Persuasion in the Political Marketplace: How Firms Snitch on Rivals to Encourage Regulatory Enforcement

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Abstract

We study an important, but largely overlooked, non-market strategy used by firms in the enforcement stage of policy: "snitching", i.e. providing intelligence about potential violations of their rivals in an attempt to persuade regulators to fine them. Building on political marketplace theory, we develop and test a theoretical model of how firms use snitching during regulatory enforcement. We show that in equilibrium, firms snitch when the rival's violations are likely to cause significant harm to the population. We then derive several boundary conditions outlining when firms will engage in more or less snitching. We find support for our theory in panel data on enforcement actions by the U.S. Environmental Protection Agency for more than 8,000 facilities over 12 years.

1 Introduction

Research on corporate political activities (CPA) frequently conceptualizes the political engagement of firms through the lens of the *political marketplace*, where companies demand public policy and government actors supply it (Hillman et al., 2004; Bonardi et al., 2005; Katic and Hillman, 2023). The literature shows that participation in this marketplace allows firms to secure a range of economic benefits through lobbying and campaign contributions (e.g. Bonardi et al., 2006; Richter et al., 2009; Ridge et al., 2017; Barber and Diestre, 2019; Huneeus and Kim, 2021). However, the vast majority of this research studies the *rule-setting* stage, the phase of the policy process in which laws and regulations are drafted and passed. Far less is known about how firms use CPA to secure benefits during the *enforcement stage*, when government regulators monitor adherence and can fine violators. This is despite the fact that regulatory compliance is costly for firms (e.g. Kalaitzandonakes et al., 2007) and that evading rules can confer competitive advantages (Becker, 1968; Magat and Viscusi, 1990), giving firms strong incentives to use CPA to shape how enforcement is carried out.

In this article, we study an important but largely overlooked non-market strategy used at the enforcement stage: firms' provision of information about potential violations by industry *rivals* to persuade regulators to fine them. The origin of this strategy lies in the fundamentally different role that regulators assume during enforcement relative to rule-setting. At the rule-setting stage, politicians and agencies make decisions over policies on which various stakeholders have different preferences, so they are interest mediators and the final rule will be a weighted average of stakeholders' preferences. The goal of CPA at this stage is to pull regulators towards a firm's ideal point (e.g. Becker, 1983; Hillman et al., 2004). In contrast, during the enforcement stage, a regulatory agency is responsible for ensuring that firms comply with established rules by detecting and penalizing violations, acting as a referee or detective. In fulfilling this role, regulatory agents are faced with an asymmetric information problem, and thus value receiving intelligence about infractions committed by facilities they monitor.

This asymmetric information problem provides an opportunity for firms to use CPA to influence the enforcement process by "snitching", that is by providing intelligence about potential violations of their competitors. Of course, gathering and communicating such information is costly. One significant cost lies in firms' ability to access and persuade the regulator, who may perceive firms' intelligence as biased or unreliable. However, the literature on CPA consistently finds that firms with long-standing relationships with regulators have better access and are more likely to sway them to gain benefits (see e.g. Snyder, 1992; Drutman, 2015). Thus, we argue pre-existing relationship between a firm and a regulator, established through prior CPA on unrelated issues, serves as a channel for the strategic transmission of information (Austen-Smith, 1993, 1996) and reduces the cost of information provision (Hillman and Hitt, 1999). In other words, in the political marketplace, such pre-existing relationships allow firms to shape enforcement to their advantage while helping regulators address the asymmetric information problem they face during enforcement.

We formalize this logic through a model of costly Bayesian persuasion (Kamenica and Gentzkow, 2011; Gentzkow and Kamenica, 2014), which explicitly links our theoretical arguments to empirically testable propositions. Our model characterizes the strategic interaction between a regulator and two competing firms. One firm (the "rival") may violate regulations, and the other firm (the "snitch") can produce a costly report to persuade the regulator to sanction it. The reporting cost decreases with the snitch's CPA, which facilitates the strategic transmission of information. In equilibrium, reporting on the rival's violations occurs *only* when they are likely to cause significant harm. In such cases, the snitch can most effectively leverage its CPA to persuade the regulator to initiate enforcement, as the snitch's incentives to curb the rival's unfair advantage align with the regulator's preferences for addressing harmful violations. We also derive several boundary conditions underpinning our proposed mechanism. First, firms need to be able to obtain private information about rivals' non-compliance, which is less costly if the offending and snitching firms are geographically proximate and when the offending firms' production processes align closely with industry standards. Second, firms must have sufficient motivation to disclose competitors' infringements, which is the case when there is greater competitive aggressiveness in an industry, and for high-performing rivals.

We then provide empirical evidence that is consistent with our theory's implications using panel data on fines issued by the U.S. Environmental Protection Agency (EPA) for over 8,000 facilities from all publicly listed companies in more than 90 industries over 12 years. To measure the ongoing exchange of information between firms and the EPA, we gather information on CPA towards the EPA (proxied by lobbying expenditures) by the parent companies of the facilities, as well as CPA towards the EPA by *other companies in the same industry.* Our results consistently show that more CPA by competitors increases the likelihood that the EPA penalizes facilities where violations are more likely to result in serious harm (proxied by the amount of toxic chemicals processed in a facility). Conversely, facilities that process less toxic chemicals are less likely to be fined if they are in industries where competitors engage in more CPA. This suggests that competitor CPA provides the EPA with information that allows it to concentrate its punitive actions more effectively. Interestingly, we find that a firm's *own* CPA has no significant effect reducing its own fines. Finally, in line with the boundary conditions of our theoretical mechanism, we find that the strength of the effect of competitor CPA depends on firms' ability to gain information about their rivals, and their motivation to disclose it.

This article makes several contributions to the literature on CPA and the political marketplace. First, by focusing on the understudied setting of regulatory enforcement, we reveal new and subtle aspects of the political marketplace. Existing work on the enforcement stage focuses on how firms' *own* CPA shapes how they are treated by a regulator (e.g. Yu and Yu, 2011; Correia, 2014; Lambert, 2018). However, research on the rule-setting stage shows that only examining a focal firm's CPA provides an incomplete understanding of outcomes (e.g. Bonardi et al., 2006; Fremeth et al., 2014, 2016, 2022). We show that ignoring the strategic nature of CPA between rival companies provides an incomplete view of enforcement as well. In addition, we demonstrate that CPA at the enforcement stage is more persuasive when it aligns with the regulator's preferences for addressing harmful violations. Our theoretical and empirical account thus reveals a nuanced and contingent political marketplace within the enforcement stage.

Second, we contribute to an ongoing discussion about when and how firms lobby. A strand of CPA research examines when firms work together or alone (e.g. Hillman and Hitt, 1999; de Figueiredo and Tiller, 2001; Hansen et al., 2005) and when acting collectively or individually is a complement or substitute (Jia, 2014). By examining the regulatory enforcement stage, we show that firms engage in CPA not just to help themselves, but also to harm rivals. Importantly, we show that the ability and desire to harm rivals depends on various characteristics, leading to heterogeneity in which industries are more likely to use CPA to pursue rivals and which firms within industries are more likely to be targeted by a regulator.

Finally, our argument contributes to the literature that highlights the channels through which CPA can improve social welfare. Lobbying has been shown to have the potential to truthfully convey policy-relevant information and to enhance the quality of policymaking (e.g. Potters and van

Winden, 1992; Grossman and Helpman, 2001). We show that the same can be true for regulatory enforcement. Our study finds that the political marketplace can provide a regulatory agency with valuable information that helps it to detect high-risk violations, and thus CPA can help agencies better fulfill their institutional missions. This offers a contrast to the literature on regulatory capture, which finds that firms can shape regulation in their favor, often at the expense of public interest groups (e.g. Dal Bó, 2006; Lambert, 2018; Hadani et al., 2018).

THEORETICAL BACKGROUND

Our argument builds on political marketplace theory, which conceptualizes firms as demanders and government officials as suppliers of political outcomes (e.g. Bonardi et al., 2005; Hillman et al., 2004; Hadani et al., 2018; Katic and Hillman, 2023). Firms pursue favorable political outcomes by offering incentives aligned with the preferences of government officials. These exchanges provide officials with valuable resources, and they reciprocate by delivering political benefits to firms. Through this mutually beneficial relationship, firms gain influence over the laws, rules, and regulations that govern them, often with considerable success (Dal Bó, 2006; Barley, 2007; de Figueiredo, 2009).

The vast majority of the literature on the political marketplace focuses on the *rule-setting stage*, where firms try to influence policy enacted by elected legislators or regulatory agencies. There is clear and consistent evidence that firms can obtain firm-specific benefits during this stage. For example, CPA has been linked to increased governmental contracts (Ridge et al., 2017), lower tax rates (Richter et al., 2009), increased profits (Huneeus and Kim, 2021), and higher prices set by regulators (Bonardi et al., 2006). Further, studies show that CPA changes the adaptation of regulation during the review process (Haeder and Yackee, 2015), affects the speed or content of regulators' decisions (Barber and Diestre, 2019), and leads to favorable policies (de Figueiredo and Edwards, 2007).

However, the rule-setting stage of policy is followed by another: the *enforcement stage*. While the literature on the political marketplace provides a great deal of insight into how firms can use CPA to influence rule-setting, less is known about how firms use CPA to affect enforcement outcomes. This is an important oversight for several reasons. First, the creation of a policy matters only if it is enforced. Thus, any benefits from regulation secured through CPA during the rule-setting stage depends on the government successfully ensuring compliance with that policy. Second, firms devote considerable resources to complying with government regulations (e.g. Kalaitzandonakes et al., 2007). Therefore, firms have an incentive to skirt costly regulation to gain an advantage over their competitors (Becker, 1968; Magat and Viscusi, 1990). Finally, policy enforcement is one of the most important jobs of government agencies, and the main task of many of their employees (Pierre and Peters, 2012). Thus, the enforcement stage is crucial for both firms and regulatory agencies, making it a key setting for the political marketplace.

Research on the political marketplace during enforcement is relatively limited, and examines how firms' CPA affects their *own* chances of being audited and fined for rule violations (Correia, 2014; Lambert, 2018; Yu and Yu, 2011). Thus, the focus is on the dyadic relationship between firms and regulators. However, we know from research on the political marketplace during rule-setting that the regulatory outcome is the product of the political activities of *multiple* actors (e.g. Bonardi et al., 2006; Fremeth et al., 2014; Haeder and Yackee, 2015; Fremeth et al., 2016; de Figueiredo and Edwards, 2007; Kingsley et al., 2012). Likewise, ignoring such strategic interactions between rival companies provides an incomplete view of how CPA affects *enforcement*.

Importantly, theoretical accounts which examine the strategic interactions among competing firms and the regulator in the political marketplace during the rule-setting stage do not directly translate to the enforcement stage. This is because the role that a regulatory agency plays during enforcement is fundamentally different from the one it plays during rule-setting. The underlying model in the literature on the political marketplace during rule-setting is one of a tug-of-war, where regulatory agencies (or legislators) are interest mediators being simultaneously pulled in different directions. The goal of CPA is to move the regulator towards a firm's preferred policy ideal point (Becker, 1983; Hillman et al., 2004). In this setting, successful CPA strategies constrain regulators' choice sets in a way that benefits the firm, and regulators make decisions over rules that balance the interests of various actors, such as firms (Bonardi et al., 2006; Barber and Diestre, 2019), NGOs (Hiatt and Park, 2013), social movements (Fremeth et al., 2022), politicians (Holburn and Vanden Bergh, 2006, 2014), and the agency's own preferences (Hiatt and Park, 2013). This means there is no ideal way for an agency to set the rules, as long as it remains within the confines of the law passed by the legislature. Instead, it makes a decision that balances the (differently weighted) policy preferences of various stakeholders.

