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The Impact of Information Frictions Within Regulators: Evidence from Workplace Safety Violations

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ABSTRACT

The Occupational Safety and Health Administration (OSHA) is decentralized, wherein field offices coordinated at the state level undertake inspections. We study whether this structure can lead to interstate frictions in sharing information and how this impacts firms' compliance with workplace safety laws. We find that firms caught violating in one state subsequently violate less in that state but violate more in other states. Despite this pattern, and in keeping with information frictions, violations in one state do not trigger proactive OSHA inspections in other states. Moreover, firms face lower monetary penalties when subsequent violations occur across state lines, likely due to the lack of documentation necessary to assess severe penalties. Finally, firms are more likely to shift violating behavior into states with greater information frictions. Our findings suggest that internal information within regulators impacts the likelihood and location of corporate misconduct.

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1. *Introduction*

How information flows within an organization is key to how that organization operates. Recent work studies the role of internal information in both facilitating and preventing corporate misconduct (e.g., Ege [2015], Heese and Pérez-Cavazos [2020]). However, this work focuses on information within firms, implicitly assuming a monolithic regulator that is constrained only by available resources. In practice, regulators also have bureaucratic structures that impact their internal information flows, potentially altering their effectiveness in detecting misconduct. Our paper explores the role of internal information in a prominent U.S. regulatory body that oversees workplace safety, the Occupational Safety and Health Administration (OSHA). Specifically, we study whether information frictions within OSHA are associated with meaningful patterns in workplace safety violations by overseen firms.

OSHA delegates significant authority to field offices run at the state level. These offices are responsible for ensuring that firms in their state comply with federal workplace safety laws. Such delegation empowers those with localized expertise (Jensen and Meckling [1995], Christie, Joye, and Watts [2003]), yielding efficient outcomes when centralization is costly (Melumad and Reichelstein [1987], Dessein [2002]). However, delegation may be less effective vis-à-vis greater centralization if information sharing and processing across an organization is important (Bolton and Dewatripont [1994], Garicano [2000]). The latter concern is particularly

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relevant to OSHA because field offices are only responsible for assessing compliance with safety standards in their own state, meaning that they do not inspect firms across state lines. Efficient information sharing between field offices is thus important to OSHA's mission of ensuring firm-wide compliance with workplace safety standards and, in turn, preventing harm to American workers.

OSHA compliance plausibly matters to firms. Prior work shows that firms' financial incentives reduce compliance with workplace safety standards (Cohn and Wardlaw [2016], Caskey and Ozel [2017]) whereas better enforcement improves compliance (Johnson, Levine, and Toffel [2023]). Beyond direct monetary fines,[1] violations result in time-consuming and costly remediation actions, heightened penalties for further noncompliance, and increased litigation risk (Li and Raghunandan [2023]). Violations, especially serious offences, also lead to local reputational damage, harming a firm's ability to do business locally (Johnson [2020]). Our setting thus provides an opportunity to assess whether firms reallocate compliance efforts across states that they operate in that is consistent with interstate information frictions within OSHA.

To motivate our empirical predictions, we develop a model in which a firm can cut production costs (e.g., reducing time spent on safety training), leading to lower workplace safety, in either of two states it operates in. The firm's conduct is monitored by separate OSHA branches in each state. The OSHA branches may share findings from their respective inspections with each other but can only do so imperfectly, leading to information asymmetry between the two branches. Imperfect information sharing within OSHA means that although both OSHA branches learn information after an initial violation in a single state, the firm has stronger disincentive to commit a future violation in the same state relative to other states. Hence, although a current-period violation in one state leads to a decrease in future violations within that state, our model shows that information frictions can play a meaningful role in the location of misconduct. Specifically, when information frictions are severe enough, firms may reallocate compliance efforts out of the state with the less-informed OSHA office to the extent that future violations in other states actually *increase*.

To complement our model, we also conducted interviews with six OSHA compliance officers in charge of workplace safety inspections. We learned in these discussions that checking OSHA's internal information system, the OSHA Information System (OIS), is a key first step in preparing to inspect a workplace. Compliance officers record firm citations in this system, but mostly excluded from OIS are qualitative inspection details, case documents related to violations, or personal notes of the OSHA compliance officer in charge of assessing citations. The officers we interviewed argued

[1] In 2019 alone, OSHA conducted thousands of inspections, resulting in over $335 million in fines.

that incomplete information sharing within OSHA makes tracking a firm's misconduct across state lines difficult, limiting OSHA inspectors' abilities to obtain broader firm-level supporting documentation necessary to effectively inspect businesses and cite violations.

We empirically test the predictions generated by our analytical model and interviews with OSHA officers using a large-sample, firm-state-year panel. Our design relies on a rich set of firm-by-state and year fixed effects. This design ensures that our results are not driven by broader firm, state, or firm-state–level cross-sectional characteristics (e.g., those related to the choice to locate a firm's headquarters or main manufacturing facilities) or time-varying market conditions.

We find that a firm's overall likelihood, collectively across all states, of violating workplace safety laws is lower if the firm had a violation in the prior year. However, after a firm is caught committing a violation in one state, it is less likely to commit a violation in the same state but more likely to commit a violation in a different state. The latter result is unlikely to reflect within-firm information frictions, given our fixed effects structure, because within-firm frictions would inhibit the firm's ability to coordinate its actions in different states. Although the reduction in future same-state violations may reflect firm learning, our cross-state results suggest that any attempt by firms to apply this learning to their operations in other states is dominated by incentives to shift compliance effort across state lines. Such shifts might involve placing emphasis on compliance and safety activities in establishments in one state over another. This is an economically rational response by firms to within-OSHA information frictions; without such frictions, the penalty for a subsequent violation should be equally severe across locations, reducing the incentive to shift compliance efforts from one location to another.[2]

Internal shifts in compliance effort require explicit or implicit coordination within a firm. Explicit coordination could involve a manager directing actions across states (Holmström and Milgrom [1991], Brüggen and Moers [2007]). Although this mechanism is theoretically straightforward, a more plausible one is implicit coordination across states, via some form of cost-cutting (as in our model) or budgeting imperative from firm headquarters. That is, a manager need not issue any formal directives regarding safety protocols.

For example, if a CEO manages a firm with plants in two states, 1 and 2, she may implore plant managers in each state to cut costs. If a violation previously occurred in state 1, the manager in state 1 will be constrained

[2] Any level differences across states are accounted for by firm-by-state fixed effects in our empirical design. Moreover, to address firm-level and state-level shocks, in an alternative specification we re-estimate our model with firm by year and state by year fixed effects. Our findings on shifts in violating behaviors remain similar. This mitigates the concern that a firm's time-varying propensity to violate is driving our results or that state-level changes in enforcement are leading to spurious shifts across state lines.

in cost-cutting and would alert the CEO, leading the CEO to apply more pressure to the manager in state 2 to cut costs. This may lead the manager in state 2 to cut corners that lead to worse compliance with workplace safety standards.[3] Such coordination can occur in several different ways in practice, as shown by theoretical work on participative budgeting (Kanodia [1993]), incentive schemes (Bernardo, Cai, and Luo [2004]), and transfer pricing (Göx and Schiller [2006]). Because we are unable to obtain within-firm data that enable a direct empirical test of this assertion, we provide an analytical model to show that this is a plausible reason for our empirical findings above.

We next explore the two key channels driving shifts in compliance efforts (and, hence, violations) by studying inspections and the severity of punishment, related to the detection and deterrence of violations, respectively. To identify the detection channel, we distinguish between three types of inspections: reactive (those in response to a trigger event such as an injury or whistleblower referral), centrally planned (those that OSHA headquarters requires field offices to conduct, but not in response to a trigger event), and discretionary (those proactively initiated by individual state-level OSHA offices). We find that a firm's likelihood of facing a reactive inspection increases after prior out-of-state violations. Many of these are required inspections following the reporting of an injury.

However, we find no change in how OSHA offices select target firms for discretionary inspections in response to out-of-state violations. This suggests that information frictions within OSHA limit the effectiveness of OSHA's violation-detection efforts.[4] These results also mitigate the possibility that our findings reflect systematic differences in the timing of OSHA inspections, rather than actual changes in firms' behavior. For example, if firms exhibit consistent behavior across states, but OSHA offices were merely detecting this behavior at different rates, then any delayed responses should show up as changes in discretionary inspections across states and time.

We next investigate the deterrence channel, that is, whether information frictions may limit OSHA's ability to assess appropriate fines that deter future misconduct. By law, fines for safety violations increase 10-fold for violations deemed *Repeat* (the employer was previously cited for a similar violation) or *Willful* (acted with disregard for worker safety). OSHA's Field Operations Manual and our interviews with officers indicate that (i) such violations require significant documentation of firms' past interactions with OSHA and (ii) OSHA's bureaucratic structure makes it more difficult to obtain documentation from out-of-state offices than from same state offices.

[3] This could be related to, for example, reallocating production time to tasks that may boost short-term output but could pull time away from safety training or proactively following safety standards.

[4] This is also consistent with what we learned from compliance officers, who argue that offices lack the qualitative information about firm-wide activity needed to effectively inspect these targets.

We find that violations designated Repeat or Willful are more likely to occur following a violation within the same state but are no more likely following a violation in another state. With less of a deterrence mechanism available to OSHA, there is a clear financial benefit to firms in shifting compliance effort related to workplace safety across state lines to avoid severe penalties.

To substantiate our findings, we explore states where information frictions may be greatest. The Occupational Safety and Health (OSH) Act permits states to substitute their own state-level agencies, called "state plans," for federally run OSHA offices. State plan offices must follow federal standards and use OIS but are partially state funded and are given more discretion in selecting inspection targets.[5] This discretion means that within-OSHA information frictions may be higher between two states when one of those states operates a state plan. Consistent with this argument, we find that shifts in violations are greater into state plan states. This result substantiates our findings on information frictions within OSHA, given that within-firm frictions are unlikely to systematically vary across two states based on whether one of those states has an OSHA state plan.

Our final set of tests explores firm-level financial motives and culture as potential explanatory factors for our empirical findings. In terms of financial motives, our main results are stronger in firms that face Repeat or Willful violations in other states, when financial incentives to shift compliance efforts across state lines are strongest. Our results are also stronger for firms that just meet or beat analyst earnings benchmarks, potentially indicative of greater cost-cutting incentives. Finally, our results are also stronger in firms with weaker compliance cultures, indicating that attitudes toward best practices play a role.

Our study makes three main contributions. First, a wide body of work highlights the costs and benefits of information sharing and delegation to an organization's effectiveness (Abernethy, Bouwens, and van Lent [2004], Li and Sandino [2018, 2021], Sani [2021], Labro, Lang, and Omartian [2023]). We contribute to this literature by providing evidence on the effects of information-sharing systems within OSHA, a key regulator responsible for the health and safety of American workers. Our findings suggest that the structure of OSHA, including bureaucratic constraints, may present information frictions that underlie a distinct cost of delegation. In this regard, our study suggests a need to better understand the effects of informational constraints within other federal regulators where multiple branches are involved in the enforcement process (e.g., Stice-Lawrence [2023]).

Second, we provide insight into how a regulator's information environment affects firms' practices. We contribute to a nascent literature on how regulators' "blind spots" may provide the opportunity to avoid enforcement (Aobdia [2018], Beuselinck et al. [2019]), and more broadly to the

[5] States that adopted state plans did so in the 1970s and 1980s, well before our sample period begins.

literature on how geographic factors affect the likelihood and location of corporate misconduct (Kedia and Rajgopal [2011], Dyreng, Hanlon, and Maydew [2012]). Because we focus on how the frequency and geography of misconduct are affected by internal information asymmetry within a regulator, we also contribute to the literature on the costs and benefits of federalism, especially in the context of workplace safety (Bradbury [2006], Morantz [2009], Jung and Makowsky [2014]).

Third, we contribute to a growing literature on the financial determinants of workplace safety (Cohn and Wardlaw [2016], Bernstein and Sheen [2016], Cohn, Nestoriak, and Wardlaw [2021]). Our study differs in two ways. First, we address workplace safety from the regulator's rather than the firm's perspective, building on work on policies enacted to deter safety violations (Johnson [2020]). We show that information frictions may reduce positive externalities of increased enforcement across jurisdictions. Second, we study actual violations of workplace safety laws rather than injury rates. Although the two constructs are related, studying violations and inspections treats OSHA as an active participant in, rather than a passive observer of, workplace safety.

2. . *Background and Institutional Setting*

2.1 OSHA ENFORCEMENT

Under the OSH Act of 1970, OSHA is responsible for inspecting and examining workplaces to ensure compliance with workplace safety regulations. OSHA is decentralized: Inspections and enforcement are federally overseen but administered by state-level offices.[6] Federal law requires inspections to be conducted without advance notice so that firms cannot preemptively cover up issues.[7] During an inspection, an OSHA inspector engages in a walkaround at the place of business, recording any safety-related issues they observe. The inspector then determines whether there was a violation and documents their findings. Violations occur if four conditions are met: (i) a workplace hazard is present; (ii) that hazard violates a relevant OSHA standard; (iii) the employer had knowledge of the standard; and (iv) there was employee exposure to the hazard. Finally, the inspector alerts the company, which includes engaging directly with company safety officers (including firm-level management). The inspector then offers a plan for remediating the violation and assesses an appropriate penalty.

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[6] Firms only face OSHA inspections at the state level, which differs from the financial sector where banks may face supervision by both federal and state regulators (Agarwal, Lucca, Seru, and Trebbi [2014]).

[7] See the OSHA Field Operations Manual. Exceptions relate to cases in which there is imminent danger, or when notice is necessary to aid in the inspection. Under the latter, advance notice "shall not be given more than 24 hours before the inspection is scheduled to be conducted" (29 CF 1903.6(b)).

Penalties come in two forms. The first is a smaller penalty assessed to a single violation, such as the lack of proper guards on a metal-stamping machine or failing to provide proper signage about hazardous chemicals. The penalty for this common violation, as of 2023, is $15,625.[8] A heightened penalty of $156,259 results for violations deemed to be *Repeat* or *Willful*. Repeat violations are assessed if the employer has been previously cited for a similar violation, whereas Willful violations reflect the employer knowingly failing to comply or acting with indifference to safety. Beyond fines, violations result in time-consuming and costly ex post remediation actions, legal risks, and the inability to secure government contracts (Johnson [2020], Li and Raghunandan [2023]). Although we cannot directly measure each of these costs, that all of these costs follow from OSHA enforcement actions underscores the relevance of understanding this process for firms.

2.2 INFORMATION FRICTIONS WITHIN OSHA

Records of injuries and illnesses must be recorded at individual worksites. These records could be kept in paper form until 2016, when OSHA introduced an electronic recordkeeping mandate. The mandate received substantial pushback from employers, consistent with the notion that many firms had previously complied by keeping paper injury and illness records. OSHA also does not require worksites to keep broader firm-level records of injuries and illnesses that occurred outside of the worksite, although some firms may choose to do this.[9] General inspection information, including violations at the firm and establishment levels, is recorded in an electronic database by OSHA compliance officers that is maintained by OSHA headquarters, the OIS. OIS contains citations for violations, assessed penalties, inspection dates, and the OSHA compliance manager involved in the case and their associated field office.

However, inspection details, case documents related to violations or remediation, and personal notes of the OSHA compliance officer in charge of assessing citations are not available on OIS. Although there are fields in OIS to include additional notes, one officer we interviewed noted that, "many compliance officers do not write enough [qualitative information in OIS]," perhaps because of a lack of incentives to do so. OSHA inspectors are not rewarded for providing information that facilitates more efficient inspections in other jurisdictions. Thus, in practice, auxiliary notes must be

[8] See https://www.osha.gov/news/newsreleases/trade/01122023.

[9] To our knowledge, applicable laws only require that worksites maintain records of local injuries and illnesses, rather than inspections. See 29 CFR Part 1904 of the OSH Act (https://www.osha.gov/laws-regs/regulations/standardnumber/1904/). In our interviews, compliance officers noted one reason that, although worksites are required to keep injury and illness information, full details of inspections and violations are kept within OSHA: many inspections arise as a response to anonymous tips, and compliance officers' notes frequently reference information obtained from tipsters prior to and during the investigation. To that end, if violation and inspection records were kept at the worksite rather than by OSHA, there would be a risk that the employer could identify and potentially retaliate against whistleblowers.

obtained directly from the relevant OSHA field office and its staff. Obtaining case documents from a past inspection requires formal requests that can only be completed by directly involving supervisors overseeing field office operations.

Technical limitations of the information-sharing system also arose during our interviews. For example, one officer noted that he or she was only recently able to begin obtaining (some of) the documents associated with out-of-state investigations electronically, albeit subject to the formal request process described above. Perhaps due to such constraints, compliance officers noted the emergence of an informal information-sharing practice across OSHA state offices for obtaining inspection details to supplement the information available on OIS. The informal system relies on supervisors from different states having a good working relationship. Otherwise, these types of requests can take months to get a response, if they are addressed at all.

The above organizational friction has a meaningful impact on how compliance officers conduct investigations, particularly for geographically dispersed employers. Officers in charge of an inspection may forgo obtaining past case documents for a firm if they must request documentation from a field office in another state. Although it is possible for OSHA compliance officers to obtain necessary documentation, they may not be sufficiently incentivized to do so if that information is not readily available, potentially due to both constraints on their time and their own personal career incentives. In fact, one officer we spoke to noted that in many cases "it would be unusual for a compliance officer to [formally] reach out to [another state OSHA office]," whereas another explicitly told us that it was "easier to contact a colleague in [name of their own state] than in [name of neighboring state]." If a compliance officer has not separately obtained detailed information about prior violations, this could negatively impact the determination of whether to classify violations as Repeat or Willful as the documentation necessary for creating the paper trail to label a violation as such does not exist on the federal centralized information system OIS. The compliance officers we spoke with indicated that obtaining documentation required to substantiate classifying a violation as Repeat or Willful was much easier to obtain if past violations were assessed by compliance officers in the same state, rather than in another state.

