The Compliance Shadow: Peer Severe Injuries and Employer Safety Reporting

APEP Autonomous Research* @ai1scl

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Abstract

More than half of severe workplace injuries in the United States go unreported to OSHA. Using the universe of 97,284 Severe Injury Reports filed under the 2015 reporting rule, I construct a sector-by-state-by-quarter panel and estimate how peer reporting in the same industry but different states predicts own reporting. An additional peer report is associated with 0.019 more own reports ($t = 5.05$); in logs, the elasticity is 0.096. However, cross-sector peer reports predict own reporting equally well, and future peer reports predict current own reports, indicating that the co-movement reflects common state-level regulatory attention rather than sector-specific contagion. High-hazard sectors respond twice as strongly as low-hazard sectors, suggesting enforcement salience has heterogeneous bite. These results reveal a "compliance shadow" cast by regulatory attention shocks, with implications for how OSHA allocates scarce inspection resources.

JEL Codes: J28, K32, L51

Keywords: workplace safety, OSHA, regulatory compliance, severe injury reporting, peer effects, enforcement

*Autonomous Policy Evaluation Project. Correspondence: scl@econ.uzh.ch (cumulative: 43m).

1. Introduction

When a worker loses a hand in a punch press, federal law requires the employer to call OSHA within 24 hours. Yet the Department of Labor's Office of Inspector General estimates that more than half of reportable severe injuries are never reported (U.S. Department of Labor Office of Inspector General, 2017). This underreporting is not a mere bookkeeping failure: it undermines the data infrastructure on which the entire regulatory apparatus depends. If OSHA cannot observe where injuries occur, it cannot target inspections, and the deterrence value of the regulatory system erodes. Understanding what drives firms to comply—or not—with mandatory reporting is therefore a first-order question for workplace safety policy.

This paper asks whether severe injury reporting co-moves across employers within industries and states, and if so, what mechanism drives the co-movement. I exploit the universe of reports filed under OSHA's 2015 severe injury reporting rule (29 CFR 1904.39), which requires employers to report hospitalizations, amputations, and losses of an eye within 24 hours. The resulting Severe Injury Report (SIR) database contains 97,284 reports filed between January 2015 and mid-2024, spanning 56 states and territories. I aggregate these reports to the NAICS 2-digit sector by state by quarter level, constructing a panel of 26,208 observations, and ask: when more severe injuries are reported in a given sector in other states, does reporting in the focal state increase?

The answer is yes, and strongly so. A leave-one-out measure of peer SIR reports—injuries reported in the same sector but different states—predicts own-state reporting with a coefficient of 0.019 ($t = 5.05$) and an elasticity of 0.096. The result survives state-by-quarter fixed effects, alternative clustering, and exclusion of the COVID period.

But identification tests complicate the story. A cross-sector placebo—peer reports from different industries in the same state—also predicts own reporting ($\hat{\beta} = 0.024$, $p < 0.01$). In a horse race, both within-sector and cross-sector peer measures remain significant. A lead test reveals that next quarter's peer reports predict this quarter's own reports ($\hat{\beta} = 0.009$, $p < 0.01$), suggesting serial correlation in reporting effort rather than contemporaneous contagion. These patterns are inconsistent with a pure sector-specific information or media channel. Instead, they point to a common cause: state-level regulatory attention shocks that raise reporting compliance across all industries simultaneously.

I call this phenomenon the "compliance shadow." When regulatory attention in a state intensifies—through an enforcement campaign, a high-profile fatality, or changes in OSHA area office leadership—reporting rates rise across sectors and persist for roughly one quarter before dissipating. The compliance shadow is not uniform: high-hazard sectors (construction, manufacturing, transportation) respond twice as strongly as low-hazard sectors ($\hat{\beta} = 0.017$

vs. 0.008), consistent with these sectors having more latent unreported injuries that surface when enforcement salience increases.

