Investing in Political Expertise: The Remarkable Scale of Corporate Policy Teams*

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Abstract

In this paper, we define and measure a previously unstudied channel by which companies react to, and attempt to shape, politics: internal policy teams. We use the text of more than 100,000 job listings to classify the roles of roughly 100 million workers, identifying more than 250,000 individuals working in policy roles in the US. We estimate that policy teams are—very roughly—13 times larger in size than lobbying teams, on average, and are increasing in size relative to lobbyists and other corporate positions over the last two decades. Policy teams and lobbyists appear to be complements; both across firms and within, increases in lobbying predict increases in policy team size. But policy team members are quite different from lobbyists: they are much less likely to have previous government experience, and they are less balanced in terms of their partisanship. Taken together, our findings show that corporations invest far more in politics than previously recognized, and suggest that a significant part of this investment goes towards developing internal expertise and communicating with a broader set of policymakers and policy-adjacent actors, rather than towards quid-pro-quo lobbying.

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1 Introduction

How do firms react to politics, and attempt to influence it? And how has this changed in recent years as American politics has changed? Substantial circumstantial evidence suggests that firms believe they can influence the policy process through lobbying (e.g., Egerod and McCrain 2023; Hirsch et al. 2023) and through campaign contributions (Fouirnaies 2018; Fouirnaies and Hall 2018; Li 2018; Sances and You 2022; Schnakenberg and Turner 2021), and that personal connections are an important mechanism for this influence (Bertrand, Bombardini and Trebbi 2014; Blanes y Vidal, Draca and Fons-Rosen 2012; Kalla and Broockman 2015; McCrain 2018; Lee and You 2023; Shepherd and You 2020). On the other hand, the total amount of money spent on lobbying and campaign contributions appears small if it truly delivers valuable policy returns (Ansolabehere, de Figueiredo and Snyder 2003), and there are reasons to doubt the potential returns at all (Fouirnaies and Fowler 2022). Moreover, lobbying data on its own does not allow us to disentangle informational lobbying from quid-pro-quo lobbying, despite the important differences between these two potential mechanisms (Hassan et al. 2019; Schnakenberg 2017; Ban, Park and You 2023; Hirsch et al. 2023; Schnakenberg 2019; Patty and Turner 2021).

In this paper, we bring new data to bear that helps to suggest how much of the influence process is missed when we only study official lobbying and campaign contribution data—especially in more recent years. The jumping off point for our study is the perhaps under-appreciated fact that large corporations have internal policy teams with hundreds of employees whose full-time jobs are to study the global policy environment, advise their companies on political matters, and seek to influence the policy process. They do this by developing policy briefs, speaking to stakeholders, commissioning polls and other studies, meeting with internal teams, attending conferences, reading academic studies, and so on—ultimately helping their companies to decide when and how to engage in the political process, what policies to fight for, and what narratives to develop around their companies and products. As we will show, these policy team members vastly outnumber lobbyists at major corporations, yet because they do not regularly speak directly to American government officials, they do not show up in lobbying disclosure data. That they are missing in the lobbying data implies we have underestimated the amount of money spent on politics inside firms, but it also

implies something more important: a large amount of money spent at firms to influence politics *isn't spent directly on lobbying government officials.*

To establish this systematically, we collect new data from LinkedIn on approximately 100 million workers.[1] Using the descriptions of job titles, we estimate that there are roughly 250,000 policy team workers across these firms. Merging in data on lobbying for a panel of 10,000 firms that Revelio tracks, we show that the average firm has roughly 1.5 policy team members but only 0.68 total lobbyists. Among the Fortune 100, the average firm has approximately 52 policy team members and 18 lobbyists.

Next, we establish that lobbying and policy teams appear to be complements; both across firms and within firms over time, increases in lobbying are associated with increases in the size of policy teams. While this may have many explanations, it is consistent with the view that policy teams produce complementary research and insights that lobbyists can use in their communications, and perhaps also communicate with complementary sets of stakeholders.

Finally, our data allows us to examine the personal characteristics of corporate policy team members, compared to other corporate workers. On average, we estimate that less than 2% of policy team members have previous U.S. state or national government experience, while nearly 70% of lobbyists do. Again, this suggests that they engage in complementary activities, with lobbyists tasked with using political connections to convey policy ideas and arguments, while policy workers study the political environment, generate information, and communicate with other stakeholders.

Also consistent with this idea, our last analysis shows that policy workers look more similar to their firm's employee base in terms of their partisanship, while lobbyists are selected to be more balanced in their partisanship—specifically, while most firms' workers are Democrats in our sample, lobbyists are over-selected for Republicans to make up for this imbalance, while policy workers are not. This makes sense if lobbyists are tasked with speaking to policymakers, many of whom are Republicans, while policy workers are not.

On the whole our findings help establish that the literature on corporate influence in politics needs to study corporate policy teams more deeply. Limited previously to data on lobbying and campaign contributions, we have missed a much larger category of firm expenditures in politics.

[1]Similar data is used for other purposes in Frake, Hurst and Kagan (2023), Gao, Wu and Zhang (2023), and Li et al. (Forthcoming).

Moreover, because this spending is definitionally not about contact with government officials, we have risked overweighting our analyses towards the part of the process more focused on personal connections and quid-pro-quo exchanges, and underweighting the role of costly information production, since much of this information can be produced inside the firm.

As the first research that seeks to measure corporate policy teams, there are two particularly important limitations to our study. First, we have no direct quantitative evidence on precisely what policy team members do on a day-to-day basis or how much of their worktime it takes up. As a result, directly comparing the number of policy team members to lobbyists, while potentially useful, is not straightforward; it could be that the average policy team member spends an important portion of their time on other, non-political tasks, for example. And second, our measure could be a lower bound on the size of policy teams if members of policy teams disproportionately avoid using LinkedIn, and we have no way to directly assess this possibility.

The remainder of the paper is organized as follows. In the next section, we provide a background on what corporate policy teams are and offer examples drawn from real job postings for corporate policy roles. Subsequently, we describe the data we assemble to study corporate policy teams. Next, we show analyses on the overall size of policy teams and how it has changed over time. In the penultimate section, we compare policy team members to lobbyists at the individual level. Finally, we conclude by reviewing what our findings mean for the study of corporate influence and by highlighting some of the major questions our research suggests for future investigation.

2 Background on Corporate Policy Teams

Firms are known to seek to influence politics through many channels, including lobbying, campaign contributions, revolving-door hiring practices, and by mobilizing pressure groups in the electorate (e.g., Bertrand et al. 2020; Hirsch et al. 2023; Kang 2016; Fos, Kempf and Tsoutsoura 2022; Li 2018; Payson 2020; Schnakenberg and Turner 2021; Patty and Turner 2021). These are some key, observable elements of a firm's overall political strategy. Where does this strategy come from, though? The point of our paper is that corporations devote large amounts of internal resources to developing and executing their political strategy. They typically concentrate these resources inside their own, internal policy teams (e.g., Christensen et al. 2024; LaPira and Thomas 2017;

Libgober and Carpenter 2024). These teams can have different labels across companies, such as Policy, Global Affairs, Regulatory Affairs, or other similar names. We will refer to them as Policy teams throughout.

Corporate policy teams serve several key functions.[2] First, they monitor and analyze ongoing policies and regulations across the world that affect their company's operations and bottom line. This involves closely tracking legislative and regulatory developments at the local, state, federal, and international levels, as well as anticipating future policy trends and risks.

Second, policy teams use this information to advise management on how to position the company in relation to key policy issues. This can include recommending when and how to engage in the political process, what specific policies to support or oppose, and how to frame the company's interests in the most compelling way. It can also involve advising on the product development process—steering the company towards product designs and strategies that are harmonious with the political environment, and away from designs and strategies that may provoke excess political backlash.

Third, and perhaps most importantly, corporate policy teams help to develop and execute their company's political influence strategy. While lobbyists are the tip of the spear in terms of direct engagement with policymakers, the policy team lays the groundwork for effective lobbying. This can include drafting policy briefs and position papers, commissioning studies and polls, building relationships with key stakeholders, and crafting persuasive narratives around the company's role in society. In many cases, policy team members will work closely with lobbyists and other political consultants to ensure that the company's messaging and advocacy are aligned and mutually reinforcing.

We can see evidence for all of these functions in the public job descriptions that corporations post for policy jobs. When companies post jobs for corporate policy roles, they describe responsibilities that go far beyond traditional lobbying. The postings emphasize relationship building, product advising, and managing a wide range of regulatory domains, often at both domestic and international levels.

[2]This description of what corporate policy teams do is primarily drawn from the authors' own experience working in corporate America. It also draws on a report from Charles River Associates: `https://media.crai.com/sites/default/files/publications/coordinated-approach-to-gobal-public-policy.pdf`

Consider a few examples pulled from our data on job descriptions, which we will describe in detail below. Netflix's Director and Head of Public Policy role highlights the dual responsibility of outward and inward influence. The description calls on the hire to "work with business partners to understand all aspects of the business and its needs; as well as explain the impact of public policy developments on the business." Externally, they are expected to "monitor and advance legislative and regulatory initiatives in the region," "develop relationships with government stakeholders at the Federal and State/Provincial level in the U.S. and Canada," and "build coalitions with peer companies and third party organizations." The issues named are wide-ranging: "entertainment and content production, internet policy, privacy and data security, competition policy, intellectual property, commerce and payments, taxation." This mix shows how companies seek policy generalists capable of tracking and managing multiple streams of political risk and opportunity at once.