2.3 STATE PLANS

Twenty-one states, listed in appendix A, have state plans to supplement the resources and standards set by federal OSHA in inspecting, monitoring, and assessing violations for private-sector employers. State plans are OSHA approved and are required by OSHA to be at least as effective as federal OSHA at protecting workers. Each year, OSHA conducts Federal Annual Monitoring Evaluations of state plans. Each state plan adopts its own additional safety and health standards and regulations. State plan state jurisdictions have significantly more discretion in undertaking inspections, but their assessment of violations and relevant penalties must follow the OSHA Field Operations Manual, as is true for federal OSHA state jurisdictions.[10]

State plan state jurisdictions were adopted early enough before our sample period to be considered exogenous to the outcomes we study (see appendix A for adoption dates). Due to state plan idiosyncrasies, there may be greater information frictions between state plan states and non–state plan states. Our discussions with OSHA compliance officers suggest that this may reflect required reciprocity in gathering relevant documents across jurisdictions. Because state plan state jurisdictions have their own set of policies, communication may be impeded.[11]

3. *Model*

There is limited work studying how within-regulator information flows affect misconduct by firms. Hence, to motivate our empirical predictions, we present a simple stylized model. Because we wish to understand how information frictions within OSHA may affect behavior within an overseen firm, our model consists of a single firm operating in two states, with a separate OSHA office in each state. To examine firms' behavior in response to anticipated enforcement, the firm's headquarters decides about the extent to which it wants to engage in cost-cutting efforts in either location. Cost cutting increases expected gross profits but also increases the likelihood of violating safety requirements. We include a more technical discussion of the model in appendix B.

3.1 THE FIRM

A single firm operates divisions in two different states $j \in \{1, 2\}$. For each division j, the gross profit π_j before potential costs associated with regulatory enforcement actions is given by $\pi_j = R_j - c$, where R denotes revenues and c reflects production costs. In each period, production costs can be high ($\tilde{c} = c_H$) or low ($\tilde{c} = c_L$). Low production costs provide the firm with additional profits per division normalized to 1 ($c_H - c_L = 1$) in each location, without loss of generality.

With probability p, the firm's production costs are naturally low. We assume that if the firm's costs are already low, it takes no cost-cutting actions with respect to workplace safety.[12] If the firm's production costs are high, however, it can take actions m_1 and m_2 to lower production costs for

[10] For further details, see the State Plan Policy and Procedures Manual (https://www.osha.gov/sites/default/files/enforcement/directives/CSP_01-00-005.pdf).

[11] This is consistent with the argument that when specialization is high and communication is costly, it is inefficient for agents within an organization to collaborate (Bolton and Dewatripont [1994]).

[12] In practice, a firm may always have some desire to engage in cost-cutting. Our insights are valid as long as this desire is convex—that is, the firm's benefit from cutting costs is higher when its costs are higher.

each market. Here, we focus on cost-cutting actions that impact workplace safety.[13]

The firm chooses a level of cost-cutting effort to engage in m_j. Because we use a binary cost structure for ease of interpretation,[14] m_j enters our model as the probability that cost-cutting efforts succeed, allowing the firm to enjoy low costs in location j. Cost-cutting efforts may not succeed because, for example, reducing workplace safety training hours may also reduce worker productivity, which would then require additional worker hours to complete a task. Without loss of generality, we normalize the benefits of successful cost-cutting efforts in one location to 1 (i.e., $c_H - c_L$). However, these efforts are costly along two dimensions: (i) nonpecuniary costs incurred regardless of whether OSHA detects the firm's actions and (ii) potential regulatory costs.

Nonpecuniary costs of the firm's two divisions choosing effort levels m_1 and m_2 are given by $[\frac{1-\theta}{2} m_1^2 + \frac{1-\theta}{2} m_2^2 + \frac{\theta}{2}(m_1 + m_2)^2]$. Constants $\frac{1-\theta}{2}$ and $\frac{\theta}{2}$ for $\theta \in (0, 1)$ reflect a normalization for the sake of parsimony. These costs, which are incurred irrespective of whether the firm's cost-cutting efforts are successful, reflect market-specific components ($\frac{1-\theta}{2} m_1^2$ and $\frac{1-\theta}{2} m_2^2$) and also a firm-level component $\frac{\theta}{2}(m_1 + m_2)^2$.[15]

Firm-level concerns include litigation risk or reputational damage that may arise due to systematically poor employee treatment. Li and Raghunandan [2023] show that firms engaging in higher levels of workplace misconduct are more likely to subsequently settle employee class-action lawsuits, with costs of over \$10 million per settlement, suggesting that the marginal cost of cutting safety expenditures increases across markets. Concerning reputation, workplace safety violations in one region may be easier for a firm to rationalize as an isolated problem. A pattern of workplace safety issues across states might be more difficult for a firm to explain. This would, in principle, make the marginal cost of cost-cutting behavior in one state increase in the amount of cost-cutting in the other region, an intuition that is captured by the presence of the interaction term $m_1 \cdot m_2$ in the firm-level component of our cost function. Firm-level costs may also arise if a culture of workplace safety is important for operational efficiency and profitability. As a practical example, Paul O'Neill's firmwide application of strict workplace safety standards at Alcoa had significant positive spillovers on overall efficiency and productivity.[16] Finally, to the extent that cost-cutting across states may erode firm culture, this would also increase the marginal costs of a violation.

[13] These actions reflect only one way to cut costs and so form part of a portfolio of cost-cutting opportunities.

[14] We also do this to focus our analysis on the compliance vs. non-compliance trade off rather than on the threshold that meets compliance.

[15] Market-specific costs include managerial career concerns or low employee morale at an unsafe facility.

[16] Harvard case: https://www.hbs.edu/faculty/Pages/item.aspx?num=26838.

We also model regulatory costs as a fine F if OSHA catches a successful cost-cutting effort.[17] We let $\widehat{b_j}$ be the firm's belief about the probability that OSHA detects the firm's illegal actions in market j. In summary, the firm's net utility from its cost-cutting efforts is given by

$$U\ (m_1, m_2 | c = c_H) = R_1 + R_2 - 2c_H + m_1\left(1 - \widehat{b_1} \cdot F\right) + m_2\left(1 - \widehat{b_2} \cdot F\right) - \left[\frac{1-\theta}{2} m_1^2 + \frac{1-\theta}{2} m_2^2 + \frac{\theta}{2}(m_1 + m_2)^2\right]. \quad (1)$$

3.2 OSHA

Two OSHA branches ("$OSHA_1$" and "$OSHA_2$") seek to detect misconduct as a result of cost-cutting when it occurs in states 1 and 2, respectively, but detecting misconduct is costly. Achieving success with probability b requires that an OSHA office expend effort $\frac{kb^2}{2}$, where k is a constant. Both OSHA branches can infer whether a plant had low or high production costs based on its reported output. An OSHA branch will therefore only consider investigating when it observes low costs for the firm because the firm's cost-cutting can only lower its costs. Each OSHA branch can infer the firm's costs (c_L or c_H) for its location, but not the other.[18]

Along with the firm's reported costs for the division in its jurisdiction, OSHA in each region observes a noisy signal $\tilde{y}_j$ of the true costs (i.e., the costs before the firm engages in any cost-cutting efforts), following Schantl and Wagenhofer [2020]. This signal is given by

$$\tilde{y}_j = \tilde{c} + \widetilde{I}_j, \quad (2)$$

where $\tilde{I}_1$ and $\tilde{I}_2$ are independent noise terms drawn from a normal distribution. This continuous signal could represent, for example, an unexpected change in an establishment's output or a whistleblower's qualitative assessment of unsafe work conditions.

Without loss of generality, we assume that in the previous year the firm had a chance to engage in cost-cutting with respect to workplace safety in only region 1. If the firm did not cut costs, or if the firm did and was not caught by $OSHA_1$, then neither $OSHA_1$ nor $OSHA_2$ learns any information and the variances of $\tilde{I}_1$ and $\tilde{I}_2$ are both given by $u^2 + \alpha^2$ for nonzero u and α. We depict the model's timeline visually in figure 1.

If $OSHA_1$ detects a violation, it gains knowledge of the firm's operational processes through its inspections and remediation efforts with the firm, increasing the precision of the signal $\widetilde{y}_j$, which we model as a reduction in the variance of $\tilde{I}_1$ to u^2 (from $u^2 + \alpha^2$). $OSHA_1$ then imperfectly conveys

[17] Regulatory fine F could include any increased litigation risks associated with being found at fault for a violation of workplace safety laws.

[18] Although this assumption is useful for tractability of the model, it does not alter our main conclusions. Moreover, as we learned from interviews with OSHA compliance officers, our reasoning is in keeping with the functional oversight OSHA offices have over firms in and out of the state.

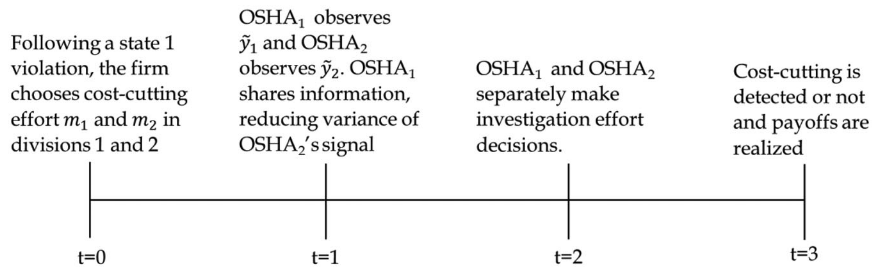

FIG. 1.—Timeline.

information to OSHA$_2$ due to information frictions in sharing information beyond the OIS. The information shared by OSHA$_1$ reduces the variance of $\tilde{I}_2$ to $u^2 + \delta^2$ (from $u^2 + \alpha^2$), where $\delta^2 < \alpha^2$. That is, OSHA$_2$'s signal is more precise than before but is still noisier than OSHA1's signal. The term δ^2 reflects the level of information frictions present.[19] A higher δ^2 means OSHA$_2$ learns less from OSHA$_1$.

3.3 MODEL EMPIRICAL IMPLICATIONS

We characterize the model's equilibrium, in terms of the firm's and both OSHA branches' optimal behaviors, in appendix B. The model's key comparative statics are derived in three propositions that directly generate empirical hypotheses. We discuss each of these below.

Our first comparative static result, summarized in Proposition B1 in appendix B, is that the firm engages in less overall cost-cutting (i.e., $m_1 + m_2$ is lower) following detection of a violation. Detecting a violation decreases how uncertain OSHA$_1$ and OSHA$_2$ are about the likelihood of cost-cutting behavior. This increases expected benefits to both OSHA$_1$ and OSHA$_2$ of expending costly detection effort, which increases the likelihood that the firm's cost-cutting behavior will be detected. In turn, the firm reduces cost-cutting efforts and, therefore, its detected violations on average. This result is consistent with prior work, both empirical (e.g., Macher, Mayo, and Nickerson [2011]) and theoretical (e.g., Laffont and Tirole [1986]), that suggests regulators can deter risky behavior by being better informed. This result implies our first empirical hypothesis:

Hypothesis 1 (HI): Firms that are sanctioned by OSHA for workplace safety violations are less likely to commit workplace safety violations in the following year.

HI governs the *average* level of detected violations, summed over divisions. Our second comparative static, summarized in Proposition B2 in

[19] We do not endogenize δ^2. In practice, OSHA1 might choose δ^2 based on information-sharing costs or investigative resources available. Moreover, as individual OSHA offices spend more effort on sharing information with other offices, they will have fewer resources available for conducting their own investigations.

appendix B, explores the tension resulting from asymmetric information between $OSHA_1$ and $OSHA_2$ and the potential differential behavior across firm divisions. The impact on the firm's division 1 behavior is clear when it faces a more informed $OSHA_1$. Because $OSHA_1$ is at least as informed as $OSHA_2$, division 1 will decrease its cost-cutting behavior. The impact on cost-cutting behavior by division 2 is less clear, depending on the size of information frictions between $OSHA_1$ and $OSHA_2$.

On one hand, $OSHA_2$ is more informed after $OSHA_1$ detects a violation. This increases the likelihood $OSHA_2$ will expend costly effort investigating division 2 of the firm, reducing division 2's cost-cutting incentives. On the other hand, the fact that $OSHA_1$ is relatively more informed makes it optimal for the firm to substitute cost cutting out of division 1 into division 2, because the firm faces a greater detection likelihood for division 1 than for division 2. With a large enough differential, the incentive to substitute is high enough that a decrease in cost-cutting behavior in division 1 could be accompanied by an increase in cost-cutting behavior in division 2.

Which of the two forces, reduced overall cost-cutting or substitution of cost-cutting across markets, dominates for division 2 depends on whether the level of information frictions exceeds a threshold. Whether this is the case is an empirical question. Based on our conversations with OSHA compliance officers, we expect that, empirically, information frictions often do exceed this theoretical threshold. We thus have a second empirical hypothesis:

Hypothesis 2 (H2): Information frictions within OSHA lead to firms shifting their compliance efforts between locations. That is, a firm that commits a violation in one location is less likely to commit a violation in the same location next year but more likely to commit a violation in a different location next year.

Our third comparative static, outlined in Proposition B3, extends Proposition B2 by showing that the level of information frictions matters. Greater information frictions may exacerbate firms' incentives to shift compliance efforts across state lines. When information frictions are more severe, $OSHA_2$'s signal is noisier relative to $OSHA_1$'s. Hence, $OSHA_2$ is less likely than $OSHA_1$ to investigate even if it anticipates cost-cutting behavior. This generates our third empirical hypothesis:

Hypothesis 3 (H3): he extent to which firms shift compliance effort between locations is positively associated with the level of information frictions within OSHA.

This result is most relevant to shifts in cost-cutting behavior induced by information frictions. However, one could imagine extending our model to include the costs of shifting compliance efforts between locations in a more general sense. For example, a firm with a stronger compliance culture might face higher nonpecuniary costs of misreporting, which in turn would increase its willingness to spend money fixing workplace issues across the firm rather than simply reallocating existing resources across state lines. Conversely, increased financial incentives should lead to greater shifts, all else equal, given that a firm must explore all possible cost-cutting opportunities. Although we do not analytically model these predictions, we explore them empirically to better evaluate relevant mechanisms that drive firm behavior.

4. *Empirical Strategy*

4.1 OSHA DATA

We obtain OSHA inspection and violation data from the U.S. Department of Labor's Enforcement Data Web page.[20] The data contain the name and address of the firm being inspected, the inspection date, inspection type, whether violations occurred, and, if violations occurred, further information about those violations. OSHA's classification of inspection types is detailed enough that we are able to distinguish between inspections that are discretionary on the part of regional OSHA offices (i.e., initiated without either a directive from federal OSHA headquarters or in response to a trigger event), inspections that are centrally planned by OSHA headquarters, and inspections that are reactive (in response to a trigger event such as a workplace injury or a whistleblower complaint). We provide further details on OSHA inspection types in appendix C.

With respect to violations, we observe for each violation the penalty amount assessed by OSHA as well as whether the violation is classified as Repeat or Willful. We collapse violation and inspection data to the firm-state-year level. Because OSHA's unit of organization is the state level, we view this as the most natural level at which to conduct our analyses.

To obtain a complete picture of where firms operate, and not just where they have had OSHA activity, we then merge these data with information on the number of establishments each firm has in each state in each year. To minimize measurement error, we aggregate the raw OSHA data and ReferenceUSA's establishment-level data to the firm-state-year level before merging data sets. We omit firm-state-years for which we do not observe at least one establishment, as well as public firms for which we do not observe at least one inspection or violation in the raw OSHA data. We make the latter conservative choice because it is possible that we were unable to match these firms to the raw OSHA data, rather than those firms genuinely never having an inspection. Our sample selection process is outlined in table 1.

4.2 BASELINE ECONOMETRIC SPECIFICATION

We begin by examining whether committing an OSHA violation in year t affects the likelihood a firm commits an OSHA violation in year t+1.

[20] https://enforcedata.dol.gov/views/data_summary.php

TABLE 1
Sample Construction

	Firm-State-Years	
	Obs. Dropped	Obs. Remaining
Start: Firm-state-years with at least one establishment from 2002 to 2016, for firms with at least one OSHA inspection (in any state in any year)		478,636
Less: Firm-state-years with missing lead/lag data	(46,329)	432,307
Less: Firm-states with missing Compustat financial statement data	(2,292)	430,015

This table outlines our sample selection process.

Because our goal in this analysis is to test H1, which reflects firm-wide behavior, our unit of analysis is the firm-year level for this test only. Because a nonlinear binary choice model (e.g., logit) cannot accommodate our fixed effects structure without significant sample attrition, we first estimate a linear probability model:

$$ViolAny_{i,t+1} = \beta_0 + \beta_1 ViolAny_{it} + \alpha Controls_{it} + \eta_i + \gamma_t + \varepsilon_{it+1}\,. \quad (3)$$

Controls include financial measures found by prior work to affect workplace safety (Cohn and Wardlaw [2016], Caskey and Ozel [2017]). These include assets, ROA, leverage, and market-to-book ratio. We also control for the firm's overall number of establishments across all states. The primary dependent variable, $ViolAny_{it+1}$, is an indicator that equals 1 if the firm committed at least one OSHA violation in any state in year *t+1*. The key independent variable is $ViolAny_{it+1}$. Standard errors are clustered by firm. Equation (3) provides insight into the *overall* likelihood a firm engages in repeated workplace safety violations. H1 predicts a negative β_1.

