Lobbying for Regulations: When Big Business Says Yes*

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Abstract

Do firms uniformly oppose regulations that increase production costs, or might industry leaders strategically support stricter standards as a competitive tool? We identify a specific mechanism through which large firms strategically support regulations to enhance their competitive position. Extending the Melitz-Chaney model of firm heterogeneity to incorporate government regulations and lobbying following Grossman-Helpman, we derive conditions under which regulations that primarily increase fixed costs disproportionately burden smaller competitors while benefiting larger survivors through reduced competition. The model predicts that firm size positively correlates with support for stringent regulations, but that larger sunk investments push firms to oppose such policies. To test these predictions, we develop a text-as-data approach using large language models to classify firm regulatory preferences from lobbying disclosures—a measurement challenge that has limited prior systematic analysis. Applying guided machine learning to over 20,000 U.S. lobbying reports, we confirm that larger firms are significantly more likely to support stricter regulations, especially in concentrated industries. Capital-intensive firms with high leverage and less redeployable assets tend to oppose regulations, suggesting that operational flexibility is crucial for extracting strategic benefits from regulatory changes. Consistent with our mechanism, industry exit rates increase with regulatory intensity.

Keywords: Strategic Lobbying, Product Standard Regulations, Firm Heterogeneity, Machine Learning

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1 Introduction

When the Environmental Protection Agency proposed stringent methane regulations in 2022, ExxonMobil—the world's largest private energy company—emerged as a surprising advocate.[1] This counterintuitive stance challenges traditional economic perspectives on regulation. The canonical view, rooted in Stigler (1971) and Peltzman (1976), emphasizes regulatory capture—the idea that industries seek to manipulate regulatory policy to their advantage, typically by securing protections or limiting competition. Yet this literature largely assumes firms within an industry share common regulatory preferences, leaving underexplored the question of which firms benefit from which types of regulation. Other disciplines have recognized that large firms may deploy sophisticated political strategies to shape their competitive environment (Baron, 1995; Hillman and Hitt, 1999), but we lack a formal mechanism explaining when and why industry leaders might support more restrictive regulations—even regulations that raise their own costs. This paper identifies such a mechanism: regulations that increase fixed costs can drive smaller firms from the market, thereby benefiting surviving firms through reduced competition.

Our core argument is that regulations increasing *fixed costs* can drive smaller firms out of the market, thereby benefiting surviving firms through reduced competition. This mechanism explains why firms with superior capabilities and resources may strategically support more stringent standards, even when such regulations increase their own costs. Using a novel empirical approach, we provide the first systematic evidence that firm size predicts support for costly regulations, with important implications for policy goals such as environmental protection and consumer safety. Notably, large firms' strategic support for regulation may lead to even more stringent standards than policymakers would otherwise implement.

This dynamic is particularly evident in international regulatory agreements, where firm involvement in the political process has expanded considerably. While Rodrik (2018) warns that deep integration may empower special interests, existing models assume firms uniformly prefer looser regulations. For instance, Maggi and Ossa (2023) develop a framework where firms act collectively to reduce regulatory stringency, potentially making countries worse off through coordinated lobbying. However, this view overlooks crucial firm heterogeneity—the same regulation may have sharply different effects on small versus large firms. Indeed, Maggi and Ossa (2023) note that outside their model of perfect competition, "tightening a (non-discriminatory) standard may increase the profits of more productive firms at the expense of less productive ones." We can view ExxonMobil's lobbying behavior through these lenses: beyond the benefits from aligning sunk investments with regulatory requirements – a separate channel highlighted by Kennard (2020) – supporting stricter regulations may lead ExxonMobil to gain market share as smaller competitors struggle relatively more with

[1] The report states "Our direct lobbying activities are aligned with limiting average global warming to well below 2 degrees Celsius and include strong support for policies that will incentivize carbon emission reductions while providing the energy security the world needs." Source: ExxonMobil climate lobbying report.

the same compliance costs. This strategic behavior, documented in environmental settings by Vogel (1995) and Delmas et al. (2016), fundamentally challenges assumptions that firms universally prefer looser standards. This aligns with seminal theories suggesting industries or firms might manipulate regulatory policies to their advantage (Stigler, 1971; Rodrik, 2018), particularly through the use of regulation to raise rivals' costs (Oster, 1982; Salop and Scheffman, 1983).

To formalize this mechanism, we integrate a modified Melitz-Chaney framework – a cornerstone in international economics – with a model of regulatory lobbying. Our model extends Melitz-Chaney in two critical ways. First, by allowing for government-imposed regulations - aimed at mitigating negative consumption externalities – that affect both fixed and marginal costs for all firms within a market. Second, we model firm lobbying behavior following Grossman and Helpman (1994) and Maggi and Ossa (2023). This integration allows us to rigorously analyze how regulatory impacts vary across firms of different sizes, providing theoretical foundations for the strategic behaviors we observe empirically. We derive firms' profits as a function of regulatory costs and a firms' own productivity, identifying a threshold firm size at which profits increase with regulations.[2]

The direction of firm lobbying is identified in the following manner. The government, in setting optimal regulatory policy, is assumed to have an objective function influenced by firms' profits – implicitly due to lobbying – with a potential bias toward either large or small firms.[3] Regulations affect surviving firms' profits through two competing mechanisms: directly increasing compliance costs, which reduces profits; and indirectly enhancing profits for survivors through reduced competition as less productive firms exit the market. We then solve for the comparative static of changes in the governments' utility – specifically the term that includes firm profits – with respect to changes in regulations. For example, if the government favors large firms and government's utility increases with regulations, we infer that large firms prefer tougher regulations and make that known through lobbying.

The model generates testable predictions: larger firms will lobby for tougher regulations when these primarily increase fixed production costs, while smaller firms favor regulations that decrease fixed costs. If regulations only affect marginal costs, firms of all sizes will resist them. This framework explains why, under specific conditions, larger firms strategically support stringent regulations despite facing increased costs themselves—the competitive advantage gained outweighs compliance costs. Importantly, this firm behavior may lead governments to achieve greater reductions in negative externalities than would occur if they focused solely on consumer welfare.

While our baseline model focuses on how fixed compliance costs reduce competition by forcing smaller competitors to exit, we extend it by also allowing the government's preference—shaped by lobbying—to be impacted through firms' adjustment costs rather than their size. The rationale is

[2]Remarkably, the stark result is derived by a relatively simple model with CES preferences. In a more complex demand system where larger firms face less elastic demand the effects of heterogeneity could be even larger (Macedoni and Weinberger, 2022; Jung et al., 2019).

[3]For completeness, the government also balances the trade-offs of lower variety and a smaller negative externality, but this is not important for the lobbying results.

that firms with large sunk capital investments may face additional adjustment costs to regulations, due to e.g., specific capital investments or financing constraints, which are not captured in a standard model and do not necessarily correlate with firm size.[4] Under this extension, the model explains why firms with large fixed capital stocks may lobby *against* stricter regulations.

To test these theoretical predictions, we analyze U.S. lobby reports from LobbyView (Kim, 2018), which compiles data required under the Lobbying Disclosure Act of 1995. We focus on lobbying related to regulatory policy areas identified in the World Bank's Deep Trade Agreements database—e.g. environmental standards, intellectual property, and technical barriers to trade—which the empirical literature has shown to operate primarily through fixed compliance costs. Since our model implies that marginal-cost regulations generate no differential size effects, any such components merely attenuate our estimates rather than bias them. To take a stand on the firm "stance", we leverage the fact that lobbying reports' texts include the content of the lobbying efforts. For example *MeadWestvaco*, a large packaging company based out of Virginia, aside from reporting the lobbying amount for each quarter, also fills out the "Specific Lobbying Issues" in the form as: "*Issues related to renewable energy... supports carbon neutrality.*" We match public firms in LobbyView with Compustat data, to obtain information on firm characteristics including size, capital intensity, and financial structure.

A key methodological contribution is our use of guided machine learning to extract firm policy preferences from unstructured lobbying reports—addressing a measurement challenge that has limited systematic analysis of regulatory preferences (Kang, 2016; Blanga-Gubbay et al., 2021). Using supervised machine learning—specifically, TF-IDF vectorization with Logistic Regression and Support Vector Machine classifiers, implemented via ChatGPT's Data Analyst tool—we train on manually classified reports and classify over 20,000 firm-year stances, achieving 86-87% out-of-sample accuracy. This method addresses two critical limitations of existing approaches: the impracticality of manually classifying thousands of reports, and the inaccuracy of simple keyword searches that often misinterpret contextual meaning. For instance, words like "support" and "oppose" might merely describe the laws that are the subject of the firms' lobbying efforts and may not accurately capture the firm's position. Following this, we conduct a formal regression analysis to examine the relationship between a firm's size and its propensity to support regulatory measures.

Our regression analysis reveals several key findings. First, we document a robust positive relationship between firm size—measured by revenue, employment, and market share—and support for more stringent regulations. The models' mechanism is further supported by heterogeneity tests: the size relationship intensifies in concentrated industries and sectors with higher fixed cost intensity, while diminishing in more competitive markets—all consistent with our theoretical predictions. Second, we find that capital-intensive firms, those with higher leverage, and those with larger tangible capital share tend to oppose regulations, suggesting that the ability to flexibly adapt to new regulatory environments is crucial for extracting strategic benefits. We also provide evidence that the

[4]For example, Brainard and Verdier (1994) argue that firms will lobby to mitigate adjustment costs.

negative effects of capital intensity are stronger in firms with less asset redeployability and narrower production scope, while firms with more intangible capital—typically more adaptable—show greater regulatory support.

Several robustness tests help distinguish our proposed mechanism from alternative explanations. Industry associations, which likely represent small firms, have a significantly smaller propensity to lobby in support of costly regulations. Not only is this expected, it also gives more credence to our classification of stances. In a test for selection bias towards large firms, the analysis shows that if anything smaller firms are more likely to provide a known stance on regulations. We also show that the size effects are not just capturing "advertising" practices, which we proxy with ESG ratings. Finally, other than our several alternative measures for size and adjustment costs that we report in the main analysis, we also control for multicollinearity by extracting the component of capital uncorrelated with sales by residualizing capital against market share and re-estimating our main specification.

To highlight the operating mechanism of the model, we also show at the industry level that an increase in regulatory intensity is strongly associated with establishment exit rates and that this dynamic is driven by the exit of relatively small firms. Relatedly, more regulated industries also become more concentrated.

Related Literature. While corporate political activity has received extensive attention (Wei et al., 2023), our work contributes to the economics literature on regulation and firm heterogeneity by combining a structural model with AI-based measurement of firm policy preferences.

Our theoretical contribution builds on the industrial organization insight that firms might strategically use government regulation to raise rivals' costs or create barriers to entry (Oster, 1982; Salop and Scheffman, 1983; Rogerson, 1984). While this literature established the theoretical possibility, systematic evidence on which firms support which regulations—and why—has remained limited. A parallel literature in strategic management has explored how firms engage in political activity to shape their competitive environment (Baron, 1995; Hillman et al., 2004), with recent empirical work showing that politically connected firms receive more favorable regulatory treatment (De Figueiredo and Silverman, 2006; Holburn and Vanden Bergh, 2014; Heitz et al., 2023). We extend this line of inquiry by providing a general equilibrium model that formally derives how firm size determines regulatory preferences, and by providing systematic empirical evidence using novel AI-based classification of firm stances.[5] While the differential impact of fixed costs on heterogeneous firms is a known property of the Melitz-Chaney framework, existing models of regulatory lobbying have not incorporated this heterogeneity.

Our approach also builds upon research examining which firms engage in the lobbying process.[6]

[5]The management literature on "non-market strategy" and corporate political activity is extensive; see Dorobantu et al. (2017) and Hillman et al. (2004) for reviews. Our contribution is to formalize the mechanism through which large firms benefit from fixed-cost regulations and to test it empirically at scale.

[6]Early theoretical works that endogenize lobby formation include Mitra (1999) and Hillman et al. (2001).

Bombardini (2008) added the perspective of individual firms to the political economy trade literature that previously viewed lobbying primarily through interest groups (Grier et al., 1994; Grossman and Helpman, 1994; Gawande, 1997; Goldberg and Maggi, 1999).[7] While subsequent work has examined determinants of lobbying participation (Bombardini and Trebbi, 2012; Kim, 2017; Kerr et al., 2014), we shift focus to the positions firms adopt once engaged.[8] By conditioning on lobbying activity and examining how firm characteristics predict regulatory stance, we provide systematic evidence that size and resource flexibility drive divergent policy preferences within industries. Our finding that large firms are more likely to support regulations in concentrated industries aligns with theoretical predictions about the elasticity of profit with respect to regulatory stringency.

From the perspective of international economics, our work contributes to the literature on the role of firms in shaping international agreements (Rodrik, 2018). While Blanga-Gubbay et al. (2024) document how large multinationals lead lobbying efforts for free trade agreements, we illuminate the dynamics of non-discriminatory regulatory policy, which has become increasingly central to the international trade landscape (Lamy, 2016). Maggi and Ossa (2023) suggest that lobbying can either enhance or undermine trade agreements depending on whether it dilutes or intensifies special interest pressure. Our model advances this understanding by demonstrating that firms within the same country often have divergent regulatory preferences based on their size. Thus, corporate lobbying need not uniformly push for deregulation suggesting that international cooperation can potentially lead to stricter, not looser, regulations when governments favor large firms.

Our model's prediction that regulations disproportionately burden smaller firms builds on empirical evidence that product standards and regulations primarily operate through fixed rather than marginal costs. Fontagné et al. (2015) and Fernandes et al. (2019) document that technical barriers to trade reduce export participation while increasing sales among surviving exporters—consistent with a fixed-cost mechanism. Macedoni and Weinberger (2022) and Rebeyrol (2023) show that non-tariff measures generate heterogeneous welfare effects across firms, while Macedoni and Weinberger (2025) demonstrate that international regulatory spillovers are transmitted primarily through fixed compliance costs. This body of evidence supports our assumption that regulations create differential burdens across the firm size distribution, generating incentives for large firms to strategically support stricter standards. In this paper we shift the focus to how *firms themselves* shape policy.

The political science literature has identified cases where businesses counter-intuitively support environmental regulations. Kennard (2020) argues that asymmetries in adjustment costs within an industry allow larger firms to gain market share from stricter standards. Our finding that a

[7] Trade papers in this literature generally use the Grossman and Helpman (1994) Protection for Sale framework, typically tested at the industry level using PAC expenditures (Goldberg and Maggi, 1999; Gawande and Bandyopadhyay, 2000) or foreign lobbying data (Gawande et al., 2006). Our approach differs by examining firm-level regulatory stances rather than industry-level trade protection.

[8] The papers cited in our work generally view lobbying as distortionary due to its quid-pro-quo nature (see also Huneeus and Kim (2021) and Dutt (2009)). However, as noted by Bombardini and Trebbi (2020), lobbying can also be understood as information transmission. For our analysis, we are concerned with how firms express preferences, regardless of the underlying mechanism.

larger fixed capital stock lowers the probability of supporting costly regulations is consistent with that channel, but adjustment costs alone cannot explain the large effects of our size proxies (such as sales) after controlling for capital stock. Similarly, Grey (2018) explores how firms lobby for environmental protections after investing in clean technology, and Delmas et al. (2016) and Fremeth and Richter (2011) document strategic support for environmental policy.[9] Our contribution extends beyond environmental policy to broader regulatory domains, formalizing a mechanism applicable across sectors.

Methodologically, we contribute to the growing use of text-as-data methods in economics (Gentzkow et al., 2019; Ash and Hansen, 2023). Measuring firm policy preferences from unstructured lobbying disclosures presents a classification challenge: keywords like "support" and "oppose" often describe legislation rather than the firm's stance, and manual coding does not scale. Following the approach outlined in Ash and Hansen (2023), we use the reading of three separate researchers on a subset of reports to generate labels and treat stance detection as a supervised learning problem, leveraging large language models to scale the human judgment to over 20,000 lobbying reports with 86-87% accuracy. This enables systematic analysis of regulatory preferences across diverse policy domains—a measurement contribution that complements our structural model.

The rest of the paper is organized as follows. Section 2 presents the model. Section 3 describes the data and the algorithm that leads to the classification of firms' stances on regulations. Section 4 shows the results of of empirical analysis. Section 5 concludes.

2 Model

2.1 Setup

We consider a closed economy version of the Melitz-Chaney model of firm heterogeneity (Melitz, 2003; Chaney, 2008).[10] There are L consumers with Constant Elasticity of Substitution (CES) preferences over a continuum of differentiated varieties supplied by monopolistically competitive firms. Firms vary in their labor productivity φ, and labor is the sole factor of production, earning a wage w. There is a fixed labor requirement denoted by f.

The timing of the model follows the standard approach. There is a pool of potential entrants. To enter, firms pay a fixed entry cost f_E in labor units and then discover their productivity draw φ. The mass of firms that pays f_E is denoted by J. Productivity is drawn from a Pareto distribution with a shape parameter κ and a shift parameter b. The CDF and pdf of the productivity distribution are $G(\varphi) = 1 - \left(\frac{b}{\varphi}\right)^{\kappa}$ and $g(\varphi) = \frac{\kappa b^{\kappa}}{\varphi^{\kappa+1}}$, respectively. Free entry drives expected profits to zero,

[9] See also You (2017), Osgood et al. (2017), Maloney and McCormick (1982), Vormedal (2011), Grumbach (2015), Vormedal and Meckling (2024), and Cai and Li (2020). On supply chain dynamics, Cory et al. (2021) show that opposition to climate policies is shaped by upstream and downstream linkages; consistent with this, we find the size-stance relationship is weaker in vertically integrated firms.