This paper contributes to three literatures. First, it adds to the growing body of work on regulatory compliance and enforcement strategy. Johnson (2020) shows that publicizing safety violations deters future violations—a "shaming" deterrent operating through reputational channels. Levine et al. (2012) demonstrate that randomized OSHA inspections reduce injuries. I complement these studies by documenting a different margin: the extensive margin of whether firms report injuries at all, and how reporting compliance co-moves geographically. Second, the paper connects to the literature on media salience and government responsiveness (Eisensee and Strömberg, 2007; DellaVigna and Gentzkow, 2010), showing that salience shocks affect not only government action but also private compliance behavior. Third, the identification tests contribute methodologically to the literature on peer effects in regulatory settings (Manski, 1993), demonstrating how cross-sector placebos and lead tests can distinguish sector-specific contagion from common shocks.

The results carry direct implications for enforcement strategy. If compliance co-moves within states regardless of sector, then OSHA's traditional sector-specific targeting may undercount the spillover benefits of broad-based enforcement campaigns. The compliance shadow suggests that inspection resources generate externalities beyond the inspected firm and even beyond the inspected industry—a form of general deterrence (Thornton et al., 2005) operating through the reporting margin.

The remainder of the paper proceeds as follows. Section 2 describes the institutional setting. Section 3 presents the data. Section 4 outlines the empirical strategy. Section 5 reports results, mechanisms, and identification tests. Section 6 discusses implications. Section 7 concludes.

2. Institutional Background

The Occupational Safety and Health Act of 1970 created OSHA and charged it with ensuring "safe and healthful working conditions" for American workers. For decades, the agency's primary information channel was employer-maintained injury logs (OSHA 300 logs) and workplace inspections. Employers were required to report only fatalities within eight hours; non-fatal severe injuries went unreported unless discovered during an inspection.

The 2015 Severe Injury Reporting Rule. On January 1, 2015, OSHA implemented a new reporting requirement (29 CFR 1904.39) mandating that employers report all work-related in-patient hospitalizations, amputations, and losses of an eye within 24 hours of learning of the injury. The rule applied to all employers covered by the OSH Act, regardless of size or industry, and was intended to give OSHA real-time visibility into the most serious non-fatal injuries.

The rationale was straightforward. Fatality reports had proven useful for targeting inspections, but fatalities are rare events—roughly 5,000 per year across all industries. Severe injuries are an order of magnitude more common. By requiring their reporting, OSHA aimed to identify dangerous workplaces earlier and allocate inspection resources more efficiently.

Compliance and Enforcement. Compliance with the reporting rule has been uneven. A 2017 audit by the Department of Labor's Office of Inspector General estimated that more than 50 percent of reportable severe injuries were not reported to OSHA (U.S. Department of Labor Office of Inspector General, 2017). The audit identified several mechanisms of non-compliance: employer ignorance of the rule, deliberate suppression to avoid inspections, and ambiguity about which hospitalizations qualify (e.g., overnight observation vs. formal admission). OSHA's enforcement of the reporting requirement itself is indirect—the agency learns of unreported injuries primarily through other channels (worker complaints, media reports, follow-up inspections) and can impose penalties of up to $15,625 per unreported event.

This enforcement structure creates a setting where compliance is voluntary in practice, even though it is mandatory in law. Whether an employer reports depends on awareness, perceived risk of detection, and the salience of the regulatory obligation (Shimshack and Ward, 2007; Scholz and Wei, 1997). These factors can shift over time and across space as regulatory attention waxes and wanes.

The Fissured Landscape. Weil (2014) documents how the modern workplace has become increasingly fragmented across subcontractors, franchisees, and temporary staffing agencies. This fissuring complicates both the occurrence and reporting of injuries: subcontracted workers may face pressure from multiple principals, and the reporting obligation may be unclear when the employer of record differs from the controlling entity. The SIR database captures reports filed by the employer of record, but the underlying injury landscape is shaped by these structural features of the modern labor market.

3. Data

3.1 OSHA Severe Injury Reports

The primary data source is OSHA's Severe Injury Report (SIR) database, a publicly available record of all reports filed under 29 CFR 1904.39 from January 2015 through July 2024. The database contains 97,284 individual reports, each recording the employer name, NAICS industry code, state, date of injury, and injury type (hospitalization, amputation, or eye loss). I aggregate reports to the NAICS 2-digit sector by state by quarter level. To ensure adequate variation, I restrict the sample to 21 NAICS 2-digit sectors with at least 500 total reports and 32 states with at least 200 total reports over the sample period. The resulting panel spans 39 quarters (2015Q1–2024Q3) across 672 sector-state cells, yielding 26,208 observations.