This is very different from the *enforcement stage*, where regulatory agencies are rule enforcers rather than interest mediators. Here, their legal mandate is to ensure that firms are following the established rules, and to punish those that are not. The role of a regulator is therefore akin to a referee or a detective. Unlike at the rule-setting stage, there *is* an ideal way to do enforcement, namely, to catch and punish violations, especially those that are most harmful to the population. This implies that regulators face a different set of incentives during the enforcement stage than during rule-setting, as their performance can be more objectively assessed by their success in identifying violations. Motivated by career advancement (Alesina and Tabellini, 2007; Bertrand et al., 2020), regulatory agents are often incentivized to pursue the most harmful violations (Duflo et al., 2018; Schinkel et al., 2020) as the most effective way to advance their agency's institutional goals given limited resources, and thereby enhance their own standing within the agency (Khan et al., 2019; Bertrand et al., 2020).

Naturally, firms have incentives to evade regulations (Becker, 1968; Magat and Viscusi, 1990), and discovering violations is not straightforward. In particular, regulators lack information about which *specific firms* are violating rules in what *specific ways*. This impedes effective monitoring. To overcome this information asymmetry during the enforcement stage, regulatory agencies need to spend time and effort to discover which firms are violating the rules. These resources are scarce, and detecting infractions through inspections is difficult, so the probability of an agency catching violators is often low (cf. Friesen, 2003). This makes the provision of information valuable for regulators, and transforms the way firms deploy CPA to engage with regulators.

In particular, we highlight that during enforcement, firms have the option of providing information about specific violations committed by their competitors. If the regulatory agency uses this intelligence, a firm can shape whom the regulator targets for enforcement. Anecdotal evidence supports that regulatory agencies do use information provided by industry rivals in their enforcement decisions. For instance, a book on EPA enforcement based on nearly 200 interviews observes:

> When the Agency conducts an investigation on the basis of citizen information, that information may have come from a variety of individuals. Citizen informants often include disgruntled employees of suspected violators, neighbors, state or local inspectors, environmental citizens' organizations, *and suspected violators' economic competitors.* (Mintz, 2012, 11, emphasis added).

This was confirmed to us by a senior official who works in the compliance and enforcement department at EPA's headquarters:

> Firms do not like to expend the funds needed to comply and then be undersold by competitors who do not do so, which is why some of them have come forward to not only disclose the violations of their competitors but also to urge EPA to take enforcement action against such entities.

However, this does not mean that firms always provide such information about their competitors. Collecting and supplying intelligence is costly, and prone to omission errors. This, in turn, means that non-complying firms may go undetected even when rivals are willing to share intelligence with the regulator. In the next section, we formalize this logic with a theoretical model of strategic persuasion in regulatory enforcement. Consistent with the core assumptions of political marketplace theory, we assume that all actors are self-interested and that firms can deploy CPA to provide information to regulators. Regulators, in turn, leverage this information to target violations likely to cause significant harm to advance their agency's institutional goals. Within this framework, we derive the equilibrium conditions under which one firm violates regulatory rules, its competitor may report this violation, and the regulator imposes fines on the offending firm. The model offers a representation of the informational structure underlying our proposed data-generating process, thereby linking our theoretical arguments directly to the empirical tests that follow.

MODEL

In this section, we adapt and extend the costly Bayesian-persuasion framework of Gentzkow and Kamenica (2014). Their model captures the strategic transmission of information to persuade a receiver to take an action favorable to a sender, and has found a natural application in the CPA and political marketplace literature (Kamenica, 2019; de Clippel and Zhang, 2022; Little, 2023). Taking their model as a foundation, we design a sequential game with three players: a regulator and two firms engaged in monopolistic competition within a large industry. We consider a scenario where one firm (the "rival") can engage in regulatory non-compliance, while the other firm (the "snitch") can send a costly signal to the regulator about the rival's non-compliance. We solve this sequential game using the concept of Sequential Equilibrium (Kreps and Wilson, 1982), hereafter referred to as "equilibrium", in which each player's strategy is optimal given their beliefs, beliefs are updated via Bayes' rule wherever possible, and off-path beliefs exhibit continuity with those along the equilibrium path.

The game unfolds as follows. At Time 1, the rival decides whether to violate regulations, which grants a cost advantage in a game of monopolistic competition at Time 2. At Time 2, the snitch may choose to gather evidence on potential non-compliance at a cost, sending a signal to the regulator about whether the rival may have violated regulations. This signal can be thought of as a report or piece of evidence intended to persuade the regulator that non-compliance has occurred.

We treat the regulator as a professional, non-corrupt actor who seeks to maximize their career prospects. Specifically, we build on recent empirical findings (Duflo et al., 2018; Schinkel et al., 2020), which show that regulators view addressing the most harmful violations as the most effective way to advance their agency's institutional goals (Duflo et al., 2018) and, in doing so, enhance their own career prospects (Alesina and Tabellini, 2007; Bertrand et al., 2020).[1] To reflect this, we assume that the regulator gets positive utility for choosing the effective action (investigating harmful violations and not investigating lesser violations) and zero utility for choosing the ineffective action (investigating lesser violations and not investigating harmful violations).[2]

The regulator has an *a priori* understanding of the probability that the rival will cause significant harm if a violation occurs. This prior belief is common knowledge and is set as $\mu_0 = \rho$. The parameter ρ is rival-specific and is calibrated so that the regulator is more vigilant toward firms whose regulatory non-compliance is more likely to result in significant harm. We assume that the regulator is risk-neutral and that $0 < \rho < \frac{1}{2}$ because, if the prior were $\frac{1}{2}$ or higher, a risk-neutral regulator would investigate directly without needing any persuasion.[3] This makes the model focus on the cases where Bayesian persuasion becomes relevant, namely where there is enough suspicion to make snitching potentially worthwhile, but not enough for automatic investigation.

At Time 2, there are two possible states of the world: *Guilty* or *Innocent*. The snitch decides whether or not to gather information, which can lead to one of two signals being sent, g for guilty

[1]More generally, when tasks are heterogeneous in their value, economic agents naturally prioritize those of greatest value. This pattern has been documented in real estate (Giustiziero, 2021), professional service firms (Garicano and Santos, 2004), the movie industry (Luo, 2014), and biotechnology (Pisano, 1997), among others.

[2]We assume that the regulator is concerned only with serious violations, modeling severity as a binary variable, so a violation either causes significant harm (exceeding a predetermined threshold) or it does not. This simplifying assumption helps avoid unnecessary technical complexity. That said, our results would remain qualitatively similar if we instead assumed that the regulator cared about both the probability and the severity of harm, and intervened only when their product exceeded a given threshold. This threshold could be micro-founded so as to reflect the regulator's productive capacity (i.e., productivity times operational scale), the distribution of harmful activities within the industry and their likelihood, as well as the mass of violations falling within the regulator's purview.

[3]In line with common practice in persuasion models, we assume the regulator chooses to investigate in cases of indifference (Kamenica and Gentzkow, 2011; Gentzkow and Kamenica, 2014; Kamenica, 2019).

or i for innocent (the signal i can be thought of as the snitch not producing any evidence or report). The snitch prefers that the rival be fined, and such a fine generates utility V. V is a function of competitive variables determined in the concurrent game of monopolistic competition.[4] If the regulator were, metaphorically speaking, "gullible", the snitch would always send the signal g, regardless of the true state. However, since the regulator engages in Bayesian updating, the snitch is constrained to send signals at a frequency consistent with the prior.[5] In a world where gathering information is costly, the snitch is expected to make both errors of omission and commission. Given that we assume the regulator is risk-neutral, they will investigate the rival if the signal g induces a posterior belief μ_g that the rival is guilty which is accurate at least 50 percent of the time. Therefore, μ_g represents the "threshold of doubt" sufficient to persuade the regulator to investigate (Felgenhauer, 2019).[6] Ultimately, if the regulator decides to investigate the rival, it will impose a fine only if the investigation reveals non-compliance, which occurs with frequency μ_g, conditional on the signal g being sent.

To gather information and send the signal, the snitch incurs a cost proportional to the expected reduction in Shannon entropy (Gentzkow and Kamenica, 2014; Shannon, 1948), a measure of the average level of uncertainty associated with the rival's actions. This cost is

$$\iota \sum_{s} \tau_s \left(H(\mu_0) - H(\mu_s) \right)$$

Where $H(\mu) = -\mu \log(\mu) - (1-\mu)\log(1-\mu)$ is the entropy function of belief μ; μ_s with $s \in \{g, i\}$ is the regulator's posterior belief that the rival is guilty, conditional on receiving signal s; and τ_s is the probability of the regulator receiving signal s. Additionally, ι is a cost parameter measuring how difficult it is for the snitch to send a persuasive signal.[7]

[4]Details in Supplementary Appendix A.4.

[5]Following the literature on Bayesian persuasion (Gentzkow and Kamenica, 2014; Kamenica, 2019; Little, 2023), we assume that the snitch commits to sending signals according to the frequencies it anticipates when it decides to gather information for the report. Consequently, the regulator updates its beliefs solely based on the information received, and the snitch does not need to account for how the regulator interprets the signals. This commitment eliminates babbling equilibria and other coordination failures commonly observed in strategic communication models.

[6]The model would yield qualitatively similar results if we set an alternative threshold of doubt.

[7]The parameter ι affects the frequency of omission errors by the snitch, which occur when the rival has not complied but no report is sent. A report may not be submitted either because gathering information about non-compliance is too costly, because the regulator may find the report unconvincing (and thus unpersuasive), or because transmitting the report to the regulator is too difficult.

We assume that $\iota \propto \frac{1}{\Lambda}$, where $\Lambda > 0$ represents the level of CPA by the snitch. In other words, we assume that engaging in CPA to a greater degree (i.e., a higher Λ) will lower the cost of sending a persuasive signal to the regulator. This assumption reflects the conception of CPA as a channel for the strategic transmission of information to government actors (Austen-Smith, 1993; Esty and Caves, 1983; Hillman and Hitt, 1999). The literature on CPA consistently finds that firms with long-standing relationships with policymakers are better able to persuade them and to gain benefits (see Snyder, 1992; Drutman, 2015, among many others). The literature also finds that the relationship CPA provides is akin to a general purpose asset, so that when a firm invests in CPA to form a connection with a policymaker for one purpose (e.g., influence legislation), this decreases the cost of exploiting this connection for other purposes (see Ridge et al., 2017; Shaffer and Hillman, 2000; Schuler et al., 2002). Building on this view, we treat Λ as exogenous. We believe this to be a reasonable assumption, as the CPA literature identifies a wide range of structural factors that motivate firms to engage in CPA (see e.g. Hillman et al., 2004; Huneeus and Kim, 2021).[8] As such, CPA is likely a general-purpose asset that firms develop over time for various reasons. The intensity of this asset cannot easily be adjusted in the short term and is therefore effectively exogenous, but it can be leveraged to report violations if needed. That said, our model would exhibit similar dynamics if Λ were endogenous, as firms would increase their CPA in proportion to the expected benefits of persuasion.