4.3 THE GEOGRAPHY OF VIOLATIONS

We next augment equation (3) to examine patterns in violations, that is, whether after a firm commits a violation in state *A* in year *t* it is (i) less likely to commit a violation in State *A* in year *t*+1 but (ii) more likely to commit a violation in some other state *B* in year *t*+1. Our unit of analysis in these and all subsequent analyses is the firm-state-year level rather than the establishment level for two reasons. First, OSHA enforcement is at the state level. Second, prior work (Haltiwanger, Jarmin, and Miranda [2013], Makridis and Ohlrogge [2017]) highlights inconsistencies in observability of individual establishments in our data sources. In particular, although ReferenceUSA (from which we obtain establishment-level data) provides a reasonable estimate of a firm's overall presence in a state, data on individual establishments are often not updated in a timely fashion to reflect address changes, openings, or closures. To that end, attempting to track individual establishments' behavior over time could yield nontrivial measurement error. Moreover, such measurement error is likely to be correlated with OSHA sanctions inasmuch as an establishment may be more likely to change its address or close (and potentially be replaced by other establishments of the firm within the state) in an effort to obfuscate its past compliance history from the broader public.

Our research design relies on firm-by-state fixed effects, which eliminate time-invariant firm, state, and joint firm-state factors as drivers of our findings. For example, although there may be cross-sectional variation across locations in both enforcement practices (Bonsall, Holzman, and Miller [2024]) and the proclivity for misconduct (Parsons, Sulaeman, and Titman [2018]), our results cannot be explained by the enforcement rate for a particular state's OSHA office or the nature of a firm's operations in that state. Importantly, our fixed effects structure also controls for firms' overall level of activity within each state.[21] We also include year fixed effects to account for macroeconomic factors, whether economy-wide or concentrated within specific industries, that may drive the underlying decision to commit a violation. We estimate the following specification:

$$\begin{aligned} \mathit{ViolInState}_{i,j,t+1} = \beta_0 &+ \beta_1 \mathit{ViolInState}_{ijt} + \beta_2 \mathit{ViolOutOfState}_{ijt} \\ &+ \alpha \mathit{Controls}_{ijt} + \theta_{ij} + \gamma_t + \varepsilon_{ijt+1}. \end{aligned} \tag{4}$$

In equation (4), i indexes firm, j indexes state, and t indexes time. The quantities θ_{ij} and γ_t denote firm-by-state and year fixed effects, respectively, whereas ε_{ijt+1} is an error term. $\mathit{Controls}_{ijt}$ includes the number of establishments that firm i has in state j in year t as well as the financial control variables outlined in section 4.2. Controlling for the number of establishments that each firm has in each state in each year addresses alternative explanations related to firm-state–level changes in economic activity over time, which are not fully captured by firm-by-state fixed effects.[22]

In equation (4), negative values of both β_1 and β_2 imply that heightened OSHA scrutiny leads to a decrease in future violations both in- and out-of-state. However, a negative β_2 does not preclude the existence of shifts in compliance efforts. We formalize this intuition in Proposition B2 of our model. Specifically, geographic shifts in compliance efforts imply only that the future deterrence effect of a current violation is stronger in-state than out-of-state; the result could still be an absolute decrease in violations both in- and out-of-state. With that said, the nature of our firm-state-year panel—where $\mathit{ViolOutOfState}_{ijt}$ captures violations across many

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[21] Without firm-by-state fixed effects, we may observe a spurious positive correlation between year-t violations and year-t+1 violations, because a firm with a larger economic presence in a state will mechanically have more violations in both years than a firm with a smaller presence in the state.

[22] Although we cannot observe firm-state–level employee counts in our data, this is a valid measure as long as a firm's economic activity in a given state is related to the number of establishments the firm has in that state. ReferenceUSA, where we obtain establishment data, does contain some information on employment but this information is known to be highly unreliable (see, e.g., Makridis and Ohlrogge [2017]).

states, whereas *ViolInState* captures only a single state—makes it difficult to interpret relative decreases to infer geographic shifts in compliance efforts within a firm in the event that both β_1 and β_2 are negative.

However, as shown in our model and discussed in H2, a positive β_2 but negative β_1 is possible if information frictions between states are high. That is, a positive β_2 would be clear evidence of underlying shifts in compliance efforts in a way that does not depend on coefficients' relative magnitudes. It also would be consistent with the existence of substantial information frictions. Of course, we acknowledge that a positive β_2 in equation (4) is insufficient on a standalone basis to conclude that within-OSHA information frictions affect firm behavior.

We emphasize that a positive β_2 is not consistent with within-firm information frictions. Within-firm frictions (e.g., if a firm learns "best practices" in its locations in state B but does not transmit information about these practices to state A) imply greater statistical independence in the firm's operations in the two states, which should lead to an insignificant coefficient on β_2. This, in turn, biases us against finding results consistent with information frictions within OSHA.

4.4 BIAS CORRECTION

Although equations (3) and (4) represent an intuitive formulation of our research question, it is well-known that the coefficient on a lagged dependent variable (i.e., β_1) in a model with unit fixed effects is biased downward (Nickell [1981]). In this section, we outline analyses that we run to assess the robustness of our results to biases that might be introduced in estimating (3) and (4).

The binary nature of our dependent variable also gives rise to the second challenge in using these techniques—especially when that dependent variable exhibits sparseness, as is the case for our firm-state-year–level analyses outlined in the next section. A well-known approach to dealing with the Nickell [1981] bias is proposed by Arellano and Bond [1991]. Although this approach is effective in examining continuous dependent variables, a linear modeling approach may not be ideal in conjunction with the Arellano-Bond approach when studying binary variables (Chamberlain [2010], Honoré and de Paula [2021]).[23]

We therefore apply logistic regression to our modeling problem, specifically relying on a recent econometric technique explicitly designed to account for binary dynamic fixed-effects structures as in our model: the split-panel jackknife (Dhaene and Jochmans [2015]). In short, the split-panel

[23] This is because linear models may be susceptible to persistence and other non-stationarity issues in the dependent variable when including lags of the dependent variable. That is, a linear model could produce an autoregressive coefficient that falls outside of the range of [-1,1], resulting in a non-unit root, a model with unbounded asymptotic properties. This specific issue does not arise for nonlinear probability models (Park and Phillips [2000[, [2001]).

jackknife splits the sample into two halves before separately computing parameter estimates on each subsample. This method then combines these estimates to generate a bias-corrected estimate of the underlying parameters, relying on the deterministic relation between the magnitude of bias in each subsample vis-à-vis the bias in the full sample. We apply this technique to a logistic regression model following prior work suggesting this to be the most appropriate choice (Chamberlain [2010], Honoré and de Paula [2021]). We provide a more detailed explanation of the intuition behind using the split-panel jackknife in appendix E.

We note that although the split-panel jackknifed logit produces unbiased coefficient estimates, and thus helps validate our qualitative conclusions from the linear model, it comes at the cost of significant sample attrition. Firm-states without any variation in the dependent variable drop out of the sample (as they would for a standard fixed-effects logit without any bias correction techniques). Moreover, even some firm-states with overall variation in the dependent variable can drop out during the jackknife process because it is identified based on firm variation within each subpanel. We do not view this as a significant concern for our main analyses because, given our fixed effects structure, the remaining observations are likely the most influential in determining our coefficients in the full-sample linear model (Breuer and deHaan [2023]).

We therefore present split-panel jackknifed logit results alongside our primary empirical implementations of equations (3) and (4) as well as our main test on inspections but rely on the linear model to exploit sufficient variation for our cross-sectional analyses. Moreover, prior literature (Ai and Norton [2003], Greene [2010]) highlights difficulties in interpreting interaction terms in nonlinear models. As many of our mechanism and cross-sectional tests rely on interactions, we believe it is easier to discuss and interpret these in a linear setting.

5. *Results*

5.1 DESCRIPTIVE STATISTICS

Panels A and B of table 2 provide descriptive information about OSHA violations and inspections by year and 2-digit NAICS industry. For a full list of variable definitions, we refer the reader to appendix D. Panel A indicates that OSHA violation and inspection rates are generally stable over time. The percentage of firm-state-years with at least one violation ranges between 3.3% and 4.5% over our sample period with an overall sample mean of 3.9%, whereas the percentage of firm-state-years with at least one inspection ranges between 5.5% and 7.0% with an overall sample mean of 6.3%. These results are consistent with our finding in the underlying inspection-level data (untabulated) that more than 60% of inspections result in at least one violation. The relatively high "hit rate" may reflect the fact that most inspections are reactive, that is, in response to a tip or trigger

TABLE 2
Descriptive Statistics

Panel A: OSHA firm-state-year violation rates by year

Year	OSHA Violations	OSHA Inspections	Discretionary OSHA Inspections
2002	0.038	0.062	0.007
2003	0.041	0.065	0.006
2004	0.041	0.065	0.007
2005	0.039	0.062	0.007
2006	0.040	0.064	0.006
2007	0.040	0.065	0.007
2008	0.041	0.065	0.007
2009	0.045	0.070	0.008
2010	0.044	0.066	0.006
2011	0.038	0.061	0.005
2012	0.038	0.063	0.006
2013	0.037	0.063	0.006
2014	0.035	0.060	0.007
2015	0.035	0.059	0.006
2016	0.033	0.055	0.005
Overall	0.039	0.063	0.006

Panel B: OSHA firm-state-year violation and inspection rates by industry

NAICS Industry	OSHA Violations	OSHA Inspections	Discretionary OSHA Inspections
Admin/Support/Waste Management	0.030	0.056	0.010
Agriculture	0.036	0.063	0.007
Arts and Recreation	0.032	0.056	0.007
Construction	0.029	0.071	0.019
Education	0.006	0.015	0.000
Finance	0.011	0.021	0.002
Healthcare	0.027	0.048	0.003
Hospitality	0.040	0.061	0.005
Information	0.013	0.025	0.001
Manufacturing	0.050	0.079	0.007
Mining, Oil, and Gas	0.026	0.050	0.009
Other	0.072	0.113	0.012
Professional Services	0.012	0.020	0.002
Real Estate	0.025	0.039	0.006
Retail Trade	0.051	0.076	0.007
Transportation	0.046	0.080	0.007
Utilities	0.031	0.061	0.010
Wholesale Trade	0.034	0.053	0.004
Overall	0.039	0.063	0.006

Panel C: Regression sample ($n = 430{,}015$)

Variable	Mean	Median	Std. Dev.	10th %ile	90th %ile
$ViolAny_t$	0.472	0.000	0.499	0.000	1.000
$ViolInState_t$	0.039	0.000	0.194	0.000	0.000

(*Continued*)

TABLE 2—*(Continued)*

Panel C: Regression sample ($n = 430{,}015$)

Variable	Mean	Median	Std. Dev.	10th %ile	90th %ile
$ViolOutOfState_t$	0.461	0.000	0.499	0.000	1.000
RWInState	0.002	0.000	0.043	0.000	0.000
AnyInspectionInState	0.063	0.000	0.243	0.000	0.000
ReactiveInState	0.033	0.000	0.178	0.000	0.000
PlannedInState	0.024	0.000	0.152	0.000	0.000
DiscInState	0.006	0.000	0.079	0.000	0.000
CleanInspInState	0.024	0.000	0.153	0.000	0.000
CleanInspOutOfState	0.123	0.000	0.328	0.000	1.000
State plan	0.412	0.000	0.492	0.000	1.000
Log establishments	1.607	1.386	1.466	0.000	3.714
Log assets	8.076	7.943	1.944	5.736	10.546
Return on assets (ROA)	0.052	0.051	0.081	-0.023	0.141
Leverage	0.227	0.197	0.192	0.000	0.483
Market to book	2.885	2.182	4.246	0.847	5.798

This table provides descriptive statistics for OSHA violations and for our regression sample. Panels A and B detail the proportion of firm-state-years with at least one OSHA violation, inspection, and discretionary inspection, respectively, broken down by year and by industry. Panel A provides descriptive statistics by year, whereas panel B provides descriptive statistics by industry. Panel C provides descriptive statistics for control variables in our final regression sample. Panel C provides descriptive statistics for all variables used in the regressions in tables 4, 6–10, and in column 1 of table 5.

event (such as an injury). In further support of this is our inspection-level finding (see appendix C) that states office-driven discretionary inspections comprise less than 8% of total inspections that OSHA undertook during our sample period.

Turning to panel B, we see that firms in the retail trade, manufacturing, transportation, and hospitality industries appear to most frequently commit OSHA violations and are inspected the most frequently by OSHA. These industries are all labor-intensive and rely on low-wage workers who may be less aware of their rights in the workplace. The relative proportion of discretionary inspections comprises a larger share of total inspections in the construction industry than in others. Surprisingly, we see similar ratios of discretionary inspections to total inspections in both high-violation industries (e.g., retail trade) and low-violation industries (e.g., healthcare).

Panel C provides descriptive statistics for our main sample. The average firm-state-year commits a violation 3.9% of the time. Nearly half (47%) of firm-state-years represent firms that committed a violation in at least one state in that year (i.e., $AnyVio\ l_{jit} = 1$). This is unsurprising, given that a single violation in a single state will set $AnyViol_{ijt}$ to 1 for all firm-states in which that firm operates. Sample firms have a median of four establishments in the states where they operate. Sample firms are also generally large, based on assets, and profitable, based on ROA.

TABLE 3

Response to Past Violations

Dependent variable: $ViolAny_{t+1}$ Model:	Linear (1)	Linear (2)	SPJ Logit (3)
$ViolAny_t$	−0.0579***	−0.0708***	−0.1982**
	[−7.44]	[−9.43]	[−2.35]
ln$Estabs_t$		0.0513***	0.2969***
		[8.81]	[2.86]
ln$Assets_t$		0.0568***	0.1593
		[7.86]	[1.50]
ROA		0.0426	0.5111
		[1.30]	[0.85]
Leverage		−0.0061	−0.0368
		[−0.21]	[−0.08]
MB		−0.0008	−0.0100
		[−1.15]	[−0.80]
Controls	No	Yes	Yes
Year FE	Yes	Yes	Yes
Firm by State FE	Yes	Yes	Yes
Adjusted/Pseudo R^2	0.3775	0.3842	0.0922
Obs.	25,594	25,594	9,274

This table provides OLS estimates of equation (3) using a firm-year panel from 2002 to 2016, where the dependent variable is *ViolAny*, an indicator for whether the firm violates an OSHA rule in any state in a given year. Columns 1 and 2 provide estimates from a linear probability model, whereas column 3 provides estimates from a logit model estimated using the split-panel jackknife technique. Column 1 includes year fixed effects and firm-by-state fixed effects. Column 2 adds additional controls. Column 3 reestimates the specification in column 2 using the split-panel jackknife technique with a logit (rather than linear) model. Control variables include the natural log of the number of establishments the firm has across all states, the natural log of assets of the firm, return on assets, leverage, and market to book. Robust standard errors are clustered by firm and corresponding *t*-statistics are presented in brackets. The markings ***, **, and * denote results significant at the 1%, 5%, and 10% levels.

5.2 BASELINE MODEL

We begin by estimating equation (3) on a firm-year panel. We present results from this test in table 3. The dependent variable in both cases is $ViolAny_{it+1}$, an indicator that equals 1 if firm i commits an OSHA rule violation in any state in year t+1. In column 1, we include only the independent variable of interest, $ViolAny_{it}$, whereas in column 2, we also include firm-level control variables. Columns 1 and 2 provide linear model estimates, whereas column 3 estimates an analog of column 2 using the split-panel jackknifed logit. We find, in all three cases, that committing an OSHA violation in any location in one year is negatively associated with committing an OSHA violation in any location in the next year. The estimate in column 2 suggests a 7.1 percentage point lower violation rate, or a 22.5% reduction in the likelihood of a violation relative to the percentage of firm-years with a violation in our sample (31.5%, untabulated). A lower firm-wide violation rate in the year following a detected violation is consistent with the prediction in our model and in H1, that OSHA sanctions serve to deter firms from committing future OSHA violations. This result is also consistent with prior work on the deterrence effect, which shows that the OSHA enforcement process reduces future violations by the same firm (Weil [1996], Levine, Toffel, and Johnson [2012]).

5.3 GEOGRAPHIC SHIFTS IN VIOLATION LOCATIONS

Although we observe a decrease in the firm-wide violation rate after a prior-year violation, this decrease need not be uniform across states in which the firm operates. Indeed, OSHA's decentralized structure provides economic reasons to expect a nonuniform effect in the context of prior literature on the costs and benefits of decentralization.[24]

Our analytical model predicts that the inability to perfectly transmit case-related information across state lines leads to within-OSHA information frictions. Thus, a violation in one state should result in a firm reducing the rate of future violations in the same state to a greater extent than in other states, because the expected cost of a future violation is higher in-state relative to out-of-state. Moreover, our model shows that the firm need not reduce subsequent out-of-state violations at all. Proposition B2 highlights that when within-OSHA information frictions are severe enough, the firm's shifting compliance effort may even result in *more* violations outside of the one where it has just been sanctioned. Our interviews with OSHA compliance officers suggest that the latter is a plausible outcome, giving rise to our stated directional prediction in H2.

We explicitly test H2 by estimating equation (4) in table 4. Column 1 includes our full set of fixed effects but no control variables, whereas column 2 introduces controls. In column 3, we reestimate equation (4) using a highly saturated fixed effect structure (firm-by-state, firm-by-year, and state-by-year) to ensure that firm-year or state-year effects are not driving our findings. Column 4 reestimates column 2 using the split-panel jackknifed logit model outlined in section 4.4. Finally, to be able to directly compare our jackknifed estimates to the linear model, in column 5, we reestimate the linear model on the split-panel jackknife sample. In all cases, we find that violations in a given state are associated with fewer violations in the same state in the next year. However, violations in out-of-state facilities are associated with more in-state violations the next year.[25] The latter result is consistent with shifting compliance effort and indicates that within-OSHA

[24] This literature argues that although decentralization empowers frontline employees who better understand localized needs (Baiman, Larcker, and Rajan [1995], Robinson and Stocken [2013]), it comes at the cost of potentially less effective communication across the organization (Melumad, Mookherjee, and Reichelstein [1992], Alonso, Dessein, and Matouschek [2008]). Moreover, even if more delegation occurs under better external information environments (Sani 2021), it may come at the cost of firms making less use of decision-relevant data (Labro, Lang, and Omartian 2023).

