Lobbying for Regulations: When Big Business Says Yes*

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Abstract

Do firms universally oppose regulations that raise production costs, or do their stances depend on intrinsic characteristics that create uneven outcomes across businesses? This question is vital for understanding firms' behavior in regulatory lobbying. We extend a standard general equilibrium model with firm heterogeneity in productivity by incorporating two key elements: (1) governments can impose regulations, and (2) firms can lobby for either stricter or more lenient regulations. While regulations aim to address consumption externalities, they also raise both marginal and fixed production costs. This can drive less productive firms out of the market, and leave surviving firms potentially better off. Our model shows that large firms are likely to lobby for stricter regulations when these regulations primarily increase fixed costs. To test these predictions, we use a guided machine learning algorithm to classify US firms' positions on regulatory issues based on their lobbying reports. Our findings reveal that larger firms, particularly in concentrated industries, tend to support more stringent regulations. Additionally, we identify a negative relationship between capital intensity, leverage, and regulatory support, suggesting that a firm's operational flexibility plays a key role in shaping its stance on regulatory changes.

Keywords: Lobbying, Regulations, Product Standards, Firm Heterogeneity

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1 Introduction

In prominent areas such as the green transition and trade agreements, regulations on production and product standards are increasingly a key point of contention. The key trade-off that governments face is that achieving improvements in a desired externality typically requires increasing production costs for firms. Consequently, it is standard to assume that firms generally oppose the implementation of product standards and lobby against rules they deem more restrictive. For instance, to reduce greenhouse gas emissions, firms are required to change their production processes or energy consumption, leading to increased costs, and therefore likely business opposition. This opposition enters the trade-off that governments face – beyond efficiency and externality concerns – through corporate influence over public policy (i.e., lobbying). One important context for this dynamic is in international regulatory agreements, where firms have increasingly contributed to their expansion in scope (Rodrik, 2018). For example, in Maggi and Ossa (2023), all firms benefit from looser regulatory product standards and act to reduce the stringency of those regulations in trade agreements such that agreements can end up making countries worse off. However, this argument fails to recognize firm heterogeneity and that the same regulation may have different effects on small and large firms. In this sense, the presence of firm interests in the regulatory arena has more nuanced implications for the final content of policy.

While the baseline case in Maggi and Ossa (2023) assumes perfect competition, the authors note in their conclusions that *with imperfect competition*: "it is conceivable that tightening a (non-discriminatory) standard may increase the profits of more productive firms at the expense of less productive ones." This concept aligns with seminal theories of regulation that suggest industries might manipulate regulatory policies to their advantage (Stigler, 1971; Oster, 1982). Examples of such dynamics are readily observable in practice. For example, *ExxonMobil*, the world's largest private energy company, stated in its 2022 climate lobbying report that its direct lobbying efforts are committed to keeping global warming well below 2 degrees Celsius.[1] Regardless of any potential benefits from aligning investments with regulatory costs (Kennard, 2020), *ExxonMobil* stands to gain if smaller competitors are unable to bear the financial burdens imposed by these regulations.

The core argument of our paper is that regulations that increase costs can drive some

[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 document advertises the company's lobbying in support of methane regulations, including a support for EPA's proposed methane rule. To connect it with our empirical analysis, we find *ExxonMobil* lobbies for more restrictive regulations in all cases where we can determine their position.

firms out of the market, thereby benefiting the surviving firms by reducing competition. We outline the theoretical conditions under which this occurs and provide new evidence showing that larger firms may support more restrictive regulations. This has significant implications for policy goals such as the green transition. In fact, large firms could support and actively lobby for such regulations, potentially leading to even more stringent standards.

We first provide a theoretical framework that extends the Melitz-Chaney model of firm heterogeneity to incorporate government-imposed regulations that affect both fixed and marginal costs for all firms selling to a given country. These regulations aim to mitigate a negative consumption externality proportional to the output produced. The second addition to the Melitz-Chaney model is the inclusion firm lobbying in the style of Grossman and Helpman (1994) and Maggi and Ossa (2023). Specifically, we assume that the government's objective function is influenced by firms' profits, with a bias toward either large or small firms. Regulations impact the profits of surviving firms in two ways. First, they increase costs for each surviving firm, thereby reducing their profits. Second, the exit of less productive firms can enhance the profits of those that remain.

The model predicts that larger firms lobby for tougher regulations if these regulations increase fixed production costs. Conversely, if regulations decrease fixed costs, smaller firms lobby in their favor. If regulations only affect marginal costs, neither large nor small firms will lobby for them. The results imply that, under certain conditions, larger firms might lobby for stringent regulations despite potential cost increases, due to the selective advantage they gain. This behavior could lead governments to achieve a greater reduction in externalities than would be expected if they were solely focused on maximizing consumer welfare.

The baseline model examines how fixed costs reduce competition for larger firms by driving smaller firms out of the market, thereby influencing lobbying behavior based on firm size. We extend this model by changing the government's preference—shaped by lobbying—based on firms' fixed costs rather than their size. The rationale is that firms 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.[2] Under this extension, the model explains why firms with high fixed costs may lobby *against* stricter regulations.

To test the predictions of the model, we use data on lobby reports in the US from LobbyView (Kim, 2018). Under the Lobbying Disclosure Act of 1995, lobbyists are required to report their activity and this is made available by the Senate Office of Public Records. LobbyView has subsequently integrated these reports into a manageable format and is widely used to examine lobbying activities (see extensive literature below). All reports include a

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

text with 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 can match public firms in LobbyView with Compustat data, to obtain information on firms' characteristics (e.g. size, capital intensity).

A key contribution of our paper is the systematic categorization of a firm's stance on tougher regulations using a novel method not previously implemented in this context. The method relies on a guided machine learning algorithm and solves two key issues related with determining firms' stances. First, a manual classification of reports can only be realistically done for a small subset of reports. Second, we demonstrate through specific examples that a simple keyword search often leads to incorrect categorization of a report as being in favor of or against regulations. 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 actual intent. To address these issues, we apply a guided machine learning algorithm to the lobby reports of US firms, using the Data Analyst Tool within ChatGPT. We train the model by manually evaluating over 3,000 reports on selected topics. Once trained, we apply the model to the remaining reports, successfully classifying over 30,000 reports into either "Support" or "Opposition" of more stringent regulations. 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 findings indicate a positive relationship between firm size and support for more stringent regulations, using several proxies. First, we demonstrate that firms with larger revenues are more likely to lobby in favor of regulations. These results remain robust when using employment and market share as proxies for size, which are the closest approximations to the firm size primitive in our model. Additionally, this relationship is also evident when using Tobin's Q, a composite measure popular in the finance literature that reflects profitability. Our model predicts that the potential increase in profits for large firms rises with industry concentration and with the initial level of fixed costs. We find support for these predictions as we find that the relationship between firm size and lobbying stance is more pronounced in concentrated industries and industries with higher regulatory costs, while effects are more subdued in competitive product markets.

We also uncover an inverse relationship between regulatory support and measures of fixed capital and leverage: more capital-intensive and debt-ridden firms tend to lobby against regulations. To explain these results, we propose that businesses benefit from regulations only if they can flexibly adapt to the new environment. Adjusting to the same stricter regulation may be more costly for firms with higher capital intensity, particularly if assets are not redeployable, and with higher levels of debt. Supporting this hypothesis, we find that the negative effects of capital intensity are pronounced in firms with less asset redeployability, a narrower scope of production, and higher risk exposure. Furthermore, firms that extensively use *intangible* capital, which is likely more general in its application, are more inclined to support regulations.

An underlying theme of our hypothesis is the significance of firm heterogeneity in driving the gains from regulation and the resulting lobbying behavior, particularly for the largest firms in a sector. The role of individual firms and lobbying has recently received growing attention in the literature on trade agreements due to their growing role in negotiations (Rodrik, 2018). Blanga-Gubbay et al. (2023) find that nearly all firms lobby in *favor* of regional free trade agreements, with large multinationals leading the effort due to the various benefits they gain from internationalization. A key aspect of their model is to include firm heterogeneity, where the largest firms have the most to gain, and the possible gains are larger than the possible losses to the purely import-competing firms. Our study is on the possible differing stances on non-discriminatory regulatory policy, which is now a major part of the trade landscape (Lamy, 2016).

In Maggi and Ossa (2023), although firm heterogeneity is not modeled, lobbying can make trade agreements welfare increasing or reducing, depending on whether agreements dilute or intensify lobbying. When the regulation is on the characteristics of the goods sold at home, which fits into our modeled regulations, the alignment of domestic and foreign firms intensifies lobbying for looser regulations and leads to a reduction in welfare relative to no trade agreement. By including firm heterogeneity, we argue that firms within the same country will not necessarily have the same preferences. There is still a role for alignment between home and foreign firms, as our model predicts that regulations benefits large enough firms from any origin. International cooperation in our model can lead to stricter regulations, when governments favor large firms.

There is also an extensive literature on the determination of which specific industries and firms participate in the lobby process.[3] Bombardini (2008) added the perspective of the individual firm to the political economy trade literature that generally viewed lobbying as done by interest groups (Grier et al., 1994; Grossman and Helpman, 1994; Gawande, 1997).[4] Using firm-specific lobbying data, Bombardini and Trebbi (2012) find that firms

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

[4]Trade papers in this literature generally use the Grossman and Helpman (1994) Protection for Sale (PfS) framework to understand how the equilibrium trade policy is shaped. Older papers that use non-lobbying types of influence include Gawande and Bandyopadhyay (2000) and Gawande et al. (2006). The former tests the PfS model using expenditures by Political Actions Committees (as in Goldberg and Maggi (1999)), while the latter uses foreign lobbying data. Related studies that establish policy returns to individual firms with lobbying data include Ludema et al. (2018).

in highly competitive sectors tend to lobby collectively through trade associations, whereas firms in more concentrated sectors with differentiated products are more likely to lobby individually. Similarly, Kim (2017) emphasizes the importance of within-industry factors in trade policy lobbying, particularly for sectors with more differentiated products. Focusing on immigration policy, Kerr et al. (2014) find that firms classified as high-skill-immigration-dependent increase their lobbying after a reduction in the H1B visa cap. We view our paper as a successor to this line of work, and explore instead the differing positions firms take in influencing policy.[5]

Our central thesis posits that firms *within* the same industry may have differing stances on regulation based on their size, and that supporting regulation can be motivated by competitive outcomes. This idea has been explored within the narrow context of climate change. Initial arguments, as found in the literature on International Organization and Strategy (Oster, 1982; Salop and Scheffman, 1983), suggest that groups within industries may view certain regulations as advantageous compared to their competitors. This rationale has since been applied to explain why corporations might lobby for climate change-related regulations, with Kennard (2020) providing a closely related analysis.[6] Kennard (2020) argues that when there are significant asymmetries in adjustment costs to regulations among firms within an industry, the potential market share gain for larger firms outweighs the increased costs. Similarly, Grey (2018) explores how firms can use lobbying to gain market share, specifically by first investing in clean technology and then advocating for stronger environmental protections. We generalize this idea to broader regulatory policy, and formalize a mechanism that is broadly applicable across sectors, wherein even equal compliance costs lead to disparate outcomes based on firms' size.

Cory et al. (2021) demonstrate that lobbying on environmental regulations is influenced by supply chain dynamics, where opposition to climate policies is shaped by upstream and downstream linkages to direct carbon producers. In our analysis, we find that the relationship between firm size and regulatory stance is less pronounced in highly vertically integrated firms, they are more aware of how new regulations impact their broader cost structures

[5] The papers cited in our work generally view lobbying as distortionary due to its *quid-pro-quo* nature (see also Huneeus and Kim (2021), who models the aggregate costs of resource misallocation through lobbying). However, as noted in the review by Bombardini and Trebbi (2020), this perspective is not the only framework for understanding lobbying. Another strand of literature considers lobbying as a form of information transmission between firms and policymakers. For our analysis, we are primarily concerned with how firms express their preferences, regardless of which type of relationship the lobbying fits into.

[6] Political science papers that highlight firm size heterogeneity in lobbying include You (2017) and Osgood et al. (2017). Moroever, there is a substantive political economy/science literature that examines businesses' stances towards regulation and why some might support environmental regulations. For example, see Maloney and McCormick (1982), Vormedal (2011), Grumbach (2015), Vormedal and Meckling (2024), and Cai and Li (2020).

through suppliers and revenue streams through customers.

A contribution of our paper is to identify firm-specific stances on regulatory policy, which is challenging because it is usually more nuanced than what can be deduced by specific words or phrases (Baumgartner et al., 2009). Kang (2016) is one of the few studies, alongside Blanga-Gubbay et al. (2021) mentioned above, that codes firms' stances on specific regulatory issues within lobbying reports. These exploited the focused area of interest to either use natural language processing (NLP) tools or manually search for stances on an issue at the firm level. This paper aims to improve upon those strategies in two ways: 1) broaden the determination of policy stances across a wide array of regulatory policies; and 2) sidestep the constraints of NLP tools that only look for select keywords to gauge a position and ignore the possible nuance in the text (which we show below can be problematic).

