Production and Externalities: How Corporate Governance Shapes Social Costs

Finance Working Paper N° 1049/2025
January 2026

Alvin Chen
Stockholm School of Economics

Michael D. Wittry
Ohio State University and ECGI

ECGI Working Paper Series in Finance

Production and Externalities: How Corporate Governance Shapes Social Costs

Working Paper N° 1049/2025
January 2026

Alvin Chen
Michael D. Wittry

For their helpful comments and suggestions, we thank Simcha Barkai, Bo Becker, Paul Décaire, Ran Duchin, Alex Edmans, Slava Fos, Janet Gao, Han Hou, Mariassunta Giannetti, Thomas Griffin, Jonathan Karpoff, Oliver Levine, Doron Levit, Nadya Malenko, Marcus Opp, Alessio Piccolo, Zach Sautner, Giorgo Sertsios, Sophie Shive, René Stulz, Petra Vokata, Michael Weisbach, Randall Wright, and seminar and conference participants at Temple University, Boston College, the University of Iowa, the European Finance Association, the Drexel Corporate Governance Conference, the Midwest Finance Association, and the University of Wisconsin Madison Junior Finance Conference. We thank Erik Gilje for many thoughtful conversations. We are grateful to Kornelia Fabisik, Rüdiger Fahlenbrach, and René Stulz for sharing data on managerial ownership. We are also very grateful to Reza Noorani and Victor Yu at the Mine Safety and Health Administration for graciously answering our many data requests and questions. Byungwook Kim, Tara Mellul, and Hoa Briscoe-Tran provided excellent research assistance.

Abstract

We study how corporate governance affects social costs, focusing on the tension between mitigating managerial moral hazards and limiting negative externalities. We develop a parsimonious principal-agent model with negative production externalities, which predicts that when monitoring costs rise, firms substitute toward performance-based compensation, leading to socially costly production decisions. Using asset-level data from the U.S. coal industry, we find that ownership dispersion—the canonical proxy for rising monitoring costs—leads to an 11% increase in production and a 33% rise in safety violations. To establish causality, we exploit politically motivated coal divestment mandates that forced key monitoring institutions to exit, generating plausibly exogenous increases in monitoring costs. Consistent with our model, affected firms raised managerial bonus thresholds and experienced higher production and more safety violations. Our findings reveal how governance choices can inadvertently amplify social costs, with implications for sustainable investing and corporate governance design.

Keywords: corporate governance, agency costs, moral hazar, monitoring, incentive contracting, production externalities, social costs

JEL Classifications: D62, G30, G32, G34, G38, J24, J28

Alvin Chen
Assistant Professor of Finance
Stockholm School of Economics
Bertil Ohlins gata 4
11350 Stockholm , Sweden
e-mail: alvin.chen@hhs.se

Michael D. Wittry*
Assistant Professor of Finance
Ohio State University
854 Fisher Hall 2100 Neil Ave
Columbus, OH 43210, USA
phone: (614) 292-3217
e-mail: wittry.2@osu.edu

*Corresponding Author

THE OHIO STATE UNIVERSITY
FISHER COLLEGE OF BUSINESS

Fisher College of Business
Working Paper Series

Charles A. Dice Center for Research in Financial Economics

Production and Externalities: How Corporate Governance Shapes Social Costs

Alvin Chen,
Stockholm School of Economics

Michael D. Wittry,
The Ohio State University and ECGI

Dice Center WP 2025-06
Fisher College of Business WP 2025-03-006

September 16, 2025

Production and Externalities: How Corporate Governance Shapes Social Costs*

Alvin Chen† and Michael D. Wittry‡

September 16, 2025

Abstract

We study how corporate governance affects social costs, focusing on the tension between mitigating managerial moral hazards and limiting negative externalities. We develop a parsimonious principal-agent model with negative production externalities, which predicts that when monitoring costs rise, firms substitute toward performance-based compensation, leading to socially costly production decisions. Using asset-level data from the U.S. coal industry, we find that ownership dispersion—the canonical proxy for rising monitoring costs—leads to an 11% increase in production and a 33% rise in safety violations. To establish causality, we exploit politically motivated coal divestment mandates that forced key monitoring institutions to exit, generating plausibly exogenous increases in monitoring costs. Consistent with our model, affected firms raised managerial bonus thresholds and experienced higher production and more safety violations. Our findings reveal how governance choices can inadvertently amplify social costs, with implications for sustainable investing and corporate governance design.

JEL classification: D62, G30, G32, G34, G38, J24, J28

Keywords: Corporate governance, agency costs, moral hazard, monitoring, incentive contracting, production externalities, social costs

*For their helpful comments and suggestions, we thank Simcha Barkai, Bo Becker, Paul Décaire, Ran Duchin, Alex Edmans, Slava Fos, Janet Gao, Han Hou, Mariassunta Giannetti, Thomas Griffin, Jonathan Karpoff, Oliver Levine, Doron Levit, Nadya Malenko, Marcus Opp, Alessio Piccolo, Zach Sautner, Giorgo Sertsios, Sophie Shive, René Stulz, Petra Vokata, Michael Weisbach, Randall Wright, and seminar and conference participants at Temple University, Boston College, the University of Iowa, the European Finance Association, the Drexel Corporate Governance Conference, the Midwest Finance Association, and the University of Wisconsin Madison Junior Finance Conference. We thank Erik Gilje for many thoughtful conversations. We are grateful to Kornelia Fabisik, Rüdiger Fahlenbrach, and René Stulz for sharing data on managerial ownership. We are also very grateful to Reza Noorani and Victor Yu at the Mine Safety and Health Administration for graciously answering our many data requests and questions. Byungwook Kim, Tara Mellul, and Hoa Briscoe-Tran provided excellent research assistance.

†Stockholm School of Economics, Email: alvin.chen@hhs.se

‡Fisher College of Business, Ohio State University, and European Corporate Governance Institute, Email: wittry.2@osu.edu.