Time 2: Snitching

Solving the sequential game by backward induction, we begin by analyzing the snitch's maximization problem at Time 2. The snitch must calibrate the probabilities with which it sends signal g and signal i, denoted as τ_g and τ_i, respectively. This is achieved by solving a maximization problem that balances the benefits of inducing the regulator to fine its rival against the costs of a persuasive report, subject to three constraints. The first two constraints trivially ensure that the probabilities of sending signal g and signal i characterize a Bernoulli distribution, such that their sum equals

[8] In Section F of the Supplementary Appendix, we analyze the specific issues companies report lobbying on in a sample of 5000 disclosure forms. Nearly 60 percent of all lobbying disclosures list legislation as the main issue.

one, and both probabilities are non-negative. The third constraint ensures that, in equilibrium, the regulator's posterior beliefs are consistent with the prior:

$$\mu_0 = \mu_g \tau_g + \mu_i \tau_i$$

Denote $v(\mu_s)$ as the function that assigns a payoff of $\mathbb{1}_{\{\mu_s \geq \frac{1}{2}\}} V$ (where $\mathbb{1}_{\{\mu_s \geq \frac{1}{2}\}}$ is the indicator function that takes the value 1 if $\mu_s \geq \frac{1}{2}$) when the posterior belief μ_s is induced in the regulator by signal s, and a payoff of 0 otherwise. Then, the maximization problem the snitch faces is:

$$\max_{\tau_g, \tau_i} {}_{\substack{s.t.\ \tau_g + \tau_i = 1, \\ 0 \leq \tau_i \leq 1, \\ E[\mu_s] = \mu_0}} \sum_s \tau_s \left(v(\mu_s) - \iota \left(H(\mu_0) - H(\mu_s) \right) \right)$$

When reports on rivals are very costly, such as when ι is large relative to V, the snitch's maximization problem results in no reports, leading to posterior $\mu_i = \mu_0$.[9] If the cost of a persuasive report ι is small relative to V, the solution to the maximization problem determines the frequencies with which the snitch expects to generate a report (signal g) and no report (signal i) when gathering information about potential non-compliance by the rival. The snitch expects these signals to be noisy: τ_g includes commission errors (cases where the snitch produces a guilty report despite the rival being innocent) while τ_i includes omission errors (instances where the snitch produces no report even though the rival is guilty). The probabilities with which the snitch expects to send each signal are:

$$\tau_g^* = \frac{2(\mu_0 - \mu_i)}{1 - 2\mu_i}, \quad \tau_i^* = \frac{1 - 2\mu_0}{1 - 2\mu_i}$$

In any equilibrium where a report is produced with positive probability, a report (signal g) moves the posterior belief that the rival is guilty to the threshold of doubt, i.e., $\mu_g = \frac{1}{2}$, sufficient for the regulator to investigate potential non-compliance. Conversely, the posterior belief $\mu_i = \frac{1}{2}\left(1 - \sqrt{1 - e^{-\frac{V}{\iota}}}\right)$ that the rival may have violated regulations despite no report being produced (i.e., signal i is sent) is increasing in the cost of sending a persuasive report relative to its benefits. For the snitch to gather information in order to generate a report ($\tau_g^* \geq 0$), it must hold that $\mu_i \leq \mu_0$. Intuitively, μ_i relates to the frequency of the snitch's omission errors. If these occur too

[9] Details in Supplementary Appendix A.1.

frequently, gathering intelligence does not help the snitch persuade the regulator to investigate. Because $\mu_0 = \rho$, the "snitching condition" can be rewritten as:

$$\mu_i \leq \rho$$

Time 1: Non-Compliance

The rival is risk-neutral, and its decision not to comply at Time 1 depends on the snitch's strategy and competitive variables at Time 2. Firms operate under constant elasticity of substitution (CES) monopolistic competition with heterogeneous linear marginal costs.[10] Companies have incentives to skirt costly regulation because they gain an advantage over their competitors if they can avoid detection (cf. Becker, 1968; Magat and Viscusi, 1990). By not complying, the rival can reduce its marginal cost c_r by a factor $d \in (0, 1)$, so that it falls to $d\, c_r$. Under the simplifying assumption that both the rival and the snitch are small relative to the market, non-compliance increases the rival's profits from π_r to $d^{1-\alpha}\pi_r$, where $\alpha > 1$ is the elasticity of substitution between products. A higher α means the goods are closer substitutes and therefore reflects greater competitive aggressiveness.[11]

If the rival is fined, we assume for simplicity that it will be prevented from producing, effectively exiting the industry for one period. This assumption not only simplifies our analysis but also represents a much stronger deterrent for the rival than simply fining it a share of its profits. If the rival is fined and exits the market, the profits of the snitch increase by V, which is an increasing function of the rival's operational scale, proxied by π_r, and competitive aggressiveness, proxied by α.[12] Since sending information is costly for the snitch and prone to omission errors, non-compliance does not automatically lead to regulatory enforcement. Conditional on non-compliance, Bayes' rule implies that the probability of the snitch failing to report is given by:

$$\frac{\mu_i \tau_i^*}{\mu_g \tau_g^* + \mu_i \tau_i^*}$$

[10] Details in Supplementary Appendix A.2.
[11] Details in Supplementary Appendix A.2.
[12] Details in Supplementary Appendix A.4.

Since $\mu_g \tau_g^* + \mu_i \tau_i^* = \mu_0 = \rho$, the expression simplifies to $\frac{\mu_i \tau_i^*}{\rho}$. If the expected likelihood of not being caught, combined with the excess profits from non-compliance, is sufficiently high at Time 2, the rival will not comply at Time 1. Formally, the rival will not comply if:

$$\frac{\mu_i \tau_i^*}{\rho} d^{1-\alpha} \pi_r \geq \pi_r$$

After some algebraic manipulations, the "non-compliance condition" derived above, along with the snitching condition $\mu_i \leq \rho$, delineate the context under which enforcement actions are observed in equilibrium:

$$\mu_i \leq \rho \leq \frac{\mu_i}{d^{\alpha-1}(1-2\mu_i)+2\mu_i}$$

With $d^{\alpha-1} < 1$, the right-hand side of the inequality is always greater than the left-hand side. The non-compliance condition implies that a rival is more likely to commit harmful violations when doing so generates sufficiently large economic benefits; otherwise, "the game is not worth the candle." Violations that are likely to cause significant harm often co-vary with potential cost savings: compliance for hazardous materials, for instance, entails more stringent cradle-to-grave requirements (e.g., manifest tracking, permitting, treatment standards) than the management of non-hazardous materials (U.S. Environmental Protection Agency, 2024). Thus, more harmful violations are typically associated with greater compliance costs, as regulatory designs intentionally impose more onerous requirements in areas where potential harm is higher.[13]

Having examined the non-compliance condition, Lemma 1 characterizes the impact of the snitch's CPA on the unconditional probability of regulatory enforcement. This probability is central to our empirical strategy because cases of undetected non-compliance, which are necessary for estimating the probability of enforcement given non-compliance, cannot be empirically observed.

Lemma 1 (Harm-Detection CPA)**.** *Let $\mu_g \tau_g^*$ denote the unconditional probability of regulatory enforcement in equilibrium. There exists a critical value d' and a threshold function $\rho^*(\Lambda) \in \left(0, \frac{1}{2}\right)$ such that, for all $d < d'$,*

$$\frac{\partial(\mu_g \tau_g^*)}{\partial \Lambda} > 0 \iff \rho \geq \rho^*(\Lambda)$$

[13] We explore the potential relationship between the cost discount parameter d and the risk of significant harm ρ in Supplementary Appendix A.6, together with the role of heterogeneity in the "propensity to comply," which may stem from risk aversion or from other factors that reduce the propensity to violate, such as reputation costs, stakeholder pressures, or ethical considerations.

That is, when non-compliance yields sufficiently large cost savings, the unconditional probability of regulatory enforcement, $\mu_g \tau_g^*$, is increasing in the snitch's CPA parameter, Λ, if and only if the risk of significant harm ρ exceeds the threshold $\rho^*(\Lambda)$. (Proof in Supplementary Appendix A.5.1.)

The threshold condition of the harm detection effect of CPA described in Lemma 1 suggests that, when regulatory non-compliance is likely to cause significant harm (and correspondingly large cost savings to the rival),[14] the snitch's CPA is most effective because it aligns with the regulator's preferences. In such cases, the snitch has strong incentives to share information about a rival's potential infractions because it is easier to persuade the regulator, who is motivated to use this information to curb the most harmful violations. Accordingly, Lemma 1 integrates the regulator's preferences with the snitch's incentives.

The harm-detection effect of CPA is non-linear, so firms are not automatically subject to stricter enforcement actions when competitors engage in CPA to a greater degree. This is because regulatory agents may be less interested in firms whose infractions are unlikely to result in significant harm. Thus, the snitch's efforts will be directed only toward competitors for whom producing a costly report can push the posterior towards the threshold of doubt, a situation that arises primarily when the rival is more likely to be engaged in risky activities.

The mechanisms outlined in Lemma 1 are likely to be observable empirically. When violations are expected to cause the greatest harm, the interests of regulatory agents and potential informant firms are likely aligned, facilitating exchanges in the political marketplace of regulatory enforcement. Regulatory agents often prioritize identifying and penalizing violators who pose the highest risk of harm (Duflo et al., 2018), while rival firms have incentives to report competitors who gain a significant advantage by evading costly regulations when they know regulators will be receptive (Glaeser and Shleifer, 2003). Thus, at the enforcement stage, firms are more likely to share information with regulators to demand actions against offenders most likely to cause significant harm. In practice, a regulatory agency's assessment of what constitutes a violation causing the greatest harm depends on multiple factors, such as the distribution of harmful activities within the industry, among others. This makes it challenging to establish a fixed threshold *a priori*. Nevertheless, independent of the specifics of this threshold, we expect that companies whose violations are more likely to harm the

[14]See Supplementary Appendix A.6 for additional discussion.

public will be more likely to face enforcement actions when their competitors are more actively engaged in information exchange with the regulatory agency. This leads to our main hypothesis:

Hypothesis 1. *Competitor CPA increases the probability of enforcement actions where violations are more likely to result in significant harm, while it decreases or has no effect on the probability of enforcement actions for violations less likely to result in significant harm.*

Informational Boundary Conditions

The mechanism described in our main hypothesis suggests that regulators are more likely to investigate when firms can share private information about potential violations. In practice, certain factors may influence how easily or cheaply potential informants can obtain such information. The empirical literature on knowledge spillovers suggests that geographic proximity and production standardization across firms can augment a firm's capacity to absorb information from competitors (Alcácer and Chung, 2007; Giustiziero et al., 2019; Griliches, 1992). To account for this, we assume that the cost of information, ι, is inversely proportional to both the geographic proximity between the two firms, γ (with $0 < \gamma \leq 1$, i.e., $\iota \propto \frac{1}{\gamma}$), and the degree to which a rival's production process is close to the industry standard, σ (with $0 < \sigma \leq 1$, i.e., $\iota \propto \frac{1}{\sigma}$).