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 multi-country version of the Melitz-Chaney model of firm heterogeneity (Melitz, 2003; Chaney, 2008). There are I countries, indexed by i for origin and j for destination. Each country has L_i 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_i. To produce a good in country i and export it to country j, firms must incur an iceberg trade cost τ_{ij} and a fixed export cost f_j in destination labor units.

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_i. Productivity is drawn from a Pareto distribution with a common shape parameter κ for all countries, and a country-specific shift parameter b_i. The CDF and pdf of the productivity distribution are $G_i(\varphi) = 1 - \left(\frac{b_i}{\varphi}\right)^{\kappa}$ and $g_i(\varphi) = \frac{\kappa b_i^{\kappa}}{\varphi^{\kappa+1}}$, respectively. Free entry drives expected profits to zero, ensuring that household income equals the wage w_i.

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 associated with their consumption (e.g., waste). 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. If the total consumption of the variety produced by firm φ in a country is $L_i q(\varphi)$ units, the total externality generated is $L_i q(\varphi) e(\varphi)$. The aggregate externality in country j is given by the integral of $L_i q(\varphi) e(\varphi)$ over the entire set of varieties consumed in the country.

The second difference from the Melitz-Chaney model is that the government of country j can impose a regulation r_j, which increases both the marginal costs and the fixed costs of selling to destination j for all firms that choose to sell there. 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

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

$$U_j = \left[\sum_{i=1}^{I} \int_{\omega \in \Omega_{ij}} q_{ij}(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right]^{\frac{\sigma}{\sigma-1}} \tag{2}$$

where $q_{ij}(\omega)$ is the quantity consumed of variety ω from exported from i to j, $\sigma > 1$ is the elasticity of substitution, and Ω_{ij} is the set of varieties exported from i to j. Solving the consumers' problem yields the following direct demand function:

$$q_{ij}(\omega) = w_j P_j^{\sigma-1} p_{ij}(\omega)^{-\sigma} \tag{3}$$

where $p_{ij}(\omega)$ is the price of variety ω and P_j is the price index and equals:

$$P_j = \left[\sum_{i=1}^{I} \int_{\omega \in \Omega_{ij}} p_{ij}(\omega)^{1-\sigma} d\omega \right]^{\frac{1}{1-\sigma}} \tag{4}$$

2.3 Firms

There is a continuum of firms in each country, and each firm supplies only one variety. Hence, we can replace the index ω with the firm's productivity parameter φ. Since firms' marginal costs are constant, we can treat the problem of a firm in each destination separately.

The government of country j imposes a non-discriminatory regulation r_j, applied equally to all firms selling to j. Specifically, when exporting to destination j, the regulation r_j affects the firm's costs in two ways. First, the fixed cost to sell to destination j depends on the level of the firm's externality and the regulation of destination j:

$$f_j(e(\varphi), r_j) = w_j f_j e(\varphi)^{\alpha} h(r_j) = w_j f_j \varphi^{\alpha\beta} h(r_j) \tag{5}$$

where we used the fact that $e(\varphi) = \varphi^{\beta}$. We assume that $h'(r_j) \geq 0$, 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 and delivery. For a firm with productivity φ from country i exporting to country j, the marginal cost equals:

$$mc_{ij}(\varphi, r_j) = \frac{w_i \tau_{ij}}{\varphi} m(r_j) \tag{6}$$

where $m(r_j)$ captures the relationship between marginal costs and the regulation, and we assume that $m'(r_j) \geq 0$. 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, 2024), 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.[7]

Firm φ's profits in destination j are given by:

$$\pi_{ij}(\varphi) = L_j q_{ij}(\varphi) p_{ij}(\varphi) - L_j q_{ij}(\varphi) \frac{w_i \tau_{ij}}{\varphi} m(r_j) - w_j f_j \varphi^{\alpha\beta} h(r_j) \tag{7}$$

where $q_{ij}(\omega)$ is defined in (3). A firm φ from country i exporting to destination j sets the price $p_{ij}(\varphi)$ by maximizing its profits while taking the price index P_j as given, due to the assumption of monopolistic competition. Profit maximization yields the standard CES

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

pricing rule with a constant markup over marginal costs:

$$p_{ij}(\varphi) = \frac{\sigma}{\sigma-1}\frac{w_i \tau_{ij} m(r_j)}{\varphi} \tag{8}$$

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

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

$$\pi_{ij}(\varphi) = \frac{(\sigma-1)^{\sigma-1}}{\sigma^{\sigma}} L_j w_j P_j^{\sigma-1} \left(w_i \tau_{ij} m(r_j)\right)^{-(\sigma-1)} \varphi^{\sigma-1} - w_j f_j \varphi^{\alpha\beta} h(r_j) \tag{9}$$

The productivity of the marginal firm φ_{ij}^* that is indifferent between exporting to j and exiting is obtained by setting profits to zero, i.e., $\pi_{ij}(\varphi_{ij}^*) = 0$. The cutoff equals:

$$\varphi_{ij}^* = \left[\frac{\sigma^{\sigma}\left(f_j m(r_j)^{\sigma-1} h(r_j)\right)\left(w_i \tau_{ij}\right)^{(\sigma-1)}}{(\sigma-1)^{\sigma-1} L_j P_j^{\sigma-1}}\right]^{\frac{1}{\sigma-1-\alpha\beta}}$$

We assume that $\sigma - 1 - \alpha\beta > 0$, to preserve the standard relationship between iceberg trade costs and the productivity cutoff (i.e., higher trade costs imply stricter selection).

Substituting the cutoff into the revenue $t_{ij}(\varphi)$ and profit $\pi_{ij}(\varphi)$ equations, we obtain the following expressions:

$$t_{ij}(\varphi) = \sigma w_j f_j h(r_j) (\varphi_{ij}^*)^{-(\sigma-1-\alpha\beta)} \varphi^{\sigma-1} \tag{10}$$

$$\pi_{ij}(\varphi) = w_j f_j h(r_j) \left((\varphi_{ij}^*)^{-(\sigma-1-\alpha\beta)} \varphi^{\sigma-1} - \varphi^{\alpha\beta}\right) \tag{11}$$

2.4 Equilibrium

The equilibrium in a Melitz-Chaney model can be characterized by three endogenous variables: the mass of firms that pay the fixed costs of entry J_i in each country, the share of expenditures from country j on goods from country i, denoted by λ_{ij} for any pair of countries, and the wage w_i in each country. In Appendix A.1, we show the derivations for the equilibrium equations that determine the equilibrium values of these three endogenous variables.[8] The mass of entrants is constant and given by:

$$J_i = \frac{L_i}{f_E}\frac{\sigma(\kappa-\alpha\beta)}{(\sigma-1-\alpha\beta)} \quad \forall i = 1, ..., I \tag{12}$$

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

The expenditure share λ_{ij} is defined by the following gravity equation:

$$\lambda_{ij} = \frac{L_i b_i^{\kappa}(w_i \tau_{ij})^{-\tilde{\kappa}}}{\sum_{v=1}^{I} L_v b_v^{\kappa}(w_v \tau_{vj})^{-\tilde{\kappa}}} \quad \forall i, j = 1, ..., I \tag{13}$$

Finally, the market clearing condition is given by:

$$\sum_j \lambda_{ij} w_j L_j = w_i L_i \quad \forall i = 1, ..., I \tag{14}$$

Hence, the equilibrium objects λ_{ij}, w_i, and J_i are determined by (12), (13), and (14). None of these equilibrium conditions are affected by the restrictiveness of regulation r_i. Thus, we can analyze the effects of more restrictive regulations without considering the endogenous responses of the mass of entrants, wages, and trade shares. This result was first established by Macedoni and Weinberger (2024), 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.

This result is driven by the fact that λ_{ij} is unaffected by the regulations, which leaves the key endogenous variables of the model independent of the regulation as well. The share λ_{ij} remains unchanged due to the non-discriminatory nature of the regulation, whereby an increase in the regulatory costs to export to country j affects all exporting countries equally. When a regulation increases these costs, some foreign exporters may exit the market of the imposing country. This exit frees up resources, allowing the remaining firms to cover the higher fixed and marginal costs of exporting. The regulation does not impact domestic production in foreign countries or their exports to other destinations. However, the quantities consumed in the imposing country will change, influencing its welfare.

Equilibrium Profits and Regulations. With the model solved, 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, which can be fully understood in the context of general equilibrium. 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. Specifically, this occurs if* $\varphi > \varphi^*_{jj}\left(\frac{\kappa-\alpha\beta}{\kappa-\sigma+1}\right)^{\frac{1}{\sigma-1-\alpha\beta}}$.[9]

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.[10]

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_j, which depends on three components: the utility of consumers (U_j), the consumption externality (E_j), and firms' profits (Π^g_j). The last term is what allows us to infer the preference of firms over the regulatory policy. The objective function of the government equals:

$$U^g_j = U_j + E_j + \gamma \Pi^g_j \tag{15}$$

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

$$E_j = E_o \left(\sum_{i=1}^{I} J_i \int_{\varphi^*_{ij}}^{\infty} L_j q_{ij}(\varphi) e(\varphi) g(\varphi) d\varphi \right)^{-\epsilon} \tag{16}$$

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

The assumption that the government's utility also depends on firms' profits is standard in the "protection for sale" literature.[11] What this modeling technique allows us to do is

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

[10] 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).

[11] For an alternative approach to modeling lobbying, see the model by Blanga-Gubbay et al. (2023).

infer the firms' preference based on how Π_i^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 the firm's productivity. Specifically,

$$\Pi_i^g = \sum_{j=1}^{I} \int_{\varphi_{ij}^*}^{\infty} \varphi^\delta \pi_{ij}(\varphi) g(\varphi) d\varphi \tag{17}$$

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 $\frac{dU_j^g}{dr_j} = 0$:

$$\frac{dE_j}{dr_j} + \gamma \frac{d\Pi_j^g}{dr_j} = -\frac{dU_j}{dr_j} \tag{18}$$

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):

$$U_j^g = \tilde{U}_j h(r_j)^{-\frac{\kappa-\sigma+1}{(\kappa-\alpha\beta)(\sigma-1)}} m(r_j)^{-1} + \tilde{E}_j h(r_j)^{\frac{-\epsilon(\beta+1)}{\kappa-\alpha\beta}} m(r_j)^{\epsilon} + \sum_{v=1}^{I} \tilde{\pi}_{jv} h(r_v)^{\frac{\delta}{\kappa-\alpha\beta}} \tag{19}$$

where $\tilde{U}_j$, $\tilde{E}j$, and $\tilde{\pi}_{jv}$ are general equilibrium objects that do not depend on the level of regulation r_j. Since regulations leave the endogenous variables unchanged, changes in regulations leave $\tilde{U}_j$, $\tilde{E}_j$, and $\tilde{\pi}_{jv}$ constant.

Regulations negatively affect the utility from consumption. The elasticity of utility with respect to $h(r_j)$ and $m(r_j)$ 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 government's utility. In fact, the elasticity of the welfare effects externality with respect to $h(r_j)$ 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_j^g only depends on regulations through its effect on fixed costs. If regulations only affect marginal costs (i.e., $m'(r_j) > 0$ and $h'(r_j) = 0$), 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 demand 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., $h'(r_j) > 0$), 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.

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.*[12]

Equation (19) 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.

[12] 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.

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.[13]

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

Proof: the profit term in the government's objective function is proportional to $f_v h(r_v)$. Hence, $\frac{\partial \Pi_j^g}{\partial r_k}$ increases in f_j 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 (19) 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.

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

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.[14] 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.

3 Data and Classification of Lobby Reports

According to Proposition 2, large firms are incentivized to lobby in favor of such regulations. In this section, we 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.[15] The lobbying reports are

[14] 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).

[15] 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).

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.[16] 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 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

[16] 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*.

as a representative set of topics that are relevant to our regulations, r_j 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.[17] 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.[18] 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., 2023; Huneeus and 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. (2023) 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

[17]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.

[18]Notice that, unlike for example Blanga-Gubbay et al. (2023) 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.

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.

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.[19]

To address these challenges, we have devised a two-step approach. Initially, we undertake the task of manually categorizing 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 "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

[19] 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".

is developed utilizing the Data Analysis tool within ChatGPT, which facilitates the application of advanced analytical techniques to discern patterns and classify reports based on their content. 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 step-by-step responses and how we provided the source files of our manual categorization and the final reports to analyze.

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. For the reports that meet this criterion, we further restrict our analysis on specific topics, namely: *agriculture, clean air quality, copyright, energy, environment, health, labor, and trade.* The goal is to build a sample that is practical to review manually, to train the machine learning model. 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.