1 Introduction

A central challenge in economics is aligning private incentives with social welfare when production generates negative externalities. While government oversight, as well as some market forces, can help firms internalize some of these costs, many production decisions—broadly defined as those involving profit-generating activities—remain difficult to observe and regulate, giving firms substantial discretion to pursue practices that impose significant social costs. For example, pharmaceutical companies may aggressively market opioids, generating large social costs through addiction and overdose that far exceed any legal liabilities. We study how corporate governance shapes such production decisions and their associated social costs.

While prior work (e.g., Shive and Forster, 2020) has linked governance to environmental and social outcomes, the underlying mechanisms remain underexplored. One prominent hypothesis is that governance affects firms' investments in abatement technologies (e.g., see Bellon, 2024; Akey and Appel, 2021). We propose and test a novel, complementary mechanism: a firm's governance framework—the array of tools it employs to mitigate internal agency problems—can inadvertently worsen externalities by distorting production decisions. In particular, we show that when monitoring management becomes more costly, firms shift toward performance-based pay, encouraging production practices that generate additional social costs—such as in the Wells Fargo cross-selling scandal, where aggressive performance targets led to the creation of millions of unauthorized accounts.

To formalize this argument and guide our empirical analysis, we develop a parsimonious principal-agent model with two key features. First, when an asset's production intensity exceeds a certain threshold, it imposes additional negative externalities, creating what we term *socially costly production*.[1] Importantly, our focus is not on the aggregate production level in an economy, industry, or firm, but rather on asset-level production decisions—how firms push individual assets' production intensity beyond thresholds where additional social costs emerge, for instance by skipping critical maintenance or safety checks. This feature of production creates a trade-off: stronger pay-for-production incentives discourage managers from living the quiet life (e.g., Bertrand and Mullainathan, 2003), but also encourage them to pursue socially costly production.

The second key feature is that the firm's owners only bear a fraction of its social costs

[1] In addition to those highlighted above, other examples include social media companies' prioritization of rapid user growth and engagement, sometimes at the cost of mental health concerns (especially for young users), fulfillment centers pushing intense productivity quotas resulting in injuries and burnout, and an airplane manufacturer taking shortcuts to meet production deadlines and maintain market share with deadly consequences.

through pecuniary penalties. For example, carbon taxes may under-represent the economic damages of CO_2 emissions borne by society (e.g., see Pastor et al., 2024).[2] This partial internalization fundamentally shapes how firms design their governance framework. In our model, the firm's owners mitigate managerial moral hazard with two broad categories of governance mechanisms: performance-based pay (e.g., production bonuses)and monitoring tools (e.g., internal controls, independent audits, board oversight). Because shareholders design governance to maximize firm value while bearing only a fraction of social costs, privately optimal governance choices may diverge significantly from those that would maximize social welfare.

These model features highlight two interconnected agency problems: the classical conflict between managers and owners, and a second between owners and society. Higher monitoring costs exacerbate both problems simultaneously—they not only make managerial shirking more likely, but also make strong performance-based pay more appealing to shareholders, despite its social costs. The model's central predictions revolve around how firms substitute across governance mechanisms as their relative costs change. In particular, when monitoring becomes more expensive, firms substitute toward performance-based pay, which boosts production but increases social costs.

The availability of alternative governance tools can mitigate these adverse effects in two ways. First, mechanisms that reduce managerial moral hazard—such as dedicated institutional blockholders, independent boards of directors, or informative stock prices—diminish the need for strong performance-based pay when direct monitoring becomes more costly. Second, market and regulatory mechanisms that raise the pecuniary cost of socially costly production—such as unions demanding hazard pay for unsafe conditions, litigation costs, or regulators imposing penalties for externalities—make strong performance-based pay less appealing to firms' owners. These alternative governance tools become especially valuable as monitoring costs rise, providing a countervailing force that limits the shift toward socially costly production.

We test these predictions using novel data from the U.S. coal mining industry.[3] This setting offers three significant advantages for studying governance and social costs. First,

[2] That firms and shareholders only partially internalize social costs does not mean pecuniary costs are trivial. For example, the landmark Big Tobacco lawsuit in 1998 was settled for a record $205 billion, yet still only represents a portion of the annual economic costs of cigarette smoking, estimated to be $1.85 trillion globally (Goodchild et al., 2018). Similarly, at least twelve companies, including both public and private opioid manufacturers and distributors, retail pharmacies, and consulting firms, have settled lawsuits totaling over $65 billion, representing just 4% of the $1.5 trillion annual economic costs of the current opioid epidemic (Beyer, 2022).

[3] The coal mining sector and the mining industry, more generally, have been used to study externalities (Green and Vallee, 2024) and agency costs (Wittry, 2021), both of which are central to this paper.

the Mine Safety and Health Administration (MSHA) collects standardized reports for *every* coal mine over a 40-year period, providing asset-level data on production, employment, and mine safety violations—a quantifiable measure of an important externality: hazardous working conditions. When firms cut corners on safety to meet aggressive production targets, the resulting workplace accidents exemplify socially costly production. These costs are substantial, totaling an estimated $3 trillion globally each year (Dorman, 2012). Workplace safety constitutes a genuine externality because society bears substantial costs beyond those internalized by firms and workers—including through social insurance programs and broader economic disruptions (Leigh et al., 2000). This externality is particularly acute in mining, where labor monopsony and limited worker mobility prevent full compensation for safety risks. Moreover, serious accidents often result in extended or permanent production stoppages that impose significant costs on suppliers, customers, and the local community.[4]

Second, the industry features a clear trade-off between production and hazardous working conditions (Gowrisankaran et al., 2018) and allows us to analyze production intensity at the mine—rather than aggregate—level. Safety maintenance often requires halting output altogether, creating a direct tension between generating output and protecting workers. One stark example of this trade-off comes from the Upper Big Branch (UBB) disaster, which killed 29 miners in Montcoal, West Virginia, on April 5, 2010. An independent investigation found that Massey Energy, UBB's public owner, "exhibited a corporate mentality that placed the drive to produce above worker safety" McAteer et al., 2011, p. 99). Figure 2 shows how this corporate policy led to a dramatic increase in production per miner hour in the two years preceding the disaster. These output gains were accompanied by nearly 1,700 safety violations and over $3 million in fines.