[10] Without affecting any of our results, the model can be easily extended to a multi-country setting.

ensuring that household income equals the wage w.

Relative to the Melitz-Chaney model, there are two key differences. First, a consumption externality motivates government intervention through regulation. This externality may capture features such as the healthiness and safety of products or the pollution generated. Specifically, there is a negative externality $e(\varphi)$ per unit of output that depends on the firm's productivity:

$$e(\varphi) = \varphi^{\beta} \tag{1}$$

There are no restrictions on β, allowing for different patterns of externality generation. If $\beta > 0$, there is a positive correlation between negative externality and productivity. If $\beta < 0$, there is a negative correlation, and if $\beta = 0$, all firms generate the same level of externality per unit of output. If the total consumption of the variety produced by firm φ in a country is $Lq(\varphi)$ units, the total externality generated is $Lq(\varphi)e(\varphi)$. The aggregate externality is given by the integral of $Lq(\varphi)e(\varphi)$ over the entire set of varieties consumed in the country.

The second difference from the Melitz-Chaney model is that the government can impose a regulation r, which increases both the marginal costs and the fixed costs of production for all firms The government sets the level of regulation to maximize the sum of consumer utility from consumption, the consumption externality, and firms' profits. Following a standard approach in the literature (Grossman and Helpman, 1994; Maggi and Ossa, 2023), we model firms' lobbying by assuming that the government is biased toward the profits of either large or small firms.

2.2 Consumers

Consumers enjoy the consumption of varieties of a differentiated good. Varieties are indexed by ω, and consumers have the following CES preferences:

$$U = \left[\int_{\omega \in \Omega} q(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right]^{\frac{\sigma}{\sigma-1}} \tag{2}$$

where $q(\omega)$ is the quantity consumed of variety ω, $\sigma > 1$ is the elasticity of substitution, and Ω is the set of varieties available for consumption. Solving the consumers' problem yields the following direct demand function:

$$q(\omega) = wP^{\sigma-1}p(\omega)^{-\sigma} \tag{3}$$

where $p(\omega)$ is the price of variety ω and P is the price index and equals:

$$P = \left[\int_{\omega \in \Omega} p(\omega)^{1-\sigma} d\omega \right]^{\frac{1}{1-\sigma}} \tag{4}$$

2.3 Firms

There is a continuum of firms, and each firm supplies only one variety. Hence, we can replace the index ω with the firm's productivity parameter φ.

The government imposes a non-discriminatory regulation r, applied equally to all active firms. Specifically, the regulation r affects the firm's costs in two ways. First, the fixed cost of production depends on the level of the firm's externality and the regulation:

$$f(e(\varphi), r) = wfe(\varphi)^{\alpha}h(r) = wf\varphi^{\alpha\beta}h(r) \tag{5}$$

where we used the fact that $e(\varphi) = \varphi^{\beta}$. We assume that $h'(r) \geq 0$, i.e., more restrictive regulations can lead to higher fixed costs. If $\alpha > 0$, higher externality leads to higher fixed costs, reflecting that regulations increase the fixed costs more if the externality is high.

Regulations can also affect the marginal costs of production. For a firm with productivity φ, the marginal cost equals:

$$mc(\varphi, r) = \frac{w}{\varphi}m(r) \tag{6}$$

where $m(r)$ captures the relationship between marginal costs and the regulation, and we assume that $m'(r) \geq 0$. Although the empirical trade literature has emphasized that regulations mainly affect fixed costs (Fernandes et al., 2019; Fontagné et al., 2015; Macedoni and Weinberger, 2022, 2025), this model adopts a general framework allowing regulations to affect both types of costs. The predictions on the effects of lobbying on regulations will crucially depend on which type of cost the regulations impact.[11]

Firm φ's profits are given by:

$$\pi(\varphi) = Lq(\varphi)p(\varphi) - Lq(\varphi)\frac{w}{\varphi}m(r) - wf\varphi^{\alpha\beta}h(r) \tag{7}$$

where $q(\omega)$ is defined in (3). A firm φ sets the price $p(\varphi)$ by maximizing its profits while taking the price index P as given, due to the assumption of monopolistic competition. Profit maximization yields the standard CES pricing rule with a constant markup over marginal costs:

$$p(\varphi) = \frac{\sigma}{\sigma - 1}\frac{wm(r)}{\varphi} \tag{8}$$

Hence, if $m'(r) > 0$, prices increase with tougher regulations.

Substituting the price into the demand function and the firm's profit equation yields the following

[11] Although general, our model does not capture the possible dynamics effects of regulations, such as on innovation and R&D.

profits:

$$\pi(\varphi) = \frac{(\sigma-1)^{\sigma-1}}{\sigma^{\sigma}} L w P^{\sigma-1} \left(w m(r)\right)^{-(\sigma-1)} \varphi^{\sigma-1} - w f \varphi^{\alpha\beta} h(r) \tag{9}$$

The productivity of the marginal firm φ^* that is indifferent between being active and exiting is obtained by setting profits to zero, i.e., $\pi(\varphi^*) = 0$. The cutoff equals:

$$\varphi^* = \left[\frac{\sigma^{\sigma} (f m(r)^{\sigma-1} h(r)) w^{(\sigma-1)}}{(\sigma-1)^{\sigma-1} L P^{\sigma-1}} \right]^{\frac{1}{\sigma-1-\alpha\beta}}$$

We assume that $\sigma - 1 - \alpha\beta > 0$. Substituting the cutoff into the revenue $t(\varphi)$ and profit $\pi(\varphi)$ equations, we obtain the following expressions:

$$t(\varphi) = \sigma w f h(r) (\varphi^*)^{-(\sigma-1-\alpha\beta)} \varphi^{\sigma-1} \tag{10}$$

$$\pi(\varphi) = w f h(r) \left((\varphi^*)^{-(\sigma-1-\alpha\beta)} \varphi^{\sigma-1} - \varphi^{\alpha\beta} \right) \tag{11}$$

2.4 Equilibrium

In a closed economy, we can normalize the wage two one. The only other equilibrium object of the model is the mass of firms that pay the fixed costs of entry J.[12] The mass of entrants is constant and given by:

$$J = \frac{L}{f_E} \frac{(\sigma - 1 - \alpha\beta)}{\sigma(\kappa - \alpha\beta)} \tag{12}$$

Hence, it does not depend on the restrictiveness of regulation r. This is a general result that was first established by Macedoni and Weinberger (2025), who proved that, given a CES demand function, a Pareto distribution of firms' attributes, and non-discriminatory regulations, the equilibrium in a multi-country model is unaffected by regulations. This result does not imply that the regulation has no welfare effects, as we will show in the next section.

Equilibrium Profits and Regulations. We can now examine how regulations affect the profits of surviving firms within a general equilibrium framework. Although regulations increase production costs for these firms, the exit of the least productive competitors shifts demand to the more efficient ones. To determine whether regulations ultimately raise or lower firm profits, it is essential to analyze their impact on market selection. The effect of regulations on firm profits is captured in the following proposition:

Proposition 1. *The impact of regulations on profits depends solely on their effect on fixed costs. Furthermore, an increase in regulations can boost profits for firms with sufficiently high productivity.*

[12] We assume that $\kappa - \sigma + 1 > 0$ to ensure positive average revenues, and $\kappa - \alpha\beta > 0$ follows from the previous assumption that $\sigma - 1 - \alpha\beta > 0$.

Specifically, this occurs if $\varphi > \varphi^* \left(\frac{\kappa-\alpha\beta}{\kappa-\sigma+1}\right)^{\frac{1}{\sigma-1-\alpha\beta}}$.[13]

Proof: see Appendix A.3.1.

This result arises because, while the increase in regulations uniformly affects the fixed costs of all firms, the associated increase in revenues due to the exit of less productive firms disproportionately benefits larger firms. Consequently, this creates a bifurcation: larger firms emerge as winners with increased profits, while smaller firms either exit the market or experience a decline in profits. In the subsequent section, we explore how this differential impact of regulations on profits shapes firms' lobbying behavior.[14]

2.5 Government's Policy

In the spirit of Grossman and Helpman (1994) and Maggi and Ossa (2023), the government is subject to lobbying pressures and therefore their utility does not coincide with consumer welfare even after accounting for the externality. The government chooses the level of regulation to maximize its objective function U^g, which depends on three components: the utility of consumers (U), the consumption externality (E), and firms' profits (Π^g). The last term is what allows us to infer the preference of firms over the regulatory policy. The objective function of the government equals:

$$U^g = U + E + \gamma\Pi^g \tag{13}$$

where γ captures the degree with which the government is biased toward firms' profits. The aggregate welfare effect of the externality, denoted by E, is given by:

$$E = E_o \left(J \int_{\varphi^*}^{\infty} Lq(\varphi)e(\varphi)g(\varphi)d\varphi \right)^{-\epsilon} \tag{14}$$

where E_o and ϵ are positive constants. Because of the negative exponent, higher externality from consumption of products by φ, $Lq(\varphi)e(\varphi)$, lowers welfare.

The assumption that the government's utility also depends on firms' profits is standard in the "protection for sale" literature.[15] What this modeling technique allows us to do is infer the firms' preference based on how Π^g moves with an increase in regulations. For example, if this last term – which implicitly captures contributions of the firm – increases with regulations, then the lobbying firms prefer regulations. To capture the fact that large firms may have different lobbying objectives than small firms, we assume the government places a weight on each firm's profits proportional to

[13] Note that $\frac{\kappa-\alpha\beta}{\kappa-\sigma+1} > 1$ since $\sigma - 1 > \alpha\beta$.

[14] In the Melitz-Chaney model with CES preferences, markups are constant, meaning stricter regulations do not affect them. However, when markups are variable, reduced competition among surviving firms due to tighter regulations leads to higher markups, with the magnitude of this increase depending on the elasticity of markups in relation to competition (Macedoni and Weinberger, 2022). This effect would further increase the profits of surviving firms. For a model of lobbying for tariffs with variable markups, see Annicchiarico and Marvasi (2019).

[15] For an alternative approach to modeling lobbying, see the model by Blanga-Gubbay et al. (2024).

the firm's productivity. Specifically,

$$\Pi^g = \int_{\varphi^*}^{\infty} \varphi^{\delta} \pi(\varphi) g(\varphi) d\varphi \tag{15}$$

If $\delta > 0$, the government is pro-big business: the profits of higher productivity firms are valued more. If $\delta < 0$, the government is pro-small business: the profits of lower productivity firms are valued more. The parameter δ is useful to differentiate the preferences of large relative to small firms.

The optimal level of regulation is determined by setting $\frac{dU^g}{dr} = 0$:

$$\frac{dE}{dr} + \gamma \frac{d\Pi^g}{dr} = -\frac{dU}{dr} \tag{16}$$

Thus, the marginal benefits from the regulation–the reduction in externality and, potentially, the increase in firms' profits–must equal the marginal cost, which is the reduction in consumer utility.

Solving the model, we can express the government's utility as follows (with full derivations in the appendix):

$$U^g = \tilde{U} h(r)^{-\frac{\kappa-\sigma+1}{(\kappa-\alpha\beta)(\sigma-1)}} m(r)^{-1} + \tilde{E} h(r)^{\frac{-\epsilon(\beta+1)}{\kappa-\alpha\beta}} m(r)^{\epsilon} + \tilde{\pi} h(r)^{\frac{\delta}{\kappa-\alpha\beta}} \tag{17}$$

where $\tilde{U}$, $\tilde{E}$, and $\tilde{\pi}$ are constants that do not depend on the level of regulation r.

Regulations negatively affect the utility from consumption. The elasticity of utility with respect to $h(r)$ and $m(r)$ are both negative. The reduction in utility from consumption is driven by the effects of regulations on both fixed costs and marginal costs. Both types of costs reduce the number of active firms in the domestic market, lowering welfare since consumers exhibit a love for variety. Additionally, regulations affecting marginal costs increase prices for all surviving firms, reducing real income.

By increasing marginal costs, regulations improve the externality: if regulations increase marginal costs, production by each firm declines, reducing the aggregate externality and improving welfare. On the other hand, the effect of regulations through increases in the fixed costs have an ambiguous effect on the externality. In fact, the elasticity of E with respect to $h(r)$ equals $\frac{-\epsilon(\beta+1)}{\kappa-\alpha\beta}$ and has an ambiguous sign depending on the value of β, which controls the relationship between externality and productivity. If regulations increase fixed costs, only the most productive firms remain in the market. This tougher selection increases production by surviving firms. If β is negative, the most productive firms, which survive the regulation, generate the least externality per unit of output. Thus, there is a possible selection effect that also reduces the aggregate externality. We assume β is small enough so that regulations unambiguously improve the externality. Absent lobbying pressures, the model provides the intuitive result that in setting regulations the government balances the utility loss with the gain in the externality.

The effect of lobbying enters through the third and final term. This profit term Π^g only depends

on regulations through its effect on fixed costs. If regulations only affect marginal costs (i.e., $m'(r) > 0$ and $h'(r) = 0$), then they leave average profit unchanged. This is because non-discriminatory regulations on marginal costs increase them proportionally for all firms, leaving each firm's revenues unchanged as the price index adjusts to offset the increased marginal costs. For this reason there will not be any differential lobbying across firms when only marginal costs change. On the other hand, if regulations affect the fixed costs (i.e., $h'(r) > 0$), then profits of surviving firms are affected. If the government favors larger firms ($\delta > 0$), higher regulation improves government utility, leading to higher regulation levels. Conversely, if the government favors smaller firms ($\delta < 0$), it will set lower regulation levels. These results also hold if $\beta = 0$ and the externality is independent of firm productivities.

We can summarize the relationship between lobbying and regulations in the following proposition:

Proposition 2. *If tougher regulations only affect marginal costs, neither large nor small firms lobby in their favor. If tougher regulations increase fixed costs, large firms lobby for regulations, and small firms lobby against them. If tougher regulations decrease fixed costs, large firms lobby against regulations, and small firms lobby in their favor.*[16]

Equation (17) further highlights how the parameters controlling the distribution of productivity and the initial level of fixed costs affect the lobbying activities of firms. We can summarize these effects in the following two propositions.

Proposition 3. *When regulations affect fixed costs, large firms tend to lobby more actively for stricter regulations in markets with higher concentration.*

Proof: the parameter κ governs the shape of the productivity distribution, and is inversely related to industry concentration. A lower value of κ implies greater dispersion in firms' productivity, leading to a higher concentration of revenue among a few firms (Chaney, 2008). The elasticity of profits with respect to fixed regulatory costs is given by $\frac{\delta\alpha}{\kappa-\alpha\beta}$, which increases as concentration rises (i.e., as κ declines).

The intuition behind this result is straightforward: in more concentrated industries, the selection effect caused by fixed-cost regulations is stronger. Hence, large firms stand to gain more from lobbying for stricter regulations, as such policies further enhance their profits.[17]

Proposition 4. *When regulations affect fixed costs, large firms tend to lobby more actively for stricter regulations in markets with higher fixed costs.*

[16] Our theoretical results mirror those arising in the models of duopoly of Michaelis (1994), Cai and Li (2020), and Grey (2018). In these papers, a firm may lobby in favor of more restrictive regulations if those disproportionally disadvantage its rival, for instance because the rival has poorer environmental standards (Cai and Li, 2020). Our model is also similar to the unpublished work by Abel-Koch (2013), who also builds a model of lobbying with firm heterogeneity, in a two-country framework.

[17] Notice that our mechanism is not related to the free riding of lobbying (Olson, 1965).

Proof: the profit term in the government's objective function is proportional to $fh(r)$. Hence, $\frac{\partial \Pi^g}{\partial r}$ increases in f provided $\delta > 0$.

The intuition for the result is similar to the previous proposition. In a market with a higher fixed cost, an increase in regulatory fixed costs has a larger effect on firms selection. Hence, large firms stand to gain more from lobbying.

2.5.1 Alternatives to the Lobbying Term

Our baseline specification for government utility in (17) is quite standard (Maggi and Ossa, 2023) in using profits in the lobbying term. Given the Melitz-Chaney structure of the model, this links firms to their size (revenues and employment). However, our model abstracts from potential adjustment costs, investments in physical capital, and financial constraints that may also interact with regulations. This idea relates to the Lavergne (1983) *status quo model*, which argues that trade policies of governments are motivated by a desire to minimize adjustment costs, and the Brainard and Verdier (1994) finding that factors will tradeoff the cost of adjustment with lobbying. For a given size, these firm-specific characteristics are likely determinants of a firms' preference for regulations (Kennard, 2020). To keep the model as tractable as possible while incorporating this additional dimension, we propose modifying the government's objective function so that the third term in the government's utility is driven by increases in *fixed costs* due to regulations. Additionally, the government may have a bias towards either high- or low-fixed cost firms, allowing us to differentiate the preferences of firms based on their fixed costs.

