Supplementary Appendix for:
"Persuasion in the Political Marketplace: How Firms Snitch on Rivals to Encourage Regulatory Enforcement"

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A Model

A.1 The Snitch's Maximization

Given the binding constraints $\mu_0 = \mu_g\tau_g + \mu_i\tau_i$ and $\tau_g = 1 - \tau_i$, the Lagrangian of the snitch's objective function can be simplified by substituting these constraints directly into the objective function, leading to:

$$\begin{aligned}\mathcal{L} = \tau_g \Big(\mathbb{1}_{\{\mu_g \geq \frac{1}{2}\}} \mu_g V - \iota \left(H(\mu_0) - H(\mu_g) \right) \Big) \\ + (1 - \tau_g) \left(-\iota \left(H(\mu_0) - H(\mu_i) \right) \right) + \lambda_1 \tau_g + \lambda_2 (1 - \tau_g).\end{aligned}$$

where $\mu_g = \frac{1}{2}$ (as discussed in the derivation of the interior and corner solutions below), and μ_i is an implicit function of τ_g defined by the constraint $\mu_0 = \mu_g\tau_g + \mu_i(1-\tau_g)$. The first-order condition is:

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial \tau_g} = \mathbb{1}_{\{\mu_g \geq \frac{1}{2}\}} \mu_g V \\ - \iota \left(H(\mu_i) - H(\mu_g) - (1 - \tau_g) \frac{\partial H(\mu_i)}{\partial \mu_i} \frac{\partial \mu_i}{\partial \tau_g} \right) + \lambda_1 - \lambda_2 = 0.\end{aligned}$$

The complementary slackness conditions are:

$$\begin{aligned}\lambda_1 \tau_g = 0, \\ \lambda_2 (1 - \tau_g) = 0.\end{aligned}$$

Interior Solution When the solution is interior, $\mu_g = \frac{1}{2}$. Any value above $\frac{1}{2}$ would raise the cost of the signal without providing additional benefits, whereas any value below $\frac{1}{2}$ would yield no benefit from signal g.
Implicitly differentiating μ_i with respect to τ_g under the constraint $\mu_0 = \tau_g\mu_g + (1-\tau_g)\mu_i$ gives

$$0 \;=\; \mu_g - \mu_i + (1 - \tau_g) \frac{\partial \mu_i}{\partial \tau_g} \qquad \Longrightarrow \qquad \frac{\partial \mu_i}{\partial \tau_g} \;=\; \frac{\mu_i - \mu_g}{1 - \tau_g}.$$

Because $\mu_g = \frac{1}{2}$,

$$\frac{\partial \mu_i}{\partial \tau_g} \;=\; \frac{\mu_i - \frac{1}{2}}{1 - \tau_g}.$$

$$H\big(\mu_g\big) \;=\; H\Big(\tfrac{1}{2}\Big) \;=\; -\frac{1}{2}\ln\Big(\tfrac{1}{2}\Big) - \frac{1}{2}\ln\Big(\tfrac{1}{2}\Big) \;=\; \ln 2.$$

The interior first-order condition for the maximization problem can therefore be written as

$$\frac{1}{2}\,\frac{V}{\iota} \;=\; H(\mu_i) - \ln 2 - \frac{\partial H(\mu_i)}{\partial \mu_i}\left(\mu_i - \tfrac{1}{2}\right).$$

Substituting

$$H(\mu_i) = -\mu_i \ln \mu_i - (1 - \mu_i)\ln(1 - \mu_i) \qquad \text{and} \qquad \frac{\partial H(\mu_i)}{\partial \mu_i} = \ln(1 - \mu_i) - \ln(\mu_i)$$

into the first-order condition gives

$$\frac{1}{2}\frac{V}{\iota} = -\mu_i \ln \mu_i - (1-\mu_i)\ln(1-\mu_i) - \ln 2 - \big(\ln(1-\mu_i) - \ln \mu_i\big)\big(\mu_i - \tfrac{1}{2}\big).$$

This simplifies to

$$\frac{1}{2}\frac{V}{\iota} = -\frac{1}{2}\ln \mu_i - \frac{1}{2}\ln(1-\mu_i) - \ln 2.$$

Multiplying through by 2 and using logarithmic identities yields

$$\frac{V}{\iota} = -\ln\big(4\mu_i(1-\mu_i)\big).$$

Solving for μ_i (with $\mu_i < \frac{1}{2}$)[1] yields

$$\mu_i = \frac{1}{2}\left(1 - \sqrt{1 - e^{-V/\iota}}\right).$$

Leading to the interior solution

$$\tau_g = \frac{2(\mu_0 - \mu_i)}{1 - 2\mu_i} \quad \text{with} \quad \mu_i = \frac{1}{2}\left(1 - \sqrt{1 - e^{-\frac{V}{\iota}}}\right), \quad \text{and} \quad \lambda_1 = \lambda_2 = 0.$$

Second-Order Condition of the Interior Solution The second-order derivative of the Lagrangian with respect to τ_g is given by

$$\frac{\partial^2 \mathcal{L}}{\partial \tau_g^2} = -\iota \frac{\partial}{\partial \tau_g}\left(H(\mu_i) - H(\mu_g) - (1-\tau_g)\frac{\partial H(\mu_i)}{\partial \mu_i}\frac{\partial \mu_i}{\partial \tau_g}\right),$$

which can be rewritten as

$$\frac{\partial^2 \mathcal{L}}{\partial \tau_g^2} = -\iota \left(2\frac{\partial H(\mu_i)}{\partial \mu_i}\frac{\partial \mu_i}{\partial \tau_g} - (1-\tau_g)\left(\frac{\partial^2 H(\mu_i)}{\partial \mu_i^2}\left(\frac{\partial \mu_i}{\partial \tau_g}\right)^2 + \frac{\partial H(\mu_i)}{\partial \mu_i}\frac{\partial^2 \mu_i}{\partial \tau_g^2}\right)\right).$$

Because

$$\frac{\partial \mu_i}{\partial \tau_g} = \frac{\mu_i - \mu_g}{1-\tau_g}, \qquad \frac{\partial^2 \mu_i}{\partial \tau_g^2} = \frac{2(\mu_i - \mu_g)}{(1-\tau_g)^2},$$

The second-order derivative can be formulated as

$$\frac{\partial^2 \mathcal{L}}{\partial \tau_g^2} = -\iota \left(\frac{\partial H(\mu_i)}{\partial \mu_i}\frac{2(\mu_i - \mu_g)}{1-\tau_g} - (1-\tau_g)\left(\frac{\partial^2 H(\mu_i)}{\partial \mu_i^2}\frac{(\mu_i - \mu_g)^2}{(1-\tau_g)^2} + \frac{\partial H(\mu_i)}{\partial \mu_i}\frac{2(\mu_i - \mu_g)}{(1-\tau_g)^2}\right)\right).$$

The terms involving $\frac{\partial H(\mu_i)}{\partial \mu_i}$ cancel out, leaving the compact form

$$\frac{\partial^2 \mathcal{L}}{\partial \tau_g^2} = \iota \frac{\partial^2 H(\mu_i)}{\partial \mu_i^2}\frac{(\mu_i - \mu_g)^2}{1-\tau_g}$$

which is negative since

$$\frac{\partial^2 H(\mu_i)}{\partial \mu_i^2} = \frac{\partial}{\partial \mu_i}\big(\ln(1-\mu_i) - \ln(\mu_i)\big) = -\big(\tfrac{1}{1-\mu_i} + \tfrac{1}{\mu_i}\big) < 0,$$

and the remaining factors are positive. This confirms that the interior solution is indeed a global maximum.

[1] $\mu_i \geq \frac{1}{2}$ is excluded by Bayesian plausibility.

Corner Solutions If $\tau_g = 0$, the Bayesian updating constraint

$$\mu_0 \;=\; \mu_g \tau_g + \mu_i(1-\tau_g)$$

implies $\mu_i = \mu_0$. Under sequential equilibrium, posteriors exhibit continuity as $\tau_g \to 0$. This imposes $\mu_g = \frac{1}{2}$. The complementary slackness conditions then yield

$$\lambda_1 = \iota\left(-\frac{1}{2}\ln\left(4\mu_0(1-\mu_0)\right)\right) - \frac{1}{2}V, \qquad \lambda_2 = 0,$$

with $\lambda_1 > 0$ if and only if

$$\frac{V}{\iota} < -\ln\left(4\mu_0(1-\mu_0)\right).$$

As shown above, the Lagrangian is strictly concave in τ_g for $\tau_g \in [0,1)$. With a strictly concave objective function and a convex feasible set (defined by linear constraints), any feasible point that satisfies the Kuhn–Tucker conditions is the unique global maximizer. Therefore, when

$$\frac{V}{\iota} < -\ln\left(4\mu_0(1-\mu_0)\right),$$

the allocation $\tau_g = 0$, $\lambda_1 = \iota\left(-\frac{1}{2}\ln\left(4\mu_0(1-\mu_0)\right)\right) - \frac{1}{2}V$, and $\lambda_2 = 0$ identifies the unique global maximum.

The solution $\tau_g = 1$ is not admissible. Under sequential equilibrium, posteriors exhibit continuity as $\tau_g \to 1$. Thus, any interior solution $\tau_g = 1-\varepsilon$, where $\varepsilon > 0$ is arbitrarily small, imposes $\mu_g = \frac{1}{2}$. The Bayesian updating constraint can then be written as

$$\mu_0 = \tfrac{1}{2}(1-\varepsilon) + \mu_i\,\varepsilon.$$

Letting $\varepsilon \to 0$ implies

$$\mu_0 \;\to\; \tfrac{1}{2}.$$

However, this contradicts the assumption that $\mu_0 < \frac{1}{2}$. Hence, $\tau_g = 1$ cannot be optimal. Metaphorically speaking, precisely because the regulator is not gullible but instead engages in Bayesian updating, the informant cannot cry wolf all the time; crying wolf all the time is optimal only when the regulator already believes the rival to be guilty with probability $\frac{1}{2}$, and would therefore investigate without needing any persuasion. Indeed, $2\mu_0 < 1$ is an upper bound on the frequency with which the snitch can send a guilty report, which can be verified by examining the behavior of the interior solution as ι becomes arbitrarily small (i.e., $\iota \to 0$).

Conclusion The interior solution

$$\tau_g = \frac{2(\mu_0-\mu_i)}{1-2\mu_i} \quad \text{with} \quad \mu_i = \frac{1}{2}\left(1-\sqrt{1-e^{-\frac{V}{\iota}}}\right), \quad \text{and} \quad \lambda_1 = \lambda_2 = 0,$$

is a global maximum if

$$\frac{V}{\iota} \geq -\ln\left(4\mu_0(1-\mu_0)\right).$$

Else, the corner solution

$$\tau_g = 0, \quad \lambda_1 = \iota\left(-\frac{1}{2}\ln\left(4\mu_0(1-\mu_0)\right)\right) - \frac{1}{2}V, \quad \text{and} \quad \lambda_2 = 0,$$

is a global maximum. The corner solution

$$\tau_g = 1, \quad \lambda_1 = 0, \quad \lambda_2 > 0,$$

is not admissible.

A.2 CES Model of Monopolistic Competition

Firms compete in a Constant Elasticity of Substitution (CES) model of monopolistic competition, with heterogeneous linear marginal costs among firms. The demand for a firm's product is given by:

$$q_i = \left(\frac{p_i}{P}\right)^{-\alpha} Q,$$

where:

- q_i: Quantity of the product demanded as a function of price,
- p_i: Price set by the firm,
- P: CES price index, defined as

$$P = \left(\sum_{j=1}^{n} p_j^{1-\alpha}\right)^{\frac{1}{1-\alpha}},$$

- Q: CES quantity index, defined as

$$Q = \left(\sum_{j=1}^{n} q_j^{\frac{\alpha-1}{\alpha}}\right)^{\frac{\alpha}{1-\alpha}},$$

  Furthermore, $Q = E/P$ with E being total expenditure.

- $\alpha > 1$: Elasticity of substitution between products, where a higher α indicates closer substitutes and greater competitive aggressiveness.

A.3 Rival's Gains from Non-compliance

When the rival reduces its cost by a factor $d < 1$, its marginal cost changes from c_r to:

$$c_r' = d\, c_r.$$

Markup Pricing Under the CES monopolistic competition model, the firm's optimal price is a constant markup over marginal cost:

$$p_r = \frac{\alpha}{\alpha - 1} c_r,$$

and after the cost reduction:

$$p_r' = \frac{\alpha}{\alpha - 1} c_r' = \frac{\alpha}{\alpha - 1}(d\, c_r) = d\, p_r.$$

Quantity The demand for the rival's product before the cost reduction is:

$$q_r = \left(\frac{p_r}{P}\right)^{-\alpha} Q.$$

Assuming that the CES quantity index Q remains approximately unchanged—since the rival's increase in quantity produced is small relative to the market—after the cost reduction and price adjustment, the new quantity demanded is:

$$\begin{aligned} q_r' &\approx \left(\frac{p_r'}{P}\right)^{-\alpha} Q \\ &= \left(\frac{dp_r}{P}\right)^{-\alpha} Q \\ &= d^{-\alpha} q_r. \end{aligned}$$

Profit Gain The rival's profit before the cost reduction is:

$$\pi_r = (p_r - c_r) q_r.$$

After the cost reduction, the profit becomes:

$$\pi_r' = (p_r' - c_r') q_r'.$$

Substituting $p_r' = d\,p_r$, $c_r' = d\,c_r$, and $q_r' \approx d^{-\alpha} q_r$:

$$\begin{aligned} \pi_r' &\approx (d\,p_r - d\,c_r) d^{-\alpha} q_r \\ &= d^{1-\alpha} (p_r - c_r) q_r \\ &= d^{1-\alpha} \pi_r. \end{aligned}$$

Conclusion Thus, the rival's profits increase by a factor of $d^{1-\alpha}$ when it reduces its cost by a factor d:

$$\pi_r' \approx d^{1-\alpha} \pi_r.$$

Since $d < 1$ and $\alpha > 1$, the exponent $1 - \alpha$ is negative, implying that $d^{1-\alpha} > 1$. Therefore, the rival's profits increase due to cost reduction through non-compliance.