Third, the institutional details of this industry facilitate an empirical strategy that addresses key endogeneity concerns. Coal producers use similar technologies to extract a commoditized good, limiting confounding variation due to technological differences, product differentiation, or market segmentation. This setting allows us to more cleanly identify the effects of governance structures. Additionally, political pressure surrounding climate change has prompted divestment by large activist institutional investors. These divestments create exogenous ownership changes that increase monitoring costs by removing key investors who engage in active monitoring and governance.

In the first part of our empirical analysis, we leverage mine-level data with a high-dimensional fixed-effects structure—spanning mine, firm, and time—to examine how production and workplace safety at individual mines respond to ownership changes, particu-

[4]See (Isikoff, 1984; Kent, 2016) for evidence on the regional economic impact of mine closures following accidents. Internet Appendix IA.1.1 provides further discussion of hazardous conditions as an externality.

larly non-PE-backed private-to-public transitions.[5] The shift from concentrated to dispersed ownership during IPOs is a *canonical* example of increased monitoring frictions (Pagano and Röell, 1998), due to free-riding (e.g., Grossman and Hart, 1980) and coordination challenges (e.g., Shleifer and Vishny, 1986). Figure 3 confirms a large and significant drop in the average ownership of the controlling shareholder following IPOs in our sample, consistent with previous findings. Unlike other industries where IPOs involve concurrent organizational changes (e.g., Borisov et al., 2021; Bias et al., 2023), the coal sector offers a key advantage because the labor and organizational structures of coal producers remain relatively stable across transitions (e.g., see Internet Appendix Table IA3), easing concerns that our results are driven by changes unrelated to monitoring costs. Overall, this setting offers a sharp empirical laboratory for studying how governance choices shape production decisions and externalities.

We find that mines undergoing a private-to-public transition—where ownership dispersion plausibly increases monitoring costs—experience a significant increase in production (11%) and safety violations (33%), with violations rising three times as much as production. Dynamic treatment effects show that the increases begin in the year of the transition (not before) and persist over time. While such transitions involve multiple organizational changes, several additional pieces of evidence support our interpretation that the effects stem from a substitution in governance mechanisms. Specifically, the effects are concentrated in firms that experience the largest ownership dispersion and those that make greater use of bonus contracting, consistent with our theoretical prediction that firms substitute toward performance-based pay when monitoring becomes more costly.

We argue that these mine-level increases reflect socially costly production rather than efficiency gains. In particular, we find that safety violations *per unit* of output also rise following the transition, which is inconsistent with efficiency improvements. Moreover, while access to public markets may relax financial constraints and facilitate firm growth overall (e.g., Brav, 2009), we do not find that capital-constrained firms expanded scale at the mine level. Instead, the evidence points to more intense extraction practices—pushing existing operations harder—rather than efficiency-driven or capacity-expanding growth.

Our empirical findings also support the ancillary predictions of our model, though we acknowledge the limitations of drawing causal inferences from cross-sectional variation. Specifically, we find that when alternative governance mechanisms are available at the firm, market, and regulatory levels, they attenuate the increase in socially costly production following

[5] Though we also analyze public-to-private transitions (excluding PE buyouts), we use the term private-to-public for ease of exposition. Internet Appendix Section IA.5 briefly discusses implications for private equity.

private-to-public transitions. Firms with dedicated institutional blockholders, independent boards, and informative stock prices at the time of IPO exhibit smaller increases in production and safety violations. Likewise, stronger safety enforcement and labor union presence similarly dampen the increase in socially costly production.

To further support a causal interpretation of our empirical results, we exploit the coal divestment mandates imposed on the California Public Employees' Retirement System (CalPERS) and Norges Bank Investment Management (NBIM) by the state of California and the Norwegian Ministry of Finance in the mid-2010s. These politically motivated mandates removed prominent governance-focused institutional investors from affected firms. Because such institutions play a pivotal role in monitoring management (Chen et al., 2007), their forced exit increases the costs of monitoring. We exploit the specific climate-focused scope of these mandates—which applied to thermal coal producers but not to metallurgical coal producers—to implement a difference-in-differences design, using metallurgical coal firms as a natural control group. Consistent with our framework, we find that production intensity and workplace safety violations increase following the divestment initiatives, with the observed effects concentrated entirely in thermal coal firms. To directly test our model's substitution mechanism, we hand-collect data on EBITDA thresholds for managerial bonuses. Consistent with a shift toward stronger performance-based pay following the increase in monitoring costs, these thresholds increase for thermal but not metallurgical coal producers.

While our empirical analysis focuses on coal mining, our findings have broad applicability to industries where social costs increase disproportionately with production intensity and managers exercise significant discretion over production policies. The core dynamic we underscore is likely present in sectors such as pharmaceuticals and finance, as previously noted, and many forms of manufacturing. For instance, in food processing and chemical production, ramping up output often requires bypassing safety protocols, increasing the risk of contamination or hazardous incidents. The Peanut Corporation of America's salmonella scandal exemplifies this tension: when told that the unavailability of salmonella testing results would delay shipment, Company President Stewart Parnell responded via email, "Shit, just ship it. I cannot afford to loose [sic] another customer." This decision contributed to a nationwide outbreak that killed nine people and sickened over 700.[6] The production pressures highlighted in these cases mirror those in our coal mining analysis, where performance-based pay encourages managers to prioritize output over limiting negative externalities. Taken together, these examples suggest that our findings likely generalize to

[6] See https://www.wired.com/2013/02/prosecution-pca/. Similarly, the official investigation into BP's Texas City refinery explosion found that "production pressures from BP Group executive managers impaired process safety performance at Texas City." (Chemical Safety and Hazard Investigation Board, "Refinery Explosion and Fire," March 2007, p. 25).

sectors where performance-based pay interacts with unobservable managerial production decisions, reinforcing the importance of corporate governance design in managing social costs.