Proposition 1 (Informational Effects on Regulatory Enforcement)**.** *In equilibrium,*

$$\frac{\partial(\mu_g \tau_g^*)}{\partial \Lambda} > 0 \quad \iff \quad \frac{\partial(\mu_g \tau_g^*)}{\partial \iota}\frac{\partial \iota}{\partial \gamma} > 0 \;\; \textit{and} \;\; \frac{\partial(\mu_g \tau_g^*)}{\partial \iota}\frac{\partial \iota}{\partial \sigma} > 0$$

That is, the unconditional probability of regulatory enforcement, $\mu_g \tau_g^*$, is increasing in the informational parameters γ and σ if and only if it is also increasing in the CPA parameter, Λ. (Proof in Supplementary Appendix A.5.2.)

Proposition 1 suggests that the unconditional probability of enforcement increases with geographic proximity and production standardization, as both lower the cost of compiling a persuasive report, provided that enforcement is responsive to the snitch's CPA. As the knowledge-spillover literature shows, geographic proximity provides localized insights into rivals' operations and know-how (Griliches, 1992). Such knowledge flows can arise through employee mobility, third-party firms active across sites, or participation in local knowledge communities (Alcácer and Chung, 2007; Jaffe et al., 1993). Naturally, these flows diminish with geographic distance. This leads to our first boundary-condition hypothesis:

Hypothesis 2. *The effect of competitor CPA on regulatory enforcement described in Hypothesis 1 is more pronounced for facilities that have a competitor who engages in CPA located in close geographical proximity.*

Empirically, production standardization is also likely to increase the probability of regulatory enforcement by reducing the cost of compiling a persuasive report. Since learning is a cumulative process that relies on a firm's absorptive capacity (Cohen and Levinthal, 1990, 1994), it is challenging for informants to understand their rivals' practices when they are based on nonstandard knowledge with little overlap with their own knowledge base. For example, when firms employ non-standard processes, rivals may struggle to understand their operations, as there may be fewer shared suppliers and limited employee mobility. This, in turn, hampers their ability to detect and understand potential violations. In contrast, standardized production modes across the industry make it easier for competitors to learn about these processes (Giustiziero et al., 2019), and should therefore facilitate the detection of violations. Thus, we predict:

Hypothesis 3. *The effect of competitor CPA on regulatory enforcement described in Hypothesis 1 is more pronounced for facilities whose production process is more similar to those of other facilities in the industry.*

Motivational Boundary Conditions

Firms must have sufficient *motivation* to disclose information about a rival's infractions to demand enforcement. In our model, the incentives to demand enforcement are driven by two parameters: competitive aggressiveness (α) and rival's performance (π_r).

Proposition 2 (Motivational Effects on Regulatory Enforcement)**.** *In equilibrium,*

$$\frac{\partial(\mu_g \tau_g^*)}{\partial \Lambda} > 0 \quad \Longleftrightarrow \quad \frac{\partial(\mu_g \tau_g^*)}{\partial V}\frac{\partial V}{\partial \alpha} > 0 \ \textit{ and } \ \frac{\partial(\mu_g \tau_g^*)}{\partial V}\frac{\partial V}{\partial \pi_r} > 0$$

That is, the unconditional probability of regulatory enforcement, $\mu_g \tau_g^*$, is increasing in the motivational parameters α and π_r if and only if it is also increasing in the CPA parameter, Λ. (Proof in Supplementary Appendix A.5.3.)

Proposition 2 demonstrates that the unconditional probability of regulatory enforcement increases with competitive aggressiveness and the rival's performance, because both amplify the returns from enforcement—as long as enforcement is influenced by the snitch's CPA. Firms operating in more aggressive competitive environments are likely to have stronger incentives to report rivals that evade costly regulations. Competitive aggressiveness raises the stakes of rivals' actions (Chen, 1996), making non-compliance by competitors particularly damaging. It can also trigger greater price competition, driving down margins and amplifying the competitive advantage of non-compliant rivals (Ferrier, 2001). Thus, we hypothesize:

Hypothesis 4. *The effect of competitor CPA on regulatory enforcement described in Hypothesis 1 is more pronounced in industries with higher levels of competitive aggressiveness.*

Consistent with Proposition 2, we also expect firms to have stronger incentives to target high-performing rivals. If firms seek to maximize the returns on their political connections (Esty and Caves, 1983; Shaffer and Hillman, 2000) and strategically prioritize which non-market goals to pursue (Barber and Diestre, 2019), they will carefully assess the value of having a particular competitor investigated and fined by regulators. Firms have strong incentives to direct such actions toward their high-performing rivals, as industry laggards pose a lower competitive threat. Regulatory fines and compliance costs can weaken strong competitors by diverting resources and ultimately reducing their market advantage. This, in turn, can create opportunities for lagging firms to narrow the performance gap and improve their competitive position. Consequently, we expect the effects of competitor CPA to vary within the same industry, with firms selectively leveraging regulatory mechanisms to shape competitive dynamics in their favor.

Hypothesis 5. *The effect of competitor CPA on regulatory enforcement described in Hypothesis 1 is more pronounced for high-performing firms in an industry.*

EMPIRICAL SETTING

U.S. Environmental Protection Agency

We test our hypotheses in the context of the U.S. Environmental Protection Agency (EPA), whose mission is to write and enforce regulations to protect the environment and citizens' health. In 2023, the EPA had about 16,000 employees and a budget of $11.9 billion.[15] The agency engages in a wide variety of activities, ranging from educational campaigns to scientific research. Most relevant for our purpose are its compliance and enforcement programs, the main goal of which is to identify and punish companies that violate environmental regulations.

These enforcement programs are a core part of the EPA's mission, with over 3,300 employees working in compliance.[16] Enforcement cases at the EPA have up to three stages (for a detailed overview see Mintz, 2012). The first phase is inspection and information gathering. Inspections may occur routinely or "for cause." Routine inspections for large facilities occur once every 12-24 months, and every five years for small facilities.[17] For cause inspections happen when there is reasonable suspicion that a violation is occurring. Information provided by industry rivals can help the agency in both instances. For cause inspections are often initiated in response to tips and complaints, including from economic competitors (Mintz, 2012). Routine inspections can also benefit from reports by competitors, as many facilities under the purview of the EPA have a large geographical footprint and contain complex technical equipment. Without additional information about what to look for, inspectors may not always be able to find violations even while in a facility. If inspectors determine that a violation has occurred, the EPA in a second step develops a case and determines what enforcement response is appropriate. The majority of successful enforcement cases end in a settlement in which the offending firm accepts that it has committed violations, pledges to resolve them, and pays a fine. However, if no resolution is found, the third step in the enforcement process is formal litigation.

The EPA is a good context to examine our argument. EPA regulators face an asymmetric information environment, as non-compliance is often hidden from public view in the complexities of firms' production process. Enforcement hinges upon inspectors finding a violation in the first place,

[15]https://www.epa.gov/system/files/documents/2022-03/fy-2024-epa-bib.pdf (p. 19).
[16]https://www.epa.gov/system/files/documents/2024-03/fy-2024-epa-bib.pdf (p. 8).
[17]https://echo.epa.gov/resources/echo-data/about-the-data.

and information from competitors can make this more likely. In addition, the EPA is one of the main targets of CPA. Between 1998 and 2023, more than 62,000 lobbying reports list the agency as a target, making it the fifth-most lobbied in the country.[18]

Data

To test our hypotheses, we assemble annual data from 2001 to 2013 on the universe of facilities under the purview of the EPA that belong to publicly listed companies, as reported by the Toxics Release Inventory (TRI) dataset. We collect information on three main variables: fines levied by the agency, lobbying activities by companies to capture their CPA, and the level of facilities' toxicity as a proxy for how harmful violations are likely to be.

EPA Fines. Information on our dependent variable, fines assessed by the EPA, stems from the Enforcement and Compliance History Online (ECHO) dataset.[19] Our dependent variable takes the value of one if a facility received a fine of $10,000 or more in a given year, and zero otherwise. We use a cutoff of $10,000 since fines below that threshold are typically imposed for administrative violations, such as maintaining incomplete records or failing to meet reporting requirements, to which our theoretical argument does not apply. However, all our results are robust to using other cutoffs and to using the logged amount of fines as the dependent variable.[20] About two percent of facilities in our sample are fined in a given year.

CPA: Competitors and Firm. To measure the strength of firms' prior connections through CPA, we use data on how much they spend on lobbying the EPA at the federal level. Lobbying information comes from OpenSecrets' lobbying database.[21] We use lobbying expenditures, a commonly employed metric in the CPA literature (see e.g. Ridge et al., 2017; Barber and Diestre, 2019; Kim, 2019; Huneeus and Kim, 2021), since it represents the most comprehensive data available on firms' use of information to influence the government. Firms are required by law to disclose each quarter how much money they spend on lobbying, which provides an intensive measure of their CPA over time.[22] Thus, while CPA can take multiple forms—including informal meetings and personal

[18] https://www.opensecrets.org/lobby/top.php?showYear=a&indexType=a.

[19] https://echo.epa.gov

[20] See Supplementary Appendix Sections E.1 and E.2.

[21] https://www.opensecrets.org/.

[22] It is important to note that the reporting requirement only applies if a firm spends at least $3,000 on outside lobbyists, has at least one employee spending more than 20 percent of their time lobbying, or spends more than $13,000 on lobbying activities within the firm. This could mean that our measure misses simple messages passed

connections that lower the cost of providing information to regulators—lobbying expenditures serve as a good proxy because, metaphorically speaking, they put a firm's money where its mouth is: they capture the intensity of firms' efforts to inform regulators in pursuit of favorable outcomes and can be specifically linked to the EPA.

Companies are not required to report lobbying expenditures on each specific agency, but they do have to list all agencies that were contacted. To calculate the amount of lobbying targeted at the EPA, we divide the total reported expenditure of a company in a given disclosure filing by the number of agencies that it lobbied. Thus, we assume that an equal amount of money is spent on each agency, which is likely a conservative estimate given that the EPA is one of the most-lobbied agencies. Because trust built through sustained interactions between the agency and the firm plays an important role for our hypothesized mechanism, we use the prior three years of lobbying. We take the logged total a firm spent lobbying the EPA.[23]

To define the set of a firm's competitors, we use the Standard Industrial Classification (SIC) 4-digit industry code derived from the Compustat database.[24] When calculating the amount spent on lobbying by a firm's competitors, we take the logged total amount spent on lobbying the EPA in the prior three years by all *other* firms that have the same SIC code.[25] In a given year, about 10 percent of firms in our sample that engage in lobbying contacted the EPA, spending an average of about $15,000.

Potential Risk of Harm: Toxicity. To measure the potential severity of a firm violating the law, we follow the literature on EPA fines and use information on the toxicity of chemicals processed by facilities (King and Lenox, 2000; Diestre and Rajagopalan, 2011). To measure the level of toxicity, we use the TRI database, which tracks usage of toxic chemicals in each facility and reports how their byproducts are disposed (air/water release or recycling/disposal). We use the total amount of chemical byproduct (released and recycled/disposed) by each facility as our basis for potential harm. To account for the fact that some toxic chemicals are more dangerous than others, and that chemicals' toxicity depends on how humans encounter them, we combine the

between the upper management and the EPA. However, if this were true, this should bias the relevant coefficients towards zero.

