How do Legislators' Occupations Predict their Behavior in Office?

Fred DeVeaux*

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Abstract

Compared to the population at large, Congress has few workers and tradespeople and many lawyers and business executives. This raises concerns about unequal representation. Yet it remains unclear how much legislators' prior careers predict behavior in office, and whether differences appear mainly in the issues they work on, the positions they take, or both. I compile occupational histories for 3,600 members of Congress, 1947–2024. Comparing same-party legislators representing the same district over time, I find that legislators focus more on issues connected to their prior occupations in speeches and sponsored bills, serve on relevant committees, and advance occupation-related legislation more effectively. But they do not vote differently on issues related to their occupation than on other issues. Instead, occupation predicts voting along traditional class lines, especially between business- and working-class legislators on employment and labor. Congress's occupational composition therefore shapes which issues receive attention and whose economic interests are represented.

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*Department of Political Science, University of California, Los Angeles; fdeveaux@ucla.edu

"I went from doctor, waitress to tech to the synagogue president and Senate. So how does it all match? Artificial intelligence, working hard, taxes and tips. We bring our whole story to the United States Senate, to our jobs, right?" — Senator Jacky Rosen (D-NV)

"Gary is by trade a developer, that's his profession. So from the time he was mayor, state assemblyman, congressman for 16 years, he had realtors' support. From the first time he became a congressman, because it was already in his heart. Those were the things that mattered to him. Being a developer, he already knew the issues. One of the first pieces of legislation he wrote was to make it easier for developers of commercial real estate — he doesn't even do commercial — to be able to start developing before the city goes through their bureaucratic processes, because it makes it easier. That was just an organic relationship. Because it was something he already knew and loved."

— Interview about Rep. Gary Miller (R-CA-31)[1]

1 Introduction

Though Congress has made progress in reflecting the racial and gender diversity of the U.S. population, its occupational makeup remains heavily skewed toward elite professions. Lawyers, business owners, and corporate executives dominate, while those with experience as manual workers or service employees are underrepresented (Carnes, 2013). This imbalance may have consequences for substantive representation if legislators from different occupational backgrounds behave differently in office (Butler, 2014; Carnes, 2013; Gilens and Page, 2014; Kirkland, 2021; O'Grady, 2019). Politicians themselves routinely cite their professional backgrounds as shaping what they do in Congress. But these occupational differences may reflect the parties and districts that elect different kinds of legislators rather than the backgrounds legislators bring into office. Do legislators' occupations predict their behavior in office, and if so, how?

Answering this question poses two main challenges. First, occupational background is difficult to isolate from the parties and constituencies that elect different kinds of legislators. Farmers may appear more focused on agricultural issues simply because they tend to represent farming districts (Adler and Lapinski, 1997; Shep-

[1] Quoted in Bawn et al. (2026).

sle, 1979). To address this, I compile complete occupational histories for all 3,600 members of Congress from 1947 to 2024 and compare legislators from different occupational backgrounds who represent the same party and district at different points in time.

Second, even where occupational differences persist, it is unclear what types of legislative behavior they predict. Occupation may operate through both expertise (Burden, 2007; Costa and Pereira, 2025; Krehbiel, 1991; Volden and Wiseman, 2014) and ideology (Carnes, 2013; Kirkland, 2021; O'Grady, 2019). These mechanisms may jointly shape behavior, so I examine their combined observable implications across two dimensions of legislative activity: issue specialization and position-taking. If occupation mainly predicts specialization, occupational imbalance skews which issues receive attention, effort, and legislative capacity without necessarily changing how legislators vote. If occupation predicts positions, occupational imbalance affects whose policy preferences are represented. Existing work typically studies one occupation or one outcome at a time, making it difficult to compare these patterns directly. I therefore bring many occupations and outcomes into a common framework across eight decades of Congress, measuring issue specialization with speeches, sponsored bills, committee requests and assignments, and issue-specific legislative effectiveness, and measuring position-taking with issue-specific roll-call votes and interest-group ratings.

The results show consistent evidence that occupational background predicts issue specialization in office. The pattern appears in both floor speeches and sponsored bills. When a district elects a legislator from a given occupational background, the share of bills they sponsor on related topics increases by 1.2 percentage points, a 36% increase, while the share of their floor speeches devoted to those issues rises by 0.9 percentage points, a 47% increase. It also extends to institutional specialization, as legislators are more likely to request and serve on committees related to their prior careers, with the likelihood of relevant committee service increasing by 13.3 percentage points, a 136% increase. Finally, this specialization translates into legislative success. Electing a legislator with a matching occupational background increases predicted issue-specific LES from 0.15 to 0.21, a 36% increase.

The pattern differs for position-taking, where occupational background matters along class rather than occupation-specific lines. I find little evidence that legislators vote differently on issues narrowly related to their occupational domains than on other issues. The clearest differences instead fall along a business–working-class divide, consistent with prior work on class representation (Carnes, 2013; Carnes and Lupu, 2023). Legislators with business backgrounds, including small business owners, corporate executives, and bankers, vote more conservatively on wages, unions, workplace regulation, and bargaining power, while those with working-class backgrounds, including manual laborers and service workers, vote less conservatively on the same issues. Together, these findings suggest that Congress's occupational composition shapes both where legislative attention and capacity are concentrated and the balance of roll-call votes on key class-based economic issues.

2 The Personal Biography Approach

Politicians bring their personal backgrounds with them into office. These backgrounds include ascriptive traits such as race and gender, as well as socializing experiences such as education, military service, and occupation. The representational concern is that differences in who holds office may translate into differences in what elected officials do: which issues they prioritize, which constituents they understand, and whose interests they advance through policy (Broockman, 2013; Chattopadhyay and Duflo, 2004; Lowande, Ritchie and Lauterbach, 2019; Pitkin, 1967).

Personal background may affect political behavior through several mechanisms. As Krcmaric, Nelson and Roberts (2020) summarize, biography may shape beliefs and values, provide skills and information, create material interests or professional networks, and affect how others perceive political elites. These mechanisms need not operate separately.

Occupations are especially useful for studying these questions because the descriptive imbalance is severe. Congress contains relatively few members from working-class backgrounds and many from business and professional backgrounds (Carnes, 2013). This raises representational concerns given evidence that policy outcomes in the United States often tilt toward the preferences of economic elites (Gilens and Page, 2014). At the same time, occupations may provide the kind of policy-specific knowledge that legislatures rely on when organizing committee work and specialization (Burden, 2007; Krehbiel, 1991).

2.1 Ideology and Policy Preferences

A central concern about the occupational composition of government is that legislators' career backgrounds may be associated with their policy preferences, particularly on economic issues. This relationship can arise in several ways. Work experience may shape political worldviews: for example, recent evidence suggests that small business ownership itself, especially the experience of managing employees and confronting regulation, contributes to more conservative views on economic policy (Malhotra, Margalit and Shi, 2025). Individuals with different ideological commitments may also select into different occupations (Reny et al., 2025). Prior careers may create material interests or professional networks that connect officeholders to particular industries or economic groups (Adolph, 2013; Alexiadou, 2016). And because politicians' perceptions of public opinion are shaped by unequal exposure and can be systematically biased, occupationally structured networks may affect which interests legislators hear most clearly (Broockman and Skovron, 2018; Pereira, 2021).

The overrepresentation of politicians from elite backgrounds may therefore have consequences for whose interests are advanced through policy. Legislators with working-class backgrounds tend to vote more in favor of economic redistribution than those with backgrounds in for-profit or business leadership positions

(Carnes and Lupu, 2023), and in major policy fights they are more likely to defend working-class interests than legislators with purely political backgrounds (O'Grady, 2019). Similar concerns appear outside Congress: mayors with business-executive backgrounds shift spending away from redistributive welfare policies (Kirkland, 2021). Other evidence points to more sector-specific occupational effects. Lawyer-legislators vote differently on tort reform (Matter and Stutzer, 2015), legislators with insurance backgrounds favor the legislative agenda of the insurance industry (Hansen, Carnes and Gray, 2019), and political leaders with financial-sector backgrounds tend to favor policies aligned with financial-sector interests (Adolph, 2013).

The occupational imbalance in Congress is unlikely to reflect voter preferences alone. Experimental evidence finds little systematic voter bias against working-class candidates or in favor of lawyers (Carnes and Lupu, 2016*b*). Access to office is also shaped by unequal campaign resources and professional networks, and party elites often recruit candidates who can finance their own campaigns or draw on wealthy donor networks (Bonica, 2017, 2020; Carnes, 2018). If legislators from different occupational backgrounds take different positions while representing the same party in the same district, those differences cannot be attributed to stable constituency preferences alone. They would indicate that legislators bring occupation-linked preferences and experiences into office.

2.2 Expertise and Specialization

A parallel line of research views occupation as a source of expertise and specialization. In this account, occupational background may shape where legislators specialize without necessarily changing the positions they take. Legislatures operate in complex informational environments, and committee systems are partly designed to help members acquire and use policy-specific expertise (Krehbiel, 1991). Legislators can draw on professional knowledge, practical experience, and occupational networks when deciding which issues to work on and where to invest scarce time and effort (Burden, 2007; Butler, 2014). When this produces a focused agenda rooted in prior experience, specialization may build policy expertise and credibility with colleagues, making legislators more effective at advancing related legislation (Volden and Wiseman, 2014).

Existing evidence is consistent with this view. Legislators tend to serve on committees related to their prior occupations (Burden, 2007; Krehbiel, 1991; Shepsle, 1979). Legislators with relevant occupational experience also introduce more bills and more innovative bills in related policy areas (Makse, 2019; Miler, 2017). Recent work further suggests that legislators with relevant professional backgrounds may be more credible to colleagues and voters, making them more persuasive and effective at advancing related policy proposals (Costa and Pereira, 2025; Makse, 2022).

The representational implications of expertise are therefore mixed. Occupational expertise may improve legislative capacity by helping members identify problems, craft proposals, and build support in specialized policy domains. But expertise can also reduce responsiveness if officials become more confident in their own views and more likely to discount disagreeing public opinion (Pereira and Öhberg, 2024). More generally, even if expertise does not alter policy preferences, its distribution can still matter. If legislators are more likely to work on issues connected to their own backgrounds, occupational imbalance can skew which issues receive attention and which policy areas benefit from legislative effort and capacity (Butler, 2014).

2.3 Interpreting Occupational Differences in Office

A central difficulty in studying occupations and legislative behavior is that the same empirical pattern can reflect different underlying forces. The classic debate over committee assignments illustrates the problem. In the distributive tradition, the overrepresentation of farmers on Agriculture or bankers on Banking and Currency reflects constituency demand for targeted benefits (Adler and Lapinski, 1997; Shepsle, 1979). In Krehbiel's informational account, the same pattern reflects low-cost specialization: legislators with relevant occupational backgrounds can acquire and use policy information more efficiently (Krehbiel, 1991).[2]

This ambiguity extends beyond committee assignments. Occupational background may be associated with expertise, preferences, material interests, networks, and credibility, and these channels may reinforce one another rather than operate independently (Burden, 2007; Carnes and Lupu, 2023). I therefore do not interpret occupational differences in behavior as evidence for a single mechanism. Instead, I focus on the observable consequences of electing legislators from different occupational backgrounds: whether they specialize in different issues, take different policy positions, or both.

3 Data Collection

3.1 Occupational Data from Congressional Biographies

To compile occupational histories for all 3,600 members of Congress who served from 1947 to 2024, I use official biographies from the *Biographical Directory of the United States Congress*. These biographies include information about legislators' birth year, education, and the list of occupations and positions they held before entering Congress.

I classify roughly 16,000 distinct occupation and position strings into one of 84 granular categories from an expanded version of Carnes (2013)'s typology. Following the "asking and averaging" approach developed by Le Mens and Gallego (2025), I combine classifications from four large language models, two closed-weight models (gpt-5-mini and gpt-4.1-mini) and two open-weight models (DeepSeek V4-Pro and GLM-5.1).

For the main analyses, I aggregate the 84 granular categories into 10 broader occupational groups that map onto identifiable policy domains and are sufficiently

[2] Krehbiel (1991, 136) writes that Shepsle's occupation variables are "perhaps the best possible measures" of low-cost specialization, but that this kind of interest "bears no necessary relationship to preferences over policy outcomes."

common to estimate separately. Table A.2 in the Appendix reports the full mapping. I exclude groups with small samples or no clear mapping to a policy domain, such as nonprofit work and arts & entertainment. Among occupation strings classified into the 10 groups, the four models agree unanimously on 81.7%. I manually review and reconcile the remaining 1,307 strings without unanimous agreement. Full details of the classification pipeline appear in Appendix A.1.

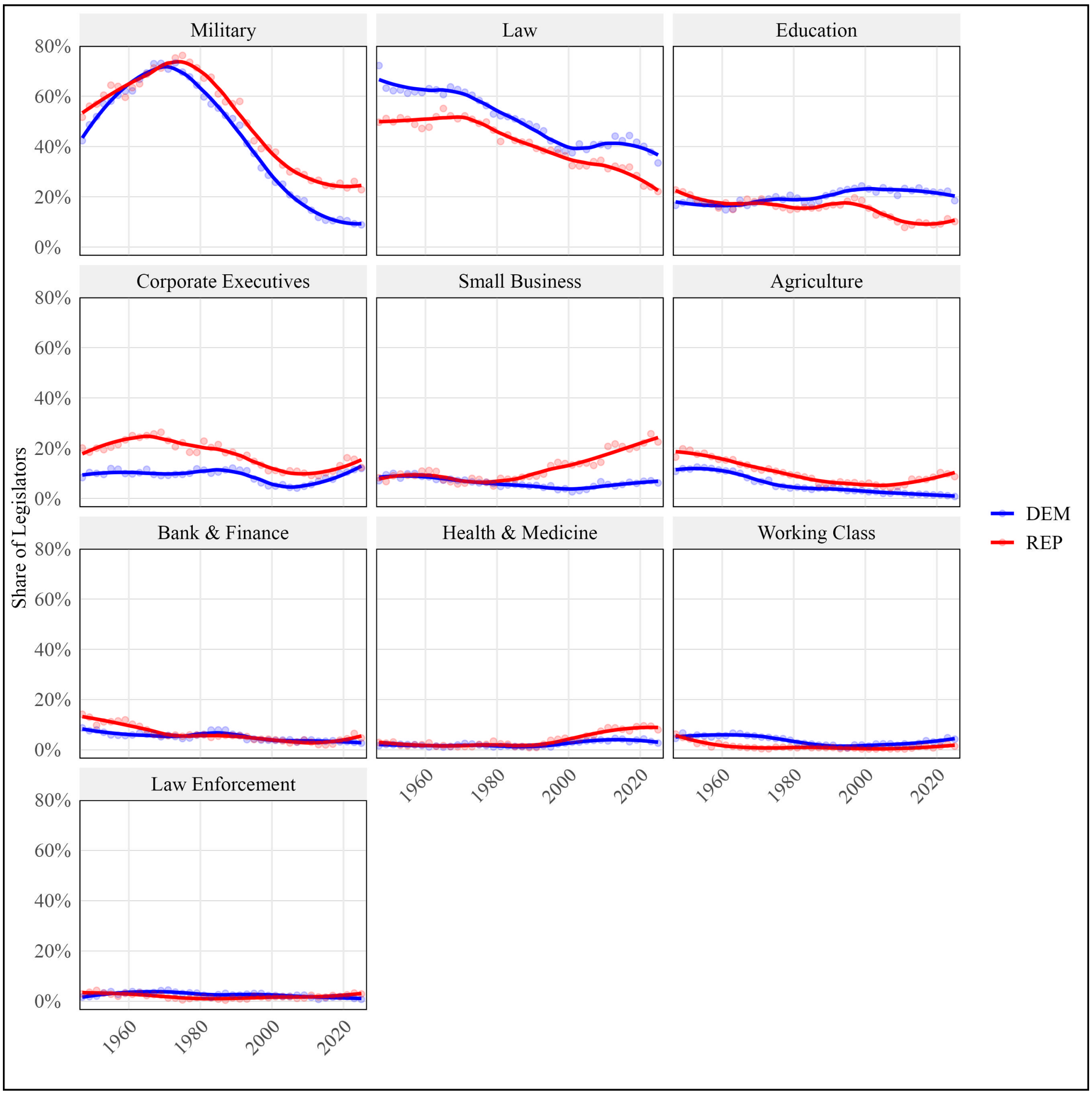
Across all members who served from 1947 to 2026, law and the military are the most common pre-political backgrounds, each held by about 44% of members, followed by education (18%), corporate executives (15%), and small business owners (10%) (Appendix Figure A.1). Figure 1 shows how the prevalence of each background changes across Congresses and parties. Each point is the share of Democratic or Republican members serving in a given Congress who had that occupational background; the lines show smoothed trends. Law declines from about 60% of members in 1947 to 28% in the 119th Congress. Military service rises from 47% to a peak of 74% in 1973, then declines to 16%. Working-class backgrounds remain uncommon in every Congress, generally accounting for about 3% of members. The figure also reveals growing partisan differences. Military and small-business backgrounds are now relatively more common among Republicans, while education and law are more common among Democrats. By contrast, corporate-executive backgrounds, which were more common among Republicans for most of the period, are now equally prevalent in both parties.

3.2 Congressional Floor Speeches

I use congressional floor speeches from the *Congressional Record* covering 1947–2016. The data combine the corpus compiled by Gentzkow, Shapiro and Taddy (2019) for 1981–2016 with earlier speeches from the digitized bound edition. I keep all speeches longer than 20 words, excluding brief interjections and procedural formalities. This yields 3.9 million speeches.

To measure whether legislators focus on policy areas related to their occupa-

Figure 1: Trends in Members of Congress' occupational backgrounds, 1947–2026



Note: This figure shows the share of members of Congress with a background in each occupational category, by party, from 1947–2026. Each point is the share of members serving in a given Congress; lines are smoothed trends. Because members can hold more than one occupation, they appear in more than one panel.

tional backgrounds, I estimate a keyword-assisted topic model (keyATM; Eshima, Imai and Sasaki, 2024). This semi-supervised method uses researcher-supplied seed keywords to anchor substantively defined topics while learning each topic's broader vocabulary from word co-occurrence in the corpus. I use a short list of seeds for each occupational topic, such as *farmer*, *rancher*, and *agriculture* for agriculture, and *doctor*, *physician*, and *health care* for health. This preserves the connection between topics and occupational categories while avoiding the main limitation of fixed keyword dictionaries, which capture only speeches that use researcher-specified terms. I also include sixteen seeded topics covering common themes such as budget, taxation, immigration, housing, and energy, along with eight unseeded topics learned from recurring patterns in the speeches. These additional topics allow the model to represent content outside the ten occupational domains.

Before estimation, I remove institutional and procedural language, such as references to the Department of Education or the Agriculture Committee, that could be mistaken for substantive discussion of a topic. Because the vocabulary of each policy area evolves over time, I estimate the model separately by Congress.

The model returns a vector of topic proportions for each speech whose elements sum to one. I define a legislator's focus on an occupational domain in a given Congress as the average estimated proportion for that topic across all of their speeches in that Congress. The occupational seed lists appear in Appendix Table A.3, the highest-probability terms learned for each occupational topic appear in Appendix Table A.4, and full estimation and validation details appear in Appendix A.2.1. Appendix Figure A.2 shows attention to each occupational topic over 1947–2016.

3.3 Bill Topics

To measure which policy areas legislators prioritize through bill sponsorship, I use data from the Congressional Bills Project covering 1947–2020 (Adler and Wilkerson, 2020; Wilkerson et al., 2025). The dataset classifies each bill into major and minor topics using the Comparative Agendas Project (CAP) coding system. I map these topics onto the occupational domains used in the analysis. Health/Medicine, Agriculture, and Education correspond directly to major topics, while the remaining occupations are matched to selected minor topics that more precisely capture their policy domains. For example, Law includes court administration and the criminal and civil code, while Military includes military readiness, personnel, procurement, National Guard affairs, and war-related issues. For each legislator–topic–Congress observation I calculate the share of bills the legislator sponsors in that Congress that fall within the corresponding occupational domain. Appendix Table A.5 reports the full mapping.

4 Estimation Strategy

Legislative behavior is shaped by institutional and electoral incentives, making it difficult to distinguish differences associated with occupational background from those associated with party agendas and constituency demand. Legislators may focus on issues their party prioritizes (Bartels, 2008; Poole and Rosenthal, 1997) or that reflect constituency interests (Adler and Lapinski, 1997; Shepsle, 1979; Shepsle and Weingast, 1995). A simple comparison across occupational backgrounds would therefore conflate occupation with partisanship and constituency demand.

To address this challenge, I compare same-party legislators with different occupational backgrounds who represent the same House district or state at different points in time. The analysis draws on a panel of 3,600 members of Congress across 39 Congresses from 1947 to 2024.[3]

I begin with two outcomes capturing issue focus: the share of bills a legislator sponsors in a given occupational domain and the share of their congressional floor-speech content devoted to that domain. I structure the data at the legislator–occupational-domain–Congress level, with ten rows for each legislator in each Congress, one for each domain. The matching-occupation indicator equals

[3]Details on the panel setup are provided in Appendix Section A.4.

one when legislator i has the occupational background corresponding to domain k. It can equal one in multiple domain rows for legislators with more than one occupational background. The pooled specification is

$$Y_{ikt} = \beta \, \mathbf{1}\{\text{Has matching occupation}\}_{ik} + \mathbf{X}'_{it}\boldsymbol{\delta} + \alpha_{kdpc} + \lambda_{ktpc} + \varepsilon_{ikt}. \tag{1}$$

where i indexes legislators, k occupational domains, and t Congresses. The outcome Y_{ikt} measures legislator i's activity in domain k during Congress t. The vector $\mathbf{X}_{it}$ includes incumbency status, gender, race, and seniority. The subscripts d, p, and c denote the legislator's constituency (House district or state), party, and chamber in Congress t.

The fixed effects α_{kdpc} absorb stable differences in domain-specific activity within each constituency–party–chamber combination. The fixed effects λ_{ktpc} absorb party-specific changes in activity within each domain over time, separately by chamber. Standard errors are clustered at the constituency–party level. The coefficient β estimates the average difference in activity within a domain when the same constituency is represented at different times by same-party legislators with and without the corresponding occupational background, pooling this comparison across domains. Appendix Section A.5.1 provides the full specification details.

For the occupation-specific estimates, I retain the same outcomes, controls, fixed effects, and clustering, but replace the pooled match indicator with a target-occupation indicator and its interaction with the corresponding domain. Let j index the target occupation. The matched-domain indicator equals one when occupational domain k corresponds to target occupation j.

I estimate the following model separately for each target occupation:

$$\begin{aligned} Y_{ikt} = {} & \theta_j \, \mathbf{1}\{\text{Has occupation } j\}_i \\ & + \tau_j \left[\mathbf{1}\{\text{Has occupation } j\}_i \times \mathbf{1}\{\text{Matched domain}\}_{kj}\right] \\ & + \mathbf{X}_{it}'\boldsymbol{\delta} + \alpha_{kdpc} + \lambda_{ktpc} + \varepsilon_{ikt}. \end{aligned} \tag{2}$$

The indicator $\mathbf{1}\{\text{Has occupation } j\}_i$ is repeated across all ten domain rows. The coefficient θ_j pools, across the nine unmatched domains, comparisons between same-party legislators with and without occupational background j who represent the same constituency at different times. The interaction coefficient τ_j captures how much larger or smaller this difference is in the corresponding domain, so $\theta_j + \tau_j$ is the total estimated difference in that domain. Because the matched-domain indicator varies only across domains, its main effect is absorbed by the occupational-domain fixed effects. In simple terms, the model asks how electing a legislator from a given occupation affects activity in the other occupational domains and whether the effect differs in the domain connected to that occupation. Appendix Section A.5.2 provides the full specification details.

I interpret the estimates as the consequences of electing representatives with different occupational backgrounds, not as the isolated causal effect of occupation itself (Bertoli and Hazlett, 2025). Occupational backgrounds are bundled with prior beliefs, skills, networks, resources, and career trajectories; they cannot be assigned independently to otherwise identical legislators.