Our study makes contributions to several strands of the literature. First, we identify a fundamental tension between reducing agency costs and minimizing social costs from production externalities. Unlike prior work that focuses on firms' abatement investments, we show that changes in governance structure can lead to higher social costs through higher production intensities at existing facilities. This distinction is critical because it suggests that policies aimed at addressing externalities should consider not only firms' mitigation strategies but also how governance design shapes core production decisions. Additionally, our study contributes to the literature on formal versus informal governance by showing how formal governance mechanisms (e.g., performance-based pay) can, in some contexts, undermine informal norms (e.g., safety-first culture) by creating competing priorities that place output above workplace safety, extending the insights of Graham et al. (2022).

Second, building on the results of Shive and Forster (2020), who examine how cross-sectional differences in governance structures relate to pollution, we use plausibly exogenous shocks to monitoring capacity—generated by political coal divestment mandates—to causally identify how shifts in governance structures affect social costs. Importantly, we show that even when external governance mechanisms do not necessarily have a strong interest in reducing externalities—because they internalize only a fraction of the social costs—their presence nonetheless curbs socially costly production by reducing firms' reliance on performance-based pay. This finding aligns with traditional shareholder-centric views of corporate governance (Shleifer and Vishny, 1997), in which closer monitoring constrains managerial distortions.

Our findings also offer a potential explanation for why traditional asset managers report that poor environmental and social performance signals broader organizational deficiencies (Edmans et al., 2024). Rather than reflecting correlated risks, our framework suggests that poor ES performance may directly result from weak governance, specifically ineffective monitoring that pushes firms toward socially costly production practices. This insight contributes to the debate on how the G component of ESG interacts with the E and S components (e.g., see Chen et al., 2024; Edmans, 2023; He et al., 2023) by showing that governance mechanisms designed purely to address agency costs can inadvertently affect environmental and social outcomes through their impact on production decisions.

Third, we contribute to a growing literature that analyzes how asset ownership structures shape firms' broader societal impact due to diverging interests among stakeholders (e.g., Bellon, 2024; Duchin et al., 2024; Cohn et al., 2021). We show that ownership changes that raise monitoring costs prompt firms to substitute toward performance-based pay, resulting in socially costly production. These findings suggest that oversight aimed at limiting the social and environmental costs of production—such as ESG ratings and SEC disclosure mandates (e.g., Karpoff et al., 2022; O'Hare, 2022)—should account for how governance frameworks influence core production decisions, not just firms' direct mitigation strategies.

Finally, our results contribute to the growing literature on unintended consequences of sustainable investment strategies—such as divestment, exclusion, and negative screening—aimed at redirecting capital away from brown firms to accelerate the green transition (e.g., see Shue and Hartzmark, 2024). We show that these initiatives can inadvertently undermine governance by removing key institutional blockholders who provide critical oversight. In our setting, divestment shocks led to an increased reliance on performance-based pay, resulting in higher output but poorer workplace safety. These findings suggest that, in the absence of alternative governance mechanisms, sustainable investing may paradoxically increase social and environmental harms rather than reduce them.

2 Hypotheses Development

To illustrate our hypotheses, we develop a parsimonious principal-agent model with production externalities. For brevity, we focus on the intuition underlying the model's results.[7]

The model has two dates: $t = 0$ and $t = 1$. The firm's production technology generates an output Q (e.g., production, profit, or other measures of firm payoff) at $t = 1$ that can be high ($Q = q_H$), low ($Q = q_L$), or zero ($Q = 0$). The distribution of Q depends on the manager's effort $e \in \{0, 1\}$, choice of production intensity $x \in \{0, 1\}$, and a firm-level productivity shock $\xi \in \{H, L\}$. High ($\xi = H$) and low ($\xi = L$) productivity shocks occur with probabilities $1 - \eta$ and η, respectively.

When operating at standard production intensity ($x = 0$), the firm's output depends on the productivity shock ξ, with Q taking values q_ξ and 0 with probabilities $p \in (0, 1)$ and $1 - p$, respectively. A low productivity ($\xi = L$) shock results in lower output (i.e., $q_L < q_H$). When operating at high production intensity ($x = 1$), the firm's output takes values q_H and 0 with probabilities p and $1 - p$, respectively, regardless of the productivity shock. At $t = 0$, the manager can shirk ($e = 0$) and extract B in private benefits.[8] Shirking by the manager reduces the conditional probabilities of the firm generating high ($Q = q_H$) and low output ($Q = q_L$) to p_H and p_L, respectively. The production technology satisfies the monotone likelihood ratio property: $\frac{p}{p_L} < \frac{p}{p_H}$. Crucially, high production intensity increases the likelihood of observing high output, which is also the most informative signal about

[7] The formal proofs of our model's results can be found in Internet Appendix Section IA.2

[8] Private benefits can take the form of living the quiet life (Bertrand and Mullainathan, 2003), empire building (Jensen, 1986), or corporate perquisites (Yermack, 2006), or self-dealing (Décaire and Sosyura, 2022).

managerial effort. This feature creates a key tension: while high output is most indicative of high managerial effort, high production intensity makes this signal more likely regardless of effort. Table 1 summarizes the production technology.

To capture the idea production intensity beyond certain levels becomes increasingly costly from a social perspective (e.g., Morgan and Tumlinson, 2019), we assume that operating at a high production intensity ($x = 1$) imposes additional social costs. This *socially costly production* increases expected firm output but generates an additional s in expected social costs while incurring only $m < s$ in expected monetary losses for the firm. For example, a coal-mining firm may increase the ratio of production shifts to maintenance shifts, increasing output but compromising workplace safety. This practice results in additional worker injuries and fatalities that trigger regulatory fines and, in severe cases, mine collapses that precipitate lawsuits and future output reductions. Importantly, these monetary losses do not fully reflect the magnitude of the firm's social costs ($m < s$). For example, estimates show that coal mining firms only bear a fraction of the direct costs associated with workplace accidents (e.g., see Internet Appendix Section IA.1.1). As a result, the firm's production policies may be optimal for its owners but inefficient for society. Our specification implies that the firm can produce up to $\bar{Q} = p(\eta q_L + (1-\eta)q_H)$ without imposing additional social costs, which we interpret as an output-externalities threshold.