We relegate the derivations to Appendix A.4 since they are similar to the setup above. The only difference is that in this case the lobbying term assumes governments care about high-fixed cost firms more.[18] We find that if the government favors firms with higher fixed costs – which could proxy for fixed capital investment and higher adjustment to redeploying capital – increased regulations reduce the utility of government. Thus, firms with high capital intensity or low redeployability of capital lobby *against* the regulation. We summarize our final prediction in the following proposition.

Proposition 5. *When regulations affect fixed costs, firms that have initially spent more resources on fixed costs lobby against stricter regulations.*

Proof: See Appendix A.4: when the government favors firms with higher fixed costs, increased regulations reduce the utility of the government.

In the empirical analysis, we also proxy firm fixed cost with capital intensity and leverage. Along with the predictions developed based on the propositions in the baseline model, we test this proposition and related mechanisms in the regressions below.

[18] This could be rationalized in various ways. If these firms have higher adjustment costs, policymakers might want to minimize the short-term impact on the economy. Firms with more fixed capital investment are likely more leveraged and face higher risk of distress (Almeida and Philippon, 2007) and default risk (Davydenko et al., 2012).

3 Data and Classification of Lobby Reports

In this section, we build a dataset that will allow us to empirically test whether large firms support or oppose more restrictive regulations, aiming to identify which assumptions of the model—regarding the nature of regulatory costs and the lobbying behavior of firms—are consistent with the evidence.

Lobbying and Firm Data. All information on lobbying is sourced from *Lobbyview* (Kim, 2018). *Lobbyview* is a firm-level lobbying dataset based on lobbying reports that firms are required to complete under the Lobbying Disclosure Act of 1995. The original universe of lobbying reports is made available by the Senate Office of Public Records, with that data being parsed and made available in a practical format in *Lobbyview*, as described in Kim (2017). Each report lists the dollar value (*amount*) of the lobbying expense, self-identifying information filled out by the lobbying firm (or the agency that represents it), and information on the specific issues discussed as part of the lobbying activity.[19] The lobbying reports are categorized across several "Topics". For example, Kim (2017) restricts the analysis to reports categorized as pertaining to international trade ("TRD" in the data). As explained below, we do not restrict our analysis to one specific topic, but we will parse out reports that we view as relevant for the types of regulations examined in the theoretical section. Lobbying reports are available starting in 1999; the starting point of our data is 2,278,086 lobbying reports from 1999-2020.

Several aspects of the data are particularly crucial for our analysis. First, each lobbying report includes a *client*, which is the firm associated with the lobbying effort.[20] The associated client identifier (GVKEY) can be used to match firms to Compustat. Using Compustat data, we can obtain annual balance sheet information for these lobbying firms, allowing us to link lobbying activities to firm characteristics. As an example, the main variables of interest from Compustat are total revenues (SALE), employment (EMP), and the capital stock (PPEGT), though we extend the analysis to many more accounting variables that differentiate firms. We also construct accounting measures typically used in the finance literature, including Tobin's Q (Covarrubias et al., 2020) and the stock of intangible capital (Peters and Taylor, 2017).

The second essential part of the data is the textual description of each lobbying activity as reported by the lobbying firm. Section 16 of the report completed by the company (see Figure B.1) allows filers to describe "Specific lobbying issues". This description generally lists the topic(s) that the lobbyist covered in their activities, with varying amount of specifics that ranges from essentially no information outside of listing the topics, to very precise details on the issue being discussed

[19] Filers are required to pick an identifying code from a list of 76 general issues (which we refer to as the "*topic*" of the report when referring specifically to the codes listed by the firm), and also also provide a textual description that is more open ended. In Figure B.1, we reproduce the example of a lobbying report shown in the Mayda et al. (2010).

[20] If a firm hires a separate lobbying firm (e.g. a K-street firm), the contracted lobbyist is listed as the *registrant*, while the firm incurring the lobbying expense is listed as the *client*. If lobbying is conducted in-house, the *registrant* is the same as the *client*. For our purposes, the subject is always the *client*.

and the position of the firm. We will exploit this description in two ways. First, we determine whether the lobbying activity pertains to a regulation relevant to our conceptual framework above. This is relatively simple as it mostly applies a widely used string matching algorithm. Second, we codify whether the text provides information on the stance of the firm on the specific topic, and if so, whether the firm supports or opposes more restrictive regulatory rules. This requires a more involved process that we detail in the subsections below.

To identify the regulations we want to examine, we follow Blanga-Gubbay et al. (2021) and start with the list of areas identified as pertaining to policy topics in Deep Trade Agreements (DTAs) by the World Bank (Mattoo et al., 2020). DTAs go beyond traditional market access tools such as tariffs, to include commitments on *rules* that governments set on issues such as agricultural standards and Intellectual Property Protection (IPR). We view these as a representative set of topics that are relevant to our regulations, r above, and also tie our analysis to the literature on the influence of firms in setting of regulatory policy in international trade agreements (Rodrik, 2018). There are 17 broad NTM issues identified by the World Bank dataset that are found most often in the text of DTAs. We eliminate 5 issues that are not relevant to the type of product standards described in our conceptual framework and are left with 12 broad issues.[21] A natural concern is that some retained policy areas—such as Trade Remedies or Labor Market Regulations—may contain marginal-cost components alongside fixed compliance costs. Importantly, our identification requires only that regulations contain some fixed-cost component, not that they operate exclusively through fixed costs. Since Proposition 2 shows that marginal-cost regulations generate no differential effects across firm sizes, any observed size-stance relationship must be driven by fixed-cost components—marginal-cost elements merely attenuate our estimates.

Notice we do not limit reports to topics specifically about trade, but instead take advantage of the fact DTAs cover *domestic* policies as well (Ederington, 2001). To identify each regulatory issue in the set lobbying reports, we use keywords that are associated with each regulation (see Table B.1) to match these to the textual description in Section 16 of the lobbying reports. We keep only lobbying reports related to these regulatory issues, which narrows our previous sample to 431,606 lobbying reports.[22] Finally, we only keep reports whose associated firm is included in Compustat, which reduces the previous sample to include 127,850 reports.

The second, and novel, way we will exploit the textual descriptions is to create an indicator for whether firms support a given regulation. The literature thus far has documented the fact that there is a positive relationship between firm size and lobbying (Blanga-Gubbay et al., 2024; Huneeus and

[21] These include: Export Restrictions, Rules of Origin, Trade Facilitation and Customs, Trade Remedies, Intellectual Property Rights, Sanitary and Phytosanitary Measures, Technical Barriers to Trade, Public Procurement, Subsidies, Services, Investment, Movement of Capital,Visa and Asylum, State Owned Enterprises, Competition Policy, Environmental Laws, and Labor Market Regulations. Out of these, we eliminate 5 issues: Public Procurement, Subsidies, Services, State Owned Enterprises, and Visa and Asylum.

[22] Notice that, unlike for example Blanga-Gubbay et al. (2024) and Kim (2017), we do not restrict these to "Trade" or "Foreign" related lobbying topics. We believe both domestic and trade-related topics might inform the broader question we are after, which is to determine how support for regulatory policy might differ across firms.

Kim, 2021), and that firms can receive returns in the form of policy influence for their lobbying (Kang, 2016; Gawande et al., 2009; Facchini et al., 2011). However, what has not been documented is to what extent firms tend to support regulations that are *restrictive* in the sense that they raise the costs of operating in the industry.

This information is not readily available, as the lobbying data does not include any variables indicating a firm's position on an issue, which can be nuanced and requires sophisticated text analysis. Our aim is to analyze the textual descriptions of lobbying reports to systematically capture firms' stances on a wide range of regulations. Two papers that have successfully extracted firms' positions on issues are Kang (2016) for energy policy and Blanga-Gubbay et al. (2024) in the context of trade agreement. These studies used focused areas of interest to either employ natural language processing (NLP) tools or manually search for stances at the firm level. Our paper aims to improve upon these strategies by broadening the determination of policy stances across a comprehensive array of regulatory policies and by overcoming the constraints of NLP tools that only look for specific keywords and may miss nuanced positions. To achieve this, we will train a machine learning algorithm to classify stances on a wide range of regulatory policies.

3.1 Textual Analysis to Determine Firms' Stance on Issues

We delineate three distinct categories for classification:

1. Support: this category encompasses reports from firms advocating for more stringent regulations or expressing opposition to any dilution of existing regulatory measures.

2. Oppose: in this category, reports reflect a firm's resistance to the introduction of more restrictive regulations, or its preference for a relaxation of current regulatory constraints.

3. Not Known: reports falling into this category do not clearly articulate the firm's position on regulatory matters, leaving its stance ambiguous.

Our 'Support' classification captures firms advocating for more stringent regulatory standards—the type of cost-increasing measures emphasized in our theoretical framework. Reports expressing support for regulatory relief, exemptions, or deregulation are classified as 'Oppose'.

A possible strategy for categorizing the reports involves detecting specific keywords such as "support" and "oppose", as in the literature on lobbying for trade agreements. These terms can sometimes accurately reflect the lobbying intent. For example, the report containing:

> Support carbon neutrality - accounting/biogenic emissions

clearly advocates for carbon neutrality, implying the firm's preference for increased regulations. Similarly,

> Worked in support of GMO labeling legislation

indicates a pro-regulation stance. On the other hand, reports like

> Clean coal power development; Opposing mandatory cuts in greenhouse gases; Opposing EPA Administrator rule of March 15, relating to the his addition of coal fired electrical units to list of major sources of hazardous air pollutants.

demonstrate a clear opposition to strict environmental regulations, such as mandatory reductions in greenhouse gases and specific EPA regulations. Likewise,

> Opposition to geographic indications.

reveals a stance against additional regulatory measures concerning labeling.

However, relying solely on keyword detection in reports is prone to considerable measurement errors due to the complexity of the content. Two primary complications arise in this context. First, reports might endorse less stringent regulations or oppose the dilution of existing ones, scenarios that a straightforward keyword search might mis-classify. For instance, the report containing:

> S.J.Res 26, a joint resolution disapproving a rule submitted by the Environmental Protection Agency relating to the endangerment finding and the cause or contribute findings for greenhouse gases under section 202(a) of the Clean Air Act – support.

ostensibly backs a resolution against EPA involvement. This stance, in effect, likely signifies opposition to the introduction of more stringent regulations.

The second challenge arises from the frequent occurrence of reports that merely enumerate bills, laws, and house and senate resolutions, which include the keywords "support" and "oppose" in their title, without explicitly stating the lobbying firm's stance. For instance, consider the report containing

> H.Con.Res 57, Expressing the opposition of the Congress to the Environmental Protection Agency's proposed rule establishing new source performance standards to limit greenhouse gas emissions from new power plants.

While the report articulates opposition to the EPA's proposed rule, it does not conclusively reveal the lobbying firm's intent. The opposition is actually stated in the House of Representatives' Concurrent Resolution number 57, and the lobbying activity pertains to this resolution without clear indication of support or opposition from the firm.[23]

To address these challenges, we have devised a two-step approach. Initially, we undertake the task of manually categorizing almost three thousand reports. In this case, we rely on the more traditional procedure to first restrict reports based on whether they include keywords that indicate

[23] Occasionally, a single report may present conflicting intentions, such as S. 312. Railroad Antitrust and Competition Enforcement Act. Opposed. H.R. 5483. Railroad Retirement Disability Earning Act. Supported." In these cases, we classify the intent as "Not Known".

"clear language" towards a stance, then manually review these reports. This meticulous process involves a thorough review of each report to accurately determine its stance with respect to regulatory measures (and whether a stance is even warranted given the examples above where it is not clear). Following this, we leverage the categorized reports as a foundational dataset for training a machine learning model. With this training dataset, we can then systematically review our full sample of 127,850 reports. This model is developed utilizing the Data Analysis tool within ChatGPT. The subsequent sections will provide a detailed exposition of these two critical steps. Figure B.2 provides the instructions given to ChatGPT that produced the machine learning categorizations in one of the models, including the prompt we provided with the source files of our manual categorization and the confusion matrix provided by the analysis.

3.1.1 Manual Categorization

To manually categorize lobbying reports, we employ a selective approach by restricting ourselves to reports that contain explicit language indicative of support or opposition. This includes reports featuring key terms such as "support", "oppose", "favor", "against", and their derivatives (e.g., "supporting", "supported"). By doing so, we aim to minimize the inclusion of ambiguous reports that cannot be definitively classified as either supporting or opposing and could therefore reduce the reliability of the manual coding process. For the reports that meet this criterion, we further restrict our analysis on specific topics, namely: *agriculture, clean air quality, copyright, energy, environment, labor, and trade*. The goal is to build a sample that is practical to review manually, to train the machine learning model. The trained model is subsequently applied to the full universe of lobbying reports, including those that do not contain explicit language on the selected topics as well as reports covering all other policy areas. Within each of these thematic areas, we systematically categorize the reports into the three predefined categories: "Support", "Oppose", and "Not Known", based on their content and the stance they convey regarding regulatory measures.

The manual categorization is conducted by three coders (the two authors and a research assistant), with each report independently reviewed by at least two coders. In cases of disagreement, we adopt the most conservative classification (e.g., assigning "Not Known" rather than "Support" or "Oppose"). Disagreements between "Support" and "Oppose" are resolved through joint discussion of the regulatory context and, when necessary, supplementary searches on the specific regulation.

Our focus on policy topics related to deep trade agreements aligns the empirical analysis with the types of regulations emphasized in the theoretical framework. Firms, however, also lobby for subsidies, redistributive policies, or government spending in specific areas. Because these lobbying activities fall outside the scope of the paper, any such reports that are not excluded during the initial screening are classified as "Not Known".

Table B.2 presents the summary statistics for our dataset, and the outcomes of the manual categorization. Initially, the dataset comprises 127,850 reports (as shown in the "Compustat" column),

with an average of 10 reports per firm annually. There is a manually evaluated column that includes reports classified in the selected topics and have clear language. We manually evaluate 2,784 reports. From this pool, 1,209 reports were categorized as "Not Known", with the rest classified either as "Support" or "Oppose". In our manually evaluated sample, the firms are generally larger than those in the full dataset which includes all lobbying firms, though with substantial standard errors.[24] The size difference emerges both from the selected topics we choose for the manual categorization (column "Sub Codes") and from the "Clear Lang." having larger average sales. Out of the 1,575 reports with a clear stance, a significant majority (1,153 reports) express support for regulations, contrasting with 422 reports that oppose them. See Appendix B.1.2 for more details.

3.1.2 Machine Learning

This section describes the process of training a classification model using the manual categorization output as input. Using supervised machine learning—specifically, TF-IDF vectorization with Logistic Regression and Support Vector Machine classifiers, implemented via ChatGPT's Data Analyst tool—we divide the data into a training set (70% of the manually categorized reports) and a test set (30%) to enable model training and evaluation. The training process is structured into three primary steps: data preparation and preprocessing, feature extraction, and the actual training of the model.

In the first step, the raw text data undergoes a preprocessing phase to make it suitable for machine learning algorithms. This includes cleaning the text by removing special characters and digits, converting all characters to lowercase for uniformity, and implementing a simplified approach to preprocessing that retains the essential content of the texts.

The second step transforms the textual data into a machine-readable format using the Term Frequency-Inverse Document Frequency (TF-IDF) vectorization method. This technique converts text into a sparse matrix of TF-IDF features, highlighting the significance of words that are unique to a report, thus capturing their importance within the text.

In the third step, two different models are employed to classify the texts: a Logistic Regression model and a Support Vector Machine (SVM) model with a Radial Basis Function (RBF) kernel. A Logistic Regression model is a statistical method used for binary classification that estimates probabilities using a logistic function. A SVM model is a machine learning method used for both classification and regression tasks, but it is primarily known for its use in classification. The SVM model with an RBF kernel transforms the input data space into a higher dimensional space to make it easier to classify the data linearly, effectively managing complex and non-linear relationships between the data points.

These models are trained using the TF-IDF-transformed data, learning to correlate the extracted features with their respective classifications. Both models have shown commendable performance,

[24] In the robustness analysis we explicitly examine the possible selection into the "Known" classification.

with the Logistic Regression model achieving an average accuracy of 86% and the SVM model achieving an average accuracy of 87%. Subsequently, the trained Logistic and SVM model were applied to the entire sample of reports.

Table 1 provides the summary statistics for the outcome of our analysis. Note that, we first collapse the data to the firm-year level, then take the average across firms for each year, and finally take the average across years. The Logistic model successfully classifies 24,607 reports while the SVM model 18,238. Similarly to the distribution of outcomes of the manual categorization, the majority of reports are listed as "Support".[25] Examining the average firm-level characteristics between the "Support" and "Oppose" groups in the raw data, we find that supporting firms tend to be larger along most dimensions, although there are large standard errors. The regressions below will provide a more formal analysis with the appropriate controls.

3.1.3 Robustness with More Restrictive Algorithm

To validate our methodology, we conduct an additional robustness exercise by manually reviewing a supplementary set of algorithm-classified reports. Specifically, we randomly select over 700 reports, equally split across the three predicted categories ("Support", "Oppose", and "Not Known"). This exercise reveals that the baseline algorithm tends to over-classify reports as either "Support" or "Oppose", whereas in many cases a manual review would have categorized them as "Not Known". In other words, the algorithm systematically assigns stronger stances than warranted by the actual report content.