Meta's posting for a Messaging Policy Manager reveals another dimension: embedding policy expertise directly in product development. The role is described as "a strategic thinker and action-oriented policy professional" who will "help develop our strategy and advise product teams on the hardest privacy and data use questions we face in the messaging space." The job combines internal advising with external engagement. The candidate is expected to engage "with civil society, policymakers, and other stakeholders to build understanding and support for our approaches and product objectives." At the same time, they must "collaborate with colleagues across the business and the globe" to make sure policy concerns are integrated into product strategy for WhatsApp, Messenger, and Instagram Direct.

Amazon's Senior Manager for Public Policy, focused on pharmacy care, shows the industry-specific tailoring of these jobs. The posting emphasizes that the hire will "develop and execute policy and advocacy strategies to advance Amazon's pharmacy initiatives" and "represent Amazon before state executives, policymakers, pharmacy boards, and other relevant health agencies and stakeholder groups." As with the tech companies, Amazon also highlights the internal function: the person must work "collaboratively with business, legal, and communications teams to ensure alignment between business priorities and public policy goals."

Roblox, in its Manager of Public Policy and US State Strategy role, illustrates the importance of subnational engagement. The responsibilities include "develop relationships with state policy-makers and political figures," "identify, monitor, and analyze policy issues affecting Roblox in the

U.S. States," and "develop strategies for engaging with state policymakers around issues important to Roblox." The role is also expected to "articulate our public policy positions in briefing papers and consultation responses" and "advise Roblox team members on public policy matters as inputs to the development of our products and business operations."

YouTube's Policy Development Lead for Child Safety underscores how companies frame policy jobs as tied directly to societal risks and company reputation. The posting calls for someone to "develop, maintain, and update our global policies focused on child safety policy and understand and communicate the risk landscape and regulatory requirements unique to child safety." The job requires assessing "the risk profile of new products and features," negotiating and finding "optimal policy solutions balancing safety and product reach and growth objectives," and proposing "new strategies and policies to improve the Trust & Safety product market fit." The role demands someone who can understand "policy challenges and needs presented by new features and emerging global online content risks" and clearly communicate them across the company.

These job descriptions all point to a common pattern. Corporate policy staff are expected to act as translators between the external political environment and the internal business environment. They must build and maintain networks with policymakers, regulators, and civil society groups. They must monitor, analyze, and anticipate emerging issues. And just as importantly, they must integrate those insights into product and business strategy, ensuring that the company's offerings align with evolving regulations and social expectations.

Consulting documents reinforce this vision of corporate policy work. In their report on policy teams in the pharmaceutical industry (cited above), Charles Rivers Associates describes a three-step model: first, "the policy toolkit needs to focus on prioritising the issues that the global environment scan indicates are flaring," second, "companies must establish an informed and overarching position on a particular policy challenge," and third, that position must be "disseminated, including supporting argumentation and evidence, in a way that can add value to other affiliates facing similar challenges."

Across industries, corporate policy roles are not narrowly about lobbying for specific bills. Instead, they are about embedding political awareness deep into the organization, shaping product and business strategy, and ensuring the firm can navigate a complex, shifting regulatory environment.

Despite their central role in shaping corporate political activity, policy teams have received scant attention from researchers, likely due to the difficulty of observing their work. Because policy team members generally do not communicate directly with government officials, they are not subject to lobbying disclosure requirements in the United States. As a result, their activities are largely invisible in the official records that have formed the basis for much of the empirical research on corporate political influence.

3 Systematic New Data on Corporate Policy Workers

This section reviews the key datasets we construct in order to study corporate policy teams systematically.

3.1 LinkedIn data

We obtain comprehensive individual-level data and workforce dynamics data from Revelio Labs, a company that collects and aggregates public LinkedIn profiles to build a workforce database. For firms in our data that are publicly traded, we use their CUSIP and CIK codes to match each firm $\times$ month observation to ComputStat North America in order to supplement our dataset with additional firm-level characteristics such as market value and average monthly stock prices.

Revelio's individual work history data tracks the public LinkedIn profiles of 768,943,741 individuals who registered for the service between 2016 and 2023. Because people typically fill out their entire work history when they create their online resume on LinkedIn, we can track an individual's career and education history back in time no matter when they joined the platform. In particular, this allows us to identify the following variables for individuals who worked in companies in our main dataset:

Job Title: We use individual's job titles to determine whether they work in a policy job (details below).

Education Experience: We use an individual's LinkedIn education background to determine whether or not they obtained a bachelor's degree, master's degree, or doctorate degree. We also use self-reported major choice to identify individuals with policy-relevant degrees in law, economics, or business.

Location: We use an individual's self-reported job location to determine their place of work. Most of our analysis are focused on individuals who work in the US.

Government Experience: An individual is considered to have government working experience if they previously worked for state or federal government. We further classified 3 types of government employees based on the branch of the govrnment they worked for: executive, legislative, and state.

We aggregate individual data to firm $\times$ month level and match it with our dataset of firms. Since the Revelio database contained only public profiles on LinkedIn, a potential concern is individuals with private LinkedIn profiles, or those who do not have LinkedIn profiles at all may be systematically left out in our data. Revelio addresses these missing data biases by assigning an inverse probability weighting to all individual $\times$ position observations they scraped from LinkedIn. The weights adjust for the probability of having an online profile given a user's occupation and location. We adopted Revelio's weights when computing key variables such as number of employees and total salary expenditure.

3.2 Identifying Policy Employees

We rely on LinkedIn job titles as the first step towards identifying policy individuals in a firm. We begin by considering a person as a possible policy worker if his or her job title includes one of the following policy-relevant keywords, and must not contain any of the non-policy keywords:

Policy-Relevant Keywords: policy, regulatory affair, government, external affair, external relation, public affair, eu affair, global affair, corruption, social initiative, environmental initiative, community investment, federal relation, legislative affair, washington operation, federal affair, washington office, international trade relation.

Non-Policy keywords: hr, human resources, insurance policy, tax policy, product policy, lecturer, professor, research associate, payment policy, reimbursement policy, engineer, credit policy, payroll policy, accounting policy, security officier, volunteer, pro bono, security manager, guard.

Using these keywords, we identified over 1.56 million potential policy positions in our LinkedIn data. This simple text classification method inevitably overestimates policy team sizes by capturing people who are not policy workers. For example, jobs such as "government contract manager" contain the keyword "government" but do not function as a corporate policy role. It is also true that sometimes jobs such as "external affairs manager" have more communication roles than policy

roles in a company. The addition of these false positive roles may bias the size of policy teams in our data upward.

In an attempt to validate our text classification method, we use Revelio's job posting dataset, which contains more than 40,000 relevant job postings for potential policy roles. A majority of these job postings came from LinkedIn, with some drawn from other job websites that Revelio has access to. Each job posting came from a company in our main data and is identified as a policy role using our text classification approach above. We then ask OpenAI's GPT-4, a large language model, to perform the same classifiction task, using only each job's cleaned job description. In particular, we query the following prompt to GPT-4:

> Your job is to read a job description. First, remove all words that also appear in the job title. Then, classify whether the job is a corporate policy team job or not using *only* its job summary and responsibilities. Output 1 if the job is policy related and 0 if not. We define corporate policy jobs as jobs in which the person is tasked with influencing the political environment and complying with regulations on behalf of the firm. This includes tasks like understanding the regulatory environment, interacting with regulatory agencies, ensuring compliance with regulatory policies, liaising with governments, engaging with politicians or political campaigns, using data to study elections, voter opinion, communicating government policies and regulations back to the firm, and generally doing anything related to politics or political policy or regulatory affairs. It should not include people who have purely administrative or operational roles or who work on setting policies related to internal corporate matters (i.e., HR policy) or product matters (i.e., content policy or cybersecurity policy). Do not include roles that work exclusively on government sales or contracts.

Table 1 compiles the GPT-4 classification results by job title keyword. The first column tracks the frequency each job title keyword appeared in the job postings we sampled. The second column counts the raw number of job postings classified as policy by GPT-4 among all jobs with a given job title keyword, while the third column computes this as a share of total jobs with this job title keyword. For example, job postings with the keyword "Policy" in their title are estimated to be policy roles only 43% of the time, but are very common on LinkedIn (almost 40% of all LinkedIn

job titles that meet our filtering conditions for potential policy roles). On the other hand, job postings with job titles containing keywords such as "federal affairs" or "government policy" are classified by GPT-4 as policy roles at very high rates, but are not very common on LinkedIn.