[23] We add 1 before taking the log.

[24] Our findings are robust when using the text-based measure of competition from the SEC's 10K filings developed by Hoberg and Phillips (2010), see Supplementary Appendix Section E.3.

[25] We again add 1 before taking the log. All results are robust when aggregating lobbying spending over the one or two years instead, see Supplementary Appendix Section E.7.

TRI data with the EPA's Risk-Screening Environmental Indicators, which standardize chemicals according to their hazardousness by exposure type.

In line with the literature (see Toffel and Marshall, 2004), we create a variable of total toxicity for every facility-year as follows: First, we multiply the toxicity from inhalation with the amount of air releases by a facility, as well as the toxicity from ingestion with the amount of water releases.[26] Then, we sum these two products to get a measure of chemical-level toxicity for a facility. Finally, we log the sum of all chemicals' toxicity in a facility-year. This creates a measure of toxicity that is comparable across facilities. We lag this measure by one year.

Sample. We make three restrictions to our dataset. First, because we are only interested in industries that are at risk of being fined by the EPA, we eliminate all industries that incur a fine less than once every two years on average. This assures that our findings are not driven by firms to whom our argument does not apply. Second, we eliminate any industry where we cannot identify any competitors for a firm using the SIC-4 code, as our argument does not apply. Finally, since we are interested in facilities that are at risk of being fined, we eliminate any facility that did not process any toxic chemicals in the previous year. Our analysis sample contains 66,411 observations at the facility-year level, stemming from just over 8,400 individual facilities that belong to 780 firms from 93 industries.

EMPIRICAL ANALYSES

Descriptive Evidence

We begin by testing our main hypothesis descriptively. Figure 1 plots the percentage of facilities that are fined by the EPA, binned into 20 groups according to their industry standardized toxicity (cf. Starr and Goldfarb, 2020). The solid line shows the relationship for all facilities. It clearly demonstrates that facilities are more likely to be fined when their production process involves a larger amount of toxic chemicals. A facility at the lowest level of toxicity has about a 0.5 percent probability of being fined. In contrast, a facility at the highest level of toxicity has an almost 7

[26]The TRI only tracks the amount of recycled/disposed chemicals. To assign this a toxicity measure, we assume recycled/disposed chemicals would be released by air/water at the firm's ratio, or, when unavailable, the average ratio for all facilities using that chemical.

percent chance of receiving a penalty. This confirms that the EPA indeed focuses its enforcement actions on facilities where violations are more likely to result in harm.

Figure 1 about here

Our main hypothesis predicts that competitor CPA increases the likelihood of being fined, especially for facilities where violations can result in greater harm. That is, we expect the slope of the line in Figure 1 to be steeper for facilities whose competitors lobby more. This is exactly what we find. The dotted line shows the probabilities of being fined for facilities who rank in the top tercile of competitor CPA, the short-dashed line shows facilities in the middle tercile, and the long-dashed line facilities in the bottom tercile. It is clear that the relationship between toxicity and the likelihood of being fined is conditioned by how much firms' competitors lobby the EPA. In all groups, high-risk facilities are more likely to be fined than low-risk ones. However, the pattern is much more pronounced for facilities whose competitors engage in more CPA. Facilities with the highest toxicity in industries with heavy competitor CPA are roughly four times more likely to receive a fine than firms with high toxicity in facilities with low competitor CPA (13.5 percent vs. 3.6 percent). Figure 1 thus provides clear descriptive evidence in favor of our main hypothesis: High-risk facilities are always more likely to be fined, but especially so when its competitors are more connected to the EPA through CPA.

Regression Analyses

While Figure 1 showed a clear pattern that is consistent with our argument, it did not control for any firm or industry covariates that may also influence fines. We therefore now turn to regression analyses of our panel data.

Empirical Specification and Control Variables

Empirical Specification. Our basic unit of analysis is the facility-year, and we model whether a facility incurs a fine in a given year as a function of the CPA efforts of its competitors in the same industry, the toxicity of the facility, and the interaction between the two:

$$Fines = \beta_1 Toxicity + \beta_2 CPA + \beta_3 Toxicity \times CPA + \gamma W + \partial_{FE} + \varepsilon$$

Our main hypothesis predicts that β_3, the interaction between competitor CPA and toxicity, will be positive.

We include different combinations of fixed effects ∂_{FE} in our models. All specifications include state and year fixed effects, combined with either industry or firm fixed effects. State fixed effects absorb any observed and unobserved differences between states. This also subsumes potential differences between the EPA's regional offices. Year fixed effects soak up time-specific effects common to all observations, such as national changes to enforcement policy. Further, we include either 4-digit SIC level industry fixed effects or firm fixed effects. Industry fixed effects absorb any time-invariant differences between industries, so this specification only analyzes variance in CPA, toxicity, and fines *within* an industry over time. Specifications with firm fixed effects only exploit changing conditions *within a firm* across facilities as well as over time.

Finally, our dependent variable is binary, but using non-linear models with many fixed effects would expose our estimation to the incidental parameters problem (Greene, 2004; Fernández-Val and Weidner, 2016). In addition, non-linear models with interactions can be severely biased and inconsistent, and marginal effects are difficult to interpret (Ai and Norton, 2003). We therefore use linear probability models, which produce more robust estimates (Angrist and Pischke, 2008; Li and Wibbens, 2022). Because competitor CPA is positively correlated across firms in an industry, we use robust standard errors clustered at the industry-level. In addition, to ease interpretation, we multiply all coefficients by one hundred. Therefore, a coefficient of one indicates that a one-unit change in the independent variable is associated with a one percent increase in the probability that a fine is given.

Control Variables. The fixed effects absorb all time-invariant differences between industries or firms. In addition, we control for a set of theoretically motivated time-varying differences, denoted by W above. At the firm-level, we control for focal firms' CPA (proxied by their own lobbying spending towards the EPA), the number of facilities it operates in a given year, the number of unique SIC codes of firms' facilities, the size of its total assets, its debt-to-equity ratio, whether a firm is foreign-owned, whether a firm has a lawyer as a member of its top management team, whether a member of the firm's top management team used to work for the EPA, the distance between a facility and the closest EPA office, and the number of fines for the facility in the past five years. To make sure that firms' lobbying spending on the EPA does not simply capture political connections in general, we also control for firms' non-EPA lobbying, as well as firms' competitors' non-EPA lobbying.

At the SIC-4 industry-level, we include time-varying measures of how strictly each industry is regulated and its Herfindahl index of sales as a measure of industry concentration. We also include a set of variables that control for the possibility that the stringency with which the EPA monitors and fines facilities depends on characteristics of the area they are located in. In particular, we control for the population size and income per capita of the county in which a facility is located. Further, we include variables that measure the total number of facilities in a 25km radius of the focal facility, as well as the total amount of toxic releases they produce. We do this separately for competitor firms in the same industry and for non-competitors.

The control variables help limit the impact of potential omitted variable bias and including state, year, as well as industry or firm fixed effects aim remove many time/space/firm-level confounding variables. However, they cannot eliminate all potential biases. For example, if EPA enforcement changes at different rates across states, this may bias our estimates. Likewise we cannot capture if a firms' probability of being fined changes differently over time for reasons not captured by our firm/industry fixed effects or time-varying firm-specific control variables. Similarly, if facilities owned by the same firm in different states are fined at different rates in ways that we are not controlling for, this would not be absorbed by our set of fixed effects. We believe these is unlikely to be a serious issue since the intensity of enforcement actions is largely determined by national-level policy as well as by the centralized EPA regional offices. Nonetheless, we cannot rule these possibilities out and thus stress our research design is observational, and are careful to interpret all estimates as associational rather than causal.

Table 1 provides summary statistics and a correlation matrix.[27] In Supplementary Appendix B, we provide a detailed discussion of the theoretical motivations behind the controls, list information on data sources, and explain how we assembled the data and created all variables.

Table 1 about here

[27] We provide summary statistics and correlation matrices for our variables demeaned by our fixed-effects in Section D of the Supplementary Appendix

Results: Main Hypothesis

Table 2 shows results from six regression models. For brevity, we only provide the coefficients for our main variables of interest.[28] Model (1) estimates the effect of toxicity on receiving a fine, controlling for our set of covariates and including state, year, and industry fixed effects. The effect of toxicity is positive ($\beta = 0.202$) and statistically significant ($p < 0.001$). A one standard deviation increase in toxicity leads to about a one percentage point increase in the probability of incurring a fine. Given the baseline probability of two percent, this is a sizable substantive effect. Model (4) replaces the industry fixed effects with firm fixed effects, and the coefficient remains of similar magnitude ($\beta = 0.197$) and statistically significant ($p < 0.001$). This again confirms that the EPA prioritizes facilities where violations can cause greater harm for enforcement.

Table 2 about here

Model (2) adds competitor CPA as an additional variable. It has a slight negative effect on fines (β = -0.017), but the coefficient is not statistically significant ($p = 0.42$). Model (5) shows the same specification with firm fixed effects. Here, the effect of competitor CPA is close to zero and statistically insignificant ($\beta = 0.004$ with $p = 0.88$). The coefficient of toxicity is nearly unchanged.

Finally, Models (3) and (6) add the interaction between toxicity and competitor CPA. In line with our main argument, the interaction terms are positive and statistically significant in both instances ($\beta = 0.019$ with $p = 0.01$ in Model (3) and $\beta = 0.017$ with $p = 0.02$ in Model (6)), suggesting that the effects of toxicity and competitor CPA are conditional on each other. For an easier interpretation of this interaction, Figure 2 plots the marginal effects, based on Model (6). Panel (a) shows the marginal effect of competitor CPA on the probability of receiving a fine, depending on a firm's level of toxicity. The impact of CPA at the higher end of toxicity is positive and statistically significant. This means that if a facility processes more, and more toxic, materials, so violations have a greater potential to result in significant harm, the facility is *more* likely to be fined when its competitors engage in CPA towards the EPA to a greater degree. Meanwhile, there is a negative marginal effect of competitor CPA for low-risk facilities, so they are *less* likely to be fined than a comparable facility with competitors who are not politically connected to the EPA. This is consistent with our argument that the regulator uses information provided by industry rivals who

[28] For full regression tables, see Supplementary Appendix C.

are connected to the agency through CPA to better focus its enforcement on high-risk facilities. At least in the case of the EPA, this is accompanied by a lessened focus on low-risk facilities, perhaps due to resource constraints. Panel (b) of Figure 2 displays the marginal effect of toxicity on the probability of receiving a fine, conditional on competitors' CPA. If a firm's competitors do not lobby the EPA, its likelihood of being fined is unaffected by how harmful its violations are likely to be. However, as a firm's competitors engage in more CPA, the marginal effect of toxicity turns positive and significant.

Figure 2 about here

The effect size of competitor CPA is substantial. Consider a facility whose competitors' CPA efforts are one standard deviation below the mean. If that facility's toxicity is one standard deviation below the mean (low-risk), it has an about 2.3 percent chance of being fined in a given year. A facility whose toxicity is one standard deviation above the mean (high-risk) has a probability of 3 percent of being fined, so only marginally higher and not statistically different from one another ($p = 0.14$). Now consider a facility whose competitors' CPA is one standard deviation above the mean. Here, a low-risk establishment only has a probability of about 0.8 percent of being fined. This is significantly lower than a comparable facility facing little competitor CPA. However, a high-risk facility receives a fine with a probability of 3.8 percent. Thus, it is almost five times more likely to be penalized than a low-risk facility with the same competitor CPA ($p < 0.001$) and more than 25 percent more likely than a comparable high-risk facility with competitor CPA one standard deviation below the mean ($p = 0.09$).