5 Legislators focus on issues related to their occupations

I begin with pooled estimates of occupation-linked issue specialization. Table 1 reports estimates of β on *Has matching occupation* from Equation 1 across four specifications. This coefficient estimates the average effect of electing a legislator with a background matching a given occupational domain on activity in that domain, pooling comparisons across all ten domains. The outcome in the top panel is the share of floor-speech content devoted to an occupational domain, and the outcome in the bottom panel is the share of sponsored bills in that domain. The "relative to baseline" row expresses each coefficient as a percentage of the mean outcome among legislators without the matching occupation.

In the speech panel, Column (1) reports the raw difference in means: legislators devote 1.18 percentage points more of their speech content to domains matching their occupations, a 62% increase over the baseline among legislators without the matching occupation. Column (2) adds race, gender, incumbency, and seniority. The estimate is essentially unchanged at 1.20 percentage points. Column (3) accounts for the fact that parties emphasize different issues at different points in time by adding domain-by-Congress-by-party-by-chamber fixed effects. The estimate remains 1.09 percentage points, or 57% above baseline. Column (4) adds domain-by-constituency-by-party-by-chamber fixed effects, comparing legislators with and without the matching occupation within the same domain, constituency, party, and chamber, net of party-specific issue agendas over time. The estimate falls to 0.89 percentage points but remains 47% above baseline.[4]

The bill sponsorship panel shows a similar pattern. In Column (1), legislators sponsor 1.18 percentage points more of their bills in domains matching their occupations, a 35% increase over baseline. Adding legislator characteristics in Column (2) leaves the estimate nearly unchanged at 1.22 percentage points. Adding domain-by-Congress-by-party-by-chamber fixed effects in Column (3) increases the estimate to 1.62 percentage points, or 48% above baseline. In the preferred within-constituency-party specification in Column (4), the estimate is 1.21 percentage points, a 36% increase over baseline.

The results show that occupation-linked specialization remains after accounting for legislator demographics, party agendas, and stable differences across constituen-

[4]Re-estimating the main specification with a simpler keyword-dictionary outcome yields similar occupation-match estimates; see Appendix Figure A.4.

cies. In the full specification, the estimate is somewhat smaller for speeches and about the same for bills.

Table 1: Occupational Background and Issue Specialization, U.S. Congress 1947–2020

	(1)	(2)	(3)	(4)
	Speech content share			
Has matching occupation	0.0118***	0.0120***	0.0109***	0.0089***
	(0.0003)	(0.0003)	(0.0005)	(0.0008)
% relative to baseline	+62%	+63%	+57%	+47%
	Bill share			
Has matching occupation	0.0118***	0.0122***	0.0162***	0.0121***
	(0.0006)	(0.0006)	(0.0010)	(0.0014)
% relative to baseline	+35%	+36%	+48%	+36%
Race, gender, incumbency, seniority		√	√	√
Topic × Congress × Party × Chamber FE			√	√
Topic × District × Party × Chamber FE				√

Note: This table reports pooled estimates of the relationship between legislators' occupational backgrounds and attention to matching occupational topics. The unit of observation is the legislator × topic × Congress. *Has matching occupation* equals one when the legislator's background matches the topic. The speech panel spans 1947–2016 (178,739 observations, 3,254 legislators); the bill panel spans 1947–2020 (201,700 observations, 3,425 legislators). Column (1) reports the raw difference in means. Column (2) adds legislator characteristics. Column (3) adds topic × Congress × party × chamber fixed effects, absorbing party-specific issue agendas within each Congress. Column (4) adds topic × district × party × chamber fixed effects, comparing legislators with and without the matching occupation within the same topic, district, party, and chamber, net of party-period shocks. The baseline is the mean among legislators without the matching occupation; the relative row expresses each coefficient as a percentage of that baseline. Standard errors are in parentheses: heteroskedasticity-robust in Columns (1)–(2), clustered by district-party in Columns (3)–(4). †p<.10, *p<.05, **p<.01, ***p<.001.

Figure 2 reports separate estimates for each occupation using Equation 2. The top panel shows effects on speech attention, and the bottom panel shows effects on bill sponsorship. The pooled estimates shown in blue correspond to the preferred estimates of β in Column (4) of Table 1.

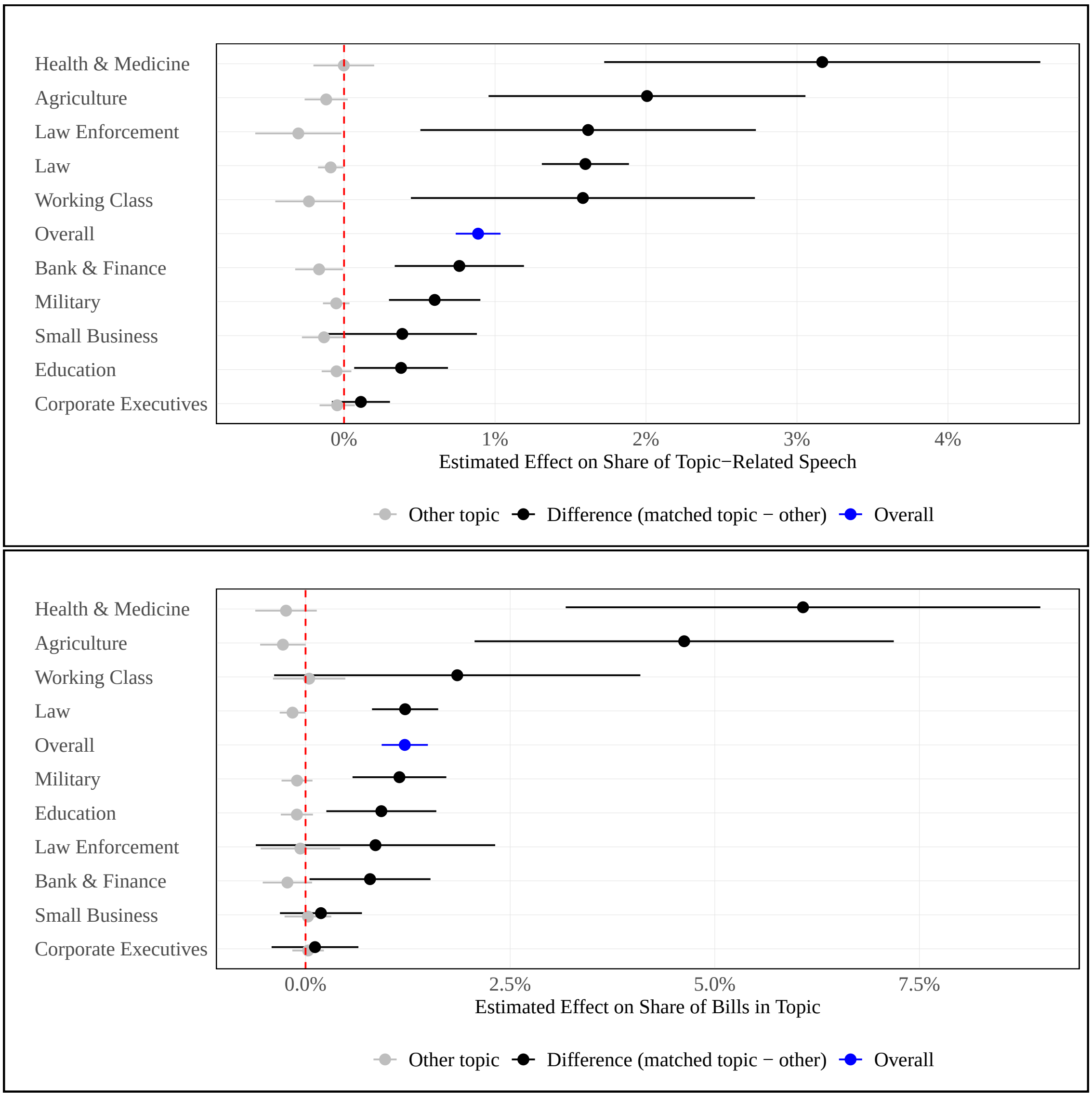
For each occupation, the grey estimate is θ_j, the pooled effect of electing a legislator with that occupational background on activity across the nine unmatched domains. The black estimate is τ_j, the additional effect in the corresponding domain relative to the unmatched-domain effect. Adding the grey and black estimates gives the total estimated effect in the corresponding domain. The contrast shows whether an occupational background changes activity broadly across domains or concentrates it in the domain connected to that occupation. Appendix Table A.8

reports the matched-domain effect, unmatched-domain effect, difference between them, and baseline mean for every occupation and outcome.

For all ten occupations, electing a legislator from that background produces a larger increase in speech attention in the related policy domain than across the other nine occupational domains. This difference is statistically distinguishable from zero for eight occupations. The largest differences appear for health and medicine, agriculture, law enforcement, law, and working-class backgrounds. When a constituency elects a legislator with a health background, such as a doctor, in place of a same-party legislator without a health background, the representative devotes an estimated 3.17 percentage points more of their speech content to health. Relative to the average share of health-related speech among legislators without a health background (1.90%), this represents a 167% increase, or roughly 2.7 times as much health-related speech content. Their attention to the other nine occupational domains remains essentially unchanged. The corresponding matched-domain differences are 2.01 percentage points for agriculture, 1.62 for law enforcement, 1.60 for law, and 1.58 for working-class domains, equivalent to 114%, 94%, 111%, and 76% of their respective baselines. The unmatched-domain effects are generally small and often negative, while speech attention increases most clearly in domains connected to legislators' own backgrounds.

The bill sponsorship estimates show a similar but more concentrated pattern. The matched-topic differences are positive for all occupations, with statistically distinguishable effects for Health/Medicine, Agriculture, Law, Military, Education, and Bank & Finance. Legislators with health backgrounds sponsor 6.08 percentage points more of their bills on health-related topics relative to unmatched topics, a 112% increase over the baseline health bill share among legislators without health backgrounds. The corresponding estimates are 4.63 percentage points for agriculture, 1.22 for law, and 1.15 for military topics, corresponding to increases of 44%, 69%, and 27% over their respective baselines. The estimates for working-class, law enforcement, small-business, and corporate-executive backgrounds are positive but

Figure 2: Occupational Background and Issue Focus in Speeches and Sponsored Bills, U.S. Congress 1947–2020



Note: The top panel shows effects on the share of floor speeches devoted to occupation-related topics. The bottom panel shows effects on the share of sponsored bills in those topics. The pooled estimate (blue) corresponds to the preferred pooled specification in Column (4) of Table 1. Separate models are estimated for each target occupation. Grey estimates show the effect of electing a legislator from the target occupation on unmatched occupational topics. Black estimates show the additional effect on the matched topic relative to unmatched topics. Models include topic × Congress × party × chamber and topic × district × party × chamber fixed effects, with legislator controls. Standard errors are clustered at the district-party level. Speech data come from Gentzkow, Shapiro and Taddy (2019) for 1981–2016, extended to 1947 using the bound Congressional Record; bill sponsorship data come from the Congressional Bills Project (Adler and Wilkerson, 2020). The full per-occupation estimates appear in Appendix Table A.8.

less precisely estimated. Together with Table 1, these results show that occupational background predicts issue specialization in both speech attention and bill sponsorship.

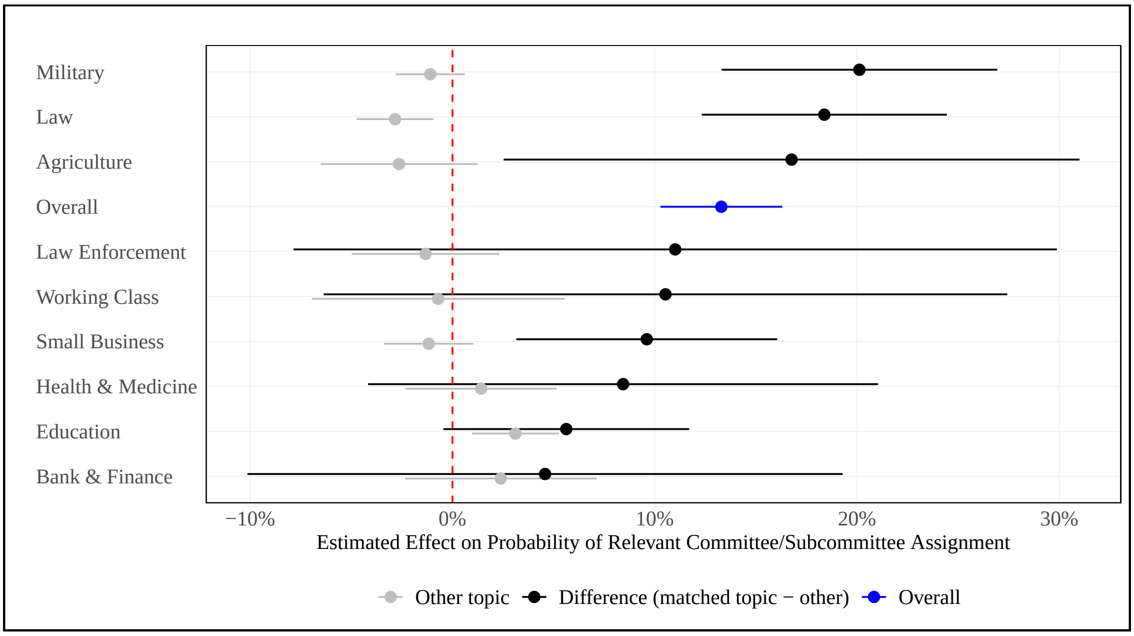
6 Legislators Join Committees Related to their Occupational Domains

The previous section shows that legislators devote more speeches and sponsored bills to issues related to their prior occupations. Committees provide a more demanding measure of specialization. They structure jurisdiction, information-gathering, and much of the day-to-day work through which members shape legislation (Fenno, 1973; Krehbiel, 1991).

To measure committee specialization, I map occupations to House committees and subcommittees with direct policy jurisdiction. The full mapping is reported in Appendix Table A.6. I exclude Appropriations and other power or procedural committees, since service there reflects institutional influence rather than occupational expertise. Some occupations map cleanly to standing committees, such as Agriculture, Law, and Military. Others require subcommittee data, which I digitize from the Congressional Directory. These data allow me to separate education from labor within the Education and Labor Committee and identify the health subcommittees within Energy and Commerce, Veterans' Affairs, and others.

Figure 3 shows that occupational background predicts relevant committee and subcommittee service. On average, electing a legislator with a given occupational background increases the probability of serving on a related committee or subcommittee by 13.3 percentage points, a 136% increase over baseline. The largest and most precisely estimated matched-committee differences appear for Agriculture, Law, and Military backgrounds. The additional effects on the matching committee or subcommittee, relative to unmatched committees, are 16.8 percentage points for Agriculture, 18.4 for Law, and 20.1 for Military. These estimates imply that, relative to legislators without the corresponding background, legislators with agriculture backgrounds are about twice as likely to serve on a relevant committee or subcommittee, lawyers nearly five times as likely, and legislators with military backgrounds about 2.1 times as likely. The estimates for Health/Medicine and Working Class also point in the same direction, though they are less precisely estimated.

Figure 3: Occupational Background and Relevant Committee or Subcommittee Service, U.S. House 1991–2024



Note: This figure shows the effect of electing a legislator from each occupational background on the probability of serving on a related House committee or subcommittee, using the same within-district-party design as the main analysis with standard errors clustered at the district-party level. The pooled estimate (blue) averages across occupations. Occupation-specific estimates are estimated separately for each target occupation: grey estimates show the effect of electing a legislator from the target occupation on unmatched committees, and black estimates show the additional effect on the matched committee or subcommittee relative to unmatched ones. Occupations are mapped to committees and subcommittees with direct policy jurisdiction (Appendix Table A.6); Corporate Executives is omitted because no House committee corresponds to that background. Standing-committee assignments come from the Garrison Nelson records for Congress 102, Stewart–Woon records for Congresses 103–115, and archived GovTrack XML for Congresses 116–118. Subcommittee assignments come from the Congressional Directory through Congress 117 and GovTrack for Congress 118. The pooled estimate is stable as fixed effects are added (Appendix Table A.7), and full per-occupation estimates appear in Appendix Table A.8.

Because the subcommittee data cover a shorter period, Appendix Figure A.7 repeats the analysis with longer-running standing-committee assignments alone (1947–2024). This coarser measure cannot include Health/Medicine or separate education from labor-related specialization, but the pooled effect is similar: 10.5 percentage points, a 120% increase over baseline.

Committee assignments could reflect legislators' own preferences, party leaders' placement decisions, or both. Appendix Figure A.8 uses committee-request data from Frisch and Kelly (2006) and shows that legislators are also more likely to request committees related to their occupational backgrounds. The pooled request effect is 10.8 percentage points, a 103% increase over baseline. This suggests that legislators themselves seek out institutional positions connected to their prior careers.

7 Legislators Are More Effective at Advancing Legislation Related to Their Occupations

Across speeches, bill sponsorship, and committee assignments, legislators consistently concentrate their attention and activity in policy domains connected to their prior occupations. I next examine whether this specialization translates into legislative success: are legislators more effective at advancing bills in their occupational domains?

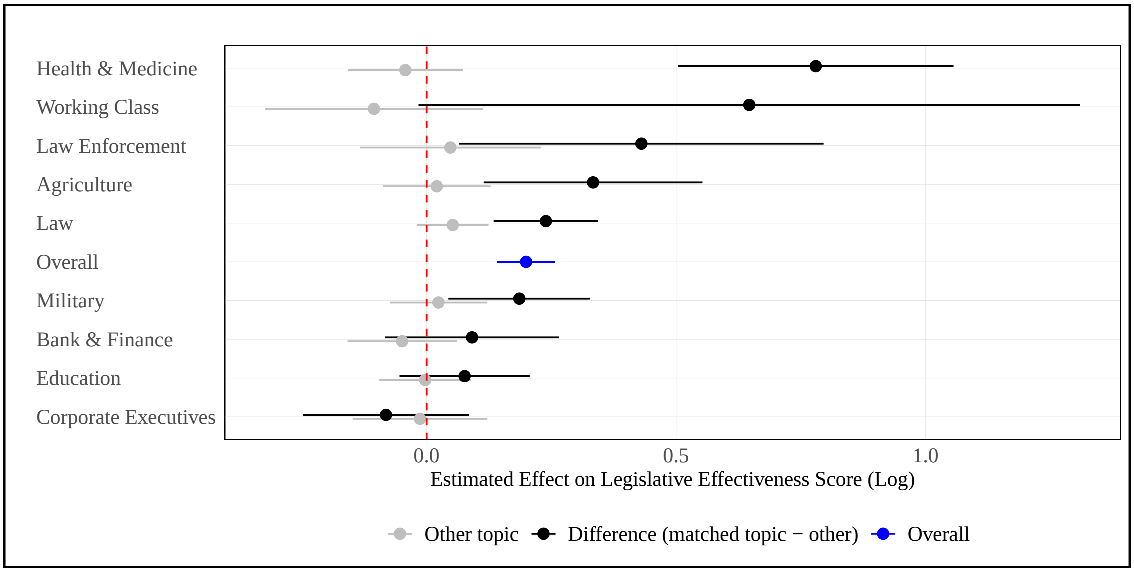
To measure legislative success, I use issue-specific Legislative Effectiveness Scores (LES) from Volden and Wiseman (2014), covering 1973–2024. LES measures each legislator's success in moving bills through the legislative process, from introduction and committee action to passage and enactment, while weighting bills by substantive significance. The issue-specific scores allow me to test whether legislators are more effective in policy domains connected to their occupational backgrounds. Because LES is highly skewed and contains many zeros, I use $\log(\text{LES} + 0.1)$ in all models.[5]

Using the same topic-stacked within-district-party design as above, Figure 4 examines whether legislators are more effective in issue areas matching their occupational backgrounds. The pooled estimate is 0.20 log points. Evaluated at the baseline issue-specific LES of 0.15 among legislators without a matching occupa-

[5]The result is robust to alternative transformations and rules for handling zero values, including $\log(\text{LES} + 0.01)$, asinh(LES), log(LES) restricted to legislators with nonzero LES, and untransformed LES. See Appendix Figure A.10.

tional background, this corresponds to an increase to about 0.21, or 36%.[6] The largest matched-domain differences are 0.78 log points for Health/Medicine, 0.65 for Working Class, 0.43 for Law Enforcement, 0.33 for Agriculture, 0.24 for Law, and 0.19 for Military backgrounds. The Working Class estimate is less precisely estimated. The unmatched-topic estimates are generally small, indicating that legislators from these occupations are not more effective across all policy areas. Instead, the effectiveness gains are concentrated in the issue domains connected to their prior careers.

Figure 4: Occupational Background and Legislative Effectiveness, U.S. Congress 1973–2024



Note: The figure shows the effect of electing legislators from different occupational backgrounds on their issue-specific Legislative Effectiveness Score, measured as log(LES + 0.1). The pooled estimate (blue) averages across occupations. Occupation-specific estimates are estimated separately for each target occupation. Grey estimates show the effect of electing a legislator from the target occupation on unmatched issue areas. Black estimates show the additional effect on the matched issue area relative to unmatched issue areas. Effects are estimated using the same within-district-party design as the main analysis, with controls for incumbency, seniority, gender, and race. Standard errors are clustered at the district-party level. LES data come from Volden and Wiseman (2014) and cover 1973–2024. The pooled estimate is stable as fixed effects are added (Appendix Table A.7), and the full per-occupation estimates appear in Appendix Table A.8.

A key identification concern is that occupation-linked estimates could reflect shifting district–party preferences rather than the contemporaneous effect of electing a legislator with a given occupational background. If district–party preferences

[6]To facilitate comparison with previous research that models LES in levels, I also estimate the specification using untransformed LES. The estimated effect is 0.35 LES points, approximately one-third of the average score and equivalent in magnitude to about four additional Congresses, or eight years, of service (Appendix Figure A.10).

change over time, the election of a legislator from a given occupation could reflect those shifts, generating apparent effects before entry or after exit from office. I therefore re-estimate the main specification including one-period leads and lags of the occupation indicator. Across all four outcomes, the contemporaneous estimates remain positive. The lead coefficients are substantively small and not statistically distinguishable from zero. The lag coefficients are also small for speeches, bills, and legislative effectiveness; for committee service, the lag is negative, opposite in sign to the main estimate. This pattern is inconsistent with anticipatory confounding (Appendix Section A.8.1). These results show that occupational specialization extends beyond attention, bill sponsorship, and committee service. Legislators are also more successful at advancing legislation in domains connected to their prior careers.

8 Occupational Background Predicts Voting Along Class Lines

The previous sections show that legislators focus on issues tied to their occupations and are more effective in those domains. I next ask whether occupational background also predicts how legislators vote. I test this in two ways. First, I focus on the divide between legislators with business backgrounds and those with working-class backgrounds. This comparison most directly connects occupations to recent research on how politicians' economic backgrounds shape substantive representation (Carnes and Lupu, 2023; Kirkland, 2021). It also reflects a stark imbalance in Congress's occupational composition. Working-class Americans make up more than half of the labor market (Carnes, 2013), yet only about 3% of members in a typical Congress during this period have experience in working-class occupations. Business owners and executives, by contrast, are heavily overrepresented. Second, I test whether occupational background predicts voting on issues related to legislators' own occupational domains, asking whether the domain-specific patterns found in speeches, bill sponsorship, committees, and legislative effectiveness also extend to roll-call voting.

I find that business-background legislators vote more conservatively than working-class legislators on issues related to employment and labor, but legislators rarely take distinctive positions on issues tied to their own occupations.

8.1 Class-based voting

I test the business–working-class divide using issue-specific Conservative Vote Probabilities (CVPs) (Fowler and Hall, 2012). Unlike NOMINATE scores, which summarize legislators' overall roll-call ideology, a CVP measures how conservatively a legislator votes within a particular issue domain relative to the median legislator in the same Congress and chamber. This allows me to examine occupational differences in the domains where theory expects them rather than only in legislators' overall ideological positions. Details of their construction appear in Appendix Section A.9.