[25] As explained in section 4.4, the sample used in column 3 is much smaller than those used in columns 1 and 2. In untabulated analyses we verify that our linear probability model yields the same conclusions for this sample as for the full sample. The consistent inferences we obtain in this restricted sample help validate our fixed effects model (Breuer and deHaan [2023]).

TABLE 4
Geographic Shifts in Violating Behavior

Dependent Variable Model:	*ViolInState*$_{t+1}$ Linear (1)	 Linear (2)	 Linear (3)	 SPJ Logit (4)	 Linear (5)
ViolInState$_t$	−0.0536***	−0.0558***	−0.0460***	−0.2094***	−0.0857***
	[−12.00]	[−12.58]	[−9.11]	[−5.48]	[−11.82]
ViolOutOfState$_t$	0.0045***	0.0027***	0.0511***	0.1600***	0.0177**
	[5.96]	[3.63]	[7.08]	[3.09]	[2.02]
Controls:					
Controls	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	Yes	Yes
Firm by State FE	Yes	Yes	Yes	Yes	Yes
Firm by Year FE	No	No	Yes	No	No
State by Year FE	No	No	Yes	No	No
Adjusted/Pseudo R^2	0.1709	0.1723	0.1761	0.0548	0.0461
Obs.	432,307	430,015	427,819	25,870	25,870

This table provides OLS estimates of equation (4) using a firm-state-year panel from 2002 to 2016. *ViolInState* is an indicator for whether the firm violates an OSHA rule in a given state in a given year. *ViolOutOfState* is an indicator for whether the firm violates an OSHA rule in any other state in a given year. Columns 1, 2, and 3 use a linear probability model, whereas column 4 reestimates the specification in column 2 using the split-panel jackknife technique with a logit model. Finally, column 5 reestimates the linear model presented in column 2 on the subsample of observations used to estimate the split-panel jackknife model. For this column, we present model coefficients. Column 1 includes only year and firm-by-state fixed effects, whereas columns 2, 3, 4, and 5 include additional controls. Finally, column 3 includes both firm-by-year and state-by-year fixed effects. Coefficients are omitted for brevity, but control variables include the natural log of the number of establishments the firm has in the state, the natural log of assets of the firm, return on assets, leverage, and market to book. Robust standard errors are clustered by firm and corresponding t-statistics are presented in brackets. The markings ***, **, and * denote results significant at the 1%, 5%, and 10% levels.

information frictions dominate any potential learning effect. The results in columns 4 and 5 also highlight that our linear model estimates of the economic magnitude of shifting may, in fact, be underestimates. The coefficients in column 4 correspond to average partial effects of −0.048 on $ViolInState_{ijt}$ and 0.027 on $ViolOutOfState_{ijt}$. These figures are both larger than the corresponding coefficients in column 5.

The findings in column 2 imply that if the results are driven by something other than firms shifting compliance effort, it must be related to worker safety outcomes but unrelated to firm performance, capital structure, or valuation. Moreover, if firms shift compliance effort across establishments, rather than across states, some of that shifting compliance effort can occur within states, biasing against our findings. Our results are also robust to using firm by year and state by year fixed effects. This indicates that our findings are unlikely to reflect firmwide learning, firm-specific shocks to operational efficiency, or state-level enforcement shocks. For example, if a firm were to have a violation in one state and then have subsequent violations in other states, these average effects will be controlled for, as all firm-level shocks, by our firm by year fixed effects.

The coefficient on *ViolInState* in table 4 is substantially larger in magnitude than the coefficient on *ViolOutOfState*, a pattern that emerges throughout our analysis. This is an artifact of the panel structure we use, where a firm-state-year is associated with only a single prior in-state observation, but potentially many prior out-of-state observations. This is illustrated by the average firm-state-year in our sample having an in-state violation rate of 3.9%, but an out-of-state violation rate of 47.2%. We can use these figures to compute a back-of-the-envelope estimate of the elasticity of violating behavior across state lines: using the coefficients in column 2, on average an additional out-of-state violation increases the likelihood of an in-state violation by 6.9% (the coefficient 0.0027 on *ViolOutOfState* divided by the mean in-state violation rate of 0.039). This figure is substantially higher (69.2%) if we instead use the average partial effects corresponding to column 4, although we caveat that the latter elasticity estimate is derived from the set of firms likely to exhibit the highest elasticities of violating behavior in light of their overall compliance records.

5.4 DO FIRMS ENGAGE IN WITHIN-STATE GEOGRAPHIC SHIFTING OF COMPLIANCE EFFORT?

We conduct our primary analyses at the firm-state-year level for the reasons outlined in section 4.3. Although we believe this is the most appropriate empirical approach for our setting, one limitation of this design choice is that it inhibits our ability to study the extent to which firms shift compliance effort within a state rather than across state lines. In this section, we therefore outline two analyses that examine potential within-state compliance effort shifting. The first is conducted at the firm-state-year level, whereas the second is conducted at the establishment level.

Our first test, conducted at the firm-state-year level, uses $ViolOutOfState_{ijt+1}$ as the dependent variable in a modified version of equation (4). We interact $ViolInState_{ijt}$ with a new variable $SameStateEstabPct_{ijt}$, which is the percentage of firm i's establishments located in state j at time t (i.e., the number of establishments firm i has in state j at time t divided by the number of establishments firm i has across all states at time t). This variable captures how feasible it is for the firm to shift compliance efforts within a state, in the sense that a firm with more of its operations within a single state will find it easier and potentially more desirable to shift within rather than across state lines. If in-state compliance effort shifting is desirable we would expect firms with more opportunities to be less concerned with out-of-state compliance effort shifting, suggesting a negative coefficient on $ViolInState \times SameStateEstabPct$. However, we do not find that this is the case in table 5, column 1, suggesting that shifting compliance effort primarily occurs across state lines—where it is difficult for OSHA to follow the firm.

To further explore potential within-state shifts, we conduct a second test, now at the establishment level. We construct three indicators: $ViolEstab_{hijt}$, which captures violations in establishment h owned by firm i in state j at

TABLE 5
Within-State Compliance Effort Shifting

Dependent Variable	$ViolOutOfState_{i,j,t+1}$ (1)	$ViolSameState_{hij,t+1}$ (2)
$ViolInState_{ijt}$	0.0112***	
	[2.99]	
$ViolEstab_{hijt}$		−0.0672***
		[−14.55]
$ViolOutOfState_{ijt}$	−0.0781***	0.0078*
	[−7.96]	[1.87]
$ViolInState_{ijt} \times SameStateEstabPct_{i,j,t+1}$	0.0091	
	[0.46]	
$SameStateEstabPct_{i,j,t+1}$	−0.2052***	
	[−7.75]	
Controls:		
Controls	Yes	Yes
Year FE	Yes	Yes
Firm by State FE	Yes	Yes
Adjusted R^2	0.4386	0.3213
Obs.	430,015	6,315,010

This table presents OLS estimates of the extent to which future out-of-state violations vary with the extent of a firm's in-state presence. In column 1 the sample is a firm-state-year panel from 2002 to 2016, whereas column 2 uses an establishment-level panel. $ViolInState_{ijt}$ is an indicator for whether firm i violates an OSHA rule in state j in year t. $ViolOutOfState_{ijt}$ is an indicator for whether firm i violates an OSHA rule in any state other than j in year t. $SameStateEstabPct_{ijt}$ represents the proportion of firm i's establishments located within state j. In column 2, the sample is all establishments such that no *other* establishment owned by the firm has an OSHA violation in the same state-year (i.e., for each establishment h owned by firm i in state j in year t, such that either firm i has no violations at all in state j in year t, or such that firm i has a violation in establishment h—but no other establishment—in state j in year t). $ViolEstab_{hijt}$ is an indicator for whether firm i violates an OSHA rule at its establishment h in state j in year t, whereas $ViolSameState_{hijt}$ is an indicator for whether firm i violates an OSHA rule in state j in year t at some establishment other than h. Coefficients are omitted for brevity, but control variables include the natural log of the number of establishments the firm has in the state, the natural log of assets of the firm, return on assets, leverage, and market to book. Robust standard errors are clustered by firm and corresponding t-statistics are presented in brackets. The markings ***, **, and * denote results significant at the 1%, 5%, and 10% levels.

time t; $ViolSameState_{hijt}$, which captures violations in establishments other than h but owned by firm i in state j at time t; and $ViolOutOfState_{ijt}$ which captures violations by firm i in states other than j at year t. To isolate potential within-state shifts, we consider firm-state-years where $ViolSameState_{hijt} = 0$ and estimate same-state violations in the next year, $ViolSameState_{hijt+1}$, as a function of $ViolEstab_{hijt}$ and $ViolOutOfState_{ijt}$. We present results from this test in table 5, column 2. The negative coefficient on $ViolEstab_{hijt}$ suggests that firms do not shift violating behavior within states.

6. *How Do Within-OSHA Information Frictions Affect Violation Locations?*

Information frictions within OSHA may inhibit inspectors' ability to assess fines through one of two channels: (i) less efficient selection of target firms to inspect and (ii) an inability to hold firms accountable for habitual violations by assessing appropriate penalties. In this section, we investigate these two channels. Because a violation requires a preceding inspection and because deterrence should be tightly related to the punishments that can be assessed, these are likely the first-order mechanisms underlying observed shifts in the locations of violations within a firm.

6.1 INSPECTIONS

If information frictions affect local OSHA inspectors' abilities to respond to violations outside their jurisdiction, then we should see patterns arise on the extensive margin of inspector behavior—inspections. To assess this possibility, we model the degree to which inspections in a state follow from prior violations inside and outside of that state. We alter equation (4) by replacing the dependent variable with $AnyInspectionInState_{ijt+1}$, a dummy variable that equals one if there is an inspection conducted of firm i in state j in year t+1, and then including dummy variables for whether or not there was a violation in the state or in another state. We also control for prior-year "clean" inspections, that is, indicators $CleanInspInState_t$ and $CleanInspOutOfState_t$, that equal one if a firm faced year t inspections but no violations in-state and out-of-state, respectively.

Most inspections are not undertaken at the discretion of state-level OSHA offices. Instead, they are more often taken in direct response to trigger events (e.g., confidential tips or workplace injuries) or are determined by a formula set at the federal level.[26] Individual OSHA offices have little say in whether to conduct these inspections, with reactive inspections occurring only after something has gone wrong. To understand how information frictions affect inspection behavior, it is therefore important to understand patterns in more discretionary, proactive inspections. Discretionary inspections rely on ad hoc decisions made at the state OSHA level and, according to OSHA compliance officers we spoke with, depend on available resources, availability of supporting case information, and information gathering that is separate from obligatory inspection triggers such as confidential tips and workplace injuries.

Our results in table 6 underscore the importance of separately identifying and studying discretionary inspections. In columns 1 and 2, we consider all inspections and find that inspections are lower (higher) in year t+1 subsequent to in-state (out-of-state) violations in year t. Unsurprisingly, we also find a negative and significant relation between in-state clean inspections in year t and the likelihood of inspection in t+1. Given OSHA's limited resources, we would expect a firm that has been inspected and found to be compliant with workplace safety laws to be less likely to immediately face

[26] OSHA highlights a list of industries to focus on each year, and the source documents underlying these lists suggest that prior-year violations likely play a role in determining this set of industries, but beyond this we are not able to fully reverse-engineer the determinants of OSHA inspections.

TABLE 6

OSHA Inspections

	AnyInspectionInState$_{t+1}$			*ReactiveInState*$_{t+1}$		*PlannedInState*$_{t+1}$		*DiscInState*$_{t+1}$	
Dependent Variable Model	Linear (1)	Linear (2)	SPJ Logit (3)	Linear (4)	Linear (5)	Linear (6)	Linear (7)	Linear (8)	Linear (9)
ViolInState$_t$	−0.0249***	−0.0284***	−0.0985**	−0.0248***	−0.0267***	−0.0176***	−0.0188***	0.0175***	0.0171***
	[−5.19]	[−6.07]	[−2.36]	[−7.39]	[−8.04]	[−5.02]	[−5.41]	[9.80]	[9.69]
ViolOutOfState$_t$	0.0072***	0.0040***	0.1434**	0.0048***	0.0032***	0.0021***	0.0010*	0.0002	-0.0003
	[6.96]	[3.98]	[2.46]	[6.36]	[4.47]	[3.71]	[1.66]	[0.69]	[−0.74]
CleanInState$_t$	−0.0563***	−0.0591***	−0.2695***	−0.0350***	−0.0363***	−0.0173***	−0.0183***	−0.0040**	−0.0045**
	[−12.30]	[−13.13]	[−5.08]	[−10.07]	[−10.50]	[−6.05]	[−6.44]	[−2.14]	[−2.39]
CleanOutOfState$_t$	−0.0005	−0.0020*	−0.0356	0.0001	−0.0008	0.0003	−0.0002	−0.0008**	−0.0010***
	[−0.41]	[−1.88]	[−0.49]	[0.07]	[−0.97]	[0.44]	[−0.27]	[−2.07]	[−2.62]
Controls:									
Controls	No	Yes	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm by State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted/Pseudo R^2	0.2281	0.2301	0.0641	0.1369	0.1375	0.1317	0.1324	0.0459	0.0459
Obs.	432,307	430,015	42,473	432,307	430,015	432,307	430,015	432,307	430,015

This table provides estimates of equation (4) but replacing the dependent variable to reflect inspections rather than violations, using a firm-state-year panel from 2002 to 2016. See appendix C for the classification of discretionary and nondiscretionary inspections. *ViolInState*$_{ijt}$ is an indicator for whether firm i violates an OSHA rule in state j in year t. *ViolOutOfState*$_{ijt}$ is an indicator for whether firm i violates an OSHA rule in any state other than j in year t. *CleanInState*$_{ijt}$ is an indicator variable for whether firm i was inspected and had no violation in state j in year t. *CleanOutOfState*$_{ijt}$ is an indicator for whether firm i was inspected and had no violation in any state other than j in year t. In columns 1–3, the dependent variable is *AnyInspectionInState*$_{ijt}$, an indicator for whether OSHA conducts an inspection of firm i in state j in year t. In columns 4 and 5, the dependent variable is *ReactiveInState*$_{ijt}$, an indicator for whether OSHA conducts a reactive inspection (i.e., in response to a trigger event) but no centrally planned or discretionary inspections of firm i in state j in year t. In columns 6 and 7, the dependent variable is *PlannedInState*$_{ijt}$, an indicator for whether there was at least one "planned" inspection (i.e., proactively requested by OSHA headquarters) of firm i in state j in year t but no inspections undertaken at the discretion of the state office. Finally, in columns 8 and 9, the dependent variable is *DiscInState*$_{ijt}$, an indicator for whether OSHA conducts a discretionary inspection of firm i (i.e., an inspection undertaken at the discretion of a state-level OSHA field office) in state j in year t. Columns 1, 4, 6, and 8 include year fixed effects and firm-by-state fixed effects, whereas columns 2, 3, 5, 7, and 9 include additional controls. Coefficients are omitted for brevity, but control variables include the natural log of the number of establishments the firm has in the state, the natural log of the firm's assets, return on assets, leverage, and market to book. Column 3 uses a split-panel jackknifed logit to estimate the model; all other columns use a linear probability model. For column 3, we present model coefficients. Robust standard errors are clustered by firm and corresponding t-statistics are presented in brackets. The markings ***, **, and * denote results significant at the 1%, 5%, and 10% levels.

reinvestigation. In addition, although we do not directly use lagged dependent variables in this specification, given that $AnyInspection_{ijt}$ represents the sum of $ViolInState_{ijt}$ and $CleanInspInState_{ijt}$, we rerun the analysis in column 2 using the split-panel jackknifed logit in column 3 to examine the robustness of our findings. These results, which are consistent with columns 1 and 2, are tabulated in column 3.

In columns 4–9, we replace the dependent variable with indicator variables based on the presence of three types of inspections. These indicator variables are $ReactiveInState_{ijt+1}$, which equals 1 for firm-state-years that only face reactive inspections; $PlannedInState_{ijt+1}$, which equals 1 for firm-state-years with at least one inspection determined by OSHA headquarters but no inspections undertaken at the state office's discretion; and $DiscInState_{ijt+1}$, which equals 1 for firm-state-years with at least one discretionary inspection. Notably, reactive inspections are by construction only undertaken in response to whistleblower tips, accidents, or injuries.

When separating inspections in this manner, we continue to find a relation between out-of-state violations in year t and reactive inspections in year t+1 in columns 4 and 5. This result is consistent with a mechanical, reactive OSHA response to shifts in violating behavior. However, we find weaker evidence in columns 6 and 7 of a relation between out-of-state violations in year t and planned inspections in year t+1, and no relation between out-of-state violations in year t and discretionary inspections in year t+1 in columns 8 and 9. The latter result is consistent with OSHA compliance officers facing informational hurdles in applying their knowledge of past violations when those past violations occur outside the state.

The results in columns 4–9 also mitigate the possibility that our findings pertaining to violations reflect OSHA responding to the same underlying firm-level behavior at different times in different states. If the shifts were due to state office-driven inspection delay, we would expect to see an increase in nonreactive inspections following an out-of-state violation. That we primarily observe a shift in reactive inspections—those taken in response to trigger events—suggests that our results are driven by actual changes in firm behavior subsequent to violations.