A.4 The Snitch's Profit Gains from Reporting, V

Before the rival exits, the snitch's profit is:

$$\pi_s = (p_s - c_s) q_s = (p_s - c_s) \left(\frac{p_s}{P}\right)^{-\alpha} Q,$$

When the rival exits the market due to being fined, the new CES price index becomes:

$$P' = \left(\sum_{\substack{j=1 \\ j \neq r}}^{n} p_j^{1-\alpha} \right)^{\frac{1}{1-\alpha}}.$$

Total expenditure E remains constant, but the aggregate quantity Q' changes to:

$$Q' = \frac{E}{P'}.$$

Changes in P and Q The rival exits only if it does not comply. The change in P due to the rival's exit is:

$$P^{1-\alpha} = \sum_{\substack{j=1 \\ j \neq r}}^{n} p_j^{1-\alpha} + (d\,p_r)^{1-\alpha}, \quad P'^{1-\alpha} = P^{1-\alpha} - (d\,p_r)^{1-\alpha}.$$

Thus:

$$P' = P\left(1 - \left(\frac{d\,p_r}{P}\right)^{1-\alpha}\right)^{\frac{1}{1-\alpha}}.$$

Since $Q = \dfrac{E}{P}$ and $Q' = \dfrac{E}{P'}$, we have:

$$Q' = Q\frac{P}{P'} = Q\left(1 - \left(\frac{d\,p_r}{P}\right)^{1-\alpha}\right)^{\frac{1}{\alpha-1}}.$$

The Snitch's Profit Gains Noting that $\pi_r = (p_r - c_r)\left(\dfrac{p_r}{P}\right)^{-\alpha} Q$ implies $\left(\frac{p_r}{P}\right)^{1-\alpha} = \frac{p_r}{PQ}\frac{\pi_r}{p_r - c_r} = \alpha\frac{\pi_r}{PQ}$ (with the last equality being driven by the constant markup rule, $p_r = \frac{\alpha}{\alpha-1}c_r$ of CES competition models), the snitch's profits after the rival exits can thus be rewritten as:

$$\begin{aligned}
\pi_s' &= (p_s - c_s)\left(\frac{p_s}{P'}\right)^{-\alpha} Q' \\
&= \pi_s \left(\frac{P}{P'}\right)^{-\alpha} Q' \\
&= \pi_s \left(1 - d^{1-\alpha}\frac{p_r^{1-\alpha}}{P^{1-\alpha}}\right)^{-1} \\
&= \pi_s \left(1 - \alpha\frac{\pi_r}{PQ}d^{1-\alpha}\right)^{-1} \approx \pi_s\left(1 + \alpha\frac{\pi_r}{PQ}d^{1-\alpha}\right),
\end{aligned}$$

where the last approximation is due to $\left(1 - \alpha\frac{\pi_r}{PQ}d^{1-\alpha}\right)^{-1}$ being the sum of the infinite geometric series $1 + \alpha\frac{\pi_r}{PQ}d^{1-\alpha} + \left(\alpha\frac{\pi_r}{PQ}d^{1-\alpha}\right)^2 ...$, which approximates to $1 + \alpha\frac{\pi_r}{PQ}d^{1-\alpha}$ under the assumption that the rival is small relative to the market ($\frac{\pi_r}{PQ} \ll 1$).

Conclusion The profit gains from snitching are thus:

$$V = \pi_s' - \pi_s \approx \pi_s\frac{\alpha\pi_r}{PQ}d^{1-\alpha}.$$

A.5 Proofs of Lemma and Propositions

A.5.1 Proof of Lemma 1

Proof. **Only-if Part.** Set $d' := \left(\frac{(1-2\rho)\mu_i}{\rho(1-2\mu_i)}\right)^{\frac{1}{\alpha-1}}$ and $\rho^*(\Lambda) := \mu_i = \frac{1}{2}\left(1 - \sqrt{1 - e^{-\frac{V}{\iota(\Lambda)}}}\right)$. If $d < d'$, the non-compliance condition holds. Furthermore, if $\frac{\partial(\mu_g\tau_g^*)}{\partial\Lambda} = \mu_g\frac{\partial\tau_g^*}{\partial\Lambda} > 0$, then τ_g^* cannot remain at a boundary value of 0 (i.e., cannot be a constant) and therefore cannot be a corner solution of the

snitch's maximization problem. But then, the solution must be interior, with the complementary slackness conditions implying $\frac{V}{\iota(\Lambda)} \geq -\ln\big(4\mu_0(1-\mu_0)\big)$, or, equivalently,

$$\rho \;=\; \mu_0 \;\geq\; \frac{1}{2}\Big(1-\sqrt{1-e^{-V/\iota(\Lambda)}}\Big) = \rho^*(\Lambda).$$

If Part. If $d < d'$, the non-compliance condition holds. Additionally, if $\rho \;= \mu_0 \geq \rho^*(\Lambda) \;= \mu_i$, the snitching condition also holds, implying it is sequentially rational for the snitch to gather evidence for a persuasive report. Consequently, the probability of enforcement conditional on non-compliance is

$$\frac{\mu_g \tau_g^*}{\mu_0} = \frac{\mu_0 - \mu_i}{\mu_0(1-2\mu_i)}.$$

By Bayes' rule, the unconditional probability of enforcement is

$$\frac{\mu_g \tau_g^*}{\mu_0}\mu_0 = \mu_g \tau_g^* = \frac{\mu_0 - \mu_i}{1-2\mu_i}.$$

Then, noting that $\iota \propto \frac{1}{\Lambda}$, $\iota \propto \frac{1}{\gamma}$, and $\iota \propto \frac{1}{\sigma}$, we may write

$$\iota = \frac{k}{\Lambda\gamma\sigma},$$

for some constant $k > 0$. Since

$$\frac{\partial(\mu_g\tau_g^*)}{\partial\mu_i} = -\frac{1-2\mu_0}{(1-2\mu_i)^2} < 0, \qquad \frac{\partial\mu_i}{\partial\iota} = \frac{Ve^{-V/\iota}}{4\iota^2\sqrt{1-e^{-V/\iota}}} = \frac{V}{\iota^2}\,\frac{\mu_i(1-\mu_i)}{1-2\mu_i} > 0,$$

and

$$\frac{\partial\iota}{\partial\Lambda} = -\frac{k}{\Lambda^2\gamma\sigma} = -\frac{\iota}{\Lambda} < 0,$$

it follows by the chain rule that

$$\frac{\partial(\mu_g\tau_g^*)}{\partial\Lambda} = \frac{\partial(\mu_g\tau_g^*)}{\partial\mu_i}\frac{\partial\mu_i}{\partial\iota}\frac{\partial\iota}{\partial\Lambda} = \left(-\frac{1-2\mu_0}{(1-2\mu_i)^2}\right)\frac{V\mu_i(1-\mu_i)}{\iota^2(1-2\mu_i)}\left(-\frac{\iota}{\Lambda}\right) > 0.$$

□

A.5.2 Proof of Proposition 1

Proof. **Only-if Part.** If

$$\frac{\partial(\mu_g\tau_g^*)}{\partial\gamma} > 0, \qquad \frac{\partial(\mu_g\tau_g^*)}{\partial\sigma} > 0,$$

then τ_g^* cannot remain at its boundary value of 0 (i.e., it cannot be constant) and therefore cannot be a corner solution of the snitch's maximization problem. The solution must then be interior, implying that the conditions of Lemma 1 apply and, consequently,

$$\frac{\partial(\mu_g\tau_g^*)}{\partial\Lambda} > 0.$$

If Part. If

$$\frac{\partial(\mu_g\tau_g^*)}{\partial\Lambda} > 0,$$

then, by Lemma 1, the benefits of non-compliance must be sufficiently large, and the unconditional probability of regulatory enforcement depends on

$$\mu_i = \frac{1}{2}\left(1 - \sqrt{1 - e^{-V/\iota}}\right).$$

Observe that $\iota \propto \frac{1}{\Lambda}$, $\iota \propto \frac{1}{\gamma}$, and $\iota \propto \frac{1}{\sigma}$. Hence, we may write $\iota = \frac{k}{\Lambda\gamma\sigma}$ for some constant $k > 0$. Using

$$\tau_g^* = 1 - \frac{1 - 2\mu_0}{1 - 2\mu_i},$$

the unconditional probability of regulatory enforcement becomes

$$\mu_g \tau_g^* = \mu_g \left(\frac{2(\mu_0 - \mu_i)}{1 - 2\mu_i}\right).$$

Since $\mu_g = \frac{1}{2}$, this simplifies to

$$\mu_g \tau_g^* = \frac{\mu_0 - \mu_i}{1 - 2\mu_i}.$$

Step 1: Derive $\frac{\partial(\mu_g\tau_g^*)}{\partial\mu_i}$.

$$\frac{\partial(\mu_g\tau_g^*)}{\partial\mu_i} = \frac{-1 + 2\mu_0}{(1 - 2\mu_i)^2}.$$

Since $\mu_0 < \frac{1}{2}$, we have $-1 + 2\mu_0 < 0$, and therefore

$$\frac{\partial(\mu_g\tau_g^*)}{\partial\mu_i} < 0.$$

Step 2: Derive $\frac{\partial\mu_i}{\partial\iota}$ and $\frac{\partial(\mu_g\tau_g^*)}{\partial\iota}$. With

$$\mu_i = \frac{1}{2}\left(1 - \sqrt{1 - e^{-V/\iota}}\right),$$

we obtain

$$\frac{\partial\mu_i}{\partial\iota} = \frac{V\, e^{-V/\iota}}{4\iota^2\sqrt{1 - e^{-V/\iota}}} = \frac{V}{\iota^2}\,\frac{\mu_i(1 - \mu_i)}{1 - 2\mu_i} > 0.$$

Hence,

$$\frac{\partial(\mu_g\tau_g^*)}{\partial\iota} = \frac{\partial(\mu_g\tau_g^*)}{\partial\mu_i}\frac{\partial\mu_i}{\partial\iota} < 0.$$

Step 3: Derive $\frac{\partial\iota}{\partial\gamma}$, $\frac{\partial\iota}{\partial\sigma}$, and chain rule derivatives.

$$\frac{\partial\iota}{\partial\gamma} = -\frac{k}{\gamma^2\Lambda\sigma} = -\frac{\iota}{\gamma}, \qquad \frac{\partial\iota}{\partial\sigma} = -\frac{k}{\sigma^2\Lambda\gamma} = -\frac{\iota}{\sigma}.$$

Thus,

$$\frac{\partial(\mu_g\tau_g^*)}{\partial\gamma} = \frac{\partial(\mu_g\tau_g^*)}{\partial\iota}\left(-\frac{\iota}{\gamma}\right) > 0, \qquad \frac{\partial(\mu_g\tau_g^*)}{\partial\sigma} = \frac{\partial(\mu_g\tau_g^*)}{\partial\iota}\left(-\frac{\iota}{\sigma}\right) > 0.$$

□

A.5.3 Proof of Proposition 2

Proof. **Only-if Part.** If

$$\frac{\partial(\mu_g \tau_g^*)}{\partial \alpha} > 0, \qquad \frac{\partial(\mu_g \tau_g^*)}{\partial \pi_r} > 0,$$

then τ_g^* cannot remain at its boundary value of 0 (i.e., it cannot be constant) and therefore cannot be a corner solution of the snitch's maximization problem. The solution must then be interior, implying that the conditions of Lemma 1 apply and, consequently,

$$\frac{\partial(\mu_g \tau_g^*)}{\partial \Lambda} > 0.$$

If Part. If

$$\frac{\partial(\mu_g \tau_g^*)}{\partial \Lambda} > 0,$$

then, by Lemma 1, the benefits of non-compliance must be sufficiently large, and the unconditional probability of regulatory enforcement depends on

$$\mu_i = \frac{1}{2}\left(1 - \sqrt{1 - e^{-V/\iota}}\right).$$

Recall that:

$$V \approx \pi_s \frac{\alpha \pi_r}{PQ} d^{1-\alpha}, \qquad \mu_g \tau_g^* = \frac{\mu_0 - \mu_i}{1 - 2\mu_i}.$$