I estimate separate CVPs for three issue domains: predistribution, redistribution, and social issues. Prior research gives reason to expect differences between business- and working-class legislators across economic issues: working-class officeholders tend to vote less conservatively, while business backgrounds are associated with more conservative economic preferences (Carnes, 2013; Carnes and Lupu, 2023; Kirkland, 2021). I distinguish predistribution from redistribution to examine whether this divide is strongest where occupational class conflict is most direct. Predistributive policies govern wages, union rights, workplace regulation, and bargaining power, shaping distribution before taxes and transfers, while redistribution concerns taxes, transfers, public spending, and social welfare (Hacker, 2011; Kuziemko, Longuet-Marx and Naidu, 2026). I expect a smaller divide on social issues because working-class voters may hold more conservative positions in this domain (Franko and Witko, 2022; Lindh and McCall, 2020).

I construct the three domains using Voteview's 97-issue typology (Lewis et al., 2022), which provides narrowly defined codes for issues such as minimum wage, workplace conditions, and union regulation. I group 22 codes into the three domains, yielding 11,752 roll calls. Because Voteview's issue typology ends with the 113th Congress, this analysis covers 1947–2014. Appendix Table A.10 reports the full mapping, vote counts, and coverage years.

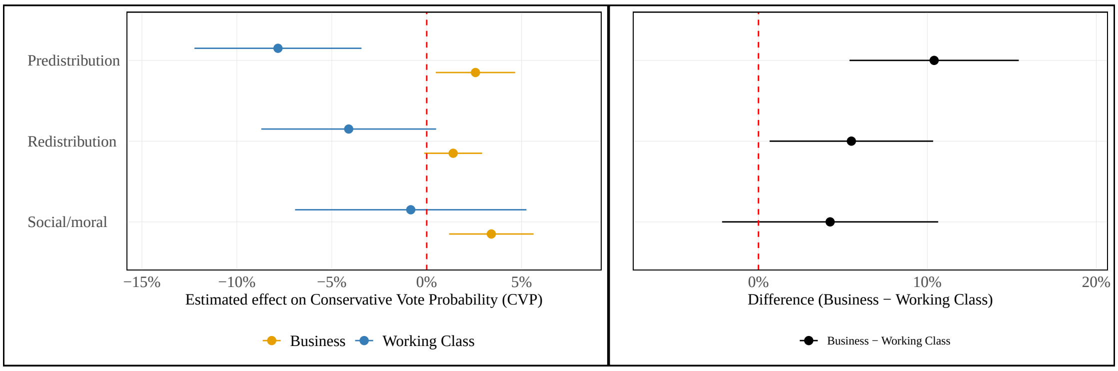
I estimate a separate model for each issue domain, with one observation per legislator–Congress and the legislator's CVP in that domain as the outcome. The predictors are indicators for business backgrounds (corporate executives, small business owners, and bankers) and working-class backgrounds (blue-collar, manual, and service occupations). Legislators with neither background form the reference category.[7] I use the same fixed-effect structure as in the issue-specialization analyses: constituency–party–chamber and Congress–party–chamber fixed effects, controls for incumbency, gender, race, and seniority, and standard errors clustered at the constituency–party level. Each coefficient compares CVP when the same constituency and party is represented at different times by a legislator with that background rather than one with neither background. The business–working-class contrast is the difference between these two coefficients. Appendix Section A.9 reports the estimating equation.

Figure 5 reports the estimates. The left panel reports separate estimates for electing a legislator with a business background and one with a working-class background. On predistributive issues, when a constituency elects a business-background legislator, its representative votes 2.6 percentage points more conservatively. When it elects a working-class legislator, its representative votes 7.8 percentage points less conservatively. The right panel reports the difference between electing a business-background legislator and a working-class legislator, a gap of 10.4 percentage points.

The same pattern appears more weakly on redistribution: business-background

[7]Some legislators have both a business and a working-class background and are coded on both indicators, consistent with the non-exclusive treatment of occupation throughout the paper. Restricting the comparison to single-background legislators leaves the results nearly unchanged; the predistribution gap moves from 10.4 to 10.6 percentage points.

Figure 5: Occupational class backgrounds and issue-specific Conservative Vote Probability, U.S. Congress, 1947–2014



Note: This figure reports estimated effects of business and working-class backgrounds on legislators' issue-specific Conservative Vote Probabilities, relative to legislators with neither background. Issue domains are defined by Voteview issue codes (Appendix Table A.10). Models control for incumbency, gender, race, and seniority and include district–party–chamber and Congress–party–chamber fixed effects. Standard errors are clustered at the district-party level.

legislators vote more conservatively than working-class legislators, but the gap is 5.5 percentage points, roughly half the predistribution gap. By contrast, the estimated gap on social issues is 4.2 percentage points and is not statistically distinguishable from zero. The class divide is therefore clearest on predistributive issues related to employment and labor.

Because roll-call voting is strongly structured by party and constituency, I compare the preferred estimate with the raw difference between business- and working-class legislators. I then add legislator controls, Congress-by-party-by-chamber fixed effects, and constituency-by-party-by-chamber fixed effects one at a time to see how much the gap changes as each is taken into account (Appendix Table A.12). The raw gap on predistributive issues is 43.6 percentage points and remains 40.6 points after adding legislator controls. Adding the Congress-by-party-by-chamber fixed effects reduces the gap to 18.8 points, while adding the constituency-by-party-by-chamber fixed effects reduces it further to 10.4 points. Party differences therefore explain most of the raw gap, constituency differences explain part of the remainder, and a substantial difference remains between same-party legislators representing the same constituency at different times, as shown in Figure 5.

The predistribution gap is robust to alternative measurement choices. It remains under strict and broad definitions of the issue domains, when Comparative Agendas Project topic codes replace Voteview issue codes, and across alternative definitions of the business and working-class groups (Appendix Figures A.13, A.14, A.12, and A.15). The pattern also appears across the individual predistribution issues that make up the domain (Appendix Figure A.11).

The main limitation is the small number of working-class legislators. Fewer than 100 serve during the 1947–2014 period, so relatively few constituencies contribute within-party changes involving a working-class legislator. The pre-election trends show no consistent anticipatory pattern, but the small number of working-class cases makes this a weak diagnostic (Appendix Figure A.17). I therefore interpret the results as evidence of an association between occupational class background and roll-call voting, with more limited causal precision than in the issue-specialization analyses.

As a secondary test, I examine interest group ratings. These ratings provide a complementary measure of how legislators vote on economic conflict because the organizations themselves select the roll calls that enter their scores. I focus on four organizations whose criteria most directly capture conflict between labor and business: the AFL-CIO and National Education Association (NEA) on the labor side, and the U.S. Chamber of Commerce and National Federation of Independent Business (NFIB) on the business side. Together, the ratings cover 1947–2024, with the Chamber ratings ending in 2020 and the NFIB ratings beginning in 1995. Using the same within-constituency-party comparison, all four differences move in the expected direction. Working-class legislators score about 5 points higher than business-background legislators on the AFL-CIO ratings and 7 points higher on the NEA ratings, while the differences on the Chamber and NFIB ratings are smaller and less precisely estimated. These results provide additional evidence that occupational class background predicts voting on economic issues.[8]

[8]Appendix Figure A.18 reports the estimates, and Appendix Section A.11 documents the rating sources.

8.2 Occupation-specific voting

I next test whether occupational background predicts roll-call voting in the same domain-specific way that it predicts speeches, bill sponsorship, committees, and legislative effectiveness. In other words, I ask whether legislators vote differently on issues related to their occupations than they do on other issues. I apply the occupation-specific specification in Equation 2 to issue-specific CVPs. I use the same occupation–CAP-topic mapping as in the bill-sponsorship analysis (Appendix Table A.5). Each legislator–Congress contributes one observation for each of nine occupational domains.[9] For each occupation, the model estimates the effect of electing a legislator from that background on CVP for roll calls in its corresponding domain and for roll calls in the other eight domains.

The estimates appear in Figure 6. In the left panel, the black estimates are the corresponding-domain effects, while the grey estimates pool effects across the other eight domains. The right panel reports the difference between the black and grey estimates. This difference shows whether voting behavior is specialized to the legislator's own occupational field.

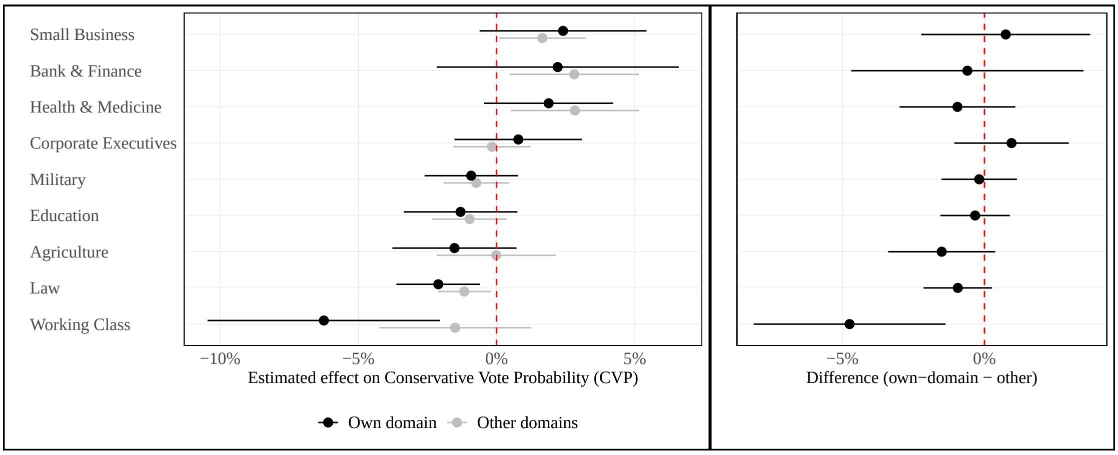
The grey estimates show several broad voting differences. Legislators with banking and health backgrounds vote 2.8 percentage points more conservatively across unrelated issue domains, while legislators with small-business backgrounds vote 1.7 points more conservatively. Because these estimates pool voting across domains unrelated to each occupation, they suggest that legislators from these backgrounds are more conservative in general.[10]

In the left panel, the black estimates show the estimated voting difference in the domain related to each occupation. When a constituency elects a working-class legislator in place of a same-party legislator without that background, its representative votes 6.2 percentage points less conservatively on wage-and-bargaining roll calls. The corresponding estimate for electing a lawyer is 2.1 points less conservative

[9] Law Enforcement is omitted to keep the occupations consistent across the CAP analysis and the Voteview robustness test, where the corresponding issue codes have limited coverage.

[10] Health and small-business legislators also have more conservative overall DW-NOMINATE scores (Appendix Figure A.19), providing a separate measure of this broader ideological difference.

Figure 6: Occupational Background and Issue-Specific Voting, U.S. Congress, 1947–2022



Note: This figure reports the estimated effect of electing legislators from each occupational background on issue-specific Conservative Vote Probability. In the left panel, black estimates show the effect on voting in the occupation's own domain, while grey estimates pool the effect across other domains. The right panel reports the difference between these estimates (own domain − other domains). Issue domains are defined using Comparative Agendas Project topic codes and the mapping in Appendix Table A.5. Each legislator–Congress observation is stacked across nine issue domains. Models control for incumbency, gender, race, and seniority and include issue-domain–constituency–party–chamber and issue-domain–Congress–party–chamber fixed effects. Standard errors are clustered at the constituency–party level. Lines show 95% confidence intervals. Full estimates appear in Appendix Table A.16.

on crime-and-law roll calls. The remaining corresponding-domain estimates are not statistically distinguishable from zero.

But I find little evidence of specialized voting on legislators' own issues. The right panel provides the direct test of domain-specific voting. For most occupations, the difference between the black and grey estimates is small and statistically indistinguishable from zero. The main exception is working-class legislators, whose voting is 4.8 percentage points more liberal on wage-and-bargaining roll calls relative to the broader difference across unrelated issue domains. This is the only clear evidence that legislators vote differently on issues related to their occupations. For lawyers, the corresponding-domain estimate differs by only 0.9 points from the estimate across unrelated domains, so their more liberal voting extends across domains. The pattern is similar under Voteview's issue typology (Appendix Figure A.16); full estimates appear in Appendix Table A.16.

The breadth of this analysis comes at the cost of depth within each issue domain. The occupation-specific CVPs summarize left-right voting across all roll calls in a domain, so targeted differences on particular policies may not be visible on this scale. More focused analyses of particular policy conflicts could uncover these narrower patterns (O'Grady, 2019).

9 Scope of the Issue-Specialization Results

In this section, I examine when occupation-linked specialization is strongest and how it varies across legislators and over time. I first ask how much of the specialization in speeches, bill sponsorship, and legislative effectiveness remains after accounting for service on a relevant committee. I then test whether the results differ between legislators with and without prior state or local government experience, whether they are stronger when the relevant occupation was the legislator's most recent substantive occupation before Congress, and whether they vary across a legislator's career or historical periods. These analyses focus on the issue-specialization outcomes rather than class-based roll-call voting, where the number of working-class legislators is too small for reliable subgroup analysis.

One open question is whether occupational background continues to predict specialization after accounting for the committees legislators join. Committee service is itself one form of occupation-linked behavior, and it also structures the issues members work on. I re-estimate the floor-speech, bill-sponsorship, and legislative-effectiveness models controlling for service on a relevant committee or subcommittee. This comparison asks whether legislators with matching occupational backgrounds still specialize more once relevant committee service is held constant. The estimates become smaller but remain statistically significant, retaining between 63 and 85 percent of their original magnitude (Appendix Table A.9). Most of the estimated relationship remains after accounting for relevant committee service.

Many members arrive in Congress after holding positions in state or local government, which may weaken the connection between earlier occupational experience and behavior in Congress. Based on the positions reported in their biographies, I identify 58 percent of members as having such experience and compare occupation-linked specialization among legislators with and without it. I find no clear differences in speech attention, bill sponsorship, or committee service. The legislative-effectiveness estimate is larger among legislators with prior government experience, but the difference is not statistically distinguishable from zero (Appendix Figure A.21).

Occupational experience may be more closely connected to behavior in Congress when it immediately precedes a legislator's entry into office. I test this by distinguishing legislators whose matching occupation was the most recent substantive occupation recorded before their first election from other legislators who held the same occupation earlier in their careers. The estimated specialization effect is roughly sixty percent larger for floor speeches, forty percent larger for bill sponsorship, and eighty-five percent larger for committee assignments. The difference is statistically distinguishable from zero for speeches and committees, but not for bill sponsorship or legislative effectiveness (Appendix Section A.15). These results suggest that recency matters most clearly for speech attention and committee service.

Occupation-linked specialization might fade as legislators move further from their prior careers, or grow as they acquire institutional experience. I test this by estimating how the occupation-match effect changes with a legislator's term of service. Specialization is present in the first term for all four outcomes. It declines modestly across terms for floor speeches and bill sponsorship. The committee estimate points in the same direction but is less precise, while the legislative-effectiveness estimate points toward a small increase. The results therefore show no common trajectory across all four outcomes, but they indicate that occupation-linked specialization is already present when legislators enter Congress rather than emerging later in their careers (Appendix Table A.19). This pattern aligns with previous work showing that relevant professional experience aids new members' legislative success and continues to matter later in their careers (Makse, 2022).

Finally, I ask whether growing party polarization has weakened occupational specialization by making legislators within each party more similar (McCarty, Poole and Rosenthal, 2006). I compare the occupation-match estimates across approximately decade-long redistricting periods. The estimates are positive in every period for speeches, bills, and legislative effectiveness. The committee estimates are positive from 1993 through 2022 and close to zero in the short periods at the beginning and end of its coverage. The speech and bill estimates decline during parts of the period but later rise or fluctuate, while the legislative-effectiveness estimates show no downward pattern. Taken together, the estimates provide no consistent evidence that occupation-linked specialization has weakened over time (Appendix Section A.13).

10 Conclusion

This paper shows that legislators' occupational backgrounds predict two dimensions of legislative behavior: the issues legislators work on and the positions they take. Legislators devote more attention to issues related to their prior careers, are more likely to serve on relevant committees, and are more effective at advancing legislation in those domains. Occupational background also predicts roll-call voting, but in a different way. I find little evidence that legislators generally take distinctive positions on issues tied narrowly to their own occupational fields. Instead, the clearest voting differences fall along a business–working-class divide on economic issues: legislators with working-class backgrounds vote less conservatively on labor-market issues, while legislators with business backgrounds vote more conservatively.

Party, constituency, and electoral incentives are central predictors of legislative behavior (Fenno, 1978; Poole and Rosenthal, 1997). These forces could plausibly leave little room for occupational background to matter. Politicians also have incentives to invoke their professional experience strategically when explaining their legislative priorities. The results show that the connection between occupational background and legislative priorities is not merely rhetorical. Even within the same party and district, legislators from different occupational backgrounds focus on different issues, hold different institutional positions, and are more effective in different policy domains.

The findings speak to longstanding debates about specialization in Congress. The informational perspective treats prior experience as a source of low-cost specialization, while the distributional perspective emphasizes how legislators use institutional positions to pursue constituency interests (Adler and Lapinski, 1997; Krehbiel, 1991; Shepsle, 1979). The evidence here shows that legislators' prior careers predict where they invest attention, where they seek institutional influence, and where they are most effective. But specialization is only part of the representational pattern. Occupational backgrounds also predict voting behavior on class-linked economic issues. The occupational composition of Congress therefore shapes both which issues receive legislative attention and whose economic interests are represented in policy conflict.

These results also help explain why occupational background is politically informative to voters. Prior work shows that voters use candidates' occupations to infer both policy competence and ideological positions (Abbott and DeVeaux, 2024; Arnesen, Duell and Johannesson, 2019; Carnes and Lupu, 2016*a*; Costa and Pereira, 2025; Kirkland and Coppock, 2018). The evidence here suggests that both types of inference have an empirical basis. Legislators specialize and are more effective in policy areas connected to their prior careers, while legislators from business and working-class backgrounds vote differently on labor-market and distributional issues.

The broader implication is that occupational representation matters for more than descriptive balance. A legislature organized for informational efficiency may benefit from members with specialized occupational knowledge (Costa and Pereira, 2025; Krehbiel, 1991). But occupational specialization is not politically neutral. The backgrounds most tied to economic class, business and working-class occupations, are associated with both policy-relevant experience and distinct positions on economic policy. Nor is there much reason to assume that Congress's occupational composition reflects only the institution's demand for expertise. Access to office is shaped by socioeconomic resources, professional networks, and donor support (Bonica, 2017, 2020; Carnes, 2018). To the extent that overrepresented occupations reflect who can run and win rather than what the institution needs to know, occupational inequality affects not only who serves in Congress, but also which issues receive attention and whose economic interests are represented.

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Appendix: Occupations in Office

Appendix Contents

A.1 Occupation Classification Pipeline

Pipeline. I extract occupations from each Member's Bioguide biography using gpt-4.1-mini at temperature 0. A regex filter removes Congressional-service boilerplate, such as "elected to the Xth Congress" and "chair, Committee on ...". For each unique extracted occupation, I use four separate LLMs to classify the entry into one of 84 granular categories adapted from Carnes (2013)'s typology: gpt-5-mini, gpt-4.1-mini, DeepSeek V4-Pro, and GLM-5.1. I collapse the resulting classifications to the 10 broader occupational categories used in the main analyses. Table A.2 reports the mapping.

Prompting rules. For extraction, the model is instructed to return only the subject's own occupations or positions, preserving the original wording. The prompt includes paid jobs and careers, elected and appointed offices, military service, ownership roles, historical occupational phrases, and ambiguous phrases that plausibly describe occupations. It excludes education, awards, birth and death information, residences, committee memberships, board memberships, volunteer roles, and civic affiliations. If one phrase contains multiple distinct occupations, the model returns them separately.

For classification, the model assigns each extracted phrase to one granular category, using the category labels exactly as provided. The prompt instructs the model to prefer the most specific applicable category, reserve "Other" categories for entries without a more specific match, and follow disambiguation rules for recurring cases, including diplomatic roles, judicial roles, line-level government employment, and vague occupational descriptions. Full prompts, category lists, model identifiers, per-call metadata, and intermediate outputs are available in the replication materials.

Agreement and manual review. I measure agreement at two levels. At the occupation-string level, the four models agree unanimously on the focal group for

81.7% of the 7,126 strings the council assigns to one of the ten categories, and I manually review and reconcile the 1,307 strings where they do not. At the legislator level, the unit of analysis, where a legislator belongs to a focal group if any of their strings is classified there, the four models agree unanimously on 82% of legislator–group memberships and reach at least three-of-four agreement on 93%. Table A.1 reports both by category. Agreement is lowest in the occupationally ambiguous categories (small business, corporate executives, banking, working class), which is where the manual review is concentrated.

Table A.1: Council agreement by focal category, prior to manual review.

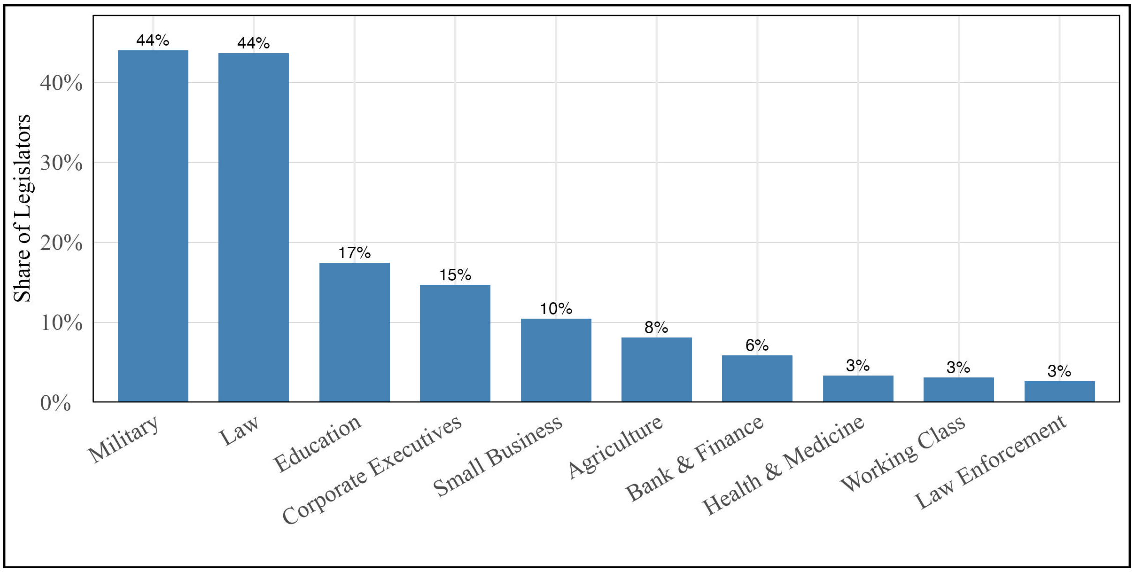
	Occupation strings		Legislators		
Focal category	N	% unan.	N	% unan.	% $\geq$3/4
Military	1,570	93.5	1,598	98.4	99.9
Education	937	87.0	683	87.7	97.1
Health & Medicine	121	86.0	132	92.4	99.2
Law	2,975	83.7	1,621	97.9	99.1
Agriculture	199	79.9	305	89.8	98.7
Law Enforcement	124	79.0	102	76.5	92.2
Working Class	171	74.9	159	54.1	89.9
Corporate Executives	615	59.8	656	59.0	91.0
Bank & Finance	174	51.7	206	51.9	88.8
Small Business	240	41.7	534	20.4	51.3

Note: This table reports agreement across the four LLMs before disagreements are resolved through manual review. The occupation-string columns count unique strings assigned to each category; a string is unanimous when all four models assign it to the same broad group. The legislator columns count members assigned to each category; "unan." requires agreement across all four models, and "$\geq$3/4" requires agreement across at least three.

