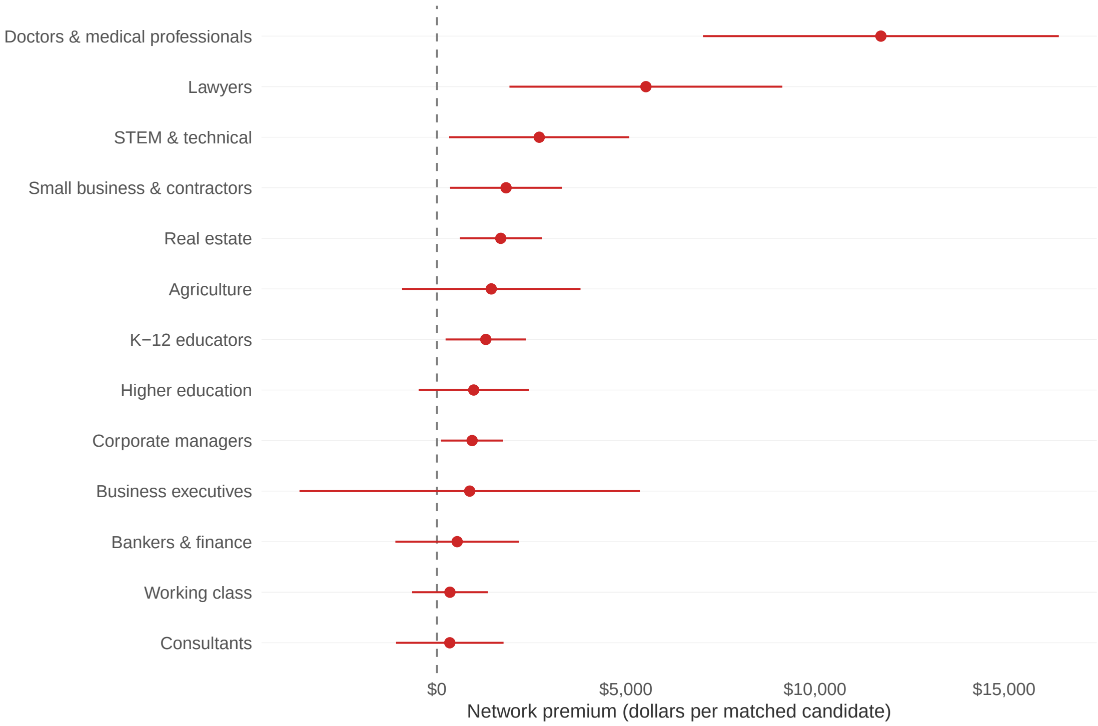
Figure A.17: Network premium in dollars, all primary contests.



Notes: Per-pool network premium in dollars, computed as in Figure 4 (each matched candidate's own-pool receipts minus their general-fundraising-rate counterfactual, averaged across matched candidates), here estimated on all primary contests (open seats and contests with incumbents pooled). Above the 5% vote-share floor, in primaries whose winner received at least 30% of the two-party vote in the general election, restricted to candidates with positive itemized individual contributions; 13 occupational donor pools, 2010–2024. N = 2,007 contests, 5,297 candidates. 95% confidence intervals; standard errors clustered by contest.