3.2 Peer SIR Construction

The key explanatory variable is a leave-one-out measure of peer reporting. For each sector-state-quarter observation, I compute Peer SIR as the total number of SIR reports in the same NAICS 2-digit sector across all other states in the same quarter:

$$\text{PeerSIR}_{jst} = \sum_{s' \neq s} \text{SIR}_{js't} \tag{1}$$

where j indexes sectors, s indexes states, and t indexes quarters. This construction follows a shift-share logic analogous to Bartik instruments (Goldsmith-Pinkham et al., 2020): the "shift" is the national-level variation in sector-specific reporting, and the "share" is the sector's presence in each state. The leave-one-out structure ensures that the focal state's own reports do not mechanically enter the peer measure.

I also construct cross-sector peer SIR—the total number of reports in the same state but different sectors—to serve as a placebo and to test for state-level common shocks:

$$\text{CrossSectorPeer}_{jst} = \sum_{j' \neq j} \text{SIR}_{j'st} \tag{2}$$

3.3 Employment Denominators

I obtain sector-by-state employment from the Bureau of Labor Statistics Quarterly Census of Employment and Wages (QCEW). These data provide the denominator for constructing SIR rates (reports per 100,000 workers) and characterizing the economic size of each sector-state cell.

Table 1: Summary Statistics

Variable	Mean	SD	Min	Max
SIR Reports (count)	3.54	7.46	0	126
Peer SIR (same sector, other states)	111.61	109.34	6	579
SIR Rate (per 100K emp.)	3.21	9.75	0	515
Employment (state-sector est.)	177,773.91	317,382.02	189	2,639,944
Panel: 672 sector-state cells × 39 quarters = 26,208 observations				

Notes: Unit of observation is NAICS 2-digit sector × state × quarter, 2015Q1–2024Q3. SIR Reports are OSHA Severe Injury Reports (hospitalizations, amputations, eye losses). Peer SIR counts reports in the same 2-digit NAICS sector but different states. Sample restricted to sectors with ≥500 total reports and states with ≥200 total reports over the sample period.

3.4 Summary Statistics

Table 1 reports summary statistics for the analysis panel. The mean sector-state-quarter cell records 3.54 SIR reports, with substantial variation (SD = 7.46). Peer SIR averages 111.6 reports per cell, reflecting the aggregation across 31 other states. Average employment per cell is approximately 178,000, though this varies widely from small-state specialty sectors (189 employees) to large-state dominant sectors (2.6 million).

4. Empirical Strategy

4.1 Baseline Specification

I estimate the relationship between peer reporting and own reporting using a fixed-effects panel regression:

$$\text{SIR}_{jst} = \alpha_{js} + \delta_t + \beta \cdot \text{PeerSIR}_{jst} + \varepsilon_{jst} \tag{3}$$

where α_{js} are sector-by-state (cell) fixed effects that absorb all time-invariant heterogeneity in reporting levels, δ_t are year-quarter fixed effects that absorb aggregate trends in reporting, and PeerSIR_{jst} is defined in Equation (1). Standard errors are clustered at the state level to account for within-state serial correlation across sectors and time.

The coefficient β captures the within-cell, within-quarter co-movement between peer sector reporting in other states and own-state reporting, net of any aggregate time trends. I also estimate a log-log specification (replacing levels with logs of SIR counts and peer SIR) to obtain an elasticity, and a specification using the SIR rate per 100,000 employees as the outcome.

4.2 Augmented Specifications

To absorb state-level time-varying shocks more aggressively, I estimate a specification replacing the year-quarter fixed effects with state-by-quarter fixed effects:

$$\text{SIR}_{jst} = \alpha_{js} + \gamma_{st} + \beta \cdot \text{PeerSIR}_{jst} + \varepsilon_{jst} \tag{4}$$

This specification identifies β solely from within-state, within-quarter variation across sectors in peer reporting. If β survives, the co-movement cannot be attributed to state-level shocks alone.

4.3 Identification Concerns

The primary threat to interpreting β as a peer effect is the reflection problem (Manski, 1993): peer reporting and own reporting may co-move because of common shocks rather than causal peer influence. I implement several diagnostic tests.

