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

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Based on the paper/presentation by Andrew B. Hall and Anna Sun.
Read the working paper here.

Part I: Investing in Political Expertise

Understanding the Scale and Structure of Corporate Policy Teams

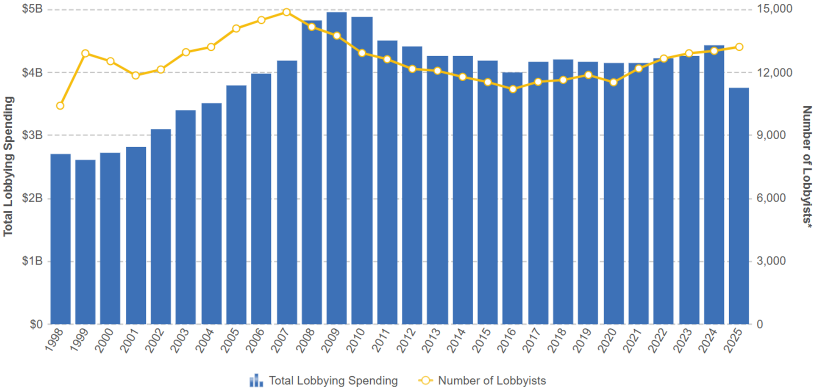
The “Textbook View” of Corporate Influence

How do corporations influence policy?

- Firms hire lobbyists to influence policy.
- Lobbyists use personal connections via the “revolving door” and expertise to shape policy.
- Firms complement lobbying efforts by sending money to legislators, such as through campaign contributions and charitable giving.

Traditional focus: lobbying and campaign contributions.

But Then, Why Is There So “Little” Lobbying?



Source: OpenSecrets

Are We Missing Something Big?

Andy's key observations in Tech:

- Figuring out strategy is much harder than communicating it to policymakers.
- It involves research, organization, and broad engagement.
- Firms devote massive effort to this.
- Most of this effort happens inside the firm, centered in what they call "Policy."

Key Challenge: No Data Beyond Lobbying

Existing data on corporate political activity relies solely on public disclosures:

- Individuals who spend >20% of their time lobbying the federal government for a paying client must register under the Lobbying Disclosure Act.
- Corporate PACs must disclose contributions to federal political candidates.

⇒ No data on internal "policy people" who are not registered as lobbyists.

This paper: collects this data for the first time.

Preview of Findings

Authors build the first dataset on corporate policy teams using 100M LinkedIn records. They find:

1. Policy teams are much larger than lobbying teams ($13\times$, on average).
2. In Fortune 100, firms average 20 lobbyists vs. 50 policy staff.
3. Policy teams are less "revolving door" than lobbyists.
4. Policy and lobbying teams are complements.
5. Policy teams are less partisan.

What Are Policy Teams?

What Do Policy Teams Do?

Corporate policy teams seek to influence the political landscape and advise companies on navigating it.

They often focus on three main activities:

1. Influence the external policy environment by monitoring global policy environment.
2. Advise on product development within regulatory contexts.
3. Shape internal corporate policies relevant to politics.

Example: Director & Head of Public Policy, Netflix

The Head of Public Policy, UCAN will:

- 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.
- 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.
- Build coalitions with peer companies and third-party organizations.

Example: Director & Head of Public Policy, Netflix

Substantively, the Head of Public Policy, UCAN, will be expected to respond to issues in the following areas:

- Entertainment and content production
- Internet policy, privacy, and data security
- Competition policy
- Intellectual property
- Commerce and payments
- Taxation

New Data on Policy Teams

Novel Data on Corporate Policy Teams

Authors build first dataset on corporate policy team members:

- Start with data on >100M U.S. workers across 10,000+ firms (Revelio Labs).
- Data is built from public LinkedIn profiles with names, job titles, employers, work history education, location, etc.
- Supplement with 100K randomly sampled job descriptions from online postings.
- Pull in public records for in-house and external lobbyists by firm.
- Merge with firm-level data on market cap, industry, etc.

Key Challenge: Classifying Policy Team Members

1. Search job titles for policy-related keywords.
2. Use job descriptions data to estimate probability that each job title is a policy role using ChatGPT.
3. Construct weighted total policy team members for each firm via a LASSO weighting process.
4. Collapse data to firm-month level by summing weighted policy-job estimates across worker job title level.