Finally, we find across all models that a firm's *own* lobbying efforts does *not* affect the probability of being fined.[29] At least when it comes to the EPA, firms cannot counteract their competitors through increased CPA. This makes sense if the EPA gains information about violations from competitors, since it can accomplish its mission regardless of what intelligence the focal firm provides.

Regression Analyses: Boundary Conditions

Hypotheses 2 to 5 argued that the relationship outlined in Hypothesis 1 depends on firms having the ability and motivation to collect and communicate information about potential violations to the

[29]See Supplementary Appendix C for the full tables.

regulator. We now test these boundary conditions of our argument looking at how the interaction of toxicity and competitor CPA differ across our various boundary variables. Since we wish to compare their marginal effects within the same sample, we model this process following Franzese and Kam (2009) and include the binary moderator variable, as well as one minus the moderator variable interacted with our variables of interest using the following estimation:

$$
\begin{aligned}
Fines = {} & \beta_1(X \times Toxicity) + \beta_2(X \times CPA) + \beta_3(X \times Toxicity \times CPA) \\
& + \beta_4\big((1-X) \times Toxicity\big) + \beta_5\big((1-X) \times CPA\big) + \beta_6\big((1-X) \times Toxicity \times CPA\big) \\
& + \gamma W + \partial_{FE} + \varepsilon
\end{aligned}
$$

where X represents the various binary moderating factors outlined for Hypotheses 2 through 5, and all other variables are as above. Importantly, by interacting our key variables ($Toxicity$ and CPA) with both the moderator variable and one minus the moderator variable, we can directly compare the effect of CPA and toxicity in high ($\beta_{1\text{-}3}$) and low ($\beta_{4\text{-}6}$) settings of our moderating scenarios.

Geographic Distance

Hypothesis 2 predicted that the effect outlined in Hypothesis 1 will be more pronounced for facilities located in proximity to a competitor who engages in CPA. To test this, we use facilities' geographic location and calculate the distance to the closest facility owned by an industry competitor that has a lobbying relationship with the EPA.[30] We then estimate the coefficients for toxicity, competitor CPA, and their interaction, separately for facilities where the distance to the closest competitor engaged in CPA is more or less than 50 km.

Table 3 and Figure 3 about here

Model (1) in Table 3 shows the relevant coefficients when using industry fixed effects, and Model (2) when using firm fixed effects. In both models, the interaction between toxicity and competitor CPA is positive, but its magnitude is about double in size for facilities where the distance to the closest lobbying competitor is below 50km away ($\beta = 0.032$ with $p < 0.01$ for Model (1) and $\beta = 0.035$ with $p = 0.01$ for Model (2)) compared to those whose closest lobbying competitor is greater

[30] Descriptive statistics and correlations with the other variables for all our boundary condition variables can be found in Table 1. See Supplementary Appendix D for a graphical representation of the location of all facilities in the sample.

than 50km ($\beta = 0.016$ with $p < 0.01$ for Model (1) and $\beta = 0.014$ with $p = 0.02$ for Model (2)). To ease interpretation, Panel (a) in Figure 3 displays the *difference* between the marginal effects, based on Model (2). It shows a positive difference at higher levels of toxicity. This means that the marginal effect of competitor CPA at a given level of toxicity is larger for facilities that have a lobbying competitor located nearby. This suggests that the ability to collect and communicate information about specific violations of rivals is made easier through co-location.

Industry Standardization

Hypothesis 3 argued that information about a facility's potential violations will be easier to understand for a rival when they use similar production processes. In our context, an important part of production standardization is the use of toxic chemicals as inputs. To measure this, we quantify how unique the inputs of each facility are in terms of the chemicals it uses in its production compared to the rest of the industry, following the procedure outlined in Diestre and Rajagopalan (2011). We estimate separate coefficients for facilities above and below median standardization.

Models (3) and (4) in Table 3 provide the relevant coefficients. We find that the magnitude of the interaction between toxicity and competitor CPA for facilities with high levels of industry standardized inputs ($\beta = 0.027$ with $p = 0.02$ for Model (3) and $\beta = 0.024$ with $p = 0.03$ for Model (4)) is nearly double of what it is in facilities using more unique inputs ($\beta = 0.013$ with $p < 0.01$ for Model (3) and $\beta = 0.010$ with $p = 0.05$ for Model (4)). Panel (b) in Figure 3 shows the difference between the marginal effects. Again, this difference is positive at higher levels of toxicity, so our main effect is more pronounced when product standardization is greater. In other words, the effectiveness of competitor CPA is inhibited in facilities that have little in common with the rest of the industry. This suggests that the provision of information about potential violations to the regulator depends on rivals' understanding of a firm's production process. Taken in combination with the results on co-location, this indicates that the effect of competitor CPA varies within the same firm, depending on the exposure of a facility to these factors.

Industry Competition

Moving to firms' motivations to collect and understand information about their competitors' potential violations, Hypothesis 4 argued the pattern in Hypothesis 1 should be more pronounced in industries with high levels of competitive aggressiveness (higher price competition and lower margins). To measure this, we follow canonical work in economics and use changes in industry-level imports, which are associated with an influx of low-cost competition into the US market and correlated with decreased domestic firm survival (e.g. Pierce and Schott, 2016). Data on imports come from Schott (2008), which we match to firms at the SIC-4 level. To calculate the level of competitive aggression within the US, we look at the change in net imports for the industry from five years prior.

Models (5) and (6) in Table 3 show the results for facilities with an above and below median level of change in net imports. Here we find the size of the effect of the interaction between toxicity and competitor CPA in industries with high competitive aggressiveness (β = 0.032 with $p = 0.06$ for Model (5) and β = 0.030 with $p = 0.06$ for Model (6)) is, again, nearly twice that when compared to the effect of the interaction between toxicity and competitor CPA in industries with low competitive aggressiveness (β = 0.014 with $p = 0.05$ for Model (5) and β = 0.012 with $p = 0.09$ for Model (6)). Panel (c) in Figure 3 plots the difference of the marginal effects of competitor CPA. Yet again, we observe a positive difference at higher levels of toxicity. This suggests that firms are more incentivized to learn about and disclose potential violations when they are subject to more aggressive competition. These results show that the effect of CPA can vary across different industries depending upon an industry's market characteristics.

Relative Performance

Our final hypothesis stated that firms that perform well compared to their peers are more likely to be subject to the dynamics of our main hypothesis. To measure a firm's performance relative to its peers, we follow Greve (2003) and use information from Compustat on the Returns on Assets (ROA) of a firm relative to the SIC-4 level average.

Models (7) and (8) in Table 3 show the results for facilities with an above and below median industry-relative ROA. Here we find the size of the effect of the interaction between toxicity and competitor CPA in firms with high performance (β = 0.023 with $p = 0.01$ for Model (7) and β = 0.020 with $p = 0.03$ for Model (8)) is about 50 percent larger than the effect of the interaction between toxicity and competitor CPA in firms with low performance (β = 0.016 with $p < 0.01$ for Model (7) and β = 0.014 with $p = 0.02$ for Model (8)). Panel (d) in Figure 3 plots the difference of the marginal effects of competitor CPA. The coefficient of the interaction is larger for facilities with a higher ROA, and the difference between the marginal effects is positive for higher levels of toxicity. However, the effect sizes are smaller than the previous boundary conditions and estimated less precisely, so the confidence intervals of the difference in the marginal effects includes zero throughout. Thus, the evidence for Hypothesis 5 is more suggestive than for the other boundary conditions.

Robustness Checks and Endogeneity Concerns

In Supplementary Appendix E, we conduct numerous robustness tests to address potential concerns related to our main analyses. Specifically, we demonstrate that our findings are robust when we use different measures for EPA fines, different model specifications, when using the Hoberg-Phillips measure of competition instead of SIC codes to identify firms' competitors, and when using alternative time windows over which we aggregate our CPA measures. We also show that non-competitor lobbying has no significant relationship with EPA fines, suggesting that the informational content of competitor CPA is what drives regulatory attention. Further, we find no evidence that a focal firm's own CPA mitigates the effect of competitor CPA. Finally, we do not find any evidence of differential pre-trends in competitor CPA between firms that do and do not get fined. Thus, the main results of our paper are robust to a wide variety of specifications.

One potential concern not addressed in the robustness tests is that competitor CPA, which we proxy with lobbying expenditures, is endogenous to enforcement activities. In our theoretical model, we treat CPA as exogenous. This assumption is supported by prior research showing that firms often engage in CPA for structural reasons unrelated to enforcement, such as shaping legislation or securing appropriations (Hillman et al., 2004).[31] Nevertheless, it is possible that CPA is partly endogenous, as firms might intensify their CPA efforts in response to competitive threats from non-complying rivals. Our formal model suggests that if that were the case, the equilibrium predictions would remain robust, as firms that expect greater benefits from persuading regulators invest more in CPA. Thus, such strategic behavior would yield the same directional effect of competitor CPA on enforcement.

Another potential concern may be our use of lobbying expenditures as a proxy for CPA. Other forms of CPA, such as informal ties, personal connections, or other unreported channels may also

[31] See also Supplementary Appendix F for descriptive evidence using our sample.

shape regulators' behavior. Some of these informal channels are unobservable and difficult to control for, and they may act as substitutes for formal lobbying. However, to the extent that firms rely on these informal mechanisms, our estimates are likely conservative and would underestimate the full effect of competitor CPA on enforcement. CPA measures that capture these additional connections between firms and agencies may therefore show stronger evidence on the relationships we demonstrate.

DISCUSSION AND CONCLUSION

Our study sheds light on the non-market strategies at the core of the political marketplace of regulatory enforcement by examining how competitor CPA can persuade regulators and thus shape enforcement outcomes. Our analyses suggest that CPA provides regulators with valuable information to better target high-risk infractions. Our theoretical model provides a formal foundation for these interactions using a Bayesian persuasion framework (Kamenica and Gentzkow, 2011; Gentzkow and Kamenica, 2014; Little, 2023), while our empirical analyses confirm that competitor CPA plays a significant role in shaping enforcement patterns in a world rife with information asymmetries and strategic non-compliance (Yu and Yu, 2011; Correia, 2014; Lambert, 2018).

By delving into the the enforcement stage of the regulatory processes, our study extends existing research on CPA and the political marketplace, which has traditionally focused on the rule-setting stage (de Figueiredo and Tiller, 2001; Fremeth et al., 2016). This shift in perspective underscores the strategic role of CPA across multiple stages of the regulatory cycle. Our findings demonstrate that CPA can serve a dual purpose: while it may confer firm-specific benefits, it can also affect rivals and enhance the broader efficiency of regulatory enforcement by addressing information asymmetries (Friesen, 2003; Magat and Viscusi, 1990; Duflo et al., 2018; Schinkel et al., 2020). To this end, our study contributes to the growing literature on information asymmetries in regulatory processes, illustrating how information from rivals can shape the enforcement environment (Friesen, 2003; Potters and van Winden, 1992).