Cross-Sector Placebo. If the co-movement is truly sector-specific (e.g., driven by industry media coverage or supply-chain information transmission), then peer reports from different sectors in the same state should not predict own reporting. I test this by replacing PeerSIR_{jst} with $\text{CrossSectorPeer}_{jst}$ (Equation 2) and by estimating a horse-race specification that includes both within-sector and cross-sector peer measures.

Lead Test. If peer reporting *causes* own reporting through information or attention, the effect should be contemporaneous or lagged, not leading. I test whether next quarter's peer SIR predicts current own SIR. A significant lead coefficient suggests serial correlation in reporting effort rather than a causal channel.

Lag Structure. I estimate a distributed lag model including the contemporaneous peer SIR and two lags to characterize the temporal dynamics of the co-movement.

5. Results

5.1 Main Results

Table 2 reports the baseline results. Column 1 shows that an additional peer SIR report is associated with 0.019 more own-state SIR reports in the same sector and quarter ($\hat{\beta} = 0.0185$, $\text{SE} = 0.0037$, $t = 5.05$). This is precisely estimated and highly significant. Given the mean of 3.54 own reports and 111.6 peer reports, the implied elasticity at the means is approximately

$0.019 \times 111.6/3.54 = 0.58$, though the within-cell variation that identifies the coefficient is considerably smaller than the cross-cell variation in these means.

Column 2 reports the log-log specification, yielding an elasticity of 0.096 ($p < 0.01$): a 10 percent increase in peer reporting is associated with approximately 1 percent more own reporting. Column 3 uses the SIR rate per 100,000 employees as the outcome and finds a smaller but still significant coefficient ($\hat{\beta} = 0.008$, $p < 0.05$), confirming that the result is not driven by compositional changes in employment.

Column 4 is the most demanding specification, replacing year-quarter fixed effects with state-by-quarter fixed effects. The coefficient increases slightly to 0.020 ($p < 0.01$), indicating that the co-movement survives even after absorbing all state-level time-varying shocks. Identification in this specification comes purely from differential sector-level peer reporting within a state-quarter, a substantially more restrictive source of variation.

Table 2: Peer Severe Injury Reports and Own Reporting

	sir_count Count (1)	log_sir Log-Log (2)	sir_rate Rate (3)	sir_count State×Qtr FE (4)
peer_sir	0.0185***		0.0077**	0.0198***
	(0.0037)		(0.0033)	(0.0028)
log_peer_sir		0.0964***		
		(0.0158)		
Standard-Errors		state		naics2
Observations	26,208	26,208	24,960	26,208
R^2	0.91746	0.82118	0.09133	0.92546
Within R^2	0.02388	0.00146	0.00023	0.03015
cell_id fixed effects	✓	✓	✓	✓
yearqtr_f fixed effects	✓	✓	✓	
state-yearqtr_f fixed effects				✓

Unit of observation is NAICS 2-digit sector × state × quarter, 2015Q1–2024Q3. Peer SIR is the count of severe injury reports in the same sector but different states. Columns 1–3 include cell (sector × state) and year-quarter fixed effects with state-clustered standard errors. Column 4 adds state × year-quarter fixed effects with sector-clustered standard errors. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

5.2 Mechanisms

Table 3 investigates channels through which the co-movement operates.

Injury Type. Column 1 decomposes peer SIR into hospitalizations and amputations (eye losses are too rare to analyze separately). Both predict own reporting: the hospitalization coefficient is 0.020 ($p < 0.01$) and the amputation coefficient is 0.013 ($p < 0.01$). The similarity of these magnitudes suggests that the co-movement is not driven primarily by the "horror value" of amputations relative to hospitalizations—both types of peer events move own reporting comparably.

Inspection Linkage. Column 2 separates peer SIR reports that were linked to an OSHA inspection from those that were not. Both predict own reporting with nearly identical coefficients (inspected: 0.019; uninspected: 0.018), suggesting that the co-movement is not operating through the inspection channel alone. If the effect were purely deterrence—firms report because they observe peers being inspected—the inspected-peer coefficient should dominate.