Search Terms for Job Titles

Title includes one of the following word stems:

policy, regulatory affairs, government, external affairs, external relations, eu affairs, global affairs, corruption, social initiatives, environmental initiatives, community investment, federal relation, legislative affair, Washington operation, Washington office, federal affair, international trade relation, external affair, public affair

Title must NOT include any of the following:

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 officer, volunteer, pro bono, security manager, guard

Job Descriptions as Validation To Job Title Search

Problem: using only job titles count overcount policy team members
Solution: use a random sample of 100k job descriptions to weigh job titles by probability of being policy

1. Use ChatGPT API to classify jobs as policy/non-policy based on job descriptions (”ground truth”)
2. Validate the job-title keyword approach by comparing it to these GPT labels
3. Use this estimated accuracy as ground truth to train a LASSO logistic model, which produces the final weights that go into company-level counts.

Instructions to ChatGPT

"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 you think 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 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."

Comparing ChatGPT to Manual Codings

	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.

ChatGPT Keyword Validation Summary

	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.

A Note on LASSO Reweighting

LASSO logistic model: creates final policy probabilities that are more stable and comparable across firms

- Take the job descriptions GPT labeled as Policy/non-Policy
- Convert each job title into TF-IDF scores for the unigrams/bigrams that appeared in the job title, selected 100 words/phrases with highest score as Lasso covariates
- Interact each selected work/phrase with NAICS industry codes, firm size, year fixed effects

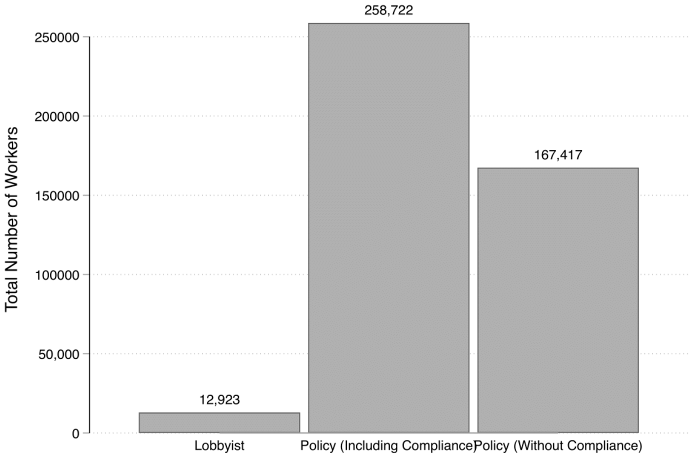
Purpose: adjust for the fact that the same job title can mean different things across industries.

- ex: External Affairs Manager in telecom vs retail

Result: policy probabilities for every worker title, which is then collapsed to firm-level

Results

Policy Teams Are Bigger Than Lobbying Teams



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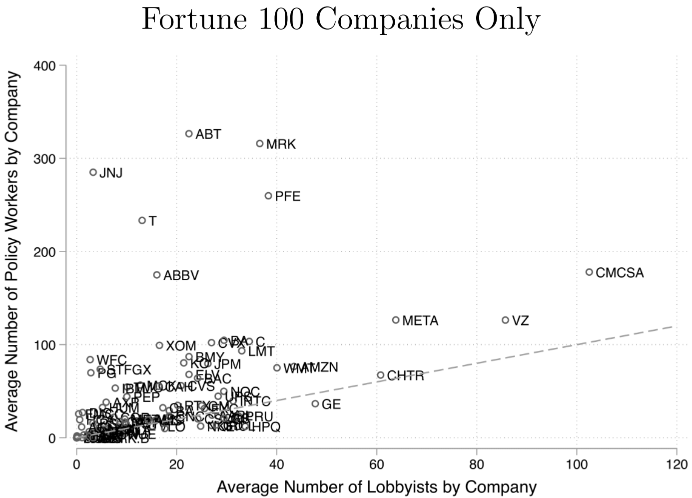
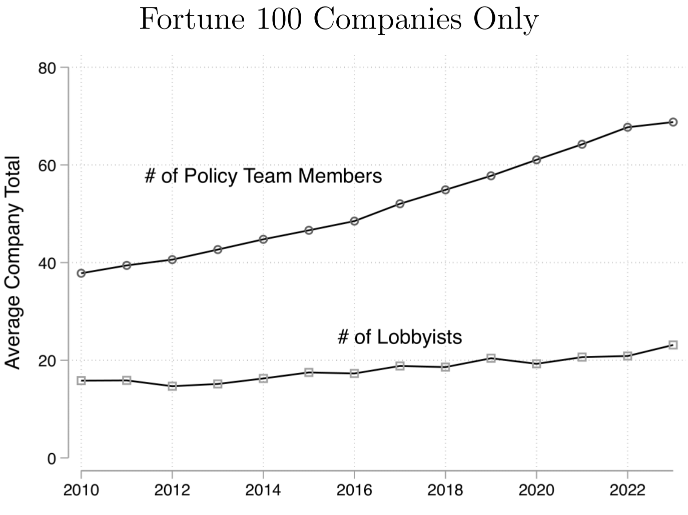
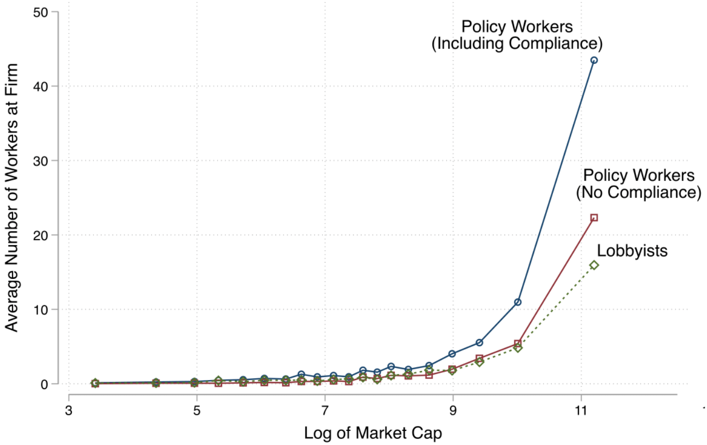