Step 1: Derive $\frac{\partial \mu_i}{\partial V}$

$$\mu_i = \frac{1}{2}\left(1 - \sqrt{1 - e^{-\frac{V}{\iota}}}\right), \quad \frac{\partial \mu_i}{\partial V} = -\frac{e^{-V/\iota}}{4\iota\sqrt{1 - e^{-V/\iota}}} = -\frac{1}{\iota}\frac{\mu_i(1-\mu_i)}{1-2\mu_i} < 0.$$

Because $\frac{\partial(\mu_g \tau_g^*)}{\partial \mu_i} = -\frac{1-2\mu_0}{(1-2\mu_i)^2} < 0$:

$$\frac{\partial(\mu_g \tau_g^*)}{\partial V} = \frac{\partial(\mu_g \tau_g^*)}{\partial \mu_i}\frac{\partial \mu_i}{\partial V} > 0.$$

Step 2: Derive $\frac{\partial V}{\partial \alpha}$, $\frac{\partial V}{\partial \pi_r}$, and chain rule derivatives.

$$\frac{\partial V}{\partial \alpha} \approx (1 - \alpha \log d)\frac{\pi_s \pi_r}{PQ} d^{1-\alpha} > 0, \quad \frac{\partial V}{\partial \pi_r} \approx \alpha \frac{\pi_s}{PQ} d^{1-\alpha} > 0,$$

since $d < 1 \Rightarrow \log d < 0$. The chain rule derivatives are:

$$\frac{\partial(\mu_g \tau_g^*)}{\partial \alpha} = \frac{\partial(\mu_g \tau_g^*)}{\partial V}\frac{\partial V}{\partial \alpha} > 0, \quad \frac{\partial(\mu_g \tau_g^*)}{\partial \pi_r} = \frac{\partial(\mu_g \tau_g^*)}{\partial V}\frac{\partial V}{\partial \pi_r} > 0.$$

□

A.6 Relationship Between d and ρ and Propensity to Comply

In this section, we explore the potential relationship between the cost discount parameter d and the risk of significant harm ρ, as well as heterogeneity in firms' propensity to comply, denoted by Γ. One way to interpret this connection is to view ρ as capturing the rival's "temptation" to violate when presented with an opportunity to increase profits by a factor $d^{1-\alpha}$. In this sense, non-compliance can be thought of as a biased "coin flip" whose bias depends on $d^{1-\alpha}$: higher profit gains (i.e., smaller d) correspond to higher values of ρ. This temptation can be counterbalanced by Γ, which captures factors inducing firms to comply—such as risk aversion, stakeholder pressures, or ethical considerations—and biases the trial toward compliance. To capture these relationships, we assume

$$\rho(d,\Gamma) = \frac{d^{1-\alpha}-1}{\Gamma + 2\,d^{1-\alpha}}, \qquad \Gamma > 0.$$

This specification satisfies:

$$\lim_{d\to 0}\rho(d,\Gamma) = \frac{1}{2}, \qquad \lim_{d\to 1}\rho(d,\Gamma) = 0,$$

as well as the comparative statics:

$$\frac{\partial\rho}{\partial(d^{1-\alpha})} > 0, \qquad \frac{\partial\rho}{\partial\Gamma} < 0, \qquad \text{for } \rho \in \left(0, \tfrac{1}{2}\right).$$

Under this mapping, Lemma 1 retains its force when the rival is not excessively risk-seeking. A reputation for high risk tolerance would raise suspicion and increase the likelihood of detection. Conversely, when the rival is known to be risk-averse, the non-compliance condition is automatically satisfied, so snitching (and thus enforcement) is triggered only for very large cost savings due to serious violations. It is reasonable to assume that most firms exhibit some degree of risk aversion when it comes to non-compliance, given that violations can entail substantial legal liabilities and political costs.

To see why some risk aversion is necessary for our results, note that if $\Gamma \;\geq\; \dfrac{1-2\mu_i}{\mu_i} - 2$, then the non-compliance condition holds for all $d \in (0,1]$. The non-compliance condition can be rewritten as $d \leq d'(\rho)$ with

$$d'(\rho) = \left(\frac{(1-2\rho)\,\mu_i}{\rho\,(1-2\mu_i)}\right)^{\frac{1}{\alpha-1}}.$$

With $\rho(d,\Gamma) = \dfrac{d^{1-\alpha}-1}{\Gamma + 2\,d^{1-\alpha}}$, a direct substitution and simplification yields the equivalent requirement

$$d^{\alpha-1} \;\geq\; 1 - \frac{(\Gamma+2)\,\mu_i}{1-2\mu_i}.$$

Define $B(\Gamma) := 1 - \dfrac{(\Gamma+2)\,\mu_i}{1-2\mu_i}$. Since $d \in (0,1)$ and $\alpha > 1$, we have $d^{\alpha-1} \in (0,1)$ and in particular $d^{\alpha-1} > 0$.

Now suppose $\Gamma \;\geq\; \dfrac{1-2\mu_i}{\mu_i} - 2$. Then $(\Gamma+2)\mu_i \geq 1-2\mu_i$, i.e., $B(\Gamma) \leq 0$. Consequently, $d^{\alpha-1} \;\geq\; B(\Gamma)$ holds for *every* $d \in (0,1)$. Thus, enforcement depends solely on the snitching condition, which is satisfied when ρ is sufficiently large (i.e., when d is sufficiently small), consistent with Lemma 1. If $\Gamma < \dfrac{1-2\mu_i}{\mu_i} - 2$, then $B(\Gamma) \in (0,1)$ imposes the lower bound $d \;\geq\; \big[B(\Gamma)\big]^{1/(\alpha-1)} \in (0,1)$, so non-compliance holds only for sufficiently large d (i.e., sufficiently small cost savings), and Lemma 1 does

not apply. It also implies that the prior ρ is not realized in equilibrium (which is not a requirement in games of Bayesian persuasion), since non-compliance will not occur with probability ρ: if ρ does not satisfy the non-compliance condition, the rival will comply instead, violating with probability 0 rather than ρ.

Remarks. From a "philosophical" standpoint—that is, insofar as it entails a particular interpretation of the model's parameters, with correct priors and regulatory enforcement occurring with positive probability in equilibrium—our framework remains internally coherent only if: (1) potential informants occasionally commit omission errors; and (2) firms are sufficiently cautious, so that non-compliance arises only in cases of serious violations yielding substantial cost savings.

B Data & Variable Creation

B.1 Dataset Construction

Our dataset comes from four sources. The basis of our data stems from the EPA's Toxic Release Inventory (TRI) dataset which monitors the release of toxic chemicals into the environment. This data is at the facility-year level and tracks the amount of each toxic chemical that is disposed by the facility, how the facility disposes it (released via air/water or recycled/disposed), the facility's longitude and latitude, and lists the facility's reported parent company. We matched this to the Enforcement and Compliance History Online (ECHO) dataset, which tracks which facilities are fined for pollution violations, and the severity of their fine. From this base sample, we took the over 14,000 parent companies from the TRI dataset and hand matched them to Compustat's North American and Global database by name. Once we had this sample, we hand match these firms to OpenSecrets LobbyView database, which contains information on firm's lobbying activities. These four datasets form the basis of the bulk of our variables.

From the ECHO dataset we derive our dependent variable of EPA Fine.

From the OpenSecrets database we derive all measures of CPA: Firm CPA (EPA), Firm CPA (Non-EPA), Competitor CPA, Competitor CPA (Non-EPA).

The Compustat database serves as the basis for the variables: Firm Assets, Debt to Equity, Industry Concentration, Foreign Company, and Relative Firm Performance.

Finally from the TRI database we compute: Toxicity, Firm Diversity, Local Competitor's Toxicity, Local Non-Competitor's Toxicity, # of Competitors $<$ 25km, # of Non-Competitors $<$ 25km, Closest Rival $<$ 50km, and a facility's Industry Standardization.

In addition to these variables from the core datasets, there are a few additional variables that come from other datasets. The variables of County Income per Capita and County Population come from the US Bureau of Economic Analysis. The variable Competitive Aggressiveness comes from Schott's (2008) data on imports by sector.

B.2 Control Variables: Discussion

In the article, we briefly list the time-varying control variables we include in our analyses. Here, we provide a more detailed, theoretically motivated discussion of our covariates.

We control for a number of firm-level characteristics. First, the literature highlights that firms can use CPA for their own advantage at the regulatory stage. We therefore control for focal firms' CPA, proxied by their own lobbying spending towards the EPA. Second, firms differ in how much they focus on compliance, which affects their baseline risk of being fined. To control for this, we use the Execucomp database to create a dummy variable for whether a firm has a lawyer as a member of its top management team. Third, facilities that are located closer to an EPA office may have greater knowledge about compliance or closer relationships with regulatory agents, resulting in a lower probability of receiving a fine. We therefore include the distance between a facility and the closest EPA office as a control. Fourth, another way for firms to influence EPA decisions or to have more knowledge about compliance is to hire employees through the revolving door. We create a dummy variable for whether a firm has an employee in the BoardEx dataset that used to work for the EPA. Fifth, foreign firms may have less connections to the government or may understand the rules less well, so we include a dummy variable for whether a firm is foreign owned. Sixth, as the scale of operations for a firm increases, compliance can become more difficult to manage. Thus, we control for the number of facilities the firm operates in a given year. Seventh, larger firms might be targeted more by the EPA and competitors, and thus have a higher baseline for fines. We therefore control for firms' size using their total assets. Eighth, a firm with more financial constraints might be less likely to comply with regulations due to needing to spend resources elsewhere. We proxy for these constraints using a firm's debt-to-equity ratio. Ninth, since firms with a wide breadth of economic activity might have greater difficulty with compliance across different regulatory rules, so we control for the number of unique SIC codes of firms' facilities as a proxy for firm diversity. Finally, since the EPA is likely to more vigorously monitor facilities that have previous violations, we include the number of fines for the facility in the past five years.

A second set of controls addresses the possibility that a firm's CPA towards the EPA, as measured through its lobbying spending, captures how politically connected the firm is in general, rather than with the EPA specifically. We control for firms' non-EPA lobbying, as well as firms' competitors' non-EPA lobbying.

Further, we control for two time-varying variables at the industry-level. First, heavily regulated industries have more rules to follow, and thus are likely to be fined more frequently. We therefore include a measure of regulation taken from QuantGov. This measure represents the regulatory burden for an industry by counting the number of clauses pertaining to each industry across all existing regulatory statutes. Since most regulatory text is restrictive, this measure provides a reasonable estimate of the overall regulatory complexity and the burdens that different industries face. Second, the EPA might find it easier to monitor industries with a few large players rather than many small ones. Thus, we include a measure of industry concentration, where we use Compustat to compute the Herfindahl index of sales for each SIC-4 digit code.

Finally, it is possible that the stringency with which the EPA monitors and fines facilities depends on the characteristics of the area they are located in. In particular, the EPA might be more vigilant if facilities are located in wealthier or more populated areas. We therefore include the population size and income per capita of the county in which a facility is located, derived from data by the Bureau of Labor Statistics. Further, the EPA might be more likely to monitor and fine locations where there are larger clusters of facilities, especially if they are discharging a lot of toxic chemicals. We therefore control for 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.

B.3 Variable Creation

Below we outline how we create each variable.

EPA Fine: Data for our dependent variable, fines assessed by the EPA, is derived from the Enforcement and Compliance History Online (ECHO) dataset.[2] The ECHO dataset compiles formal actions taken by the EPA against the facilities it monitors, when the violations were first filed, and the final outcome of those actions in terms of fines and compliance costs. Since all of this information is timestamped, this tells us whether a facility was penalized in a particular year. We dichotomize this variable, by assigning a value of one if a facility received a fine in a given year, and zero otherwise. However, we exclude penalties that are imposed for administrative or trivial violations, such as maintaining incomplete records or failing to meet reporting requirements, as our theoretical argument does not apply to them. Fines for such offenses typically range between $1,000 and $8,000, so we choose a conservative cutoff of $10,000 for exclusion. We considered eliminating all fines that contained an administrative component. However, since the EPA often cites multiple violations against facilities, administrative issues may be flagged in conjunction with fines for facility violations. Our approach allows us to focus on more serious violations. However, our results are robust to various specifications of this measure.

Firm CPA (EPA): We derive information about all CPA from lobbying reports compiled in the OpenSecrets database. The OpenSecrets database tracks all lobbying activities disclosed in the government-mandated reports submitted by registered lobbyists. In accordance with the Lobbying Disclosure Act of 1995, all lobbyists, whether internal or external to the firm, must file reports about their lobbying activities. We collect the data from 1998 to 2014, and the reports feature the name of the client/employer and all expenses for lobbying. We match the name of firms from the OpenSecrets database to our firms in the matched sample from the TRI/Compustat database to get the lobbying reports for all of the firms. This information is filed quarterly (or bi-yearly if before 2008), for the amount the firm spent on lobbyists that quarter, and lists agencies they 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. Using this measure we take the total amount of lobbying a firm does towards the EPA in the prior three years and then log this amount (plus one).

Competitor CPA: First we define the set of a firm's competitors, we use the Standard Industrial Classification (SIC) 4-digit industry code derived from the Compustat database. To calculate the amount spent on lobbying by a firm's competitors, we take the logged total amount spent by all other firms that have the same SIC code. We use the past three years of lobbying because, as we have outlined above, trust built through sustained interactions between the agency and the firm plays an important role for our hypothesized mechanism. We log this amount (plus one).