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 3,086 reports. From this pool, 1,265 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. 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. Upon further analysis of the known sample, a distinction emerges between firms that support and those that oppose regulations. Firms with higher sales, employment, and Tobin's Q are more inclined to support regulatory measures. Conversely, firms with greater capital are more likely to oppose them. Out of the 1,850 reports with a clear stance, a significant majority (1,434 reports) express support for regulations, contrasting with 387 reports that oppose them, underscoring a general tendency among firms to favor regulatory initiatives, at least when providing a clear stance. 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. This process is facilitated by the Data Analyst tool within ChatGPT and involves dividing the data into a training set (70% of the manually categorized reports) and a test set (30%) to enable effective 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 Support Vector Machine (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, with the Logistic Regression model achieving an average accuracy of 81% and the SVM model achieving an average accuracy of 86%. 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. The Logistic model successfully classifies 34,289 reports while the SVM model 33,417. Similarly to the distribution of outcomes of the manual categorization, the majority of reports are listed as "Support" (33,203 in the Logistic model and 32,265 in the SVM model). There are only 1,086 reports that oppose regulations in the Logistic model and 1,152 in the SVM model.

To compute summary statistics, 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. Examining the average firm-level characteristics between the "Support" and "Oppose" groups, we find that supporting firms tend to be larger along most dimensions, with the exception of fixed capital, These differences are in line with the manually evaluated sample (Table B.2). In a robustness analysis below, we examine the selection of firms into a "known" policy stance.

Table 1: Summary Statistics

		Logistic		SVM	
	Compustat	Support	Oppose	Support	Oppose
Sales	19 (38)	25 (47)	18 (39)	27 (50)	21 (31)
Employment	47 (108)	59 (129)	27 (46)	62 (137)	44 (73)
Assets	72 (225)	84 (244)	36 (54)	88 (251)	50 (86)
Capital	15 (33)	19 (41)	28 (34)	21 (42)	27 (25)
Intangible	5 (12)	7 (15)	5 (11)	7 (16)	7 (14)
Tobin Q	7 (30)	7 (28)	2 (3)	6 (20)	2 (3)
Reports per firm	10 (14)	5 (6)	3 (2)	5 (6)	3 (2)
# of Reports	127,850	33,203	1,086	32,265	1,152
# of Firms	9,713	5,332	331	5,027	373

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 millions. 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. Support: reports that are classified as a "Known" stance and indicate support for more restrictive regulations. Oppose: reports that are classified as a "Known" stance and indicate opposition for more restrictive regulations. The machine algorithm is imposed on all reports, using the manually evaluated reports as an input.

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:

$$\text{Support}_{aft} = \beta_0 + \beta_1 \text{Size}_{ft} + \alpha_{ts} + \gamma_a + \epsilon_{ft} \tag{20}$$

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. Note that 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 sample includes about 10,000 observations based on the known stances, depending on whether we employ the Logistic or SVM models.

The variable Size_{ft} represents the size of the firm, and is operationalized through the natural logarithm of various size metrics, including sales, employment, capital, intangible capital, Tobin's Q, and leverage. α_{ts} represents sector-year fixed effects, 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.[20] The term ϵ_{ft} is the error term and we cluster standard errors by firm.

4.1 Firm Size and Support for Regulations

First, we estimate the regression (20) using a pooled sample of firms across all sectors. For each variable that measures firm size, we evaluate the impact of supporting regulations as predicted by both the Logistic regression model and the SVM model. In the main analysis, we examine the entire sample of classified reports. For robustness, Appendix C presents results from a subset of reports focused on the specific topics used to train our model.

In Table 2, we use firm sales as the only size characteristic and consider several specifications. In the first two columns, we report the size relationship with no fixed effects for both the Logistic and SVM model results in determining the firm stance on regulations. 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 all cases, we find the expected positive relationship between firm sales and the firm stance being pro-regulations.

In the fifth and sixth columns, we include both fixed effects together, and also weight observations based on the value amount reported for each corresponding lobbying report.

[20] 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.

This specification might more accurately reflect the actual effect on policymakers if firms that spend more money get more attention. The final columns estimate the baseline unweighted specification across a set of "selected topics" which include only topics used for our manual (training) categorization. Across the specifications, the coefficient is quite consistent. The specification with lobbying (dollar) value weights intuitively results in much stronger size effects, but the observational weights themselves might drive the result as the lobbying amount is likely correlated with the size of the firm. Our preferred specification and the one we use from now includes the full sample, both set of fixed effects, and is not weighted (columns (3) and (4)).

Table 3 extends the results on firm size, as we illustrate the relationship between a firm's sales, employment level, market share, and Tobin's Q and its support for regulations. We report the firm sales results for comparison, and observe that firms with higher employment levels are even more likely to support regulations, evidenced by a positive and statistically significant coefficient across both models. The same relationship is seen with market share, calculated as the share of sales across all firms in our Compustat sample by 3-digit NAICS industry. 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. These characteristics, especially the first three, are the firm outcomes that most closely parallel the productivity draw, φ, in our model. Previous literature has documented that larger firms are more likely to lobby (Bombardini, 2008; Blanga-Gubbay et al., 2023); we show, consistent with our model predictions, that conditional on lobbying, the larger firms are also more likely to support restrictive regulations.

Table 2: Firm Size and Firm Stance on Regulations: Specification checks

	Firm Stance = Support by Model							
	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)
Log Sales	0.0027***	0.0018**	0.0014**	0.0012*	0.0050***	0.0059***	0.0026**	0.0022*
	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0016)	(0.0015)	(0.0012)	(0.0012)
Sector*Year FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Topic FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Weighted	No	No	No	No	Yes	Yes	No	No
Selected Topics	No	No	No	No	No	No	Yes	Yes
Obs.	10,834	10,297	10,826	10,286	10,519	10,008	4,735	5,005
R2	0.001	0.000	0.147	0.192	0.182	0.292	0.163	0.160

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). We group industries into 7 sectors in order to control for sector-level fixed effects (interacted with the year dummies). The first two columns have no controls, while the next two control for topic and sector-year FEs. In columns (5) and (6), we weight by lobbying amount, while in (7) and (8), we restrict the sample to selected topics. Computed standard errors are heteroskedastic-robust. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 3: Firm Size and Firm Stance on Regulations: All Proxies

	Firm Stance =1 if Support Regulations, by Model							
	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)
Log Sales	0.002***	0.001*						
	(0.001)	(0.001)						
Log Employment			0.005***	0.003***				
			(0.001)	(0.001)				
Market Share					0.240***	0.155***		
					(0.034)	(0.051)		
Log Tobin Q							0.013***	0.015***
							(0.003)	(0.004)
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Topic FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	10,185	9,673	10,184	9,670	10,192	9,677	8,287	7,799
R2	0.140	0.191	0.142	0.192	0.142	0.192	0.146	0.196

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 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. Tobin's Q is computed as the firm's market value divided by the total assets, taken from Gutiérrez and Philippon (2017). Market value is computed (in Compustat variables) as is defined in that paper: $ME + LT + PSTK$. Computed standard errors are heteroskedastic-robust. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4.1.1 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 interactions of firm characteristics with several variables in order to capture different mechanisms. 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).[21] Column (1) reports the interaction of HHI with sales: the positive relationship between sales and lobbying in favor is larger at larger levels of HHI (or more concentration).

Related to concentration, in the next column size, is interacted with a firm-specific "product market similarity" score produced by Hoberg and Phillips (2016).[22] The goal of this measure is to identify the degree to which specific firms are similar to their competitors, which should proxy for fiercer competition (an inverse to differentiation). As expected, firms with a higher similarity score to their competitors are less likely to lobby in favor of regulations as they would find it more difficult to recoup the fixed costs from a sufficient rise in their market share.

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

[22] Hoberg and Phillips (2016) conduct textual analysis of firms' 10-K annual filings that describe products sold by the firm. They then create firm-by-firm pairwise similarity scores that are used for the "total similarity measure". The advantage of these scores is that they are calculated at the firm-level and can be matched to our Compustat sample.

According to Proposition 4, the lobbying of large firms intensifies the higher the initial level of fixed costs. As a measure of fixed costs, we explore how lobbying is influenced by the regulatory intensity of the industry. Results are in the third column of Table 4. To judge regulatory intensity, we use a measure produced in Kalmenovitz (2023), which employs a supervised machine learning algorithm to gauge the firm-specific costs of *all* federal paperwork regulations. We employ his aggregate measure at the Fama-French 48 (ff48) industry level due to endogeneity concerns of the firm-level measure.[23] The intensity measure counts the number of regulations on the books that apply to each industry. Consistent with the model, we find a higher number of regulations at the industry level is associated with firms more likely to lobby in favor of regulations, and *this effect increases with firm size*.[24]

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."[25] The last 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.

4.1.2 Selection Bias in Firm Stance Classification and its Implications

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

[23] The algorithm first ties each firm to the universe of federal regulations, then attempts to calculate the regulatory burden of each regulation. The measures are available at the firm and industry level, but we use the industry measure.

[24] We only report the interacted effect to be consistent with the rest of the table, but when we include only the regulatory intensity and size measures without the interaction effect there is a positive and significant coefficient on the regulatory intensity exposure.

[25] 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.

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

	Firm Stance =1 if Support Regulations			
	HHI-Size	Similarity-Size	RegulatoryIntens-Size	VI-Size
Log Sales	-0.001	0.002**	0.000	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
HHI (NAICS3)	-0.444**			
	(0.215)			
HHI*Sales	0.080***			
	(0.024)			
Similarity Score (HP)		-0.010		
		(0.034)		
SimilarityScore*Sales		-0.022***		
		(0.004)		
RegulatoryIntensity (Num)			-0.178*	
			(0.107)	
RegulatoryIntensity*Sales			0.032***	
			(0.011)	
VerticalIntegScore (HP)				3.068***
				(0.673)
VerticalIntegScore*Sale				-0.271***
				(0.070)
Sector*Year FE	Yes	Yes	Yes	Yes
Topic FE	Yes	Yes	Yes	Yes
Obs.	10,185	8,548	10,185	8,548
R2	0.144	0.146	0.142	0.144

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. Similarity is based on Hoberg and Phillips (2016)'s textual analysis of firms' 10-K annual filings that describe products sold by the firm. They create firm-by-firm pairwise similarity scores that are used for the "total similarity measure" for each focal firm. The industry (Fama French 48) regulation index (*RegulatoryIntensity (Num)*) is a logged variable from the one produced in Kalmenovitz (2023), which employs a supervised machine learning algorithm to gauge the firm-specific costs of all federal paperwork regulations. The interaction effect is the interaction of industry regulatory intensity with firm sales. 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. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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. (2023)). 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 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.

4.2 Alternative Determinants of Lobbying

While in our baseline model, large firms may lobby in favor of more regulations, in the extension of Section 2.5.1, we show that an alternative motivation for lobbying firms is to keep their fixed costs low. In Table 5, we investigate firm characteristics that intuitively could be linked to fixed costs and firms' stances on regulations.

Perhaps surprisingly given the size results, but consistent with Proposition 5, firms with substantial capital are more inclined to *oppose* regulations. The negative and statistically significant coefficient on (logged) total capital stock is consistent across models. These empirical findings also hold for more capital intense firms (fixed capital relative to employment). Moreover, 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.[26]

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.[27] Furthermore, the higher cost of distress risk that is associated with more leverage (Almeida and Philippon, 2007; Korteweg, 2010) is consistent with these organizations being less likely to support new restrictive rules that require adaptation.[28]

[26]In Appendix Table C.3, we complement the results on capital intensity by showing the separate effects of total fixed capital and employment, and also include a specification with debt-to-assets ratio together with employment. Firm size as proxied for employment continues to be associated with a positive probability of firms being pro-regulation, even as greater levels of fixed assets and leverage have the opposite effect (now controlling for employment). The positive effect of employment and negative effect of capital are stronger than when using these characteristics independently.

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

[28]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

Consistent with the effect on asset specificity and costs to redeployment of capital, we also find, in the last two columns of Table 5, that firms with more *intangible capital* are more likely to support regulations.[29] 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 argue more intangible-intense firms are more adaptable to regulatory change.

These results suggest 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 5: Firm Capital Intensity and Firm Stance on Regulations

	Firm Stance = 1 if Support Regulations							
	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)
Log Capital	-0.002***	-0.002***						
	(0.001)	(0.001)						
K intens. (K/L)			-0.021***	-0.016***				
			(0.002)	(0.002)				
Debt-to-Assets Ratio					-0.002*	-0.003***		
					(0.001)	(0.001)		
Intang. K Intensity							0.054***	0.056***
							(0.006)	(0.007)
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Topic FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	10,170	9,659	10,184	9,670	8,797	8,260	8,468	7,976
R2	0.140	0.191	0.152	0.197	0.104	0.179	0.150	0.200

Notes: Capital refers to total gross fixed assets (PPEGT variable in Compustat), while capital intensity is capital over employment (EMP). Debt-to-Assets ratio is the total debt (DT in Compustat) over total assest (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)). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

lobbying to garner favorable regulations.

[29] 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.