Table 1: Summary of Production Technology

Output	q_H	q_L	0
Standard Production Intensity ($x = 0$):			
Manager Works ($e = 1$)	$(1-\eta)p$	ηp	$1-p$
Manager Shirks ($e = 0$)	$(1-\eta)p_H$	ηp_L	$1-(1-\eta)p_H-\eta p_L$
High Production Intensity ($x = 1$):			
Manager Works ($e = 1$)	p	0	$1-p$
Manager Shirks ($e = 0$)	p_H	0	$1-p_H$

Our model aims to highlight the tension between lowering agency rents and mitigating social costs arising from unobservable managerial effort and production intensity choices. The production technology's monotone likelihood ratio property implies that higher-powered incentives reduce agency rents. However, these same incentives also induce socially costly production. To capture the frictions that limit contracting on hard-to-measure externalities (e.g., Hart and Zingales, 2017), we assume that the manager's compensation, $W(Q)$, can only depend on the firm's output at $t = 1$. Allowing the firm to contract on a social cost measure does not qualitatively alter our conclusions as long as the measure is sufficiently noisy.[9] The manager is protected by limited liability. For simplicity, we set the manager's outside option to zero so the participation constraint (IR) is always satisfied.[10]

In addition to compensation contracting, the firm can engage in costly monitoring to mitigate moral hazard. Specifically, the firm can pay a monitoring cost of $\frac{c}{2}(\Delta_B)^2$ at $t = 0$ to reduce the private benefits that the manager can extract by Δ_B. We assume that c is sufficiently large such that the optimal amount of monitoring is interior (i.e., $\Delta_B^* < B$). The firm selects a governance framework consisting of a monitoring policy and a managerial compensation contract to maximize its expected output net of monitoring costs, compensation costs, and internalized monetary costs (m) of negative externalities, if any. To emphasize the choice between governance mechanisms, we assume that the firm finds it optimal to deter private benefits. Otherwise, its optimal governance structure involves neither monitoring ($\Delta_B^* = 0$) nor incentive pay ($W_H^* = W_L^* = W_0^*$).[11] The firm and the manager are risk-neutral and have a common discount factor of 1. Table 2 summarizes the model's timing.

Table 2: Summary of Model Timing

$t = 0$	The firm sets the monitoring and compensation policies, Δ_B and $W(Q)$. The manager chooses whether to extract private benefits and pursue socially costly production.
$t = 1$	The firm's output and externalities, if any, are realized. The manager receives pay $W(Q)$ and private benefits, if any.

2.1 Governance Mechanisms

We begin by characterizing incentive compatibility for the manager and highlighting the inherent tension between deterring the "quiet life" through incentive pay and limiting social costs. For notational convenience, let $W(q_i) = W_i$, which specifies the manager's pay when the firm's output is high ($i = H$), low ($i = L$), and zero ($i = 0$). Given the firm's compensation and monitoring policies (W_H, W_L, W_0, Δ_B), the manager's incentive-compatibility (IC)

[9] Internet Appendix IA.3 provides additional details for this extension.

[10] One can also formulate this tension with a multi-tasking model (e.g., see Holmstrom and Milgrom, 1991; Bénabou and Tirole, 2016). This traditional approach emphasizes the convexity of total effort costs: higher bonuses per unit of production incentivize more production effort, increasing the marginal cost of workplace safety efforts. In contrast, our framework highlights the convexity of the social cost of production (e.g., see Internet Appendix Section IA.1). The incentive for socially costly production comes from the *structure* of production bonuses rather than their *level*.

[11] When deterring private benefits is not a given, the different governance mechanisms may be complements rather than substitutes (e.g., see Hartzell and Starks, 2003; Cronqvist and Fahlenbrach, 2008). When managerial effort is not optimal, the firm does not use either governance mechanism. When managerial effort becomes optimal, the firm uses some combination of both.

constraint is

$$\begin{aligned}
&\underbrace{\Big((1-\eta)+\eta x\Big)(p-p_H)W_H+\eta(1-x)(p-p_L)W_L}_{\text{extra pay due to effort}} \\
\geq \quad &\underbrace{(B-\Delta_B)}_{\text{private benefits of shirking}} \quad + \underbrace{\Big(p-\Big((1-\eta)+\eta x\Big)p_H-\Big(\eta(1-x)\Big)p_L\Big)}_{\text{extra chance of zero output when shirking}} W_0.
\end{aligned} \tag{1}$$

Additionally, the manager avoids socially costly production ($x=0$) if and only if

$$\begin{aligned}
(1-\eta)pW_H+\eta pW_L+(1-p)W_0 \geq\ & pW_H+(1-p)W_0 \\
W_L \geq\ & W_H.
\end{aligned} \tag{2}$$

We refer to (2) as the manager's social-compatibility (SC) constraint. The SC constraint implies that contracts with high–powered incentives ($W_H > W_L$) induce socially costly production. Avoiding such production practices requires contracts that flatten incentives.

Lemma 1: The lowest-cost, IC managerial contract is

$$W_H = \frac{1}{p}\left(\frac{B-\Delta_B}{1-\phi_H^{-1}}\right) > W_L = W_0 = 0,$$

where $\phi_H = \frac{p}{p_H}$ is the likelihood ratio associated with high output ($Q = q_H$).