Firm CPA (Non-EPA): This variable is created by following the same procedure as for Firm CPA (EPA), but all other (non-EPA) lobbying expenditures.

Competitor CPA (Non-EPA): This variable is created by following the same procedure as for Competitor CPA, but all other (non-EPA) lobbying expenditures.

Toxicity: We proxy the level of toxicity using the EPA's Toxics Release Inventory database which tracks the management of every toxic chemical in each facility.[3] Since the EPA's purview revolves around toxic chemicals affecting the environment, the TRI reports how each facility disposes each toxic chemical's byproduct by either releasing it into the environment (through the air or in

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

[3] https://www.epa.gov/toxics-release-inventory-tri-program. For details on reporting requirements, see https://www.epa.gov/toxics-release-inventory-tri-program/tri-threshold-screening-tool.

the water), or by recycling/disposing of it. Because we argue the EPA cares about the absolute risk stemming from the toxicity of the chemicals processed at the facility, we use the total amount of chemical byproduct (released and recycled/disposed) created by each facility as our basis for potential harm.

However, some toxic chemicals are more dangerous than others. Further, how humans are exposed to chemicals determines their toxicity. To account for this, we combine the TRI data on each facility's chemical byproducts with the EPA's Risk-Screening Environmental Indicators, which standardizes each chemical according to their hazardousness and exposure type.

For example, while both poisonous, exposure to a pound of lead is nearly 8800 times more hazardous when compared to a pound of methanol. To see how this affects the toxicity measure, take the median facility in our sample processing methanol (conditional upon processing the chemical at all) which produces 3400 pounds of byproduct. If this facility processed 500 more pounds of methanol it would increase toxicity of the facility, but that would still register less toxic than the median facility processing lead in our sample which produces 4.4 pounds of lead byproduct. Or, for example, take phosphorous (white or yellow) which can be lethal when ingested but is simply hazardous when inhaled. This is why our measure of toxicity weights water releases of phosphorous by over 9500 times more than releases in the air.

Thus, in line with the literature on the environmental impact of toxicity (Toffel & Marshall 2004), we create a variable of total toxicity for every facility-year in four steps.

First we multiply the toxicity from inhalation with the amount of air releases by a facility, second we multiply the toxicity from ingestion with the amount of water releases by the facility, third we sum these two products to get a measure of chemical-level toxicity for a facility, and finally we sum all chemicals in a facility-year together. This can be quantified by the following equation:

$$\text{Toxicity}_{it} = log\Big(\sum_{m}(\text{Air Releases}_{itm} \times \text{Inhalation Toxicity}_{m} + \text{Water Releases}_{itm} \times \text{Ingestion Toxicity}_{m}) + 1\Big)$$

for facility i in each year t, with chemical m.

This creates a measure of toxicity that is comparable across facilities since it takes into account that some materials are more harmful than others, and that their environmental impact is different depending on how they are released.

Note that the TRI data only accounts for how toxic chemicals are released into the environment (i.e. air or water), but not if they are recycled/disposed. Since we desire the total potential toxicity we need to combine these measures, therefore we assume a facility's 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. However, our results are robust to various specifications. We lag this measure by one year.

Logged Assets: This variable is created by taking the logged total assets of a firm plus one in a given year from Compustat's database.

# of Facilities: This variable is created by counting the number of TRI facilities for a firm in a given year.

Debt to Equity: This variable is created by dividing Long-Term Debt by Common Equity for a firm in a given year in the Compustat database.

Firm Diversity: This variable is created by adding up all of the unique SIC-4 digit industries a firm is active in during given year from the TRI database.

Foreign Firm: This variable is a dichotomous variable, taking the value of one if the location of the firm is not in the USA according to the Compustat database, and zero otherwise.

Local Toxicity Competitors: This variable is created in three steps. First, by using the longitude and latitude of each facility from the TRI dataset, we were able to locate all firms within a 25km radius. Second, we restricted this sample to facilities belonging to firms within the same SIC-4 digit code as the focal firm. Finally, we summed the toxicity of all these facilities together and logged that value adding one.

Local Toxicity Non-Competitors: This variable is created by following the same steps as Local Toxicity Competitors, but by using facilities that were not owned by a firm operating in the same SIC-4 digit code.

# of Local Competitors: This variable is created by following the same steps as Local Toxicity Competitors, but instead of summing the toxicity, we simply counted the number of facilities belonging to the firms within the same SIC-4 digit code as the focal firm.

# of Local Non-Competitors: This variable is created by following the same steps as # of Local Competitors but counting facilities that were not owned by a firm operating in the same SIC-4 digit code.

Previous Fines: This variable is the number of fines the facility has received in the past five years.

Logged Income per Capita: This variable comes from the Bureau of Labor Statistics, which keeps track of income by county. We divided the income value by population and log this value.

Logged Population: This variable comes from the Bureau of Labor Statistics, which keeps track of population by county. We log this value.

Regulations: Data on regulations comes from QuantGov.org, an open-source policy analytics platform from Mercatus Center at George Mason University. QuantGov compiles the RegData datasets which quantifies regulations by industry. They assess the probability that a given regulatory restriction is targeting a specific industry, creating an industry-specific measure of regulation over time. RegData uses the NAICS classification system, and therefore we matched this data to the NAICS of the firm in Compustat. The RegData has gaps in its NAICS coverage. For example, they have data on regulation for NAICS 3262, but not NAICS 3261, yet they have data on regulation at the NAICS three digit level – 326. Therefore, we match all possible firms in our sample using the four digit NAICS code, and then the three digit NAICS code for those that are missing, and then the two digit NAICS code for those left over. We log this value.

Industry Concentration: This variable is created by creating a Herfindahl index of sales for each SIC-4 digit code in Compustat's database.

Closest Rival <50km: By using the longitude and latitude of each facility from the TRI dataset, for each facility in each firm, we are able to calculate the distance of the closest rival in the same SIC-4 digit code. We then create a dichotomous variable to split our sample, which is one if the closest rival is within 50km of a given facility or zero if it is not.

Industry Standardization: This variable is created by following the procedure outlined in Diestre and Rajagopalan (2011), which borrows from work by Sampson (2007). There they create a measure of chemical relatedness by looking at the distribution of emissions across all regulated chemicals for separate industries. The underlying assumption is that two industries that had similar distributions had a higher level of relatedness than those pairs of industries with very different chemical distributions. We take this concept and apply it to the facility level.

Therefore our measure of industry standardization is given by the formula:

$$\text{Production Standardization}_{kdt} = \frac{C_{kt}C'_{dt}}{\sqrt{(C_{kt}C'_{kt})(C_{dt}C'_{dt})}}$$

where t is the year, k is the focal facility, d is the industry, and where $C_t = {C_t}^1 \dots {C_t}^n$ is an n-dimensional vector for all of the chemical compounds produced in a year with ${C_t}^s$ being the total amount of chemical s produced. The resulting variable varies from zero (the facility is completely unique in the industry) to one (the facility exact same as the rest of the industry on average). In our analysis we split our sample along the median value of our dataset to test our hypothesis.

Competitive Aggressiveness: We proxy competitive aggressiveness by the amount of imports to the domestic market. We derive the data from Schott (2008), found on his website.[4] We match this data to the firms at the SIC-4 level. To calculate the level of competitive aggression that firms within the US face, we look at the change in the net imports (imports minus exports) for the industry compared to five years prior. We used the net imports since, if imports are rising within the industry, but at a slower rate than exports, we would not expect there to be increased pressure in terms of lower margins and the need to cut costs. However, our measure is robust to various specifications. In our analysis we split our sample along the median value of our dataset to test our hypothesis.

Relative Firm Performance: Our proxy for relative firm performance is based upon the measure of relative ROA from Greve (2003). Following their recommendation we divide EBITDA by total assets in the Compustat database for each firm. Then at the SIC-4 digit level, we find the average ROA in a given year. To get the relative ROA we subtract the ROA of the firms from this mean value. In our analysis we split our sample along the median value of our dataset to test our hypothesis.

[4] https://sompks4.github.io/sub_data.html

C Complete Tables from Manuscript

Table C1: Full Results for Table 2. Effect of Toxicity and Competitor CPA 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)
Firm CPA (EPA)	-0.023	-0.025	-0.032	-0.032	-0.032	-0.033
	(0.025)	(0.025)	(0.026)	(0.027)	(0.027)	(0.026)
General Counsel	-0.077	-0.079	-0.077	-0.203	-0.203	-0.199
	(0.241)	(0.241)	(0.240)	(0.304)	(0.304)	(0.301)
Former EPA Official	-0.009	0.002	0.012	-0.136	-0.139	-0.169
	(0.271)	(0.270)	(0.273)	(0.300)	(0.302)	(0.298)
Distance to EPA	0.001	0.001	0.000	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm Assets	0.108	0.107	0.089	0.146	0.148	0.127
	(0.106)	(0.106)	(0.108)	(0.248)	(0.246)	(0.244)
# of Firm Establishments	-0.007	-0.007	-0.006	0.001	0.001	0.001
	(0.006)	(0.006)	(0.006)	(0.018)	(0.018)	(0.018)
Local Competitors Toxicity	0.035	0.035	0.034	0.034	0.034	0.033
	(0.014)	(0.014)	(0.013)	(0.015)	(0.015)	(0.015)
Local Non-Competitors Toxicity	0.003	0.003	0.003	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# of Competitors <25km	-0.213	-0.213	-0.201	-0.182	-0.182	-0.174
	(0.091)	(0.091)	(0.086)	(0.073)	(0.073)	(0.069)
# of Non-Competitors <25km	0.005	0.005	0.005	0.003	0.003	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
County Income	0.134	0.136	0.121	0.000	-0.000	-0.029
	(0.407)	(0.407)	(0.409)	(0.417)	(0.417)	(0.418)
County Population	-0.093	-0.094	-0.073	-0.082	-0.082	-0.066
	(0.080)	(0.079)	(0.081)	(0.087)	(0.087)	(0.089)
Firm CPA (Non-EPA)	-0.019	-0.019	-0.017	-0.012	-0.012	-0.013
	(0.016)	(0.016)	(0.015)	(0.025)	(0.025)	(0.025)
Competitors CPA (Non-EPA)	-0.027	-0.021	-0.027	-0.023	-0.024	-0.027
	(0.031)	(0.030)	(0.030)	(0.042)	(0.040)	(0.039)
Debt to Equity	0.044	0.044	0.045	0.020	0.020	0.021
	(0.030)	(0.030)	(0.030)	(0.025)	(0.025)	(0.025)
Industry Regulation	-0.854	-0.922	-0.965	0.909	0.879	1.360
	(2.141)	(2.141)	(2.104)	(5.021)	(5.030)	(4.955)
Firm Diversity	-0.250	-0.257	-0.246	0.030	0.032	0.052
	(0.223)	(0.223)	(0.221)	(0.394)	(0.396)	(0.390)
Industry Concentration	-0.560	-0.570	-0.474	-0.567	-0.564	-0.476
	(0.558)	(0.554)	(0.542)	(0.648)	(0.646)	(0.642)
Foreign Company	-0.266	-0.262	-0.206			
	(0.282)	(0.281)	(0.280)			
Fines Past 5 Years	5.267	5.264	5.196	4.566	4.566	4.518
	(0.773)	(0.773)	(0.735)	(0.755)	(0.756)	(0.724)
State FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
SIC 4-Digit FE	✓	✓	✓			
Firm FE				✓	✓	✓
Observations	66,411	66,411	66,411	66,411	66,411	66,411
R^2	0.090	0.090	0.091	0.112	0.112	0.112

Robust standard errors clustered by industry in parentheses.

Table C2: Full Results for 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.