Table 1 – Using Job Descriptions to Validate Search Terms for Identifying Policy Jobs

	Number of Job Postings		Probability	
	With Search Term	Predicted as Policy Jobs based on Job Descriptions	ChatGPT	LinkedIn
Federal Relations	10	10	1.000	0.000
Government Policy	90	89	0.989	0.001
Federal Affairs	75	71	0.947	0.005
Legislative Affairs	17	16	0.941	0.001
Government Affairs	1919	1802	0.939	0.029
Government Relations	1250	1162	0.930	0.032
Public Policy	1031	939	0.911	0.028
Regulatory Affairs	14400	12430	0.863	0.196
External Affairs	503	383	0.761	0.022
Global Policy	82	60	0.732	0.002
Corruption	151	106	0.702	0.004
Public Affairs	1507	873	0.579	0.092
Washington Operations	7	4	0.571	0.000
Environmental Initiatives	2	1	0.500	0.000
Policy	7942	3446	0.434	0.396
Global Affairs	18	6	0.333	0.002
External Relations	241	38	0.158	0.022
Social Initiatives	14	2	0.143	0.000
Community Investment	61	8	0.131	0.003
Other Government Roles	13741	736	0.054	0.164

Notes: This table summarizes the share of job postings identified as policy jobs by ChatGPT using their job descriptions text, grouped by job title keyword. Column 1 reports the number of job postings containing each job title keyword. Column 2 shows how many of those were classified as policy jobs by ChatGPT. Column 3 presents the proportion of those postings that were labeled as policy jobs by ChatGPT. Column 4 displays the share of job postings with the keyword among all policy jobs in the LinkedIn data.

To validate our GPT results, we randomly sampled 500 jobs. We read each job's job description and manually coded them as policy/non-policy. Using our hand-coded job classifcations as the ground truth, we compare them to the GPT-4 classification results. Our human classification is consistent with the GPT-4 codings for 95.8% of the job postings. Table 2 shows the confusion matrix for our GPT-4 model. The low error rate $\leq 5\%$ suggests our GPT-4 classfications are fairly accurate.

Table 2 – Validating ChatGPT Classification with Manual Coding Results.

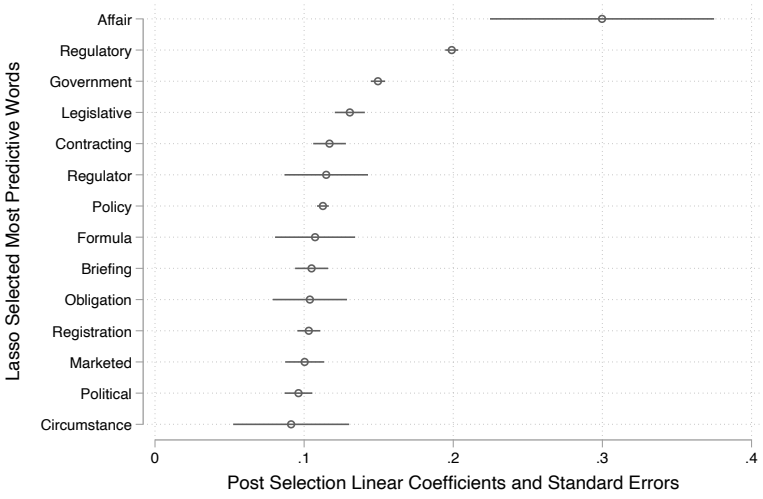
	Manual Coding (Ground Truth)	
	Policy	No Policy
Predicted Policy	200	18
	(40.00)	(3.60)
Predicted No Policy	3	279
	(0.60)	(55.80)

Notes: Table compares a set of 500 manually classified job postings to their corresponding ChatGPT-predicted labels. The percent accuracy rates are reported in parentheses.

In a further validation test, we randomly sampled 103,354 job postings, where around 10% are labeled as "policy" and 90% are labeled as "non-policy" according to our policy classification method based on their job title, and compare the words used in the two set of job postings. Then, we fit a Lasso linear model to predict whether a job is a policy role or not using tokenized words in the job postings. Common stop words, as well as words that appeared in $\geq 90\%$ and $\leq 10\%$ of the job postings, are dropped from the Lasso. The Lasso regularization helps identify words with the strongest predictive power in each setting without concerns for overfitting. The estimated models identified 1,558 words with nonzero predictive power for predicting a policy job. Figure 1 plots the words with most predict power for policy jobs, as well as their coefficient and standard errors. Words such as "regulatory", "government", and "legislative" have strong positive predictive power and fit with responsibilities of a policy position.

One concern of our preferred ChatGPT prompt is it might include employees who hold strictly regulatory compliance roles and do not engage in *influencing* politics, as we have defined it. This is a tricky issue, because we do want to include people who work in roles that involve compliance, but who in fact seek to influence politics through these roles—which may be quite common. For example, someone whose job is to ensure compliance with FDA requirements for clinical trials may on their face simply do compliance work, but in reality, they may be frequently working with government and non-government officials and producing materials meant to advocate for changes to the regulatory process. At the same time, we want to make sure we do not inflate our total estimate of policy workers by including people who are truly focused on compliance without influence.

Figure 1 – Using Lasso to Select Policy Words from Job Postings



In a second prompt we asked ChatGPT, we therefore narrowed our instructions and asked ChatGPT to exclude people with compliance responsibilities:

> Your job is to read a job description. First, remove all words that also appear in the job title. Then, classify whether the job is a corporate policy team job or not using only its job summary and responsibilities. Output 1 if the job is policy related and 0 if not. We define corporate policy jobs as jobs in which the person is tasked with influencing the political environment. This includes tasks like understanding the policy environment, liaising with governments or state regulators, engaging with politicians, political campaigns or regulatory agencies, using data to study elections, voter opinion, communicating government policies back to the firm, and generally doing anything related to politics, political policy, or regulatory affairs. It should not include people who have purely administrative or operational roles or who work on setting policies related to internal corporate matters (i.e., HR policy) or product matters (i.e., content policy or cybersecurity policy). Do not include roles that work exclusively on government sales or contracts, or regulatory compliance.

While we include compliance positions in our preferred policy headcount estimate, we also use the policy headcount excluding compliance positions for comparison in most of our analyses in this paper.

3.3 Lasso Reweighting

The results from our ChatGPT exercise give us estimated probabilities that each LinkedIn job title is a policy job, as we define it. We could simply use these probabilities directly to create firm-level aggregates that sum up the number of policy workers weighted by these probabilities. However, it is possible that job titles mean different things in different industries, for larger vs. smaller firms, or that their usage has changed over time. We can account for this by using a more flexible model that predicts policy jobs in our ground truth data using not only the job title but also firm covariates—particularly the firm's industry, size, and the year.

Specifically, we estimate the following lasso logistic model to predict whether a job posting is policy or not:

$$\hat{\theta}_\lambda = \text{argmin}_\theta \left[-log(\Pi_{i=1}^{n} P(Policy_j | \mathbf{w}_j, \text{industry}_j, \text{size}_j, \text{year})) + \lambda ||\theta||_1 \right], \quad (1)$$

where $||\theta||_1 = \sum_{j \geq 1} |\theta^j|$. Lasso regularization helps to identify job title keywords within each industry with the strongest predictive power while avoiding over-ftting.

We use the set of 46,631 job postings classified by ChatGPT as a policy job or not as training data. Since there are two sets of classifications based on different prompts (i.e., strictly policy v.s. policy or compliance), we prepare two sets of training samples and run a separate lasso model on each. For each job, we compute the Term Frequency - Inverse Document Frequency (TF-IDF) scores for unigrams/bigrams that appeared in the job title. TF-IDF score measures the relevance of a word across all job titles, and we selected 100 words/phrases with the highest scores as Lasso covariates. To uncover the difference across industry sectors in naming policy roles, we also interact each selected word or phrase with the set of 2-digit NAICS industry codes. We also control for firm size and year fixed effects.

In the prediction step, we use our trained lasso logit model to compute the probability of each job being policy. Our testing sample is the set of LinkedIn positions we identified as potential policy roles using their job title keywords. Each lasso predicted probability is then used to re-weight the likelihood of each role being policy.

3.4 Lobbying

To study the relationship between lobbying and policy team, we also collect lobbyist and lobbying expenditure data from the US Senate's Lobbying Disclosure dataset (LD-1/LD-2). Prior datasets in lobbying, such as Lobbyview (Kim 2018) only tracks the total lobbying expenditure for each company at the report level, and is only updated through 2020. Instead we scrape our own lobbying data for all Revelio companies in our sample by collecting all reports returned by searching a company's name on LD-1/LD-2. For each company $\times$ month observation, we observed its total number of in-house and external lobbyists, as well as the total amount spent in in-house lobbying and external lobbying.

3.5 Partisanship

We match 23,497,286 LinkedIn users to the L2 voter registration data. Each LinkedIn user has reported to work for at least one of the firms in our main data in the US. Our current version of the L2 data contain voter snapshots from 2018 to 2023. The L2 data has party registration records for voters in 33 states, which we use in our matching process. We adopt various combinations of name, age, and work location to match between LinkedIn and the voter file. We enforce the matched profiles to have the same middle initial when it is not missing. Individuals matched with more than one L2 voter records are dropped from our dataset. Since most people do not report their date of birth on LinkedIn, our date of birth variable is estimated using each individual's self-reported education history, prioritizing:

1. Year of high school graduation date + 19
2. Year of college graduation date + 23
3. Year of master graduation date + 25
4. Year of Ph.D. graduation date + 30
5. Year of first job starting date + 22

We map each user's work location to their corresponding (lattitude, longitude) coordinates and compute its distance from matched L2 residence addresses. When matching between LinkedIn

and L2, we gradually relax restrictions on the distance between the LinkedIn user's self-reported location and the voter's residence address, starting at $\leq$5 miles, then 25 miles, then 50 miles, then 100 miles, and finally the state. We also try to first match birth years in a 3-year window, and then relax the difference to less than 10 years.[3] For names, we first match using first name, middle name and last name, then first name and last name, and finally using only the first 4 letters of first name and last name. Together, we are able to match 8,654,236 individuals, yielding a final matching rate of 36%. We perform the same procedure for the subset of policy employees and lobbyists, who we match to their LinkedIn profiles first.[4]

We also merge in firm-level political contributions data from DIME (Bonica 2023). To best identify all PACs associated with a firm, we match company names in our Revelio sample to all corporate donors in DIME. In the matching process we also compute a text similarity score between the Revelio company name and the PAC name. We keep all identical matches, as well as matches with a similarity score ≥ 0.72. Then, we perform an additional round of screening to remove incorrect matches. This process allows us to identify 1,179 firms that has made at least one political contribution since 2010. We further break down the political contribution by party, and compute the total amount of political contributions a firm donated to democrats, republicans, and other political parties.