The monotone likelihood ratio property implies that high output is associated with the maximum likelihood ratio. Following standard optimal contracting arguments, the lowest-cost IC contract only pays the manager for high output, implying that it is high-powered ($W_H > W_L$). The expected cost of this high-powered compensation contract is

$$A_H = \frac{B-\Delta_B}{1-\phi_H^{-1}}.$$

Paying the manager more for high output than for low output reduces the cost of satisfying the manager's IC constraint (1), but violates the SC constraint (2). Thus, the very feature that minimizes incentive costs—high-powered incentives—induces socially costly production.

Lemma 2: The lowest-cost compensation contract that satisfies both IC and SC is

$$W_H = W_L = \frac{1}{p}\left(\frac{B-\Delta_B}{1-\phi_L^{-1}}\right) > W_0 = 0,$$

where $\phi_L = \frac{p}{p_H(1-\eta)+p_L\eta}$ is the likelihood ratio associated with positive output ($Q > 0$).

The IC constraint (1) requires that compensation reward positive output. The SC constraint (2) further requires equal pay for high and low output. Together, these imply that the firm punishes the manager most for generating no output ($W_0 = 0$), while providing equal low-powered incentives for positive output ($W_H = W_L > 0$). The payment for generating positive output ($Q = q_H$ or $Q = q_L$) binds the IC constraint (1). The expected cost of this low-powered compensation contract is

$$A_L = \frac{B - \Delta_B}{1 - \phi_L^{-1}}.$$

The production technology's monotone likelihood ratio property implies that $\phi_L < \phi_H$. Hence, high-powered incentives are less costly than low-powered ones: $\Delta_A = A_L - A_H > 0$. However, this reduction in the cost of providing incentives comes at the expense of additional social costs, which the firm's owners partially internalize through the monetary penalty m.

Lemma 3: High-powered incentives and direct monitoring are substitutes.

Both monitoring and high-powered contracting mitigate managerial moral hazards: employing one governance mechanism lessens the necessity of the other. Increased monitoring lowers potential private benefits, which decreases the incentive cost savings associated with high-powered incentives. High-powered incentives lower the probability that the manager receives agency rents, which reduces the marginal benefit of monitoring. Our model's main predictions revolve around the firm's substitution of one governance mechanism for another when their relative costs change.

2.2 Optimal Governance Framework and Firm Policies

Our model generates clear predictions about how relative governance costs shape the firm's governance framework, with significant implications for managerial incentives and production externalities. We begin by characterizing the firm's optimal governance framework as a function of its monitoring costs.

Proposition 1: There exists a threshold $\bar{c} > 0$ such that

- *If $c \leq \bar{c}$ (monitoring is cheap), the optimal governance framework features high monitoring and low-powered incentives:*

$$\Delta_B^* = \frac{1}{(1-\phi_L^{-1})c} \text{ and } W_H^* = W_L^* = \frac{B-\Delta_B^*}{p-(p_H(1-\eta)+p_L\eta)} > W_0^* = 0,$$

- *If $c > \bar{c}$ (monitoring is expensive), the optimal governance framework features low* *monitoring and high-powered incentives:*

$$\Delta_B^* = \frac{1}{(1-\phi_H^{-1})c} \textit{ and } W_H^* = \frac{B-\Delta_B^*}{p-p_H} > W_L^* = W_0^* = 0.$$

Firms with high monitoring costs implement less monitoring and rely on high-powered incentives to discipline the manager. Conversely, firms with low monitoring costs employ more monitoring and use low-powered incentive contracts, limiting socially costly production. Figure 1 illustrates the relationship between the firm's optimal governance framework and its monitoring cost.

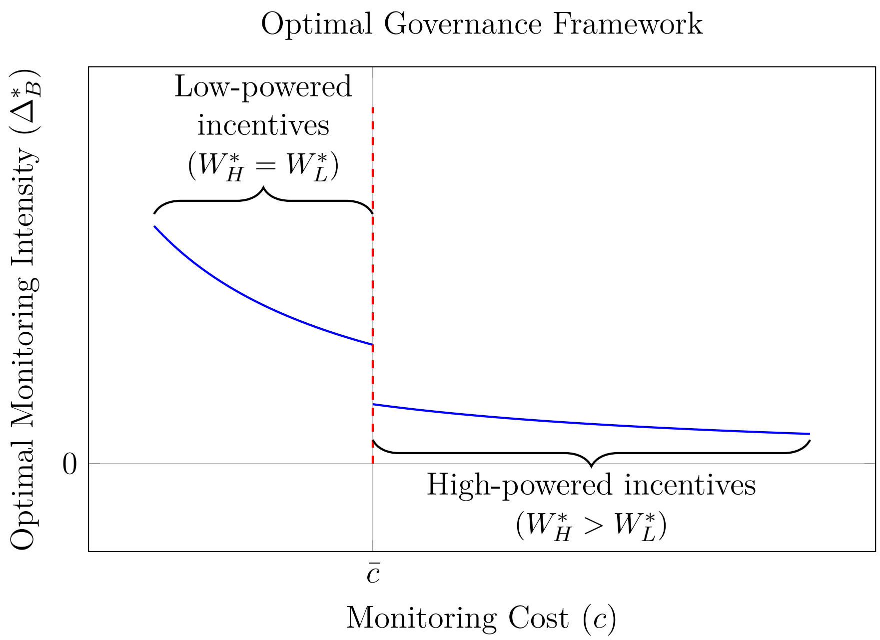


Figure 1: Optimal Governance Framework vs. Monitoring Cost. This figure illustrates the firm's optimal governance framework as a function of its monitoring cost (c). When monitoring costs are low ($c < \bar{c}$), the firm employs a low-powered managerial contract along with a high level of monitoring. An increase in monitoring costs reduces the optimal level of monitoring. At the incentive-monitoring threshold ($\bar{c}$), there is a discrete drop in the optimal level of monitoring accompanied by the switch to a high-powered managerial contract.