Furthermore, our study identifies boundary conditions that influence the effectiveness of CPA in enforcement contexts. We provide empirical evidence for the roles of geographic proximity (Alcácer and Chung, 2007), production standardization (Cohen and Levinthal, 1990, 1994; Diestre and

Rajagopalan, 2011), and competitive aggressiveness (Esty and Caves, 1983; Ferrier, 2001) in moderating the persuasiveness of competitor CPA. These factors determine the extent to which firms can gather actionable intelligence about their rivals, as well as their incentives to communicate it to regulatory agencies. Our findings suggest that firms located closer to their competitors or operating in industries with standardized production processes are better positioned to leverage CPA as a tool for influencing enforcement actions. Similarly, heightened competitive aggressiveness appears to amplify the incentives for firms to disclose information about rivals' violations, further validating the importance of contextual factors in understanding the dynamics of CPA.

Our findings suggest that CPA can enhance regulatory efficiency by enabling agencies to prioritize high-risk violations. This aligns with prior research that finds CPA can enhance some aspects of policymaking (Potters and van Winden, 1992; Grossman and Helpman, 2001) and stands in contrast to research showing how firms can alter policy outcomes at the public's expense through regulatory capture (Dal Bó, 2006; Lambert, 2018; Hadani et al., 2018). However, this increased efficiency may come at a cost. In line with prior studies, our findings suggests that firms with greater resources and stronger political connections may disproportionately shape regulatory enforcement. One priority for future research will be to explore whether and how persuasion at the enforcement stage alters the competitive landscape.

Of course, our study has limitations that should be addressed in follow-up research. Most obviously, we examine a complex phenomenon without the benefit of being able to exploit natural experiments or exogenous shocks (Angrist and Pischke, 2008; Fernández-Val and Weidner, 2016). This constrains our ability to draw causal inferences. Instead, our goal was to develop a coherent theoretical framework with clear boundary conditions, and document empirical patterns consistent with its predictions. Despite these patterns being consistent across multiple analyses and robustness checks, future research should make it a priority to test our theoretical argument leveraging quasi-experimental designs or novel data sources to more precisely identify causal effects.

As for our theory, one caveat is that it assumes that self-interested regulatory agents want to maximize their career prospects within the agency, and are thus interested in catching and fining violators. We maintain that this assumption is justified in countries with lower levels of public sector corruption and a professional bureaucracy, such as our empirical context (Duflo et al., 2018; Bertrand et al., 2020). However, in other environments, regulatory agents may be looking to engage in *quid pro quo* corruption. If this is the case, our argument does not apply, and future work could examine this conditionality in more detail.

Another theoretical issue that we largely set aside concerns the potential for retaliation. In tightly connected industries, firms may hesitate to report rivals' infractions out of concern for future reprisals. Such retaliation, however, presupposes that the rival can identify the snitch. Often this is not possible, since agencies typically do not disclose the source of the initial information that gets an investigation going. It can also be hard for firms to correctly guess who the snitch was, since they may have more than one nearby competitor, and the information may also have come from other sources, such as former or current employees, neighbors, or environmental organizations. Thus, we are confident that in our empirical context, and perhaps in many others, fear of retaliation is not a major concern. Although retaliation is therefore unlikely in many contexts, the mere possibility may still deter reporting. This dynamic could contribute to conservative estimates and may help explain the weak support for Hypothesis 5, which predicted that high-performing rivals are more likely to be reported. If firms perceive such rivals as more capable of retaliating, they may refrain from reporting them. Future research should examine this issue in greater depth.

In conclusion, our study highlights the contingent nature of the political marketplace during regulatory enforcement and underscores the strategic importance of CPA in shaping regulatory outcomes. By emphasizing the informational role of CPA, we demonstrate that it can enhance regulatory efficiency and effectiveness in targeting high-risk violations. However, our findings also underscore the complexities and potential inequities of these dynamics, suggesting that the role of CPA in enforcement processes warrants more scrutiny. As such, this study serves as a foundation for future inquiries into the interplay between political strategy, regulatory behavior, and market competition.

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Tables

Table 1: Descriptive Statistics and Correlations.

		N	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
(1)	EPA Fine	66,411	2.51	15.65	1																										
(2)	Firm CPA (EPA)	66,411	3.98	5.79	0.03	1																									
(3)	Competitor CPA	66,411	7.85	6.33	0.06	0.15	1																								
(4)	Firm CPA (Non-EPA)	66,411	8.04	7.32	0.01	0.68	0.14	1																							
(5)	Competitor CPA (Non-EPA)	66,411	12.54	6.36	0.05	0.13	0.71	0.18	1																						
(6)	Toxicity	66,411	16.72	4.68	0.08	0.06	0.01	0.01	0.04	1																					
(7)	Compliance Officer	66,411	0.22	0.41	0	0.12	0.03	0.19	0.04	0.05	1																				
(8)	EPA Official on TMT	66,411	0.35	0.77	0.02	0.05	0.36	0.05	0.3	0.13	0.07	1																			
(9)	Distance to EPA Office	66,411	328.20	249.60	0.01	0.03	0.04	0.01	0	0	0.01	-0.03	1																		
(10)	Logged Assets	66,411	9.16	1.92	0.03	0.46	0.19	0.49	0.19	-0.01	0.03	0.04	0.02	1																	
(11)	# of Facilities	66,411	32.40	31.98	-0.02	0.16	-0.02	0.3	-0.04	-0.21	-0.03	-0.2	0	0.24	1																
(12)	Debt to Equity	66,411	0.13	2.78	0.01	0	-0.01	0	-0.01	-0.01	0.01	0	0	0.05	0.01	1															
(13)	Firm Diversity	66,411	1.78	0.98	-0.04	0.18	-0.18	0.3	-0.14	-0.15	0.07	-0.33	-0.01	0.28	0.69	0.01	1														
(14)	Foreign Firm	66,411	0.27	0.44	0	-0.12	0.14	-0.09	0.16	-0.14	-0.27	-0.06	-0.02	0.32	0.12	0.04	0.04	1													
(15)	Local Toxicity Competitors	66,411	6.74	22.23	0.08	0.06	0.15	0.02	0.15	0.01	-0.01	0.01	0.03	0.1	-0.04	0.02	-0.03	0.03	1												
(16)	Local Toxicity Non-Competitors	66,411	36.35	81.61	0.03	0.01	0.03	0.02	0.02	0.03	0.02	0.01	-0.05	0.01	0	0.01	0.01	0.01	0.04	1											
(17)	# of Local Competitors	66,411	0.69	1.95	0.06	0.06	0.17	0.02	0.15	-0.05	-0.02	0	0.04	0.1	-0.02	0	-0.02	0.04	0.76	-0.01	1										
(18)	# of Local Non-Competitors	66,411	24.16	29.63	0.02	0.02	0.02	0.01	0.02	-0.1	0.02	-0.04	-0.04	0.02	0.01	0	0.04	-0.01	0.36	-0.09	0.47	1									
(19)	Fines in Past 5 Years	66,411	0.26	0.67	0.27	0.08	0.11	0.04	0.09	0.18	0.01	0.05	0.03	0.04	-0.04	0	-0.07	-0.02	0.12	0.06	0.09	0.03	1								
(20)	Logged Income per Capita	66,411	3.55	0.25	0.01	0.01	0.02	0.06	0.03	-0.12	0.04	0.01	-0.16	0.07	0.06	0	0.11	0.03	0.11	0.09	0.17	0.37	0	1							
(21)	Logged Population	66,411	12.36	1.61	0	0.01	0.01	0.02	0.01	-0.16	0.01	-0.02	-0.02	0.07	0.08	0.01	0.1	0.03	0.25	-0.03	0.35	0.71	-0.03	0.55	1						
(22)	Regulations	66,411	9.73	1.41	0.07	0.14	0.42	0.09	0.42	-0.05	0.02	0.13	0.03	0.1	0.01	-0.01	-0.03	0.05	0.14	0.05	0.12	0.06	0.13	0.03	0.03	1					
(23)	Industry Concentration	66,411	0.32	0.24	-0.01	0.02	-0.03	-0.01	-0.06	0.02	0.02	0.04	0.01	-0.03	0.05	0	0.03	-0.11	0	-0.05	-0.01	0.03	0	-0.15	0.01	-0.04	1				
(24)	Closest Rival <50km	66,411	0.15	0.36	0.05	0.08	0.37	0.05	0.27	-0.05	-0.02	0.08	-0.02	0.13	-0.01	0	-0.04	0.08	0.4	0.03	0.46	0.27	0.09	0.15	0.22	0.23	-0.02	1			
(25)	Industry Standardization	64,744	0.51	0.50	-0.05	-0.09	-0.09	-0.05	-0.1	-0.26	-0.02	-0.13	-0.02	-0.05	0.12	0.01	0.21	0.06	-0.07	0	-0.06	0.06	-0.1	0.08	0.08	-0.01	-0.01	-0.05	1		
(26)	Competitive Aggressiveness	32,717	0.54	0.50	-0.01	0.05	0.09	0.05	0.05	-0.08	0.02	0.11	-0.01	0	0.09	-0.04	0.08	0.02	-0.01	0.06	0.01	-0.01	0.02	0.14	0.02	0.19	-0.12	0.07	0.03	1	
(27)	Relative Firm Performance	66,292	0.51	0.50	0	0.03	0.02	0	-0.05	-0.03	-0.03	0.07	-0.01	0.11	0.03	0.03	-0.09	0.11	0	0.01	0	-0.04	0.01	-0.02	-0.01	-0.09	-0.11	0	-0.02	0.16	1

Table 2: Effect of Toxicity and Competitor Lobbying on EPA Fines. Results of linear probability models for facilities between 2001 and 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Toxicity	0.202	0.202	0.045	0.197	0.197	0.063
	(0.035)	(0.034)	(0.038)	(0.039)	(0.039)	(0.041)
Competitor CPA		-0.017	-0.351		0.004	-0.293
		(0.021)	(0.121)		(0.027)	(0.123)
Competitor CPA × Toxicity			0.019			0.017
			(0.007)			(0.007)
Controls, State FE, and Year FE	✓	✓	✓	✓	✓	✓
SIC 4-Digit FE	✓	✓	✓			
Firm FE				✓	✓	✓
Observations	66,411	66,411	66,411	66,411	66,411	66,411
R^2	0.085	0.085	0.087	0.114	0.114	0.115

Controls included in every model: Firm EPA Lobbying, General Counsel in TMT, Former EPA Official, Closest EPA Office, Firm Assets, # of Facilities, Local Competitors Toxic Releases, Local Non-Competitors Toxic Releases, # of Competitors <25km, # of Non-Competitors <25km, County Income, County Population, Firm CPA (Non-EPA), Competitor CPA (Non-EPA), Debt to Equity, Foreign Company, Industry Regulation, Firm Diversity, Industry Concentration, Facility Previous Fines.
Note: Robust standard errors clustered by industry in parentheses.

Table 3: Effect of Toxicity and Competitor CPA on EPA Fines Conditional on Information and Motivation. Results of linear probability models for facilities between 2001 and 2013.