	Dependent Variable: EPA Fine							
	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)
Firm CPA (EPA)	-0.034	-0.034	-0.038	-0.042	-0.038	-0.021	-0.032	-0.034
	(0.026)	(0.026)	(0.026)	(0.028)	(0.032)	(0.034)	(0.025)	(0.027)
Firm General Counsel	-0.081	-0.199	0.074	0.017	-0.106	-0.256	-0.084	-0.206
	(0.238)	(0.302)	(0.247)	(0.314)	(0.260)	(0.270)	(0.243)	(0.304)
Former EPA Official	0.005	-0.178	-0.054	-0.177	-0.233	0.165	0.000	-0.186
	(0.269)	(0.301)	(0.276)	(0.317)	(0.210)	(0.355)	(0.272)	(0.298)
Distance to EPA	0.000	0.001	0.001	0.001	0.001	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm Assets	0.090	0.112	0.095	0.251	-0.088	0.268	0.088	0.119
	(0.106)	(0.244)	(0.119)	(0.288)	(0.096)	(0.268)	(0.106)	(0.240)
# of Firm Establishments	-0.006	0.001	-0.010	-0.012	-0.017	-0.025	-0.006	0.000
	(0.006)	(0.018)	(0.007)	(0.014)	(0.007)	(0.020)	(0.006)	(0.018)
Local Competitors Toxicity	0.034	0.032	0.033	0.032	0.034	0.034	0.034	0.033
	(0.013)	(0.014)	(0.012)	(0.014)	(0.012)	(0.014)	(0.013)	(0.015)
Local Non-Competitors Toxicity	0.003	0.002	0.002	0.002	0.002	0.001	0.003	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# of Competitors <25km	-0.169	-0.154	-0.206	-0.177	-0.234	-0.197	-0.206	-0.178
	(0.069)	(0.064)	(0.081)	(0.069)	(0.073)	(0.063)	(0.089)	(0.072)
# of Non-Competitors <25km	0.005	0.003	0.005	0.003	0.008	0.004	0.005	0.003
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
County Income	0.165	0.008	0.008	-0.090	0.108	0.219	0.099	-0.058
	(0.401)	(0.408)	(0.459)	(0.491)	(0.601)	(0.625)	(0.405)	(0.412)
County Population	-0.072	-0.065	-0.084	-0.095	-0.041	-0.012	-0.071	-0.062
	(0.083)	(0.090)	(0.093)	(0.101)	(0.078)	(0.092)	(0.080)	(0.088)
Firm CPA (Non-EPA)	-0.018	-0.013	-0.010	-0.004	0.000	0.003	-0.017	-0.012
	(0.015)	(0.024)	(0.016)	(0.027)	(0.018)	(0.023)	(0.015)	(0.025)
Competitors CPA (Non-EPA)	-0.027	-0.027	-0.030	0.004	-0.016	-0.017	-0.026	-0.028
	(0.030)	(0.040)	(0.019)	(0.022)	(0.022)	(0.023)	(0.030)	(0.040)
Debt to Equity	0.046	0.021	0.017	0.024	0.022	0.036	0.046	0.021
	(0.030)	(0.025)	(0.023)	(0.030)	(0.010)	(0.020)	(0.030)	(0.025)
Industry Regulation	-0.765	1.719	-3.306	-3.281	-6.710	-3.801	-0.799	1.218
	(2.087)	(4.964)	(2.321)	(3.579)	(6.522)	(4.440)	(2.130)	(5.000)
Firm Diversity	-0.230	0.084	-0.146	0.159	0.013	0.537	-0.247	0.025
	(0.224)	(0.404)	(0.250)	(0.433)	(0.148)	(0.447)	(0.220)	(0.386)
Industry Concentration	-0.461	-0.473	-0.430	-0.296	-0.790	-0.871	-0.483	-0.435
	(0.538)	(0.641)	(0.549)	(0.647)	(0.693)	(0.824)	(0.541)	(0.636)
Foreign Company	-0.212		-0.109		0.180		-0.218	
	(0.283)		(0.307)		(0.233)		(0.282)	
Fines Past 5 Years	5.169	4.496	5.255	4.623	5.910	5.352	5.198	4.518
	(0.717)	(0.706)	(0.746)	(0.735)	(1.067)	(1.020)	(0.733)	(0.719)
State FE	✓	✓	✓	✓	✓	✓	✓	✓
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	0.092	0.113	0.095	0.114	0.116	0.134	0.091	0.113

Robust standard errors clustered by industry in parentheses.

D Descriptive Statistics & Correlation Tables

Figure D1 provides the location of all facilities in the continental United States in our sample. Tables D1 and D2 provide correlation tables and descriptive statistics for our sample de-meaned by the fixed effects we use in our analysis, in line with Kalnins (2018). In Table D1 we de-mean by State, Year, and Industry and in Table D2 we de-mean by State, Year, and Firm.

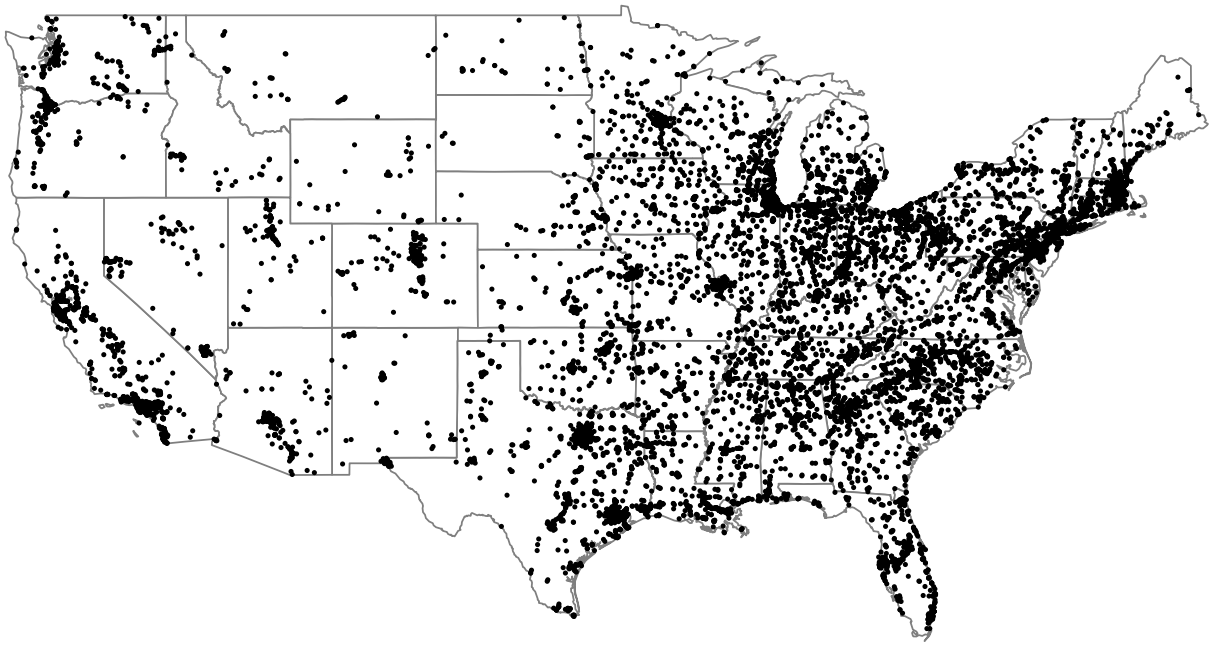

Figure D1: Facility Locations. Location of all facilities in the continental United States in our sample. Facilities in Alaska and Hawaii are not pictured.

Table D1: Descriptive Statistics and Correlation Table. Number of Observations, Mean, Standard Deviation, and Correlation Between All Variables De-Meaned by State, Year, and Industry.

		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	0	15.39	1																										
(2)	Firm CPA (EPA)	66,411	0	4.60	-0.01	1																									
(3)	Competitor CPA	66,411	0	3.52	-0.01	-0.26	1																								
(4)	Firm CPA (Non-EPA)	66,411	0	5.87	-0.02	0.62	-0.21	1																							
(5)	Competitor CPA (Non-EPA)	66,411	0	3.00	0	-0.13	0.35	-0.24	1																						
(6)	Toxicity	66,411	0	3.96	0.1	0.04	-0.02	0	-0.02	1																					
(7)	Compliance Officer	66,411	0	0.36	0	0.06	-0.03	0.15	-0.02	0.01	1																				
(8)	EPA Official on TMT	66,411	0	0.33	0	-0.18	0.11	-0.14	0.03	-0.03	0.01	1																			
(9)	Distance to EPA Office	66,411	0	121.75	0.01	0	-0.01	-0.01	-0.01	0.04	0.01	0.01	1																		
(10)	Logged Assets	66,411	0	1.47	0	0.34	-0.16	0.34	-0.15	0.03	-0.02	-0.13	-0.01	1																	
(11)	# of Facilities	66,411	0	21.78	-0.04	0.2	-0.11	0.38	-0.14	-0.09	0.04	-0.13	-0.02	0.29	1																
(12)	Debt to Equity	66,411	0	2.76	0.01	0	0	0	0	0	0.02	0.02	0	0.05	-0.01	1															
(13)	Firm Diversity	66,411	0	0.71	-0.03	0.25	-0.17	0.37	-0.19	-0.06	0.09	-0.11	-0.01	0.36	0.72	0.01	1														
(14)	Foreign Firm	66,411	0	0.34	0	-0.11	0.06	-0.17	0.07	-0.02	-0.23	0.1	-0.01	0.31	-0.05	0.03	-0.09	1													
(15)	Local Toxicity Competitors	66,411	0	20.11	0.05	-0.01	0.01	-0.03	0.01	0.01	-0.01	0	0.05	0.01	-0.04	0.02	-0.05	0.01	1												
(16)	Local Toxicity Non-Competitors	66,411	0	76.43	0.03	0	-0.01	0	0	0.02	0	0	0	0	0	0.01	-0.01	0	0.04	1											
(17)	# of Local Competitors	66,411	0	1.70	0.02	0	0.01	-0.03	0.02	-0.01	0	-0.01	0.04	0	-0.05	0	-0.05	-0.01	0.72	0	1										
(18)	# of Local Non-Competitors	66,411	0	25.01	0	0.03	0.01	0.02	0.01	-0.06	0.02	0.01	0.02	0	0.01	0	0	-0.02	0.3	-0.08	0.41	1									
(19)	Fines in Past 5 Years	66,411	0	0.63	0.23	0	-0.03	-0.02	-0.01	0.2	0	-0.01	0.01	0	-0.06	0	-0.05	-0.01	0.06	0.04	0.04	0	1								
(20)	Logged Income per Capita	66,411	0	0.18	-0.01	0.03	0	0.04	0	-0.07	0.01	0.01	-0.19	0.05	0.03	0.01	0.02	0	0.12	-0.02	0.16	0.4	-0.01	1							
(21)	Logged Population	66,411	0	1.22	-0.01	0.04	-0.01	0.05	-0.01	-0.09	0.01	0	-0.05	0.04	0.04	0	0.02	-0.01	0.19	-0.02	0.26	0.67	-0.03	0.59	1						
(22)	Regulations	66,411	0	1.41	0	0.06	-0.05	0.02	0	0.01	-0.02	-0.04	0.04	0.03	0.03	0.01	0.03	0.01	0	-0.01	0	-0.01	0.01	-0.03	-0.02	1					
(23)	Industry Concentration	66,411	0	0.16	-0.01	-0.01	-0.02	-0.01	-0.01	0	0.01	0.14	0	-0.01	0	-0.01	-0.01	-0.01	0.01	-0.01	0	-0.01	0	0	0	0.07	1				
(24)	Closest Rival <50km	66,411	0	0.31	0	-0.08	0.18	-0.09	0.06	-0.02	-0.02	0.03	-0.01	-0.03	-0.05	0	-0.07	0.02	0.3	0.01	0.36	0.22	0.01	0.13	0.17	-0.01	-0.01	1			
(25)	Industry Standardization	64,744	0	0.25	0.05	0.02	0.01	0	0.01	0.26	-0.01	-0.03	0.01	0.04	-0.02	0	-0.08	0.02	0.03	0	0.03	-0.02	0.1	-0.04	-0.04	0.01	0	0.02	1		
(26)	Competitive Aggressiveness	32,717	0	14.30	0	0.02	0.01	0.03	-0.02	-0.01	-0.02	-0.1	0	0.03	0.03	0.01	0.04	0	0	0	-0.01	0	-0.01	0	0.01	0.05	0.06	0.02	-0.02	1	
(27)	Relative Firm Performance	66,292	0	3.45	0	0.02	-0.04	0.01	0.01	0	0	-0.1	0	0.01	0.01	0	0.01	0	0	0	0	0	-0.01	0	0	0.02	-0.02	0	0	0.03	1

Table D2: Descriptive Statistics and Correlation Table. Number of Observations, Mean, Standard Deviation, and Correlation Between All Variables De-Meaned by State, Year, and Firm.