Proposition 1 predicts that rising monitoring costs lead to less intensive monitoring and more high-powered incentives, consistent with Piskorski and Westerfield (2016). Related empirical studies find that publicly traded firms rely more heavily on strong incentive contracts than privately held ones, which benefit from more concentrated ownership and lower monitoring costs (Gao and Li, 2015; Ke et al., 1999). Industry reports, such as Aon's 2019 executive compensation survey, highlight negligible differences in base executive salaries for public and private firms but large differences in target bonuses and long-term incentive pay (Strey, 2020).[12] Importantly, our model also predicts that the shift toward high-powered

[12] A shift to high-powered executive incentives following private-to-public transitions, both in terms of the

incentives also induces more socially costly production, underscoring an important but often overlooked consequence of governance changes.

H1: An increase in the cost of monitoring results in an increase in socially costly production.

2.3 Other Governance Factors

Our main hypotheses examine how changes in monitoring costs shape the firm's governance framework and subsequent production externalities. This section considers how other firm-, market-, and regulatory-level factors affect the firm's response to rising monitoring costs.

First, a direct implication of Proposition 1 is that factors that offset the increase in monitoring costs reduce the likelihood of the firm transitioning to high-powered incentives. Intuitively, mitigating factors that help contain monitoring costs increase the distance to the cost threshold ($\bar{c}$), making a transition into a high-powered incentive regime less likely. For instance, the corporate governance literature often emphasizes how the cost of monitoring is reduced in the presence of institutional blockholders (e.g., Shleifer and Vishny, 1986; Edmans, 2014), independent boards (e.g., Hermalin and Weisbach, 1998), and additional signals of managerial effort (e.g., Ferreira et al., 2011). Accordingly, our model generates the following hypotheses:

H2a: Dedicated institutional shareholders attenuate the increase in socially costly production following shocks to monitoring costs.

H2b: Independent boards attenuate the increase in socially costly production following shocks to monitoring costs.

H2c: More informative stock prices attenuate the increase in socially costly production following shocks to monitoring costs.

Second, pecuniary penalties imposed by market participants and regulators influence governance decisions. Strong unions may demand additional hazard pay for deteriorating safety conditions at work. Regulators may impose monetary fines or suspend production when the firm adversely affects society. Other stakeholders may sue for relief. These external governance mechanisms create additional financial consequences for socially costly production.

Proposition 2: A higher pecuniary penalty associated with the negative externality raises the monitoring cost threshold at which the firm adopts high-powered incentives: $\frac{d\bar{c}}{dm} > 0$.

dollar amount of the incentive and the level of the performance metric, appears consistently in our sample when analyzing firms' form S-1s and 10-ks (for examples, see Internet Appendix Section IA.4).

A larger pecuniary penalty compels the firm's owners to internalize more of its externalities. Pecuniary penalties operate like an external monitoring technology, making high-powered incentives less attractive when monitoring costs rise. In other words, larger pecuniary penalties mitigate the agency problem between the firm's owners and its other stakeholders. Proposition 2 generates the following prediction in our setting:

H3: The increase in socially costly production following shocks to monitoring costs is less pronounced when firms face larger pecuniary penalties for negative externalities, such as increased legal liability, hazard pay, and regulatory fines.

Together, H2 and H3 highlight how both internal governance mechanisms (ownership structure, board independence, and information environments) and external enforcement mechanisms (pecuniary penalties) shape whether rising monitoring costs translate into socially costly production. Internal mechanisms contain monitoring costs directly, while external penalties raise the effective cost of socially costly production to the firm's owners. In both cases, these forces push firms farther from the threshold $\bar{c}$, reducing the likelihood of transitioning into high-powered incentive regimes.

3 Empirical Setup

3.1 Data

Our empirical setting provides an ideal laboratory for testing our model's implications. The Mine Safety and Health Administration (MSHA) collects comprehensive data on coal production quantities and workplace safety for the universe of all U.S. coal mines. Under the Code of Federal Regulations (30 CFR Part 50), all coal mining operators must file mine-level reports on production, safety violations, accidents, injuries, civil penalties, and employment. MSHA also maintains historical records of inspection districts and ultimate ownership.

We augment the mine-level data from MSHA with data from several additional sources. First, we hand-collect data on the public listing status and merger history of a mine's ultimate owner. We verify this data using multiple sources, including firm SEC filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website. Second, to test cross-sectional predictions generated by our model, we collect data on executive compensation from Execucomp, data on institutional ownership from Thomson Reuters Institutional Holdings (13F) database, data on Bushee's (1998) classification of dedicated institutions from Brian Bushee's website, data on boards of directors from BoardEx, data on relative price informativeness (Dávila and Parlatore, 2024) from Eduardo Davila's website, data on unionization at the mine level from the Energy Information Association (EIA), and data on managerial ownership kindly provided by Fabisik et al. (2021).

Finally, for the analysis of coal divestment in Section 6, we supplement our dataset with additional hand-collected information. We obtain NBIM and CalPERS ownership data from their annual investment reports, EBITDA performance targets from firm proxy filings, and thermal versus metallurgical coal classifications from industry sources, such as the Metallurgical Coal Producers Association, as well as public filings. Appendix Table A1 provides definitions and sources for all variables.

3.2 Empirical Measure of Externalities

Prior research has typically focused on measurable *environmental* externalities, such as toxic emissions (Shive and Forster, 2020). Our model, however, predicts that an increase in monitoring costs will likely have minimal impact on such externalities: while the switch to high-powered incentives encourages additional production, due to the emergence of cost-effective abatement technology, the resulting emissions can be abated at low cost. This is consistent with the results in recent studies analyzing toxic emissions across various ownership structures (e.g., Bellon, 2024; Duchin et al., 2024).

In coal mining, by contrast, the threshold for production without imposing additional negative externalities (through a deterioration in workplace safety) is arguably very low. For example, Figure 4 suggests a 60-80% increase in safety violations when mines cross the 50th percentile of production per employee hour. Gowrisankaran et al. (2018) note that progressive digging to produce coal gradually weakens the roof support in underground mines, increasing the potential of a fatal collapse. This feature of the production technology makes the coal mining industry a unique laboratory for studying the trade-off between production and externalities across governance mechanisms.