It is plausible that our results on inspections are driven by information spillovers across workers. Although Johnson [2020] finds that media coverage of OSHA violations is primarily local, it could still be the case that a firm's employee in one state learns of a violation by the firm in another state, raising her awareness of related workplace safety issues in her own place of work. This, in turn, may increase the likelihood that the employee reports these issues to OSHA, triggering a whistleblower-induced inspection. Of course, a whistleblowing complaint may also arise because of actual operational changes that arise from geographic shifts in violating behavior. Nonetheless, to test the argument above, in untabulated analyses, we separately investigate whistleblower-induced and accident- or injury-driven inspections. Across both types of reactive inspections, we find similar results to those in table 6, columns 4 and 5. As such, although we cannot rule

TABLE 7
Repeat and Willful Violations

Dependent Variable: $RWInState_{i,j,t+1}$	(1)	(2)
$ViolInState_t$	0.0035***	0.0034***
	[3.52]	[3.39]
$ViolOutOfState_t$	0.0002	0.0001
	[1.29]	[0.76]
Controls:		
Controls	No	Yes
Year FE	Yes	Yes
Firm by State FE	Yes	Yes
Adjusted R^2	0.0524	0.0521
Obs.	432,307	430,015

This table provides OLS estimates of equation (4) but replacing the dependent variable and adding additional interaction terms, using a firm-state-year panel from 2002 to 2016. The dependent variable, *RWInState*, is an indicator for whether OSHA assesses a Repeat or Willful violation for the firm in a given state in a given year. *ViolInState* is an indicator for whether the firm violates an OSHA rule in a given state in a given year. *ViolOutOfState* is an indicator for whether the firm violates an OSHA rule in any other state in a given year. *StatePlan* is an indicator for whether the state administers its own State Plan OSHA. Column 1 includes year fixed effects and firm-by-state fixed effects. Column 2 includes additional controls. Coefficients are omitted for brevity, but control variables include the natural log of the number of establishments the firm has in the state, the natural log of assets of the firm, return on assets, leverage, and market to book. Robust standard errors are clustered by firm and corresponding t-statistics are presented in brackets. The markings ***, **, and * denote results significant at the 1%, 5%, and 10% levels.

out the possibility that employee learning induces some nondiscretionary inspections, it does not appear to be the driver of our results on nondiscretionary inspections.

6.2 REPEAT AND WILLFUL VIOLATIONS

Typical penalties for OSHA violations are on the order of tens of thousands of dollars. Although this is significant for smaller firms, such penalties would have less of an effect among the publicly traded firms we study. However, penalties associated with *Repeat* and *Willful* violations are 10-fold in size, as mandated by federal statute (29 CFR 1903.15). These penalties are also publicized by OSHA via press releases, leading to additional reputation costs (Johnson [2020]).

Internal information sharing plays an important role in OSHA's ability to detect and assess Repeat and Willful violations. Case notes and knowledge of past inspections at other plants are often necessary to substantiate the decision to label a violation as Repeat or Willful. If, as the OSHA compliance officers we spoke with assert, information frictions lead to difficulties in obtaining said documentation, then one should expect that local OSHA inspectors have less supporting information to pursue severe penalties for Repeat and Willful violations. In turn, it may be cheaper for a firm to shift workplace safety resources rather than risk another violation in the same state. This prediction represents a firm-level analog of crime displacement and patterns in individuals' misconduct decisions (Iyengar [2008]).

In columns 1 and 2 of table 7, we investigate whether information frictions play a role in assessing these severe penalties. We estimate a modified version of equation (4) that replaces the dependent variable with $RWinState_{ijt}$, an indicator that equals one if firm i has a Repeat or Willful (RW) violation in state j in year t. We find that a violation in a given state leads to an increase in the likelihood that an RW violation is assessed in the same state the next year. This result is consistent with a lack of information frictions making it easier to assess severe fines, as OSHA compliance officers have unfettered access to case materials from their own files and from files of other officers in the same state. Given our findings in table 4, our results also indicate an increase in the rate of RW violations specifically rather than violations more broadly.

In contrast to the result above, we do not find a link between year t general violations and year t+1 RW violations across state lines (where information frictions play a role). In conjunction with our results in table 4, this result indicates that although the overall rate of violations increases following an out-of-state violation, the RW violation rate—conditional on a violation occurring—goes down. We interpret this finding as indicative that violations that should be flagged by OSHA branches in other states as Repeat or Willful are not being assessed as such, due to information frictions. In sum, our findings in tables 6 and 7 suggest that OSHA's internal information frictions reduce the efficacy of inspections and the assessing of penalties.

6.3 STATE PLANS

OSHA offices in 21 states employ State Plans, which follow similar standards to federal OSHA offices but exert more discretion in certain areas. As noted in section 2, this discretion may lead to less information sharing between State Plan states and other states. To further rule out within-firm frictions as a driver of our results, we explore shifts into State Plan versus non–State Plan states. Ceteris paribus, there is no reason within-firm information frictions should vary according to whether a given state uses an OSHA state plan. Analyzing where information frictions may be highest also provides a more formal test of H3. In table 7, we estimate an augmented version of equation (4) that incorporates interactions of both $ViolInState$ and $ViolOutState$ with $StatePlan$, an indicator that equals one for firm-states overseen by a State Plan (SP). We find stronger geographic shifts into SP states, consistent with greater information frictions.

To understand the mechanism underlying the results in table 8, we examine inspection patterns in State Plan states. State Plan offices have greater discretion in selecting inspection targets, which they may use to make more efficient decisions. To test this possibility, in table 9 we interact *StatePlan* with our violation and inspection variables. In columns 1–4, we find mixed evidence of differences between State Plan and non–State Plan states for inspections outside of states' discretion (Reactive and Planned). However, we find no evidence in columns 5 and 6 that State Plan states undertake more efficient discretionary inspections, suggesting that the results in table 8 are not driven by intentional differences in inspection patterns.

TABLE 8

Geographic substitution into State Plan states

Dependent variable: $ViolInState_{t+1}$	(1)	(2)
$ViolInState_t$	-0.0607***	-0.0630***
	[−10.86]	[−11.27]
$ViolOutOfState_t$	0.0028***	0.0009
	[3.43]	[1.14]
$ViolInState_t \times StatePlan$	0.0135**	0.0138**
	[2.06]	[2.09]
$ViolOutOfState_t \times StatePlan$	0.0040***	0.0042***
	[2.71]	[2.84]
Controls:		
Controls	No	Yes
Year FE	Yes	Yes
Firm by State FE	Yes	Yes
Adjusted R^2	0.1710	0.1724
Obs.	432,307	430,015

This table provides OLS estimates of equation (4) adding in additional interaction terms and using a firm-state-year panel from 2002 to 2016. *ViolInState* is an indicator for whether the firm violates an OSHA rule in a given state in a given year. *ViolOutOfState* is an indicator for whether the firm violates an OSHA rule in any other state in a given year. *StatePlan* is an indicator for whether the state administers its own State Plan OSHA. Additional interactions are included between *StatePlan* and each of *ViolInState* and *ViolOutOfState*. Column 1 includes year fixed effects and firm-by-state fixed effects, whereas column 2 includes additional controls. Coefficients are omitted for brevity, but control variables include the natural log of the number of establishments the firm has in the state, the natural log of assets of the firm, return on assets, leverage, and market to book. Robust standard errors are clustered by firm and corresponding *t*-statistics are presented in brackets. The markings ***, **, and * denote results significant at the 1%, 5%, and 10% levels.

7. *What Drives Geographic Shifts in Violating Behavior?*

Our final set of tests explores strategic factors, related to firms' decisions to engage in misconduct, that may affect how firms respond to information frictions within OSHA. We examine factors relevant to OSHA monitoring, financial incentives, and corporate culture, roughly corresponding to the three sides of the fraud triangle (Wilks and Zimbelman [2004]).

Our first test examines firms' responses to shifts in regulatory scrutiny. Heightened OSHA scrutiny and penalties within one state may shift a firm's perceived opportunities for cost cutting within that state, thereby increasing the incentive to shift compliance efforts across states. To assess the role of such pressures, we consider out-of-state Repeat or Willful violations. A firm receiving a Repeat or Willful violation may face increased monitoring, as well as the likelihood that further violations in the same state will also be classified as Repeat or Willful. However, if there are information frictions within OSHA, heightened monitoring and penalties should not follow a firm across states, as shown in table 7. Consistent with this idea, when we include both $ViolOutOfState_{ijt}$ and $RWOutOfState_{ijt}$ in a modified version of equation (4), we find a stronger effect in column 1 of table 10 when an out-of-state violation in year t is classified as Repeat or Willful.[27]

[27] Sample sizes vary across table 10 due to differences in data availability.

TABLE 9
State Plan Discretion in Inspections

	$ReactiveInState_{t+1}$		$PlannedInState_{t+1}$		$DiscInState_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$ViolInState_t$	−0.0266***	−0.0287***	−0.0218***	−0.0231***	0.0173***	0.0170***
	[−5.69]	[−6.18]	[−4.64]	[−4.89]	[6.04]	[5.99]
$ViolOutOfState_t$	0.0045***	0.0029***	0.0013**	0.0001	−0.0002	−0.0006*
	[5.23]	[3.42]	[2.03]	[0.20]	[−0.46]	[−1.85]
$CleanInspInState_t$	−0.0400***	−0.0414***	−0.0231***	−0.0241***	−0.0032	−0.0035
	[−8.17]	[−8.49]	[−5.80]	[−6.08]	[−1.19]	[−1.33]
$CleanInspOutOfState_t$	0.0004	−0.0004	0.0002	−0.0002	−0.0008**	−0.0011**
	[0.45]	[−0.38]	[0.32]	[−0.29]	[−1.96]	[−2.52]
$ViolInState_t \times StatePlan$	0.0034	0.0040	0.0083	0.0082	0.0004	0.0001
	[0.61]	[0.70]	[1.47]	[1.46]	[0.10]	[0.04]
$ViolOutOfState_t \times StatePlan$	0.0008	0.0010	0.0021*	0.0021*	0.0009	0.0010
	[0.56]	[0.65]	[1.74]	[1.68]	[1.41]	[1.42]
$CleanInspInState_t \times StatePlan$	0.0096	0.0099	0.0112**	0.0112**	−0.0017	−0.0019
	[1.46]	[1.51]	[2.01]	[2.00]	[−0.45]	[−0.53]
$CleanInspOutOfState_t \times StatePlan$	−0.0009	−0.0011	0.0002	0.0001	0.0000	0.0001
	[−0.55]	[−0.66]	[0.14]	[0.05]	[0.05]	[0.11]
Controls:						
Controls	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm by State FE	Yes	Yes	Yes	Yes	Yes	Yes

(*Continued*)

TABLE 9—*(Continued)*

	ReactiveInState$_{t+1}$		*PlannedInState*$_{t+1}$		*DiscInState*$_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Adjusted R^2	0.1369	0.1375	0.1318	0.1325	0.0459	0.0459
Obs.	432,307	430,015	432,307	430,015	432,307	430,015

This table provides OLS estimates of equation (4) but replacing the dependent variable and adding further interaction terms, using a firm-state-year panel from 2002 to 2016. *ViolInState* is an indicator for whether the firm violates an OSHA rule within a given state in a given year. *ViolOutOfState* is an indicator for whether the firm violates an OSHA rule in any other state in a given year. *StatePlan* is an indicator for whether the state administers its own State Plan OSHA. *CleanInspInState* is an indicator variable for whether the firm was inspected and had no violation in a given state in a given year. *CleanInspOutOfState* is an indicator for whether the firm was inspected and had no violation in any other state in a given year. In columns 1 and 2, the dependent variable is *ReactiveInState*, an indicator for whether OSHA conducts a reactive inspection but no centrally planned or discretionary inspections of the firm in a given state in a given year. In columns 3 and 4, the dependent variable is *PlannedInState*, an indicator for whether there was at least one "planned" inspection of the firm in a given state in a given year but no inspections undertaken at the discretion of the state office. In columns 5 and 6, the dependent variable is *DiscInState*, an indicator for whether OSHA conducts a discretionary inspection of the firm in a given state in a given year. Additional interactions are included between *StatePlan* and each of *ViolInState*, *ViolOutOfState*, *CleanInState*, and *CleanOutOfState*. Columns 1, 3, and 5 include year fixed effects and firm-by-state fixed effects, whereas columns 2, 4, and 6 include additional controls. Coefficients are omitted for brevity, but control variables include the natural log of the number of establishments the firm has in the state, the natural log of assets of the firm, return on assets, leverage, and market to book. Robust standard errors are clustered by firm and corresponding t-statistics are presented in brackets. The markings ***, **, and * denote results significant at the 1%, 5%, and 10% levels.

TABLE 10
When Is Compliance Effort Shifting Greater?

Dependent variable: $ViolInState_{t+1}$	(1)	(2)	(3)
$ViolInState_t$	-0.0559***	-0.0531***	-0.0471***
	[−12.64]	[−11.42]	[−10.36]
$ViolOutOfState_t$	0.0024***	0.0026***	0.0010
	[3.23]	[3.21]	[1.00]
$RWOutOfState_t$	0.0066**		
	[2.26]		
$ViolOutOfState_t \times MeetOrBeat_{t+1}$		0.0037*	
		[1.73]	
$MeetOrBeat_{t+1}$		−0.0012	
		[−1.09]	
$ViolOutOfState_t \times WeakCompliance_{t+1}$			0.0043***
			[2.72]
$WeakCompliance_{t+1}$			0.0000
			[0.05]
Controls:			
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm by State FE	Yes	Yes	Yes
Adjusted R^2	0.1724	0.1712	0.1749
Obs.	430,015	389,000	356,879

This table provides OLS estimates of equation (4) with additional interaction terms, using a firm-state-year panel from 2002 to 2016. All specifications tabulated reflect extensions of column 2 of table 4. *ViolInState* is an indicator for whether the firm violates an OSHA rule in a given state in a given year. *ViolOutOfState* is an indicator for whether the firm violates an OSHA rule in any other state in a given year. In this panel, we consider the role of incentives using three measures. The first, *RWOutOfState*, is an indicator for whether OSHA assesses a Repeat or Willful violation for the firm in any other state in a given year. The second, *MeetOrBeat* is an indicator for whether the firm just meet or beat analyst consensus earnings per share by zero or one cents per share. The third, *WeakCompliance*, is an indicator for whether the firm has had non–OSHA-related fines in the past three years. In all columns, we interact these proxies with *ViolOutOfState*. All columns include year fixed effects, firm-by-state fixed effects, and additional controls. Coefficients are omitted for brevity, but control variables include the natural log of the number of establishments the firm has in the state, the natural log of assets of the firm, return on assets, leverage, and market to book. Robust standard errors are clustered by firm and corresponding t-statistics are presented in brackets. The markings ***, **, and * denote results significant at the 1%, 5%, and 10% levels.

Our next test focuses on firms' financial incentives. Prior literature finds that poor labor practices can arise in response to financial pressures (Cohn and Wardlaw [2016], Raghunandan [2021]). We examine one clear and periodic incentive that firms face: meeting short-term earnings benchmarks. Prior work finds that firms that just meet or beat earnings benchmarks see more workplace injuries (Caskey and Ozel [2017]) and wage theft (Raghunandan [2021]). Building on these studies, we test whether firms in meet-or-beat years see greater shifts in violating behavior. We construct an indicator, $MeetorBeat_{it}$, that equals one if firm i just meets or beats the analyst consensus forecast, which we interact with $ViolOutOfState_{ijt}$. Our results in column 2 of table 10 suggest that firms with meet-or-beat incentives are more likely to shift violating behavior, consistent with the notion that safety may suffer in the face of short-term financial incentives.

We next turn to firms' abilities to rationalize shifting compliance effort, in lieu of taking remedial actions. To do so, we construct a measure of firms' compliance culture, as firms with a greater tendency to break rules may be more likely to shift violating behavior rather than improving workplace safety across the organization. To measure compliance culture, we follow Kedia, Luo, and Rajgopal [2019] to measure culture, creating an indicator $WeakCompliance$ that equals one if the firm faced federal penalties for non-OSHA violations in the prior three years. We obtain penalty data from Violation Tracker, a data set on corporate misconduct assessed by more than 50 federal agencies published by the nonprofit entity Good Jobs First. The most common types of violations are environmental violations (assessed by the Environmental Protection Agency), wage-related violations (assessed by the Wage and Hour Division), and antitrust and consumer protection violations (assessed by the Department of Justice). In column 3 of table 10, we observe a positive and significant coefficient on the interaction between $WeakCompliance$ and $ViolOutOfState$, suggesting shifts in violating behavior are indeed more prevalent in firms with a weaker compliance culture. These findings complement recent work showing that better internal information environments can assist positive culture in promoting workplace safety (e.g., Heese and Pérez-Cavazos [2020], Hope et al. [2022]).

8. *Conclusion*

We study whether information frictions within the OSHA affect firm violations of workplace safety laws. We find that firms caught violating in one state subsequently violate less in that state, instead shifting compliance effort elsewhere. These geographic shifts cannot be explained by differential enforcement rates across states and are more pronounced in states with greater regulatory information frictions, indicating that shifts are not driven by information frictions within firms. We also investigate how information frictions affect OSHA inspection behavior and the potential deterrence effects of severe penalties. We find that out-of-state violations impact reactive investigations (those based on whistleblowers or injuries), but not centrally planned inspections or those taken at the discretion of local offices. Additionally, violations in one state lead to an increase in severe (Repeat or Willful) penalties in the same state, but the severe penalty rate decreases for firms previously violating in a different state. This result is consistent with frictions limiting the sharing of documentation required by statute to assess these penalties.