To address this, we extend our manually evaluated dataset by including the additional 700 reports, yielding a total of 3,517 manually categorized reports. We then retrain the machine learning model on this expanded training set. Because the retrained model is more conservative and classifies fewer reports as having a known stance, we refer to it as the *Reduced* model. For comparison, the baseline model described above—which classifies more reports—is referred to as the *Expanded* model.

Panel B of Table B.3 presents the summary statistics for the Reduced model and the corresponding manual categorization. In this case, the number of reports classified as "Not Known" rises substantially to 1,882, while the counts of "Support" and "Oppose" reports increase only modestly. Panel B of Table 1 presents the summary statistics for the categorized reports. The Reduced model under-categorizes reports as the number of "Known" stances is 3,845 in the Logistic model and 3,169 in the SVM model.

[25] Although our procedure clearly tends to find relatively more "Support" stances, we provide several checks on whether this is reasonable. First, as pointed out above, we check in the robustness that this does not seem to bias us towards large firms. Second, we show below that the algorithm produces significantly smaller "Support" stances for industry associations relative to firms, as would be expected (Bombardini and Trebbi, 2012). Finally, we also use a "Reduced sample" as well that is much more conservative. The baseline results in Table 2 are remarkably consistent across the expanded and reduced models, as well as using only the manually classified reports. Notice that we are still able to leverage the variation in "Support" relative to "oppose" even if there are more instances of support.

Table 1: Summary Statistics

Panel A: Expanded Model

	Compustat	Logistic		SVM	
		Support	Oppose	Support	Oppose
Sales	36 (57)	37 (59)	21 (33)	37 (59)	28 (37)
Employment	81 (174)	85 (188)	63 (95)	85 (179)	67 (92)
Assets	146 (391)	126 (324)	176 (551)	126 (324)	220 (609)
Capital	29 (56)	31 (57)	15 (18)	33 (60)	10 (12)
Intangible	13 (25)	14 (26)	7 (14)	14 (26)	11 (18)
Tobin Q	6 (23)	6 (27)	4 (5)	6 (30)	5 (7)
# Reports	127,850	22,037	2,570	16,592	1,646
# Firms	1,408	842	110	757	99
Panel B: Reduced Model					
# Reports	127,850	2,563	1,282	1,803	1,366
# Firms	1,408	342	137	261	159

Notes: The table reports average sales, employment, capital (fixed and intangible), Tobin's Q across samples. Panel A: "Expanded" model using manual categorization as training. Panel B: "Reduced", or more conservative, model, with manual review of algorithm-classified reports. Variables collapsed to one observation per firm-year, then averaged. Sales, assets, capital, and intangible assets in billions USD. Employment in thousands. Standard deviations in parentheses. Compustat: full sample. Support/Oppose: reports classified as "Known" stance for/against restrictive regulations.

4 Analysis of Support for Regulations across Firms

We employ a regression model to examine the relationship between a firm's size and its propensity to support regulatory measures. The regression equation for a firm f in year t for topic a is defined as follows:

$$\text{Support}_{aft} = \beta_0 + \beta_1 \text{Size}_{ft} + \beta_2 \text{FixedCap}_{ft} + \alpha_{ts} + \gamma_a + \epsilon_{aft} \tag{18}$$

where Support_{aft} is a binary indicator that equals 1 if firm f in year t has lobbied in favor of regulations in issue-code a, and 0 if it has lobbied against them. We collapse the report-level data from above to the firm-lobbying issue-year level. We exclude from our analysis any firms that have records of lobbying both for and against regulations within the same year and same topic, as well as firms for which the stance on regulations is unknown. Hence, a firm lobbied in favor of regulations if it has at least one report classified as "Support" and no reports classified as "Oppose". Conversely, a firm lobbied against regulations if it has at least one report classified as "Oppose" and no reports classified as "Support".

The variable Size_{ft} represents the size of the firm, and is operationalized through the natural logarithm of sales and employment. FixedCap_{ft} is meant to represent the adjustment costs for the

firm, which we proxy with capital and leverage.[26] Clearly there is a positive relationship between size and capital stock in the data; by including both measures simultaneously, we isolate the pure size effect (through sales holding adjustment costs constant) and the pure adjustment cost effect.[27] Our heterogeneous-firm model that incorporates regulatory costs predicts that $\beta_1 > 0$ and $\beta_2 < 0$. Implicitly, we assume that all regulations include at least *some* fixed cost component, with any marginal cost component not systematically biasing the size relationship. The heterogeneity tests and mechanisms will support this assumption. Sector-year fixed effects are given by α_{ts}, where a sector is defined in Table C.1. Therefore, we compare *across* firms *within* sector-year in examining whether there is a systematic relationship between firm size and support for regulatory measures. γ_a represents issue-code fixed effects. Issue codes refer to the reported topic in the lobbying reports using a string code.[28] The term ϵ_{ft} is the error term – we report heteroskedastic robust standard errors.

4.1 Firm Size and Support for Regulations

First, we estimate the regression (18) using a pooled sample of firms across all sectors. We evaluate the likelihood of supporting regulations as predicted by both the Logistic regression model and the SVM model. In Table 2, we consider several specifications using firm sales as the size characteristic and the stock of fixed capital as a proxy for adjustment costs. Panel A reports results with the firm stance defined in our Expanded model, which likely over-categorizes stances. Panel B reports the results of Reduced model, which is more conservative and likely under-categorizes stances. In the first two columns, we report the relationships with no fixed effects for both the Logistic and SVM models. In the next two columns, we report specifications with both sector-year and topic fixed effects, again for the Logistic and SVM models. These fixed effects allow us to restrict the variation to a (repeated) cross-section of firms within sector-year, while controlling for systematic differences across lobbying issues. In columns (5) and (6), we restrict the sample to "selected" topics, which include only topics used for our manual (training) categorization. Finally, in the last column we include *only* manually classified stances. The goal is to increase the confidence in our algorithm, which in itself is an expansion on these manually classified stances.[29]

In all cases, we find the expected positive relationship between firm sales and the firm stance being pro-regulations. Previous literature has documented that larger firms are more likely to lobby (Bombardini, 2008; Blanga-Gubbay et al., 2024); we show, consistent with our model predictions,

[26] We also differentiate with *intangible* capital which we hypothesize the firm can redeploy more easily.

[27] A possible concern is that since these are correlated, it amplifies the magnitude of the two coefficients. This is likely the case to some degree in the baseline specification, but we point out that: 1) results are robust to using alternative size (e.g market share) and adjustment cost (e.g. debt ratio) measures which are much less cross-correlated; and 2) we are more interested in testing the predicted signs of the model than quantifying the precise magnitude of the effect.

[28] For example, Kim (2017) restricts to the sample to the topic "TRD" which refers to trade related issues. Firms might lobby on multiple topics in one year, so that these would come up as multiple observations in our data.

[29] Recall that the Reduced model has a larger set of manually classified reports.

that conditional on lobbying, the larger firms are also more likely to support restrictive regulations. Furthermore, there is also a robust negative relationship between the fixed capital stock and pro-regulatory stance – firms with substantial capital are more inclined to *oppose* regulations for any given level of sales. Although these are not meant to show causal relationships, the associations are clearly in line with the direction of lobbying predicted in Propositions 2 and 5. The interquartile range spans approximately 4 log units for both sales and capital. Across this range, higher sales (holding capital constant) is associated with a 12 percentage point increase in support for restrictive regulation , while higher capital (holding sales constant) shows the opposite effect of equal magnitude (columns (3) and (4) in Panel A).

Across the specifications, the coefficient is quite consistent, though not surprisingly the reduced model is more noisy in moving from the specification with no fixed effects to the full set of controls. Importantly, even when we include only the manually classified reports with a much smaller sample size, the results are qualitatively the same. Overall, there is no evidence that expanding our measure of observed regulatory stance using machine learning biases our results. The regression specification that we use from now includes the Expanded model with both set of fixed effects.

Table 2: Firm Characteristics and Firm Stance on Regulations

Panel A: Firm Size/Capital and Firm Stance: Expanded Model

	Firm Stance = Support by Model						
	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)	(Manual Class.)
Log Sales	0.062***	0.060***	0.027***	0.030***	0.041***	0.041***	0.079***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.006)	(0.006)	(0.026)
Log Capital	-0.064***	-0.060***	-0.028***	-0.030***	-0.042***	-0.041***	-0.087***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)	(0.024)
Sector*Year FE	No	No	Yes	Yes	Yes	Yes	Yes
Topic FE	No	No	Yes	Yes	Yes	Yes	Yes
Select Topics	No	No	No	No	Yes	Yes	Yes
Obs.	8,141	6,074	8,133	6,059	4,058	3,560	513
R2	0.07	0.06	0.28	0.28	0.29	0.28	0.46

Panel B: Firm Size/Capital and Firm Stance: Reduced Model

	Firm Stance = Support by Model						
	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)	(Manual Class.)
Log Sales	0.146***	0.161***	0.048***	0.078***	0.048***	0.087***	0.081***
	(0.012)	(0.015)	(0.013)	(0.017)	(0.014)	(0.019)	(0.026)
Log Capital	-0.149***	-0.170***	-0.047***	-0.075***	-0.048***	-0.078***	-0.087***
	(0.010)	(0.013)	(0.011)	(0.016)	(0.012)	(0.016)	(0.024)
Sector*Year FE	No	No	Yes	Yes	Yes	Yes	Yes
Topic FE	No	No	Yes	Yes	Yes	Yes	Yes
Select Topics	No	No	No	No	Yes	Yes	Yes
Obs.	1,389	1,054	1,369	1,027	893	744	538
R2	0.18	0.17	0.55	0.55	0.51	0.52	0.47

Notes: A firms' stance on a regulation is identified through a textual classification algorithm that is first trained through manual classification of lobbying report. We report the results for two separate textual classification models (Logistic and SVM). Firm sales are taken from Compustat (variables SALE). Capital refers to total gross fixed assets (PPEGT variable in Compustat). The first two columns have no controls, while the next two control for topic and sector-year FEs, where the sector is defined as a 2-digit NAICS industry. In columns (5) and (6), we restrict the sample to selected topics. In the last column we include only manually classified stances (that was not passed through the ChatGPT algorithm). Computed standard errors (in parentheses) are heteroskedastic-robust. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 3 extends the results on firm size and adjustment costs. First, in Panel A, we expand on the size proxy to also include employment and market share. Firms with higher employment levels are more likely to support regulations, evidenced by a positive and statistically significant coefficient across both linguistic models. The coefficient on log employment is of a very similar magnitude to that of sales. The same relationship is seen with market share, calculated as the share of sales across all firms in our Compustat sample by detailed 4-digit NAICS industries. Finally, in the last two columns we use the firms' Tobin's Q, or the ratio of market value to assets (Gutiérrez and Philippon, 2017), as a measure of profitability. In summary, sales, employment and market share are the firm outcomes that most closely parallel the productivity draw, φ, in our model, and all are clearly associated with a higher likelihood of lobbying relatively more in *support* of restrictive regulations.

The negative and statistically significant coefficient on capital stock is also consistent across several measures (Panel B, Table 3). As reported in the first two columns, we find that firms with a higher debt-to-assets ratio (a proxy for leverage), tend to oppose more restrictive regulations. This is consistent with the model if leverage raises financing costs. This result points toward the potential importance of asset specificity (Williamson, 1988; Shleifer and Vishny, 1992) and the nature of the sunk investment cost in driving the stance of firms. If the sunk cost invested is not easily converted to comply with a new regulation, the firm is less likely to adjust in a way that increases its profits.[30] More leverage is associated with a higher cost of distress (Almeida and Philippon, 2007; Korteweg, 2010), which is consistent with these organizations being less likely to support new restrictive rules that require adaptation.[31]

Furthermore, in columns (3) and (4) we report the same relationship using the tangibility share of a firms' assets, or the ratio fixed capital to total assets.[32] Thus, our results are not driven by just the firms with a large asset base, but specifically where a large share is fixed capital as would be expected if adjustment costs were an important concern.

Consistent with the effect on asset specificity and costs to redeployment of capital, we also find, in the last two columns of Table 3, that firms with more *intangible capital* are more likely to support regulations.[33] Although intangible capital is on one hand seen as less collateralizable (Crouzet and Eberly, 2019), it can offer broader redeployability (Eisfeldt and Papanikolaou, 2013), and it is of more general use within and across organizations (Bloom et al., 2013). For the latter reason, we

[30] To Kennard (2020)'s argument, adjustment costs to regulatory change are asymmetric across firms.

[31] In fact, the finance literature has already pointed out that default costs are higher for firms with higher leverage ratios (Davydenko et al., 2012). Our findings parallel the negative relationship uncovered between debt leverage and tax aggressiveness (in terms of tax shelters) uncovered in Graham and Tucker (2006); in our case, firms with less flexibility in terms of having more fixed capital and debt are less likely to use lobbying to garner favorable regulations.

[32] The measure is computed as the fixed capital stock ($PPEGT$) over total assets (AT).

[33] To construct intangible capital intensity, we first use the data on intangible capital constructed by firm in Peters and Taylor (2017). We then use the same definition as Ayyagari et al. (2024) for the *share of intangible capital in total capital* – intangible capital over the sum of net fixed assets (PPENT in Compustat) and intangibles (from Peters and Taylor (2017)). The positive coefficient is also present if we include the level of intantagible capital from instead of the ratio to total capital.

argue that more intangible-intense firms are more adaptable to regulatory change.

Overall, we find that large firms, in terms of sales, employment, and market share, may encounter a trade-off when lobbying for more restrictive regulations. On one hand, the exit of competitors could lead to increased market share for the remaining firms, which leads to the positive association between size and support for regulations documented above. On the other hand, the rise in fixed costs may erode the potential revenue gains. This effect is more pronounced for firms that are less adaptable to regulatory changes, particularly those with higher levels of fixed capital and leverage, as evidenced by the negative correlation between support for regulations and these measures.

Table 3: Alternative Size/Capital Measures and Firm Stance on Regulations

Panel A: Alternative Size Measures: Expanded Model

	Firm Stance = Support by Model					
	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)
Log Employment	0.026***	0.023***				
	(0.003)	(0.003)				
Market Share			0.240***	0.213***		
			(0.028)	(0.036)		
Log Tobin Q					0.016***	0.025***
					(0.006)	(0.007)
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Topic FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	8,133	6,060	8,137	6,063	6,652	4,930
R2	0.28	0.28	0.28	0.27	0.29	0.28

Panel B: Alternative Capital Measures: Expanded Model

	Firm Stance = Support by Model					
	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)
Debt-to-Assets Ratio	-0.005***	-0.007***				
	(0.002)	(0.002)				
Tangible K-share			-0.086***	-0.089***		
			(0.013)	(0.016)		
Intang. K Intensity					0.055***	0.066***
					(0.011)	(0.013)
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Topic FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	6,919	5,062	8,153	6,064	6,839	5,072
R2	0.27	0.27	0.28	0.27	0.29	0.28

Notes: Employment refers to the *EMP* variable in Compustat. Market share is defined as the firm sales over total sales in that firms' 4-digit NAICS industry. Debt-to-Assets ratio is the total debt (DT in Compustat) over total assest (AT), while the Tangible K-share refers to *PPEGT* relative to *AT*. Intensity of intangible capital takes the level of intangible capital produced by Peters and Taylor (2017) relative to total capital (as produced in Ayyagari et al. (2024)). All variables are logged. In all specifications we include at least one size measure and one capital measure, although this is omitted from the reported table for clarity (e.g. all of Panel A also includes the capital stock as a control). Computed standard errors (in parentheses) are heteroskedastic-robust. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

4.2 Mechanisms for Size-Regulatory Stance Relationship

We now explore mechanisms behind the baseline results by estimating how the effects above differ across types of firms or industries. The goal is to reinforce the connection between our empirical

findings and the theoretical framework.

Table 4 presents results of the interaction of firm sales and capital with several variables. First, Proposition 3 states that large firms tend to lobby more actively for stricter regulations in industries with higher concentration. In order to test this proposition, we construct an industry level Herfindahl-Hirschmann Index (HHI) using each firm's market share in its 3-digit NAICS industry (in our sample of firms).[34] Column (1) reports the interaction of HHI with sales: the positive relationship between sales and a pro-regulatory lobbying stance is clearly *larger* at higher levels of HHI (or more concentration).[35] There is thus strong evidence for a key mechanism in the model, which is that the profits large firms increase more with restrictions as concentration rises.[36]

According to Proposition 4, the lobbying of large firms intensifies the higher the initial level of fixed costs. We explore how lobbying is influenced by the intensity of fixed costs in the industry as a whole, creating a comparable measure of fixed costs in the data. This is implemented through the ratio of total fixed costs reported in the industry relative to its variable costs.[37] The reported results in the second column of Table 4 is consistent with the model. A larger fixed cost intensity in the firms' operating industry is associated with a heightened size-lobbying relationship.