4.2.1 Mechanisms for Capital-Regulatory Stance Relationship

Table 6 reports 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 first column with an interaction of capital intensity with a firm-level measure of asset redeployability constructed in Kim and Kung (2017).[30] The positive interaction coefficient signifies that our finding of negative effects of capital intensity on the propensity to lobby for regulations *get dampened* as the firms' asset redeployability score increases.[31] In the next column, a similar interpretation can be confirmed using the scope of a firms' operations as measured in Hoberg and Phillips (2023).[32] Firms more likely to operate in a higher number of segments are less likely to lobby against regulations relative to their capital intensive peers.

Sector Sub-Samples. In Appendix Table C.4, we explore how the results hold in sector sub-samples. We report the main results from above on a sub-sample of Manufacturing, Information, and Trade sectors.[33] For each sector, we regress the firm dummy if they support a regulation on, respectively, a firm size measure (employment), capital (K/L), and intangible capital intensity. We find that the size results are driven by the Information and Trade sectors, the negative capital intensity results are driven by the Manufacturing and Trade sectors[34], and the positive intangible capital results are driven by Manufacturing and Trade. The capital intensive results are likely the most obvious, as Manufacturing and Trade are the most intensive in fixed physical assets. The size effects being present in Information likely

[30]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.

[31]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.

[32]As in the previous measure of product similarity, Hoberg and Phillips (2023) use descriptions from 10-K reports to try to gauge how many industries a firm likely belongs to.

[33]These are the 3 sectors with the largest sample size and provide the most obvious industry-specific characteristics.

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

Table 6: Firm Stance on Regulations: Heterogeneity of Capital Effects

	Firm Stance =1 if Support Regulations	
	Redeploy-Cap.	Scope-Cap.
Log Capital	-0.020***	-0.006***
	(0.005)	(0.002)
Redeployability	-0.181*	
	(0.098)	
Log ProductScopeScore (HP)		-0.017**
		(0.007)
Redeploy*Capital	0.045***	
	(0.012)	
Scope*Capital		0.002**
		(0.001)
Sector*Year FE	Yes	Yes
Topic FE	Yes	Yes
Obs.	7,303	8,740
R2	0.160	0.144

Notes: 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 (2023) that uses descriptions from 10-K reports to try to gauge how many industries a firm likely belongs to. In both columns the firm exposure measures are interacted with log capital stock. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

reflects the fast-growing and concentrated technology industries being more likely to lobby for regulations.

5 Conclusion

This paper offers a novel perspective on the intersection of firm heterogeneity, regulatory policy, and lobbying. Our findings challenge the conventional wisdom that firms universally oppose stringent regulations, revealing that larger firms may strategically support such measures to enhance their market position by driving out less productive competitors. This result is firmly grounded in a standard theoretical framework of firm heterogeneity. Moreover, our empirical analysis, employing a machine-learning algorithm, uncovers a positive correlation between firm size and support for more stringent regulations, particularly in concentrated industries. These results are consistent across various proxies for firm size and remain robust under different specifications. The observed inverse relationship between capital intensity, leverage, and lobbying behavior introduces additional complexity, suggesting that a firm's flexibility is a critical factor in determining its stance on regulatory changes.

Our findings have significant policy implications, particularly for international cooperation in regulatory agreement setting, which is a growing field of research (Grossman et al., 2021; Parenti and Vannoorenberghe, 2022; Macedoni and Weinberger, 2024). In Appendix A.3.2, we demonstrate that unilateral regulatory actions can lead to suboptimal outcomes by failing to account for positive externalities on foreign firms' profits. Cooperation among governments can result in more optimal regulatory levels, benefiting either larger or smaller firms depending on the government's bias. For instance, governments might prioritize the profits of their own large firms over smaller ones, yet their regulatory policies may not assist those firms abroad. Through cooperation, more stringent regulations can be implemented in a manner that benefits large foreign firms domestically, in exchange for foreign policies that favor a country's own large firms abroad. Investigating the role of lobbying in the context of international regulatory agreements presents a promising avenue for future research.

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Appendix

A Model Derivations

A.1 Equilibrium

Let us begin by computing aggregate revenues:

$$T_{ij} = J_i \int_{\varphi_{ij}^*}^{\infty} \kappa b_i^{\kappa} t_{ij}(\varphi) \varphi^{-\kappa-1} d\varphi = \tag{21}$$

$$= J_i \kappa b_i^{\kappa} \sigma w_j f_j h(r_j) (\varphi_{ij}^*)^{\kappa-(\sigma-1-\alpha\beta)} \int_{\varphi_{ij}^*}^{\infty} \varphi^{-\kappa+\sigma-2} d\varphi = \tag{22}$$

$$= \frac{J_i \kappa b_i^{\kappa} \sigma w_j f_j h(r_j)}{\kappa - \sigma + 1} (\varphi_{ij}^*)^{-\kappa+\alpha\beta} = \tag{23}$$

$$= \frac{\kappa \sigma w_j f_j h(r_j)}{\kappa - \sigma + 1} (w_j \tau_{jj})^{-\frac{(-\kappa+\alpha\beta)(\sigma-1)}{\sigma-1-\alpha\beta}} (\varphi_{jj}^*)^{-\kappa+\alpha\beta} J_i b_i^{\kappa} (w_i \tau_{ij})^{\frac{(-\kappa+\alpha\beta)(\sigma-1)}{\sigma-1-\alpha\beta}} \tag{24}$$

To ease notation, let:

$$\tilde{\kappa} = \frac{(\kappa - \alpha\beta)(\sigma - 1)}{\sigma - 1 - \alpha\beta} \tag{25}$$

We can write the cutoff from i to j as a function of the domestic cutoff of destination j:

$$\varphi_{ij}^* = \varphi_{jj}^* \left(\frac{w_i \tau_{ij}}{w_j \tau_{jj}} \right)^{\frac{\sigma-1}{\sigma-1-\alpha\beta}}$$

Aggregate revenues can then be written as:

$$T_{ij} = \frac{\kappa \sigma w_j f_j h(r_j)}{\kappa - \sigma + 1} (w_j \tau_{jj})^{\tilde{\kappa}} (\varphi_{jj}^*)^{-\kappa+\alpha\beta} J_i b_i^{\kappa} (w_i \tau_{ij})^{-\tilde{\kappa}} \tag{26}$$

We can write the gravity equation as:

$$\lambda_{ij} = \frac{T_{ij}}{\sum_{v=1}^{I} T_{vj}} = \frac{J_i b_i^{\kappa} (w_i \tau_{ij})^{-\tilde{\kappa}}}{\sum_{v=1}^{I} J_v b_v^{\kappa} (w_v \tau_{vj})^{-\tilde{\kappa}}} \tag{27}$$

Let us now consider the expected profits from i to j

$$E[\pi_{ij}] = \int_{\varphi_{ij}^*}^{\infty} \kappa b_i^{\kappa} \pi_{ij}(\varphi) \varphi^{-\kappa-1} d\varphi = \tag{28}$$

$$= \kappa b_i^{\kappa} w_j f_j h(r_j) \int_{\varphi_{ij}^*}^{\infty} \left((\varphi_{ij}^*)^{-(\sigma-1-\alpha\beta)} \varphi^{\sigma-1} - \varphi^{\alpha\beta} \right) \varphi^{-\kappa-1} d\varphi = \tag{29}$$

$$= \kappa b_i^\kappa w_j f_j h(r_j) \left[\frac{(\varphi_{ij}^*)^{-\kappa+\alpha\beta}}{\kappa - \sigma + 1} - \frac{(\varphi_{ij}^*)^{-\kappa+\alpha\beta}}{\kappa - \alpha\beta} \right] = \tag{30}$$

$$= \frac{\kappa(\sigma - 1 - \alpha\beta) b_i^\kappa w_j f_j h(r_j)}{(\kappa - \sigma + 1)(\kappa - \alpha\beta)} (\varphi_{ij}^*)^{-\kappa+\alpha\beta} = \tag{31}$$

$$= \frac{T_{ij}(\sigma - 1 - \alpha\beta)}{J_i \sigma(\kappa - \alpha\beta)} \tag{32}$$

Therefore, the zero profit condition yields the mass of entrants:

$$E[\pi_i] = \sum_{j=1}^{I} E[\pi_{ij}] = w_i f_E \tag{33}$$

$$\frac{(\sigma - 1 - \alpha\beta)}{J_i \sigma(\kappa - \alpha\beta)} \sum_{j=1}^{I} T_{ij} = w_i f_E \tag{34}$$

$$\frac{(\sigma - 1 - \alpha\beta)}{J_i \sigma(\kappa - \alpha\beta)} w_i L_i = w_i f_E \tag{35}$$

$$J_i = \frac{L_i}{f_E} \frac{\sigma(\kappa - \alpha\beta)}{(\sigma - 1 - \alpha\beta)} \quad \forall i = 1, ..., I \tag{36}$$

Substituting this result into the gravity equation (27), we obtain:

$$\lambda_{ij} = \frac{L_i b_i^\kappa (w_i \tau_{ij})^{-\tilde{\kappa}}}{\sum_{v=1}^{I} L_v b_v^\kappa (w_v \tau_{vj})^{-\tilde{\kappa}}} \quad \forall i, j = 1, ..., I \tag{37}$$

A.2 Government

A.2.1 Consumer's Utility

The indirect consumer's utility equals

$$U_j = \frac{w_j}{P_j} \tag{38}$$

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:

$$P_j = \left[\kappa \sum_{i=1}^{I} J_i b_i^\kappa \int_{\varphi_{ij}^*} p_{ij}(\varphi)^{1-\sigma} \varphi^{-\kappa-1} d\varphi \right]^{\frac{1}{1-\sigma}} = \tag{39}$$

$$= \frac{\sigma}{\sigma - 1} \left[\kappa \sum_{i=1}^{I} J_i b_i^{\kappa} (\tau_{ij} w_i m(r_j))^{-(\sigma-1)} \int_{\varphi_{ij}^*} \varphi^{-\kappa+\sigma-2} d\varphi \right]^{\frac{1}{1-\sigma}} = \tag{40}$$

$$= \frac{\sigma m(r_j)}{\sigma - 1} \left[\frac{\kappa}{\kappa - \sigma + 1} \sum_{i=1}^{I} J_i b_i^{\kappa} (\tau_{ij} w_i)^{-(\sigma-1)} (\varphi_{ij}^*)^{-\kappa+\sigma-1} \right]^{\frac{1}{1-\sigma}} = \tag{41}$$

$$= \frac{\sigma m(r_j)}{\sigma - 1} \left[(\varphi_{jj}^*)^{-\kappa+\sigma-1} (\tau_{jj} w_j)^{-\frac{(-\kappa+\sigma-1)(\sigma-1)}{(\sigma-1-\alpha\beta)}} \frac{\kappa}{\kappa - \sigma + 1} \sum_{i=1}^{I} J_i b_i^{\kappa} (\tau_{ij} w_i)^{-(\sigma-1)+\frac{(-\kappa+\sigma-1)(\sigma-1)}{(\sigma-1-\alpha\beta)}} \right]^{\frac{1}{1-\sigma}} = \tag{42}$$

$$= \frac{\sigma m(r_j)}{\sigma - 1} \left[(\varphi_{jj}^*)^{-\kappa+\sigma-1} (\tau_{jj} w_j)^{-\frac{(-\kappa+\sigma-1)(\sigma-1)}{(\sigma-1-\alpha\beta)}} \frac{\kappa}{\kappa - \sigma + 1} \sum_{i=1}^{I} J_i b_i^{\kappa} (\tau_{ij} w_i)^{-\frac{(\kappa-\alpha\beta)(\sigma-1)}{\sigma-1-\alpha\beta}} \right]^{\frac{1}{1-\sigma}} = \tag{43}$$

$$= \frac{\sigma m(r_j)}{\sigma - 1} \left[(\varphi_{jj}^*)^{-\kappa+\sigma-1} (\tau_{jj} w_j)^{-\frac{(-\kappa+\sigma-1)(\sigma-1)}{(\sigma-1-\alpha\beta)}} \frac{\kappa}{\kappa - \sigma + 1} \sum_{i=1}^{I} J_i b_i^{\kappa} (\tau_{ij} w_i)^{-\tilde{\kappa}} \right]^{\frac{1}{1-\sigma}} = \tag{44}$$

$$= \frac{\sigma m(r_j)}{\sigma - 1} \left[(\varphi_{jj}^*)^{-\kappa+\sigma-1} (\tau_{jj} w_j)^{-\frac{(-\kappa+\sigma-1)(\sigma-1)}{(\sigma-1-\alpha\beta)}} \frac{\kappa}{\kappa - \sigma + 1} \lambda_{jj}^{-1} J_j b_j^{\kappa} (\tau_{jj} w_j)^{-\frac{(\kappa-\alpha\beta)(\sigma-1)}{\sigma-1-\alpha\beta}} \right]^{\frac{1}{1-\sigma}} = \tag{45}$$

$$= \frac{\sigma(\tau_{jj} w_j m(r_j))}{\sigma - 1} \left[(\varphi_{jj}^*)^{-\kappa+\sigma-1} \frac{\kappa}{\kappa - \sigma + 1} \lambda_{jj}^{-1} \frac{L_j}{f_E} \frac{\sigma(\kappa - \alpha\beta)}{(\sigma - 1 - \alpha\beta)} b_j^{\kappa} \right]^{\frac{1}{1-\sigma}} = \tag{46}$$

$$= \frac{\sigma (b_j^{\kappa} L_j)^{\frac{1}{1-\sigma}} (\tau_{jj} w_j m(r_j)) \lambda_{jj}^{-\frac{1}{1-\sigma}}}{\sigma - 1} \left[\frac{\sigma\kappa(\kappa - \alpha\beta)}{f_E(\kappa - \sigma + 1)(\sigma - 1 - \alpha\beta)} \right]^{\frac{1}{1-\sigma}} (\varphi_{jj}^*)^{\frac{-\kappa+\sigma-1}{1-\sigma}} = \tag{47}$$

$$= \frac{\sigma(\tau_{jj} w_j m(r_j)) \lambda_{jj}^{\frac{1}{\sigma-1}}}{(\sigma - 1)(b_j^{\kappa} L_j)^{\frac{1}{\sigma-1}}} \left[\frac{f_E(\kappa - \sigma + 1)(\sigma - 1 - \alpha\beta)}{\sigma\kappa(\kappa - \alpha\beta)} \right]^{\frac{1}{\sigma-1}} (\varphi_{jj}^*)^{\frac{\kappa-\sigma+1}{\sigma-1}} \tag{48}$$