Table A.2: Occupation Classification Schema: Granular Categories and Broader Group Mapping. *Note:* N counts distinct Members of Congress (1947–2024) with at least one occupational string classified into the granular category.

Broader Group	**Granular Category**	**N Members**
Law	Lawyer, private practice	1,108
	Lawyer, unspecified	1,047
	Government attorney	708
	Judge	216
	Law clerk	71
	Lawyer, other	16
	Lawyer, corporate	22
Military	Military service member	1,596
Education	College professor (except law schools)	288
	Elementary or secondary school teacher	240
	Elementary or secondary school administrator	74
	College administrator	86
	Other education professional	55
	Law school professor	50
	Librarian	3
Corporate Executives	Executive of a medium- or large-sized business	313
	Media executive, publisher, or media owner	107
	Owner of a medium- or large-sized business	46
	Manager in a medium- or large-sized business	72
Small Business	Owner of a small/local business	414
	Contractor	32
	Manager of a small/local business	26
Agriculture	Farmer, rancher, farm owner, ranch owner	285
	Farm manager	6
	Other agriculture professional	15
Bank & Finance	Bank manager/investment banker/stock broker	86
	Bank owner/banker	110
Working Class	Manual laborer	65
	Union employee/official	39
	Service industry worker	29
	Other working-class	5
Law Enforcement	Law enforcement officer or patrolman	64
	Law enforcement manager/director	48
	Law enforcement analyst	0
Health & Medicine	Medical doctor	58
	Hospital/medical services administrator	22
	Dentist	13
	Pharmacist	9
	Nurse	8
	Psychiatrist/psychologist	7
	Veterinarian	5
	Other healthcare professional	13

Figure A.1: Legislator Occupational Backgrounds, U.S. Congress, 1947–2026



Note: This figure shows the share of members of Congress with a background in each occupational category from 1947–2026. Because members can hold more than one occupation, category shares do not sum to 100%.

A.2 Congressional Speech Topics

A.2.1 Measuring Speech Focus

I measure how much of a legislator's floor speech focuses on each occupational topic using a keyword-assisted topic model (keyATM; Eshima, Imai and Sasaki, 2024). keyATM lets me define labeled topics and supply seed keywords for each, and then estimates every speech's composition across topics, guided by those seeds. This identifies speeches that are substantively about a topic even when they do not use a specific keyword.

I seed one topic for each occupational category using the keywords in Table A.3, and add a set of distractor topics (for example budget, welfare, taxation, and energy) so that pervasive non-occupational themes do not contaminate the occupational topics. Before fitting, I mask committee and agency names and non-labor uses of the word "union." I estimate the model separately for each Congress. The model returns, for each speech, a vector of estimated topic proportions. I define a legislator's focus on an occupational domain in a given Congress as the average of these topic proportions across all of the legislator's speeches. I construct this measure for all ten occupational categories.

Because the model is estimated separately for each Congress, I inspect the discovered top words for each topic and era, and exclude any topic-era cell whose vocabulary does not correspond to the intended concept. This affects Law Enforcement before 1959, whose top words reflect race and civil-rights discourse rather than crime, and Small Business before 1979, when the topic is too rare to recover reliably. Table A.4 lists each topic's most frequent discovered words pooled across all Congresses. Figure A.2 plots average focus on each topic over time. The topics track their intended concepts and shift sensibly across eras, with agricultural focus declining, health focus rising, and law-enforcement focus emerging after 1959.

The main analysis uses these continuous topic proportions directly. As a robustness check, I re-estimate the speech results using a binary classification of speech focus instead. I classify a speech as focused on a topic when its estimated proportion for that topic is at least 0.30 (0.50 for Education, whose vocabulary co-occurs densely with adjacent social-policy topics), and define the outcome as the share of a legislator's speeches so classified. Hand-coding a random sample of classified speeches confirms about 85% precision at this threshold. Figure A.3 reports the estimates under this alternative outcome. The pattern matches the continuous measure: the same occupations show significant own-domain effects, and the pooled effect is 1.2 percentage points, a 56% increase over baseline. The only difference is Education, which is significant under the continuous measure but not under the stricter 0.50 threshold.

Table A.3: Seed keywords for the keyATM speech-focus measure

Occupation	Seed keywords
Agriculture	farmer, farmers, rancher, ranchers, agriculture, farm, farms
Bank & Finance	bank, banks, banking, savings and loan, thrift, thrifts, banker, bankers, investor, investors, lender, lenders, loan, loans, lending, mortgage, mortgages, deposit, deposits, securities, wall street, brokerage, finance, financial, fdic, deposit insurance, federal reserve, bankruptcy, foreclosure
Corporate Executives	ceo, ceos, businessman, businessmen, corporate, corporation, corporations, merger, mergers, shareholder, shareholders, antitrust, deregulation, multinational, conglomerate, monopoly, monopolies, big business
Education	teacher, teachers, professor, professors, education, educational, school, schools, classroom, classrooms, student, students, pupil, tuition, curriculum, kindergarten, faculty, dropout, literacy, scholarship, undergraduate, campus, college, colleges, university, universities, elementary school, secondary school, high school, public school, school district, higher education, community college
Health & Medicine	doctor, doctors, physician, physicians, healthcare, health care
Law	lawyer, lawyers, attorney, attorneys, judicial, prosecution
Law Enforcement	police officer, police officers, sheriff, sheriffs, law enforcement, crime, crimes
Military	soldier, soldiers, veteran, veterans, military
Small Business	small business, small businesses, small business owner, small business owners, business owner, business owners, entrepreneur, entrepreneurs, entrepreneurship, self-employed, sole proprietor, small firm, small firms, family business, family-owned, mom and pop, main street, franchisee, startup, startups, small employer, small employers, small manufacturer, small manufacturers, sba, small business administration, small business loans, microbusiness
Working Class	worker, workers, working family, working families, working class, blue collar, working people, mechanic, plumber, plumbers, electrician, electricians, carpenter, carpenters, steelworker, steelworkers, miner, miners, factory worker, factory workers, construction worker, construction workers, truck driver, truck drivers, welder, welders, janitor, janitors, waitress, waiter, waiters, cashier, cashiers, minimum wage, cost of living, income inequality, collective bargaining, wage, wages, overtime, workplace, paycheck, paychecks, labor, layoff, layoffs, union, unions

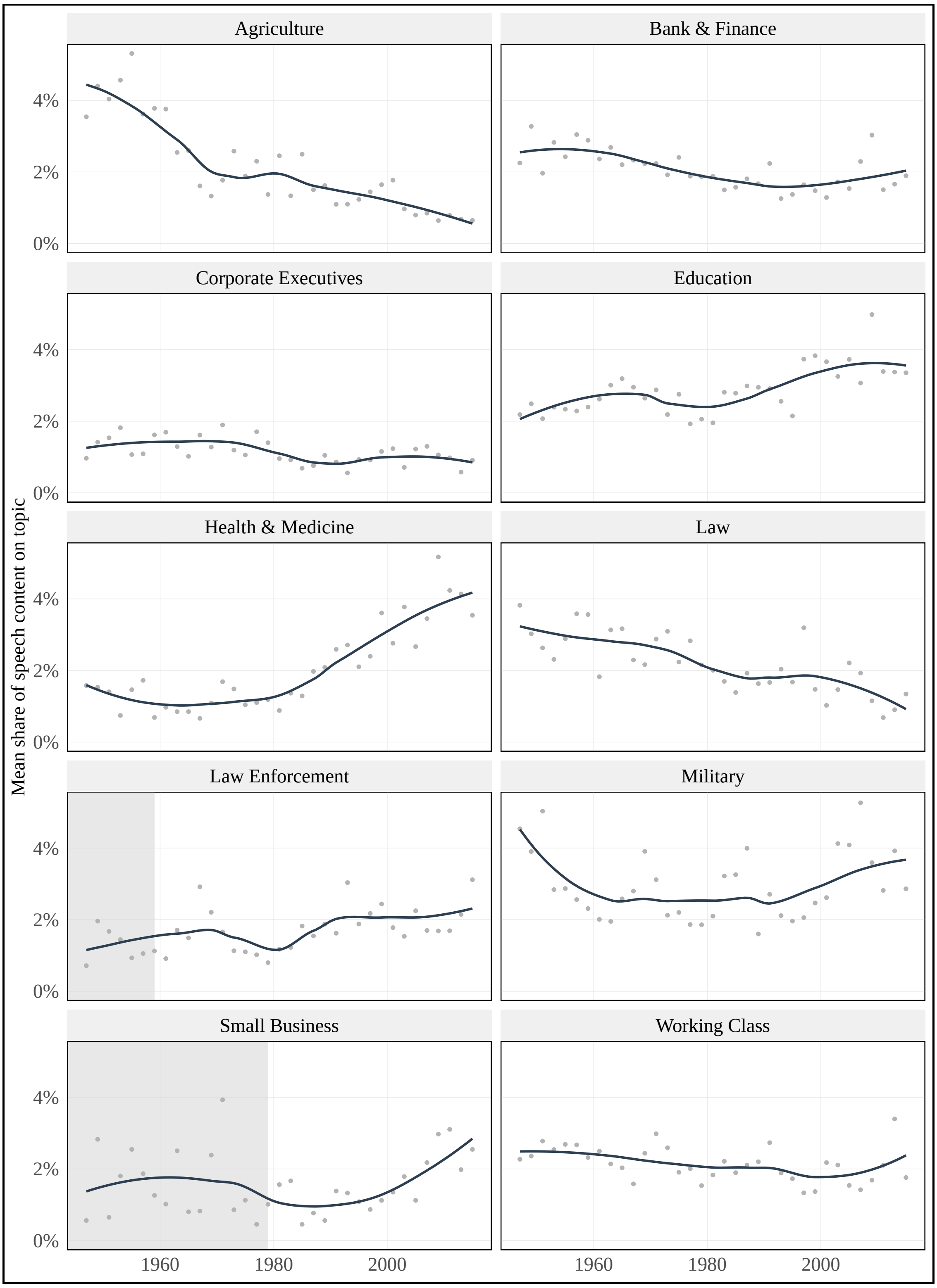
Note: This table lists the seed keywords used to anchor each occupational topic in the keyATM model. The model learns each topic's broader vocabulary from corpus co-occurrence; the seeds only anchor it.

Table A.4: Discovered keyATM top words by occupation

Occupation	Discovered top words
Agriculture	farm, farmers, program, food, agricultural, agriculture, price, bill
Bank & Finance	loan, bank, loans, interest, financial, credit, money, banks
Corporate Executives	companies, government, service, bill, company, business, corporation, public
Education	education, school, schools, state, children, program, students, federal
Health & Medicine	health, medical, care, health care, insurance, hospital, services, medicare
Law	court, law, federal, states, case, constitution, rights, supreme
Law Enforcement	crime, federal, law enforcement, criminal, drug, violence, state, bill
Military	military, war, veterans, forces, force, air, men, army
Small Business	small businesses, new, small business, business, program, businesses, economic, economy
Working Class	workers, employees, labor, work, jobs, benefits, bill, pay

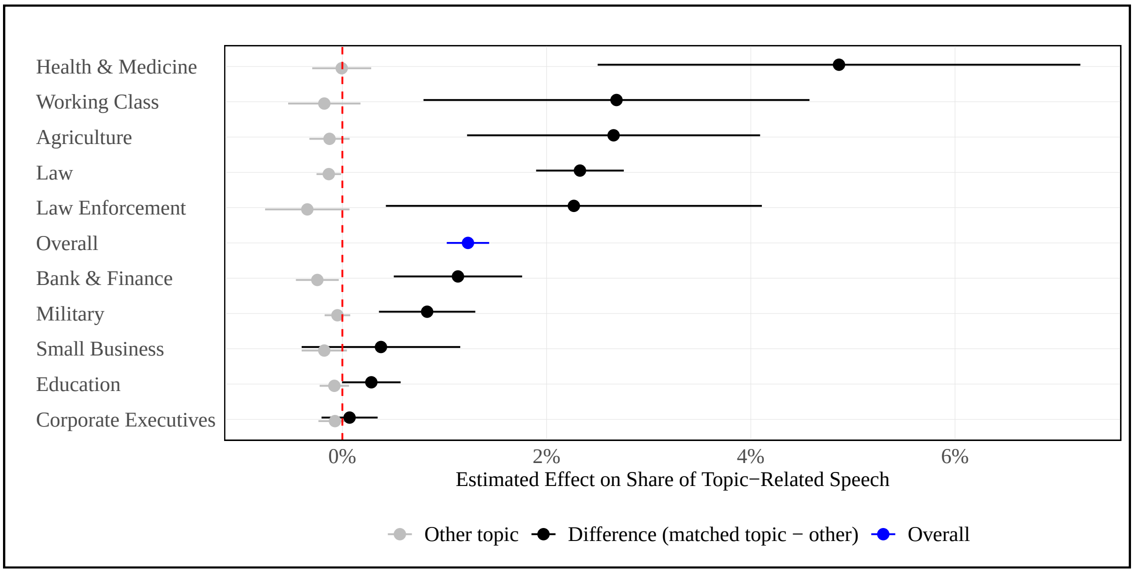
Note: This table reports the most frequent high-probability words in each keyATM topic, pooled across all Congresses (1947–2016). Law Enforcement before 1959 and Small Business before 1979 are excluded because those topic-era cells are not used in the analysis.

Figure A.2: Average legislator speech focus by occupation topic, 1947–2016



Note: This figure plots the mean estimated topic proportion in legislators' floor speeches for each occupational topic by Congress, with a loess-smoothed trend over the per-Congress means (faint points). The shaded regions mark Law Enforcement before 1959 and Small Business before 1979, which are excluded from the analysis.

Figure A.3: Estimated Effect of Legislators' Occupations on Speech Focus, Binary Threshold Measure, U.S. Congress 1947–2016



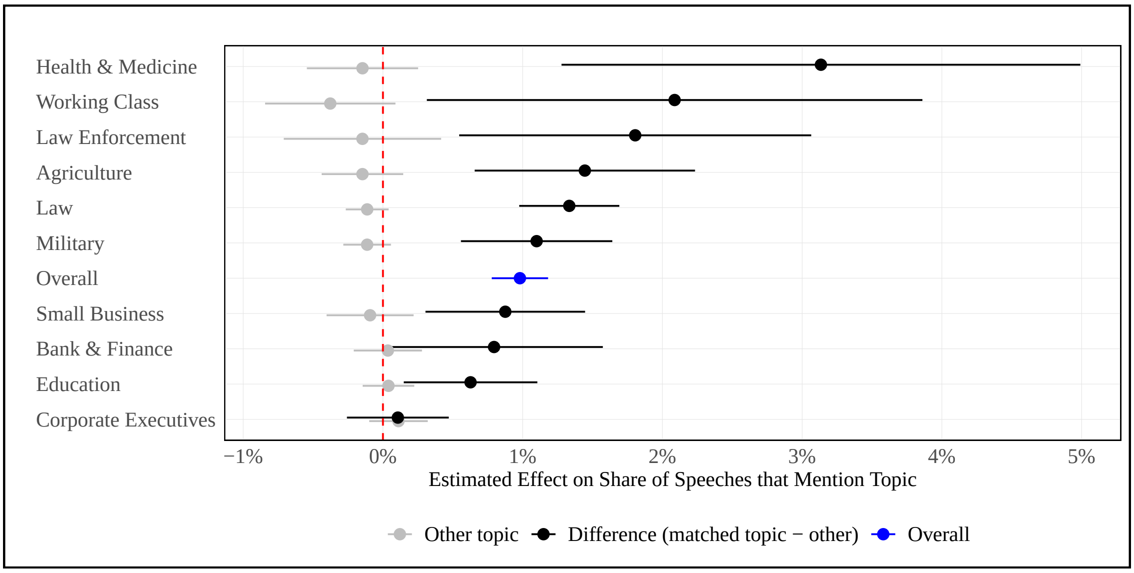
Note: This figure reports estimates from the topic-stacked panel specification for floor-speech focus using a binary threshold classification of the keyATM topic proportions (a speech counts as focused on a topic when its estimated proportion is at least 0.30, or 0.50 for Education) in place of the continuous measure used in the main text. The unit of observation is the legislator × topic × Congress. Grey estimates show the effect of electing a legislator from the target occupation on unmatched occupational topics; black estimates show the additional effect on the matched topic relative to unmatched topics; the blue estimate is the pooled effect. Models include topic–district–party–chamber and topic–Congress–party–chamber fixed effects with legislator controls, and standard errors clustered at the district-party level.

A.2.2 Robustness: Keyword Dictionary

The primary speech measure uses the keyATM topic model described above. As a robustness check, I re-estimate the speech results using a simpler fixed keyword dictionary. For each of the ten occupational categories, I construct a dictionary of policy-area keywords that unambiguously identify discussion of that policy area; for example, the Health & Medicine dictionary includes "healthcare" and "health care," and the Agriculture dictionary includes "agriculture" and "farm." I search all 3.9 million floor speeches from Congress 79–114 (1945–2016) for these terms. Because many policy terms also appear in procedural contexts (e.g., "Department of Labor," "Committee on Education"), I extract a 50-word context window around each match and exclude windows containing "committee," "department," or "secretary of." The outcome for each legislator–Congress–topic cell is the share of the legislator's speeches with at least one clean match for that topic.

Figure A.4 reports estimates from the topic-stacked panel specification using this dictionary outcome, following the same specification as the main speech results. The occupation-match estimate is positive for every occupation and statistically significant for all categories except Corporate Executives, and the pooled effect is 0.98 percentage points, a 27% increase over baseline. This confirms that the speech findings are not an artifact of the topic-model measure.

Figure A.4: Estimated Effect of Legislators' Occupations on Share of Speeches Mentioning Occupation-Related Topics (Keyword Dictionary), U.S. Congress 1947–2016



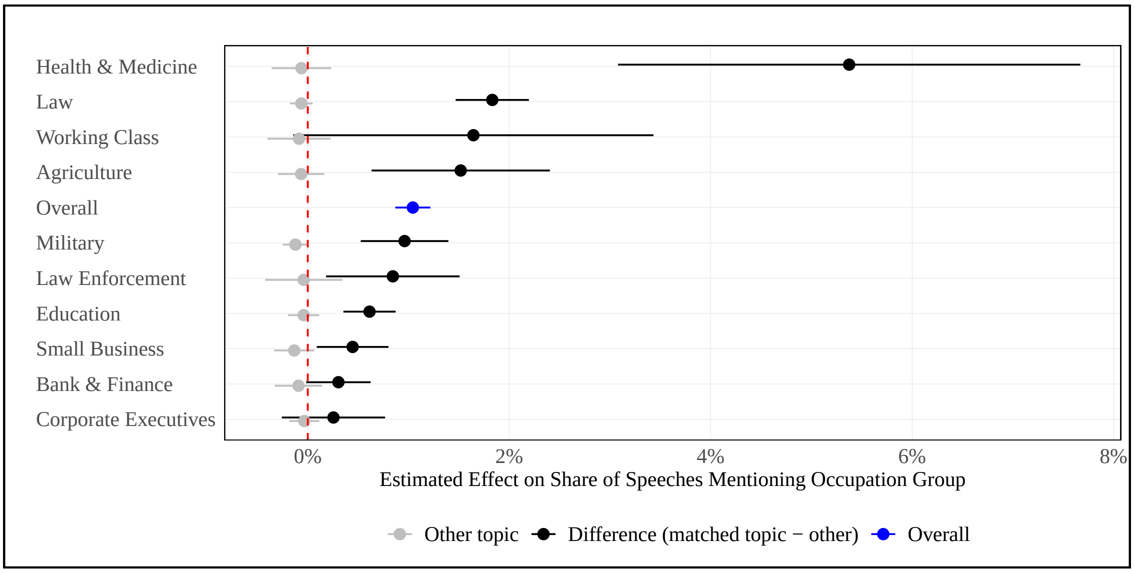
Note: This figure reports estimates from the topic-stacked panel specification with the outcome built from a fixed keyword dictionary rather than the keyATM topic model. The unit of observation is the legislator × topic × Congress. Grey estimates show the effect of electing a legislator from the target occupation on unmatched occupational topics; black estimates show the additional effect on the matched topic relative to unmatched topics; the blue estimate is the pooled effect. Models include topic–district–party–chamber and topic–Congress–party–chamber fixed effects with legislator controls, and standard errors clustered at the district-party level.

A.2.3 Robustness: Occupation Group Mentions

Beyond the keyword topic dictionary, I also construct a separate *group* dictionary that captures person-nouns referring to members of each occupational group (e.g., "farmer," "doctor," "veteran"). Whereas the topic dictionary measures whether legislators discuss the *policy area* associated with their occupation, the group dictionary measures whether they mention the *people* in that occupation on the floor.

Figure A.5 presents estimates from the topic-stacked panel specification using the group dictionary. The matched-topic differences are statistically significant for Health/Medicine, Agriculture, Law Enforcement, Law, Military, Education, and Small Business, while the estimates for Working Class, Bank & Finance, and Corporate Executives are not statistically significant. The overall effect is 1.0 percentage points. The positive pooled effect across independent sets of search terms confirms that the speech results are not an artifact of dictionary construction.

Figure A.5: Estimated Effect of Legislators' Occupations on Share of Speeches Mentioning Occupation Group Names, U.S. Congress 1947–2016



Note: The group dictionary uses person-nouns (e.g., "farmer," "teacher," "doctor," "veteran") rather than policy-area terms. The unit of observation is the legislator × topic × Congress. Estimates are from the same topic-stacked panel specification as the main speech results, with topic–district–party–chamber and topic–Congress–party–chamber fixed effects, controls for incumbency, gender, race, and seniority, and standard errors clustered at the district-party level.

A.3 Bill Topics

Table A.5: Mapping Between Occupations and Bill Topics

Occupation	Bill Topics (Comparative Agendas Project)
Health & Medicine	3 – Health
Agriculture	4 – Agriculture 21 – Public Lands and Water Management
Working Class	501 – Worker Safety and Protection (OSHA) 503 – Employee Benefits 504 – Employee Relations and Labor Unions 505 – Fair Labor Standards
Education	6 – Education
Law Enforcement	1201 – Executive Branch Agencies Dealing with Law and Crime 1202 – White Collar Crime and Organized Crime 1203 – Illegal Drug Production, Trafficking, and Control 1205 – Prisons 1209 – Police, Fire, and Weapons Control 1615 – Civil Defense & Homeland Security
Law	1204 – Court Administration 1206 – Juvenile Crime and the Juvenile Justice System 1207 – Child Abuse and Child Pornography 1208 – Family Issues and Domestic Violence 1210 – Criminal and Civil Code
Bank & Finance	1501 – U.S. Banking System and Financial Institution Regulation 1502 – Securities and Commodities Regulation 1504 – Consumer Finance, Mortgages, and Credit Cards 1507 – Bankruptcy
Corporate Executives	1500 – General Banking, Finance, and Domestic Commerce 1520 – Corporate Governance and Antitrust Issues 1522 – Intellectual Property 1524 – Tourism 1705 – Science and Technology Transfer, International Scientific Cooperation 1706 – Telephone and Telecommunication Regulation 1707 – Broadcast Industry Regulation (TV, Cable, Radio), Broadband Internet and Spectrum 1802 – Trade Negotiations, Disputes, and Agreements
Small Business	1521 – Small Business Issues
Military	1603 – Military Intelligence, CIA, Espionage 1604 – Military Readiness, Coordination of Armed Services Air Support and Sealift Capabilities 1608 – Manpower, Military Personnel and Dependents 1609 – Veterans Affairs and Other Issues 1610 – Military Procurement and Weapons System Acquisitions and Evaluation 1612 – National Guard and Reserve Affairs 1616 – DOD Civilian Personnel, Civilian Employment by the Defense Industry, Military Base Closings 1617 – Oversight of Defense Contracts and Contractors 1619 – Direct War Related Issues and Foreign Operations

Note: Health & Medicine, Agriculture, and Education are mapped using CAP major topics. The remaining occupational categories are mapped using CAP minor topics.