Finally, we step away from the implications of our one-sector Melitz-Chaney model and examine heterogeneous size effects that capture possible supply chain (SC) linkages. As an example in the trade literature, Blanchard et al. (2023) have argued that optimal trade policy depends on the domestic value-added content of final goods. Intuitively, SC linkages intertwine country's interests and reduce import protection as tariffs hurt a country's own factors. A parallel argument can be made in our setting; firms that have interests across industries would be less likely to support regulations in upstream or downstream sectors which may affect their marginal costs or their revenues. We identify a firms' exposure to up- and downstream effects with Frésard et al. (2020)'s vertical integration score, which is intended to capture "the potential of a given firm's products to be vertically related to the other products sold by the same firm."[38] The third column of Table 4 reports that the positive size effect of being in favor of regulations is significantly mitigated in firms with higher vertical integration scores.

[34] We also replicated the same qualitative results using more and less aggregated industries (2 and 4 digits).

[35] In all interactions, we center the sales and capital measures around zero for ease of interpretation of the non-interacted term. More specifically, we take the average sales and capital stocks across all firms in a year and subtract those from the firm-specific measure.

[36] Related to concentration, we have also checked product market measures produced by Hoberg and Phillips (2016) that track "product market similarity". This should be positively correlated with competition, and in fact we find that more competitive product markets experience a smaller lobbying effect. According to our model, these firms would find it more difficult to recoup the fixed costs from a sufficient rise in their market share.

[37] As is typical in the literature (e.g. De Loecker et al. (2020)), fixed costs are proxied by the *XSGA* variable in Compustat, which captures costs not directly tied to producing goods, such as marketing, salaries for non-production staff, rent for office space, and other operational costs. The proxy for variable costs is *COGS*, which includes the direct costs of producing or purchasing goods for sale.

[38] Frésard et al. (2020) effectively merge the vocabulary from product descriptions with their vertical relationships in the BEA input-output tables, aligning these with the products each firm reports in its 10-K filings. As they explain, a firm exhibits a higher degree of vertical integration when its business description includes numerous word-pairs that are vertically related—indicating that the firm's product vocabulary spans across vertically connected markets.

The last two columns of Table 4 report a set of interactions that examine heterogeneity across firms with respect to the capital effects uncovered above. Our hypothesis is that capital intensity and leverage reduce the benefits a firm receives from a regulation (at least relative to competitors) because these characteristics generally reduce flexibility, and thus lead to higher adjustment costs. One of the more direct measures to test this hypothesis is the degree to which firms employ *redeployable* capital. The more specific (and less redeployable) the capital stock, the stronger would be the negative relationship between the capital intensity and lobbying in favor of regulations. This is exactly what we find in the fourth column with an interaction of capital with a firm-level measure of asset redeployability constructed in Kim and Kung (2017).[39] The positive interaction coefficient signifies that the negative effects of the stock of fixed capital on the propensity to lobby for regulations *get dampened* as the firms' asset redeployability score increases.[40] In the next column, a similar interpretation can be confirmed using the scope of a firms' operations as measured in Hoberg and Phillips (2025).[41] Firms more likely to operate in a higher number of segments are less likely to lobby against regulations relative to their capital intensive peers.

4.3 Robustness: Possible Biases

Selection Bias A possible concern with the interpretation of our results that compare across firms within sector groups-years, is that there are selection issues present pertaining to the sample of firms that have a "Known" stance on their preference for more restrictive regulations. Most reports cannot be classified as either supporting or opposing regulations, so we must condition on the smaller sample that our algorithm has conservatively labeled as "Known". Given that our paper examines a large sample of regulations, it is impractical to categorize the unknown reports through online searches (as in Blanga-Gubbay et al. (2024)). Consequently, our findings may be subject to selection bias. For instance, if firms that clearly state their positions are typically larger, we might be overlooking a significant number of smaller firms, which may actually support the regulations.

In Figure C.1, we plot the distribution of firm sales for both the sample with known lobbying stances and the sample with unknown stances. The two distributions are generally similar. Notably, firms in the middle of the sales distribution are less likely to clearly indicate their intent, whereas smaller firms are over-represented in the sample of known reports, and the share of larger firms is the same in both samples. In a regression analysis, we replicate our baseline regressions where the

[39] This is computed using an asset-level score of redeployability. The BEA capital flow table is used to compute an asset-level score as the proportion of firms that use a given asset. Then, this allows for the industry-level redeployability index as the value-weighted average of each asset's redeployability score, and the firm-measure is simply a weighted average of the segments the firm operates in. The dataset is only available until 2015 which is why the number of observations is lower.

[40] Interacting asset redeployability with a firms' sales also produces a significant positive coefficient, suggesting the size effect is stronger for firms with less asset specificity. Furthermore, firms with more redeployable assets are more likely to lobby in favor of regulations.

[41] Hoberg and Phillips (2025) use descriptions from 10-K reports to try to gauge how many industries a firm likely belongs to.

Table 4: Firm Stance on Regulations: Heterogeneity of Size Effects

	Firm Stance =1 if Support Regulations				
	HHI-Size	FixedInten-Size	VI-Size	ReDeploy-K	Scope-K
HHI (NAICS3)	0.034				
	(0.096)				
HHI*Sales	0.101***				
	(0.033)				
FixedInten		-0.011**			
		(0.005)			
FixedInten*Size		0.002*			
		(0.001)			
VertInteg (HP)			2.803***		
			(0.391)		
VertInteg*Sales			-0.577***		
			(0.109)		
Redeployability				0.007	
				(0.072)	
Redeploy*Capital				0.081***	
				(0.020)	
Log PrdctScope (HP)					-0.008*
					(0.004)
Scope*Capital					0.004***
					(0.001)
Sector*Year FE	Yes	Yes	Yes	Yes	Yes
Topic FE	Yes	Yes	Yes	Yes	Yes
Obs.	8,153	8,133	6,856	5,905	7,041
R2	0.274	0.279	0.289	0.289	0.285

Notes: Industry level Herfindahl-Hirschmann Index (HHI) using each firms' market share in its 3-digit NAICS industry (in our sample of firms). Index is constructed as sum of squared market shares. FixedInten is the intensity of fixed costs relative to marginal costs. This is computed as total industry fixed costs ($XSGA$) relative to total industry cost of goods sold ($COGS$). Exposure to Vertical Integration (VI) is taken from Frésard et al. (2020), who combine the vocabularies of product descriptions and their vertical connections in the BEA input-output tables with the products produced by each firm as identified in their 10-K reports. In all columns, each of the exposure measures are interacted with log sales. Firm asset redeployability (Redeploy) is based on an asset-level score of redeployability produced inKim and Kung (2017) from the BEA capital flow table. Firm scope refers to the (logged) measure in Hoberg and Phillips (2025) that uses descriptions from 10-K reports to try to gauge how many industries a firm likely belongs to. We center the sales and capital measures using the annual average, so that the coefficient on the non-interacted term can be interpreted as the effect on the "average" firm. Computed standard errors (in parentheses) are heteroskedastic-robust. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

dependent variable is a dummy that equals one if the firm has lobbied either in favor or against a regulation in a given year, and zero if the firm's intentions are not known to the researcher. Table C.2 shows that firms with known stances tend to have lower sales, employment, and market share. Our analysis shows that smaller firms are over-represented in the sample of known stances, which is re-assuring in that it indicates that our size results are not biased by a higher likelihood of larger firms clearly indicating their intent. If anything, by over-representing smaller firms, our size effects are biased downwards because the relationship between size and policy stance is larger for the largest firms.

Industry Associations Another way to possibly differentiate the preferences of small vs. large firms is to use the stances from industry-wide associations. Bombardini and Trebbi (2012) argue

that smaller firms are more likely to lobby through industry associations, rather than directly.[42] On this front, what we are able to do is compare the propensity to lobby for regulations between direct lobbying (firms) and industry associations. From the full set of lobbying reports, after eliminating firms, we use the client names to tag industry associations (see Appendix B.1.3 for a detailed procedure to identify associations that might represent firms on an industry-wide basis). Having tagged 282 organizations that likely represent firms, we separate their 12,000 lobbying reports and went through the same process as with our baseline firms: first we tagged 942 reports with a "clear message" and manually classified these as "Support", "Oppose", and "Not Known" (again using the logic that "Support" includes language that suggests a backing of costly regulations). Then, the same algorithms described in the baseline analysis are used to classify the stance for the rest of the lobbying reports.

After aggregating to the association-year level, we append the new observations to the previous dataset. We now have firm stances for "firms" and "associations", with the former representing direct lobbyers. Given that associations tend to represent smaller firms, we hypothesize that the propensity to support regulations will be *lower* among the latter group. Appendix Table C.3 shows that the hypothesis is strongly supported by the data. An indicator for whether the client is an industry association is strongly negatively associated with support for regulations. This is not surprising: in our classification of lobbying by the associations, we find that only about 50% of lobbying is in support, far below what we find for regular firms, which is around 80%.[43]

Corporate Social Responsibility (CSR) Concerns The finding that certain firms will publicly push for policies that raise their own costs also speaks to the literature on CSR practices (Werner, 2015).[44] On the one hand, our paper complements this literature by identifying a new mechanism through which these practices are beneficial – not as a marketing strategy but as way to induce rival exit. On the other hand, our regressions above could be capturing a type of advertising by large firms that is transmitted through its lobbying practices, separate from our models' mechanism.[45] The idea is that lobbying is parallel, for example, to raising a firms' Environment, Social, and Governance (ESG) score, and thus the strategic goal of the firm is to raise its access to capital, workers, and costumers.

To start, we note that the concern above is likely mitigated by the fact that lobbying practices are not salient to the general public, so that a firm would get much more value with a more direct

[42] Huneeus and Kim (2021) report that lobbying by associations is less than a quarter of all lobbying expenses, but it might still be interesting to use these as the basis for the stance of "small" firms.

[43] The fact that only around half of association stances are pro-regulatory, using the same methodology as for the firm data, also gives more credence that we are not severely over-categorizing the firm stances as positive.

[44] A review of this large literature is beyond the scope of this paper, but the idea is effectively that firms adopt costly CSR practices as they create long-term value through reputation, capital access, and attracting workers and customers.

[45] Below, we will examine the exit rate at the industry level.

form of advertising.[46] Although firms must report lobbying data due to the LDA – which is the source of our empirical tests – actually acquiring this data is quite cumbersome for the general public. Still, we attempt to engage with the concern above by controlling for the ESG score of a firm, as a test of whether the size indicators we use contain variation outside of what is captured by theses scores.[47] Table C.4 in the appendix reports the results. First, we confirm that a higher ESG rating is associated with more lobbying, as would be expected if firms are *also* advertising and making changes to their operations consistent with their lobbying behavior. However, when we control for the ESG rating in our baseline specification, the effect of size is robust, suggesting our mechanism is separate from a firms' CSR practices.[48]

Moreover, the heterogeneity results in Table 4 help distinguish our mechanism from reputational or ESG-driven motives. Corporate social responsibility would not predict stronger size effects in more concentrated industries or in sectors with higher fixed-cost intensity—yet these are precisely the patterns predicted by our model's selection mechanism.

Residualized version of Capital A potential problem with the baseline specification is that sales and capital stock are highly correlated, and although our theory predicts opposite-signed effects, multicollinearity could potentially inflate the magnitudes of the coefficients. The alternate size measures in Table 3 attenuate this concern. In Appendix Table C.5 we also residualize the capital stock measure to examine if this is an important issue. Specifically, we first regress the log capital stock on the firm market share in a 3 digit industry plus year and sector fixed effects. The residual of this regression is saved, with the goal of eliminating pure size effects from the capital measure.[49] Finally, this residualized capital stock measure is used in the baseline regressions. The results for all classification models are mostly unchanged.

Sector Sub-Samples. In Appendix Table C.6, we explore how the results hold in sector sub-samples. We report the main results from above on a sub-sample of Manufacturing, Information, Trade, and Finance sectors.[50] For each sector, we regress the firm support dummy on firm size (sales) and measures of total and intangible capital. We find that the size results are driven by the Information and Trade sectors, and still positive in the Manufacturing and Services sectors.

[46] In fact, Culpepper (2010) makes the point that the public rarely pays attention to many business-related policy issues, albeit in a setting outside the United States.

[47] We acquire the measures through MSCI ESG Ratings for Global Equities Historical Data. ESG ratings are calculated by adding together the environmental pillar score, social pillar score, and governance pillar score. MSCI also applies various weights to each score to adjust for companies across different industries. Specifically, we use their *INDUSTRY_ADJUSTED_SCORE*, which normalizes the final ESG rating to the industry peer set, and produces a value from 1 (lowest) to 10 (highest).

[48] Note that the number of observations drops in half due to availability of ESG data. For that reason the magnitudes are hard to compare, though the magnitude on sales actually increases relative to the baseline.

[49] The market share captures market position/dominance rather than operational choices about capital intensity. A firm could have high market share through efficiency rather than capital investment, allowing us to keep the variation "we want" from the capital stock measure.

[50] These are the 5 sectors with the largest sample size and provide the most obvious industry-specific characteristics.

However, they are not present in Finance. The negative capital intensity results are present in all sectors other than Finance, and the positive intangible capital results are driven by Manufacturing, Trade, and Services. The capital intensive results are likely the most obvious, as Manufacturing and Trade are the most intensive in fixed physical assets.[51] The size effects being relatively large in Information likely reflects the fast-growing and concentrated technology industries being more likely to lobby for regulations. Finally, we believe the null results in Finance build *more* confidence in our categorization of stances as the dynamics in that sector are likely more idiosyncratic. First, fixed capital investments are very different in that sector. Second, there is documented opposition of large banks against Basel III (Cecchetti et al., 2025), as capital requirements tend to hurt large banks more. Thus, we would not expect to find that large firms are pro-regulations in that sector.

4.4 Lobbying and Industry Dynamics: The Exit Rate Mechanism

While our firm-level regressions establish that larger firms are more likely to support stricter regulations, which the model attributes to the large firms driving out competitors, we cannot directly observe the competitive effects of such lobbying. Our heterogeneity results support this mechanism through the strong lobbying-size relationships in more concentrated and less differentiated sectors. As further suggestive evidence for the model's selection mechanism, we examine whether regulatory intensity is associated with establishment exit patterns at the industry level. These correlations are descriptive and do not establish causality, but they provide context consistent with our theoretical framework.

If the large firms act in the strategic manner highlighted in this paper, we should observe the corresponding exit dynamics in response to higher regulatory intensity.[52] To capture these dynamics, we use the Business Dynamics Statistics (BDS) provided by the U.S. Census, which includes exit rates by 3-digit NAICS and year. At this same level of aggregation, we also leverage the industry regulation intensity from Kalmenovitz (2023), which attempts to build a measure of industry regulatory intensity by counting the total number of regulations on the books that apply to each industry.[53]

Table 5 shows strong support for the expected exit dynamics. The first two columns present the relationship for the regulatory intensity measures, controlling for NAICS-3 industry and year fixed

[51] Kim and Kung (2017) also find manufacturing and transportation/trade to be two of the sectors with the least redeployable assets, so this finding is entirely consistent with our asset redeployability interaction above.

[52] There is some evidence for this link in the literature, but causal links remain scarce due to the difficulty in identification. See for example Cui and Moschini (2020), that link environmental regulations with establishment exit. An older paper on the Clean Air Act, Biorn et al. (1998), finds more mixed evidence on exit. We are aware our specification cannot establish the exogeneity of regulatory intensity, but we believe it is important to establish the correlation with exit rates.

[53] Kalmenovitz (2023) employs a supervised machine learning algorithm to gauge the firm-specific costs of *all* federal paperwork regulations. The measures are available at the firm and industry level, but we employ his aggregate measure at the Fama-French 48 (ff48) industry level due to endogeneity concerns of the firm-level measure. The algorithm first ties each firm to the universe of federal regulations, then attempts to calculate the regulatory burden of each regulation.

effects, as well as time-varying industry controls: the log real gross output (from BEA) and the concurrent entry rate from the BDS data. Both measures of regulations are positively associated with exit rates, and overall the relationship is statistically robust. Moreover, we examine what types of firms drive this relationship, using the size bins provided by BDS.[54] The next two columns report an interaction of regulatory intensity with the size bin, where we replace the industry controls with strict industry× year fixed effects as well as size bin fixed effects – thus identifying only the relative effect of regulatory intensive *across size bins* controlling for any industry-specific macro trends. There is very strong evidence that the exit rates are driven entirely by the small firms, as the effect decreases with the firm size. Finally, in the last two columns we repeat the cross-industry regression but with industry concentration as the outcome. Although noisy, there is consistent evidence that as industries become more regulated they also become more concentrated.[55]

Table 5: Effect of Regulatory Intensity on Establishment Exit Rates

	Exit Rate				Industry Concentration (HHI)	
	(# Regulations)	(Regul. Compliance)	(# Regulations)	(Regul. Compliance)	(# Regulations)	(Regul. Compliance)
Regulatory Intensity	1.531**	1.053***			0.034	0.032**
	(0.642)	(0.391)			(0.043)	(0.016)
RegInt x Size			-0.794***	-0.485***		
			(0.209)	(0.101)		
Fixed Effects	Industry, Year	Industry, Year	IndustryxYear, Size Bin	IndustryxYear, Size Bin	Industry, Year	Industry, Year
Controls	Ind3d	Ind3d			Ind3d	Ind3d
Obs.	1,576	1,576	14,948	14,948	1,791	1,791
R2	0.777	0.778	0.527	0.527	0.808	0.808

Notes: The dependent variable is the exit rate in the first 4 columns (establishment exit in year t over the average number of establishments in t and $t-1$, as reported by BDS) and the industry concentration in the last two (sum of squared market shares within a NAICS3 industry). Regulatory intensity (the independent variable) includes two separate measures: the simple count of active paperwork regulations (# Regulation) and the total number of regulatory responses received by the regulatory agency (Regul. Compliance). These measures are described in Kalmenovitz (2023), which also provides alternative compliance cost measures we omit for brevity. In the first 2 columns, controls include logged real gross output of the corresponding 2-digit sector, provided by BEA, as well as the entry rate available from BDS in the same industry. They also include separate 3-digit NAICS and year fixed effects. In the next 2 columns, RegInt × Size represents the interaction between regulatory intensity and establishment size bins, where the size bins increase with firm size. Here, we control for size bins as well as industry-year interacted fixed effects, and thus no other controls are included. The last two columns include separate industry and year fixed effects, as well as a control for logged real gross output. Computed standard errors (in parentheses) are heteroskedastic-robust.. *** p<0.01, ** p<0.05, * p<0.10.