Let us now substitute in the definition of the productivity cutoff:

$$\varphi_{jj}^* = \left[\frac{\sigma^{\sigma} (f_j m(r_j)^{\sigma-1} h(r_j)) (w_j \tau_{jj})^{(\sigma-1)}}{(\sigma - 1)^{\sigma-1} L_j P_j^{\sigma-1}} \right]^{\frac{1}{\sigma-1-\alpha\beta}}$$

$$= \left[\frac{\sigma^{\sigma} (f_j h(r_j)) (w_j \tau_{jj} m(r_j))^{(\sigma-1)}}{(\sigma - 1)^{\sigma-1} L_j P_j^{\sigma-1}} \right]^{\frac{1}{\sigma-1-\alpha\beta}}$$

We obtain:

$$P_j = \frac{\sigma(\tau_{jj} w_j m(r_j)) \lambda_{jj}^{\frac{1}{\sigma-1}}}{(\sigma-1)(b_j^{\kappa} L_j)^{\frac{1}{\sigma-1}}} \left[\frac{f_E(\kappa-\sigma+1)(\sigma-1-\alpha\beta)}{\sigma\kappa(\kappa-\alpha\beta)}\right]^{\frac{1}{\sigma-1}} \left[\frac{\sigma^{\sigma}(f_j h(r_j))\,(w_j \tau_{jj} m(r_j))^{(\sigma-1)}}{(\sigma-1)^{\sigma-1} L_j P_j^{\sigma-1}}\right]^{\frac{\kappa-\sigma+1}{(\sigma-1-\alpha\beta)(\sigma-}} \tag{49}$$

$$\left(\frac{P_j L_j^{\frac{1}{\sigma-1}}(\sigma-1)}{\sigma\tau_{jj} w_j m(r_j)}\right)^{1+\frac{\kappa-\sigma+1}{\sigma-1-\alpha\beta}} = \left[\frac{\sigma^{\frac{\kappa-\sigma+1}{\sigma-1-\alpha\beta}} f_E(\kappa-\sigma+1)(\sigma-1-\alpha\beta)}{\sigma\kappa(\kappa-\alpha\beta)}\right]^{\frac{1}{\sigma-1}} (f_j h(r_j))^{\frac{\kappa-\sigma+1}{(\sigma-1-\alpha\beta)(\sigma-1)}} \left(\frac{\lambda_{jj}}{b_j^{\kappa}}\right)^{\frac{1}{\sigma-1}} \tag{50}$$

$$\left(\frac{P_j L_j^{\frac{1}{\sigma-1}}(\sigma-1)}{\sigma\tau_{jj} w_j m(r_j)}\right)^{\frac{\tilde{\kappa}}{\sigma-1}} = \left[\frac{\sigma^{\frac{\kappa-\sigma+1}{\sigma-1-\alpha\beta}} f_E(\kappa-\sigma+1)(\sigma-1-\alpha\beta)}{\sigma\kappa(\kappa-\alpha\beta)}\right]^{\frac{1}{\sigma-1}} (f_j h(r_j))^{\frac{\kappa-\sigma+1}{(\sigma-1-\alpha\beta)(\sigma-1)}} \left(\frac{\lambda_{jj}}{b_j^{\kappa}}\right)^{\frac{1}{\sigma-1}} \tag{51}$$

$$\frac{P_j L_j^{\frac{1}{\sigma-1}}(\sigma-1)}{\sigma\tau_{jj} w_j m(r_j)} = \left[\frac{\sigma^{\frac{\kappa-\sigma+1}{\sigma-1-\alpha\beta}} f_E(\kappa-\sigma+1)(\sigma-1-\alpha\beta)}{\sigma\kappa(\kappa-\alpha\beta)}\right]^{\frac{1}{\tilde{\kappa}}} (f_j h(r_j))^{\frac{\kappa-\sigma+1}{\tilde{\kappa}(\sigma-1-\alpha\beta)}} \left(\frac{\lambda_{jj}}{b_j^{\kappa}}\right)^{\frac{1}{\tilde{\kappa}}} \tag{52}$$

$$\frac{w_j}{P_j} = \frac{L_j^{\frac{1}{\sigma-1}}(\sigma-1) f_j^{-\frac{\kappa-\sigma+1}{(\kappa-\alpha\beta)(\sigma-1)}}}{\sigma\tau_{jj} h(r_j)^{\frac{\kappa-\sigma+1}{(\kappa-\alpha\beta)(\sigma-1)}} m(r_j)} \left[\frac{\sigma^{\frac{\kappa-\sigma+1}{\sigma-1-\alpha\beta}} f_E(\kappa-\sigma+1)(\sigma-1-\alpha\beta)}{\sigma\kappa(\kappa-\alpha\beta)}\right]^{-\frac{1}{\tilde{\kappa}}} \left(\frac{\lambda_{jj}}{b_j^{\kappa}}\right)^{-\frac{1}{\tilde{\kappa}}} \tag{53}$$

Let

$$P_o = \frac{\sigma-1}{\sigma} \left[\frac{\sigma^{\frac{\kappa-\sigma+1}{\sigma-1-\alpha\beta}} f_E(\kappa-\sigma+1)(\sigma-1-\alpha\beta)}{\sigma\kappa(\kappa-\alpha\beta)}\right]^{-\frac{1}{\tilde{\kappa}}} \tag{54}$$

The utility of consumers equal:

$$U_j = P_o \frac{b_j^{\frac{\kappa}{\tilde{\kappa}}} L_j^{\frac{1}{\sigma-1}}}{\tau_{jj}} f_j^{-\frac{\kappa-\sigma+1}{(\kappa-\alpha\beta)(\sigma-1)}} h(r_j)^{-\frac{\kappa-\sigma+1}{(\kappa-\alpha\beta)(\sigma-1)}} m(r_j)^{-1} \lambda_{jj}^{-\frac{1}{\tilde{\kappa}}} \tag{55}$$

A.2.2 Cutoff

Finally, we can re-write the cutoff as:

$$\varphi_{jj}^{*} = \left[\frac{\sigma^{\sigma}(f_j h(r_j))\,(w_j \tau_{jj} m(r_j))^{(\sigma-1)}}{(\sigma-1)^{\sigma-1} L_j P_j^{\sigma-1}}\right]^{\frac{1}{\sigma-1-\alpha\beta}} =$$

$$= \left[\frac{\sigma^{\sigma}(f_j h(r_j))\,(w_j \tau_{jj} m(r_j))^{(\sigma-1)}\, P_o^{\sigma-1} \frac{L_j}{(w_j\tau_{jj})^{\sigma-1}} f_j^{-\frac{\kappa-\sigma+1}{(\kappa-\alpha\beta)(\sigma-1)}} h(r_j)^{-\frac{\kappa-\sigma+1}{(\kappa-\alpha\beta)(\sigma-1)}} m(r_j)^{-(\sigma-1)} \left(\frac{\lambda_{jj}}{b_j^{\kappa}}\right)^{-\frac{\sigma-1}{\tilde{\kappa}}}}{(\sigma-1)^{\sigma-1} L_j}\right]^{\frac{1}{\sigma-1-}}$$

$$= \left[\frac{\sigma^\sigma P_o^{\sigma-1} (f_j h(r_j))^{\frac{\sigma-1-\alpha\beta}{\kappa-\alpha\beta}} \left(\frac{\lambda_{jj}}{b_j^\kappa}\right)^{-\frac{\sigma-1}{\tilde{\kappa}}}}{(\sigma-1)^{\sigma-1}} \right]^{\frac{1}{\sigma-1-\alpha\beta}} =$$

$$= \left[\frac{\sigma^\sigma P_o^{\sigma-1}}{(\sigma-1)^{\sigma-1}} \right]^{\frac{1}{\sigma-1-\alpha\beta}} (f_j h(r_j))^{\frac{1}{\kappa-\alpha\beta}} \left(\frac{\lambda_{jj}}{b_j^\kappa}\right)^{-\frac{\sigma-1}{\frac{(\kappa-\alpha\beta)(\sigma-1)}{\sigma-1-\alpha\beta}(\sigma-1-\alpha\beta)}} =$$

$$= \varphi_o \left(\frac{b_j^\kappa f_j h(r_j)}{\lambda_{jj}} \right)^{\frac{1}{\kappa-\alpha\beta}}$$

where

$$\varphi_o = \left[\frac{\sigma^\sigma P_o^{\sigma-1}}{(\sigma-1)^{\sigma-1}} \right]^{\frac{1}{\sigma-1-\alpha\beta}} \tag{56}$$

Hence, the cutoff depends on the regulation only through its effect on fixed costs and not on marginal costs.

A.2.3 Externality

The total quantity of variety φ exported from i to j equals:

$$L_j q_{ij}(\varphi) = \left(\frac{\sigma-1}{\sigma}\right)^\sigma L_j w_j P_j^{\sigma-1} (w_i \tau_{ij} m(r_j))^{-\sigma} \varphi^\sigma =$$

$$= \left(\frac{\sigma-1}{\sigma}\right)^\sigma \frac{w_j \sigma^\sigma (f_j h(r_j)) (w_j \tau_{jj} m(r_j))^{(\sigma-1)}}{(\varphi_{jj}^*)^{\sigma-1-\alpha\beta}} (w_i \tau_{ij} m(r_j))^{-\sigma} \varphi^\sigma =$$

$$= \frac{(\sigma-1) w_j (f_j h(r_j)) (w_j \tau_{jj} m(r_j))^{(\sigma-1)}}{(\varphi_{jj}^*)^{\sigma-1-\alpha\beta}} (w_i \tau_{ij} m(r_j))^{-\sigma} \varphi^\sigma =$$

$$= \frac{(\sigma-1) w_j f_j h(r_j) m(r_j)^{-1}}{\tau_{jj} (\varphi_{jj}^*)^{\sigma-1-\alpha\beta}} \left(\frac{w_i \tau_{ij}}{w_j \tau_{jj}}\right)^{-\sigma} \varphi^\sigma$$