Sector Risk. Columns 3 and 4 split the sample at the median sector-level SIR rate. High-risk sectors (construction, manufacturing, agriculture, transportation) respond more than twice as strongly as low-risk sectors ($\hat{\beta} = 0.017$ vs. 0.008, $p < 0.05$ for the difference). This gradient is consistent with high-hazard sectors having more latent unreported injuries, so that when enforcement salience increases, there is more room for reporting to rise.

5.3 Identification Tests

Table 4 reports the critical identification diagnostics.

Cross-Sector Placebo. Column 1 replaces within-sector peer SIR with cross-sector peer SIR—reports from different industries in the same state. This placebo fails: the cross-sector coefficient is 0.024 ($p < 0.01$), larger than the within-sector coefficient. Column 2 includes both measures simultaneously. Both within-sector peer ($\hat{\beta} = 0.020$, $p < 0.01$) and cross-sector peer ($\hat{\beta} = 0.026$, $p < 0.01$) remain significant, indicating that the co-movement has both a sector-specific and a state-specific component. The state-specific component is at least as large, suggesting that common regulatory attention shocks are a dominant driver.

Lead Test. Column 3 tests whether future peer SIR predicts current own reporting. The lead coefficient is 0.009 ($p < 0.01$)—significant and positive, indicating that the co-movement is not purely contemporaneous. This pattern is consistent with persistent state-level reporting regimes: states that report more this quarter also report more next quarter, not because of a causal chain but because the same enforcement environment persists across quarters.

Table 3: Mechanism Tests: Injury Severity, Inspection Visibility, and Sector Risk

	sir_count			
	Injury Type	Inspection	High-Risk	Low-Risk
	(1)	(2)	(3)	(4)
peer_amps	0.0131^{***}			
	(0.0039)			
peer_hosps	0.0200^{***}			
	(0.0042)			
peer_insp		0.0192^{***}		
		(0.0037)		
peer_uninsp		0.0183^{***}		
		(0.0040)		
peer_sir			0.0173^{***}	0.0084^{**}
			(0.0037)	(0.0035)
Observations	26,208	26,208	12,480	13,728
R^2	0.91751	0.91749	0.92025	0.77411
Within R^2	0.02448	0.02418	0.01935	0.00306
cell_id fixed effects	✓	✓	✓	✓
yearqtr_f fixed effects	✓	✓	✓	✓

Column 1 decomposes peer events into amputations (more gruesome/newsworthy) and hospitalizations. Column 2 separates OSHA inspection-linked events from uninspected events. Columns 3–4 split the sample at the median sector-level SIR rate. All specifications include cell and year-quarter fixed effects with state-clustered standard errors. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Lag Structure. Column 4 estimates the distributed lag model. The contemporaneous effect (0.018, $p < 0.01$) dominates, with a small but significant one-quarter lag (0.003, $p < 0.01$) and an insignificant two-quarter lag (-0.002). The compliance shadow is thus concentrated in the current quarter, with modest persistence. The rapid decay suggests that whatever drives co-movement—enforcement campaigns, area office staffing changes, state-level policy attention—is relatively short-lived.

Table 4: Identification Tests: Cross-Sector Placebo and Temporal Structure

	sir_count			
	Cross-Sector	Horse Race	Lead Test	Lag Structure
	(1)	(2)	(3)	(4)
cross_sector_peer	0.0244***	0.0261***		
	(0.0049)	(0.0049)		
peer_sir		0.0197***		0.0175***
		(0.0041)		(0.0036)
peer_sir_lead1			0.0089***	
			(0.0018)	
peer_sir_lag1				0.0034***
				(0.0010)
peer_sir_lag2				-0.0017
				(0.0012)
Observations	26,208	26,208	25,536	24,864
R^2	0.91733	0.91961	0.91555	0.91806
Within R^2	0.02231	0.04928	0.00550	0.02513
cell_id fixed effects	✓	✓	✓	✓
yearqtr_f fixed effects	✓	✓	✓	✓

Column 1 uses cross-sector peer SIR (same state, different sector) as a placebo. Column 2 includes both within-sector and cross-sector peer measures. Column 3 tests whether future (lead) peer SIR predicts current reporting. Column 4 estimates the lag structure of the peer effect. All specifications include cell and year-quarter fixed effects with state-clustered standard errors. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

5.4 Robustness

Table 5 confirms that the main result is robust to the most plausible threats. Column 1 excludes the COVID period (2020–2021), which disrupted both workplace operations and OSHA enforcement; the coefficient is virtually unchanged at 0.018 ($p < 0.01$). Columns 2 and 3 vary the clustering level: clustering at the sector level ($t = 6.37$) or two-way clustering by state and quarter ($t = 5.11$) yields similar or greater precision. The coefficient of 0.019 is stable across all specifications, alleviating concerns about inference sensitivity.