		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	0	15.06	1																										
(2)	Firm CPA (EPA)	66,411	0	2.84	-0.01	1																									
(3)	Competitor CPA	66,411	0	3.01	0	0.02	1																								
(4)	Firm CPA (Non-EPA)	66,411	0	2.79	-0.01	0.29	0.07	1																							
(5)	Competitor CPA (Non-EPA)	66,411	0	2.42	0	0.09	0.24	0.05	1																						
(6)	Toxicity	66,411	0	3.59	0.08	-0.01	0	0	0	1																					
(7)	Compliance Officer	66,411	0	0.27	0	-0.01	-0.01	0.02	0	0.01	1																				
(8)	EPA Official on TMT	66,411	0	0.26	0	-0.04	0.06	-0.03	-0.02	0.02	0.02	1																			
(9)	Distance to EPA Office	66,411	0	113.83	0.01	0	-0.01	0	0	0.03	0	0	1																		
(10)	Logged Assets	66,411	0	0.33	0	0.06	-0.05	0.08	0	0	0.08	-0.07	0	1																	
(11)	# of Facilities	66,411	0	6.55	-0.01	-0.01	0.02	-0.02	0.03	-0.07	0.05	0	-0.01	0.19	1																
(12)	Debt to Equity	66,411	0	2.62	0.01	0.01	0	0.02	0	0	0.01	0.01	0	0.04	0.01	1															
(13)	Firm Diversity	66,411	0	0.28	-0.01	0.03	-0.02	0.01	0.02	-0.06	0.02	-0.04	-0.01	0.21	0.63	0	1														
(14)	Foreign Firm	66,411	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1													
(15)	Local Toxicity Competitors	66,411	0	18.84	0.04	-0.01	0	-0.01	0	0.01	0	0	0.03	0.01	0	0.02	0	0	1												
(16)	Local Toxicity Non-Competitors	66,411	0	75.46	0.02	0	0	0	0	0.02	0	0	0	0	-0.01	0	0	0	0.04	1											
(17)	# of Local Competitors	66,411	0	1.57	0.02	0	0	0	0.01	-0.01	0	-0.01	0.04	0	0.02	0	0.03	0	0.69	-0.01	1										
(18)	# of Local Non-Competitors	66,411	0	23.36	0	0	0	-0.01	0	-0.04	0.01	0	0.03	0.01	0	0	0.01	0	0.29	-0.08	0.41	1									
(19)	Fines in Past 5 Years	66,411	0	0.59	0.19	-0.01	-0.02	-0.01	0	0.17	0	0	0.01	0	-0.03	0	-0.02	0	0.06	0.03	0.03	0	1								
(20)	Logged Income per Capita	66,411	0	0.17	0	0	0	0.01	0.01	-0.05	0.01	0	-0.17	0.02	0.01	0	0.01	0	0.11	-0.02	0.15	0.39	0	1							
(21)	Logged Population	66,411	0	1.12	-0.01	0	0	0	0	-0.06	0.01	-0.01	-0.02	0.01	0.01	0	0.01	0	0.18	-0.03	0.25	0.66	-0.02	0.58	1						
(22)	Regulations	66,411	0	0.02	0	0.04	0.04	-0.02	0.07	0	-0.01	-0.07	0	0.03	0.06	0.01	0.04	0	0.01	-0.01	0.01	0.01	-0.01	0.01	0.01	1					
(23)	Industry Concentration	66,411	0	0.16	-0.01	-0.04	-0.02	-0.05	-0.02	0	0	0.18	0	-0.05	-0.02	-0.02	-0.02	0	0.01	-0.01	0	0	0	0	0	0.13	1				
(24)	Closest Rival <50km	66,411	0	0.29	0	0.01	0.14	0.01	0.02	0	0	0	-0.01	0	0.02	0	0.03	0	0.26	0.02	0.32	0.2	0.02	0.12	0.15	0.01	-0.01	1			
(25)	Industry Standardization	64,744	0	0.22	0.05	-0.01	0	0	-0.01	0.23	0.01	0	0.02	0.01	-0.02	0	-0.01	0	0.02	0	0.02	-0.02	0.09	-0.03	-0.03	-0.01	0	0.02	1		
(26)	Competitive Aggressiveness	32,717	0	14.16	0	0.03	0.02	0.04	-0.02	-0.01	-0.04	-0.12	0	0.09	0.07	0	0.08	0	0	0	-0.01	0	-0.01	0	0.01	0.06	0.07	0.02	-0.03	1	
(27)	Relative Firm Performance	66,292	0	3.41	0	0.02	-0.03	0	0.02	0	-0.01	-0.11	0	0.04	0.01	0	0.02	0	0	0	0	0	0	0	0	0.03	-0.02	0.01	0	0.03	1

E Robustness Tests

In this section, we provide some alternative tests that support our main hypotheses.

In Table E1 we show that our results hold for severe violations as categorized by fines levied by the EPA over $500,000. This suggests that our findings are not being driven by insignificant violations. Further, our results hold if we simply used the logged amount of fines as shown in Table E2. This shows that our finding it robust to various specifications of fines. Finally, our results are present even without any controls, as seen in Table E3 suggesting our findings are robust to model specification.

Some scholars argue SIC categorizations at the firm level are inaccurate when trying to capture a firm's competition. To ensure our results are not picking up noise in this competitive measure, Table E4 uses Hoberg-Phillips' measure of how related firms' markets are in order to create an alternative measure of Competitor CPA. We find similar results, suggesting that our findings are robust to various measures of competition.

In Table E5 we show that there is not a similar relationship between non-Competitor CPA and EPA fines, suggesting it is something about the types of firms that are lobbying that provide more information to the regulators. Here we define non-competitors by looking at firms who share the same SIC 2 digit but not the same SIC 4 digit. Thus we are able to capture firms that may be in tangential industries, and therefore may be privy to information the firm has, but not direct competitors to the firms. We would not expect our results to hold in this scenario since these non-competitor firms ought to have no motivation to pass along this information to the EPA.

Perhaps focal firms are able to counteract competitor's influence through CPA by engaging in CPA themselves. Our main models suggest there is no overall effect of a focal firm's engagement of CPA with the EPA, implying that CPA by the focal firm has a negligible overall effect. However, perhaps focal firms are also divulging information about high risk facilities to counteract any competitor information. If this were the case it would imply the effect would be an interaction between the focal firm's CPA and the toxicity of the facility, just as the competitor's interaction. We test this in Table E6. Here we still find no relationship between a focal firm's engagement in CPA on the EPA's decision to fine the firm. This suggests that once the regulatory agency has information about potential violations, it is difficult to counteract this with CPA.

In Table E7 we show that our findings are not dependent upon the prior three years of lobbying by competitors, and our results are robust to looking at the past year or the past two years of competitor lobbying.

In Table E8, we address a common identification concern in panel data analyses—namely, the presence of differential trends prior to treatment. To assess this possibility, we follow Angrist and Pischke (2008) and include one- and two-year lags of our main explanatory variables (Competitor CPA, Toxicity, and their interaction). Models (2) and (4) include both contemporaneous and lagged variables, while Models (1) and (3)—the baseline specifications from the main text—serve as points of comparison. We find that even after including all lagged terms, the interaction between Competitor CPA and Toxicity remains statistically significant and economically meaningful. By contrast, none of the lagged explanatory variables are statistically significant, suggesting limited concern about anticipatory effects.

Finally, in Table E9, we replicate the baseline analysis using county-level proximity instead of a distance radius; results remain substantively unchanged.

E.1 Fines for Severe Violations

Table E1: Effect of Toxicity and Competitor CPA on Severe Violations. Results of linear probability models for facilities between 2001 and 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Toxicity	0.066	0.066	0.005	0.065	0.065	0.014
	(0.018)	(0.018)	(0.013)	(0.019)	(0.019)	(0.017)
Competitor CPA		0.009	-0.123		0.022	-0.092
		(0.014)	(0.054)		(0.014)	(0.059)
Competitor CPA × Toxicity			0.008			0.007
			(0.003)			(0.003)
Firm CPA (EPA)	-0.020	-0.019	-0.022	-0.015	-0.015	-0.015
	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)
Firm General Counsel	-0.089	-0.088	-0.087	-0.165	-0.163	-0.161
	(0.174)	(0.174)	(0.176)	(0.231)	(0.233)	(0.233)
Former EPA Official	0.089	0.083	0.087	-0.076	-0.093	-0.105
	(0.179)	(0.181)	(0.180)	(0.228)	(0.229)	(0.228)
Distance to EPA	0.000	0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm Assets	0.049	0.050	0.043	-0.031	-0.021	-0.029
	(0.054)	(0.054)	(0.054)	(0.144)	(0.145)	(0.145)
# of Firm Establishments	0.003	0.003	0.003	0.022	0.022	0.022
	(0.003)	(0.003)	(0.003)	(0.009)	(0.009)	(0.009)
Local Competitors Toxicity	0.006	0.006	0.005	0.007	0.007	0.007
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)
Local Non-Competitors Toxicity	0.001	0.001	0.001	0.001	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# of Competitors <25km	-0.062	-0.062	-0.058	-0.036	-0.036	-0.033
	(0.023)	(0.023)	(0.021)	(0.012)	(0.012)	(0.012)
# of Non-Competitors <25km	0.001	0.001	0.001	0.001	0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
County Income	0.232	0.231	0.225	0.146	0.145	0.134
	(0.182)	(0.183)	(0.186)	(0.184)	(0.184)	(0.186)
County Population	-0.060	-0.059	-0.051	-0.035	-0.034	-0.028
	(0.043)	(0.043)	(0.045)	(0.040)	(0.040)	(0.041)
Firm CPA (Non-EPA)	-0.012	-0.012	-0.011	-0.033	-0.034	-0.035
	(0.011)	(0.011)	(0.011)	(0.014)	(0.014)	(0.014)
Competitors CPA (Non-EPA)	-0.028	-0.031	-0.033	-0.021	-0.027	-0.028
	(0.017)	(0.016)	(0.016)	(0.022)	(0.021)	(0.020)
Debt to Equity	0.045	0.045	0.046	0.029	0.029	0.029
	(0.046)	(0.046)	(0.046)	(0.039)	(0.039)	(0.039)
Industry Regulation	1.113	1.147	1.129	3.776	3.601	3.785
	(1.092)	(1.082)	(1.065)	(2.894)	(2.950)	(2.963)
Firm Diversity	-0.198	-0.194	-0.190	-0.205	-0.196	-0.188
	(0.129)	(0.131)	(0.130)	(0.166)	(0.169)	(0.171)
Industry Concentration	-0.072	-0.067	-0.029	-0.070	-0.057	-0.023
	(0.267)	(0.266)	(0.259)	(0.258)	(0.257)	(0.255)
Foreign Company	-0.382	-0.384	-0.361			
	(0.164)	(0.164)	(0.160)			
Fines Past 5 Years	0.966	0.968	0.941	0.700	0.702	0.684
	(0.186)	(0.186)	(0.169)	(0.181)	(0.180)	(0.166)
State FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
SIC 4-Digit FE	✓	✓	✓			
Firm FE				✓	✓	✓
Observations	66,411	66,411	66,411	66,411	66,411	66,411
R^2	0.023	0.023	0.023	0.049	0.049	0.049

Robust standard errors clustered by industry in parentheses.

E.2 Fines for Size of Fine

Table E2: Effect of Toxicity and Competitor CPA on Size of Fine. Results of linear models for facilities between 2001 and 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Toxicity	0.028	0.028	0.007	0.029	0.029	0.009
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Competitor CPA		-0.002	-0.048		0.002	-0.042
		(0.003)	(0.017)		(0.004)	(0.018)
Competitor CPA × Toxicity			0.003			0.003
			(0.001)			(0.001)
Firm CPA (EPA)	-0.002	-0.002	-0.003	-0.003	-0.003	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Firm General Counsel	-0.038	-0.038	-0.038	-0.059	-0.058	-0.058
	(0.040)	(0.041)	(0.041)	(0.054)	(0.054)	(0.053)
Former EPA Official	0.004	0.005	0.007	-0.020	-0.021	-0.026
	(0.035)	(0.034)	(0.035)	(0.035)	(0.035)	(0.034)
Distance to EPA	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm Assets	0.013	0.012	0.010	0.007	0.007	0.004
	(0.013)	(0.013)	(0.013)	(0.034)	(0.034)	(0.034)
# of Firm Establishments	-0.001	-0.001	-0.001	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)
Local Competitors Toxicity	0.004	0.004	0.004	0.004	0.004	0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Local Non-Competitors Toxicity	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# of Competitors <25km	-0.027	-0.027	-0.025	-0.020	-0.020	-0.019
	(0.010)	(0.010)	(0.009)	(0.007)	(0.007)	(0.007)
# of Non-Competitors <25km	0.001	0.001	0.001	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
County Income	0.012	0.012	0.010	-0.006	-0.006	-0.010
	(0.052)	(0.052)	(0.052)	(0.056)	(0.056)	(0.055)
County Population	-0.021	-0.021	-0.018	-0.020	-0.020	-0.017
	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.012)
Firm CPA (Non-EPA)	-0.003	-0.003	-0.003	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Competitors CPA (Non-EPA)	-0.005	-0.004	-0.005	-0.004	-0.005	-0.005
	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.005)
Debt to Equity	0.006	0.006	0.007	0.004	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Industry Regulation	0.078	0.072	0.066	0.735	0.722	0.793
	(0.368)	(0.369)	(0.365)	(1.005)	(1.010)	(0.998)
Firm Diversity	-0.028	-0.029	-0.027	0.003	0.003	0.006
	(0.031)	(0.031)	(0.031)	(0.052)	(0.052)	(0.052)
Industry Concentration	-0.036	-0.036	-0.023	-0.044	-0.043	-0.030
	(0.090)	(0.090)	(0.088)	(0.094)	(0.094)	(0.093)
Foreign Company	-0.076	-0.076	-0.068			
	(0.037)	(0.037)	(0.037)			
Fines Past 5 Years	0.780	0.780	0.770	0.681	0.681	0.674
	(0.091)	(0.091)	(0.085)	(0.090)	(0.090)	(0.085)
State FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
SIC 4-Digit FE	✓	✓	✓			
Firm FE				✓	✓	✓
Observations	66,411	66,411	66,411	66,411	66,411	66,411
R^2	0.107	0.107	0.108	0.127	0.127	0.128

Robust standard errors clustered by industry in parentheses.

E.3 No Controls

Table E3: Effect of Toxicity and Competitor CPA on EPA Fines with No Controls. Results of linear probability models for facilities between 2001 and 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Toxicity	0.381	0.381	0.124	0.331	0.331	0.132
	(0.095)	(0.095)	(0.052)	(0.089)	(0.089)	(0.053)
Competitor CPA		-0.025	-0.557		-0.021	-0.457
		(0.026)	(0.227)		(0.031)	(0.218)
Competitor CPA × Toxicity			0.031			0.025
			(0.013)			(0.013)
State FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
SIC 4-Digit FE	✓	✓	✓			
Firm FE				✓	✓	✓
Observations	66,411	66,411	66,411	66,411	66,411	66,411
R^2	0.043	0.043	0.046	0.080	0.080	0.082

Robust standard errors clustered by industry in parentheses.