A.4 Constructing the Stacked Panel Dataset

I construct a panel of congressional seats observed in each Congress. The panel begins with the 80th Congress, which served from 1947 to 1948, and continues through the 118th Congress, which served from 2023 to 2024. House districts are defined separately for each redistricting cycle so that changes in district boundaries produce distinct observational units. This ensures that each unit represents a stable constituency. As a result, House districts are unique within each decennial redistricting period, while only at-large House districts and Senate seats (which do not undergo decennial redistricting) span multiple periods.

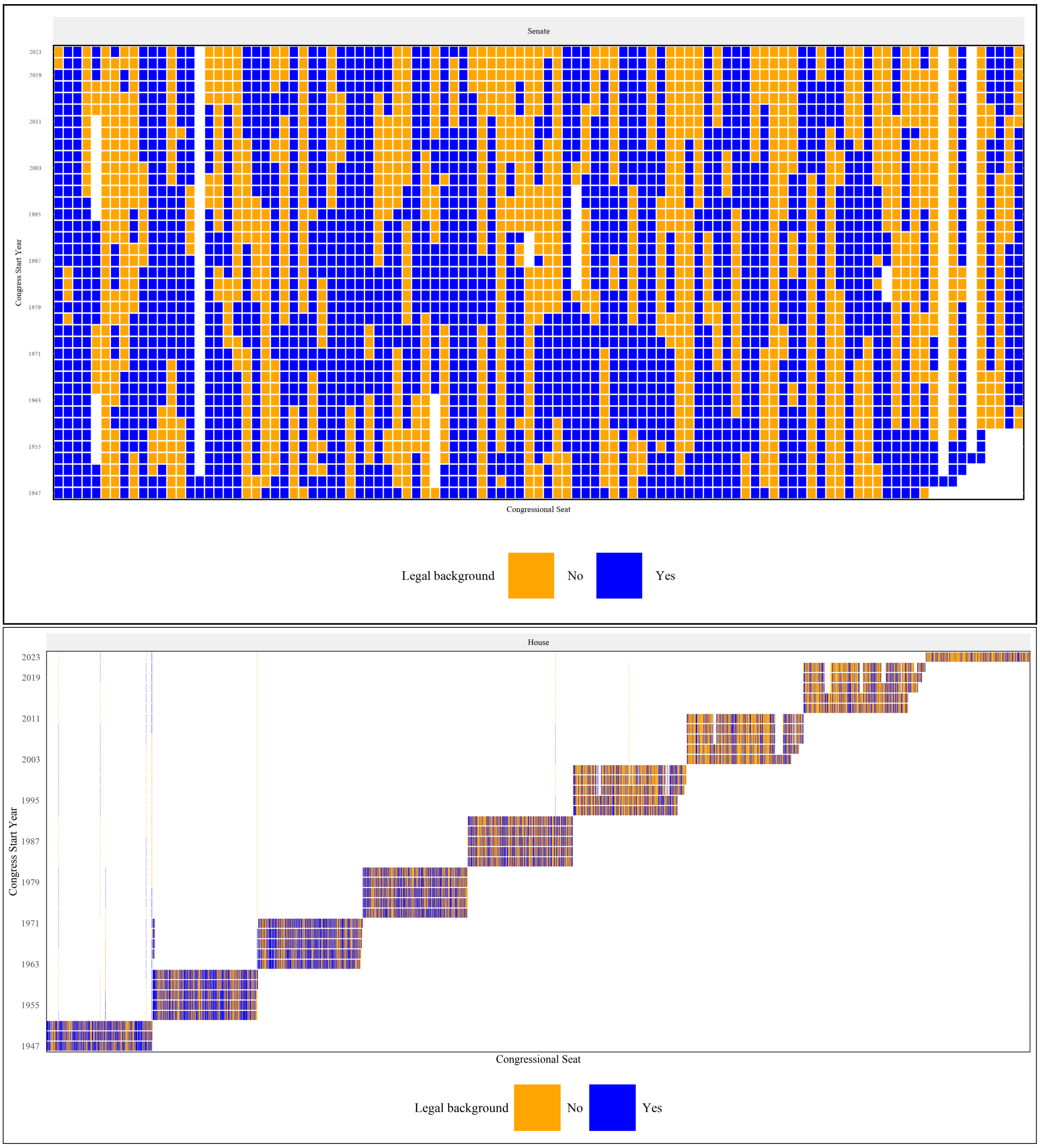
The resulting panel includes 4,024 unique House districts observed across nine decennial and several mid-decade redistricting periods (2–5 Congresses per period), along with the 100 Senate seats (distinguished by state and Senate class) observed across 39 Congresses between 1947 and 2024. Before stacking by occupation, the dataset contains 21,318 legislator–seat–Congress observations.

Each legislator–seat–Congress observation corresponds to the behavior of a legislator serving in a given seat during a given Congress. Because legislators can possess multiple occupational backgrounds simultaneously, I reshape the data into a long format organized around ten occupational categories. This stacking procedure creates one row for each legislator–seat–Congress–occupation combination, yielding 213,180 observations. This structure allows direct comparisons of whether legislators behave differently on outcomes related to occupations they possess versus those they do not.

Figure A.6 visualizes the panel for one occupational category (Law). Each column corresponds to a congressional seat and each cell represents that seat in a given Congress, with colors indicating treatment status. Cells represented by legislators with a legal background are shown in blue, while those without such experience are shown in orange.

Finally, in the main model specification I further split districts into district–party units to accommodate district–party fixed effects, which absorb both constituency-specific differences and stable partisan differences within a district.

Figure A.6: Treatment Variation in Legal Background Across Congressional Seats, U.S. Congress, 1947–2024



Note: This figure shows whether each Senate seat (top) and House district (bottom) was represented by a legislator with a legal background in each Congress from 1947 to 2024. Blue cells indicate a legal background, and orange cells indicate no legal background. White cells indicate Congresses in which a seat unit was not observed. House districts are defined separately across redistricting periods, and Senate seats are distinguished by Senate class.

A.5 Model Specification

The analysis uses a panel stacked by occupational domain. Comparisons come from changes in the occupational backgrounds of same-party legislators representing the same House district or state at different points in time. Domain–constituency–party–chamber fixed effects absorb stable differences in domain-specific activity within constituencies, while domain–Congress–party–chamber fixed effects absorb party-specific shifts in activity across Congresses. Standard errors are clustered at the constituency–party level throughout.

A.5.1 Pooled Occupation Effects

Pooled occupation effects (presented in blue in the main figures) estimate the average effect of electing a legislator with the corresponding occupational background on activity in a domain, using a common coefficient pooled across occupations.

The matching-occupation indicator equals one when legislator i has the occupational background corresponding to domain k.

$$Y_{ikt} = \beta\,\mathbf{1}\{\text{Has matching occupation}\}_{ik} + \mathbf{X}'_{it}\boldsymbol{\delta} + \alpha_{kdpc} + \lambda_{ktpc} + \varepsilon_{ikt}$$

- **Indices.** i indexes legislators, k occupational domains, and t Congresses. The data are stacked by domain, so each legislator–Congress contributes one row per domain. Y_{ikt} measures legislator i's behavior in domain k in Congress t, while d_{it}, p_{it}, and c_{it} denote the legislator's constituency (House district or state), party, and chamber. Four occupation-specific outcomes are constructed:
  - Bill Sponsorship Share
  - Speech Share
  - Committee Assignment

- Legislative Effectiveness (log)

- **Independent Variables:**
  - $\mathbf{1}\{\text{Has matching occupation}\}_{ik}$: Indicator equal to 1 if legislator i has the occupational background corresponding to domain k. It can equal 1 in multiple domain rows for legislators with more than one occupational background. The coefficient β compares activity in that domain when the same constituency is represented by same-party legislators with and without the corresponding occupational background, pooled across domains.
  - $\mathbf{X}_{it}$: Vector of legislator characteristics: incumbency, gender, race, and seniority.

- **Fixed Effects:**
  - α_{kdpc}: Constituency $\times$ party $\times$ occupational domain $\times$ chamber fixed effects. Each domain within each constituency–party–chamber combination receives its own intercept, absorbing stable differences in domain-specific activity.
  - λ_{ktpc}: Congress $\times$ party $\times$ occupational domain $\times$ chamber fixed effects. These absorb party-specific changes in activity within each domain over time, separately by chamber.

A.5.2 Occupation-Specific Effects on Matched and Unmatched Topics

The matched-domain indicator equals one when occupational domain k corresponds to target occupation j.

$$\begin{aligned} Y_{ikt} = {} & \theta_j \, \mathbf{1}\{\text{Has occupation } j\}_i \\ & + \tau_j \left[\mathbf{1}\{\text{Has occupation } j\}_i \times \mathbf{1}\{\text{Matched domain}\}_{kj}\right] \\ & + \mathbf{X}_{it}'\boldsymbol{\delta} + \alpha_{kdpc} + \lambda_{ktpc} + \varepsilon_{ikt} \end{aligned}$$

- **Indices.** i indexes legislators, j the target occupation, k occupational domains, and t Congresses. Y_{ikt} measures legislator i's behavior in domain k in Congress t, while d_{it}, p_{it}, and c_{it} denote the legislator's constituency (House district or state), party, and chamber. A separate model is estimated for each target occupation j.
- **Independent Variables:**
  - $\mathbf{1}\{\text{Has occupation } j\}_i$: Indicator equal to 1 if legislator i has the target occupational background j, and 0 otherwise. This variable is constant across all domain rows k for a given legislator–Congress. The coefficient θ_j captures the effect of electing a legislator with background j on unmatched domains.
  - **Occupation $\times$ matched-domain interaction:** Interaction between the target-occupation indicator and an indicator equal to 1 when outcome domain k corresponds to occupation j. The coefficient τ_j is the additional effect in the corresponding domain relative to unmatched domains. The total effect in the corresponding domain is $\theta_j + \tau_j$. The occupational-domain fixed effects absorb the main effect of the matched-domain indicator.

  - $\mathbf{X}_{it}$: Vector of legislator characteristics: incumbency, gender, race, and seniority.

- **Fixed Effects:**
  - α_{kdpc}: Constituency $\times$ party $\times$ occupational domain $\times$ chamber fixed effects. These absorb stable differences in domain-specific activity within each constituency–party–chamber combination.
  - λ_{ktpc}: Congress $\times$ party $\times$ occupational domain $\times$ chamber fixed effects. These absorb party-specific changes in activity within each domain over time, separately by chamber.

A.6 Committee Membership

Committee assignments offer one channel through which occupational backgrounds could shape legislative behavior. If legislators with relevant experience select onto related committees, this would partly account for the patterns of specialization documented above.

The main-text committee measure combines standing-committee and subcommittee service: a legislator is coded as serving on a related committee if they sit on the mapped standing committee or on a topically matched, non-Appropriations subcommittee. Table A.6 reports the full mapping. Appropriations subcommittees are excluded because service there reflects spending power rather than occupational expertise. Subcommittee assignments are an original dataset digitized from the Congressional Directory for Congresses 102–117 and extended through Congress 118 using archived GovTrack XML. The standing-committee assignments come from the Garrison Nelson records for Congress 102, Stewart–Woon records for Congresses 103–115, and GovTrack for Congresses 116–118. The estimation window is therefore Congresses 102–118 (1991–2024). Corporate Executives is omitted because no House committee corresponds to that background.

Table A.6: Occupation–Committee/Subcommittee Matching

Occupation	Matched Committee or Subcommittee
Agriculture	Agriculture (all subcommittees); Natural Resources: Energy & Mineral Resources, Mining, Forests
Bank & Finance	Financial Services (all subcommittees)
Law	Judiciary (all subcommittees)
Law Enforcement	Homeland Security (all subcommittees)
Military	Armed Services (all subcommittees); Veterans' Affairs (non-health subcommittees)
Small Business	Small Business (all subcommittees)
Education	Education & Labor: education subcommittees (e.g., Early Childhood & Secondary Education; Higher Education; Post-secondary Education)
Working Class	Education & Labor: labor subcommittees (e.g., Workforce Protections; Labor Standards; Employer–Employee Relations)
Health & Medicine	Energy & Commerce: Health; Veterans' Affairs: Health; Education & Labor: Health & Safety

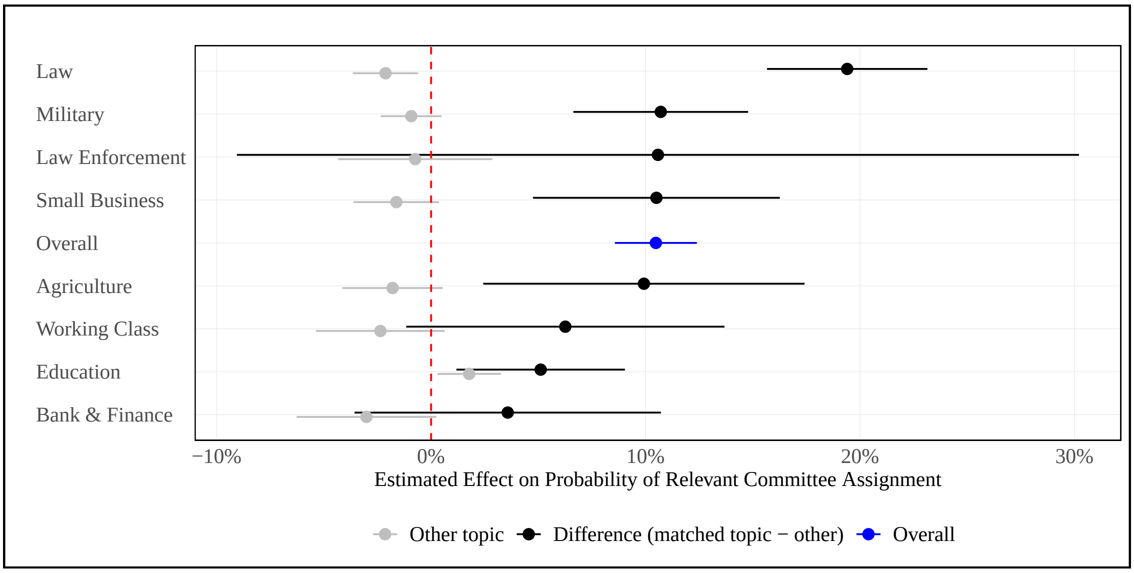
Notes: The indicator equals one if the legislator serves on the listed standing committee or subcommittee. For the top six occupations any subcommittee of the mapped standing committee counts; for Education, Working Class, and Health & Medicine, which share standing committees, matching is based on the listed subcommittees only. Appropriations subcommittees are excluded because service there reflects spending power and committee influence rather than occupation-specific policy jurisdiction. Corporate Executives has no corresponding House committee and is omitted. Subcommittee names vary across Congresses; representative names are shown.

A.6.1 Robustness: Standing Committees Only

The main committee measure relies on subcommittee data, which I digitized only back to 1991. As a robustness check, I re-estimate the analysis using standing-committee assignments alone, which extend back to 1947. Here each occupation is matched to its standing committee from Table A.6 rather than to specific subcommittees. Three occupations are affected: Education and Working Class both attach to the Education and Labor Committee, so the standing-committee measure cannot separate education from labor specialization, and Health/Medicine, which matches only at the subcommittee level, has no standing-committee match and is dropped. The pooled effect is nonetheless similar to the main measure. The standing-committee assignments come from the Garrison Nelson records for Congresses 80–102, Stewart–Woon records for Congresses 103–115, and archived GovTrack XML for Congresses 116–118.

Figure A.7 shows the results. On average, electing a legislator with a given occupational background increases the probability of serving on a related standing committee by 10.5 percentage points, a 120% increase over baseline. The largest occupation-specific differences are for law (+19.4 pp), the military (+10.7 pp), and law enforcement (+10.6 pp), although the law-enforcement estimate is imprecise.

Figure A.7: Estimated Effect of Legislators' Occupations on Probability of Joining Relevant Committee, U.S. House 1947–2024

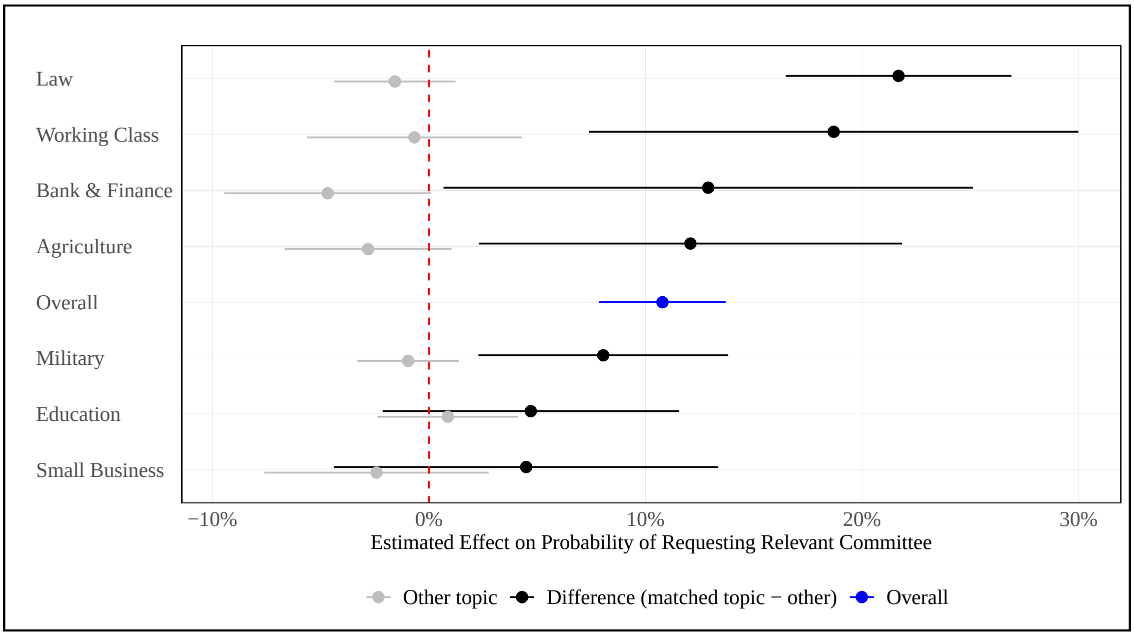


Note: This figure shows the effect of electing legislators from different occupational backgrounds on the probability of serving on a related House standing committee, using the same within-district-party panel specification as the main text. The pooled estimate (blue) averages across occupations. Occupation-specific estimates are estimated separately for each target occupation: grey estimates show the effect of electing a legislator from the target occupation on unmatched committees, and black estimates show the additional effect on the matched committee relative to unmatched ones. Health/Medicine and Corporate Executives are excluded because no single standing committee maps directly to these backgrounds. Committee assignments come from the Garrison Nelson records for Congresses 80–102, Stewart–Woon records for Congresses 103–115, and archived GovTrack XML for Congresses 116–118.

A.6.2 Committee Assignment Requests

Committee assignments could reflect legislators' own preferences, party leaders' strategic placement, or both. To distinguish these channels, I use the Frisch and Kelly (2006) committee assignment request data, which records the ranked committee preferences that House members submit to party leadership when seeking new assignments. Democratic request records cover the 80th through 103rd Congresses except the 85th, while Republican records cover the 86th through 102nd Congresses. Because only freshmen and members seeking transfers submit requests, I code each legislator as having "requested a matching committee" if they submitted a request for a committee corresponding to their occupational background at any point during the covered portion of their House career. I carry this indicator across the covered Congresses they served and estimate the same within-district-party panel specification as in the main analysis. The overall effect is 10.8 percentage points, a 103% increase over baseline: when a district switches to a legislator with a given occupational background, that legislator is significantly more likely to have requested the corresponding committee. The effect is largest for lawyers requesting Judiciary (+21.7 pp) and working-class legislators requesting labor-related committees (+18.7 pp). This suggests that occupation–committee alignment is driven substantially by legislators' own preferences, not solely by party leaders assigning members to relevant committees.

Figure A.8: Estimated Effect of Legislators' Occupations on Probability of Requesting Relevant Committee, U.S. House 1947–1994



Note: This figure shows the effect of electing a legislator with a given occupational background on the probability that they ever requested assignment to the corresponding committee during the covered portion of their House career. The pooled estimate (blue) averages across occupations. Occupation-specific estimates are estimated separately for each target occupation: grey estimates show the effect of electing a legislator from the target occupation on requesting unmatched committees, and black estimates show the additional effect on requesting the matched committee relative to unmatched ones. Request data come from Frisch and Kelly (2006). Democratic request records cover the 80th–103rd Congresses except the 85th; Republican records cover the 86th–102nd Congresses. The specification is identical to the main within-district-party panel analysis. Health/Medicine is excluded because the data do not include subcommittee requests, Corporate Executives because no House committee corresponds to that background, and Law Enforcement because the Homeland Security Committee did not exist during this period.

A.7 Regression Estimates by Outcome

This section collects the regression estimates behind the coefficient figures for all four outcomes: the share of floor speeches on an occupation's topic, the share of sponsored bills on that topic, the probability of serving on a related committee or subcommittee, and issue-specific legislative effectiveness. Table A.7 reports the pooled effect of holding the matching occupation across four specifications, building from a raw difference in means to the full within-district design, and shows how the estimate changes as fixed effects are added. Table A.8 then reports the full per-occupation decomposition at the preferred specification: for each occupation, the effect on the matched domain, the effect on other domains, and the difference between them, with standard errors and baselines.