	Conditional Variable:							
	Geographic Proximity		Standardization		Comp. Aggressiveness		Firm Performance	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low Conditional Variable × Toxicity	0.050	0.066	0.009	0.037	0.021	0.039	0.054	0.066
	(0.036)	(0.039)	(0.038)	(0.043)	(0.054)	(0.055)	(0.039)	(0.043)
Low Conditional Variable × Competitor CPA	-0.285	-0.235	-0.287	-0.215	-0.347	-0.306	-0.311	-0.238
	(0.091)	(0.095)	(0.082)	(0.095)	(0.139)	(0.131)	(0.095)	(0.095)
Low Conditional Variable × Competitor CPA × Toxicity	0.016	0.014	0.013	0.010	0.014	0.012	0.016	0.014
	(0.005)	(0.006)	(0.004)	(0.005)	(0.007)	(0.007)	(0.005)	(0.006)
High Conditional Variable × Toxicity	-0.016	-0.074	0.016	0.049	0.009	0.023	0.036	0.060
	(0.061)	(0.086)	(0.045)	(0.050)	(0.056)	(0.054)	(0.037)	(0.039)
High Conditional Variable × Competitor CPA	-0.502	-0.421	-0.460	-0.368	-0.533	-0.501	-0.403	-0.356
	(0.192)	(0.179)	(0.205)	(0.181)	(0.279)	(0.261)	(0.161)	(0.161)
High Conditional Variable × Competitor CPA × Toxicity	0.032	0.035	0.027	0.024	0.032	0.030	0.023	0.020
	(0.010)	(0.013)	(0.012)	(0.011)	(0.017)	(0.016)	(0.009)	(0.009)
Controls, State FE, and Year FE	✓	✓	✓	✓	✓	✓	✓	✓
SIC 4-Digit FE	✓		✓		✓		✓	
Firm FE		✓		✓		✓		✓
Observations	66,411	66,411	55,682	55,682	32,717	32,717	66,292	66,292
R^2	0.069	0.166	0.096	0.194	0.056	0.124	0.095	0.146

Controls included in every model: Firm EPA Lobbying, General Counsel in TMT, Former EPA Official, Closest EPA Office, Firm Assets, #of Facilities, Local Competitors Toxic Releases, Local Non-Competitors Toxic Releases, # of Competitors <25km, # of Non-Competitors <25km, County Income, County Population, Firm CPA (Non-EPA), Competitor CPA (Non-EPA), Debt to Equity, Foreign Company, Industry Regulation, Firm Diversity, Industry Concentration, Facility Previous Fines.
Notes: Robust standard errors clustered by industry in parentheses. High conditional variable refers to facilities with a lobbying competitor closer than 50km (geographical proximity), above-median production standardization (standardization), above-median change in net imports (competitive aggressiveness) and above-median industry-relative ROA (firm performance).

Figures

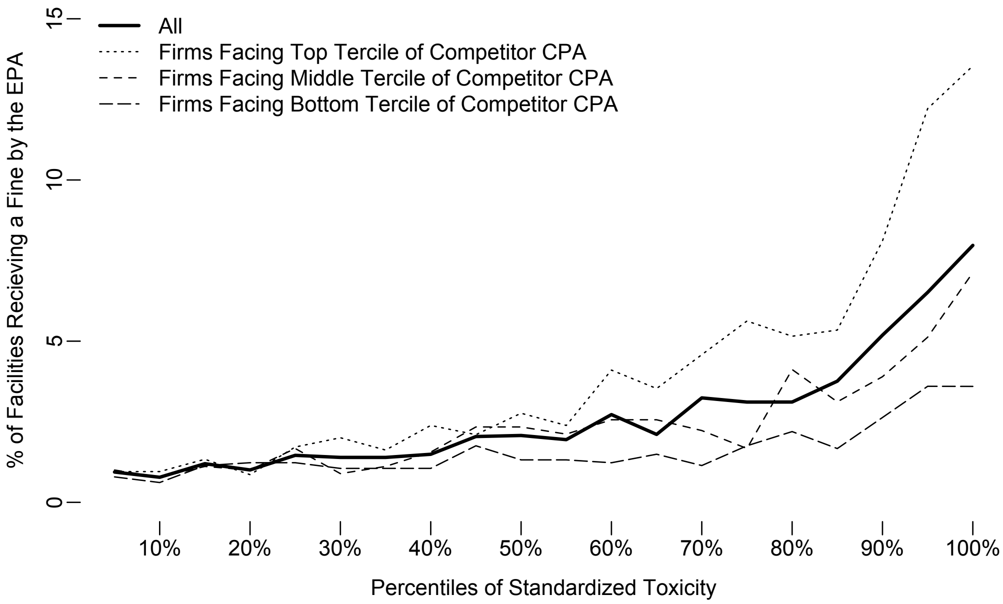
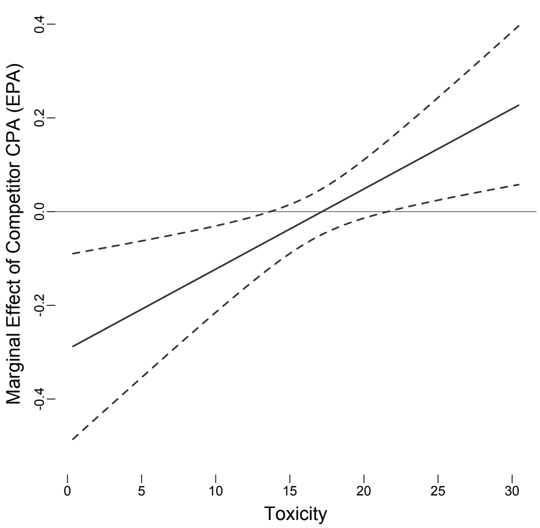
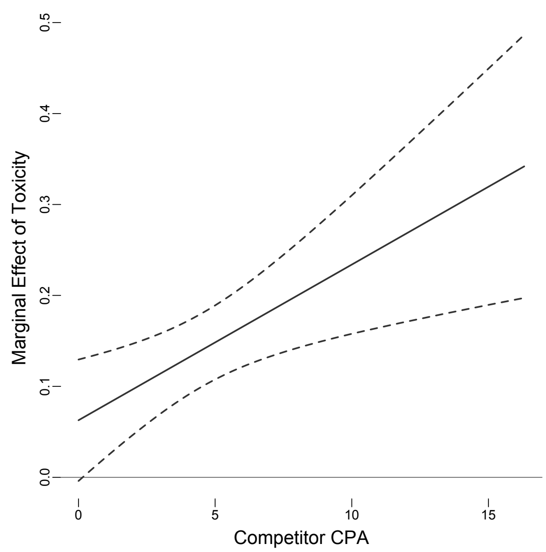


Figure 1: Competitor CPA, Risk of Potential Violations, and Probability of Being Fined. Percentage of facilities incurring an EPA fine (vertical axis), binned into 20 groups according to their standardized toxicity by industry (horizontal axis). Standardized toxicity was computed by subtracting the industry-year mean from each observation to ensure comparability across industries that handle different levels of hazardous materials.

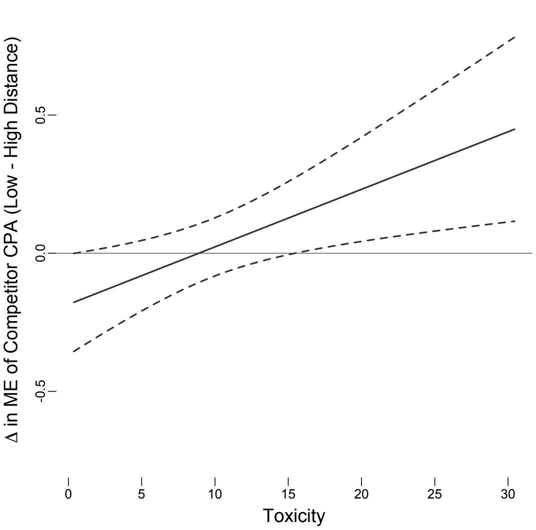


(a) Marginal Effect of Competitor CPA

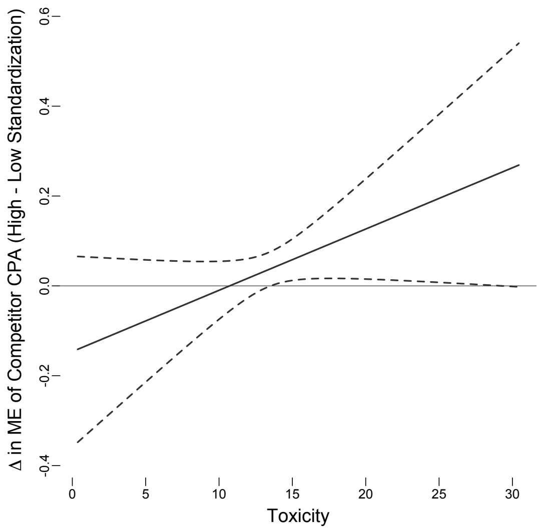


(b) Marginal Effect of Toxic Releases

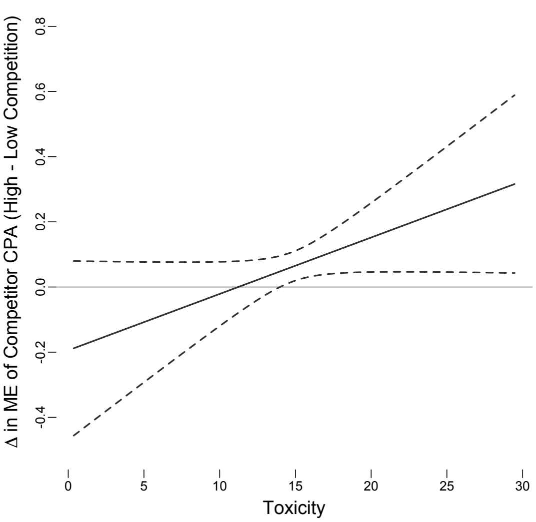
Figure 2: Marginal Effects of Competitor CPA and Toxicity on Probability of Being Fined. Based on Model (6) in Table 2, which includes firm fixed effects. 90 percent confidence intervals.



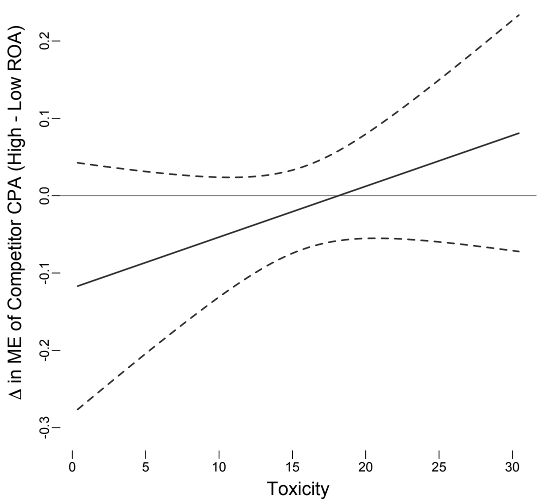
(a) Geographic Proximity



(b) Standardization



(c) Competitive Aggressiveness



(d) Firm Performance

Figure 3: Boundary Conditions. Difference in marginal effects of competitor CPA depending on high and low information (Panels a and b) and high and low motivation (Panels c and d). Based on Models 2, 4, 6, and 8 in Table 3, which include firm fixed effects. 90 percent confidence intervals.