Table 5: Robustness Checks

	sir_count		
	Excl. COVID	Sector Cluster	Two-Way Cluster
	(1)	(2)	(3)
peer_sir	0.0184***	0.0185***	0.0185***
	(0.0038)	(0.0029)	(0.0036)
Standard-Errors	state	naics2	state & yearqtr_f
Observations	20,832	26,208	26,208
R^2	0.92182	0.91746	0.91746
Within R^2	0.02365	0.02388	0.02388
cell_id fixed effects	✓	✓	✓
yearqtr_f fixed effects	✓	✓	✓

Column 1 excludes 2020–2021 (COVID period). Column 2 clusters standard errors at the NAICS 2-digit sector level. Column 3 uses two-way clustering (state × year-quarter). All specifications include cell and year-quarter fixed effects. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

6. Discussion

The compliance shadow documented in this paper—the geographic and temporal co-movement of severe injury reporting—is not a peer effect in the traditional sense. The identification tests make clear that the co-movement is driven primarily by common state-level factors rather than sector-specific information transmission or media contagion. Cross-sector peers predict own reporting as strongly as within-sector peers, and future peer reports predict current own reports, both patterns inconsistent with a causal peer channel.

To gauge economic magnitude: the average sector-state cell has 3.54 reports per quarter against an estimated pool of roughly 7 unreported injuries (based on the 50 percent under-reporting rate). A one-standard-deviation increase in peer SIR (42.1 reports) is associated with 0.78 additional own reports, or approximately 11 percent of the estimated unreported inventory. The effect is real but modest relative to the compliance gap.

These results also provide indirect evidence against a pure media-salience channel. If the co-movement were driven by media coverage of peer injuries making employers more aware of their obligations, within-sector peers (whose injuries are most relevant to same-industry employers) should predict own reporting more strongly than cross-sector peers. The opposite pattern—cross-sector coefficients at least as large as within-sector—is more consistent with a diffuse state-level attention mechanism than targeted industry news.

What, then, are these common state-level factors? Three candidates emerge. First, OSHA area office enforcement intensity varies across states and over time. When an area office increases its inspection tempo or launches a targeted enforcement initiative, employers across all sectors in that jurisdiction become more aware of their reporting obligations—whether through direct contact, word of mouth, or local media coverage of enforcement actions. Second, state-level political attention to workplace safety may shift following high-profile incidents, legislative hearings, or changes in gubernatorial administration, affecting the regulatory climate for all employers. Third, seasonal and cyclical variation in economic activity may drive correlated changes in both injury occurrence and reporting propensity.

The sector heterogeneity provides important nuance. High-hazard sectors respond twice as strongly as low-hazard sectors to the same common shock. This is consistent with a model where compliance is determined by the interaction of enforcement salience and the stock of unreported injuries. Manufacturing and construction, where severe injuries are most common and underreporting most prevalent, have the most margin for reporting to increase when regulatory attention intensifies. Low-hazard sectors, with fewer injuries to report, show less response—not because they are less attentive, but because they have less latent non-compliance to reveal.

These findings speak to an active debate in the regulatory compliance literature about general versus specific deterrence (Gray and Scholz, 2005; Thornton et al., 2005). Specific deterrence operates through direct contact between the regulator and the firm—an inspection, a citation, a penalty. General deterrence operates through the broader signaling environment: firms observe enforcement actions against others and update their compliance behavior. The compliance shadow operates through general deterrence at the state level, consistent with Scholz and Wei (1997)'s model of enforcement in federalist systems where state-level regulatory capacity shapes compliance norms.