Table A.7: Pooled Effect of Occupational Background Across Specifications, by Outcome

	(1)	(2)	(3)	(4)
	Panel A. Floor speeches (pp)			
Has matching occupation	1.18***	1.20***	1.09***	0.89***
	(0.03)	(0.03)	(0.05)	(0.08)
% relative to baseline	+62%	+63%	+57%	+47%
	Panel B. Sponsored bills (pp)			
Has matching occupation	1.18***	1.22***	1.62***	1.21***
	(0.06)	(0.06)	(0.10)	(0.14)
% relative to baseline	+35%	+36%	+48%	+36%
	Panel C. Committee service (pp)			
Has matching occupation	10.27***	10.48***	11.42***	13.29***
	(0.46)	(0.46)	(0.80)	(1.54)
% relative to baseline	+105%	+108%	+117%	+136%
	Panel D. Legislative effectiveness (log pts)			
Has matching occupation	0.158***	0.154***	0.251***	0.199***
	(0.011)	(0.011)	(0.018)	(0.030)
Legislator controls		√	√	√
Topic × Congress × Party × Chamber FE			√	√
Topic × District × Party × Chamber FE				√

Note: This table reports the pooled effect of holding the matching occupation (*Has matching occupation*) for each of the four outcomes across four specifications. Column (1) is the raw difference in means; column (2) adds legislator controls (incumbency, gender, race, seniority); column (3) adds topic × Congress × party × chamber fixed effects; column (4) adds topic × district × party × chamber fixed effects, the full within-district specification, which equals the pooled estimate in the corresponding figure. Every fixed effect is interacted with the occupation topic, so the effect is identified within a topic. Panels A–C are in percentage points, with the difference expressed as a percent of the baseline mean among legislators without the matching occupation; Panel D is in log pts. Panel A spans 1947–2016, Panel B 1947–2020, Panel C Congresses 102–118 (1991–2024), and Panel D 1973–2024. Standard errors in parentheses: heteroskedasticity-robust in columns (1)–(2), clustered by district–party in columns (3)–(4). $^{\dagger}p < .1$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table A.8: Effect of Occupational Background on Speeches, Bill Sponsorship, Committee Service, and Legislative Effectiveness, by Occupation

Occupation	Matched topic	Other topic	Difference (matched − other)	Baseline	% over baseline
Panel A. Floor speeches (pp)					
Health & Medicine	3.17*** (0.73)	-0.00 (0.10)	3.17*** (0.74)	1.90	+167%
Agriculture	1.89*** (0.53)	-0.12 (0.07)	2.01*** (0.54)	1.76	+114%
Law Enforcement	1.31* (0.56)	-0.30* (0.15)	1.62** (0.57)	1.71	+94%
Law	1.51*** (0.14)	-0.09* (0.04)	1.60*** (0.15)	1.44	+111%
Working Class	1.35* (0.57)	-0.23* (0.11)	1.58** (0.58)	2.07	+76%
Bank & Finance	0.60** (0.21)	-0.17* (0.08)	0.76*** (0.22)	2.02	+38%
Military	0.55*** (0.14)	-0.05 (0.04)	0.60*** (0.15)	2.73	+22%
Small Business	0.25 (0.24)	-0.13† (0.07)	0.39 (0.25)	1.49	+26%
Education	0.33* (0.16)	-0.05 (0.05)	0.38* (0.16)	2.70	+14%
Corporate Executives	0.07 (0.08)	-0.05 (0.06)	0.11 (0.10)	1.14	+10%
Panel B. Sponsored bills (pp)					
Health & Medicine	5.84*** (1.45)	-0.24 (0.19)	6.08*** (1.48)	5.44	+112%
Agriculture	4.35*** (1.25)	-0.28† (0.14)	4.63*** (1.31)	10.48	+44%
Working Class	1.90† (1.03)	0.04 (0.23)	1.85 (1.14)	2.19	+85%
Law	1.06*** (0.20)	-0.16* (0.08)	1.22*** (0.21)	1.77	+69%
Military	1.04*** (0.27)	-0.10 (0.10)	1.15*** (0.29)	4.22	+27%
Education	0.82* (0.32)	-0.11 (0.10)	0.93** (0.34)	2.93	+32%
Law Enforcement	0.79 (0.68)	-0.06 (0.25)	0.85 (0.75)	1.87	+46%
Bank & Finance	0.57† (0.34)	-0.22 (0.15)	0.79* (0.38)	1.84	+43%
Small Business	0.22 (0.20)	0.03 (0.15)	0.19 (0.26)	0.72	+26%
Corporate Executives	0.15 (0.26)	0.03 (0.10)	0.12 (0.27)	1.78	+6%
Panel C. Committee service (pp)					
Military	19.02*** (3.50)	-1.10 (0.87)	20.12*** (3.47)	16.63	+121%
Law	15.55*** (2.74)	-2.84** (0.97)	18.38*** (3.09)	4.09	+449%
Agriculture	14.13* (6.47)	-2.64 (1.98)	16.76* (7.26)	14.12	+119%
Law Enforcement	9.68 (9.86)	-1.33 (1.86)	11.01 (9.62)	7.65	+144%
Working Class	9.82 (7.80)	-0.71 (3.19)	10.53 (8.62)	6.58	+160%
Small Business	8.43** (3.21)	-1.18 (1.12)	9.60** (3.29)	7.33	+131%
Health & Medicine	9.85 (6.45)	1.42 (1.90)	8.43 (6.43)	8.68	+97%
Education	8.74** (3.03)	3.11** (1.09)	5.63† (3.10)	6.89	+82%
Bank & Finance	6.97 (6.63)	2.39 (2.42)	4.58 (7.50)	14.30	+32%
Panel D. Legislative effectiveness (log pts)					
Health & Medicine	0.737*** (0.155)	-0.043 (0.059)	0.780*** (0.141)		
Working Class	0.541† (0.321)	-0.105 (0.111)	0.647† (0.338)		
Law Enforcement	0.478* (0.238)	0.048 (0.092)	0.430* (0.186)		
Agriculture	0.354** (0.116)	0.020 (0.055)	0.334** (0.112)		
Law	0.291*** (0.071)	0.052 (0.037)	0.239*** (0.053)		
Military	0.209** (0.068)	0.024 (0.049)	0.186* (0.073)		
Bank & Finance	0.042 (0.113)	-0.049 (0.056)	0.091 (0.089)		
Education	0.073 (0.078)	-0.003 (0.047)	0.076 (0.067)		
Corporate Executives	-0.095 (0.082)	-0.013 (0.069)	-0.081 (0.085)		

Note: This table reports, for each occupational background, its estimated effect on four legislative outcomes: the share of floor speeches on the occupation's topic (Panel A), the share of sponsored bills on that topic (Panel B), the probability of serving on a related committee or subcommittee (Panel C), and issue-specific legislative effectiveness (Panel D). For each occupation, *Matched topic* is the effect on the occupation's own domain, *Other topic* the effect on unmatched domains, and *Difference* the additional effect on the matched domain (the estimate plotted in the corresponding figure). Panels A–C are in percentage points, with the baseline mean among legislators without the matching occupation and the difference as a percent of that baseline; Panel D is in log pts, for which no share baseline applies. Each row is from a separate topic-stacked panel model with domain–constituency–party–chamber and domain–Congress–party–chamber fixed effects and controls for incumbency, gender, race, and seniority; standard errors clustered at the constituency–party level in parentheses. Floor speeches span 1947–2016, sponsored bills 1947–2020, committee service Congresses 102–118 (1991–2024), and legislative effectiveness 1973–2024. $^{\dagger}p < .1$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

A.7.1 Specialization Beyond Committee Service

Table A.9 re-estimates the floor-speech, bill-sponsorship, and legislative-effectiveness models with and without a control for serving on the relevant committee, on the identical committee-covered sample (Congresses 102–118). Because committee service is itself measured after a legislator takes office, this comparison shows how much of the estimated specialization remains after accounting for committee service, rather than isolating a causal channel. The occupation effects attenuate modestly but remain statistically significant.

Table A.9: Occupational Specialization Conditional on Relevant Committee Service

	(1) Without committee control	(2) With committee control
	Floor speeches (pp)	
Has matching occupation	1.13^{***}	0.96^{***}
	(0.15)	(0.15)
On relevant committee		1.37^{***}
		(0.11)
% of column (1) estimate retained		85%
Observations	49,312	49,312
	Sponsored bills (pp)	
Has matching occupation	1.74^{***}	1.13^{**}
	(0.36)	(0.35)
On relevant committee		4.66^{***}
		(0.28)
% of column (1) estimate retained		65%
Observations	57,349	57,349
	Legislative effectiveness (log pts)	
Has matching occupation	0.255^{***}	0.159^{***}
	(0.048)	(0.046)
On relevant committee		0.679^{***}
		(0.037)
% of column (1) estimate retained		63%
Observations	57,614	57,614
Relevant committee control		√
Legislator controls	√	√
Full within-district fixed effects	√	√

Note: This table reports the effect of holding an occupation on three specialization outcomes without (column 1) and with (column 2) a control for serving on the relevant committee or subcommittee (*On relevant committee*, the best-match measure used in the main text). The unit of observation is the legislator × topic × Congress; both columns use the identical sample of Congresses 102–118 (1991–2024), where committee data are available. Panels for floor speeches and sponsored bills are in percentage points; the legislative-effectiveness panel is in log pts. "% of column (1) estimate retained" is the column-2 estimate as a share of column 1. Under the standing-committee-only measure (which excludes the hand-collected health subcommittees), the retained shares are 57%, 31%, and 40% respectively. All models control for incumbency, gender, race, and seniority and use the full within-district-party specification, with standard errors clustered at the district-party level. $^{\dagger}p < .1$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

A.8 Robustness Checks

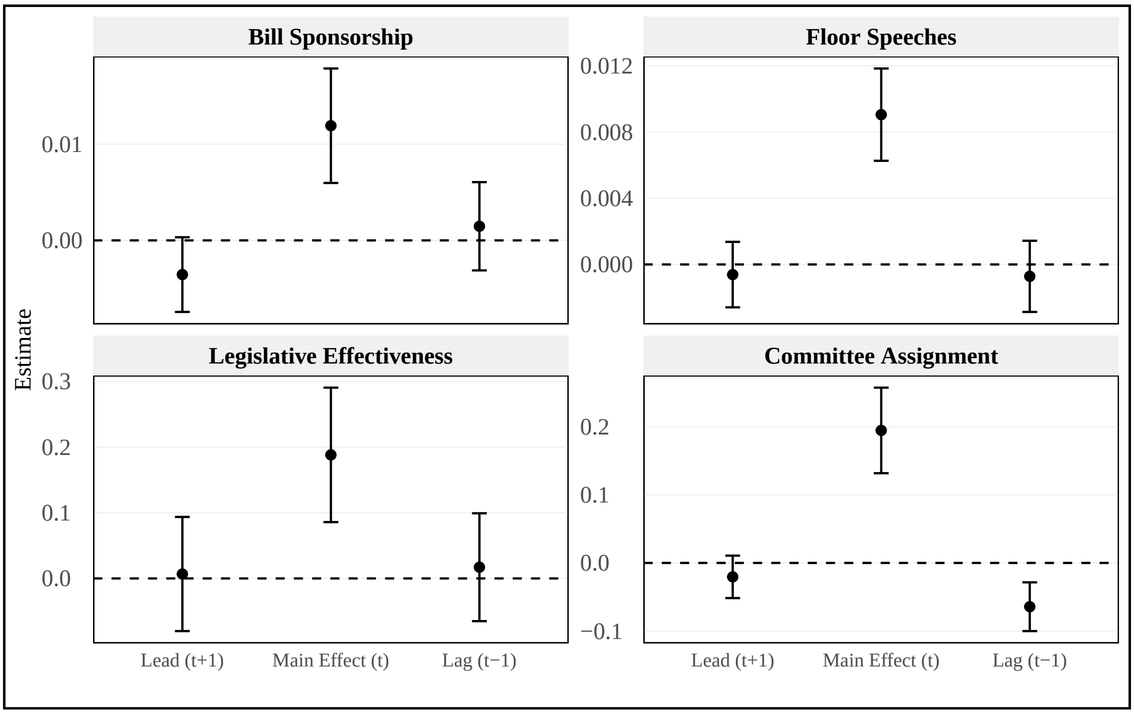
A.8.1 Anticipatory and Persistence Effects

A key concern is that occupation-linked estimates could reflect changing district preferences rather than the occupational backgrounds of elected legislators. If districts begin shifting their behavior before electing a legislator from a particular occupation, the estimated effects may capture these underlying trends rather than the consequences of electing a representative with that background. Similarly, if occupation-linked behavior persists after a legislator leaves office, the estimates may reflect longer-run district characteristics rather than contemporaneous representation.

To assess these possibilities, I re-estimate the main specification including one-period leads and lags of the occupational background indicator. For each district–party panel, I construct a lag term, Lag $(t-1)$, indicating whether the legislator in the previous Congress possessed the relevant occupational background, and a lead term, Lead $(t+1)$, indicating whether the legislator in the next Congress will possess that background. The lead term provides a test for anticipatory behavior: if districts already behave differently before electing an occupation-matched legislator, the lead coefficient should be nonzero. The lag term provides a test for persistence: if occupation-linked behavior remains after a legislator leaves office, the lag coefficient should be nonzero.

Figure A.9 plots the estimates for Lead (t+1), Main Effect (t), and Lag (t-1) across four overall outcomes: bill sponsorship, floor speeches, legislative effectiveness, and committee assignments. Across all four outcomes, the contemporaneous coefficients remain positive and statistically significant. The lead coefficients are small and not statistically distinguishable from zero. The lag coefficients are also small for speeches, bills, and legislative effectiveness; for committee service, the lag is negative. The estimates do not show occupation-related behavior rising before occupation-matched legislators enter office.

Figure A.9: Pre- and Post-Treatment Effects of Legislators' Occupations on Related Behavior

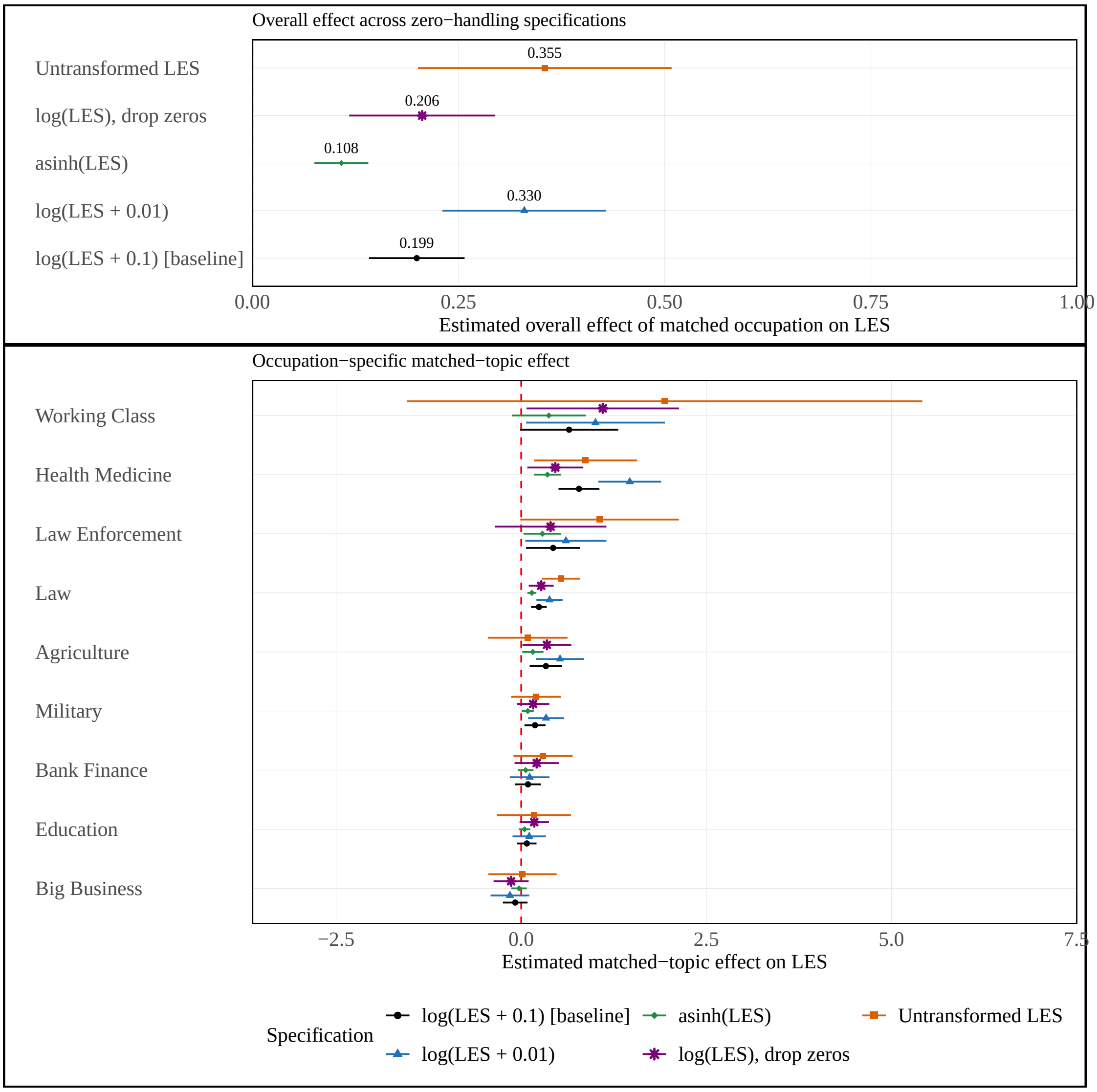


Note: This figure shows the pooled contemporaneous, lead, and lag estimates for bill sponsorship, floor speeches, legislative effectiveness, and committee assignments. The lead tests whether occupation-related behavior appears before an occupation-matched legislator enters office; the lag tests whether it persists after that legislator leaves. Leads and lags are defined only across consecutive Congresses within the same seat-party panel; cells with multiple same-party legislators serving in the same seat and Congress are excluded. Bill sponsorship spans 1947–2020, floor speeches 1947–2016, legislative effectiveness 1973–2024, and committee assignments 1991–2024. All models use the same topic-stacked within-district-party specification as the main analysis, with controls for incumbency, seniority, gender, and race. Standard errors are clustered at the district-party level; lines show 95% confidence intervals.

A.8.2 Sensitivity to LES Transformation and Zero Handling

Issue-specific LES contains many zero values (legislators with no activity in a given policy domain). The main analysis applies $\log(\text{LES} + 0.1)$; the figure below shows the headline effect under four alternative transformations and rules for handling zero values. The pooled estimate remains positive and statistically significant across all specifications.

Figure A.10: Sensitivity of LES Results to Outcome Transformation, U.S. Congress 1973–2024



Note: This figure shows the pooled and occupation-specific matched-topic estimates using log(LES + 0.1) and four alternatives: log(LES+0.01), asinh(LES), log(LES) after excluding zero values, and untransformed LES. All models use the same topic-stacked within-district-party specification as the main analysis, with controls for incumbency, seniority, gender, and race. Standard errors are clustered at the district-party level; lines show 95% confidence intervals.

A.9 Conservative Vote Probability (CVP) Estimation

To measure legislators' positions within defined policy domains, I estimate Conservative Vote Probabilities (CVPs) following Fowler and Hall (2012). A CVP summarizes how conservatively a legislator votes relative to the median member of the chamber within a policy domain. I construct two sets of CVPs. The class-based analysis groups selected Voteview issue codes into predistribution, redistribution, and social issues (Table A.10). The occupation-specific analysis groups roll calls using the Comparative Agendas Project topic classification and the occupation–topic crosswalk used for the bill-sponsorship analysis (Table A.5). I also use Voteview's issue typology for the occupation-specific robustness tests (Table A.11).

Constructing conservative vote indicators. For each roll call, I compute the Democratic and Republican yea–nay shares. A roll call is initially coded as "conservative" if Republican legislators are more likely than Democrats to vote yea. Each legislator's vote is coded as $Y_{ir} = 1$ if they cast the vote aligned with this inferred conservative position and 0 otherwise. Abstentions and non-votes are dropped.

Weighting by roll-call competitiveness. To downweight unanimous votes, I assign each roll call r a competitiveness weight:

$$w_r \;=\; 1 - 2\left|\frac{\text{support}_r}{100} - 0.5\right|,$$

which equals 1 for a 50–50 vote and approaches 0 for unanimous votes. The analyses below use weighted CVPs.

CVP model. Within each Congress and chamber, I estimate the two-way fixed effects model:

$$Y_{ir} \;=\; \alpha + \lambda_i + \gamma_r + \varepsilon_{ir},$$

where λ_i is a legislator fixed effect and γ_r is a roll-call fixed effect. Votes receive weight w_r. The legislator fixed effects $\hat{\lambda}_i$ provide the raw CVP scores, which I center so that the median legislator has a CVP of zero within each Congress–chamber.

Iterative roll-call polarity correction. Following Fowler and Hall (2012), I use an iterative procedure that re-estimates the model and flips the coding of any roll call whose vote coding is negatively correlated with the estimated legislator effects. This process continues until no roll call exhibits a negative correlation or a maximum of ten iterations is reached. In practice, convergence typically occurs within a small number of steps.

Data Summary. The full Voteview record covers the 80th–118th Congresses (1947–2024) and contains 60,215 roll calls, of which 33,446 have at least one Voteview issue code. Voteview's 97-issue typology extends through the 113th Congress, so the class-based analysis covers the 80th–113th Congresses (1947–2014). It uses 11,752 roll calls assigned to 22 issue codes across the three main domains. The CAP-based occupation-specific analysis covers the 80th–117th Congresses (1947–2022).

Outputs. For each policy domain, Congress, and chamber, the CVP estimation procedure produces weighted legislator-level CVP scores and the number of relevant votes cast. These CVPs form the dependent variable in the class-based and occupation-specific analyses reported in the main text.

Class-based estimating equation. For each issue domain I estimate the linear model

$$\mathrm{CVP}_{idt} = \beta_B\,\mathrm{Business}_i + \beta_W\,\mathrm{WorkingClass}_i + X_{it}'\gamma + \phi_{dpc} + \psi_{tpc} + \varepsilon_{idt},$$

where i indexes legislators, d districts, p parties, c chambers, and t Congresses. $\mathrm{Business}_i$ and $\mathrm{WorkingClass}_i$ indicate the legislator's occupational background, with legislators of neither background as the baseline; X_{it} collects incumbency, gender, race, and seniority; ϕ_{dpc} are district×party×chamber fixed effects and ψ_{tpc} are Congress×party×chamber fixed effects. Standard errors are clustered at the district–party level. The coefficients β_B and β_W are the within-district-party differences reported in Figure 5; their build-up across specifications, together with the control estimates, appears in Table A.12.

Occupation-specific estimating equation. For the occupation-specific analysis, I stack each legislator–Congress observation across occupational domains. The predictors are an indicator for the occupational background being tested and its interaction with an indicator for the occupation's own domain. The interaction is the own-domain difference reported in the right panel of Figure 6. Models include domain–constituency–party–chamber and domain–Congress–party–chamber fixed effects, the same controls as the class-based analysis, and standard errors clustered at the constituency–party level.

A.10 Class Ideology Results

This appendix collects supporting material for Section 8. The class-based test (Section 8.1) uses Voteview's issue typology; the occupation-specific test (Section 8.2) uses the Comparative Agendas Project (CAP) topic classification. The first subsection documents the Voteview issue-code mappings used in Section 8.1 and in the appendix Voteview robustness check for Section 8.2. The remaining subsections present the decomposition of the class gap, per-issue disaggregations, strict and broad alternative compositions, a business-group composition check, and pre-election trends.

Voteview Issue Code Mappings

Tables A.10 and A.11 document Voteview's issue typology. Voteview's typology contains 97 issue codes; the class-based test (Section 8.1) uses 22 of them grouped into three main issue domains (predistribution, redistribution, social/moral). Table A.11 documents Voteview's occupation–issue mapping, used in the Section 8.2 Voteview robustness check; three occupations use a proxy where no Voteview category targets the background directly. **Corporate Executives** are mapped to Interstate Commerce/Anti-trust/Restraint of Commerce, regulations that primarily constrain large enterprises operating across state lines. **Small Business** is mapped to Consumer Protection/Consumer Protection Agency, regulations whose compliance burden falls disproportionately on small operations and around which small-business interest groups (such as the NFIB) have historically organized. **Health/Medicine** is mapped to Public Health, covering medical practice, health workforce, drug regulation, and public-health funding. Roll-call counts are the number of unique votes coded to each issue between the 80th and 113th Congresses (1947–2014).

Table A.10: Mapping Between Issue Domains and Voteview Issue Codes

Issue Domain	**Voteview Issue**	**Bills**	**Coverage**
Predistribution	Union Regulation/Davis-Bacon/Situs Picketing	697	1947–2013
	Minimum Wage	269	1947–2013
	Workplace conditions/8 hour day	153	1947–2013
Redistribution	Tax rates	2,478	1947–2013
	Public Health	1,457	1949–2013
	Housing/Housing Programs/Rent Control	1,068	1947–2013
	Unemployment/Jobs	960	1947–2013
	Children (aid, infant mortality, etc.)	753	1947–2013
	Military Pensions/Veterans Benefits	709	1947–2013
	Welfare	604	1947–2013
	Social Security	498	1947–2013
	Food Stamps/Food Programs	395	1955–2013
	Handicapped	198	1959–2013
	Emergency Fuel Assistance	56	1973–2011
Social/moral	Civil Rights/Desegregation/Busing/Affirmative Action	939	1947–2013
	Abortion/Care of deformed newborns	496	1973–2013
	Narcotics	377	1953–2013
	Firearms	283	1967–2013
	Voting Rights	223	1947–2013
	Women's Equality	208	1949–2013
	Religion	153	1947–2013
	Homosexuality	117	1977–2013

Table A.11: Mapping Between Occupations and Voteview Issue Codes

Occupation	Voteview Issue	Roll calls	Coverage
Agriculture	Agriculture	1,936	1947–2013
Bank / Finance	Banking and Finance	1,335	1947–2013
Corporate Executives*	Interstate Commerce/Anti-trust/Restraint of Commerce	285	1947–2009
Education	Education	1,733	1947–2013
Health / Medicine*	Public Health	1,457	1949–2013
Law	Judiciary	1,371	1947–2013
Military	Military Pensions/Veterans Benefits	709	1947–2013
	Selective Service (The Draft)	153	1947–2011
Small Business*	Consumer Protection Agency/Consumer Protection	341	1947–2013
Working Class	Union Regulation/Davis-Bacon/Situs Picketing	697	1947–2013
	Minimum Wage	269	1947–2013
	Workplace conditions/8 hour day	153	1947–2013

* Proxy mapping: no Voteview category targets the occupation directly.