4 Corporate Policy Teams and Lobbying

In this section, we analyze our new data on the size and composition of corporate policy teams.

4.1 The Estimated Size of Corporate Policy Teams

We begin by reporting the results from our Lasso procedure for estimating the number of people working in policy, across all firms and years in our data.

[3] However, if either the LinkedIn individual's estimated age or the voter's age is unavailable, we relax the age restrictions.

[4] We use a lobbyist's first name, middle initial, and last name when matching to LinkedIn. If the lobbyist is in-house, we match them to individuals who worked in the same company at the time of lobbying. If the lobbyist is external, we match them to individuals who worked at their lobbying firm at the time of lobbying. If the lobbyist does not have a matching LinkedIn profile, they are directly matched to the L2 voter file for DC/Maryland/Virgina, where most of the lobbyists in our dataset worked.

Figure 2 – Policy and Lobbyist Team Size across All Firms.

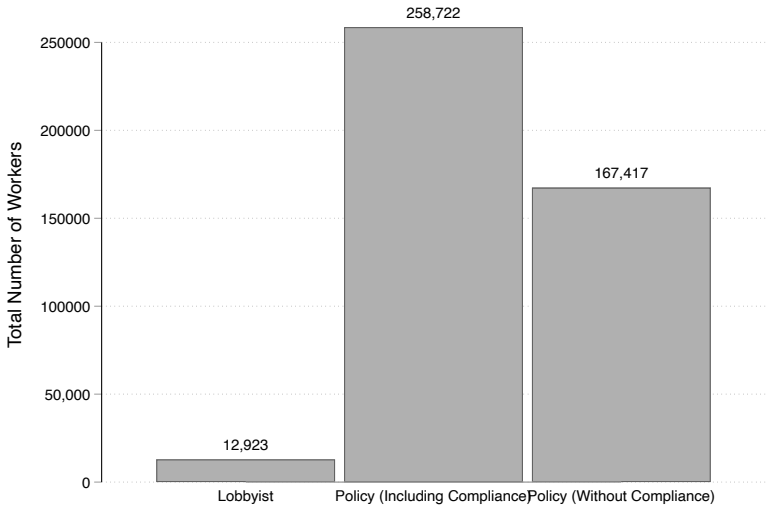


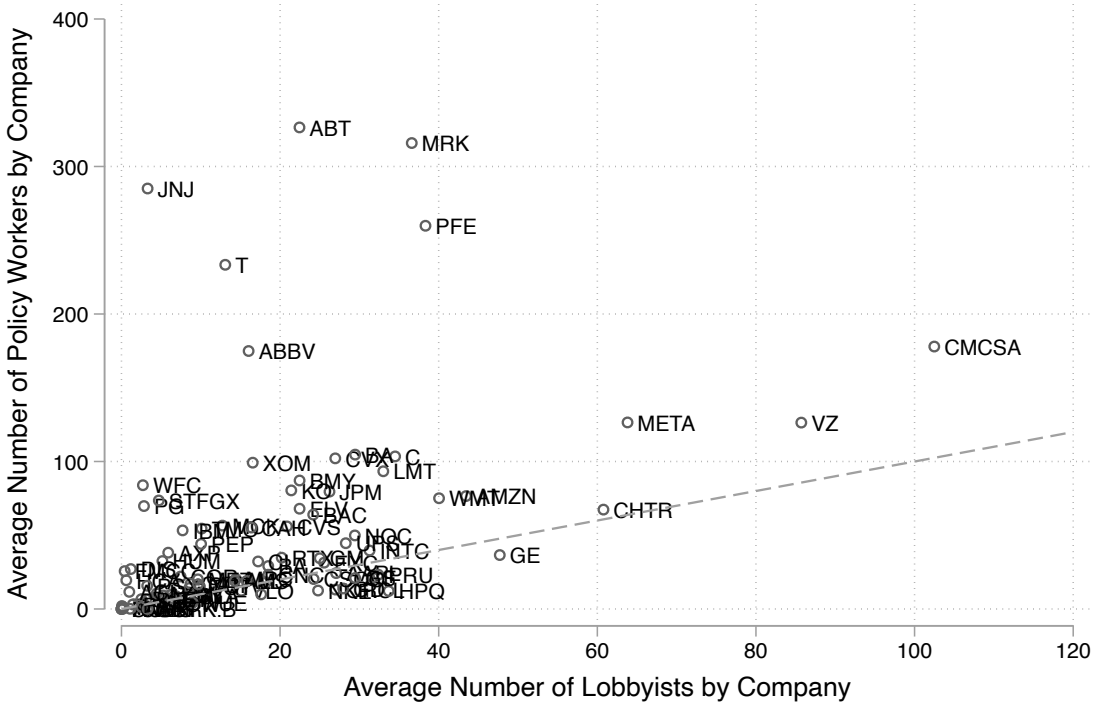
Figure 2 shows our overall estimates. The bar "Policy (With Compliance)" is estimated using the training data generated from the first GPT prompt, while the bar "Policy (Without Compliance)" is generated from the lasso model with training data generated by asking ChatGPT to exclude compliance roles when classifying policy roles. For comparison, the first bar in the plot shows the total number of lobbyists found in the lobbying disclosure data for this same universe of firms.

As the plot shows, whichever way we treat compliance-related roles, we find many more policy workers than lobbyists. We find just shy of 13,000 total lobbyists engaged by our firms, compared to nearly 260,000 policy workers all told, and roughly 167,000 when we strictly exclude compliance-related roles—20x and 13x the number of lobbyists, respectively. As we emphasized in our introduction, exactly what these ratios mean is not clear. A policy worker might devote all of their working hours to policy-related tasks, or could be split across responsibilities. Lobbyists might only work part time for a given client. Exactly how much greater company's investment in policy teams is versus lobbyists is unclear, but the fact that the magnitudes are so different strongly suggests that policy teams are important and deserve much deeper study.

We can get more texture on the size of policy teams by examining it at the firm level. Figure 3 presents a scatterplot comparing the size of company's lobbying teams (x-axis) and their policy teams (y-axis) for the Fortune 100, with the points labeled by the company's ticker symbol. A line

of equality is drawn in dashed gray, indicating where firms would lie if they had equally sized policy and lobbying teams.

Figure 3 – Policy Team Size and Lobbying Breakdown Across Companies, Fortune 100.



As the figure shows, most companies are above the line, indicating that they have larger policy teams, and a number are way above the line. These include major pharmaceutical companies (Johnson & Johnson, Abbot Labs, Merk, Pfizer) as well as telecommunication companies (AT&T, whose ticker is T, Comcast, Verizon), and major tech companies (Amazon, Meta).

To get further texture, Table 3 lists the companies in our data with the largest average estimated policy team size. For each company, the table also provides the percent of their workforce estimated to be in Policy, the average number of lobbyists they engage, and their NAICS industry code. Pharmaceutical and Healthcare companies are the most common among the top firms, but Defense, Finance, Telecom, and Tech companies are also represented.

Table 3 – Top Companies by Number of Policy Workers

Name	Policy Workers	% Policy Workers	Lobbyists	NAICS Code
Abbott Laboratories	326.50	0.24	22.45	Surgical and Medical Instrument Manufacturing
Merck & Co.	315.90	0.36	36.60	Pharmaceutical Preparation Manufacturing
Johnson & Johnson	285.08	0.19	3.30	Pharmaceutical Preparation Manufacturing
Pfizer Inc.	259.82	0.22	38.33	Pharmaceutical Preparation Manufacturing
AT&T	233.35	0.10	13.08	Wireless Telecommunications Carriers
Comcast	177.92	0.10	102.49	Wireless Telecommunications Carriers
AbbVie	174.89	0.28	16.03	Pharmaceutical Preparation Manufacturing
Meta Platforms	126.48	0.13	63.81	Web Search Portals and All Other Information Services
Verizon	126.36	0.09	85.72	Wireless Telecommunications Carriers
The Boeing Co.	104.66	0.11	29.46	Guided Missile and Space Vehicle Manufacturing
Citigroup	103.43	0.05	34.51	Commercial Banking
Chevron	102.12	0.13	26.96	Bituminous Coal and Lignite Surface Mining
Exxon Mobil	99.20	0.11	16.55	Bituminous Coal and Lignite Surface Mining
Lockheed Martin	93.35	0.10	33.01	Guided Missile and Space Vehicle Manufacturing
Bristol Myers Squibb	87.11	0.21	22.46	Pharmaceutical Preparation Manufacturing
Wells Fargo & Co.	83.91	0.03	2.70	Commercial Banking
The Coca-Cola Co.	80.41	0.07	21.41	Soft Drink Manufacturing
JPMorgan Chase & Co.	79.58	0.03	26.23	Commercial Banking
Amazon	76.53	0.01	43.45	Internet Department Store Sites
Walmart	75.08	0.02	40.04	Warehouse Clubs and Supercenters
State Farm Mutual	73.56	0.10	4.70	Direct Property and Casualty Insurance Carriers
Procter & Gamble Co.	69.78	0.07	2.84	Soap and Other Detergent Manufacturing
Elevance Health	67.97	0.11	22.46	Direct Health and Medical Insurance Carriers
Charter Communications	67.38	0.13	60.77	Wireless Telecommunications Carriers
Bank of America	63.97	0.03	24.17	Commercial Banking