Collectively, our findings show that information frictions within a decentralized regulator have a measurable impact on misconduct. These frictions may reduce positive externalities derived from increased enforcement actions across jurisdictions. Our findings thus highlight a cost that decentralized organizations face. OSHA imposes a federal standard for workplace safety, but it delegates authority in implementing that standard to state offices. If OSHA were to address information frictions, it would likely need to better align objectives for individual OSHA offices with the entire organization (Nagar [2002]), increasing the incentive to share information across states. Our results also suggest the need for decentralized organizations to invest in internal information systems and to ensure that there are incentives for employees to fully use these information systems, as both the formal and informal the limitations of the internal OIS repeatedly arose in conversations with compliance officers. We caution that the costs of such an investment must be weighed, as prior research shows that better local disclosure can also improve enforcement efficiency (Johnson [2020]). Overall, our study suggests a need for future research into other institutional factors to obtain a fuller picture of enforcement efficiency in regulators.

APPENDIX A: STATE PLAN ADOPTION YEARS

The table below presents a list of states in which workplace safety laws are enforced through state plans, as well as the years that these state plans went into effect. We obtain this information from OSHA's website directly (https://www.osha.gov/stateplans).

State	Year State Plan Adopted	State	Year State Plan Adopted
Alaska	1977	New Mexico	1984
Arizona	1981	North Carolina	1976
California	1977	Oregon	1982
Hawaii	1978	South Carolina	1976
Indiana	1981	Tennessee	1978
Iowa	1976	Utah	1976
Kentucky	1980	Vermont	1977
Maryland	1980	Virginia	1984
Michigan	1981	Washington	1982
Minnesota	1976	Wyoming	1980
Nevada	1981		

APPENDIX B: MODEL IN DETAIL

MODEL SETUP

FIRM'S PROBLEM

A single representative firm operates divisions in two different states $j \in \{1, 2\}$. For each division j, the gross profit π_j before potential costs associated with regulatory enforcement actions is given by $\pi_j = R_j - c$, where R denotes revenues and c reflects production costs. In each period, production costs can be high ($\tilde{c} = c_H$) or low ($\tilde{c} = c_L$). With probability p the firm's production costs are naturally low. The firm's costs are the same in both locations, that is, the realization of $\tilde{c}$ is common across the firm. "High" and "low" costs could reflect whether the firm's prior investments into improving efficiency or automation succeeded, for example. In the absence of any cost-cutting efforts, the firm's profits are therefore given by $\pi = R_1 + R_2 - 2\tilde{c}$.

We assume that if the firm observes low costs, it takes no cost-cutting actions—cost-cutting efforts increase the likelihood of a violation—with respect to workplace safety. If the firm's production costs are high, however, it can take actions m_1 and m_2 to lower its production costs for each market.

The firm chooses a level of cost-cutting effort, m_j, in states $j \in \{1, 2\}$. Because we use a binary cost structure for ease of interpretation, m_j enters our model as the probability that cost-cutting efforts succeed, allowing the firm to enjoy low costs in location j. Cost-cutting efforts may not be successful because, for example, reducing workplace safety training hours may also reduce worker productivity, which would then require additional worker hours to complete a task. Without loss of generality, we normalize the benefits of successful cost-cutting efforts in one location to 1 (i.e., $c_H - c_L$). However, these efforts are costly along two dimensions: (i) nonpecuniary costs that are incurred regardless of whether OSHA detects the firm's actions and (ii) potential regulatory costs.

Nonpecuniary costs of the firm's two divisions choosing cost-cutting effort levels m_1 and m_2 are given by $[\frac{1-\theta}{2}m_1^2 + \frac{1-\theta}{2}m_2^2 + \frac{\theta}{2}(m_1 + m_2)^2]$. The constants $\frac{1-\theta}{2}$ and $\frac{\theta}{2}$ for $\theta \in (0, 1)$ reflect a normalization for the sake of parsimony. These costs, which are incurred irrespective of whether the firm's cost-cutting efforts are successful, reflect market-specific components, $\frac{1-\theta}{2}m_1^2$ and $\frac{1-\theta}{2}m_2^2$, and a firm-level component $\frac{\theta}{2}(m_1 + m_2)^2$. Firm-level concerns include litigation risk or reputational damage that may arise due to systematically poor employee treatment.

We also model regulatory costs as a fine F if OSHA catches a successful cost-cutting effort. We let $\widehat{b_j}$ be the firm's belief about the probability that OSHA detects the firm's illegal actions in market j. We explicitly characterize this quantity in appendix B.1.2, below. In summary, the firm's net utility from cost-cutting is given by

$$U\ (m_1, m_2 | c = c_H\ ) = R_1\ + R_2 - 2c_H + m_1\left(1 - \widehat{b_1} \cdot F\right) + m_2\left(1 - \widehat{b_2} \cdot F\right) - \left[\frac{1-\theta}{2}m_1^2 + \frac{1-\theta}{2}m_2^2 + \frac{\theta}{2}(m_1 + m_2)^2\right]. \quad \text{(1, repeated)}$$

The structure of equation (1) closely follows that in Schantl and Wagenhofer [2020].

When the firm sees $c = c_L$, it does not cut costs. If instead the firm sees $c = c_H$, it chooses cost-cutting effort levels in each of the two markets. The first-order conditions for equation (1) with respect to these effort levels m_1 and m_2 are

$$m_1 = (1 - b_1 \cdot F)\ - \theta m_2, \tag{B1}$$

$$m_2 = (1 - b_2 \cdot F)\ - \theta m_1. \tag{B2}$$

Rearranging yields the following optimal levels of cost-cutting efforts:

$$m_1 = \frac{1}{1+\theta} - \frac{F \cdot \left(\widehat{b_1} - \theta \widehat{b_2}\right)}{1-\theta^2}, \tag{B3}$$

$$m_2 = \frac{1}{1+\theta} - \frac{F \cdot \left(\widehat{b_2} - \theta \widehat{b_1}\right)}{1-\theta^2}. \tag{B4}$$

From (B3) and (B4), we see that optimal cost-cutting in each region is *decreasing* in the conjectured probability of inspection in that region but *increasing* in the conjectured probability of inspection in the other region.

OSHA

Two OSHA branches ("OSHA_1" and "OSHA_2") seek to detect misconduct as a result of cost-cutting when it occurs in states 1 and 2, respectively, but detecting misconduct is costly. Achieving success with probability b requires that an OSHA office expend effort $\frac{kb^2}{2}$, where k is a constant. Both OSHA branches can infer whether a plant had low or high production costs based on its reported output. An OSHA branch will therefore only consider investigating when it observes low costs for the firm because the firm's cost-cutting can only lower its costs. Each OSHA branch can infer the firm's costs (c_L or c_H) for its location, but not the other.[28] Without investigation, an OSHA branch does not know whether the firm's cost structure is inherently low or whether the firm has engaged in potentially risky cost-cutting efforts.

Let r_j denote the firm's observable signal of production costs in region j. If the firm does not engage in cost-cutting efforts and has naturally high costs, then $r_j = r_H$. Conversely, if the firm either naturally has low costs or has inherently high costs but engages in cost-cutting efforts, then $r_j = r_L$. Because the firm has no incentive to increase its costs, when $r_j = r_H$ OSHA in region j knows that the firm has not taken any potentially risky actions and thus does not investigate. An investigation only occurs when low costs are reported.

In addition to observing the firm's reported costs for the division in its jurisdiction, OSHA in each region observes a noisy signal $\widetilde{y_j}$ of the true costs (i.e., the costs before the firm engages in any cost-cutting efforts), following Schantl and Wagenhofer [2020]. This signal is given by

$$\widetilde{y_j} = \tilde{c} + \tilde{I}_j, \tag{2, repeated}$$

where $\tilde{I}_1$ and $\tilde{I}_2$ are independent noise terms. The variance of $\tilde{I}$ depends on previous-year outcomes. Without loss of generality, we assume that in the previous year the firm had a chance to engage in cost-cutting with respect to workplace safety in only region 1. If the firm did not cut costs, or if the

[28] Although this strict assumption is useful for tractability of the model, it does not alter our main conclusions.

firm did and was not caught by OSHA_1, then neither OSHA_1 nor OSHA_2 learns any information and the variances of $\tilde{I}_1$ and $\tilde{I}_2$ are both given by $u^2 + \alpha^2$ for nonzero u and α.

If OSHA_1 detects a violation, it gains knowledge of the firm's operational processes through its inspections and remediation efforts with the firm, increasing the precision of the signal $\widetilde{y}_j$, which we model as a reduction in the variance of $\tilde{I}_1$ to u^2 (from $u^2 + \alpha^2$). OSHA_1 then imperfectly conveys information to OSHA_2 due to information frictions in sharing information beyond the OIS. The information shared by OSHA_1 reduces the variance of $\tilde{I}_2$ to $u^2 + \delta^2$ (from $u^2 + \alpha^2$), where $\delta^2 < \alpha^2$. That is, OSHA_2's signal is more precise than before but is still noisier than OSHA_1's signal. The term δ^2 reflects the level of information frictions present.[29] A higher δ^2 means OSHA_2 learns less from OSHA_1.

Upon receiving a signal, OSHA in region j must choose its investigative effort. Given its quadratic investigation costs, the level of investigation b maximizes

$$\max_{b_j} \mathbb{P}\left(\tilde{c} = c_H \mid r_j = c_L , y_j\right) \cdot b - \frac{kb^2}{2}, \tag{B5}$$

which yields $b = \frac{\mathbb{P}(\tilde{c}=c_H|r_j=c_L,y_j)}{k}$.

Equilibrium

Let σ_j^2 denote the variance of the signal y_j in period j, conditional on knowing the true cost c. If OSHA_1 catches a violation in the previous year, then $\sigma_1^2 = u^2$ and $\sigma_2^2 = u^2 + \delta^2$. By contrast, if OSHA_1 does not catch a violation in the previous year, then $\sigma_1^2 = \sigma_2^2 = u^2 + \alpha^2$. If OSHA in region j observes r_L and conjectures a level of cost-cutting effort $\hat{m}_j$ then, for a given realization of the signal y_j, the ex post likelihood that the firm has engaged in cost cutting is given by

$$P\left(c = c_H \mid r_L, y_j\right) = \frac{p\hat{m}_j\phi\left(y_j|r_L,\sigma_j^2\right)}{p\hat{m}_j\phi\left(y_j|r_L,\sigma_j^2\right)+(1-p)\phi\left(y_j+1|r_L,\sigma_j^2\right)} = \frac{1}{1+\frac{1-p}{p\hat{m}_j}\cdot\frac{\phi\left(y_j+1|r_L,\sigma_j^2\right)}{\phi\left(y_j|r_L,\sigma_j^2\right)}}, \tag{B6}$$

where $\phi(\cdot)$ represents the normal distribution with mean zero.

To solve for the rational expectations equilibrium, we set the conjectured level of cost-cutting $\hat{m}_j$ equal to the firm's actual cost-cutting effort in region j. Because the probability of investigation b_j is given by

[29] We do not endogenize δ^2. In practice, OSHA1 might choose δ^2 based on information-sharing costs or investigative resources available. Moreover, as individual OSHA offices spend more effort on sharing information with other offices, they will have fewer resources available for conducting their own investigations.

$b_j = \frac{1}{k}\,\mathbb{P}(c = c_H \mid r_L, y_j)$, this implies that, in equilibrium, the firm's cost-cutting effort levels in the two markets are given by

$$m_1 = \frac{1}{1+\theta} - \frac{F}{(1-\theta^2)k} \cdot \mathbb{E}_{y_1,y_2}\left(\frac{1}{1+\frac{1-p}{pm_1}\cdot\frac{\phi(y_1+1|r_L,\sigma_1^2)}{\phi(y_1|r_L,\sigma_1^2)}} - \theta \frac{1}{1+\frac{1-p}{pm_2}\cdot\frac{\phi(y_2+1|r_L,\sigma_2^2)}{\phi(y_2|r_L,\sigma_2^2)}} \right), \quad \text{(B7)}$$

$$m_2 = \frac{1}{1+\theta} - \frac{F}{(1-\theta^2)k} \cdot \mathbb{E}_{y_1,y_2}\left(\frac{1}{1+\frac{1-p}{pm_2}\cdot\frac{\phi(y_2+1|r_L,\sigma_2^2)}{\phi(y_2|r_L,\sigma_2^2)}} - \theta \frac{1}{1+\frac{1-p}{pm_1}\cdot\frac{\phi(y_1+1|r_L,\sigma_1^2)}{\phi(y_1|r_L,\sigma_1^2)}} \right). \quad \text{(B8)}$$

From (B7) and (B8), we can establish the model's main results and, hence, empirical predictions. We summarize these results in three propositions below, each of which directly generates testable empirical hypotheses. After each proposition, we state the corresponding empirical hypothesis. All three propositions are proved in appendix B.3.

Our first proposition concerns the *overall* level of cost-cutting by the firm across all its divisions, m_1+m_2, when OSHA_1 has observed a prior-year violation relative to the case where no prior-year violation was observed. Stated formally, we have the following:

Proposition B1. If OSHA_1 has observed a violation in the previous year, overall cost-cutting effort—that is, $m_1 + m_2$—is lower than in the case where OSHA1 did not observe a violation in the previous year.

Proposition B1 implies that when OSHA becomes more informed *in aggregate*, the firm's overall level of cost-cutting (the sum across all markets) decreases. This is consistent with prior literature, both empirical (e.g., Macher, Mayo, and Nickerson [2011]) and theoretical (e.g., Laffont and Tirole [1986]), which suggests that regulators can deter risky behavior by being better informed. Proposition B1 therefore directly implies our first empirical hypothesis:

Hypothesis 1. Firms that are sanctioned by OSHA for workplace safety violations are less likely to commit workplace safety violations in the following year.

Our second proposition, also derived from (B7) and (B8), concerns the relative levels of cost-cutting undertaken by the firm in the two states in which it operates. That is, although $m_1 + m_2$ is lower subsequent to OSHA_1 detecting a violation, it does not necessarily follow from (B7) and (B8) that each of m_1 and m_2 will be lower. Whether this is the case depends on the level of information frictions present. Stated formally, we have the following:

Proposition B2. Cost-cutting in market 1, m_1, is always lower when OSHA_1 has observed a prior-year violation compared to when OSHA_1 has not observed a prior-year violation. However, cost-cutting in market 2, m_2, when OSHA_1 has observed a prior-year violation, may be either higher or lower compared to when OSHA_1

did not observe a prior-year violation. Specifically, there is some threshold value $\overline{\delta^2} \in [0, \alpha^2]$ *such that* m_2 *when* $OSHA_1$ *has observed a prior-year violation is higher than* m_2 *when* $OSHA_1$ *has not observed a prior violation if and only if* $\delta^2 > \overline{\delta^2}$.

Proposition B2 implies the need for empirical tests because of two countervailing forces that occur as a result of OSHA1 being informed about $\tilde{I}$. On the one hand, OSHA2 is *more* informed when OSHA1 learns $\tilde{I}$ because $\delta^2 < \alpha^2$, meaning that, all else equal, it is more likely to investigate for any given signal. On the other hand, the fact that OSHA1 is *better* informed than OSHA2 encourages the firm to substitute away from cutting costs in market 1 to instead cut costs in market 2. Proposition B2 shows that which of these two forces dominate depends on whether the level of information frictions exceeds a threshold $\overline{\delta^2}$. Whether this is the case is an empirical question. Based on our conversations with OSHA compliance officers, we expect that, empirically, $\delta^2 > \overline{\delta^2}$. This generates our second empirical hypothesis:

Hypothesis 2. Information frictions within OSHA lead to shifts in violating behavior. That is, a firm that commits a violation in one location is less likely to commit a violation in the same location next year but more likely to commit a violation in a different location next year.

Our third proposition, again generated by expressions (B7) and (B8), provides additional detail on how cost-cutting efforts vary with the level of information frictions. Stated formally, we have the following:

Proposition B3. The level of cost-cutting in market 1, m_1*, decreases when the level of information frictions* δ^2 *increases whereas cost-cutting in market 2,* m_2*, increases as a function of* δ^2.

Proposition B3 extends Proposition B2 by establishing that the *level* of information frictions matters: Greater information frictions lead the firm to substitute away from cost-cutting in market 1 toward cost-cutting in market 2. The intuition is as follows: When information frictions are more severe, $OSHA_2$'s signal is noisier relative to $OSHA_1$'s. Hence, $OSHA_2$ is less likely to investigate even when it sees a high signal, because there is a higher likelihood of a false positive. This generates our third empirical hypothesis:

Hypothesis 3. *The level of shifting in violating behavior by the firm is positively associated with the level of information frictions within OSHA.*

PROOFS OF PROPOSITIONS B1, B2, AND B3

PROPOSITION B1

To verify Proposition B1, first note that we can add cross-terms and cancel $(1-\theta)$ in the denominator of the second term of the expressions for m_1, m_2 to rewrite overall cost-cutting efforts $m_1 + m_2$ as

$$m_1 + m_2 = \frac{2}{1+\theta} - \frac{F}{(1+\theta)k}\mathbb{E}_{y_1,y_2}\left(\frac{1}{1+\frac{1-p}{pm_1}\cdot\frac{\phi\left(y_1+1|r_L,\sigma_1^2\right)}{\phi\left(y_1|r_L,\sigma_1^2\right)}} + \frac{1}{1+\frac{1-p}{pm_2}\cdot\frac{\phi\left(y_2+1|r_L,\sigma_2^2\right)}{\phi\left(y_2|r_L,\sigma_2^2\right)}}\right). \quad \text{(B9)}$$

Recall that the variances of the signals received in both markets y_1, y_2 are lower when a violation has been previously observed in market 1 in period 1, relative to the case where no violation was observed. Verifying Proposition B1, then, is equivalent to verifying that the right-hand side of (A1) is increasing in σ_1^2 and σ_2^2. In turn, this is equivalent to verifying that

$$G \equiv \mathbb{E}_{y_1,y_2}\left(\frac{1}{1+\frac{1-p}{pm_1}\cdot\frac{\phi\left(y_1+1|r_L,\sigma_1^2\right)}{\phi\left(y_1|r_L,\sigma_1^2\right)}} + \frac{1}{1+\frac{1-p}{pm_2}\cdot\frac{\phi\left(y_2+1|r_L,\sigma_2^2\right)}{\phi\left(y_2|r_L,\sigma_2^2\right)}}\right) \quad \text{(B10)}$$

is decreasing in σ_1^2 and σ_2^2.