Law Enforcement is omitted: Public Safety and Narcotics cover only 690 roll calls.

Decomposition of the Class Vote Gap

Table A.12 builds each domain's business–working-class gap from the raw association to the full within-district-party specification, showing how much of the raw gap is absorbed as legislator controls, party fixed effects, and district–party fixed effects are added, and reporting the estimated effects of all controls.

Table A.12: Decomposition of the Business–Working-Class Vote Gap, U.S. Congress 1947–2014

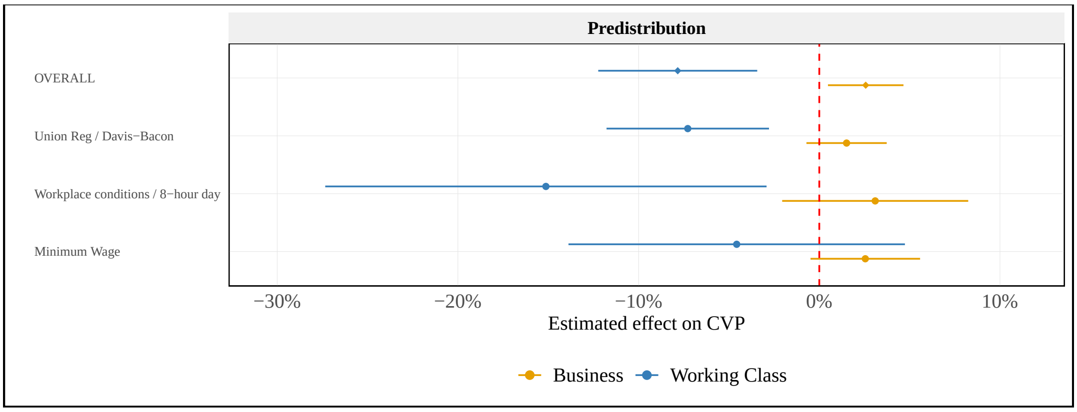
	Conservative Vote Probability (CVP)			
	(1)	(2)	(3)	(4)
		Predistribution		
Business	13.85***	12.79***	4.02***	2.57*
	(0.81)	(0.79)	(0.85)	(1.07)
Working class	-29.77***	-27.82***	-14.75***	-7.83***
	(1.70)	(1.71)	(2.14)	(2.24)
Difference	43.62***	40.60***	18.77***	10.40***
	(1.90)	(1.91)	(2.35)	(2.56)
Incumbent		-1.00	0.20	-1.40**
		(1.05)	(0.60)	(0.52)
Female		-11.94***	-4.58***	-1.24
		(1.32)	(1.02)	(1.37)
Nonwhite		-33.10***	-8.00***	-4.31*
		(1.05)	(0.81)	(2.06)
Seniority		-0.18†	-0.06	0.07
		(0.09)	(0.10)	(0.11)
		Redistribution		
Business	13.57***	12.17***	2.53***	1.39†
	(0.67)	(0.64)	(0.59)	(0.78)
Working class	-19.40***	-17.91***	-7.12***	-4.11†
	(1.48)	(1.42)	(1.41)	(2.35)
Difference	32.97***	30.08***	9.64***	5.50*
	(1.63)	(1.57)	(1.56)	(2.47)
Incumbent		-0.56	0.02	-0.57*
		(0.84)	(0.36)	(0.29)
Female		-15.65***	-5.08***	-1.57†
		(1.25)	(0.82)	(0.94)
Nonwhite		-37.07***	-8.05***	-1.88
		(1.05)	(0.55)	(1.50)
Seniority		-0.57***	-0.09	0.08
		(0.08)	(0.07)	(0.07)
		Social/moral		
Business	11.62***	10.46***	3.65***	3.40**
	(0.69)	(0.67)	(0.83)	(1.14)
Working class	-15.52***	-13.32***	-2.33	-0.84
	(1.63)	(1.45)	(2.12)	(3.11)
Difference	27.15***	23.78***	5.98**	4.24
	(1.78)	(1.61)	(2.29)	(3.26)
Incumbent		-2.28**	-2.75***	-1.00†
		(0.88)	(0.61)	(0.52)
Female		-16.08***	-9.14***	-5.17**
		(1.10)	(1.21)	(1.68)
Nonwhite		-33.82***	-12.65***	-3.70
		(0.94)	(1.08)	(2.41)
Seniority		-0.24**	-0.02	-0.11
		(0.08)	(0.10)	(0.10)
Congress × Party × Chamber FE			√	√
District × Party × Chamber FE				√

Note: This table reports the effect of business and working-class backgrounds on issue-specific Conservative Vote Probability (CVP), for three issue domains, across four specifications. The unit of observation is the legislator–Congress–issue-domain. Column (1) reports the raw specification; column (2) adds legislator controls (incumbency, gender, race, seniority); column (3) adds Congress × party × chamber fixed effects; column (4) adds district × party × chamber fixed effects, the full within-district-party specification used in the main text. Coefficients are in percentage points of the CVP scale, and the difference row is the business minus working-class contrast. Standard errors in parentheses are heteroskedasticity-robust in columns (1)–(2) and clustered by district-party in columns (3)–(4). $^{\dagger}p < .1$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Per-Issue and Specification Robustness

The figures below test the robustness of the class-based results in Section 8.1 to per-issue heterogeneity, alternative issue-domain compositions, and specification choice. The pattern in the main figure holds across each test.

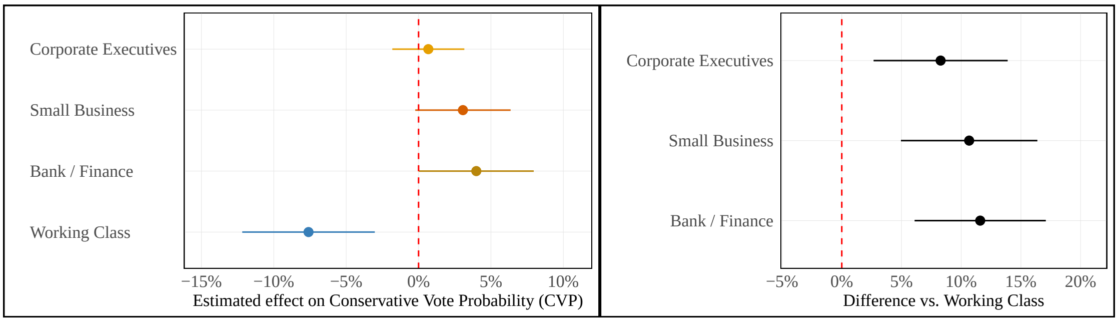
Figure A.11: Estimated Effect of Legislators' Occupation on Conservative Vote Probability, by Predistribution Issue, U.S. Congress 1947–2014



Note: This figure reports the estimated effects of business and working-class backgrounds on Conservative Vote Probability for each of the three Voteview issues in the predistribution domain. Models control for incumbency, gender, race, and seniority and include district–party–chamber and Congress–party–chamber fixed effects. Standard errors are clustered at the district-party level.

The predistribution gap is also not an artifact of how the business group is defined. Figure A.12 splits business into its three components, corporate executives, small business owners, and bankers, and estimates each separately. All three vote significantly more conservatively than working-class legislators on predistribution, so the gap does not depend on which business occupations are included.

Figure A.12: Predistribution Class Gap by Business Sub-Group, U.S. Congress 1947–2014



Note: This figure reports the effect of each business sub-group (corporate executives, small business owners, bankers) and of working-class background on predistribution Conservative Vote Probability. The left panel reports effects relative to the baseline (legislators with none of these backgrounds); the right panel reports each business sub-group's difference from working-class legislators. The combined business–working-class gap is 10.4 percentage points. Models control for incumbency, gender, race, and seniority and include district–party–chamber and Congress–party–chamber fixed effects; standard errors are clustered at the district-party level.

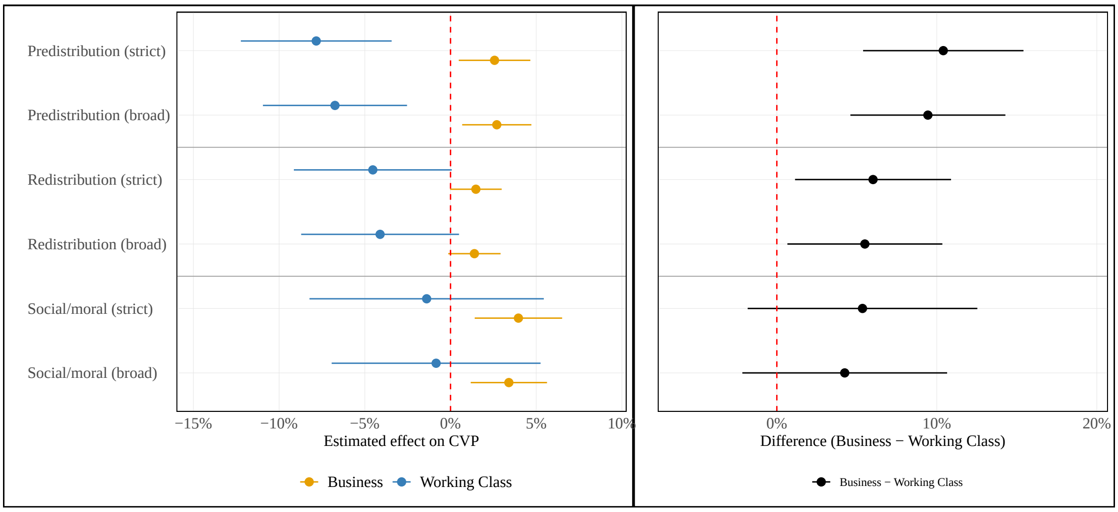
Strict and Broad Issue-Domain Compositions

To verify that the differences in roll-call voting estimated in the main text are robust to measurement choices, I re-estimate the three-class test under two alternatives: classifying roll calls with the Comparative Agendas Project's topic codes rather than Voteview's issue codes, and using stricter and broader definitions of each issue domain. Tables A.13 and A.14 report the domain compositions, and Figures A.13 and A.14 the corresponding estimates. The business–working-class predistribution gap remains significant across both classifications and both strictness levels, ranging from about 7.5 percentage points (CAP, broad) to 10 percentage points (Voteview, strict). The redistribution gap is similarly stable at roughly 5.5 to 6 percentage points, while the social-issues gap is not significant under either classification.

Table A.13: Voteview Strict and Broad Issue-Domain Compositions

Issue Domain	**Composition**	**Voteview Issue**	**Roll calls**
Predistribution	Strict	Minimum Wage	269
		Workplace conditions/8 hour day	153
		Union Regulation/Davis-Bacon/Situs Picketing	697
	Broad	Adds: OSHA	113
		Adds: Coal Mining Regulation/Strip Mining/Black Lung	189
Redistribution	Strict	Tax rates	2,478
		Welfare	604
		Food Stamps/Food Programs	395
		Children (aid, infant mortality, etc.)	753
		Social Security	498
		Housing/Housing Programs/Rent Control	1,068
		Handicapped	198
		Emergency Fuel Assistance	56
	Broad	Adds: Military Pensions/Veterans Benefits	709
		Adds: Public Health	1,457
		Adds: Unemployment/Jobs	960
Social/moral	Strict	Civil Rights/Desegregation/Busing/Affirmative Action	939
		Voting Rights	223
		Women's Equality	208
		Abortion/Care of deformed newborns	496
	Broad	Adds: Firearms	283
		Adds: Religion	153
		Adds: Narcotics	377
		Adds: Homosexuality	117

Figure A.13: Estimated Effect of Legislators' Occupation on Conservative Vote Probability, Voteview Strict and Broad Compositions, U.S. Congress 1947–2014

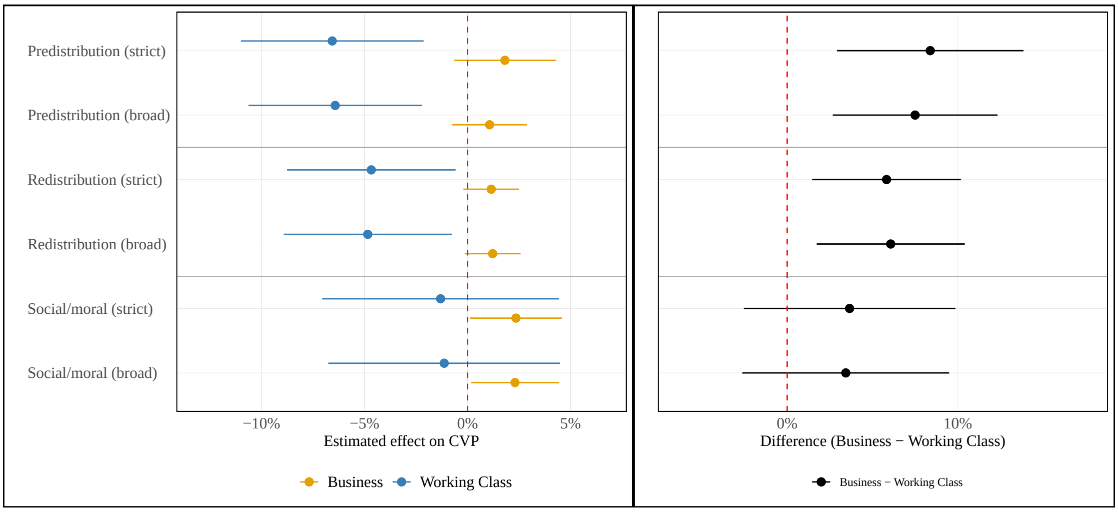


Note: This figure reports the estimated effects of business and working-class backgrounds on Conservative Vote Probability under strict and broad definitions of the three Voteview issue domains. Models control for incumbency, gender, race, and seniority and include district–party–chamber and Congress–party–chamber fixed effects. Standard errors are clustered at the district-party level.

Table A.14: CAP Strict and Broad Issue-Domain Compositions

Issue Domain	**Composition**	**CAP Topic Code**	**Roll calls**
Predistribution	Strict	504 – Employee Relations and Labor Unions	410
		505 – Fair Labor Standards	316
	Broad	Adds: 501 – Worker Safety and Protection (OSHA)	204
		Adds: 503 – Employee Benefits	549
Redistribution	Strict	105 – Tax Code, Tax Policy	1,906
		1302 – Low-income food assistance	583
		1303 – Elderly issues (Social Security)	403
		1304 – Aid to children, single parents	84
		1305 – Charities and charitable giving	130
		1308 – Social services and volunteer associations	98
		1408 – Housing assistance for low-income	29
	Broad	Adds: 1609 – Veterans Affairs	63
Social/moral	Strict	201 – Minority/Ethnic Civil Rights	327
		202 – Gender/Sexual Orientation	405
		206 – Voting Rights	302
		207 – Privacy (includes abortion)	200
	Broad	Adds: 1203 – Illegal Drug Production/Trafficking	200

Figure A.14: Estimated Effect of Legislators' Occupation on Conservative Vote Probability, CAP Strict and Broad Compositions, U.S. Congress 1947–2022

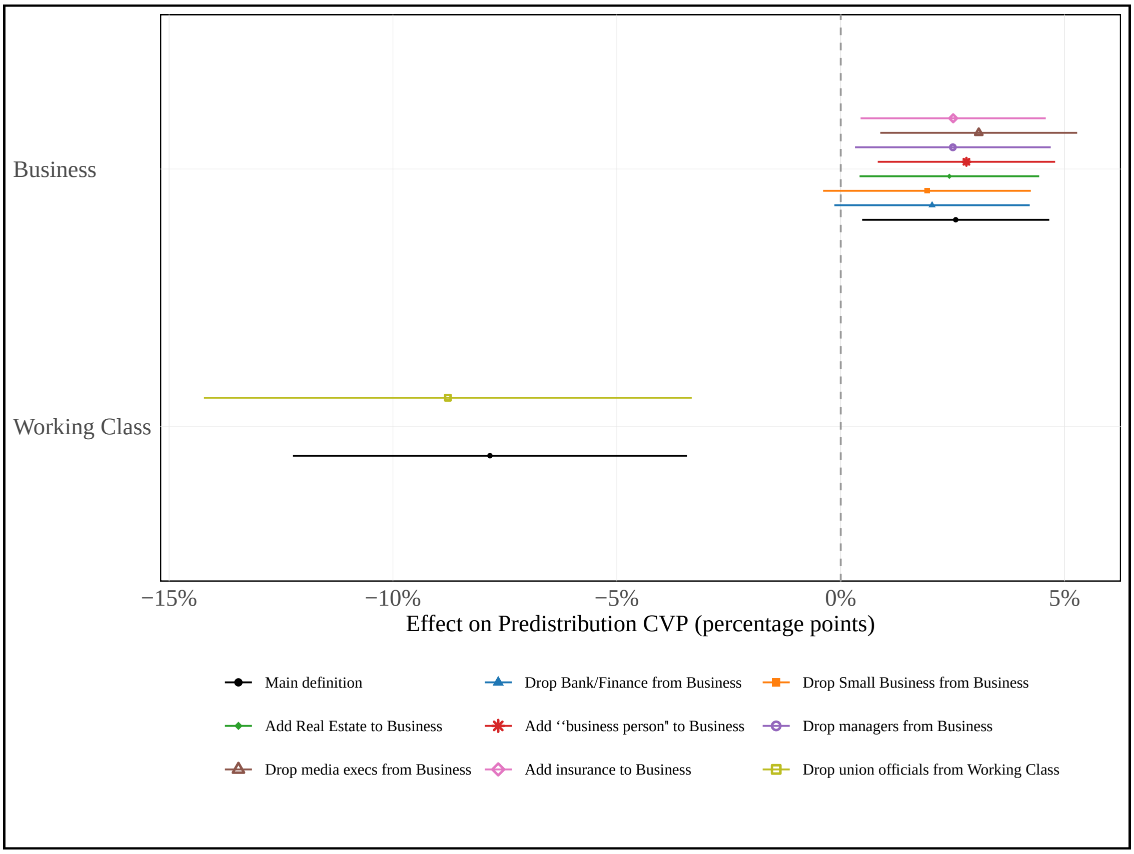


Note: This figure reports the estimated effects of business and working-class backgrounds on Conservative Vote Probability under strict and broad definitions of the three CAP issue domains. Models control for incumbency, gender, race, and seniority and include district–party–chamber and Congress–party–chamber fixed effects. Standard errors are clustered at the district-party level.

Sensitivity to Occupation Definitions

Figure A.15 re-estimates the baseline predistribution specification under a range of alternative definitions of the business and working-class groups, spanning both the composition of the business group (which occupational categories count as business) and finer reclassification choices. Table A.15 describes each specification. Business-background estimates remain positive throughout, while working-class estimates remain negative and statistically significant.

Figure A.15: Estimated Effect of Legislators' Occupation on Predistribution Conservative Vote Probability, Across Occupation-Definition Specifications, U.S. Congress 1947–2014



Note: This figure plots the business and working-class effects on predistribution Conservative Vote Probability under alternative definitions of the two class groups (described in Table A.15). Each estimate is from the full within-district-party specification with controls for incumbency, gender, race, and seniority. Standard errors are clustered at the district-party level.

Table A.15: Occupation-Definition Specifications in Figure A.15

Specification	**Description**	**Class affected**
Main definition	Business = Big Business + Small Business + Bank/Finance.	—
Drop Bank/Finance from Business	Business = Big Business + Small Business (financial sector excluded).	Business
Drop Small Business from Business	Business = Big Business + Bank/Finance (elite-business only).	Business
Add Real Estate to Business	Business = Big Business + Small Business + Bank/Finance + Real Estate.	Business
Add "business person" to Business	"Business person, no further information" reclassified Other → Business.	Business
Drop managers from Business	Manager in a medium- or large-sized business reclassified Business → Other.	Business
Drop media execs from Business	Media executives/publishers reclassified Business → Other.	Business
Add insurance to Business	Insurance agents/brokers reclassified Other → Business.	Business
Drop union officials from Working Class	Union employees/officials reclassified Working Class → Politics/Government.	Working Class

Occupation-Specific Voting: Full Estimates

Table A.16 reports the estimates behind Figure 6: for each occupation, the effect across other occupational domains, the own − other difference, and the own-domain effect (their sum). Working-class legislators vote 6.2 percentage points less conservatively on roll calls in their own domain and 4.8 points less conservatively than across unrelated domains. Lawyers vote 2.1 points less conservatively on crime-and-law roll calls, but no differently than across unrelated domains.

Table A.16: Occupational Background and Issue-Specific Conservative Vote Probability: Own-Domain and Other-Domain Estimates, U.S. Congress 1947–2022

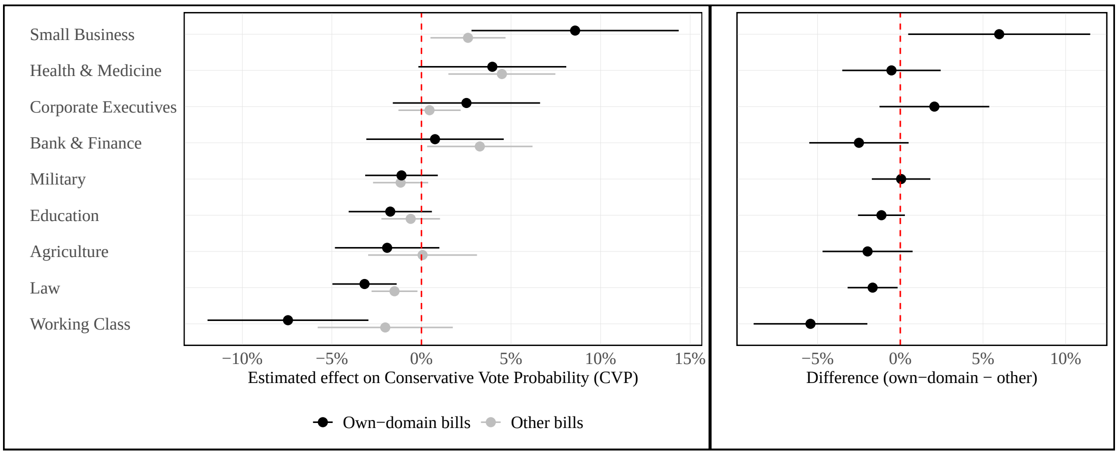
Occupation	Own-domain level	Other-domain level	Difference (own − other)	N
Working Class	−6.25** (2.15)	−1.50 (1.40)	−4.75** (1.72)	147,998
Law	−2.11** (0.77)	−1.17* (0.49)	−0.94 (0.62)	147,998
Agriculture	−1.52 (1.15)	−0.02 (1.10)	−1.51 (0.96)	147,998
Education	−1.30 (1.05)	−0.98 (0.69)	−0.33 (0.62)	147,998
Military	−0.92 (0.86)	−0.74 (0.61)	−0.19 (0.68)	147,998
Corporate Executives	0.79 (1.18)	−0.17 (0.72)	0.95 (1.03)	147,998
Health & Medicine	1.88 (1.19)	2.84* (1.18)	−0.95 (1.04)	147,998
Bank & Finance	2.21 (2.23)	2.81* (1.19)	−0.60 (2.09)	147,998
Small Business	2.40 (1.54)	1.66* (0.80)	0.75 (1.52)	147,998

Note: This table reports estimated effects of each occupational background on Conservative Vote Probability (CVP), in percentage points. “Own-domain level” is the total effect on voting in the occupation’s own domain; “Other-domain level” is the pooled effect across other occupational domains; “Difference (own − other)” is the additional own-domain effect. The own-domain level is the sum of the other-domain level and the difference (standard error by the delta method). Each model stacks legislator–Congress observations across occupational domains and includes issue-domain–constituency–party–chamber and issue-domain–Congress–party–chamber fixed effects, controlling for incumbency, gender, race, and seniority. Standard errors clustered at the constituency–party level are in parentheses. $^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Occupation-Specific Test under Voteview Classification

Figure A.16 reports the Section 8.2 occupation-specific test using Voteview's issue typology in place of the CAP classification (Voteview occupation–issue mapping in Appendix Table A.11). The pattern matches the CAP-based results: working-class legislators vote about 5 percentage points less conservatively on roll calls in their own domain than across unrelated domains, close to the CAP-based estimate.