A.6.3 Contests with a same-party incumbent

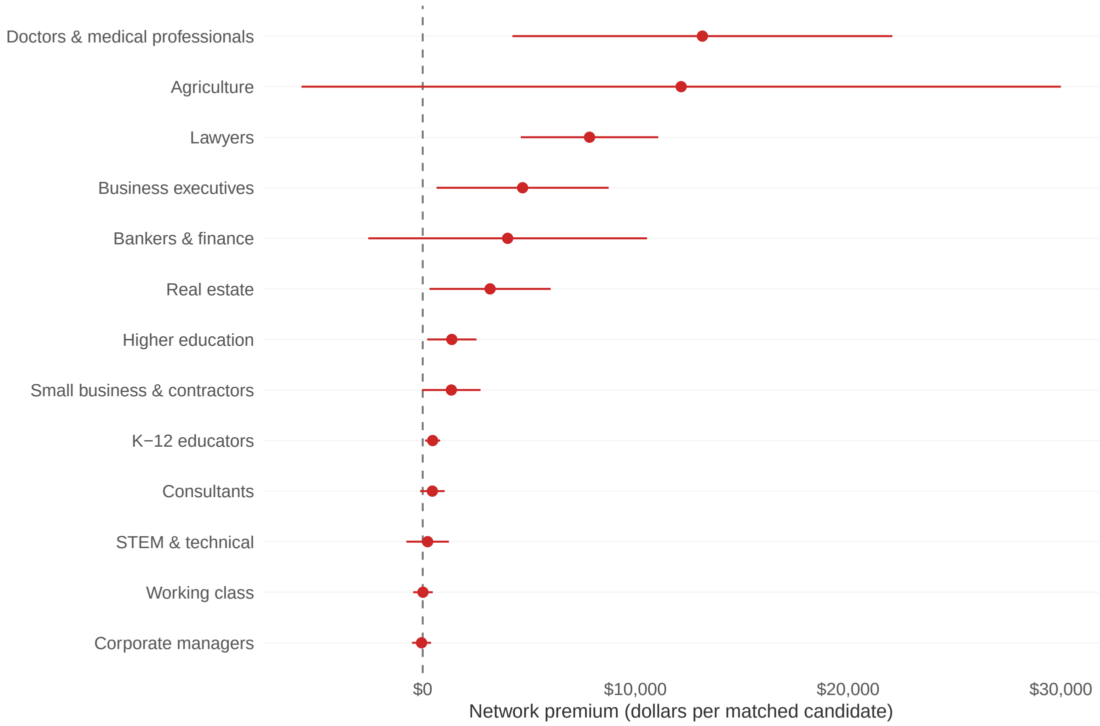
Figure A.18: Network premium in dollars, contests with a same-party incumbent.



Notes: Same construction as Figure A.17, restricted to primaries in which the same-party incumbent is running. $N = 758$ contests, 1,711 candidates. 95% confidence intervals; standard errors clustered by contest.

A.6.4 Contests with an opposite-party incumbent

Figure A.19: Network premium in dollars, contests with an opposite-party incumbent.

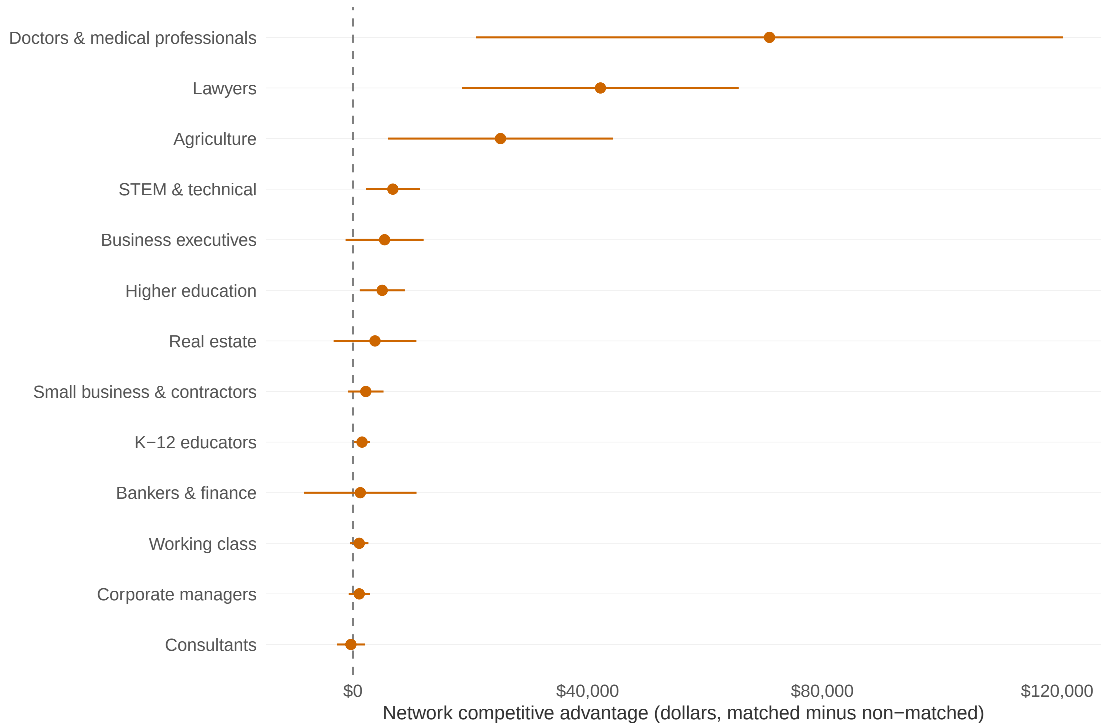


Notes: Same construction as Figure A.17, restricted to primaries in which the seat's incumbent is from the opposing party (no same-party incumbent in this primary). N = 773 contests, 2,036 candidates. 95% confidence intervals; standard errors clustered by contest.