To verify that this is the case, we can rewrite the expression above using the integral equivalent:

$$\begin{aligned} G = & \int_{\mathbb{R}} \frac{1}{1+\frac{1-p}{pm_1}\cdot\frac{\phi\left(y_1+1|r_L,\sigma_1^2\right)}{\phi\left(y_1|r_L,\sigma_1^2\right)}}\phi\left(y_1|r_L,\sigma_1^2\right)dy_1 \\ & + \int_{\mathbb{R}} \frac{1}{1+\frac{1-p}{pm_2}\cdot\frac{\phi\left(y_2+1|r_L,\sigma_2^2\right)}{\phi\left(y_2|r_L,\sigma_2^2\right)}}\phi\left(y_2|r_L,\sigma_2^2\right)dy_2. \end{aligned} \quad \text{(B11)}$$

Using the formula for a normal distribution, each term of the two terms in the expression above can be rewritten as

$$\frac{1}{\sqrt{2\pi\sigma_i^2}}\int_{\mathbb{R}} \frac{e^{-\frac{(2x+1)}{\sigma_i^2}}}{1+\frac{1-p}{pm_i}\cdot e^{-\frac{(2x+1)}{\sigma_i^2}}}\cdot e^{-x^2/2\sigma_i^2}\,dy_i\,. \quad \text{(B12)}$$

By differentiating under the integral sign, it is straightforward to verify that for any value of m_i, we have

$$\frac{\partial}{\partial\sigma_i^2}\int_{\mathbb{R}} \frac{1}{1+\frac{1-p}{pm_i}\cdot e^{-\frac{(2x+1)}{\sigma_i^2}}} e^{-\frac{x^2}{2\sigma_i^2}}dy_i = \int_{\mathbb{R}}\left[\frac{\partial}{\partial\sigma_i^2}\frac{e^{-\frac{x^2}{2\sigma_i^2}}}{1+\frac{1-p}{pm_i}\cdot e^{-\frac{(2x+1)}{\sigma_i^2}}}\right]dy_i < 0\,. \quad \text{(B13)}$$

Applying the product rule implies that the overall expression given in (B12) is decreasing in σ_i^2 as well. As a result, when both σ_1^2 and σ_2^2 *decrease* as a result of OSHA_1 successfully detecting a violation in period 1, total cost-cutting across the two markets decreases.

PROPOSITIONS B2 AND B3

We next turn to market-by-market cost-cutting, as described in Propositions B2 and B3. To do so, we rely on specific expressions for the variances σ_1^2, σ_2^2. We can subtract (B8) from (B7) to obtain

$$m_1 - m_2 = \frac{F}{(1-\theta)k} \cdot \mathbb{E}_{y_1,y_2}\left(\frac{1}{1+\frac{1-p}{pm_2}\cdot\frac{\phi\left(y_2+1|r_L,\sigma_2^2\right)}{\phi\left(y_2|r_L,\sigma_2^2\right)}} - \frac{1}{1+\frac{1-p}{pm_1}\cdot\frac{\phi\left(y_1+1|r_L,\sigma_1^2\right)}{\phi\left(y_1|r_L,\sigma_1^2\right)}}\right). \quad \text{(B14)}$$

Because the expression

$$\mathbb{E}_{y_1,y_2}\left[\frac{1}{1+\frac{1-p}{pm_i}\cdot\frac{\phi\left(y_i+1|r_L,\sigma_i^2\right)}{\phi\left(y_i|r_L,\sigma_i^2\right)}}\right]$$

is decreasing in σ_i^2, we know that for any $x > 0$ and any $\delta^2 > 0$, we must have

$$\mathbb{E}_{y_1,y_2}\left[\frac{1}{1+\frac{1-p}{px}\cdot\frac{\phi\left(y_i+1|r_L,u^2\right)}{\phi\left(y_i|r_L,u^2\right)}}\right] > \mathbb{E}_{y_1,y_2}\left[\frac{1}{1+\frac{1-p}{px}\cdot\frac{\phi\left(y_i+1|r_L,u^2+\delta^2\right)}{\phi\left(y_i|r_L,u^2+\delta^2\right)}}\right]. \quad \text{(B15)}$$

Using (B14) and (B15), we can establish that $m_1 < m_2$ when a prior-period violation has occurred. To see this, first note that when the variance of the signal in both periods is the same—that is, when $\sigma_1^2 = \sigma_2^2$—we will have a symmetric solution $m_1 = m_2$, that is, $m_1 - m_2 = 0$. As a result, the right-hand side of equation (B14) must also equal zero. This, in turn, implies that

$$\frac{1}{1+\frac{1-p}{pm_2}\cdot\frac{\phi\left(y_2+1|r_L,u^2+\delta^2\right)}{\phi\left(y_2|r_L,u^2+\delta^2\right)}} = \frac{1}{1+\frac{1-p}{pm_1}\cdot\frac{\phi\left(y_1+1|r_L,u^2+\delta^2\right)}{\phi\left(y_1|r_L,u^2+\delta^2\right)}}. \quad \text{(B16)}$$

Expression (B15) also implies that

$$\mathbb{E}_{y_1,y_2}\left(\frac{1}{1+\frac{1-p}{pm_1}\cdot\frac{\phi\left(y_1+1|r_L,u^2+\delta^2\right)}{\phi\left(y_1|r_L,u^2+\delta^2\right)}}\right) < \mathbb{E}_{y_1,y_2}\left(\frac{1}{1+\frac{1-p}{pm_1}\cdot\frac{\phi\left(y_1+1|r_L,u^2\right)}{\phi\left(y_1|r_L,u^2\right)}}\right). \quad \text{(B17)}$$

For equation (B14) to hold, it must therefore be the case that m_1 decreases or m_2 increases (or both) when $\sigma_1^2 = u^2$, $\sigma_2^2 = u^2 + \delta^2$ (relative to the case $\sigma_1^2 = \sigma_2^2 = u^2 + \alpha^2$). Either case would imply that $m_1 < m_2$ when a prior-period violation has occurred.

Finally, to establish that m_1 decreases after a violation relative to the no-prior-violation case, let the superscripts V and NV denote a violation and nonviolation having occurred in the prior period, respectively. Proposition B1 can be restated as

$$m_1^V + m_2^V < m_1^{NV} + m_2^{NV}. \quad \text{(B18)}$$

Although, as described above, expressions (B16) and (B17) imply that

$$m_1^V < m_2^V. \quad \text{(B19)}$$

The combination of expressions (B18) and (B19), plus the fact that, by symmetry, we must have $m_1^{NV} = m_2^{NV}$, implies that

$$2m_1^V < m_1^V + m_2^V < m_1^{NV} + m_2^{NV} = 2m_1^{NV}. \tag{B20}$$

The inequality chain (B20) implies that $m_1^V < m_1^{NV}$, that is, that the level of cost-cutting in market 1 is lower after a prior-period violation has been detected in market 1. This establishes the first part of Proposition B2.

To establish the second part of Proposition B2, that is, to document the link between m_2^V and m_2^{NV}, we consider two extreme values for the level of information frictions present δ^2: (i) $\delta^2 = 0$ (i.e., perfect information transmission from OSHA1 to OSHA2) and (ii) $\delta^2 = \alpha^2$ (i.e., no information transmission at all).

Consider first the case of perfect information transmission between OSHA1 and OSHA2, that is, where $\delta^2 = 0$. In this case, $\sigma_1^2 = \sigma_2^2 = u^2$. When $\sigma_1^2 = \sigma_2^2$, the convexity of the penalty function implies a symmetric equilibrium (i.e., with equal cost-cutting in both markets). In conjunction with the inequality in (B18), it must therefore be the case that

$$m_2^V = m_1^V < m_1^{NV} = m_2^{NV}$$

and so cost-cutting in market 2 is lower after a violation in market 1 in the prior period.

Now consider the case where there is no information transmission from OSHA1 to OSHA2, that is, where $\delta^2 = \alpha^2$. Cost cutting in market 2 after a violation in market 1 is given by:

$$m_2^V = \frac{1}{1+\theta} - \frac{F}{(1-\theta^2)k} \cdot \mathbb{E}_{y_1,y_2}\left(\frac{1}{1+\frac{1-p}{pm_2^V}\cdot\frac{\phi\left(y_2+1|r_L,u^2+\alpha^2\right)}{\phi\left(y_2|r_L,u^2+\alpha^2\right)}} - \theta\frac{1}{1+\frac{1-p}{pm_1^V}\cdot\frac{\phi\left(y_1+1|r_L,u^2\right)}{\phi\left(y_1|r_L,u^2\right)}}\right). \tag{B21}$$

Define the quantities

$$X_1^V \equiv \mathbb{E}_{y_1,y_2}\left[\frac{1}{1+\frac{1-p}{pm_1^V}\cdot\frac{\phi\left(y_1+1|r_L,u^2\right)}{\phi\left(y_1|r_L,u^2\right)}}\right],$$

$$X_1^{NV} \equiv \mathbb{E}_{y_1,y_2}\left[\frac{1}{1+\frac{1-p}{pm_1^{NV}}\cdot\frac{\phi\left(y_1+1|r_L,u^2+\alpha^2\right)}{\phi\left(y_1|r_L,u^2+\alpha^2\right)}}\right].$$

It is straightforward to establish that $X_1^V > X_1^{NV}$ using the same approach as in the proof of Proposition B1. When $\delta^2 = \alpha^2$ we know that m_2^V is the value of μ that solves the equation

$$\mu = \frac{1}{1+\theta} - \frac{F}{(1-\theta^2)k} \cdot \left(\mathbb{E}_{y_1,y_2}\left(\frac{1}{1+\frac{1-p}{p\mu}\cdot\frac{\phi\left(y_2+1|r_L,u^2+\alpha^2\right)}{\phi\left(y_2|r_L,u^2+\alpha^2\right)}}\right) - \theta X_1^V\right), \tag{B22}$$

whereas m_2^{NV} is the value of μ that solves the equation

$$\mu = \frac{1}{1+\theta} - \frac{F}{\left(1-\theta^2\right)k} \cdot \left(\mathbb{E}_{y_1, y_2} \left(\frac{1}{1+\frac{1-p}{p\mu} \cdot \frac{\phi\left(y_2+1 | r_L, u^2+\alpha^2\right)}{\phi\left(y_2 | r_L, u^2+\alpha^2\right)}} \right) - \theta X_1^{NV} \right). \qquad \text{(B23)}$$

In equations (B18) and (B19), the only term that is different is X_1^V in (B22) versus X_1^{NV} in (B23). Because $X_1^V > X_1^{NV}$, the value of μ that solves (B22) must be greater than the value of μ that solves (B23), that is, when $\delta^2 = \alpha^2$ and no information is transmitted, we have $m_2^V > m_2^{NV}$.

We have thus established that when $\delta^2 = \alpha^2$, a previous-period violation in market 1 leads to *more* violation in market 2 (i.e., $m_2^{NV} < m_2^V$), whereas when $\delta^2 = 0$, a previous-period violation in market 1 leads to *less* violation in market 2 (i.e., $m_2^{NV} > m_2^V$). Because of continuity, Proposition B3 holds—that is, if $\frac{\partial m_2^V}{\partial \delta^2} > 0$ and $\frac{\partial m_1^V}{\partial \delta^2} < 0$—then there must be some threshold $\overline{\delta^2}$ such that a previous-period violation in market 1 leads to a higher likelihood of violations in market 2 if and only if $\delta^2 > \overline{\delta^2}$.

To verify Proposition B3, we need to show that $\frac{\partial m_2^V}{\partial \delta^2} > 0$ and $\frac{\partial m_1^V}{\partial \delta^2} < 0$ in the system of equations (B7) and (B8). We have already proven that for $i \in \{1, 2\}$,

$$\frac{\partial}{\partial \sigma_i^2} \left[m_1 + m_2 \right] > 0 . \qquad \text{(B24)}$$

Because of the chain rule, inequality (B24) implies that

$$\frac{\partial}{\partial \delta^2} \left[m_1 + m_2 \right] > 0,$$

that is, that

$$\frac{\partial m_1}{\partial \delta^2} + \frac{\partial m_2}{\partial \delta^2} > 0 . \qquad \text{(B25)}$$

Hence, in order to verify Proposition B3—and to therefore establish the existence of the threshold value $\overline{\delta^2}$—it suffices to show that $\frac{\partial m_1}{\partial \delta^2} < 0$. To do so, we consider the right-hand side of equation (B7). Because the distribution of y_1 is invariant to δ^2, to show that $\frac{\partial m_1}{\partial \delta^2} < 0$ it suffices to show that

$$\frac{\partial}{\partial \delta^2} \mathbb{E}_{y_1, y_2} \left(\frac{1}{1+\frac{1-p}{p m_2^V} \cdot \frac{\phi\left(y_2+1 | r_L, u^2+\delta^2\right)}{\phi\left(y_2 | r_L, u^2+\delta^2\right)}} \right) < 0 . \qquad \text{(B26)}$$

Inequality (B26) can be verified by differentiating under the integral sign exactly as in the case of inequality (B13), confirming the proof of Proposition B3.

APPENDIX C: OSHA INSPECTION CLASSIFICATION

OSHA classifies inspections into two types: programmed or unprogrammed. These two types of inspections are then further subdivided into 13 categories, as we detail in table C1. The goal of this section is

TABLE C1
OSHA Inspection Types

Inspection Type	Category	Classification	Number of Investigations in Sample
Programmed	Planned	Centrally planned	22,859
Programmed	Programmed related	Discretionary	659
Programmed	Programmed other	Discretionary	361
Unprogrammed	Accident	Reactive	4,454
Unprogrammed	Fatality/catastrophe	Reactive	550
Unprogrammed	Complaint	Reactive	28,132
Unprogrammed	Referral	Reactive	7,926
Unprogrammed	Monitoring	Discretionary	490
Unprogrammed	Variance	Discretionary	3
Unprogrammed	Follow-up	Discretionary	1,614
Unprogrammed	Unprogrammed related	Discretionary	2,022
Unprogrammed	Unprogrammed other	Discretionary	70
Unprogrammed	Other	Discretionary	235
Total			69,375

to delineate between inspections that are reactive, those that are centrally planned by OSHA headquarters, and those that are undertaken at the discretion of individual state-level OSHA offices (i.e., proactive). We outline our categorization below. For more details on inspection types and methods, refer to the OSHA field operations manual (available at https://www.osha.gov/enforcement/directives/cpl-02-00-164).

PROGRAMMED INSPECTIONS

Programmed inspections are random, with target selection generated by a formula that is centrally determined by federal OSHA headquarters in Washington, D.C. Although OSHA does not disclose its exact formula, the Field Operations Manual suggests that the formula is based on factors such as industry, establishment size, recency of past inspections, and history of workplace safety violations. Although state plans ("SP states") may amend this formula (e.g., to place greater focus on specific industries), their amended formula must follow similar guidelines and be formally approved by federal OSHA headquarters. The approval process limits the discretion that state plans may take in determining targets of programmed inspections. The primary reason for these strictures is to ensure that firms cannot anticipate programmed inspections with any precision.

There are three types of programmed inspections: (i) *planned*, (ii) *programmed related*, and (iii) *programmed other*. Planned inspections are those that are conducted by a state office in response to a direct order from federal OSHA, rather than at the discretion of state-level offices, and so we classify these as centrally planned. However, in the course of preparing for and conducting a planned inspection, a state-level office may encounter issues that lead it to conduct additional, related inspections (falling under

(ii) or (iii) above). These additional inspections are undertaken at the discretion of the state office, and so we classify them as discretionary.

UNPROGRAMMED INSPECTIONS

Unprogrammed inspections reflect any OSHA inspection that is not programmed and encompass inspections undertaken for a wide range of reasons. The majority of unprogrammed inspections are those conducted in response to triggering events such as the reporting of a workplace accident or fatality/catastrophe, a complaint made by an employee, or a referral from someone knowledgeable of a workplace safety issue at a place of business (e.g., factory, warehouse, or retail location). The latter two cases (employee complaint or referral) comprise what is more commonly known as whistleblowing. Because these four types of inspections (accident, fatality/catastrophe, complaint, and referral) are in response to trigger events, rather than proactively undertaken on OSHA's part, we classify them as reactive.

Finally, other types of unprogrammed inspections include those taken at the explicit discretion of state-level OSHA offices. Most common among these are *monitoring* and *follow-up* inspections, which reflect a state-level office proactively checking in on a facility (often in response to a prior safety issue in that workplace). On rare occasions, OSHA explicitly gives a firm an exemption from complying with a given standard (referred to as a *variance*—for details on the variance program, see https://www.osha.gov/variance-program). An inspection classified as *variance* reflects OSHA checking in on these exempt establishments to ensure that no other workplace safety procedures are ignored. Finally, as in the case of programmed inspections, when an OSHA state office conducts an unprogrammed inspection, it may encounter issues that lead it to conduct additional, related inspections. These are classified as *unprogrammed related*, *unprogrammed other*, or *other*. All of these inspections reflect a proactive decision by a state-level OSHA office (rather than a directive from federal OSHA or a trigger event) to undertake an inspection, and so we classify these as discretionary inspections.