E.4 Hoberg-Phillips Measure of Competitors

Table E4: Effect of Toxicity and CPA using Hoberg-Phillips Competitors on EPA Fines. Results of linear probability models for facilities between 2001 and 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Toxicity	0.202	0.200	0.132	0.197	0.213	0.118
	(0.035)	(0.043)	(0.029)	(0.039)	(0.044)	(0.029)
Competitor CPA		0.032	-0.178		0.033	-0.262
		(0.032)	(0.111)		(0.034)	(0.100)
Competitor CPA × Toxicity			0.012			0.017
			(0.007)			(0.007)
Firm CPA (EPA)	-0.023	-0.009	-0.011	-0.032	-0.019	-0.020
	(0.025)	(0.032)	(0.032)	(0.027)	(0.032)	(0.032)
Firm General Counsel	-0.077	-0.084	-0.075	-0.203	-0.271	-0.270
	(0.241)	(0.271)	(0.267)	(0.304)	(0.318)	(0.317)
Former EPA Official	-0.009	0.045	0.026	-0.136	-0.185	-0.210
	(0.271)	(0.308)	(0.314)	(0.300)	(0.384)	(0.387)
Distance to EPA	0.001	0.000	0.000	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm Assets	0.108	0.067	0.062	0.146	0.274	0.285
	(0.106)	(0.198)	(0.201)	(0.248)	(0.464)	(0.466)
# of Firm Establishments	-0.007	0.001	0.001	0.001	0.019	0.019
	(0.006)	(0.014)	(0.015)	(0.018)	(0.054)	(0.055)
Local Competitors Toxicity	0.035	0.021	0.020	0.034	0.022	0.021
	(0.014)	(0.014)	(0.014)	(0.015)	(0.016)	(0.016)
Local Non-Competitors Toxicity	0.003	0.003	0.003	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# of Competitors <25km	-0.213	-0.182	-0.178	-0.182	-0.167	-0.160
	(0.091)	(0.113)	(0.109)	(0.073)	(0.106)	(0.102)
# of Non-Competitors <25km	0.005	0.010	0.010	0.003	0.008	0.008
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
County Income	0.134	0.505	0.507	0.000	0.197	0.167
	(0.407)	(0.406)	(0.409)	(0.417)	(0.447)	(0.446)
County Population	-0.093	-0.169	-0.164	-0.082	-0.184	-0.175
	(0.080)	(0.096)	(0.093)	(0.087)	(0.109)	(0.105)
Firm CPA (Non-EPA)	-0.019	-0.012	-0.011	-0.012	-0.046	-0.046
	(0.016)	(0.021)	(0.021)	(0.025)	(0.034)	(0.034)
Competitors CPA (Non-EPA)	-0.027	-0.028	-0.027	-0.023	-0.028	-0.027
	(0.031)	(0.039)	(0.039)	(0.042)	(0.048)	(0.048)
Debt to Equity	0.044	0.055	0.055	0.020	0.020	0.020
	(0.030)	(0.036)	(0.035)	(0.025)	(0.027)	(0.027)
Industry Regulation	-0.854	-0.946	-1.089	0.909	0.810	1.077
	(2.141)	(2.674)	(2.757)	(5.021)	(7.223)	(7.197)
Firm Diversity	-0.250	-0.495	-0.473	0.030	-0.244	-0.240
	(0.223)	(0.288)	(0.302)	(0.394)	(0.621)	(0.618)
Industry Concentration	-0.560	-0.401	-0.400	-0.567	-0.391	-0.400
	(0.558)	(0.656)	(0.657)	(0.648)	(0.758)	(0.760)
Foreign Company	-0.266	1.328	1.335			
	(0.282)	(0.506)	(0.507)			
Fines Past 5 Years	5.267	4.891	4.871	4.566	4.258	4.233
	(0.773)	(0.699)	(0.686)	(0.755)	(0.658)	(0.647)
State FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
SIC 4-Digit FE	✓	✓	✓			
Firm FE				✓	✓	✓
Observations	66,411	46,259	46,259	66,411	46,259	46,259
R^2	0.090	0.086	0.087	0.112	0.106	0.106

Robust standard errors clustered by industry in parentheses.

E.5 Non-Competitor CPA

Table E5: Effect of Toxicity and Non-Competitor CPA on EPA Fines. Results of linear probability models for facilities between 2001 and 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Toxicity	0.203	0.206	0.015	0.198	0.202	0.054
	(0.035)	(0.035)	(0.208)	(0.039)	(0.040)	(0.263)
Non-Competitor CPA		-0.013	-0.234		-0.040	-0.216
		(0.052)	(0.251)		(0.061)	(0.323)
Non-Competitor CPA × Toxicity			0.013			0.010
			(0.015)			(0.018)
Firm CPA (EPA)	-0.024	-0.025	-0.026	-0.032	-0.034	-0.035
	(0.026)	(0.026)	(0.026)	(0.028)	(0.028)	(0.028)
Firm General Counsel	-0.082	-0.116	-0.115	-0.211	-0.229	-0.230
	(0.242)	(0.242)	(0.241)	(0.308)	(0.312)	(0.312)
Former EPA Official	-0.008	-0.004	-0.004	-0.133	-0.126	-0.129
	(0.273)	(0.276)	(0.276)	(0.300)	(0.297)	(0.296)
Distance to EPA	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm Assets	0.109	0.110	0.108	0.156	0.201	0.199
	(0.105)	(0.106)	(0.106)	(0.251)	(0.257)	(0.257)
# of Firm Establishments	-0.007	-0.007	-0.008	0.001	0.000	0.000
	(0.006)	(0.006)	(0.006)	(0.018)	(0.019)	(0.019)
Local Competitors Toxicity	0.035	0.035	0.035	0.034	0.034	0.034
	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)
Local Non-Competitors Toxicity	0.003	0.003	0.003	0.002	0.003	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# of Competitors <25km	-0.214	-0.215	-0.215	-0.182	-0.185	-0.185
	(0.091)	(0.091)	(0.091)	(0.073)	(0.073)	(0.073)
# of Non-Competitors <25km	0.005	0.006	0.006	0.003	0.003	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
County Income	0.096	0.059	0.058	-0.031	-0.078	-0.080
	(0.400)	(0.401)	(0.402)	(0.411)	(0.414)	(0.414)
County Population	-0.095	-0.102	-0.101	-0.083	-0.085	-0.084
	(0.080)	(0.081)	(0.081)	(0.087)	(0.089)	(0.089)
Firm CPA (Non-EPA)	-0.014	-0.014	-0.013	-0.009	-0.011	-0.012
	(0.015)	(0.015)	(0.015)	(0.026)	(0.025)	(0.026)
Competitors CPA (Non-EPA)	-0.411	-0.614	-0.570	-0.249	-0.487	-0.456
	(0.437)	(0.430)	(0.424)	(0.455)	(0.395)	(0.394)
Debt to Equity	0.044	0.044	0.045	0.022	0.023	0.024
	(0.030)	(0.030)	(0.030)	(0.024)	(0.023)	(0.023)
Industry Regulation	-0.667	-0.345	-0.336	1.183	1.908	1.854
	(2.170)	(2.101)	(2.082)	(4.708)	(4.704)	(4.689)
Firm Diversity	-0.241	-0.236	-0.226	0.028	0.027	0.033
	(0.223)	(0.224)	(0.223)	(0.384)	(0.399)	(0.399)
Industry Concentration	-0.572	-0.614	-0.611	-0.565	-0.617	-0.612
	(0.560)	(0.559)	(0.557)	(0.648)	(0.637)	(0.636)
Foreign Company	-0.281	-0.288	-0.279			
	(0.282)	(0.285)	(0.284)			
Fines Past 5 Years	5.259	5.236	5.234	4.560	4.548	4.547
	(0.774)	(0.781)	(0.779)	(0.757)	(0.763)	(0.762)
State FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
SIC 4-Digit FE	✓	✓	✓			
Firm FE				✓	✓	✓
Observations	66,311	65,689	65,689	66,311	65,689	65,689
R^2	0.090	0.090	0.090	0.112	0.111	0.111

Robust standard errors clustered by industry in parentheses.

E.6 Focal Firm CPA

Table E6: Effect of Toxicity, Competitor CPA, and Focal Firm CPA on EPA Fines. Results of linear probability models for facilities between 2001 and 2013.

	(1)	(2)	(3)	(4)
Toxicity	0.202	0.035	0.197	0.035
	(0.034)	(0.043)	(0.039)	(0.043)
Competitor CPA × Toxicity		0.019		0.016
		(0.007)		(0.007)
Firm CPA (EPA) × Toxicity		0.003		0.008
		(0.004)		(0.003)
Competitor CPA	-0.017	-0.347	0.004	-0.281
	(0.021)	(0.118)	(0.027)	(0.119)
Firm CPA (EPA)	-0.025	-0.087	-0.032	-0.164
	(0.025)	(0.067)	(0.027)	(0.056)
Firm General Counsel	-0.079	-0.085	-0.203	-0.207
	(0.241)	(0.241)	(0.304)	(0.303)
Former EPA Official	0.002	0.024	-0.139	-0.166
	(0.270)	(0.274)	(0.302)	(0.298)
Distance to EPA	0.001	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Firm Assets	0.107	0.090	0.148	0.122
	(0.106)	(0.107)	(0.246)	(0.243)
# of Firm Establishments	-0.007	-0.006	0.001	0.001
	(0.006)	(0.006)	(0.018)	(0.018)
Local Competitors Toxicity	0.035	0.034	0.034	0.033
	(0.014)	(0.013)	(0.015)	(0.015)
Local Non-Competitors Toxicity	0.003	0.003	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
# of Competitors <25km	-0.213	-0.202	-0.182	-0.173
	(0.091)	(0.086)	(0.073)	(0.069)
# of Non-Competitors <25km	0.005	0.005	0.003	0.003
	(0.004)	(0.004)	(0.004)	(0.004)
County Income	0.136	0.125	-0.000	-0.037
	(0.407)	(0.409)	(0.417)	(0.417)
County Population	-0.094	-0.073	-0.082	-0.063
	(0.079)	(0.081)	(0.087)	(0.090)
Firm CPA (Non-EPA)	-0.019	-0.017	-0.012	-0.012
	(0.016)	(0.015)	(0.025)	(0.025)
Competitors CPA (Non-EPA)	-0.021	-0.025	-0.024	-0.025
	(0.030)	(0.029)	(0.040)	(0.039)
Debt to Equity	0.044	0.045	0.020	0.021
	(0.030)	(0.030)	(0.025)	(0.025)
Industry Regulation	-0.922	-0.944	0.879	1.412
	(2.141)	(2.108)	(5.030)	(4.934)
Firm Diversity	-0.257	-0.240	0.032	0.037
	(0.223)	(0.223)	(0.396)	(0.386)
Industry Concentration	-0.570	-0.466	-0.564	-0.455
	(0.554)	(0.540)	(0.646)	(0.642)
Foreign Company	-0.262	-0.214		
	(0.281)	(0.279)		
Fines Past 5 Years	5.264	5.190	4.566	4.504
	(0.773)	(0.730)	(0.756)	(0.718)
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
SIC 4-Digit FE	✓	✓		
Firm FE			✓	✓
Observations	66,411	66,411	66,411	66,411
R^2	0.085	0.087	0.114	0.115

Robust standard errors clustered by industry in parentheses.

E.7 Alternative CPA Lags

Table E7: Effect of Toxicity and Prior Competitor CPA on EPA Fines. Results of linear probability models for facilities between 2001 and 2013.

	Competitor CPA Time Frame:			
	Prior Year		Prior 2 Years	
	(1)	(2)	(3)	(4)
Toxicity	0.062	0.071	0.059	0.075
	(0.033)	(0.033)	(0.037)	(0.040)
Competitor CPA	-0.395	-0.357	-0.357	-0.302
	(0.131)	(0.127)	(0.126)	(0.128)
Competitor CPA × Toxicity	0.020	0.019	0.019	0.017
	(0.007)	(0.007)	(0.007)	(0.007)
Firm CPA (EPA)	-0.037	-0.034	-0.035	-0.034
	(0.026)	(0.027)	(0.026)	(0.026)
Firm General Counsel	-0.073	-0.210	-0.079	-0.204
	(0.239)	(0.301)	(0.240)	(0.302)
Former EPA Official	0.027	-0.165	0.021	-0.153
	(0.270)	(0.294)	(0.270)	(0.292)
Distance to EPA	0.000	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Firm Assets	0.087	0.112	0.089	0.124
	(0.107)	(0.243)	(0.108)	(0.243)
# of Firm Establishments	-0.005	0.004	-0.006	0.000
	(0.006)	(0.017)	(0.006)	(0.018)
Local Competitors Toxicity	0.034	0.033	0.034	0.033
	(0.013)	(0.015)	(0.013)	(0.015)
Local Non-Competitors Toxicity	0.003	0.002	0.003	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
# of Competitors <25km	-0.197	-0.171	-0.201	-0.174
	(0.084)	(0.068)	(0.085)	(0.069)
# of Non-Competitors <25km	0.004	0.003	0.005	0.003
	(0.004)	(0.004)	(0.004)	(0.004)
County Income	0.109	-0.045	0.119	-0.030
	(0.413)	(0.421)	(0.411)	(0.418)
County Population	-0.071	-0.066	-0.073	-0.067
	(0.080)	(0.089)	(0.080)	(0.089)
Firm CPA (Non-EPA)	-0.020	-0.016	-0.018	-0.013
	(0.015)	(0.024)	(0.015)	(0.024)
Competitors CPA (Non-EPA)	-0.024	-0.023	-0.023	-0.023
	(0.029)	(0.039)	(0.030)	(0.039)
Debt to Equity	0.045	0.020	0.045	0.020
	(0.030)	(0.025)	(0.030)	(0.025)
Industry Regulation	-0.132	0.335	-0.123	0.347
	(0.260)	(0.720)	(0.265)	(0.712)
Firm Diversity	-0.252	0.051	-0.253	0.042
	(0.222)	(0.394)	(0.221)	(0.392)
Industry Concentration	-0.485	-0.470	-0.473	-0.488
	(0.522)	(0.614)	(0.531)	(0.623)
Foreign Company	-0.207		-0.209	
	(0.278)		(0.280)	
Fines Past 5 Years	5.191	4.511	5.197	4.519
	(0.732)	(0.721)	(0.735)	(0.725)
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
SIC 4-Digit FE	✓		✓	
Firm FE		✓		✓
Observations	66,411	66,411	66,411	66,411
R^2	0.091	0.112	0.091	0.112

Robust standard errors clustered by industry in parentheses.