A.6.5 Competitive advantage

The premium π_{ig} measures the resource the network provides a matched candidate. Because primary fundraising is a contest over a finite set of donors, the same matching also shifts the within-contest balance against rivals. The competitive advantage is the difference, within a contest, between matched and non-matched candidates' premium (in contest-pool cells with at least one of each). Because pool shares sum to one, non-matched candidates under-capture the pool on average, so this difference exceeds the matched candidates' over-capture alone: it combines what matched candidates gain with what their rivals forgo. The absolute premium describes the resource the network provides; the competitive advantage describes the edge it creates over rivals. Figure A.20 reports it for open-seat primaries.

Figure A.20: Network competitive advantage in dollars, open-seat primaries.



Notes: Per-pool mean of the within-contest gap between matched and non-matched candidates' premium π_{ig} (each candidate's own-pool receipts minus their general-rate counterfactual). Open-seat primaries in the main analysis sample, 2010–2024, restricted to contest-pool cells with at least one matched and one non-matched candidate. 95% confidence intervals; standard errors clustered by contest.

A.7 Why Dollar-Based Estimates Conflate Occupational Networks and Donor-Pool Differences

Bonica (2020) provides the closest precedent to this paper. Using congressional campaigns from 2010–2014, he shows that candidates from professions such as law and medicine raise far more money from donors in their own professions. My results are broadly consistent with this conclusion. The central challenge is determining how much of these fundraising advantages reflects occupational affinity itself, rather than differences in the fundraising environment. This appendix documents three features of occupational donor pools that motivate the share-based panel design used in the main analysis, which isolates a candidate's capture of their own occupational pool from these differences, so the network premium reflects occupational affinity rather than the size, growth, or general reach of the donor pool.

A.7.1 Occupational donor pools are unevenly distributed across districts

Candidates from an occupation do not run in a random set of districts. Districts that ever field candidates from a given occupation tend to contain much larger donor pools from that occupation than districts that never do.

To illustrate, in cycles when no such candidate is on the ballot, I compare the occupational donor money in districts that ever field a candidate from occupation g with districts that never do. Table A.9 reports the ratio for each occupational donor pool.

Districts that have ever fielded lawyer-candidates contain about 3.7 times as much lawyer-donor money as districts that never have. Similar patterns appear across most occupational groups. These differences imply that candidates from some occupations are disproportionately likely to run where donors from their occupation are already abundant. Bonica controls for district median household income and partisan lean, but two districts alike on both can still hold very different amounts of a given occupation's donor money. A dollar-based estimate therefore combines occupational affinity with these cross-district differences in the size of occupational donor pools.

Table A.9: Occupational donor pools are larger in districts that field the occupation.

Occupation	Never-field	Ever-field	Ratio
Lawyers	\$35,955	\$134,685	3.7*
Agriculture	\$7,544	\$24,867	3.3*
Working class	\$6,823	\$16,936	2.5
Doctors & medical professionals	\$48,739	\$106,672	2.2*
Small business & contractors	\$42,727	\$81,758	1.9
Higher education	\$17,281	\$32,325	1.9
Business executives	\$68,221	\$110,458	1.6*
K-12 educators	\$8,962	\$14,051	1.6
STEM & technical	\$38,343	\$60,048	1.6
Bankers & finance	\$54,439	\$77,495	1.4*
Consultants	\$20,181	\$28,056	1.4
Real estate	\$28,333	\$31,414	1.1
Corporate managers	\$21,911	\$21,814	1.0