We summarize our approach in table C1. Our investigations sample includes 69,375 individual inspections of public company establishments (which we then aggregate to the firm-state-year level, as outlined in section 4). We provide the distribution of these investigations by type below.

APPENDIX D: EMPIRICAL VARIABLE DEFINITIONS

We define below each of the variables used in our regression specifications.

Variable	Unit of Measurement	Definition
$ViolAny_{it}$	Firm-year	Indicator variable that equals 1 if firm i committed at least one OSHA violation in year t, in any state
$ViolInState_{ijt}$	Firm-state-year	Indicator variable that equals 1 if firm i committed at least one OSHA violation in state j in year t
$ViolOutOfState_{ijt}$	Firm-state-year	Indicator variable that equals 1 if firm i committed at least one OSHA violation in any state other than j in year t
$RWInState_{ijt}$	Firm-state-year	Indicator variable that equals 1 if firm i committed at least one *Repeat* or *Willful* violation in state j in year t
$RWOutOfState_{ijt}$	Firm-state-year	Indicator variable that equals 1 if firm i committed at least one *Repeat* or *Willful* violation in any state other than j in year t
$AnyInspectionInState_{ijt}$	Firm-state-year	Indicator variable that equals 1 if firm i faced at least one OSHA inspection (regardless of whether inspection was discretionary, reactive, or centrally planned, and regardless of whether a violation was found or not) in state j in year t
$ReactiveInState_{ijt}$	Firm-state-year	Indicator variable that equals 1 if firm i faced at least one reactive OSHA inspection but no centrally planned or discretionary inspections (regardless of whether a violation was found or not) in state j in year t
$PlannedInState_{ijt}$	Firm-state-year	Indicator variable that equals 1 if firm i faced at least one centrally planned OSHA inspection but no discretionary inspections (regardless of whether a violation was found or not) in state j in year t
$DiscInState_{ijt}$	Firm-state-year	Indicator variable that equals 1 if firm i faced at least one discretionary OSHA inspection (regardless of whether a violation was found or not) in state j in year t
$CleanInState_{ijt}$	Firm-state-year	Indicator variable that equals 1 if firm i faced at least one OSHA inspection but did not commit any violations in state j in year t
$CleanOutOfState_{ijt}$	Firm-state-year	Indicator variable that equals 1 if firm i faced at least one OSHA inspection but did not commit any violations in any state other than j in year t
$StatePlan_j$	State	Indicator variable that equals 1 if state j operates an OSHA State Plan
$MeetOrBeat_{it}$	Firm-year	Indicator variable that equals one if firm i just meet or beat analyst consensus earnings per share by zero or one cents per share in year t

Variable	Unit of Measurement	Definition
WeakCompliance$_{it}$	Firm-year	Indicator variable that equals one if firm i received federal sanctions for non-OSHA violations in years t-2 through t. Non-OSHA violation data obtained from Good Jobs First's *Violation Tracker* database and reflects sanctions from over 50 federal agencies. Among the most commonly occurring are fines assessed by Environmental Protection Agency, Wage & Hour Division, and Department of Justice
LogEstabs$_{ijt}$	Firm-state-year	Natural logarithm of the number of distinct establishments firm i operates in state j in year t
LogAssets$_{it}$	Firm-year	Natural logarithm of firm-year total assets
ROA$_{it}$	Firm-year	Return on assets, measured as ratio of net income to lagged assets
Leverage$_{it}$	Firm-year	Ratio of total short- and long-term debt to assets
MarketToBook$_{it}$	Firm-year	Market to book ratio

APPENDIX E: BRIEF OVERVIEW OF SPLIT-PANEL JACKKNIFE ESTIMATOR

We provide a discussion below to supplement the intuition given in section 4.4 for the split-panel jackknife estimator we use for our main analyses. For full details of the method and its applications, we refer the reader to Dhaene and Jochmans [2015].

The split-panel jackknife approach of Dhaene and Jochmans [2015] adds a novel correction technique to previous analytical methods to address bias in maximum likelihood estimation in dynamic models (Lancaster [2002], Arellano and Hahn [2006], Arellano and Bonhomme [2009], Hahn and Kuersteiner [2011]). This approach accounts for independent variables that are not strictly exogenous—in particular, a lag of the dependent variable—while also addressing the incidental parameters problem that afflicts logit models (Neyman and Scott [1948], Chamberlain [1984]). This is key in a setting such as ours that employs a high-dimensional fixed effects structure that can otherwise bias inferences from key independent variables.

To provide intuition, we outline the simplest version of the split-panel jackknife approach (applicable to perfectly balanced panels with an even number of time periods). In this case, the split-panel jackknife evenly splits the panel across time into two subpanels. Jackknifed maximum likelihood estimates of the underlying model are then estimated separately on each subpanel. These estimates are averaged across subpanels, and then subtracted from estimates from the entire panel to remove bias and obtain true model parameters θ_0.

In a balanced panel with an even number of years, this approach splits the data evenly into two halves and then separately produces estimates from the first half of the data, $\theta_{FirstHalf}$, and then again from the second half of the data, $\theta_{SecondHalf}$. These estimates are then averaged and subtracted from double the full-sample jackknife estimate θ_{Full}. Because bias doubles with every halving of the data, the resulting estimate produces the bias-corrected true parameters.[30] In other words, because bias contained in $\theta_{FirstHalf}$ and $\theta_{SecondHalf}$ should be double that in θ_{Full}, we have

$$2*\theta_{Full} - \frac{\theta_{FirstHalf}+\theta_{SecondHalf}}{2} = 2*(\theta_0 + Bias) - \frac{\theta_0+2\cdot Bias+\theta_0+2\cdot Bias}{2} = \theta_0. \tag{E1}$$

This approach generalizes to unbalanced panels with an even or odd number of time periods, but the algebra is more complicated.

REFERENCES

Abernethy, M. A.; J. Bouwens; and L. Van Lent "Determinants of Control System Design in Divisionalized Firms." *The Accounting Review* 79 (2004): 545–70.

Agarwal, S.; D. Lucca; A. Seru; and F. Trebbi "Inconsistent Regulators: Evidence from Banking." *Quarterly Journal of Economics* 129 (2014): 889–938.

Ai, C., and E. C. Norton "Interaction Terms in Logit and Probit Models." *Economics Letters* 80 (2003): 123–29.

Alonso, R.; W. Dessein; and N. Matouschek "When Does Coordination Require Centralization?" *American Economic Review*, 98 (2008): 145–79.

Aobdia, D. "The Impact of the PCAOB Individual Engagement Inspection Process—Preliminary Evidence." *The Accounting Review* 93 (2018): 53–80.

Arellano, M., and S. Bond "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations." *Review of Economic Studies* 58 (1991): 277–97.

Arellano, M., and S. Bonhomme "Robust Priors in Nonlinear Panel Data Models." *Econometrica* 77 (2009): 489–536.

Arellano, M., and J. Hahn "A Likelihood-Based Approximate Solution to the Incidental Parameter Problem in Dynamic Nonlinear Models with Multiple Effects." Working Paper, CEMFI and UCLA, 2006.

Baiman, S.; D. F. Larcker; and M. V. Rajan "Organizational Design for Business Units." *Journal of Accounting Research* 33 (1995): 205–29.

[30] Although this approach is likely useful in our setting, we caveat that this doubling of bias might not fully materialize if the underlying model is non-stationary. However, this is less likely to be an issue for three reasons. First, Dhaene and Jochmans [2015] show, in several examples, that their method accounts for most of the bias associated with non-stationarity, with one example being the Honoré and Kyriazidou [2000] discrete choice model. Second, non-stationarity does not arise in a logistic model from the parameters alone, as it can in a linear model. Third, although it is possible that nonstationarity could arise from nonstationary control variables (Park and Phillips [2000, 2001]), given that our controls—reflecting firm fundamentals such as size—are relatively stable over time within most firms, this is unlikely to be an issue. Finally, in untabulated analyses we verify that our results hold in the absence of control variables.

Bernardo, A. E.; H. Cai; and J. Luo "Capital Budgeting in Multidivision Firms: Information, Agency, and Incentives." *Review of Financial Studies* 17 (2004): 739–67.

Bernstein, S., and A. Sheen "The Operational Consequences of Private Equity Buyouts: Evidence from the Restaurant Industry." *Review of Financial Studies* 29 (2016): 2387–418.

Beuselinck, C.; S. Cascino; M. Deloof; and A. Vanstraelen "Earnings Management Within Multinational Corporations." *The Accounting Review* 94 (2019): 45–76.

Bolton, P., and M. Dewatripont "The Firm as a Communication Network." *Quarterly Journal of Economics* 109 (1994): 809–39.

Bonsall, S.; E. Holzman; and B. Miller "Wearing Out the Watchdog: SEC Case Backlog and Investigation Likelihood." The Accounting Review 99 (2024): 81–104.

Bradbury, J. C. "Regulatory Federalism and Workplace Safety: Evidence from OSHA Enforcement, 1981–1995." *Journal of Regulatory Economics* 29 (2006): 211–24.

Breuer, M., and E. deHaan "Using and Interpreting Fixed Effects Models." Working Paper, Columbia University and Stanford University, 2023.

Brüggen, A., and F. Moers "The Role of Financial Incentives and Social Incentives in Multi-Task Settings." *Journal of Management Accounting Research* 19 (2007): 25–50.

Caskey, J., and N. B. Ozel "Earnings Expectations and Employee Safety." *Journal of Accounting and Economics* 63 (2017): 121–41.

Chamberlain, G. "Panel Data." *Handbook of Econometrics* 2 (1984): 1247–318.

Chamberlain, G. "Binary Response Models for Panel Data: Identification and Information." *Econometrica* 78 (2010): 159–68.

Christie, A. A.; M. P. Joye; and R. L. Watts "Decentralization of the Firm: Theory and Evidence." *Journal of Corporate Finance* 9 (2003): 3–36.

Cohn, J. B., and M. I. Wardlaw "Financing Constraints and Workplace Safety." *Journal of Finance* 71 (2016): 2017–58.

Cohn, J.; N. Nestoriak; and M. Wardlaw "Private Equity Buyouts and Workplace Safety." *Review of Financial Studies* 34 (2021): 4832–75.

Dessein, W. "Authority and Communication in Organizations." *Review of Economic Studies* 69 (2002): 811–38.

Dhaene, G., and K. Jochmans "Split-Panel Jackknife Estimation of Fixed-Effect Models." *Review of Economic Studies* 82 (2015): 991–1030.

Dyreng, S. D.; M. Hanlon; and E. L. Maydew "Where Do Firms Manage Earnings?" *Review of Accounting Studies* 17 (2012): 649–87.

Ege, M. S. "Does internal Audit Function Quality Deter Management Misconduct?" *The Accounting Review* 90 (2015): 495–527.

Garicano, L. "Hierarchies and the Organization of Knowledge in Production." *Journal of Political Economy* 108 (2000): 874–904.

Göx, R. F., and U. Schiller "An Economic Perspective on Transfer Pricing." *Handbooks of Management Accounting Research* 2 (2006): 673–95.

Greene, W. "Testing Hypotheses About Interaction Terms in Nonlinear Models." *Economics Letters* 107 (2010): 291–96.

Hahn, J., and G. Kuersteiner "Bias Reduction for Dynamic Nonlinear Panel Models with Fixed Effects." *Econometric Theory* 27 (2011): 1152–91.

Haltiwanger, J.; R. S. Jarmin; and J. Miranda "Who Creates Jobs? Small Versus Large Versus Young." *Review of Economics and Statistics* 95 (2013): 347–61.

Heese, J., and G. Pérez-Cavazos "When the Boss Comes to Town: The Effects of Headquarters' Visits on Facility-Level Misconduct." *The Accounting Review* 95 (2020): 235–61.

Holmström, B., and P. Milgrom "Multitask Principal-Agent Analyses: Incentive Contracts, Asset Ownership, and Job Design." *Journal of Law, Economics, & Organization* 7 (1991): 24.

Honoré, B. E., and Á. De Paula "Identification in Simple Binary Outcome Panel Data Models." *Econometrics Journal* 24 (2021): C78–C93.

Honoré, B. E., and E. Kyriazidou "Panel Data Discrete Choice Models with Lagged Dependent Variables." *Econometrica* 68 (2000): 839–74.

Hope, O.-K.; D. Wang, H. Yue; and J. Zhao "Information Quality and Workplace Safety." *Journal of Management Accounting Research* 34 (2022): 133–62.

Iyengar, R. "I'd Rather Be Hanged for a Sheep than a Lamb: The Unintended Consequences of 'Three-Strikes' Laws." Working Paper, Harvard University, 2008.

Jensen, M. C., and W. H. Meckling "Specific and General Knowledge, and Organizational Structure." *Journal of Applied Corporate Finance* 8 (1995): 4–18.

Johnson, M. S. "Regulation by Shaming: Deterrence Effects of Publicizing Violations of Workplace Safety and Health Laws." *American Economic Review* 110 (2020): 1866–904.

Johnson, M. S.; D. I. Levine; and M. W. Toffel "Improving Regulatory Effectiveness Through Better Targeting: Evidence from OSHA." *American Economic Journal: Applied Economics* 15 (2023): 30–67.

Jung, J., and M. D. Makowsky "The Determinants of Federal and State Enforcement of Workplace Safety Regulations: OSHA Inspections 1990–2010." *Journal of Regulatory Economics* 45 (2014): 1–33.

Kanodia, C. "Participative Budgets as Coordination and Motivational Devices." *Journal of Accounting Research* 31 (1993): 172–89.

Kedia, S., and S. Rajgopal "Do the SEC's Enforcement Preferences Affect Corporate Misconduct?" *Journal of Accounting and Economics*, 51 (2011): 259–78.

Kedia, S.; S. Luo; and S. Rajgopal "The Association Between Compliance History and Financial Misreporting." Working Paper, Rutgers University, Hong Kong University, and Columbia University, 2019.

Labro, E.; M. Lang; and J. D. Omartian "Predictive Analytics and Centralization of Authority." *Journal of Accounting and Economics* 75 (2023): 101526.

Laffont, J.-J., and J. Tirole "Using Cost Observation to Regulate Firms." *Journal of Political Economy* 94 (1986): 614–41.

Lancaster, T. "Orthogonal Parameters and Panel Data." *Review of Economic Studies* 69 (2002): 647–66.

Levine, D. I.; M. W. Toffel; and M. S. Johnson "Randomized Government Safety Inspections Reduce Worker Injuries with No Detectable Job Loss." *Science* 336 (2012): 907–11.

Li, S. X., and T. Sandino "Effects of an Information Sharing System on Employee Creativity, Engagement, and Performance." *Journal of Accounting Research* 56 (2018): 713–47.

Li, S. X., and T. Sandino "From Online Content to Offline Results: Effects of a Best Practices Initiative on an Enterprise Social Network." Working Paper, University of Southern California and Harvard University, 2021.

Li, X., and A. Raghunandan "Institutional Ownership and Labor-Related Misconduct: Evidence from US Federal Violations." Working Paper, London School of Economics, 2023.

Macher, J. T.; J. W. Mayo; and J. A. Nickerson "Regulator Heterogeneity and Endogenous Efforts to Close the Information Asymmetry Gap." *Journal of Law and Economics* 54 (2011): 25–54.

Makridis, C. A., and M. Ohlrogge "Validating RefUSA Micro-Data with the Longitudinal Employer-Household Dynamics Data." *Economics Letters* 152 (2017): 83–87.

Melumad, N. D., and S. Reichelstein "Centralization Versus Delegation and the Value of Communication." *Journal of Accounting Research* 25 (1987): 1–18.

Melumad, N.; D. Mookherjee; and S. Reichelstein "A Theory of Responsibility Centers." *Journal of Accounting and Economics* 15 (1992): 445–84.

Morantz, A. D. "Has Devolution Injured American Workers? State and Federal Enforcement of Construction Safety." *Journal of Law, Economics, & Organization* 25 (2009): 183–210.

Nagar, V. "Delegation and Incentive Compensation." *The Accounting Review* 77 (2002): 379–95.

Neyman, J., and E. L. Scott "Consistent Estimates Based on Partially Consistent Observations." *Econometrica* 16 (1948): 1–32.

Nickell, S. "Biases in Dynamic Models with Fixed Effects." *Econometrica* 49 (1981): 1417–26.

Park, J. Y., and P. C. Phillips "Nonstationary Binary Choice." *Econometrica* 68 (2000): 1249–80.

Park, J. Y., and P. C. Phillips "Nonlinear Regressions with Integrated Time Series." *Econometrica* 69 (2001): 117–61.

Parsons, C. A.; J. Sulaeman; and S. Titman "The Geography of Financial Misconduct." *Journal of Finance* 73 (2018): 2087–137.

RAGHUNANDAN, A. "Financial Misconduct and Employee Mistreatment: Evidence from Wage Theft." *Review of Accounting Studies* 26 (2021): 867–905.

ROBINSON, L. A., and P. C. STOCKEN "Location of Decision Rights Within Multinational Firms." *Journal of Accounting Research* 51 (2013): 1261–97.

SANI, J. "Delegation of Decision Rights Within Firms and the Role of Peer Information Environment." Working Paper University of Illinois, 2021.

SCHANTL, S. F., and A. WAGENHOFER. "Deterrence of Financial Misreporting When Public and Private Enforcement Strategically Interact." *Journal of Accounting and Economics* 70 (2020): 101311.

STICE-LAWRENCE, L. "SEC Attention, A to Z." Working Paper University of Southern California, 2023.

WEIL, D. "If OSHA Is so Bad, Why Is Compliance so Good?" *RAND Journal of Economics* 27 (1996): 618–40.

WILKS, T. J., and M. F. ZIMBELMAN "Decomposition of Fraud-Risk Assessments and Auditors' Sensitivity to Fraud Cues." *Contemporary Accounting Research* 21 (2004): 719–45.