Policy Teams Are Growing Faster than Lobbying



Policy Teams Concentrated Among Largest Firms

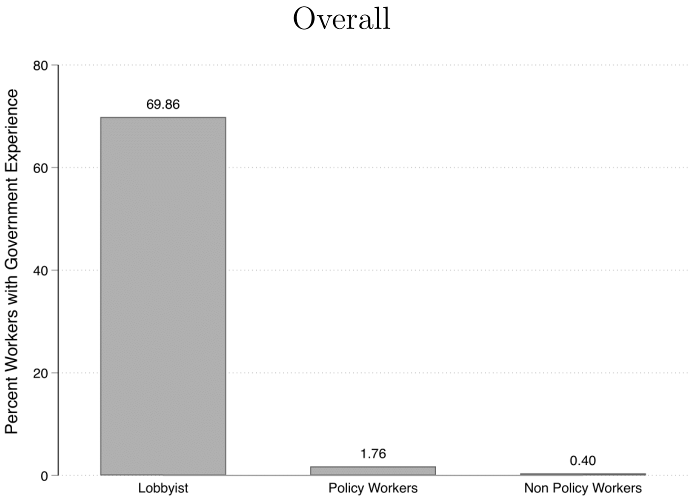


Policy Team Size and Lobbying Are Correlated

	# 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

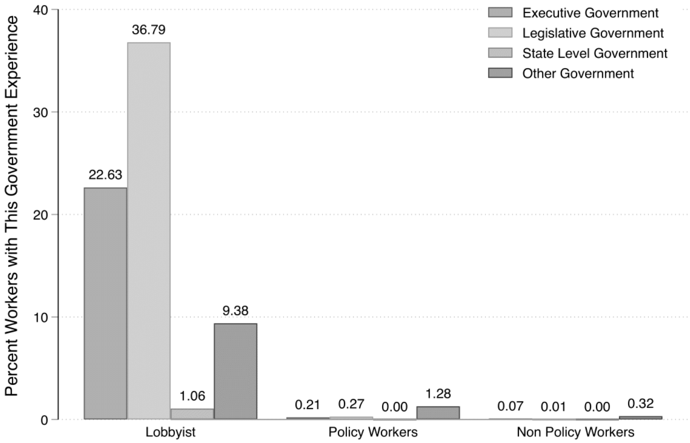
Notes: Robust standard errors clustered at company level.

Policy Have Less Gov Experience Than Lobbyists

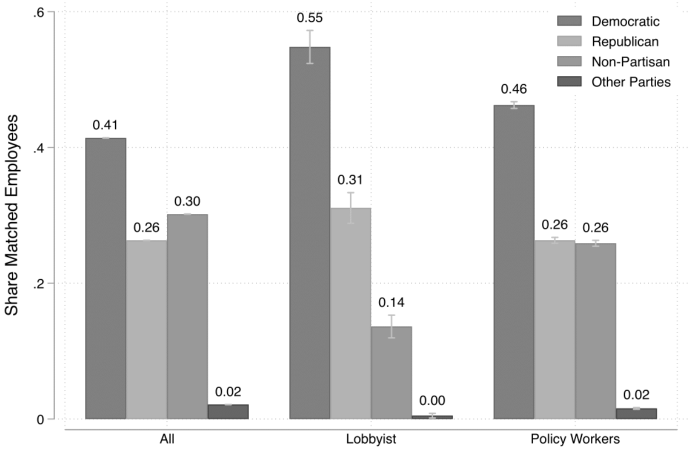


Policy Have Less Gov Experience Than Lobbyists

By Experience Type



Policy Teams Are Less Partisan Than Lobbyists



Summing Up

First paper to define and quantify corporate policy teams.