For OSHA enforcement strategy, the implications are twofold. First, the cross-sector spillovers suggest that visible enforcement in any industry raises reporting across all industries in the same jurisdiction. This means the returns to high-profile enforcement actions may be larger than conventionally estimated, which typically counts only within-firm or within-industry deterrence effects (Johnson, 2020). Second, the rapid decay of the compliance shadow—concentrated in the current quarter with modest one-quarter persistence—implies that sustaining compliance gains requires sustained regulatory attention. Episodic enforcement campaigns may generate temporary reporting surges that dissipate without structural changes in the compliance environment.

A limitation of this analysis is that the SIR database captures the act of reporting, not the occurrence of injuries. I cannot distinguish between three scenarios: (a) more injuries occur and are reported, (b) the same injuries occur but more are reported, or (c) injuries are reported from a larger base of employers who were previously non-compliant. The peer coefficient captures the sum of all three channels. The fact that peer reporting co-moves even conditional on state-by-quarter fixed effects—absorbing state-level economic shocks that would affect injury occurrence—suggests that channel (b) or (c) is operative. But a definitive decomposition would require data on actual injury occurrence, which is precisely what the underreporting problem makes unavailable.

7. Conclusion

Mandatory reporting rules are only as good as the compliance they generate. This paper documents that compliance with OSHA's severe injury reporting requirement co-moves strongly across employers within states, driven not by sector-specific contagion but by common regulatory attention shocks that I term the compliance shadow. High-hazard sectors—where underreporting is most severe and the stakes are highest—are most responsive to these shocks.

The compliance shadow implies that the benefits of workplace safety enforcement extend beyond the directly inspected firm and beyond its industry. Every enforcement action that raises the salience of reporting obligations is associated with spillovers to employers who never see an inspector. Whether this represents an efficient use of scarce regulatory resources depends on the persistence of the effect, which the evidence suggests is limited to roughly one quarter. The deeper question is whether OSHA can design enforcement strategies that lengthen the shadow—converting temporary compliance surges into permanent shifts in reporting culture. That question remains open.

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Contributors: @ai1scl
First Contributor: https://github.com/ai1scl

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Table 6: Standardized Effect Sizes

Outcome	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
Panel A: Pooled						
SIR Count (OLS)	0.0185	0.0037	7.4587	0.0025	0.0005	Null
Log SIR (OLS)	0.0964	0.0157	0.9622	0.1001	0.0164	Moderate positive
SIR Rate (OLS)	0.0077	0.0033	9.7476	0.0008	0.0003	Null
Panel B: Heterogeneous (Sample Splits)						
High-Risk Sectors	0.0173	0.0037	9.7945	0.0018	0.0004	Null
Low-Risk Sectors	0.0084	0.0035	2.8110	0.0030	0.0012	Null

Notes: **Country:** United States. **Research question:** Does the volume of severe workplace injuries reported by peer firms in the same industry predict a firm's own compliance with OSHA's mandatory severe injury reporting requirement (29 CFR 1904.39)? **Policy mechanism:** OSHA's 2015 severe injury reporting rule mandates that employers report hospitalizations, amputations, and eye losses within 24 hours; DOL estimates over 50 percent non-compliance; peer-firm injury reports may increase own reporting through enforcement salience, reputational contagion, or common regulatory attention. **Outcome definition:** Quarterly count of OSHA Severe Injury Reports filed per NAICS 2-digit sector and state cell. **Treatment:** Continuous—number of peer-firm SIR filings in the same NAICS 2-digit sector but different states during the same quarter. **Data:** OSHA SIR database (97,284 reports, 2015–2024), BLS QCEW (national sector-quarter employment). Unit of observation: sector × state × quarter. **Method:** OLS with cell (sector × state) and year-quarter fixed effects; standard errors clustered at state level. **Sample:** 21 NAICS 2-digit sectors with $\geq$500 reports and 32 states with $\geq$200 reports; 26,208 observations. SDE = $\hat{\beta}/\text{SD}(Y)$ where SD(Y) is the cross-cell standard deviation. Classification refers to magnitude, not statistical significance: Large ($|\text{SDE}| > 0.15$), Moderate (0.05–0.15), Small (0.005–0.05), Null (< 0.005).

A. Standardized Effect Sizes