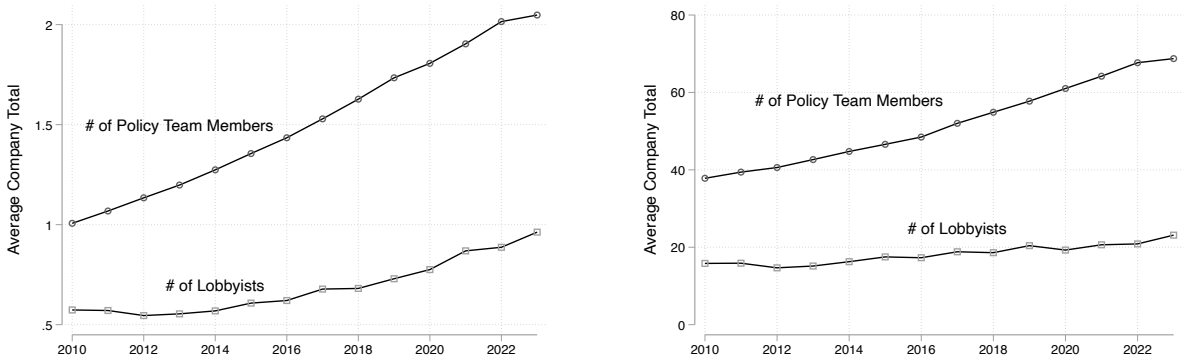
Notes: Table shows the top companies by average number of policy workers, percent of total workforce as policy workers, total number of lobbyists, and the company's NAICS 6-digit industry code.

4.2 Policy Teams Growing Over Time More Than Lobbying

Next, we disaggregate the estimated size of policy teams over time, compared to the number of lobbyists retained by these same firms (again, including both internal and external lobbyists). Figure 4 shows the results; in the left panel, we include all companies, while in the right panel, we zoom in on the Fortune 100. In both cases, we see that the average size of policy teams is growing steadily over time between 2010 and 2024; doubling from approximately 1 to 2 across all firms, and increasing from 40 to nearly 70 for F100 firms. Over the same time period, we see a meaningful but smaller increase in lobbyists across all firms, and essentially no growth at all in lobbyists for the F100.

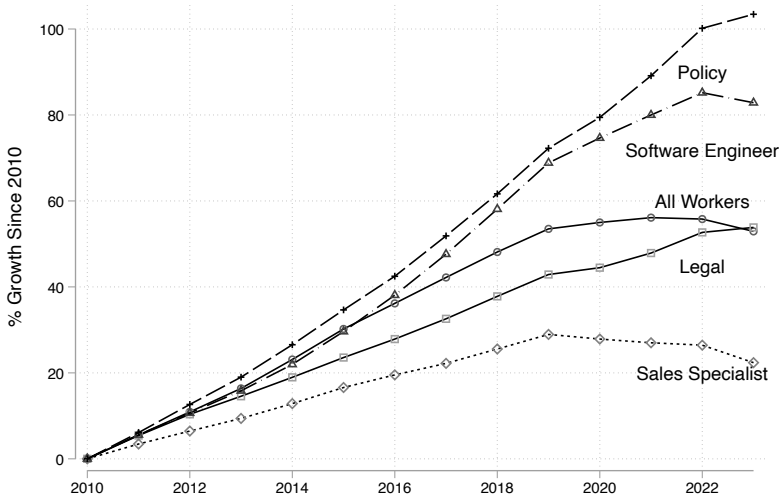
It is possible that the growth we find in policy teams reflects either an artifact of the LinkedIn data—since the lobbyist counts come from disclosure data, not the LinkedIn data—or is related to an overall growth in the average size of firms, which might tell us something about returns to scale of policy teams but might be more mechanical than related to intentional investments in politics. As a way to assess these possibilities, Figure 5 compares the growth rate in policy jobs to the same rate for a number of other LinkedIn-generated jobs. As the plot shows, the growth in Policy teams is higher than the growth of Software Engineers, Legal, and Sales workers, and is also noticeably

Figure 4 – Policy Team Size and Lobbyists Over Time.



(a) All Companies **(b) Fortune 100**

Figure 5 – Job Growth Over Time.

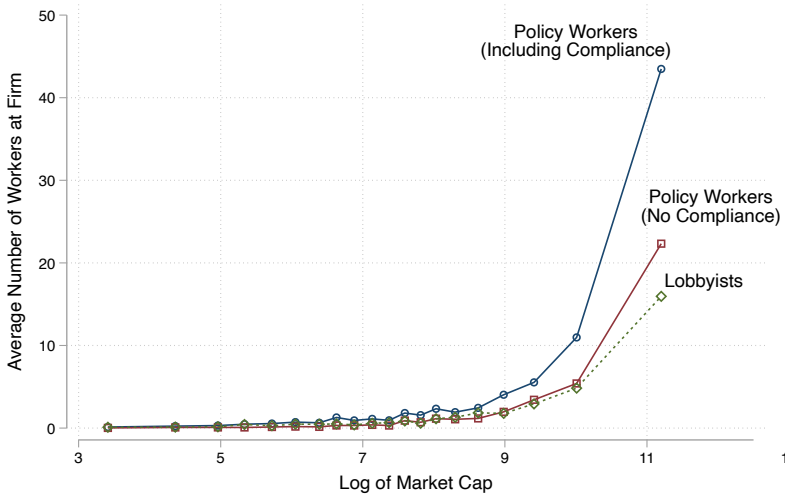


higher than the overall growth rate for firms ("All Workers"). Interestingly, while the growth rate for Policy has always been higher than these other categories across our sample of years, the gap seems to have increased most noticeably since 2018.

4.3 Policy Teams Are Concentrated Among Largest Firms

It is well known that lobbying, campaign contribution, and overall efforts to influence politics are concentrated among the largest firms. Here, we confirm that the same pattern holds for policy teams. Figure 6 plots binned averages of the average number of policy workers (with and without compliance-related roles as separate lines) and lobbyists across the company's average market cap.

Figure 6 – Policy and Lobbying Team Size by Marketvalue.



As we can see, in the same manner as lobbyists, policy workers are most concentrated at the largest firms—and moreover, the gap between the size of policy teams and lobbying teams is largest for these largest firms.

5 How Are Policy Teams Different from Lobbyists?

We have shown suggestive evidence that corporate policy teams are larger in size than lobbying teams, and are growing faster, too. This suggests that the literature has undersestimated the scope of corporate spending on politics. But is that the whole story? Are policy teams simply lobbyists by another name? Or does the size of policy teams also tell us something about *how* companies perceive the political landscape and how they can influence it?

We now turn to three analyses that, together, suggest that policy teams are importantly distinct from, and complementary to, lobbyists. First, we show that policy teams and lobbying teams grow together, suggesting that they are complementary to one another. Second, we show that policy team members are much less likely to have previous experience in government than lobbyists, suggesting that they are not hired for their connections the way lobbyists are. And third, we show that policy team members reflect the typical partisan make-up of their companies more than lobbyists too—while lobbyists are selected somewhat to match policymakers in both parties, policy team members

are less so, again suggesting that they are not in the "relationship business" with policymakers to the same degree that lobbyists are.

5.1 Corporate Policy Teams and Lobbying Appear Complementary

To investigate the potential correlation between the size of a company's policy and lobbying teams, we estimate equations of the form

$$\#\ Policy\ Workers_{it} = \beta \#\ Lobbyists_{it} + X_{it} + \gamma_i + \delta_t + \epsilon_{it}, \tag{2}$$

where the outcome variable is the estimated number of policy workers at company i in year t; the key regressor is the number of lobbyists at company i in year t, and we add an optional vector of control variables as well as firm and year fixed effects in different specifications.

Table A.4 shows the results for a number of specifications, and for the policy measure including compliance roles (first four columns) and excluding them (last four columns). In column 1, we see that, looking across time within companies, an increase of one to the lobbying team predicts an increase of 1.4 policy workers, on average—indicating that the two teams grow in size together. In column 2, we add year fixed effects to net out aggregate trends across companies, finding that an increase of one to the lobbying team predicts a 0.6 increase in the number of policy workers, on average.

In columns 3 and 4, we investigate whether policy teams are stronger complements to in-house lobbyists or external lobbyists. Interestingly, we find that the growth of in-house lobbyists has a larger association with the growth of policy teams than does the growth of external lobbyists, though both are large and positive coefficients. In column 4, we control directly for firm size, in case there are heterogeneous trends in firm size that might mechanically explain some of the associations, finding very similar results. The last four columns replicate these analyses for the no-compliance version of the measure, arriving at the same qualitative conclusions.

5.2 Policy Team Members Are Not Hired for Government Relationships

If policy team members are simply lobbyists by another name, then we should expect them to share similar professional backgrounds—and in particular, we should expect them to be part of

Table 4 – Policy Team and Lobbyists Are Complements.