5 Conclusion

This paper challenges a fundamental assumption in political economy literature: that firms uniformly resist costly regulations. By integrating a modified Melitz-Chaney framework with empirical analysis of U.S. lobbying data, we demonstrate that regulations increasing fixed costs can serve as strategic tools for market leaders to reduce competition. Our theoretical model formalizes the mechanism through which firm heterogeneity generates divergent regulatory preferences within industries, while our machine learning classification of nearly 10,000 lobbying reports provides systematic evidence that larger firms indeed support more stringent regulations—particularly in concentrated sectors

[54] The exit rate data is provided for 10 separate size bins, from smallest to largest. In this case, the data is expanded such that exit rates by industry-year-size bin.

[55] Kalmenovitz (2023) also report that more regulated firms spend a larger revenue share on fixed costs, consistent with our concentration results and suggesting compliance likely includes a fixed cost component.

where competitive selection effects are strongest. The negative relationship between capital intensity, leverage, and regulatory support further reveals that flexibility and adaptability mediate firms' ability to extract strategic value from regulatory change.

These findings carry important implications for both regulatory design and our understanding of corporate political strategy. Policymakers cannot assume that industry opposition signals excessive regulatory burden, nor that industry support indicates insufficient stringency. When large firms advocate for regulations, they may be pursuing competitive advantage rather than social responsibility, potentially leading to more restrictive standards than welfare maximization would prescribe. For strategic management scholars, our results highlight a specific mechanism—market selection through fixed-cost barriers—that complements existing theories of non-market strategy. This extends beyond the quid-pro-quo or information transmission frameworks that dominate lobbying research, revealing how firms can reshape competitive landscapes through seemingly neutral, non-discriminatory policies that nonetheless have asymmetric effects across the size distribution.

Several avenues for future research emerge from this work. First, while our analysis focuses on cross-sectional variation in firm characteristics, dynamic extensions could examine how regulatory ratcheting occurs when large firms repeatedly support incremental tightening. Second, our framework could be applied to international regulatory harmonization, where firm heterogeneity within countries may explain divergent national positions in trade negotiations over standards. Third, with access to a dataset with clearer reference to specific legislation up for a vote, the machine learning methodology we develop for classifying regulatory stances could be extended to identify specific regulations/statutes that are especially relevant (for example comparing explicit marginal vs fixed costs).

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Appendix

A Model Derivations

A.1 Equilibrium

We begin by computing aggregate revenues:

$$T = J \int_{\varphi^*}^{\infty} \kappa b^{\kappa} \, t(\varphi) \, \varphi^{-\kappa-1} \, d\varphi \tag{19}$$

$$= \frac{J \, \kappa b^{\kappa} \, \sigma w f h(r)}{\kappa - \sigma + 1} \, (\varphi^*)^{-\kappa+\alpha\beta}. \tag{20}$$

By market clearing, aggregate revenues equal aggregate income, so that

$$T = wL. \tag{21}$$

Expected profits for an entrant are

$$E[\pi] = \int_{\varphi^*}^{\infty} \kappa b^{\kappa} \, \pi(\varphi) \, \varphi^{-\kappa-1} \, d\varphi \tag{22}$$

$$= \frac{T(\sigma - 1 - \alpha\beta)}{J\sigma(\kappa - \alpha\beta)}. \tag{23}$$

The free-entry condition requires $E[\pi] = w f_E$. Substituting $T = wL$, we obtain the mass of entrants:

$$J = \frac{L}{f_E} \, \frac{\sigma - 1 - \alpha\beta}{\sigma(\kappa - \alpha\beta)}. \tag{24}$$

We can now eliminate J from the expression for aggregate revenues. Substituting back, the cutoff equals:

$$\varphi^* = \left[\frac{\kappa(\sigma - 1 - \alpha\beta)}{(\kappa - \sigma + 1)(\kappa - \alpha\beta)} \, \frac{b^{\kappa} f h(r)}{f_E} \right]^{\frac{1}{\kappa - \alpha\beta}}. \tag{25}$$

A.2 Government

A.2.1 Consumer's Utility

The indirect consumer's utility equals:

$$U = \frac{w}{P} \tag{26}$$

Hence, we need to solve for the price index (and the productivity cutoff) to obtain the equilibrium expression for consumer's utility.

The price index equals:

$$P = \left[\kappa J b^{\kappa} \int_{\varphi^*} p(\varphi)^{1-\sigma} \varphi^{-\kappa-1} d\varphi\right]^{\frac{1}{1-\sigma}} =$$
$$= \frac{\sigma}{\sigma-1}\left[\kappa J b^{\kappa} (w m(r))^{-(\sigma-1)} \int_{\varphi^*} \varphi^{-\kappa+\sigma-2} d\varphi\right]^{\frac{1}{1-\sigma}} =$$
$$= \frac{\sigma m(r)}{\sigma-1}\left[\frac{\kappa}{\kappa-\sigma+1} J b^{\kappa} (w)^{-(\sigma-1)} (\varphi^*)^{-\kappa+\sigma-1}\right]^{\frac{1}{1-\sigma}}$$

Let us now substitute the equilibrium mass of entrants and the productivity cutoff:

$$P = \frac{\sigma w\, m(r)}{\sigma-1}\left[\frac{\kappa}{\kappa-\sigma+1}\cdot\frac{L}{f_E}\cdot\frac{\sigma-1-\alpha\beta}{\sigma(\kappa-\alpha\beta)}\cdot b^{\kappa}\right]^{-\frac{1}{\sigma-1}}\left[\frac{\kappa(\sigma-1-\alpha\beta)}{(\kappa-\sigma+1)(\kappa-\alpha\beta)}\cdot\frac{b^{\kappa} f h(r)}{f_E}\right]^{\frac{\kappa-\sigma+1}{(\kappa-\alpha\beta)(\sigma-1)}}.$$

Normalizing the wage to one yields the expression for the utility:

$$U = \frac{1}{P} = = \frac{\sigma-1}{\sigma} m(r)^{-1}\left[\frac{\kappa}{\kappa-\sigma+1}\cdot\frac{L}{f_E}\cdot\frac{\sigma-1-\alpha\beta}{\sigma(\kappa-\alpha\beta)}\cdot b^{\kappa}\right]^{\frac{1}{\sigma-1}}\left[\frac{\kappa(\sigma-1-\alpha\beta)}{(\kappa-\sigma+1)(\kappa-\alpha\beta)}\cdot\frac{b^{\kappa} f h(r)}{f_E}\right]^{-\frac{\kappa-\sigma+1}{(\kappa-\alpha\beta)(\sigma-1)}}. \tag{27}$$

Define:

$$\tilde{\kappa} \equiv \frac{(\kappa-\alpha\beta)(\sigma-1)}{\sigma-1-\alpha\beta}, \qquad P_o \equiv \frac{\sigma-1}{\sigma}\,\sigma^{-\frac{1}{\sigma-1}}\,\left[\frac{\kappa(\sigma-1-\alpha\beta)}{(\kappa-\sigma+1)(\kappa-\alpha\beta)}\right]^{\frac{1}{\tilde{\kappa}}}\, f_E^{-\frac{1}{\tilde{\kappa}}}. \tag{28}$$

Using these definitions, utility can be expressed compactly as:

$$U = P_o\, b^{\kappa/\tilde{\kappa}}\, L^{\frac{1}{\sigma-1}}\, f^{-\frac{\kappa-\sigma+1}{(\kappa-\alpha\beta)(\sigma-1)}}\, h(r)^{-\frac{\kappa-\sigma+1}{(\kappa-\alpha\beta)(\sigma-1)}}\, m(r)^{-1}. \tag{29}$$

A.2.2 Externality

The total quantity produced by a firm of productivity φ is:

$$Lq(\varphi) = \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} L P^{\sigma-1} m(r)^{-\sigma}\,\varphi^{\sigma} = \frac{(\sigma-1) f h(r)\, m(r)^{-1}}{(\varphi^*)^{\sigma-1-\alpha\beta}}\,\varphi^{\sigma}, \tag{30}$$

where we used the definition of the cutoff. Hence, the baseline externality term (before applying the convexity parameter ϵ) is:

$$\hat{E} = J\,\kappa b^{\kappa}\int_{\varphi^*}^{\infty} Lq(\varphi)\, e(\varphi)\,\varphi^{-\kappa-1} d\varphi \tag{31}$$
$$= J b^{\kappa}\,\frac{(\sigma-1) f h(r)}{(\varphi^*)^{\sigma-1-\alpha\beta}}\, m(r)^{-1}\,\kappa\int_{\varphi^*}^{\infty}\varphi^{\beta+\sigma-\kappa-1}\, d\varphi \tag{32}$$

$$= Jb^{\kappa} \frac{(\sigma-1)fh(r)}{(\varphi^*)^{\sigma-1-\alpha\beta}} m(r)^{-1} \frac{\kappa}{\kappa-\beta-\sigma} (\varphi^*)^{\beta+\sigma-\kappa}. \tag{33}$$

Substituting the equilibrium mass of entrants and the cutoff and simplifying, we obtain:

$$\hat{E} = e_o L (b^{\kappa})^{\frac{\beta+1}{\kappa-\alpha\beta}} f^{\frac{\beta+1}{\kappa-\alpha\beta}} h(r)^{\frac{\beta+1}{\kappa-\alpha\beta}} m(r)^{-1}, \tag{34}$$

where:

$$e_o = \frac{\kappa(\sigma-1)(\sigma-1-\alpha\beta)}{\sigma(\kappa-\alpha\beta)(\kappa-\beta-\sigma)} f_E^{-\frac{\beta+1}{\kappa-\alpha\beta}} \left[\frac{\kappa(\sigma-1-\alpha\beta)}{(\kappa-\sigma+1)(\kappa-\alpha\beta)}\right]^{\frac{\beta+1}{\kappa-\alpha\beta}-1}. \tag{35}$$

The aggregate externality is then defined as:

$$E = \hat{E}^{-\epsilon} = e_o^{-\epsilon} L^{-\epsilon} (b^{\kappa})^{-\frac{(\beta+1)\epsilon}{\kappa-\alpha\beta}} f^{-\frac{(\beta+1)\epsilon}{\kappa-\alpha\beta}} h(r)^{-\frac{(\beta+1)\epsilon}{\kappa-\alpha\beta}} m(r)^{\epsilon}. \tag{36}$$

A.2.3 Profits

Let us solve Π^g :

$$\Pi^g = J\kappa b^{\kappa} \int_{\varphi^*}^{\infty} \varphi^{\delta} fh(r) \left[(\varphi^*)^{-(\sigma-1-\alpha\beta)} \varphi^{\sigma-1} - \varphi^{\alpha\beta}\right] \varphi^{-\kappa-1} d\varphi \tag{37}$$

$$= Jb^{\kappa} \frac{\kappa(\sigma-1-\alpha\beta)}{(\kappa-\delta-\sigma+1)(\kappa-\delta-\alpha\beta)} fh(r) (\varphi^*)^{-\kappa+\delta+\alpha\beta}. \tag{38}$$

Substituting J and the cutoff φ^* gives:

$$\Pi^g = \pi_o L (b^{\kappa})^{\frac{\delta}{\kappa-\alpha\beta}} f^{\frac{\delta}{\kappa-\alpha\beta}} h(r)^{\frac{\delta}{\kappa-\alpha\beta}}, \tag{39}$$

where:

$$\pi_o = \frac{(\sigma-1-\alpha\beta)}{\sigma(\kappa-\alpha\beta)} \cdot \frac{\kappa(\sigma-1-\alpha\beta)}{(\kappa-\delta-\sigma+1)(\kappa-\delta-\alpha\beta)} f_E^{-\frac{\delta}{\kappa-\alpha\beta}} \left[\frac{\kappa(\sigma-1-\alpha\beta)}{(\kappa-\sigma+1)(\kappa-\alpha\beta)}\right]^{\frac{-\kappa+\delta+\alpha\beta}{\kappa-\alpha\beta}}. \tag{40}$$

A.3 Optimal Regulation

The government's objective is:

$$U^g = U + E + \gamma\Pi^g = \tag{41}$$

$$= \tilde{U} h(r)^{-\frac{\kappa-\sigma+1}{(\kappa-\alpha\beta)(\sigma-1)}} m(r)^{-1} + \tilde{E} h(r)^{-\frac{\epsilon(\beta+1)}{\kappa-\alpha\beta}} m(r)^{\epsilon} + \tilde{\pi} h(r)^{\frac{\delta}{\kappa-\alpha\beta}}. \tag{42}$$

The three prefactors are defined as:

$$\tilde{U} = P_o b^{\frac{\kappa}{\tilde{\kappa}}} L^{\frac{1}{\sigma-1}} f^{-\frac{\kappa-\sigma+1}{(\kappa-\alpha\beta)(\sigma-1)}}, \tag{43}$$

$$\tilde{E} = e_o^{-\epsilon} L^{-\epsilon} (b^{\kappa})^{-\frac{(\beta+1)\epsilon}{\kappa-\alpha\beta}} f^{-\frac{(\beta+1)\epsilon}{\kappa-\alpha\beta}}, \tag{44}$$

$$\tilde{\pi} = \gamma \pi_o \, L \, (b^{\kappa})^{\frac{\delta}{\kappa - \alpha\beta}} \, f^{\frac{\delta}{\kappa - \alpha\beta}}. \tag{45}$$

A.3.1 Profits and Regulations

In this section, we show the relationship between equilibrium profits and regulations. The profits of a firm with productivity φ are:

$$\pi(\varphi) = f h(r) \left((\varphi^*)^{-(\sigma - 1 - \alpha\beta)} \, \varphi^{\sigma - 1} - \varphi^{\alpha\beta} \right), \tag{46}$$

where the cutoff is:

$$\varphi^* = \left[\frac{\kappa(\sigma - 1 - \alpha\beta)}{(\kappa - \sigma + 1)(\kappa - \alpha\beta)} \, \frac{b^{\kappa} f h(r)}{f_E} \right]^{\frac{1}{\kappa - \alpha\beta}}. \tag{47}$$

The derivative of the cutoff with respect to regulations is:

$$\frac{\partial \varphi^*}{\partial r} = \frac{\varphi^*}{\kappa - \alpha\beta} \, \frac{h'(r)}{h(r)}. \tag{48}$$

Hence, the effect of a change in r on profits is:

$$\begin{aligned}
\frac{\partial \pi(\varphi)}{\partial r} &= f h'(r) \left((\varphi^*)^{-(\sigma - 1 - \alpha\beta)} \varphi^{\sigma - 1} - \varphi^{\alpha\beta} \right) && (49) \\
&\quad - (\sigma - 1 - \alpha\beta) f h(r) (\varphi^*)^{-(\sigma - 1 - \alpha\beta) - 1} \varphi^{\sigma - 1} \frac{\partial \varphi^*}{\partial r} && (50) \\
&= f h'(r) \left[(\varphi^*)^{-(\sigma - 1 - \alpha\beta)} \varphi^{\sigma - 1} \left(1 - \frac{\sigma - 1 - \alpha\beta}{\kappa - \alpha\beta} \right) - \varphi^{\alpha\beta} \right] && (51) \\
&= f h'(r) \left[(\varphi^*)^{-(\sigma - 1 - \alpha\beta)} \varphi^{\sigma - 1} \frac{\kappa - \sigma + 1}{\kappa - \alpha\beta} - \varphi^{\alpha\beta} \right]. && (52)
\end{aligned}$$

Therefore, $\frac{\partial \pi(\varphi)}{\partial r} > 0$ if:

$$\begin{aligned}
(\varphi^*)^{-(\sigma - 1 - \alpha\beta)} \varphi^{\sigma - 1} \frac{\kappa - \sigma + 1}{\kappa - \alpha\beta} &> \varphi^{\alpha\beta}, && (53) \\
\varphi^{\sigma - 1 - \alpha\beta} \frac{\kappa - \sigma + 1}{\kappa - \alpha\beta} &> (\varphi^*)^{\sigma - 1 - \alpha\beta}, && (54) \\
\varphi &> \varphi^* \left(\frac{\kappa - \alpha\beta}{\kappa - \sigma + 1} \right)^{\frac{1}{\sigma - 1 - \alpha\beta}}. && (55)
\end{aligned}$$

Notice that $\frac{\kappa - \alpha\beta}{\kappa - \sigma + 1} > 1$ since $\sigma - 1 > \alpha\beta$.