Figure A.16: Estimated Effect of Legislators' Occupations on Conservative Vote Probability, Voteview Issue Typology, U.S. Congress 1947–2014

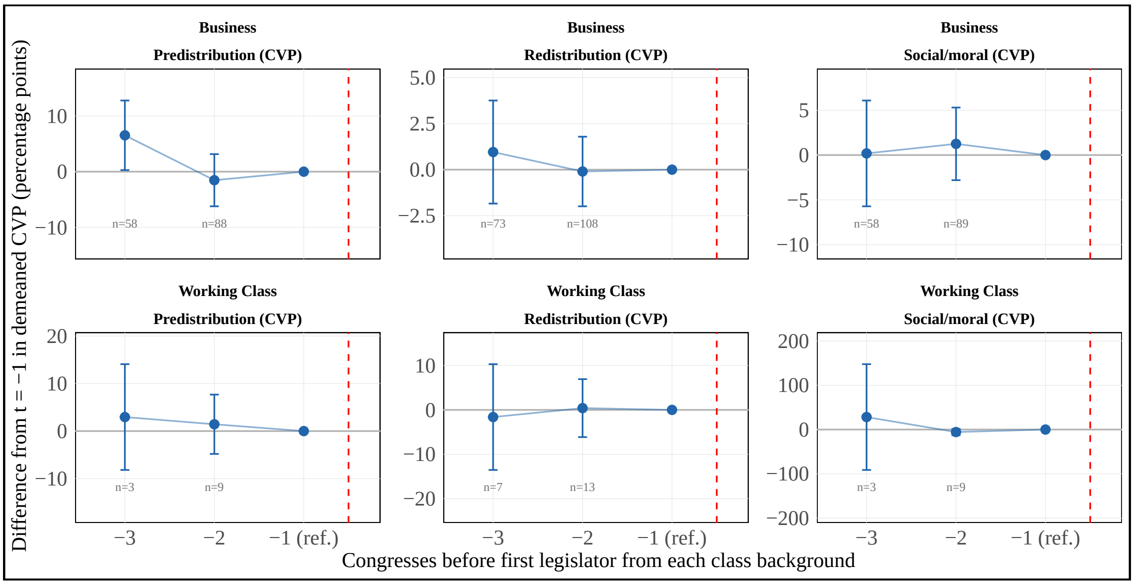


Note: This figure reports the occupation-specific estimates using Voteview's issue typology to define each occupation's domain. The left panel reports the own-domain and other-domain effects; the right panel reports the difference between them. Models control for incumbency, gender, race, and seniority and include domain–constituency–party–chamber and domain–Congress–party–chamber fixed effects. Standard errors are clustered at the constituency–party level.

Pre-Trends for the Class Ideology Results

The within-district-party design assumes that a seat is not already trending toward the estimated outcome when it elects a legislator from a given class background. Figure A.17 examines this by comparing Conservative Vote Probability in the same seat two and three Congresses before it first elects a legislator from each class background with the period immediately before election ($t-1$). The estimates show no consistent anticipatory pattern. For business backgrounds, the estimates are close to zero at $t-2$ across all three domains; the predistribution estimate at $t-3$ is positive rather than part of a consistent pre-election trajectory. For working-class backgrounds, the small number of qualifying seats makes the estimates imprecise: between 9 and 13 seats contribute at $t-2$ and between 3 and 7 at $t-3$. I therefore find no consistent evidence of anticipatory trends, while acknowledging that the working-class comparison is a weak diagnostic.

Figure A.17: Pre-Treatment Conservative Vote Probability Before a Seat Elects Each Class Background, U.S. Congress 1947–2014

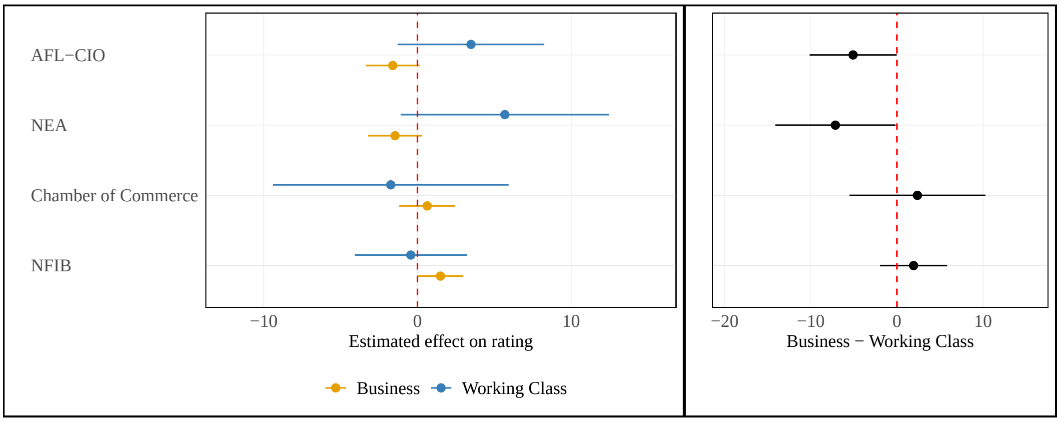


Note: This figure compares each seat's Congress–party–chamber-demeaned Conservative Vote Probability two and three Congresses before it first elects a legislator from each class background with the same seat's outcome in the Congress immediately before election ($t-1$). The $t-1$ value is fixed at zero and used as a baseline for comparison. Lines show 95% confidence intervals; sample sizes are the number of seats observed in both periods. Few seats contribute to the working-class comparisons.

A.11 Interest Group Ratings

I assemble interest group ratings for four groups whose evaluation criteria most directly capture economic distributional conflict: the AFL-CIO and the National Education Association (NEA) on the labor side, and the U.S. Chamber of Commerce (CCUS) and the National Federation of Independent Business (NFIB) on the business side. Ratings come from two sources. First, I digitize AFL-CIO, NEA, and CCUS ratings for Congresses 80–104 (1947–1996) from the *Directory of Congressional Voting Scores and Interest Group Ratings* (Sharp, 2000). Second, I supplement these data with Project Vote Smart ratings (Vote Smart, n.d.). After matching ratings to the Congress associated with each rating year, these data extend AFL-CIO and NEA coverage through the 118th Congress (2023–2024), CCUS through the 116th Congress (2019–2020), and add NFIB from the 104th through the 118th Congresses (1995–2024).

Figure A.18: Estimated Effect of Legislators' Occupation on Interest Group Ratings, Business vs. Working Class, U.S. Congress 1947–2024

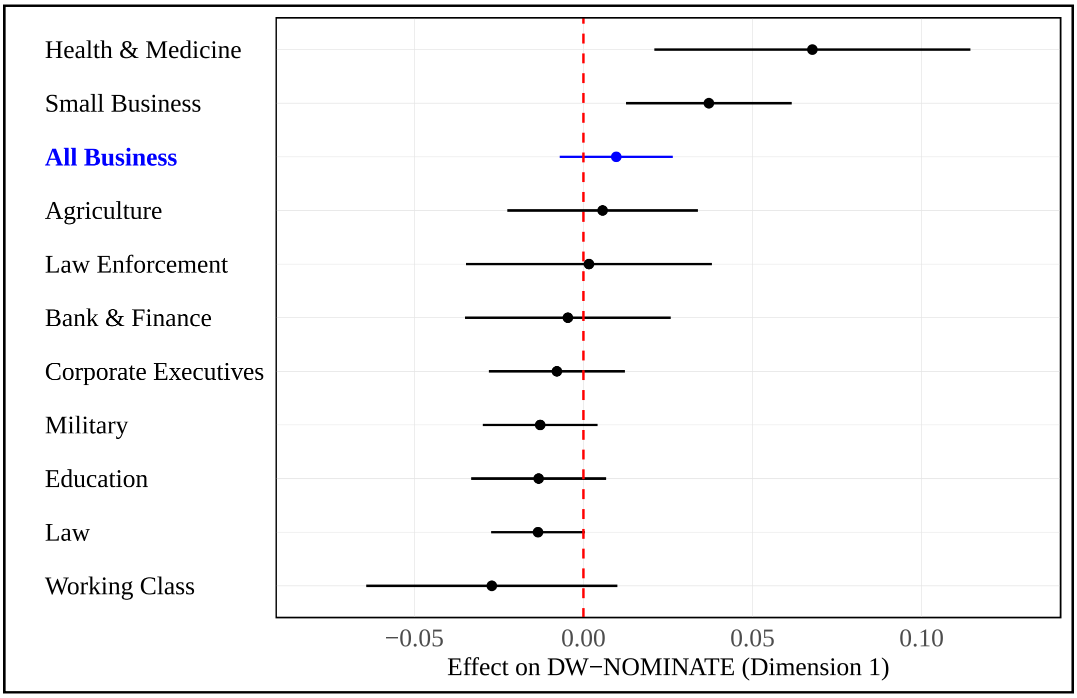


Note: This figure reports the estimated effects of business and working-class backgrounds on AFL-CIO, NEA, Chamber of Commerce, and NFIB ratings, relative to legislators with neither background. The unit of observation is a legislator–Congress rating. Ratings range from 0 to 100; higher values indicate greater agreement with each organization's positions. AFL-CIO and NEA ratings cover 1947–2024, Chamber of Commerce ratings 1947–2020, and NFIB ratings 1995–2024. The left panel reports the two effects; the right panel reports the business–working-class difference. Models control for incumbency, gender, race, and seniority and include district–party–chamber and Congress–party–chamber fixed effects. Standard errors are clustered at the district-party level.

A.12 DW-NOMINATE

Section 8.1 measures ideology with issue-specific Conservative Vote Probabilities. Here I examine whether the broad ideological leanings in the occupation-specific results also appear in first-dimension DW-NOMINATE scores, which summarize a legislator's overall left-right position across all roll-call votes. I use the same district-party and time fixed effects as the main text. Most backgrounds are unrelated to overall ideology, but the broad leanings from the issue-specific results reappear here: small-business owners and health professionals vote modestly more conservatively overall. This corroborates the occupation-specific voting results in Section 8.2, which show that some occupational backgrounds carry general ideological leanings even where voting is not specialized to the occupation's own domain.

Figure A.19: Estimated Effect of Legislators' Occupations on DW-NOMINATE First-Dimension Score, U.S. Congress 1947–2024



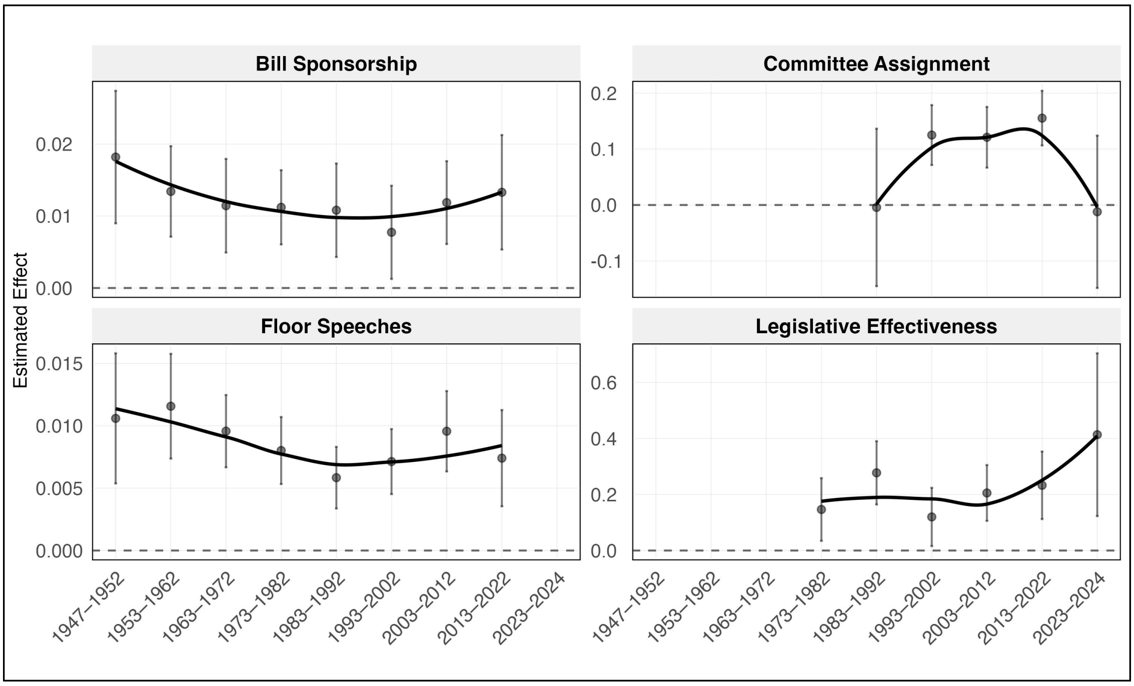
Note: This figure reports the estimated effect of each occupational background on first-dimension DW-NOMINATE scores relative to legislators without that background. Each occupation is estimated in a separate model; the pooled business estimate is shown in blue. The unit of observation is a legislator–Congress. Models control for incumbency, gender, race, and seniority and include district–party–chamber and Congress–party–chamber fixed effects. Standard errors are clustered at the district-party level. Positive values indicate more conservative voting. The sample covers the U.S. House and Senate, 1947–2024.

A.13 Have the Expertise Effects of Occupation Changed Over Time?

To test whether the expertise effects of occupational background have changed over time, I interact the treatment indicator with redistricting-period dummies (approximately decade-long intervals). Figure A.20 shows the period-specific estimates for the four expertise outcomes: bill sponsorship, floor speeches, legislative effectiveness, and committee assignment.

A parallel analysis by redistricting period on the class-based ideology outcomes (CVP, interest group ratings, DW-NOMINATE) is underpowered: subsetting the sample to short periods leaves too little within-district variation for the full fixed-effects specification used in Section 8.1. Period-specific estimates are individually noisy and not informative; I therefore restrict the time-stability analysis to the expertise outcomes.

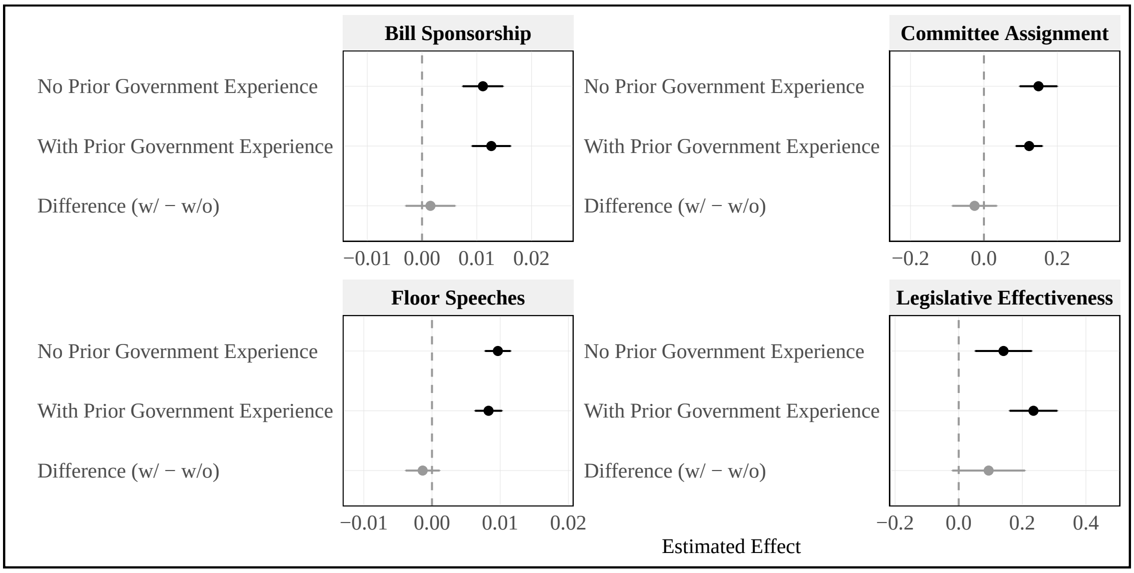
Figure A.20: Estimated Effect of Legislators' Occupations on Occupation-Specific Behavior, by Redistricting Period, U.S. Congress, 1947–2024



Note: This figure shows the estimated effect of legislators' occupational backgrounds on bill sponsorship (1947–2020), floor speeches (1947–2016), legislative effectiveness (1973–2024), and committee assignment (1991–2024), by redistricting period. Points are period-specific estimates; vertical bars are 95% confidence intervals, and lines are smoothed trends. Floor-speech focus is the keyATM issue-attention measure; legislative effectiveness is measured as log(LES + 0.1); committee assignment is the best-match measure (holding a matching standing committee or subcommittee seat). The unit of observation is a legislator–Congress–occupational-domain cell. Models include domain–constituency–party–chamber and domain–Congress–party–chamber fixed effects, control for incumbency, gender, race, and seniority, and cluster standard errors at the constituency–party level.

A.14 Does Previous State or Local Government Experience Attenuate the Effects of Occupation?

Figure A.21: Occupational Background, State or Local Government Experience, and Occupation-Specific Specialization, U.S. Congress, 1947–2024



Note: This figure reports the estimated effect of legislators' occupational backgrounds on floor speeches (1947–2016), bill sponsorship (1947–2020), legislative effectiveness (1973–2024), and committee assignment (1991–2024), estimated separately for legislators with and without prior state or local government experience. Prior experience includes elected or appointed positions in state or local government. "Difference" is the interaction between occupational background and prior government experience; none of the four difference estimates reaches the 5 percent significance level. This measure is available for 3,581 of the 3,669 members. The unit of observation is a legislator–Congress–occupation cell. Models include domain–constituency–party–chamber and domain–Congress–party–chamber fixed effects, control for incumbency, gender, race, and seniority, and cluster standard errors at the constituency–party level.

A.15 Most Recent Substantive Occupation

The main results treat occupational background as a binary: a legislator either held a given occupation before Congress or did not. Here, I test whether the effect is stronger when the matched occupation was the legislator's most recent substantive occupation before Congress.

Measurement. From the same reviewed occupational histories used throughout the paper, I identify each legislator's most recent substantive (non-political) occupation recorded before their first election to Congress. A legislator's occupation match is coded as *most recent* when it equals this occupation. I use this categorical measure rather than the share of pre-Congress adult years covered by a dated spell in the occupation because biographical entries frequently lack dates, and the missingness is concentrated in business and agriculture, where a majority of members have no dated occupational spell. This measure is therefore well populated only for law and military; for those two groups it points in the same direction (a higher dated occupation share predicts a larger speech effect), but I do not rely on it because it cannot be measured comparably across occupations. The most-recent measure does not require complete dating, so it is defined for every focal occupation.

Specification. The model is identical to the main expertise specification for each outcome: the same stacked legislator–Congress–occupation panel, the same fixed effects, the same controls (race, gender, incumbency, seniority), the same clustering, and the same committee-window restriction. The only change is an interaction between the occupation-match indicator and the most-recent indicator. The occupation-match coefficient then gives the matching-occupation effect for legislators who hold the occupation but did not hold it most recently; the interaction gives the additional effect for those who did.

Results. Table A.17 shows a consistent directional pattern. For the three activity and issue-focus outcomes, legislators whose matched occupation was their most recent substantive occupation show a substantially larger matching-occupation effect than other legislators who held the same occupation: their speech effect is roughly sixty percent larger, their bill-sponsorship effect roughly forty percent larger, and their probability of a matching committee assignment roughly eighty-five percent larger. The interaction is not distinguishable from zero for bill sponsorship or legislative effectiveness. The expertise effect is therefore stronger when the occupation was the legislator's most recent substantive occupation before Congress, particularly for speech, bills, and committees.

Table A.17: Most Recent Substantive Occupation and Specialization

	(1) **Speech** content share	(2) **Bills** sponsored share	(3) **Committee** match	(4) **Effectiveness** (log LES)
Has matching occupation	0.0069***	0.0101***	0.0870***	0.1593***
	(0.0009)	(0.0021)	(0.0215)	(0.0422)
× Most recent substantive occupation	0.0040**	0.0041	0.0739**	0.0709
	(0.0014)	(0.0025)	(0.0280)	(0.0493)
Legislator controls	✓	✓	✓	✓
Full panel fixed effects	✓	✓	✓	✓
Observations	178,739	201,700	65,413	126,900
Legislators	3,261	3,432	1,602	2,488

This table reports estimates of the matching-occupation effect and its interaction with an indicator for whether the matched occupation was the legislator's most recent substantive occupation, for four outcomes. The unit of observation is a legislator–Congress–occupation cell; the sample, fixed effects, controls, and clustering match the main specification for each outcome. "Has matching occupation" is the estimated effect for legislators who hold the occupation but did not hold it most recently; the interaction row gives the additional effect for those who did. Standard errors, clustered by district-party, are in parentheses. Legislative effectiveness is measured as log(LES + 0.1). $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Robustness to how intensity is measured. The directional pattern is similar across the three measures. Table A.18 repeats the interaction for three operationalizations: the most recent substantive occupation used above; the occupation in which the legislator spent the most (datable) career time; and a continuous dated-occupation share, estimated among members whose histories are datable. All three point the same way, positive for speech, bills, and committee assignment and absent for effectiveness. The continuous share is the least precise, because it is defined only for members with dated occupational histories, which excludes most legislators in business and agriculture, and because it pools occupations with very different dating coverage. The categorical most-recent measure is the most broadly defined and is the one reported above.

Table A.18: Alternative Measures of Occupational Intensity

Intensity moderator	**Speech**	**Bills**	**Committee**	**Effectiveness**
Most recent substantive occupation	0.0040**	0.0041	0.0739**	0.0709
	(0.0014)	(0.0025)	(0.0280)	(0.0493)
Longest-held occupation (dated records)	0.0029*	0.0010	0.0640*	-0.0017
	(0.0013)	(0.0024)	(0.0289)	(0.0524)
Dated occupation share	0.0077*	0.0083	0.0953	0.1715
	(0.0038)	(0.0065)	(0.0932)	(0.1660)

This table reports, for each intensity measure and outcome, the coefficient on the interaction between the occupation-match indicator and the intensity moderator, from the same specification as Table A.17. The three moderators are whether the occupation is the legislator's most recent substantive occupation before Congress, the longest-held occupation based on dated records, and the share of pre-Congress adult years covered by a dated spell in the occupation (occupation-holders with a dated spell only). Each cell is a separate regression. Legislative effectiveness is measured as $\log(\text{LES} + 0.1)$. Standard errors, clustered by district-party, are in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

A.16 Specialization Over Legislative Careers

Table A.19 reports whether occupation-linked specialization changes over legislators' terms in office.

Table A.19: Occupational Specialization Over the Legislative Career

	Change per term	Implied effect at		
		Term 1	Term 5	Term 10
Floor speeches (pp)	-0.05***	1.08***	0.89	0.66
	(0.01)	(0.09)		
Sponsored bills (pp)	-0.06**	1.44***	1.22	0.94
	(0.02)	(0.17)		
Committee service (pp)	-0.37	14.54***	13.08	11.25
	(0.25)	(1.85)		
Legislative effectiveness (log pts)	0.008	0.158***	0.190	0.231
	(0.005)	(0.036)		

Note: This table reports, for each specialization outcome, the interaction of the matched-occupation effect with the legislator's term of service (*Change per term*) and the implied matched-occupation effect at terms 1, 5, and 10, from the full within-district-party specification. Standard errors (in parentheses) are shown for the per-term change and the term-1 effect; term-of-service is the legislator's term number (range 1–30). The floor-speech, bill, and committee rows are in percentage points; the effectiveness row is in log points for log(LES + 0.1). Standard errors are clustered at the district-party level. $^{\dagger}p < .1$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.