	# of Policy Employees							
	Policy Workers (Including Compliance)				Policy Workers (No Compliance)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total # of Lobbyists	1.434	0.581			0.792	0.344		
	(0.164)	(0.116)			(0.093)	(0.087)		
# In-House Lobbyists			1.538	1.508			1.048	1.038
			(0.538)	(0.536)			(0.479)	(0.478)
# External Lobbyists			0.505	0.499			0.288	0.285
			(0.100)	(0.100)			(0.062)	(0.062)
Log(# of Employees)				0.811				0.276
				(0.278)				(0.089)
N	1687390	1687390	1687390	1684041	1687390	1687390	1687390	1684041
Year FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

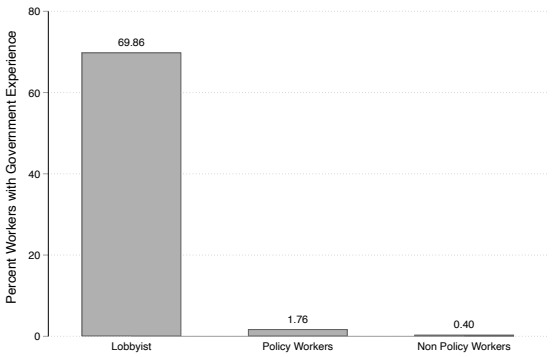
Notes: Robust standard errors clustered at company level.

the "revolving door" in which many lobbyists have experience working in government and have relationships to many current government officials. On the other hand, if policy members are carrying out other activities that are complementary to but distinct from lobbying, we might not expect them to have similar government experience.

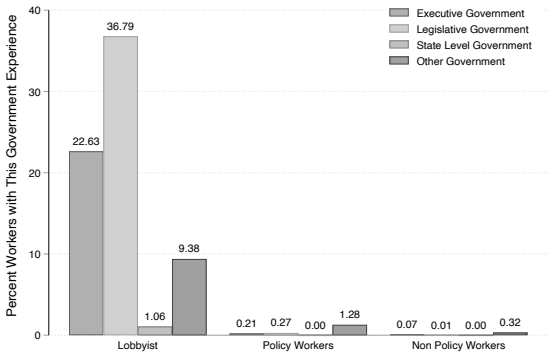
Figure 7 makes this comparison, both for overall experience in American national and state government (left panel), and decomposed into different types of government experience (right panel). As we see, there is an extremely stark difference. While nearly 70% of lobbyists have former government experience, less than 2% of policy workers do. For comparison, the left panel also includes the rate of government experience for the entire set of workers at these companies that we estimate do not work in Policy; roughly 0.4% of these workers have past government experience. Policy workers are therefore roughly 4 times more likely than non-policy workers to have government experience, yet have less than 40 times as much experience as lobbyists. Interestingly, as the right panel shows, lobbyist experience is relatively concentrated in the national executive branch and legislature, while Policy workers' more limited experience is more concentrated in our category of Other Government (which includes the military, law enforcement, and national labs, among others).

In sum, policy workers look radically different from lobbyists. While lobbyists are quite likely to have past government experience—with past research suggesting the direct economi value of

Figure 7 – Policy Team Size and Government Experience Across Industries.



(a) All



(b) By Government Experience

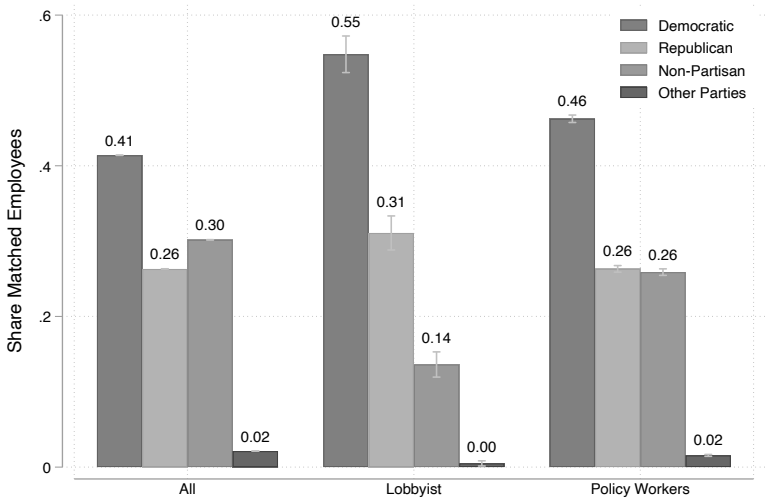
the connections formed through this experience—policy workers are very unlikely to have this experience. Hence, policy workers are complements to lobbyists, yet seem to be delivering value in a different way.

5.3 Policy Workers Are Less Balanced by Partisanship Than Lobbyists

Similar to the logic in the previous section, if policy team members are essentially lobbyists, then we should also expect them to be selected for partisanship in the same way as lobbyists. Since companies need to maintain relationships with whichever party is in power in many cases, we might expect them to make efforts to hire lobbyists from both parties. Do policy team members reflect the same partisanship as lobbyists?

Figure 8 shows the partisan breakdown for all company workers (left), lobbyists (middle), and policy workers (right), conditioning on all individuals for whom we are able to find a party registration. Looking at the left panel, we see that workers tend to skew left; roughly 40% of workers with voter registrations we can find are Democrats, 30% are independents, and only 26% are registered Republicans. In the middle, we see this is somewhat different. Lobbyists are less lkely to be registered independents (only 13%) and more likely to be Democrats *and* Republicans. While there are far more registered Democrats than Republicans (55% vs. 31%), there are more Republican lobbyists than Republican workers (31% vs. 26%). The policy workers do not show a similar pattern and look much more like the overall worker base, with only 26% being Republicans.

Figure 8 – Partisanship Breakdown



The main difference between the policy workers and the worker base as a whole is that Policy workers are 5 percentage points more likely to be Democrats, and a corresponding 4 percentage points less likely to be independents.

Hence, similar to the government experience analysis in the previous section, we again find evidence that policy workers look different from lobbyists. While lobbyists have in some way been selected to represent Republicans at a higher rate than the overall worker base—consistent with the idea that lobbyists need to be able to speak to both sides of the aisle—policy workers have not been selected in the same way.

6 What Do Policy Teams Actually Do? Evidence from Job Postings

We've demonstrated that corporate policy teams are large and distinct from pure lobbyists. One of the major limitations of our analyses, though, is that we can't actually observe what policy team members are really doing on a daily basis. In an ideal world, we would somehow see all the work they're doing, and compute what fraction of it looks like lobbying, what fraction looks like research, and so on.

We can't do that, but instead, we build on the policy job descriptions previously classified by ChatGPT and again rely on large language models for further analysis. We provide Gemini with

a job posting and ask it to classify the role into one of seven mutually exclusive categories. Each category, to the best of our knowledge, represents a main function of policy jobs. The roles are research/policy analysis/policy review, advocacy with policy makers, advocacy with non-policy makers, internal product counseling, company policy development, regulatory compliance, and other for jobs previously misclassified and do not pertain any policy roles. We ask Gemini to use *only* the job description text provided by each job posting in the classification process. The complete prompt is listed in section 6 of the online appendix.

Table 5 reports the share of job postings assigned to each category. After classification, we also ask Gemini to report each job posting's probability of being assigned into each category, which serves as a measure for model confidence. Higher confidence indicates that, based on Gemini's assessment, a job posting is more likely to belong to the corresponding role classification. Gemini's average classification confidence rate is 97.5%, suggesting each policy role is quite mutually exclusive from another. In other words, most policy job postings in our sample appear to serve distinct functions, and it is rare for a job to have joint roles and be multifunctional.

For each job posting, we also ask the AI model to help us select out the strongest action verbs or keywords that best define the job's core responsibilities.[5] In 5, we also list each job role's top 5 most frequently used keywords, as well as the share of job postings containing them. These summarized keywords provide a holistic view on the key tasks performed by each job role.

Regulatory compliance roles account for the largest share of policy job postings. More than 40% of the positions in our sample fall into this category, with primary responsibilities such as preparing regulatory submissions and ensuring compliance with regulatory requirements. Their large share aligns with our findings in Figure A.3, which shows almost half of the ChatGPT-classified policy jobs are held by compliance workers who do not directly engage in policy.

Advocacy with policymakers and policy research are the next two largest categories, each accounting for around 15% of policy job postings in our sample. Workers who work on advocacy are mainly responsible for building government relations, lobbying, and engaging in government affairs. Policy research roles, on the other hand, focus mainly on policy analysis and development, with some positions also involving data analysis.