- Much larger than lobbying teams
- Less likely to have government experience, less partisan than lobbyists.
- Policy teams complement, not substitute, lobbyists.

Two takeaways:

1. Existing literature has massively underestimated corporate political spending by not counting spending inside the firm.
2. Much of this spending may not be on lobbying, but on informational complements to lobbying.

Part II: Extensions to the Research

Mapping When and How Firms Build Political Expertise

Overview of Ongoing Extensions

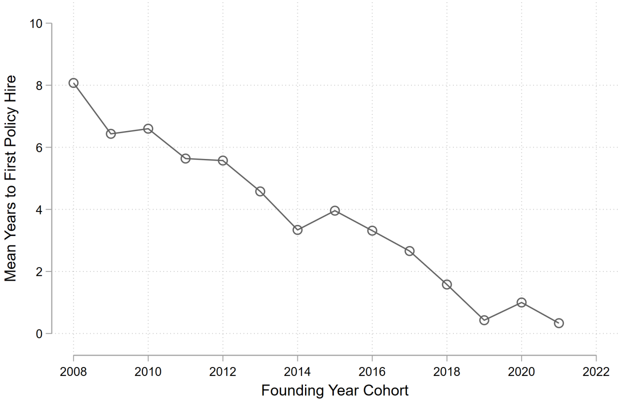
Goal: Extend Hall & Sun's analysis by tracing how and when firms build internal political capacity.

- Current extensions focus on three fronts:
    1. Timing: When firms first hire policy employees.
    2. Hierarchy: How internal policy leadership is structured.
    3. Scope: How these patterns vary within the technology sector.

First-to-Hire Analysis

Goal: investigate the timing of first policy hires.

- Compute years between founding and first observed policy hire.
- Collapse to founding-year cohorts to assess trends over time.
- Early trend: newer firms are hiring policy staff much sooner.



Next Steps in First-Hire Timing

- Expand beyond means to study the full distribution of lag times.
- Examine whether the lag between founding and first hire has shortened over time.
- Explore variation by sector, firm size, and funding stage.

Hierarchy Analysis

Goal: investigate the hierarchical structure of policy teams.

- Use GPT-based classification to identify within-company policy leadership structures.
- Detect single policy leads ("Head of Policy") vs. multi-tier divisions (President → VP → Director → Head → Manager).
- Compare hierarchy depth by firm size, sector, age, and other characteristics.

(Preliminary analysis — visualizations forthcoming.)

Hypothesized Hierarchy Structures

- Hierarchy depth may be correlated with regulatory exposure, firm size.
- Large and mature firms may tend to have multi-tier policy divisions.
- Smaller or younger firms may rely on a single policy lead.
- Ongoing work will quantify these structural differences across sectors.

Sub-Analyses on Tech Companies

Goal: build a technology-sector subset of firms to analyze policy team dynamics.

- Problem: "Tech" is not consistently defined across datasets/industry classifications.
- Solution: Use PitchBook verticals and industry codes to classify tech firms.
  - Example Verticals: Artificial Intelligence & Machine Learning, Big Data, Ridesharing, SaaS, Robotics and Drones, etc.
  - Example Industry Codes: Communication Software, Database Software, Internet Software, Social/Platform Software, etc.
- Restrict to firms classified as tech under both systems for precision.

Task: Merging PitchBook and Revelio Data

Goal: integrate PitchBook's firm metadata with Revelio's workforce data to connect tech classifications to policy employment data.

- Multi-step, iterative merge process:
  1. Begin with extensive name standardization (removing punctuation, suffixes, case normalization).
  2. Conduct initial merge on standardized firm names, setting aside unmatched cases.
  3. Run a cyclical merge on secondary identifiers — including URL, CUSIP, and year founded — to capture remaining firms.
- Desired Result: ∼250,000 unique tech firms successfully linked to policy data.

Extending Analyses to Tech Firms

Goal: Re-run all analyses on the tech-only subset.

- Compare tech vs. non-tech in:
    1. Timing of first policy hire.
    2. Team size and hierarchy depth.
    3. Relationship between policy teams and lobbying intensity.
- Evaluate whether tech firms build political capacity earlier or differently.

Conclusion

Rather than focusing solely on lobbying and campaign finance, this research shows that internal policy expertise—built within firms—is a central, yet often invisible, channel of corporate political influence.

Moving forward, we aim to deepen this picture by tracing:

- Timing: when firms first begin investing in political capacity.
- Structure: how internal policy hierarchies develop and differ across firms.
- Scope: where these patterns are most pronounced and rapidly evolving

Together, these extensions deepen the current account of corporate policy teams—moving from measuring their existence to understanding their emergence and organization.

SURVEY

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