E.8 Competitor CPA Pre-Trends

One concern with identifying effects in panel data is the trends in the data before the treatment is given. To test if this is occurring, follow Angrist and Pischke (2008) and lag our main explanatory variables (Competitor CPA, Toxicity, and their interaction) by one and two years. We then include all of these variables in the regression together in Models (2) and (4), while Models (1) and (3), the models from the paper, serve as a comparison point. We find that even after the inclusion of all the lagged variables, the interaction term of Competitor CPA and Toxicity remains statistically significant and substantial. Meanwhile none of our lagged explanatory variables, are statistically significant, suggesting limited concern about anticipatory effects.

Table E8: Pre-Trend Analysis of Main Models on EPA Fines. Results of linear probability models for facilities between 2003 and 2013.

	(1)	(2)	(3)	(4)
Toxicity	0.045	0.009	0.063	0.013
	(0.038)	(0.060)	(0.041)	(0.060)
Competitor CPA	5.196	5.329	4.518	4.451
	(0.735)	(0.736)	(0.724)	(0.732)
Competitor CPA x Toxicity	0.019	0.010	0.017	0.009
	(0.007)	(0.006)	(0.007)	(0.006)
Toxicity (1 Year Lead)		-0.042		-0.023
		(0.058)		(0.056)
Firm CPA (EPA) (1 Year Lead)		0.051		0.043
		(0.048)		(0.049)
Competitor CPA (EPA) x Toxicity (1 Year Lead)		-0.218		-0.175
		(0.124)		(0.115)
Toxicity (2 Year Lead)		-0.200		-0.207
		(0.136)		(0.141)
Firm CPA (EPA) (2 Year Lead)		0.012		0.010
		(0.006)		(0.006)
Competitor CPA (EPA) x Toxicity (2 Year Lead)		0.009		0.011
		(0.007)		(0.007)
Controls	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
SIC 4-Digit FE	✓		✓	
Firm FE		✓		✓
Observations	66,411	51,765	66,411	51,765
R^2	0.091	0.098	0.112	0.125

Controls included in every model: Firm EPA Lobbying, General Counsel in TMT, 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.
Robust standard errors clustered by industry in parentheses.

E.9 Competitor Distance and CPA

Our argument is that firms that are located in close geographical proximity are more likely to possess information on each other's violations. We operationalize this as a binary variable taking the value of one when a facility has a competitor who has a relationship with the EPA through CPA within a 50km radius, and zero if not. The main advantage of this measure is that it does not rely on arbitrarily drawn boundaries. When using geographic areas such as counties or EPA regions, the issue is that they vary dramatically in size. For example, two facilities located in a big county (say Los Angeles County) might be located several hours by car away from each other, and are thus unlikely to share suppliers or have employee movement between them. Two facilities located in a small county are much more likely to do so. There are also problems for facilities located near the borders of counties/MSAs/regions. For example, facilities located near county borders may not have competitors who engage in CPA in the same county, but perhaps in a neighboring county that is only a few minutes away. Using a distance radius for each facility avoids all of these issues and therefore, in our view, is best equipped to test our hypothesized theoretical mechanism.

That being said, as a robustness check, we tested our models using alternative specifications at the county and EPA level. Table E9 shows the coefficients when using a variable that is one if a facility has a competitor in the same industry engaged in a CPA relation with the EPA in the same county. The results are very similar to our original models. Table E10 uses EPA regions as the relevant areas. Here, the results are less pronounced. However, it is important to keep in mind that there are only ten EPA regions. This means that a facility in e.g. Miami is considered to have a lobbying competitor "nearby" when such a facility is located in southern Kentucky (a 15 hour drive away). Indeed, nearly 75 percent of facilities in our sample have a lobbying competitor in the same EPA region. Our argument about how firms acquire knowledge of potential violations does not apply in such a situation. Thus, we take the fact that such a specification does not find the expected effect, whereas models that use smaller geographic distances do, as further evidence in support of our argument.

Table E9: Effect of Toxicity and Competitor CPA on EPA Fines Conditional on Lobbying Competitors in the Same County. Results of linear probability models for facilities between 2001 and 2013.

	(1)	(2)
No Competitors in County: Toxicity	0.048	0.046
	(0.036)	(0.044)
No Competitors in County: Competitor CPA	-0.266	-0.202
	(0.074)	(0.075)
No Competitors in County: Competitor CPA x Toxicity	0.013	0.011
	(0.004)	(0.005)
Competitors in County: Toxicity	0.024	0.035
	(0.055)	(0.063)
Competitors in County: Competitor CPA	-0.497	-0.403
	(0.196)	(0.207)
Competitors in County: Competitor CPA x Toxicity	0.029	0.024
	(0.012)	(0.014)
Controls	✓	✓
State FE	✓	✓
Year FE	✓	✓
SIC 4-Digit FE	✓	
Firm FE		✓
Observations	46,123	44,929
R^2	0.080	0.105

Controls included in every model: Firm EPA Lobbying, General Counsel in TMT, 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.
Robust standard errors clustered by industry in parentheses.

Table E10: Effect of Toxicity and Competitor CPA on EPA Fines Conditional on Lobbying Competitors in the Same EPA Region. Results of linear probability models for facilities between 2001 and 2013.

	(1)	(2)
No Competitors in EPA Region: Toxicity	0.043	0.041
	(0.032)	(0.040)
No Competitors in EPA Region: Competitor CPA	-0.321	-0.225
	(0.078)	(0.093)
No Competitors in EPA Region: Competitor CPA x Toxicity	0.016	0.012
	(0.004)	(0.005)
Competitors in EPA Region: Toxicity	0.045	0.046
	(0.040)	(0.046)
Competitors in EPA Region: Competitor CPA	-0.288	-0.225
	(0.094)	(0.090)
Competitors in EPA Region: Competitor CPA x Toxicity	0.015	0.013
	(0.006)	(0.006)
Controls	✓	✓
State FE	✓	✓
Year FE	✓	✓
SIC 4-Digit FE	✓	
Firm FE		✓
Observations	46,123	44,929
R^2	0.079	0.105

Controls included in every model: Firm EPA Lobbying, General Counsel in TMT, 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.
Robust standard errors clustered by industry in parentheses.

F Auxiliary Analysis

F.1 Lobbying Issues

In our theoretical model, we treat the level of CPA a firm engages in as exogenous. We argue that this is appropriate since snitching on rivals may not be the primary motivation for firms to engage in CPA, which is typically driven by a broader set of considerations.

To examine the validity of this claim, we examine the quarterly Lobbying Disclosure Act report filings that are the basis for our lobbying expenditure data. In these reports, lobbying entities have to provide brief descriptions of the specific issues they lobbied on. We drew a random sample of 5,000 issue descriptions and coded each into one of seven issues:

- Legislation (Bills & Resolutions, Lobbying on specific bills or resolutions in Congress, Advocating for or against proposed legislative changes, Efforts to shape bill text, amendments, or legislative markups)
- Appropriations & Budget (Seeking funding in federal appropriations bills; Advocacy related to discretionary vs. mandatory spending; Requests for specific program funding in the federal budget; etc.)
- Regulation & Rulemaking (Engaging with federal agencies on proposed regulations; Commenting on agency rulemaking processes; Seeking regulatory exemptions, modifications, or delays; etc.)
- Regulatory Enforcement & Compliance (Lobbying to influence how agencies enforce existing regulations; Seeking leniency, exemptions, or reduced penalties in enforcement actions; Seeking stricter enforcement actions on other companies or industries; Advocating for changes in compliance standards or reporting requirements; etc.)
- Government Contracts & Procurement (Lobbying for government contracts and procurement decisions; Efforts to influence Defense, Infrastructure, or R&D contracts; Advocating for specific vendors or industry preferences; etc.)
- Executive Branch & Administrative Action (Lobbying directed at the White House, OMB, or Executive Orders; Advocacy for agency-level guidance or discretionary actions; Seeking changes in administrative enforcement or interpretations; etc.)
- Judicial & Legal Issues (Lobbying around court cases or legal interpretations; Amicus briefs and efforts to influence judicial decisions; Advocacy for or against DOJ enforcement actions; etc.)

Figure F1 shows that the vast majority of issues that firm report lobbying about relate to legislation. This is followed by regulation and rulemaking, and appropriations and budget concerns. Only very few firms report lobbying on regulatory enforcement and compliance.

However, we caution that this does not mean that firms do not use CPA to shape the enforcement stage of regulation. There is no standardized way in which the lobbying issues have to be reported, and we are not aware of efforts to ensure their accuracy. Thus, the descriptions tend to be brief and do not list every single issue that firms' lobbyists talked about. Instead, they tend to focus on the primary issue(s) that motivated the firm to seek contact with elected officials or government agencies. Consistent with our argument, this is driven by issues unrelated to regulatory enforcement, and our argument holds that these pre-existing contacts facilitate the communication of information on potential violations by competitors.

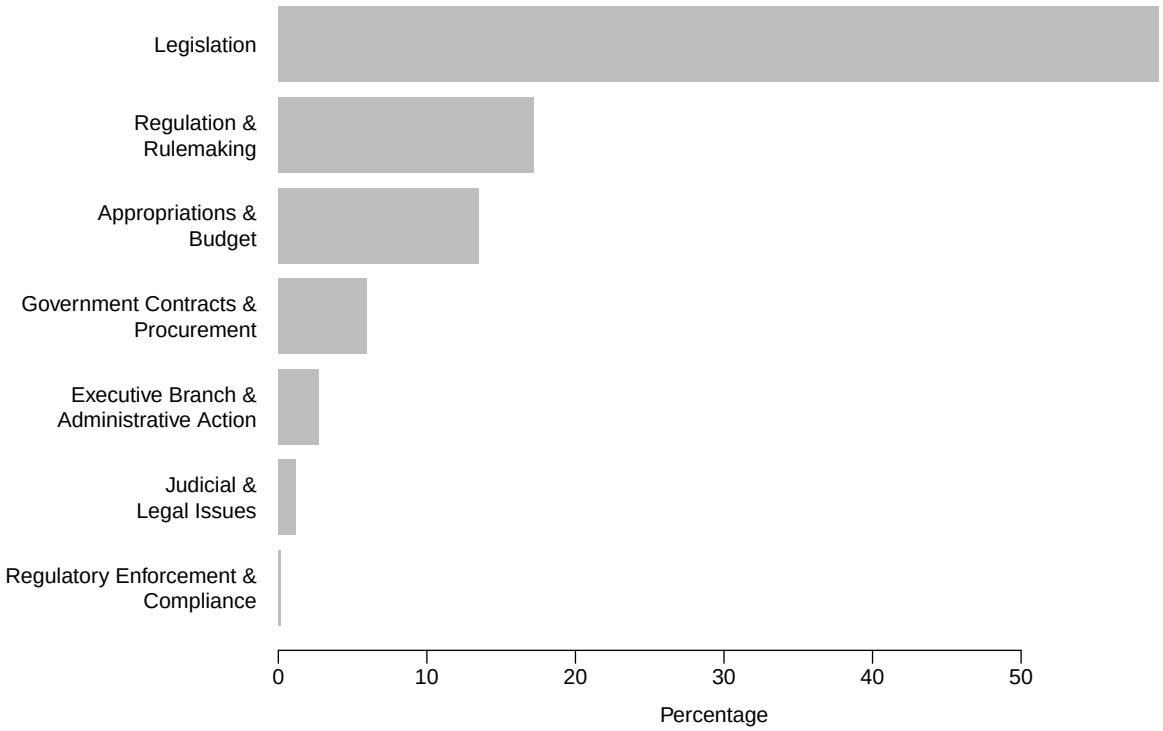

Figure F1: Lobbying Issues. Random sample of 5,000 issue descriptions provided in the quarterly Lobbying Disclosure Act report filings that are the basis for our lobbying expenditure data.