[5]Our exact query to Gemini is "A list of the top 3-5 strongest action verbs or keywords that define the job's core responsibilities". For each returned keyword, we performed de-stemming and lemmatization. As our list of keywords also contain phrases, we combined phrases that have similar meaning (i.e., analyze policy, policy analysis)

Table 5 – Summary of Policy Job Roles Using Job Description

Job Role	Avg. Share of Job Role	Key Word	Share of Postings with Word
Policy Research	0.152	Research	0.207
		Analysis	0.136
		Policy Analysis	0.097
		Policy Development	0.066
		Data Analysis	0.051
Advocacy with Policy Makers	0.157	Advocacy	0.227
		Government Relations	0.139
		Lobbying	0.068
		Government Affairs	0.066
		Build Relationships	0.058
Advocacy with Non-Policy Makers	0.038	Media Relations	0.201
		Community Outreach	0.112
		Stakeholder Engagement	0.092
		Communication	0.073
		Community Engagement	0.070
Internal Product Counseling	0.026	Policy Development	0.074
		Advise	0.054
		Evaluate	0.052
		Analysis	0.041
		Guidance	0.036
Company Policy Development	0.005	Policy Development	0.333
		Develop	0.218
		Maintain	0.137
		Policy Management	0.128
		Write	0.107
Regulatory Compliance	0.420	Regulatory Compliance	0.347
		Regulatory Submissions	0.233
		Regulatory Requirements	0.191
		Regulatory Affairs	0.174
		Compliance	0.124
Other Non-Policy Relevant Information	0.203	Troubleshoot	0.016
		Sale	0.012
		Project Management	0.011
		Customer Service	0.010
		Account Management	0.008

Notes: This first two columns of this table presents the share of job postings classified into each job role category by Gemini. The next 2 columns show the distribution of the top 5 most used keywords or phrases across all job postings classified into each category. Keywords are lemmatized and destemmed such that words or phrases with similar meanings are grouped together.

An additional 3.8% of the policy jobs work on advocacy with non-policy makers, such as building media relations, community outreach and stakeholder engagement. 2.6% focus on internal product counseling, with responsibilities such as advising, evaluating, and providing guidance for product policy. Only 0.5% of the policy job postings are dedicated to company policy development and maintainence.

In sum, the job descriptions seem largely consistent with the more systematic, indirect evidence we've presented above: corporate policy team members carry out a variety of functions that include regulatory compliance, policy research, and advocacy with both policymakers and non-policymakers.

7 Conclusion

In this paper, we have uncovered a crucial but overlooked aspect of how corporations both respond to and seek to influence politics: internal policy teams. Using new data on these teams across a large sample of U.S. firms, we have shown that they are far larger than previously recognized. The average firm's policy team is much larger, in terms of people, than its lobbying team, particularly for larger companies who spend more time engaging in politics. Moreover, policy teams have been steadily growing in size over the past two decades, while lobbyists have not—making policy teams an increasingly important part of the political landscape, and offering a different picture of how companies are perceiving the political environment.

Our results suggest that corporations invest far more in shaping policy than what can be observed through lobbying disclosures or campaign finance records. And our subsequent analyses also suggest that policy teams are not just lobbyists by another name—they are carrying out different duties and providing different value. Although we cannot directly observe what they do on a daily basis, qualitative accounts suggest that they focus more on developing expertise, monitoring the global policy environment, bringing together data and research and combining it with firm-specific knowledge to create political strategies that lobbyists then help to execute on by conveying to policymakers. Our statistical analyses indirectly suggest the plausibility of these accounts, by showing that policymakers are complements to lobbyists—growing at the same time that lobbyists do within firms—but that they do not have the same kinds of government experience

or partisan balance that lobbyists have. They are an important component of how companies seek to react to and influence politics, but they do not seem to be in the government relationship business.

We hope that future work will expand our understanding of these important people and the nature of their roles. While we have documented some useful, basic facts about corporate policy teams, there are many unanswered questions. How do policy teams allocate their time and effort? What impact do they have on policy? How much do companies spend on their policy teams, and what is their return on this investment? These are some of the foundational questions that we hope can be studied based on the foundational data collected and analyzed in this first study.

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Online Appendix

Intended for online publication only.

Contents

A.1 Summary Statistics

Table A1 presents summary statistics from our data for firms (panel A), policy workers (panel B), and lobbyists (panel C).

Table A.1 – Summary Statistics

	Mean	SD	Median	P10	P90	Obs.
Panel A - Firm Characteristics						
Total Workers (1,000)	8.531	26.646	1.586	0.082	19.406	1687390
Salary (millions $)	370.483	1190.614	67.800	4.463	804.413	1687390
Policy Workers	3.931	36.127	0.000	0.000	2.961	1687390
Total Policy Salary (millions $)	0.489	3.684	0.000	0.000	0.497	1687390
Number of Lobbyists	0.684	4.029	0.000	0.000	0.000	1687390
Lobbying Expenditure (millions $)	0.023	0.185	0.000	0.000	0.000	1687390
Log(Regulatory Restriction Words)	7.974	1.732	7.626	5.958	11.094	1035936
Overall Economic Uncertainty Index	162.566	67.699	152.182	96.413	229.245	1687390
Firm Political Risk	130.064	235.046	65.332	0.000	298.453	317680
% Donations to Democrats	40.061	37.906	33.333	0.000	100.000	33640
% Donations to Republicans	59.939	37.906	66.667	0.000	100.000	33640
% with Government Experience	0.402	1.275	0.000	0.000	1.192	1684041
Panel B - Policy Worker Characteristics						
% US	35.199	47.759	0.000	0.000	100.000	441328
% Female	51.822	49.967	100.000	0.000	100.000	441328
% with Bachelor's Degree	82.372	38.106	100.000	0.000	100.000	349120
% with Master's Degree or Above	51.655	49.973	100.000	0.000	100.000	349120
% with Advanced Law Degrees	3.672	18.808	0.000	0.000	0.000	349120
% with Advanced Economics Degrees	1.711	12.968	0.000	0.000	0.000	349120
% with Advanced Business Degrees	15.021	35.728	0.000	0.000	100.000	349120
% with Government Experience	4.216	20.096	0.000	0.000	0.000	441328
% Democrats	46.731	49.894	0.000	0.000	100.000	36550
% Republicans	25.620	43.654	0.000	0.000	100.000	36550
% Other Parties	1.560	12.390	0.000	0.000	0.000	36550
% Non-Partisan	26.090	43.913	0.000	0.000	100.000	36550
Panel C - Lobbyist Characteristics						
% Female	38.490	48.661	0.000	0.000	100.000	6212
% with Bachelor's Degree	73.986	43.875	100.000	0.000	100.000	6212
% with Master's Degree or Above	46.442	49.877	0.000	0.000	100.000	6212
% with Advanced Law Degrees	22.408	41.701	0.000	0.000	100.000	6212
% with Advanced Economics Degrees	0.982	9.861	0.000	0.000	0.000	6212
% with Advanced Business Degrees	7.083	25.656	0.000	0.000	0.000	6212
% with Government Experience	48.951	49.993	0.000	0.000	100.000	5816
% Democrats	56.432	49.591	100.000	0.000	100.000	3615
% Republicans	31.259	46.361	0.000	0.000	100.000	3615
% Other Parties	0.332	5.753	0.000	0.000	0.000	3615
% Non-Partisan	11.978	32.475	0.000	0.000	100.000	3615
% Policy among In-House Lobbyists	25.069	43.345	0.000	0.000	100.000	5816

Notes: Summary statistics for firm-month observations. Sample period is 2010-2023.

A.2 Stickiness in Policy Roles Suggests Policy-Specific Expertise

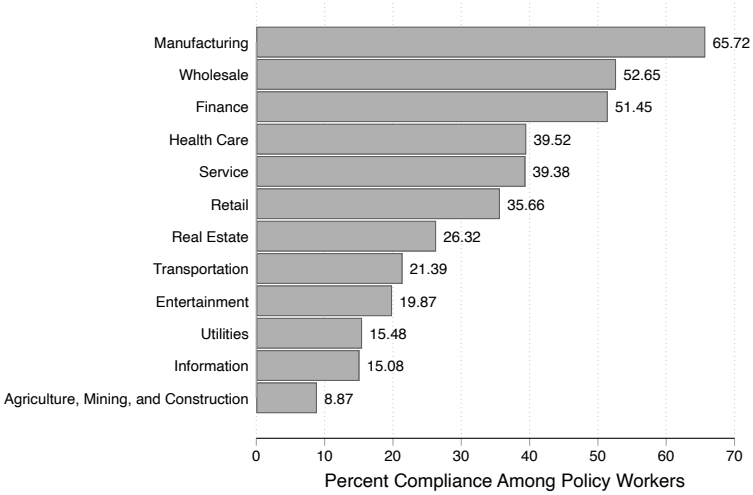
Table A.2 – Past Experiences of Policy Workers

	Indicator for Policy Role			
	(1)	(2)	(3)	(4)
Previously Worked in Policy	0.296	0.299	0.296	0.296
	(0.009)	(0.010)	(0.010)	(0.010)
# of Years Previously Worked in Policy	0.020	0.020	0.020	0.020
	(0.001)	(0.001)	(0.001)	(0.001)
Previously Worked in the Same Company	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
# of Years Previously Worked in the Same Company	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Previously Worked in Policy in the Same Company		-0.009	-0.009	-0.009
		(0.005)	(0.005)	(0.005)
# of Years Previously Worked in Policy in the Same Company		0.000	0.000	0.000
		(0.005)	(0.005)	(0.005)
Executive Government Experience			-0.003	-0.003
			(0.001)	(0.001)
Legislative Government Experience			0.036	0.036
			(0.004)	(0.004)
State Government Experience			-0.001	-0.001
			(0.004)	(0.004)
N	34,848,402	34,848,02	20,414,284	20,414,284
Year FE	Yes	Yes	Yes	Yes
company FE	Yes	Yes	Yes	Yes
Control for Self-Reported LinkedIn Education	No	No	No	Yes
Control for Self-Reported LinkedIn Skills	No	No	No	Yes

Notes: Robust standard errors clustered at company level.