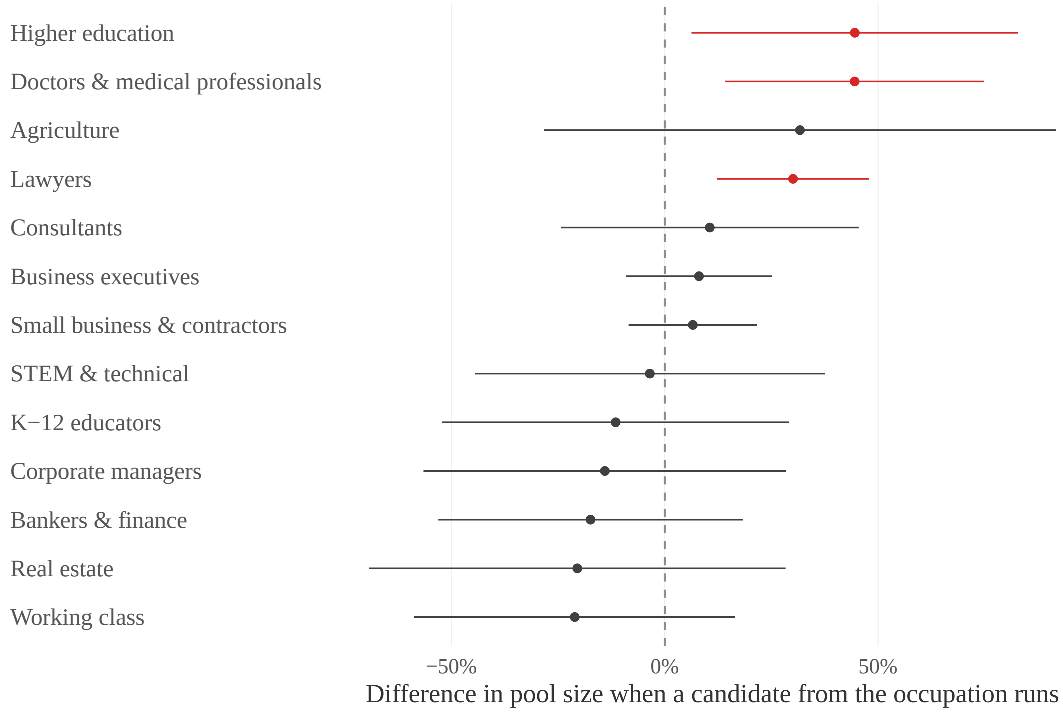
Notes: Average pool contributions per district in districts that have never versus ever fielded a candidate from the occupation, measured in cycles with no such candidate on the ballot, with the ratio of the two. General-election panel, 2010–2024. * ratio significant at the 5% level; standard errors clustered by redistricted district.

A.7.2 Occupational donor pools expand when one of their own runs

Occupational donor pools also vary over time within districts. When a candidate from occupation g enters a race, donors from that occupation may become more likely to contribute, increasing the total amount of money available from the pool.

To examine this, I compare each occupational donor pool within the same district across cycles in which a candidate from that occupation runs and cycles in which none does. Figure A.21 reports the proportional difference for each pool in general elections.

Figure A.21: Occupational donor pools expand when a candidate from the occupation runs.



Notes: Proportional difference in each pool's total contributions between general-election cycles in which a candidate from that occupation runs and cycles in which none does, within district (inverse hyperbolic sine of the pool total on a match indicator, with district and cycle fixed effects). Points significant at the 5% level in red; 95% confidence intervals. Standard errors clustered by redistricted district.

For several occupations, the pool is larger when one of their own is on the ballot. The lawyer donor pool is about 30% larger in cycles when a lawyer-candidate runs than when none does, with similar increases for doctors and higher-education candidates. As a result, candidates from these occupations can raise more same-occupation money even when they capture no larger share of the pool. These comparisons are descriptive: a shock that raised both a candidate's entry and the pool in the same district and cycle would produce the same pattern.

A.7.3 Occupational networks and general fundraising strength

A final challenge is distinguishing occupational donor networks from broader fundraising advantages. Candidates from some occupations may be stronger fundraisers overall, attracting more support from all donors rather than specifically from donors who share their occupation.

The main analysis addresses this by comparing a candidate's share of their own occupational donor pool with their share of all other donor dollars in the same contest. Figure 2 decomposes the result into a non-matched effect, a matched-pool effect, and the resulting network premium.

For some occupations, particularly lawyers, candidates enjoy broader fundraising advantages that extend beyond donors who share their occupation. For most occupations, however, the network premium reflects disproportionate support from co-occupational donors rather than a general fundraising advantage.