A.4 Government's Bias for Minimizing Firms Fixed Costs

In this section, we explore an extension to the baseline model by modifying the government's objective function to reflect a different lobbying pattern. In our baseline model, we assume that firms' lobbying efforts are driven by profits. However, our model abstracts from potential adjustment costs,

investments in physical capital, and financial constraints that may interact with regulations, making the costs of these regulations firm-specific. To keep the model as tractable as possible while incorporating this additional dimension, we propose modifying the government's objective function so that the government's utility is affected by increases in fixed costs due to regulations. Additionally, the government may have a bias towards either high- or low-fixed cost firms.

Specifically, we assume that the government's objective function depends on the resources spent on fixed costs, with the government assigning different weights to each firm's fixed cost:

$$F^g = -\int_{\varphi^*}^{\infty} f(e(\varphi), r)^{1+\zeta} g(\varphi) d\varphi \tag{56}$$

where ζ captures the government's bias. If $\zeta > 0$, the government favors firms with larger fixed costs, while if $\zeta < 0$, the government favors firms with smaller fixed costs. Recall that the fixed cost is a function of productivity, given by $f(e(\varphi), r) = wfe(\varphi)^{\alpha} h(r) = wf\varphi^{\alpha\beta} h(r)$ and can either increase or decrease in productivity depending on whether β is positive or negative. The negative sign in front of the integral indicates that higher fixed costs reduce the government's utility.

Let us solve for F^g, normalizing $w = 1$:

$$\begin{aligned}
F^g &= -Jb^{\kappa}(fh(r))^{1+\zeta}\kappa \int_{\varphi^*}^{\infty} \varphi^{\zeta\alpha\beta+\alpha\beta-\kappa-1} d\varphi = \\
&= -\frac{\kappa}{\kappa - \zeta\alpha\beta - \alpha\beta}(fh(r))^{1+\zeta} Jb^{\kappa}(\varphi^*)^{-\kappa+\zeta\alpha\beta+\alpha\beta} = \\
&= -\frac{(\kappa - \sigma + 1)}{\sigma(\kappa - \zeta\alpha\beta - \alpha\beta)} \underbrace{\frac{\sigma\kappa}{\kappa - \sigma + 1} Jb^{\kappa} fh(r)(\varphi^*)^{-\kappa+\alpha\beta}}_{=T} (fh(r))^{\zeta}(\varphi^*)^{\zeta\alpha\beta} = \\
&= -\frac{(\kappa - \sigma + 1)}{\sigma(\kappa - \zeta\alpha\beta - \alpha\beta)} T(fh(r))^{\zeta}(\varphi^*)^{\zeta\alpha\beta} = \\
&= -\frac{(\kappa - \sigma + 1)}{\sigma(\kappa - \zeta\alpha\beta - \alpha\beta)} L(fh(r))^{\zeta}(\varphi^*)^{\zeta\alpha\beta} = \\
&= -\frac{(\kappa - \sigma + 1)}{\sigma(\kappa - \zeta\alpha\beta - \alpha\beta)} L(fh(r))^{\zeta} \left[\frac{\kappa(\sigma - 1 - \alpha\beta)}{(\kappa - \sigma + 1)(\kappa - \alpha\beta)} \frac{b^{\kappa} fh(r)}{f_E}\right]^{\frac{\zeta\alpha\beta}{\kappa - \alpha\beta}} = \\
&= -\frac{(\kappa - \sigma + 1)}{\sigma(\kappa - \zeta\alpha\beta - \alpha\beta)} \left[\frac{\kappa(\sigma - 1 - \alpha\beta)}{(\kappa - \sigma + 1)(\kappa - \alpha\beta)}\right]^{\frac{\zeta\alpha\beta}{\kappa - \alpha\beta}} L(fh(r))^{\zeta} \left[\frac{b^{\kappa} fh(r)}{f_E}\right]^{\frac{\zeta\alpha\beta}{\kappa - \alpha\beta}} = \\
&= -F_o \, L \, (b^{\kappa})^{\frac{\zeta\alpha\beta}{\kappa - \alpha\beta}} \, f^{\frac{\zeta\kappa}{\kappa - \alpha\beta}} \, h(r)^{\frac{\zeta\kappa}{\kappa - \alpha\beta}},
\end{aligned}$$

where

$$F_o = \frac{(\kappa - \sigma + 1)}{\sigma(\kappa - \zeta\alpha\beta - \alpha\beta)} \left[\frac{\kappa(\sigma - 1 - \alpha\beta)}{(\kappa - \sigma + 1)(\kappa - \alpha\beta)}\right]^{\frac{\zeta\alpha\beta}{\kappa - \alpha\beta}} f_E^{-\frac{\zeta\alpha\beta}{\kappa - \alpha\beta}} \tag{57}$$

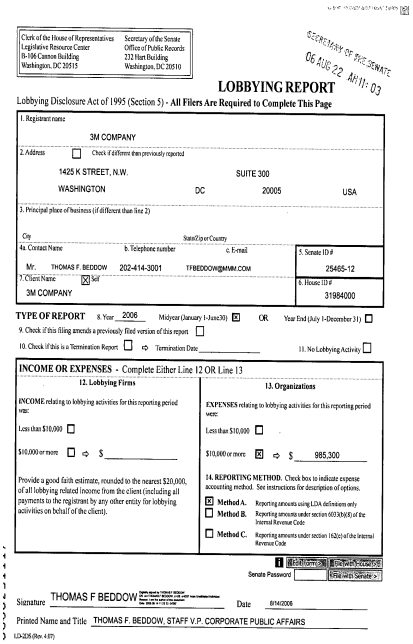
Hence, if the government favors firms with higher fixed costs ($\zeta > 0$), then increased regulations reduce the utility of the government. This extension allows us to rationalize why firms with high

capital intensity or with assets that have low redeployability lobby against regulations.

B Data Supplementary Material

Figure B.1: Example of Lobbying Report: 3M

Figure B2. Sample Lobbying Report - 3M Company



Clerk of the House of Representatives
Legislative Resource Center
B-106 Cannon Building
Washington, DC 20515

Secretary of the Senate
Office of Public Records
232 Hart Building
Washington, DC 20510

SECRETARY OF THE SENATE
06 AUG 22 AM 11: 03

LOBBYING REPORT

Lobbying Disclosure Act of 1995 (Section 5) - **All Filers Are Required to Complete This Page**

1. Registrant name: 3M COMPANY
2. Address ☐ Check if different than previously reported: 1425 K STREET, N.W. SUITE 300 WASHINGTON DC 20005 USA
3. Principal place of business (if different than line 2): City ____ State/Zip or Country ____
4a. Contact Name: Mr. THOMAS F. BEDDOW — b. Telephone number: 202-414-3001 — c. E-mail: TFBEDDOW@MMM.COM
5. Senate ID #: 25465-12
7. Client Name: ☒ Self — 3M COMPANY
8. House ID #: 31984000

TYPE OF REPORT 8. Year 2006 Mid-year (January 1-June30) ☒ OR Year End (July 1-December 31) ☐

9. Check if this filing amends a previously filed version of this report ☐

10. Check if this is a Termination Report ☐ ⇨ Termination Date ____ 11. No Lobbying Activity ☐

INCOME OR EXPENSES - Complete Either Line 12 OR Line 13

12. Lobbying Firms

INCOME relating to lobbying activities for this reporting period was:

Less than $10,000 ☐

$10,000 or more ☐ ⇨ $ ____

Provide a good faith estimate, rounded to the nearest $20,000, of all lobbying related income from the client (including all payments to the registrant by any other entity for lobbying activities on behalf of the client).

13. Organizations

EXPENSES relating to lobbying activities for this reporting period were:

Less than $10,000 ☐

$10,000 or more ☒ ⇨ $ 985,300

14. REPORTING METHOD. Check box to indicate expense accounting method. See instructions for description of options.

☒ **Method A.** Reporting amounts using LDA definition only
☐ **Method B.** Reporting amounts under section 6033(b)(8) of the Internal Revenue Code
☐ **Method C.** Reporting amounts under section 162(e) of the Internal Revenue Code

Senate Password ____ Enter with Senate >

Signature THOMAS F BEDDOW Date 8/14/2006

Printed Name and Title THOMAS F. BEDDOW, STAFF V.P. CORPORATE PUBLIC AFFAIRS

LD-2(R (Rev. 4/97)

47

Registrant Name 3M COMPANY Client Name 3M COMPANY

LOBBYING ACTIVITY. Select as many codes as necessary to reflect the general issue areas in which the registrant engaged in lobbying on behalf of the client during the reporting period. **Using a separate page for each code,** provide information as requested. Attach additional page(s) as needed.

15. General issue area code TRD - Trade (Domestic & Foreign) (one per page)

16. Specific lobbying issues

FREE TRADE AGREEMENTS AND COMPLIANCE
SANCTIONS REFORM
AFRICA GROWTH & OPPORTUNITY ACT
DUTY SUSPENSIONS

17. House(s) of Congress and Federal agencies contacted ☐ None ☒ House ☒ Senate ☒ Other

USTR
DEPARTMENT OF COMMERCE

18. Name of each individual who acted as a lobbyist in this issue area

Name		Covered Official Position (if applicable)	New
MILDRED	HAYNES		☐
THOMAS	BEDDOW		☐
			☐
			☐
			☐
			☐
			☐
			☐
			☐

19. Interest of each foreign entity in the specific issues listed on line 16 above ☒ Check if None

146

Table B.1: Keywords used to Identify Relevant Regulatory Issues

Competition
competition|Competition|Competitor|competitor|competitors|Competitors|antitrust|Antitrust|monopoly|Monopoly|Monopolies|monopolies|monopolist|Monopolist|Monopolists|monopolists|Cartel|cartel| Cartels|market dominance|Market Dominance|Market dominance|undertaking|Undertaking|State Aid|State aid|state aid|anticompetitive|Anticompetitive|Mergers and Acquisitions|Mergers and acquisitions| mergers and acquisitions| M&A|collusive|Collusive|Collusion|collusion|merger|Merger|Mergers|mergers|Acquisition|acquisition|acquisitions|Acquisitions|Takeover|takeover|Takeovers|takeovers
Environmental Laws
Environmental|environmental|environment|Environment|biodiversity|Biodiversity|emission|Emission|emissions|Emissions|Pollution|pollution|Pollutants|pollutants|Sustainable|sustainable|Sustainability| sustainability|species|Species|Toxic|toxic|toxicity|Toxicity|Waste|waste|Conservation|conservation|Hazardous|hazardous|Clean Energy|clean energy|Clean energy|renewable|Renewable|Climate Change| climate change|Climate change|Climate Security|Climate security|climate security|greenhouse|Greenhouse|Ozone|ozone|Ozone-depleting|ozone-depleting| Ozone Depleting|Ozone depleting|ozone depleting|deforestation|Deforestation|GHG|particle|Particle|Particles|particles|carbon|Carbon
Export Restrictions:
Export restriction|export restriction|Export Restriction|Export Restrictions|export restrictions|Export restrictions|Export Tax|export tax| Export tax|Export Taxes|export taxes|Export taxes|export duty|Export Duty|Export duty|Export duties|Export Duties|export duties|export quota|Export quota|Export Quota|Export quotas| Export Quotas|export quotas|export licensing|Export Licensing|Export licensing|Export License|export license|Export license|Export Licenses|Export licenses|export licenses|Export Fee| Export fee|export fee|Export Fees|Export fees|export fees|Export Ban|Export ban|export ban|Export Bans|Exbort bans|export bans|export price control|Export price control| Export Price Control|Export Price Controls|Export price controls| Quantitative Restrictions on Exports|Quantitative restrictions on exports|quantitative restrictions on exports|QRE| Export Rationing|Export rationing|export Export Shortage|export shortage|Export shortage|Export Shortages|export shortages|Export Certificate of Origin|export certificate of origin|Export Certificate of Origin
Intellectual Property Restrictions (IPR):
Intellectual Property|Intellectual property|intellectual property|IPR|IP|patent|Patent|patents|Patents|copyright|Copyright|Copyrights|copyrights|trademark|Trademark|trademarks| Trademarks|Geographical Indications|geographical indications|Geographical indications|GI|compulsory licensing|Compulsory Licensing|Compulsory licensing|Compulsory License| Compulsory license|compuslory license|compulsory licenses|Compulsory Licenses|Compulsory licenses|Data Protecction|data protection|Data protection|Industrial Design|Industrial design|industrial design|TRIPS
Investment:
Investment|investment|investments|Investments|Investors|investors|Investor|investor|FDI|portfolio|portfolios|Portfolio|Portfolios|Expropriation|expropriation|Fair and Equitable Treatment| Fair and equitable treatment|fair and equitable treatment|FET|International Investment Agreement|international investment agreement|International investment agreement|IIA| bilateral investment treaty|Bilateral Investment Treaty|Bilateral investment treaty|BIT|dispute settlement|Dispute Settlement|Dispute settlement|ISDS|Arbitration|arbitration|court|Court| Trade-Related Investment Measures|Trade Related Investment Measures|trade-related investment measures|trade related investment measures|Trade-related investment measures|trade-related investment measures|TRIM
Labor Mkt Regs:
labor|Labor|Employment Regulations|employment regulations|Employment regulations|Working conditions|Working Conditions|working conditions| corporate social responsibility|Corporate social responsibility|Corporate Social Responsibility|CSR|Collective Bargaining|collective bargaining|Collective bargaining
Capital Movement:
Capital|capital|financial|Financial|Currency|currency|Currencies|currencies
Rules of Origin:
Rules of Origin|rules of origin|Rules of origin|ROO|Certificate of Origin|certificate of origin|Certificate of origin|Cumulation|cumulation|Value Content|value content|Value content
SPS:
Sanitary|sanitary|Sanitation|sanitation|phytosanitary|Phytosanitary|phytosanitation|Phytosanitation|sps|Sps|SPS|MRL|Pesticide|pesticide|Pesticides|pesticides|hormone|Hormone| Hormones|hormones|standard|Standard|standards|Standards
TBT:
Technical Barriers to Trade|Technical barriers to trade|technical barriers to trade|Technical Barrier to Trade|Technical barrier to trade|technical barrier to trade|TBT|Conformity|conformity
Trade Customs Facilitation
Trade Facilitation|Trade facilitation|trade facilitation|customs|Customs|Shipment Inspection|Shipment inspection|shipment inspection|Shipment Inspections| Shipment inspections|shipment inspections| Border Agency|Border agency| border agency|Border Agencies|Border agencies|border agencies| Bali|Trade Facilitation Agreement|Trade facilitation agreement|trade facilitation agreement|TFA
Trade Remedies:
Trade Remedy|Trade remedy|trade remedy|Trade Remedies|Trade remedies|trade remedies|Dumping|dumping|Anti-dumping|anti-dumping|AD| zeroing|Zeroing|Price Undertaking|Price undertaking|price undertaking|Injury|injury|fair trade|Fair Trade|Fair trade|Countervailing|counterveiling|CVD|State Subsidies|state Subsidies| state subsidies|State Subsidy|State subsidy|state subsidy|Overseas Subsidies|Overseas subsidies|overseas subsidies|Overseas Subsidy|Overseas subsidy|overseas subsidy| Illegal Subsidies|Illegal subsidies|illegal subsidies|Illegal Subsidy|Illegal subsidy|illegal subsidy|Prohibitive Subsidies|Prohibitive subsidies|prohibitive subsidies|Prohibitive Subsidy|Prohibitive subsidy|prohibitive subsidy|non-market economy|Non-market economy|Non-Market Economy|Non-market Economy

B.1 Textual Analysis

B.1.1 Instructions to ChatGPT Advanced Data Analysis Tool

Log in Sign up for free

This is a copy of a conversation between ChatGPT & Anonymous.
Report conversation

Uploaded a file

Instructions for Regenerating Text Classification Outcomes
1. Introduction and Data Upload:
o I have a dataset for text classification into categories "Not Known," "Oppose," and "Support," related to lobbying reports.
o [Upload the dataset here.]
2. Machine Learning Model Training and Application:
o Request to train a Support Vector Machine (SVM) model with a Radial Basis Function (RBF) kernel on part of the data.
o Request an evaluation of the model with a classification report and confusion matrix on the test data.
3. Final Steps:
o Once the model is trained and evaluated, request to apply this classification method to any additional datasets you have for lobbying report classification

Your dataset has been successfully loaded. It contains:

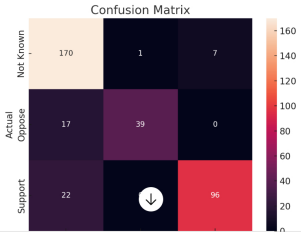
Message ChatGPT

- `issue_text` : the text to classify
- `outcome` : the label — "Not Known", "Oppose", or "Support"

Next, I'll proceed to:

1. Split the data into training and test sets
2. Train a **Support Vector Machine (SVM)** model with an **RBF kernel**
3. Evaluate it using a **classification report** and **confusion matrix**

Proceeding with model training now.