A.3 Compliance Rates by Industry

Figure A.1 – Size of Compliance Workers by Industry.



A.4 Government Experience

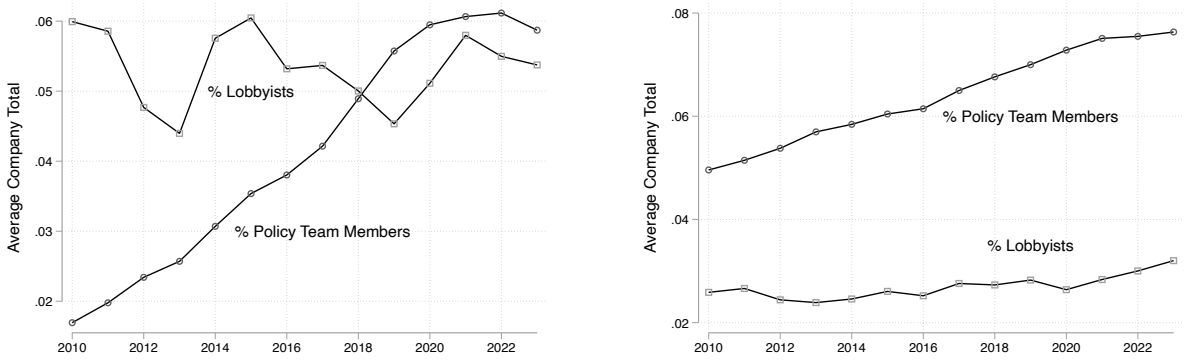
Table A.3 – Comparing Government Experience of Lobbyists and Policy Workers

	Type of Government Experience							
	All		Legislative		Executive		State	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lobbyist	0.371	0.371	0.440	0.441	0.279	0.278	0.017	0.017
	(0.023)	(0.023)	(0.026)	(0.026)	(0.027)	(0.027)	(0.005)	(0.005)
Democrat	0.031	0.031	0.014	0.014	0.018	0.017	-0.000	-0.000
	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)	(0.000)	(0.000)
Republican	0.023	0.022	0.016	0.018	0.006	0.004	-0.000	-0.000
	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)	(0.000)	(0.001)
Other Party	-0.021	-0.021	-0.005	-0.004	-0.012	-0.013	0.003	0.003
	(0.012)	(0.012)	(0.005)	(0.005)	(0.007)	(0.007)	(0.004)	(0.004)
Age		0.004		-0.007		0.006		0.000
		(0.003)		(0.001)		(0.002)		(0.000)
N	35614	35614	35614	35614	35614	35614	35614	35614
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors clustered at company level.

A.5 Analysis Using Percent Policy as Dependent Variable

Figure A.2 – Policy Team Size and Lobbyists Over Time.



(a) All Companies **(b) Fortune 100**

Figure A.3 – Policy and Lobbying Team Size by Marketvalue.

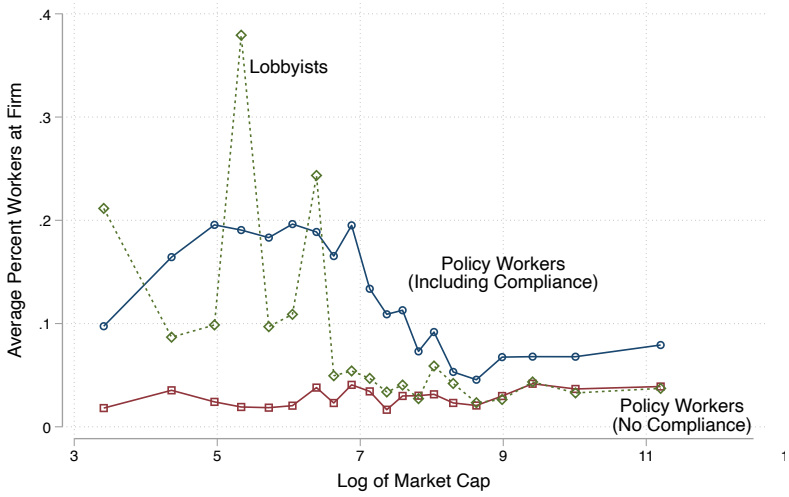


Figure A.4 – Policy Team Size and Lobbying Breakdown Across Companies, Fortune 100.

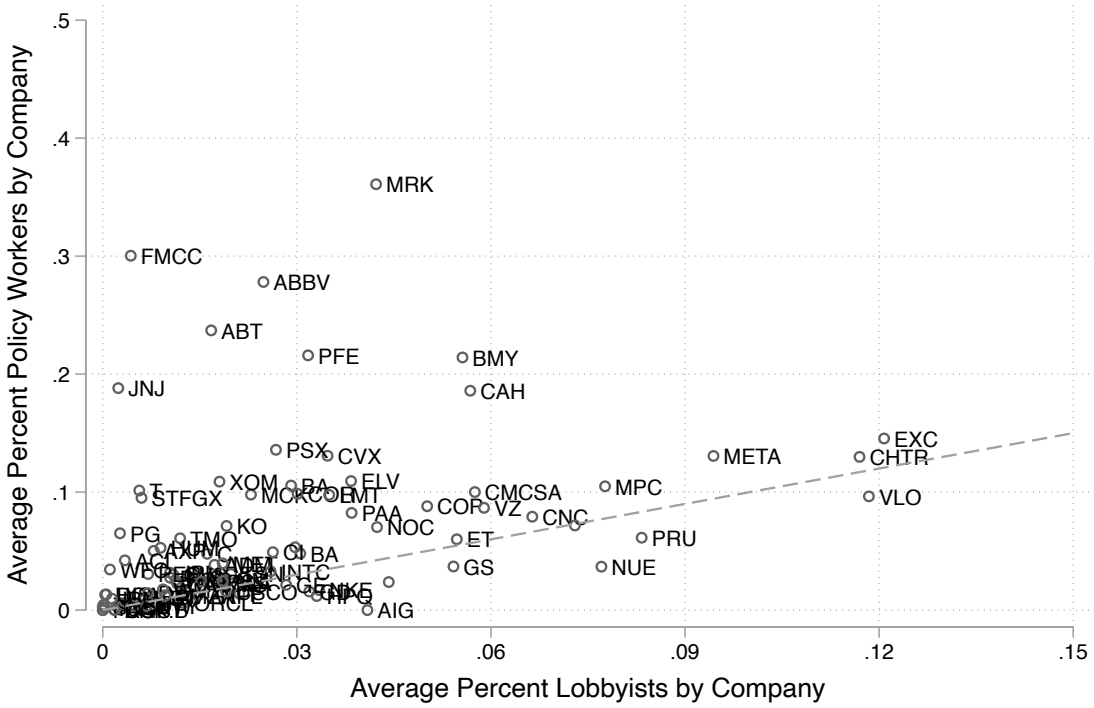


Table A.4 – Policy Team and Lobbyists Are Complements.

	% Policy Employees							
	Policy Workers (Including Compliance)				Policy Workers (No Compliance)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
% Total Lobbyists	0.008	0.006			0.001	0.001		
	(0.005)	(0.005)			(0.001)	(0.001)		
% In-House Lobbyists			0.036	0.036			0.011	0.011
			(0.028)	(0.030)			(0.008)	(0.008)
% External Lobbyists			0.005	0.009			0.001	0.002
			(0.004)	(0.004)			(0.001)	(0.001)
Log(# of Employees)				0.087				0.017
				(0.009)				(0.002)
N	1684041	1684041	1684041	1684041	1684041	1684041	1684041	1684041
Year FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors clustered at company level.

A.6 Summary of Policy Job Postings

We provide the following prompt to Gemini to help us better understand the role breakdown of policy job postings in our Revelio sample. The prompt takes in a job posting and its job description and outputs a single classified job role, as well as a list of the top 3-5 strongest action verbs or keywords that define the job's core responsibilities.[6]

> Your task is to act as a Policy Job Role Classifier. You must analyze the provided JOB DESCRIPTION TEXT and categorize the role based strictly on the responsibilities described. Your final output must be a single JSON object conforming to the required schema and containing the appropriate classification code.
>
> Policy Job Role Coding:
>
> 1. Research/Policy Analysis/Policy Review (i.e., gather data, draft reports, conduct policy reviews, prepare policy briefings)
> 2. Advocacy with Policy Makers (i.e., connect with lobbyists, policy makers and government agencies to influence company politics, build government relations, note and apply for government contracts and funding opportunities)
> 3. Advocacy with Non-Policy Makers (i.e., connect with other firms to ensure industry policy alignment, community outreach, maintain media or academic relations, engage with non-government stakeholders who are otherwise relevant to the policy process)
> 4. Internal Product Counseling (i.e., work cross-functionally with other teams on products that meet policy or regulatory requirements, develop or advise on product policies)
> 5. Company Policy Development (i.e., develop company's internal political advocacy policies, draft regulatory or political proposals for the company)
> 6. Regulatory Compliance (i.e., enforce regulatory compliance, ensure consistency with regulations, monitor local and national government regulations)
> 7. No information - This job description does not describe any policy job roles and cannot be classified.
>
> Note: Use ONLY the job descriptions and/or key responsibilities for classification. DO NOT classify based on any generic company/job information (e.g., company values, employee discrimination statements, boilerplate text, or non-policy-related duties).

[6] Although not mentioned in the main prompt, the list of summarized keywords is a separate data field passed by our response schema in each job posting query.