Hence, the externality generated in j from the consumption of products from i equals:

$$E_{ij} = J_i b_i^\kappa \kappa \int_{\varphi_{ij}^*}^\infty L_j q_{ij}(\varphi) e(\varphi) \varphi^{-\kappa-1} d\varphi =$$

$$= J_i b_i^\kappa \frac{(\sigma-1) w_j f_j h(r_j) m(r_j)^{-1}}{\tau_{jj} (\varphi_{jj}^*)^{\sigma-1-\alpha\beta}} \left(\frac{w_i \tau_{ij}}{w_j \tau_{jj}}\right)^{-\sigma} \kappa \int_{\varphi_{ij}^*}^\infty \varphi^{\beta+\sigma-\kappa-1} d\varphi =$$

$$= J_i b_i^\kappa \frac{(\sigma-1) w_j f_j h(r_j) m(r_j)^{-1}}{\tau_{jj} (\varphi_{jj}^*)^{\sigma-1-\alpha\beta}} \left(\frac{w_i \tau_{ij}}{w_j \tau_{jj}}\right)^{-\sigma} \frac{\kappa}{\kappa-\beta-\sigma} (\varphi_{ij}^*)^{\beta+\sigma-\kappa} =$$

$$= L_i b_i^\kappa \frac{\sigma\kappa(\sigma-1)(\kappa-\alpha\beta) w_j f_j h(r_j) m(r_j)^{-1}}{f_E(\kappa-\beta-\sigma)(\sigma-1-\alpha\beta)\tau_{jj}(\varphi_{jj}^*)^{\sigma-1-\alpha\beta}} \left(\frac{w_i \tau_{ij}}{w_j \tau_{jj}}\right)^{-\sigma} (\varphi_{ij}^*)^{\beta+\sigma-\kappa} =$$

$$
\begin{aligned}
&= L_i b_i^\kappa \frac{\sigma\kappa(\sigma-1)(\kappa-\alpha\beta)w_j f_j h(r_j) m(r_j)^{-1}}{f_E(\kappa-\beta-\sigma)(\sigma-1-\alpha\beta)\tau_{jj}(\varphi_{jj}^*)^{\sigma-1-\alpha\beta}} \left(\frac{w_i\tau_{ij}}{w_j\tau_{jj}}\right)^{-\sigma} (\varphi_{jj}^*)^{\beta+\sigma-\kappa} \left(\frac{w_i\tau_{ij}}{w_j\tau_{jj}}\right)^{\frac{(\sigma-1)(\beta+\sigma-\kappa)}{\sigma-1-\alpha\beta}} = \\
&= L_i b_i^\kappa \frac{\sigma\kappa(\sigma-1)(\kappa-\alpha\beta)w_j f_j h(r_j) m(r_j)^{-1}}{f_E(\kappa-\beta-\sigma)(\sigma-1-\alpha\beta)\tau_{jj}} (\varphi_{jj}^*)^{-\kappa+(1+\alpha)\beta+1} \left(\frac{w_i\tau_{ij}}{w_j\tau_{jj}}\right)^{\frac{(\sigma-1)(\beta-\kappa)+\sigma\alpha\beta}{\sigma-1-\alpha\beta}} = \\
&= L_i b_i^\kappa \frac{\sigma\kappa(\sigma-1)(\kappa-\alpha\beta)w_j f_j h(r_j) m(r_j)^{-1}}{f_E(\kappa-\beta-\sigma)(\sigma-1-\alpha\beta)\tau_{jj}} \left(\frac{w_i\tau_{ij}}{w_j\tau_{jj}}\right)^{\frac{(\sigma-1)(\beta-\kappa)+\sigma\alpha\beta}{\sigma-1-\alpha\beta}} \left[\varphi_o \left(\frac{b_j^\kappa f_j h(r_j)}{\lambda_{jj}}\right)^{\frac{1}{\kappa-\alpha\beta}}\right]^{-\kappa+\beta+\alpha\beta+1} = \\
&= \varphi_o^{-\kappa+\beta+\alpha\beta+1} \frac{\sigma\kappa(\kappa-\alpha\beta)(\sigma-1)}{f_E(\sigma-1-\alpha\beta)(\kappa-\beta-\sigma)} \frac{L_i b_i^\kappa f_j h(r_j) m(r_j)^{-1}}{\tau_{jj}} \left(\frac{w_i\tau_{ij}}{w_j\tau_{jj}}\right)^{\frac{(\sigma-1)(\beta-\kappa)+\sigma\alpha\beta}{\sigma-1-\alpha\beta}} \left(\frac{b_j^\kappa f_j h(r_j)}{\lambda_{jj}}\right)^{\frac{-\kappa+\beta+\alpha\beta+1}{\kappa-\alpha\beta}} \\
&= e_o \frac{L_i b_i^\kappa f_j h(r_j) m(r_j)^{-1}}{\tau_{jj}} \left(\frac{w_i\tau_{ij}}{w_j\tau_{jj}}\right)^{\frac{(\sigma-1)(\beta-\kappa)+\sigma\alpha\beta}{\sigma-1-\alpha\beta}} \left(\frac{b_j^\kappa f_j h(r_j)}{\lambda_{jj}}\right)^{\frac{-\kappa+\beta+\alpha\beta+1}{\kappa-\alpha\beta}} = \\
&= e_o \frac{f_j h(r_j) m(r_j)^{-1}}{\tau_{jj}\left(w_j\tau_{jj}\right)^{\frac{(\sigma-1)(\beta-\kappa)+\sigma\alpha\beta}{\sigma-1-\alpha\beta}}} \left(\frac{b_j^\kappa f_j h(r_j)}{\lambda_{jj}}\right)^{\frac{-\kappa+\beta+\alpha\beta+1}{\kappa-\alpha\beta}} L_i b_i^\kappa \left(w_i\tau_{ij}\right)^{\frac{(\sigma-1)(\beta-\kappa)+\sigma\alpha\beta}{\sigma-1-\alpha\beta}} = \\
&= e_o \frac{f_j h(r_j) m(r_j)^{-1}}{\tau_{jj}} \left(w_j\tau_{jj}\right)^{\tilde{\beta}-\tilde{\alpha}} \left(\frac{b_j^\kappa f_j h(r_j)}{\lambda_{jj}}\right)^{\frac{-\kappa+\beta+\alpha\beta+1}{\kappa-\alpha\beta}} L_i b_i^\kappa \left(w_i\tau_{ij}\right)^{-\tilde{\beta}+\tilde{\alpha}} = \\
&= e_o \frac{f_j^{\frac{\beta+1}{\kappa-\alpha\beta}}}{\tau_{jj}} \left(w_j\tau_{jj}\right)^{\tilde{\beta}-\tilde{\alpha}} \left(\frac{b_j^\kappa}{\lambda_{jj}}\right)^{\frac{-\kappa+\beta+\alpha\beta+1}{\kappa-\alpha\beta}} h(r_j)^{\frac{\beta+1}{\kappa-\alpha\beta}} m(r_j)^{-1} L_i b_i^\kappa \left(w_i\tau_{ij}\right)^{-\tilde{\beta}+\tilde{\alpha}}
\end{aligned}
$$

where

$$e_o = \frac{\kappa\sigma(\kappa-\alpha\beta)\varphi_o^{-(\kappa-\beta)}}{f_E(\kappa-\beta)(\sigma-1-\alpha\beta)} \tag{57}$$

and

$$\tilde{\beta} = \frac{(\kappa-\beta)(\sigma-1)}{\sigma-1-\alpha\beta} \tag{58}$$

and

$$\tilde{\alpha} = \frac{\sigma\alpha\beta}{\sigma-1-\alpha\beta} \tag{59}$$

The regulation affects the externality in two ways. First, by raising marginal costs ($m'(r_j) > 0$), it reduces production of all surviving firms and, thus, it reduces the externality. Second, by raising the fixed costs, it affects selection, so that only the most productive firms (which are the ones that produce more, but emit less per unit of output if $\alpha < 0$) survive. This reduces the externality if $\beta + 1 < 0$. Recall that if more productive firms emit less per unit of output, $\beta < 0$.

To simplify the notation, let

$$\lambda_{ij}^E = \frac{E_{ij}}{\sum_{v=1}^I E_{vj}} = \frac{L_i b_i^\kappa \left(w_i\tau_{ij}\right)^{-\tilde{\beta}+\tilde{\alpha}}}{\sum_{v=1}^I L_v b_v^\kappa \left(w_v\tau_{vj}\right)^{-\tilde{\beta}+\tilde{\alpha}}} \tag{60}$$

which we can interpret as the externality gravity equation: the share of externality in country j that is caused by goods produced by i.

The aggregate externality in country j equals:

$$
\begin{aligned}
E_j &= E_o \left(\sum_{i=1}^{I} E_{ij} \right)^{-\epsilon} = \\
&= E_o e_o^{-\epsilon} \frac{f_j^{\frac{-\epsilon(\beta+1)}{\kappa-\alpha\beta}}}{\tau_{jj}^{-\epsilon}} (w_j \tau_{jj})^{\epsilon(-\tilde{\beta}+\tilde{\alpha})} \left(\frac{b_j^{\kappa}}{\lambda_{jj}} \right)^{-\frac{(-\kappa+\beta+\alpha\beta+1)\epsilon}{\kappa-\alpha\beta}} h(r_j)^{\frac{-\epsilon(\beta+1)}{\kappa-\alpha\beta}} m(r_j)^{\epsilon} \left(\sum_{i=1}^{I} L_i b_i^{\kappa} (w_i \tau_{ij})^{-\tilde{\beta}+\tilde{\alpha}} \right)^{-\epsilon} = \\
&= E_o e_o^{-\epsilon} \frac{f_j^{\frac{-\epsilon(\beta+1)}{\kappa-\alpha\beta}}}{\tau_{jj}^{-\epsilon}} (w_j \tau_{jj})^{\epsilon(\tilde{\beta}-\tilde{\alpha})} \left(\frac{b_j^{\kappa}}{\lambda_{jj}} \right)^{\frac{-(-\kappa+\beta+\alpha\beta+1)\epsilon}{\kappa-\alpha\beta}} h(r_j)^{\frac{-\epsilon(\beta+1)}{\kappa-\alpha\beta}} m(r_j)^{\epsilon} \left(L_j b_j^{\kappa} (w_j \tau_{jj})^{-\tilde{\beta}+\tilde{\alpha}} \right)^{-\epsilon} (\lambda_{jj}^{E})^{\epsilon} = \\
&= E_o e_o^{-\epsilon} \frac{f_j^{\frac{-\epsilon(\beta+1)}{\kappa-\alpha\beta}}}{\tau_{jj}^{-\epsilon}} \left(\frac{b_j^{\kappa}}{\lambda_{jj}} \right)^{\frac{-(-\kappa+\beta+\alpha\beta+1)\epsilon}{\kappa-\alpha\beta}} h(r_j)^{\frac{-\epsilon(\beta+1)}{\kappa-\alpha\beta}} m(r_j)^{\epsilon} \left(L_j b_j^{\kappa} \right)^{-\epsilon} (\lambda_{jj}^{E})^{\epsilon} = \\
&= E_o e_o^{-\epsilon} \tau_{jj}^{\epsilon} f_j^{\frac{-\epsilon(\beta+1)}{\kappa-\alpha\beta}} \left(\frac{b_j^{\kappa}}{\lambda_{jj}} \right)^{\epsilon-\frac{(\beta+1)\epsilon}{\kappa-\alpha\beta}} \left(L_j b_j^{\kappa} \right)^{-\epsilon} (\lambda_{jj}^{E})^{\epsilon} h(r_j)^{\frac{-\epsilon(\beta+1)}{\kappa-\alpha\beta}} m(r_j)^{\epsilon} \\
&= E_o e_o^{-\epsilon} \tau_{jj}^{\epsilon} L_j^{-\epsilon} \left(\frac{b_j^{\kappa} \lambda_{jj}}{f_j} \right)^{\frac{(\beta+1)\epsilon}{\kappa-\alpha\beta}} \left(\frac{\lambda_{jj}^{E}}{\lambda_{jj}} \right)^{\epsilon} h(r_j)^{\frac{-\epsilon(\beta+1)}{\kappa-\alpha\beta}} m(r_j)^{\epsilon}
\end{aligned}
$$

A.2.4 Profits

Let us solve Π_i^g :

$$
\begin{aligned}
\Pi_i^g &= \sum_{j=1}^{I} J_i b_i^{\kappa} \kappa \int_{\varphi_{ij}^*}^{\infty} \varphi^{\delta} w_j f_j h(r_j) \left((\varphi_{ij}^*)^{-(\sigma-1-\alpha\beta)} \varphi^{\sigma-1} - \varphi^{\alpha\beta} \right) \varphi^{-\kappa-1} d\varphi = \\
&= J_i b_i^{\kappa} \kappa \sum_{j=1}^{I} w_j f_j h(r_j) \int_{\varphi_{ij}^*}^{\infty} \left((\varphi_{ij}^*)^{-(\sigma-1-\alpha\beta)} \varphi^{-\kappa+\delta+\sigma-2} - \varphi^{-\kappa+\delta+\alpha\beta-1} \right) d\varphi = \\
&= J_i b_i^{\kappa} \kappa \sum_{j=1}^{I} w_j f_j h(r_j) \left(\frac{1}{\kappa-\delta-\sigma+1} - \frac{1}{\kappa-\delta-\alpha\beta} \right) (\varphi_{ij}^*)^{-\kappa+\delta+\alpha\beta} = \\
&= J_i b_i^{\kappa} \frac{\kappa(\sigma-1-\alpha\beta)}{(\kappa-\delta-\sigma+1)(\kappa-\delta-\alpha\beta)} \sum_{j=1}^{I} w_j f_j h(r_j) (\varphi_{ij}^*)^{-\kappa+\delta+\alpha\beta} = \\
&= \frac{(\sigma-1-\alpha\beta)(\kappa-\sigma+1)}{\sigma(\kappa-\delta-\sigma+1)(\kappa-\delta-\alpha\beta)} \sum_{j=1}^{I} \underbrace{\frac{\sigma\kappa}{\kappa-\sigma+1} J_i b_i^{\kappa} w_j f_j h(r_j) (\varphi_{ij}^*)^{-\kappa+\alpha\beta}}_{=T_{ij}} (\varphi_{ij}^*)^{\delta} = \\
&= \pi_o \sum_{j=1}^{I} T_{ij} (\varphi_{ij}^*)^{\delta} =
\end{aligned}
$$

$$= \pi_o \sum_{j=1}^{I} \lambda_{ij} w_j L_j (\varphi^*_{jj})^{\delta} \left(\frac{w_i \tau_{ij}}{w_j \tau_{jj}}\right)^{\frac{\delta(\sigma-1)}{\sigma-1-\alpha\beta}} =$$

$$= \pi_o \varphi_o^{\delta} \sum_{j=1}^{I} \lambda_{ij} w_j L_j \left(\frac{b_j^{\kappa} f_j h(r_j)}{\lambda_{jj}}\right)^{\frac{\delta}{\kappa-\alpha\beta}} \left(\frac{w_i \tau_{ij}}{w_j \tau_{jj}}\right)^{\frac{\delta(\sigma-1)}{\sigma-1-\alpha\beta}}$$

where

$$\pi_o = \frac{(\sigma - 1 - \alpha\beta)(\kappa - \sigma + 1)}{\sigma(\kappa - \delta - \sigma + 1)(\kappa - \delta - \alpha\beta)} \tag{61}$$