Message ChatGPT

Your **SVM model with RBF kernel** has been trained and tested. Here's a summary of the performance:

📊 **Classification Report**

Class	Precision	Recall	F1-score	Support
Not Known	0.81	0.96	0.88	178
Oppose	0.98	0.70	0.81	56
Support	0.93	0.81	0.87	118
Accuracy			**0.87**	

The model performs best in predicting **"Not Known"**, but slightly underperforms in **recall for "Oppose"**, meaning it misses some "Oppose" cases.

If you have **another dataset you'd like to classify using this trained method**, please upload it and I'll apply the model directly to generate predictions.

Uploaded a file

apply to this dataset and return an excel file with the classified reports

The classification has been successfully applied to your dataset of 68,056 reports.

Download the classified reports here (`classified_lobbying_reports.xlsx`)

Let me know if you'd like summaries, visualizations, or to re-train with more data.

Message ChatGPT

Attach Study Voice

ChatGPT can make mistakes. Check important info.

B.1.2 Summary Statistics of Textual Analysis

Table B.2 presents the summary statistics for our dataset, and the outcomes of the manual categorization for our expanded sample. Initially, the dataset comprises 127,850 reports (as shown in the "Compustat" column), with an average of 10 reports per firm annually. There are a total of 9,713 firms that make up these reports. In column "Sub Codes", we refine our dataset to include only those reports classified in the specific topics we focus on in our manual procedure (agriculture, clean air quality, copyright, energy, environment, health, labor, and trade). The are over 49,000 reports that fit into these issue codes. In the next column, "Clear Lang.", we restrict our sample to those reports featuring explicit language indicative of support or opposition – but for all issues.[56] When we restrict our sample to those reports featuring explicit language indicative of support or opposition (as noted in the "Clear Lang." column), the count narrows down to 8,168 (out of 127K) reports. Both the sub codes we select and the sample of firms with "clear language" reports seem to consist of slightly larger firms, as evidenced by higher average figures for sales, employment, capital, and market value compared to the broader dataset. However, due to substantial standard errors, the differences in these variables between the full and refined samples are not statistically significant. Finally, there is a manually evaluated column that includes reports classified in the selected topics *and* have clear language.

Table B.3 presents the summary statistics for our dataset, and the outcomes of the manual categorization for our restricted sample.

[56]The point is to see how each refinement of the data affects the sample.

Table B.2: Summary Statistics for Manually Categorized Reports - Expanded Model

	Compustat	Sub Codes	Clear Lang.	Manually Eva.	Not Known	Support	Oppose
Sales	19	23	24	25	28	23	29
	(38)	(45)	(40)	(47)	(45)	(33)	(50)
Employment	47	59	60	63	63	58	111
	(108)	(133)	(124)	(142)	(112)	(88)	(230)
Assets	72	59	69	58	70	55	41
	(225)	(189)	(207)	(182)	(192)	(125)	(51)
Capital	15	19	22	23	26	18	29
	(33)	(38)	(40)	(42)	(44)	(27)	(31)
Intangible	5	6	8	8	8	11	8
	(12)	(14)	(18)	(17)	(16)	(19)	(16)
Tobin Q	7	6	6	7	3	14	2
	(30)	(25)	(20)	(23)	(5)	(37)	(2)
Reports	10	7	4	3	2	3	3
per firm	(14)	(7)	(5)	(3)	(2)	(4)	(2)
# of Reports	127.850	49.315	8.168	2.784	1.209	1.153	422
# of Firms	9.713	5.829	1.801	803	470	329	148

The table reports the average sales, employment, capital (fixed and intangible), Tobin's Q, and reports per firm in different samples. For each variable, we first collapse the reports to include one observation per firm per year, then take the average and standard deviation for each variable across firms annually, and then compute the average of these figures across all years. For each sample, the table reports the total number of reports. Sales, assets, capital, and intangible assets are in billions of dollars. Employment is in thousands. Intangible capital is taken from Peters and Taylor (2017). Tobin's Q is computed as the market value relative to total capital stock. The columns include the following samples. Compustat: full sample matched to the Compustat data. Sub Codes: reports included in the topics: agriculture, clean air quality, copyright, energy, environment, health, labor, and trade. Clear Lang.: reports that include clear language indicating support or opposition (all topics). Manually Eva.: sample of manually evaluated reports; topics included: agriculture, clean air quality, copyright, energy, environment, health, labor, and trade. Not Known: manually evaluated reports that cannot be categorized in support or oppose. Support: manually evaluated reports that indicate support for more restrictive regulations. Oppose: manually evaluated reports that indicate opposition for more restrictive regulations.

Table B.3: Summary Statistics for Manually Categorized Reports - Reduced Model

	Compustat	Sub Codes	Clear Lang.	Manually Eva.	Not Known	Support	Oppose
Sales	19	23	24	25	26	25	28
	(38)	(45)	(40)	(41)	(42)	(36)	(49)
Employment	47	59	60	61	60	62	108
	(108)	(133)	(124)	(119)	(100)	(91)	(224)
Assets	72	59	69	63	70	70	41
	(225)	(189)	(207)	(181)	(198)	(174)	(51)
Capital	15	19	22	22	23	19	30
	(33)	(38)	(40)	(38)	(42)	(30)	(32)
Intangible	5	6	8	9	9	11	8
	(12)	(14)	(18)	(17)	(17)	(19)	(16)
Tobin Q	7	6	6	6	3	14	2
	(30)	(25)	(20)	(19)	(6)	(38)	(2)
Reports	10	7	4	3	2	3	3
per firm	(14)	(7)	(5)	(3)	(2)	(3)	(2)
# of Reports	127.850	49.315	8.168	3.517	1.882	1.192	443
# of Firms	9.713	5.829	1.801	1.116	779	349	156

The table reports the average sales, employment, capital (fixed and intangible), Tobin's Q, and reports per firm in different samples. For each variable, we first collapse the reports to include one observation per firm per year, then take the average and standard deviation for each variable across firms annually, and then compute the average of these figures across all years. For each sample, the table reports the total number of reports. Sales, assets, capital, and intangible assets are in billions of dollars. Employment is in thousands. Intangible capital is taken from Peters and Taylor (2017). Tobin's Q is computed as the market value relative to total capital stock. The columns include the following samples. Compustat: full sample matched to the Compustat data. Sub Codes: reports included in the topics: agriculture, clean air quality, copyright, energy, environment, health, labor, and trade. Clear Lang.: reports that include clear language indicating support or opposition (all topics). Manually Eva.: sample of manually evaluated reports; topics included: agriculture, clean air quality, copyright, energy, environment, health, labor, and trade. Not Known: manually evaluated reports that cannot be categorized in support or oppose. Support: manually evaluated reports that indicate support for more restrictive regulations. Oppose: manually evaluated reports that indicate opposition for more restrictive regulations.

B.1.3 Tagging Trade Associations

The idea is that smaller firms might not lobby directly, but due to free riding concerns will contribute to industry-wide associations that represents their interests (Olson, 1965; Bombardini and Trebbi, 2012) Therefore, we want to identify these associations; specifically, business associations that represent firms and industries and NOT other social interests or broader advocacy (e.g. labor interests, gun rights, etc). To tag lobbying reports as coming from trade associations, we use the following procedure:

1. Provide Claude Sonnet our list of lobbying clients, including over 11,000 names. The first step is to ask it to classify what it believes to be an "an industry association that represents firms". It came up with name patterns and then created the following scoring system:

- Primary association terms (3 points each): ASSOCIATION, FEDERATION, COALITION, COUNCIL, ALLIANCE
- Industry terms (2 points each): MANUFACTURERS, INDUSTRY, TRADE, CHAMBER, BOARD, INSTITUTE
- Scope terms (1 point each): AMERICAN, NATIONAL, INTERNATIONAL, WORLDWIDE, GLOBAL
- Business terms (1 point each): BUSINESS, COMMERCIAL, INDUSTRIAL, CORPORATE, ENTERPRISES

This analysis came up with 1,662 organizations with a score of 3 or above.

2. With these possible organizations, we manually analyzed the first 400 names and included a tag of whether we "agreed" or not that this was indeed the type of industry association we wanted to include. Out of the 400 rated entries, 138 were correctly classified as industry associations, and 262 were incorrectly classified initially. An example of a correct classification is "ASSOCIATION OF INTERNATIONAL AUTOMOBILE MANUFACTURERS INC", while an incorrect classification is "National Rifle Association".

3. We then fed this back into the Claude AI model, which based on our feedback, re-analyzed the 1,662 organizations. It then created a new classification, which using our training dataset of 400 organizations, had a 77% accuracy.

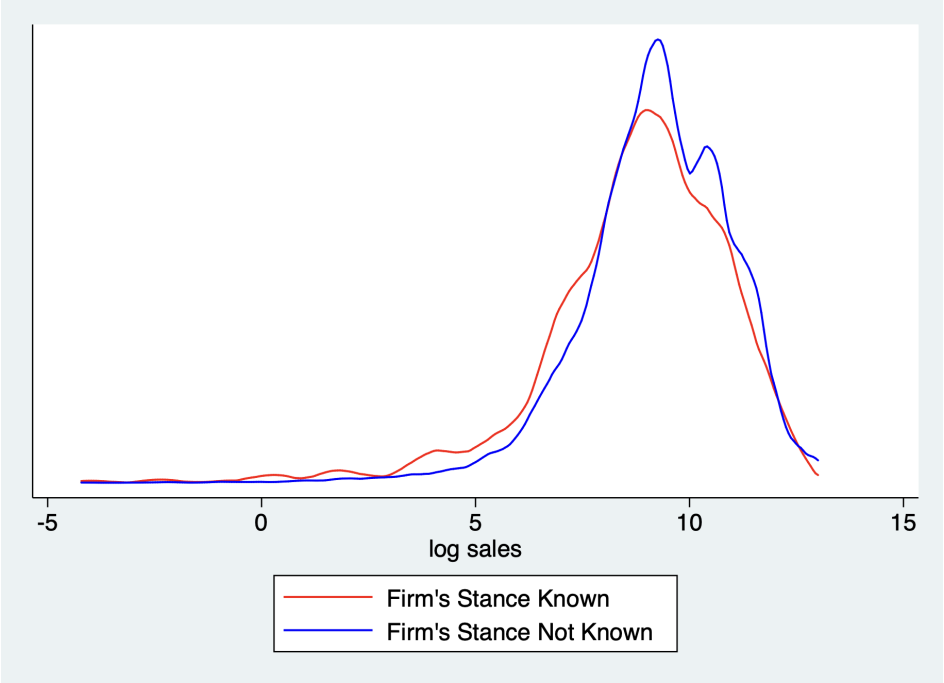
4. In the end, we have **282 industry associations**, and we tag all lobbying reports where the client is one of these associations.

C Regression Analysis Supplementary Material

Table C.1: Sectors and Their Corresponding 2-Digit Codes

Sector Name	**2-Digit Sectors**
Natural Resources and Mining	11, 21
Construction	23
Manufacturing	31, 32, 33
Trade, Transportation, and Utilities	22, 42, 44, 45, 48, 49
Information	51
Financial Activities	52, 53
Other Services	54, 55, 56, 61, 62, 71, 72, 81
Nonclassifiable	99

Figure C.1: Kernel Density Plots of Log Sales (Logistic Model)



The plot shows the kernel density plot of log sales for the sample of firms for which we know the lobbying intent (either support or oppose) and for firms for which we are not able to classify their reports. This plot is for the expanded model with a greater number of known stances.

Table C.2: Robustness: Firm Size and Known Indicator

	Firm Stance = Known (Logistic Method)					
	(Expanded Model)	(Reduced Model)	(Expanded Model)	(Reduced Model)	(Expanded Model)	(Reduced Model)
Log Sales	-0.016***	-0.005***				
	(0.001)	(0.001)				
Log Employment			-0.015***	-0.005***		
			(0.001)	(0.001)		
Market Share					-0.052***	-0.070***
					(0.019)	(0.008)
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Topic FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	30,288	30,288	29,683	29,683	26,353	26,353
R2	0.195	0.047	0.194	0.045	0.190	0.048

Notes: The dependent variable is a dummy that equals one **if a firms' stance on a regulation is identified** and zero if the reports cannot be classified. A firms' stance on a regulation is identified through a textual classification algorithm that is first trained through manual classification of lobbying report. We report the results for the logistic method of textual classification, in both the "expanded" and "reduced" models (depending on whether we allow the algorithm to provide a stance for a greater number of reports). Firm sales and employment are taken from Compustat (variables SALE and EMP), while market share is computed as the share of sales within a 3 digit NAICS industry. Market value is computed (in Compustat variables) as is defined in that paper: $ME + LT + PSTK$. Computed standard errors are heteroskedastic-robust. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table C.3: Support Propensity of Industry Associations relative to Firms

	Firm Stance =1, Expanded Model		Firm Stance =1, Reduced Model	
	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)
Industry Association	-0.338***	-0.400***	-0.170***	-0.181***
	(0.015)	(0.023)	(0.020)	(0.028)
Sector*Year FE	Yes	Yes	Yes	Yes
Topic FE	Yes	Yes	Yes	Yes
Obs.	9,294	6,604	2,513	1,571
R2	0.317	0.324	0.357	0.375

Notes: In this table we compare the propensity to support regulations between direct lobbyers (firms) and industry associations. The dependent variable is the indicator for support/oppose for the known stances. The independent variable is an indicator equal to one if the client is an industry association. Computed standard errors are heteroskedastic-robust. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table C.4: Robustness: Lobbying and ESG Ratings

	Firm Stance = Support (Logistic Method)					
	(Expanded Model)	(Reduced Model)	(Expanded Model)	(Reduced Model)	(Expanded Model)	(Reduced Model)
ESG Rating	0.007***	0.018***	0.006***	0.015***	0.005***	0.017***
	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)	(0.005)
Log Sales			0.062***	0.141***		
			(0.005)	(0.018)		
Log Employment					0.045***	0.087***
					(0.004)	(0.012)
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Topic FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4,312	726	4,303	726	4,303	726
R2	0.203	0.433	0.248	0.532	0.244	0.519

Notes: In this table examine how lobbying is associated with ESG ratings, and whether this relationship impacts the size relationship. Columns 3-6 control for log capital as in the baseline analysis. Changes in the number of observations are due to availability of ESG ratings. We acquire the ESG ratings through *MSCI ESG Ratings for Global Equities Historical Data*. ESG ratings are calculated by adding together the environmental pillar score, social pillar score, and governance pillar score. MSCI also applies various weights to each score to adjust for companies across different industries. Specifically, we use their $INDUSTRY_ADJUSTED_SCORE$, which normalizes the final ESG rating to the industry peer set, and produces a value from 1 (lowest) to 10 (highest). The (unadjusted) ESG rating – and coding the ratings (e.g. AAA, AA, etc.) from 1 to 7 – has a 0.88 correlation with the industry-adjusted ones we use. For brevity and to include both the expanded and reduced models (over- and under-categorized), we use only the Logistic textual method. Computed standard errors are heteroskedastic-robust. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table C.5: Robustness: Residualized Capital Stock Measure

	Firm Stance =1, Expanded Model		Firm Stance =1, Reduced Model		Manual Clasifs
	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)	(Manual)
Log Sales	0.025***	0.026***	0.044***	0.066***	0.058**
	(0.003)	(0.003)	(0.010)	(0.015)	(0.023)
Log K (Residualized)	-0.027***	-0.027***	-0.046***	-0.067***	-0.069***
	(0.002)	(0.003)	(0.009)	(0.014)	(0.022)
Sector*Year FE	Yes	Yes	Yes	Yes	Yes
Topic FE	Yes	Yes	Yes	Yes	Yes
Obs.	8,133	6,059	1,369	1,027	513
R2	0.282	0.277	0.554	0.547	0.452

Notes: This table replicates the baseline specification of Panels A and B in Table 2, but with a residualized capital measure. Specifically, we first regress the log capital stock on the firm market share in a 3 digit industry and year and sector fixed effects. The residual of this regression is saved and used as the capital stock measure in the baseline regressions. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table C.6: Firm Stances on Regulations by Broad Sector

	Firm Stance =1 if Support Regulations using Logistic Model									
	(Manufacturing)	(Information)	(Trade)	(Finance)	(Services)	(Manufacturing)	(Information)	(Trade)	(Finance)	(Services)
Log Sales	0.007**	0.035***	0.059***	-0.002	0.010*	-0.002*	0.015***	0.004	-0.008**	0.001
	(0.003)	(0.011)	(0.011)	(0.006)	(0.005)	(0.001)	(0.005)	(0.007)	(0.004)	(0.001)
Log Capital	-0.010***	-0.018**	-0.066***	-0.005	-0.011**					
	(0.003)	(0.007)	(0.012)	(0.008)	(0.005)					
Intang. K Intensity						0.022	-0.012	0.080*	-0.007	0.058**
						(0.016)	(0.013)	(0.045)	(0.015)	(0.023)
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Topic FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4,121	929	1,551	546	481	3,112	903	1,421	503	434
R2	0.093	0.095	0.319	0.642	0.198	0.110	0.085	0.323	0.643	0.243

Notes: Capital refers to total gross fixed assets (PPEGT variable in Compustat). Intensity of intangible capital takes the level of intangible capital produced by Peters and Taylor (2017) relative to total capital (as produced in Ayyagari et al. (2024)). ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.