A.3 Optimal Regulation

The government's utility can be written as:

$$\begin{aligned} U_j^g &= U_j + E_j + \gamma \Pi_j^g = \\ &= P_o \frac{b_j^{\frac{\kappa}{\tilde{\kappa}}} L_j^{\frac{1}{\sigma-1}}}{\tau_{jj}} f_j^{-\frac{\kappa-\sigma+1}{(\kappa-\alpha\beta)(\sigma-1)}} h(r_j)^{-\frac{\kappa-\sigma+1}{(\kappa-\alpha\beta)(\sigma-1)}} m(r_j)^{-1} \lambda_{jj}^{-\frac{1}{\tilde{\kappa}}} + \\ &+ E_o e_o^{-\epsilon} \tau_{jj}^{\epsilon} L_j^{-\epsilon} \left(\frac{b_j^{\kappa} \lambda_{jj}}{f_j}\right)^{\frac{(\beta+1)\epsilon}{\kappa-\alpha\beta}} \left(\frac{\lambda_{jj}^E}{\lambda_{jj}}\right)^{\epsilon} h(r_j)^{\frac{-\epsilon(\beta+1)}{\kappa-\alpha\beta}} m(r_j)^{\epsilon} + \\ &+ \pi_o \varphi_o^{\delta} \sum_{v=1}^{I} \lambda_{jv} w_v L_v \left(\frac{b_v^{\kappa} f_v h(r_v)}{\lambda_{vv}}\right)^{\frac{\delta}{\kappa-\alpha\beta}} \left(\frac{w_j \tau_{jv}}{w_v \tau_{vv}}\right)^{\frac{\delta(\sigma-1)}{\sigma-1-\alpha\beta}} \end{aligned}$$

To highlight the various components, let us introduce the following variables:

$$\tilde{U}_j = P_o \frac{b_j^{\frac{\kappa}{\tilde{\kappa}}} L_j^{\frac{1}{\sigma-1}}}{\tau_{jj}} f_j^{-\frac{\kappa-\sigma+1}{(\kappa-\alpha\beta)(\sigma-1)}} \lambda_{jj}^{-\frac{1}{\tilde{\kappa}}} \tag{62}$$

$$\tilde{E}_j = E_o e_o^{-\epsilon} \tau_{jj}^{\epsilon} L_j^{-\epsilon} \left(\frac{b_j^{\kappa} \lambda_{jj}}{f_j}\right)^{\frac{(\beta+1)\epsilon}{\kappa-\alpha\beta}} \left(\frac{\lambda_{jj}^E}{\lambda_{jj}}\right)^{\epsilon} \tag{63}$$

$$\tilde{\pi}_{jv} = \pi_o \varphi_o^{\delta} \lambda_{jv} w_v L_v \left(\frac{b_v^{\kappa} f_v}{\lambda_{vv}}\right)^{\frac{\delta}{\kappa-\alpha\beta}} \left(\frac{w_j \tau_{jv}}{w_v \tau_{vv}}\right)^{\frac{\delta(\sigma-1)}{\sigma-1-\alpha\beta}} \tag{64}$$

As reported in the main text, the utility can be written as:

$$U_j^g = \tilde{U}_j h(r_j)^{-\frac{\kappa-\sigma+1}{(\kappa-\alpha\beta)(\sigma-1)}} m(r_j)^{-1} + \tilde{E}_j h(r_j)^{\frac{-\epsilon(\beta+1)}{\kappa-\alpha\beta}} m(r_j)^{\epsilon} + \sum_{v=1}^{I} \tilde{\pi}_{jv} h(r_v)^{\frac{\delta}{\kappa-\alpha\beta}} \tag{65}$$

A.3.1 Profits and Regulations

In this section, we show the relationship between equilibrium profits and regulations. Recall that the profits of a firm from j in j equal:

$$\pi_{jj}(\varphi) = w_j f_j h(r_j) \left((\varphi_{jj}^*)^{-(\sigma-1-\alpha\beta)} \varphi^{\sigma-1} - \varphi^{\alpha\beta} \right) \tag{66}$$

where the cutoff is defined as:

$$\varphi_{jj}^* = \varphi_o \left(\frac{b_j^\kappa f_j h(r_j)}{\lambda_{jj}} \right)^{\frac{1}{\kappa-\alpha\beta}} \tag{67}$$

and where

$$\varphi_o = \left[\frac{\sigma^\sigma P_o^{\sigma-1}}{(\sigma-1)^{\sigma-1}} \right]^{\frac{1}{\sigma-1-\alpha\beta}} \tag{68}$$

Let us consider the derivative of the cutoff with respect to regulations:

$$\frac{\partial \varphi_{jj}^*}{\partial r_j} = \varphi_o \left(\frac{b_j^\kappa f_j h(r_j)}{\lambda_{jj}} \right)^{\frac{1}{\kappa-\alpha\beta}} \frac{1}{\kappa-\alpha\beta} \frac{h'(r_j)}{h(r_j)} = \frac{\varphi_{jj}^*}{\kappa-\alpha\beta} \frac{h'(r_j)}{h(r_j)} \tag{69}$$

We can now study the effects of a change in r_j on profits:

$$\frac{\partial \pi_{jj}(\varphi)}{\partial r_j} = w_j f_j h'(r_j) \left((\varphi_{jj}^*)^{-(\sigma-1-\alpha\beta)} \varphi^{\sigma-1} - \varphi^{\alpha\beta} \right) + \tag{70}$$

$$- (\sigma-1-\alpha\beta) w_j f_j h(r_j) (\varphi_{jj}^*)^{-(\sigma-1-\alpha\beta)-1} \varphi^{\sigma-1} \frac{\partial \varphi_{jj}^*}{\partial r_j} = \tag{71}$$

$$= w_j f_j h'(r_j) \left((\varphi_{jj}^*)^{-(\sigma-1-\alpha\beta)} \varphi^{\sigma-1} - \varphi^{\alpha\beta} \right) + \tag{72}$$

$$- \frac{\sigma-1-\alpha\beta}{\kappa-\alpha\beta} w_j f_j h'(r_j) (\varphi_{jj}^*)^{-(\sigma-1-\alpha\beta)} \varphi^{\sigma-1} = \tag{73}$$

$$= w_j f_j h'(r_j) \left[(\varphi_{jj}^*)^{-(\sigma-1-\alpha\beta)} \varphi^{\sigma-1} \left(1 - \frac{\sigma-1-\alpha\beta}{\kappa-\alpha\beta} \right) - \varphi^{\alpha\beta} \right] = \tag{74}$$

$$= w_j f_j h'(r_j) \left[(\varphi_{jj}^*)^{-(\sigma-1-\alpha\beta)} \varphi^{\sigma-1} \left(\frac{\kappa-\sigma+1}{\kappa-\alpha\beta} \right) - \varphi^{\alpha\beta} \right] \tag{75}$$

Hence, $\frac{\partial \pi_{jj}(\varphi)}{\partial r_j} > 0$ if

$$(\varphi_{jj}^*)^{-(\sigma-1-\alpha\beta)} \varphi^{\sigma-1} \left(\frac{\kappa-\sigma+1}{\kappa-\alpha\beta} \right) > \varphi^{\alpha\beta} \tag{76}$$

$$\varphi^{\sigma-1-\alpha\beta} \left(\frac{\kappa-\sigma+1}{\kappa-\alpha\beta} \right) > (\varphi_{jj}^*)^{\sigma-1-\alpha\beta} \tag{77}$$

$$\varphi > \varphi^*_{jj} \left(\frac{\kappa - \alpha\beta}{\kappa - \sigma + 1} \right)^{\frac{1}{\sigma - 1 - \alpha\beta}} \tag{78}$$

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

A.3.2 Unilateral regulation VS cooperation

In this section, we prove that international cooperation leads to a different optimal level of regulations relative to the case in which countries choose regulations unilaterally. Consider the FOC of the problem for country j that chooses r_j unilaterally:

$$\begin{aligned} \text{FOC}_{uni}(r_j) = \frac{\partial U^g_j}{\partial r_j} &= \left(- \frac{(\kappa - \sigma + 1)}{(\kappa - \alpha\beta)(\sigma - 1)} \frac{h'(r_j)}{h(r_j)} - \frac{m'(r_j)}{m(r_j)} \right) \tilde{U}_j h(r_j)^{-\frac{\kappa - \sigma + 1}{(\kappa - \alpha\beta)(\sigma - 1)}} m(r_j)^{-1} + \\ &+ \left(\frac{\epsilon(-\beta - 1)}{\kappa - \alpha\beta} \frac{h'(r_j)}{h(r_j)} + \epsilon \frac{m'(r_j)}{m(r_j)} \right) \tilde{E}_j h(r_j)^{\frac{-\epsilon(\beta+1)}{\kappa - \alpha\beta}} m(r_j)^{\epsilon} + \\ &+ \frac{\delta}{\kappa - \alpha\beta} \frac{h'(r_j)}{h(r_j)} \tilde{\pi}_{jj} h(r_j)^{\frac{\delta}{\kappa - \alpha\beta}} = 0 \end{aligned}$$

Notice that FOC_{uni} is increasing in r_j.

Let us now consider the optimal regulation r_j that would be chosen in cooperation across countries. The FOC would be given by:

$$\text{FOC}_{coop}(r_j) = \text{FOC}_{uni}(r_j) + \frac{\delta}{\kappa - \alpha\beta} \sum_{v \neq j} \tilde{\pi}_{vj} \frac{h'(r_j)}{h(r_j)} h(r_v)^{\frac{\delta}{\kappa - \alpha\beta}} = 0$$

Hence, in cooperation the effect of r_j on the profits of firms from other countries are internalized. Since $\text{FOC}_{uni}(r_j)$ is increasing in r_j, and assuming that $h'(r_j) > 0$, we obtain the following relationship between the optimal regulation set under cooperation (r_j^{coop}) and in the unilateral case r_j^{uni}:

$$\begin{aligned} r_j^{coop} &> r_j^{uni} \qquad \text{if } \delta > 0 \\ r_j^{coop} &= r_j^{uni} \qquad \text{if } \delta = 0 \\ r_j^{coop} &< r_j^{uni} \qquad \text{if } \delta < 0 \end{aligned}$$

When δ is positive, the optimal regulation under cooperation is higher than under unilateral decision-making. This is because the cooperative approach internalizes the positive externalities that r_j has on other countries, leading to a higher level of regulation. Hence, when governments have a bias for larger firms, cooperation leads to more restrictive regulations. When δ is zero, the optimal regulation is the same whether decided unilaterally or cooperatively. Finally, when δ is negative, the optimal regulation under cooperation is lower than under unilateral decision-making. Here, governments have a bias for smaller firms, and the cooperatively set regulation is less restrictive that the unilateral one.

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:

$$F_i^g = -\sum_{j=1}^{I} \int_{\varphi_{ij}^*}^{\infty} f_j(e(\varphi), r_j)^{1+\zeta} g(\varphi) d\varphi \tag{79}$$

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 $f_j(e(\varphi), r_j) = w_j f_j e(\varphi)^\alpha h(r_j) = w_j f_j \varphi^{\alpha\beta} h(r_j)$ 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_i^g:

$$\begin{aligned}
F_i^g &= -\sum_{j=1}^{I} J_i b_i^\kappa (w_j f_j h(r_j))^\zeta \kappa \int_{\varphi_{ij}^*}^{\infty} w_j f_j h(r_j) \varphi^{\zeta\alpha\beta+\alpha\beta-\kappa-1} d\varphi = \\
&= -\frac{\kappa}{\kappa - \zeta\alpha\beta - \alpha\beta} \sum_{j=1}^{I} (w_j f_j h(r_j))^{1+\zeta} J_i b_i^\kappa (\varphi_{ij}^*)^{-\kappa+\zeta\alpha\beta+\alpha\beta} = \\
&= -\frac{\kappa(\kappa-\sigma+1)}{\sigma(\kappa-\zeta\alpha\beta-\alpha\beta)} \sum_{j=1}^{I} \underbrace{\frac{\sigma\kappa}{\kappa-\sigma+1} J_i b_i^\kappa w_j f_j h(r_j) (\varphi_{ij}^*)^{-\kappa+\alpha\beta}}_{=T_{ij}} (w_j f_j h(r_j))^\zeta (\varphi_{ij}^*)^{\zeta\alpha\beta} =
\end{aligned}$$

$$= -\pi_o \sum_{j=1}^{I} T_{ij}(w_j f_j h(r_j))^{\zeta}(\varphi_{ij}^*)^{\zeta\alpha\beta} =$$
$$= -\pi_o \sum_{j=1}^{I} \lambda_{ij} w_j L_j \left(\frac{w_i \tau_{ij}}{w_j \tau_{jj}}\right)^{\frac{\delta(\sigma-1)}{\sigma-1-\alpha\beta}} (w_j f_j h(r_j))^{\zeta}(\varphi_{ij}^*)^{\zeta\alpha\beta} =$$
$$= -\pi_o \varphi_o^{\zeta\alpha\beta} \sum_{j=1}^{I} \lambda_{ij} w_j L_j \left(\frac{w_i \tau_{ij}}{w_j \tau_{jj}}\right)^{\frac{\delta(\sigma-1)}{\sigma-1-\alpha\beta}} \left(\frac{b_j^{\kappa} f_j h(r_j)}{\lambda_{jj}}\right)^{\frac{\zeta\alpha\beta}{\kappa-\alpha\beta}} (w_j f_j h(r_j))^{\zeta}$$
$$= -\pi_o \varphi_o^{\zeta\alpha\beta} \sum_{j=1}^{I} \lambda_{ij} w_j L_j \left(\frac{w_i \tau_{ij}}{w_j \tau_{jj}}\right)^{\frac{\delta(\sigma-1)}{\sigma-1-\alpha\beta}} \left(\frac{b_j^{\kappa} f_j}{\lambda_{jj}}\right)^{\frac{\zeta\alpha\beta}{\kappa-\alpha\beta}} (w_j f_j)^{\zeta} h(r_j)^{\frac{\zeta\kappa}{\kappa-\alpha\beta}}$$

where

$$\pi_o = \frac{\kappa(\kappa - \sigma + 1)}{\sigma(\kappa - \zeta\alpha\beta - \alpha\beta)} \tag{80}$$

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	Secretary of the Senate
Legislative Resource Center	Office of Public Records
B-106 Cannon Building	232 Hart Building
Washington, DC 20515	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

6. House ID # 31984000

TYPE OF REPORT 8. Year 2006 Midyear (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 definitions 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

Edit Form > File with House >
Senate Password File with Senate >

Signature THOMAS F BEDDOW Date 8/14/2006

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

LD-2DS (Rev. 4.07)

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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

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
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 Shortage—export shortage—Export shortage—Export Shortages—export shortages—Export Certificate of Origin—export certificate of origin—Export Certificate of Origin
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

Model Evaluation: LogReg & TF-IDF

September 19, 2024

ⓘ This chat contains files or images produced by Advanced Data Analysis which are not yet visible in Shared Chats.

---

file_for_learning.xlsx
Spreadsheet

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 Logistic Regression model using TF-IDF vectorization 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 method to any additional datasets you have for lobbying report classification.

To begin, I'll follow the instructions provided:

1. **Introduction and Data Upload:**
   - I will first load the dataset you uploaded to understand its structure and content.
2. **Machine Learning Model Training and Application:**
   - I will proceed to train a Logistic Regression model using TF-IDF vectorization on a portion of the data.

- I'll then evaluate the model with a classification report and confusion matrix on the test data.

3. **Final Steps:**
   - After training and evaluating the model, I'll be ready to apply this method to any additional datasets you have for lobbying report classification.

Let's start by loading and examining the uploaded dataset.

The dataset contains two columns: `issue_text` , which likely contains text from lobbying reports, and `outcome` , which classifies these reports into categories "Not Known," "Oppose," and "Support."

Next, I will split the data into a training set and a test set. Then, I will train a Logistic Regression model using TF-IDF vectorization on the training set and evaluate its performance on the test set with a classification report and confusion matrix. Let's proceed with these steps.

The Logistic Regression model has been trained and evaluated on the test data. Here are the results:

Classification Report:

markdown Copy code

```
              precision    recall  f1-score   support

   Not Known       0.67      1.00      0.80         2
      Oppose       1.00      0.75      0.86         4
     Support       0.86      0.86      0.86         7

    accuracy                           0.85        13
   macro avg       0.84      0.87      0.84        13
weighted avg       0.88      0.85      0.85        13
```

Confusion Matrix:

The confusion matrix, with labels ordered as "Not Known", "Oppose", "Support", is presented as:

lua Copy code

```lua
[[2, 0, 0],
 [1, 3, 0],
 [0, 1, 6]]
```

This matrix is read as follows:

- For "Not Known": 2 correct predictions, and no incorrect predictions for "Oppose" or "Support".
- For "Oppose": 1 misclassified as "Not Known", 3 correct predictions, and none misclassified as "Support".
- For "Support": none misclassified as "Not Known", 1 misclassified as "Oppose", and 6 correct predictions.

These results provide a detailed view of the model's performance across the different categories. If you have additional datasets for lobbying report classification, we can proceed to apply this trained model to them.

all_reports.xlsx
Spreadsheet

please apply the model to the attached file and provide the answers in a separate file

I will apply the trained Logistic Regression model to classify the text in the newly uploaded file, `all_reports.xlsx`. After processing, I'll save the results to a separate file. Let's start by loading and applying the model to the new dataset.

It seems there was an issue applying the model to the new dataset, specifically an `AttributeError` related to the Logistic Regression model. This error typically occurs if the model was not properly trained or saved in the previous steps, which could have been caused by a disruption in the session state or an error in the model training process.

To resolve this, I'll retrain the model on the original dataset and then apply it to the new dataset again. Let's proceed with these steps.

The process of retraining the model and applying it to the new dataset took longer than expected and was interrupted due to time constraints. This could be due to the size of the dataset or the complexity of the text data being processed.

To address this, I will attempt to streamline the process by either optimizing the model training step or processing the new dataset in smaller batches. Let me try a more efficient approach.

It looks like the variable `output_file_path` was not defined due to the interruption of the previous execution. I'll define it again and proceed with saving the data with predictions to a new Excel file.

The model has been successfully applied to the new dataset, and the results with predictions have been saved to an Excel file. You can download the classified reports using the link below:

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. 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 53,000 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.[35] 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.

In our manually evaluated sample, the firms are generally larger than those in both the full dataset and similar in size to the subsets with clear language indications of support or opposition. Notice that this sample only includes reports from selected topics and the average values are in line with the entire sample of reports for the same topics (column "Sub Codes"). This sample of manually evaluated reports consists of 3,086 reports, among which there are numerous duplicates—reports with identical text across different years. From this pool, 1,265 reports were categorized as "Not Known", and 1,821 were identified as "Known" (classified either as "Support" or "Oppose").

Upon further analysis of the "Known" sample, a distinction emerges between firms that support and those that oppose regulations. Firms with higher sales, employment, and Tobin's Q are more inclined to support regulatory measures. Conversely, firms with greater capital are more likely to oppose them. Out of the 1,850 reports with a clear stance, a significant majority (1,434 reports) express support for regulations, contrasting with 387 reports that oppose them, underscoring a general tendency among larger firms to favor regulatory initiatives.

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

Table B.2: Summary Statistics for Manually Categorized Reports

	Compustat	Sub Codes	Clear Lang.	Manually Eva.	Not Known	Support	Oppose
Sales	19	23	24	25	26	30	25
	(38)	(44)	(40)	(46)	(42)	(49)	(41)
Employment	47	57	60	63	57	83	77
	(108)	(130)	(124)	(137)	(98)	(163)	(146)
Assets	72	56	69	57	71	57	43
	(225)	(183)	(207)	(177)	(203)	(126)	(54)
Capital	15	18	22	22	23	22	30
	(33)	(37)	(40)	(41)	(42)	(38)	(30)
Intangible	5	6	8	9	9	11	8
	(12)	(14)	(18)	(18)	(17)	(19)	(16)
Tobin Q	7	6	6	7	4	13	2
	(30)	(26)	(20)	(23)	(7)	(34)	(2)
Reports	10	7	4	3	2	3	3
per firm	(14)	(7)	(5)	(3)	(2)	(3)	(2)
# of Reports	127,850	53,600	8,168	3,086	1,265	1,434	387
# of Firms	9,713	6,302	1,801	895	493	408	143

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 millions. 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.

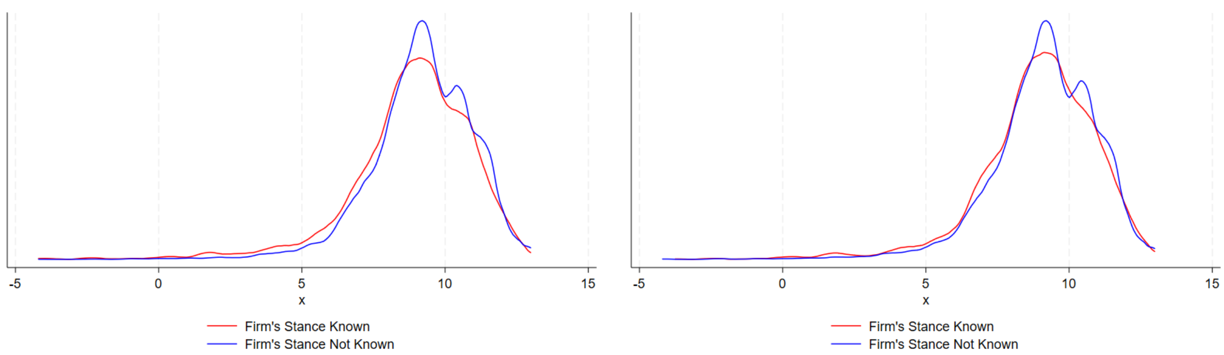
C Regression Analysis Supplementary Material

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

(a) Logistic Model **(b)** SVM Model



The plots show the kernel density plots 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.

Table C.2: Firm Size and Firm Stance on Regulations: All Proxies

	Firm Stance = Support by Model					
	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)
Log Sales	-0.015***	-0.008***				
	(0.001)	(0.001)				
Log Employment			-0.012***	-0.005***		
			(0.001)	(0.001)		
Market Share					-0.034**	0.037**
					(0.017)	(0.017)
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	0.170	0.203	0.168	0.202	0.173	0.209

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 two separate textual classification models (Logistic and SVM). 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: Firm Capital Intensity and Firm Stance on Regulations: Add Employment

	Firm Stance =1 if Support Regulations							
	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)	(Logistic Model)	(SVM Model)
Log Capital	-0.020***	-0.016***					-0.021***	-0.018***
	(0.001)	(0.002)					(0.002)	(0.002)
Log Employment	0.023***	0.017***	0.003***	0.002***	0.005***	0.003***	0.017***	0.007**
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
Debt-to-Assets Ratio			-0.002*	-0.003***			-0.001	-0.004***
			(0.001)	(0.001)			(0.001)	(0.001)
Intang. K Intensity					0.057***	0.057***		
					(0.006)	(0.007)		
Log Intang. K							0.008***	0.013***
							(0.003)	(0.003)
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Topic FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	10,166	9,656	8,790	8,254	8,463	7,972	7,083	6,578
R2	0.156	0.200	0.105	0.181	0.153	0.201	0.137	0.200

Notes: In this table we include size and capital measures together in the specification. In the first three pair of columns we include employment plus one of: fixed capital, debt-to-assets ratio, or intangible capital intensity. In the last pair of columns we include all measures together. 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)). In the last two columns we use the level of intangible capital (in logs) because the intensity measure has total capital in the denominator. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table C.4: Firm Stances on Regulations by Broad Sector

	Firm Stance =1 if Support Regulations using SVM Model								
	(Manufacturing)	(Information)	(Trade)	(Manufacturing)	(Information)	(Trade)	(Manufacturing)	(Information)	(Trade)
Log Employment	0.000	0.008**	0.012***						
	(0.001)	(0.004)	(0.003)						
K intens. (K/L)				-0.003*	0.009	-0.037***			
				(0.002)	(0.009)	(0.004)			
Intang. K Intensity							0.025***	-0.033	0.165***
							(0.009)	(0.021)	(0.025)
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Topic FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	5,067	1,103	1,947	5,067	1,103	1,947	3,796	1,082	1,792
R2	0.132	0.093	0.239	0.132	0.088	0.252	0.154	0.090	0.274

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)). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.