Following Filer and Golbe (2003) and Cohn et al. (2021), who use Occupational Safety and Health Administration (OSHA) safety violations, we focus on an ex-ante measure of workplace safety.[13] Specifically, we use the number of safety violations MSHA cites for potential accidents. Unlike OSHA violations, which mainly stem from infrequent and irregular inspections, safety violations in coal mining largely result from regular MSHA inspections mandated by Section 103(a) of the Federal Mine Safety and Health Act of 1977. This law requires the inspection of underground mines at least four times per year and surface mines at least twice per year, mitigating concerns about endogeneity in inspection timing.

Finally, the data include MSHA's classification on the probability a violation will cause an

[13] While accidents are almost certainly correlated with ex-ante firm policies, they include a random component that may muddle inferences. Moreover, injuries are often under-reported (Almberg et al., 2018). We nonetheless show consistent results using such ex-post measures in Internet Appendix Table IA1.

accident, which further validates the use of workplace safety in coal mining as an externality measure.[14] In particular, MSHA reserves the high-probability classification for egregious infractions that often immediately suspend production, such as inadequate ventilation systems in underground coal mines. Internet Appendix Table IA2 shows that only high-probability violations are associated with fatalities, arguably the most pressing coal mining externality.

3.3 Empirical Strategy

Our baseline empirical strategy uses private-to-public transitions as an instrument for discrete increases in monitoring costs. These transitions, e.g., IPOs, represent the textbook example of increased oversight costs due to the extreme dispersion of ownership (Pagano and Röell, 1998; Grossman and Hart, 1980; Shleifer and Vishny, 1986). We document an economically and statistically significant reduction in the stake of the controlling shareholder during the IPOs in our sample (e.g., see Figure 3). Specifically, in the subsample where we can clearly measure such a stake using S-1 filings, controlling shareholder ownership drops from 60% to just over 30%, consistent with previous studies (e.g., see Mikkelson et al., 1997; Helwege et al., 2007). Helwege et al. (2007) further show that director and officer ownership continues to fall post-IPO, reaching 20% just five years later.

Importantly, unlike other industries (e.g., Borisov et al., 2021; Bias et al., 2023), the coal sector features relatively stable labor and organizational structures across listing status changes (e.g., see Internet Appendix Table IA3), easing concerns that our results are driven by changes unrelated to monitoring costs. This setting allows us to trace individual asset ownership across listing status changes in a commodity industry where producers are price-takers using similar production technologies.

Moreover, we employ high-dimensional fixed effects to control for unobservable heterogeneity that may impact public listing status, production, and workplace safety:

1. County-by-year fixed effects absorb relevant variations in local coal prices and other time-varying unobservables, such as regional labor supply.
2. Mine fixed effects control for the type of coal being mined, and thus, the expected mine cash flow and investment opportunities, the production technology (e.g., surface versus underground), any organic safety features of the mine (e.g., natural ventilation systems, seam height), and the baseline mine size and reserves.
3. Firm fixed effects absorb time-invariant firm characteristics.

[14] We use slightly different language than MSHA for ease of exposition. MSHA classifies low-probability violations as those "unlikely" to occur and high-probability violations as those "reasonably likely" or "highly likely" to occur. For more information on these classifications and examples of each, see Watkins (2020).

Our identification thus arises from within-firm variation in listing status—through IPOs, going-private transactions, or acquisitions—rather than from cross-sectional differences between public and private firms. Figure 5 displays the prevalence of each of these listing status changes throughout our sample period.[15]

4 Baseline Empirical Results

4.1 Summary Statistics

Table 3 displays the summary statistics for our main sample[16]. It consists of 5,332 coal mines owned by 1,614 ultimate parents (67 that are public at some point in the sample) for a total of 26,151 mine-firm-year observations from 1983 through 2022 for production and employment, and from 1994 through 2022 for safety violations.[17]

The average (median) mine in our sample is cited for 52 (17) safety violations each year and produces just under 700,000 (125,000) short tons of clean coal across 116,560 (45,566) employee hours annually, for an average (median) of 3.45 (2.77) tons of coal per employee hour. Finally, 18% of the mine-year observations in our main sample represent mines owned by a public firm.

4.2 Socially Costly Production (H1)

4.2.1 Production

We begin by examining how mine production changes when its owner transitions from private to public ownership. We measure output as the total short tons of coal produced scaled by the total number of employee hours logged each year. To account for correlation across different mines owned by the same firm, we cluster standard errors at the firm level.

The results for production appear in Models (1) and (2) of Table 4. Model (1) displays the results with the full set of fixed effects but without additional time-varying control variables.

[15] While some transitions cluster in specific years (e.g., ICG's IPO and its acquisition of Horizon Natural Resources, both in 2005), there is significant variation across the sample. Internet Appendix Table IA4 verifies that our results remain similar if we (a) exclude 2005, or (b) exclude all mine-year observations for ICG and Horizon Natural Resources.

[16] We impose the following data filters in our main sample: (1) the mine employs at least 10 workers, (2) the mine produces bituminous coal and is not part of a joint venture, and (3) the ultimate owner of the mine is not foreign, not a sole proprietorship or a partnership, not a private equity firm, and owns at least one other mine (two mines total). There are only 6 PE deals in our sample affecting only private firms and less than 20 mines. Internet Appendix Section IA.5 briefly discusses implications for private equity.

[17] Though the safety violations data also extends back to the late 1980s, the early period is sparse. Based on conversations with MSHA representatives, we focus on a sample of 1994-2022 for safety violations to ensure the highest data quality in our empirical tests.

Model (2) adds the log of total mines owned by the firm and the log of the average number of mine employees as parsimonious controls for time-varying firm and firm scale.

Our key coefficient of interest is on *Public owner*$_{ist}$, which is an indicator variable equal to 1 if mine i's owner, firm s, is publicly listed at time t, and 0 otherwise. The coefficients on *Public owner* are positive and statistically significant at the 1% level in both specifications. The magnitude of the coefficient in Model (2) suggests that upon a private-to-public transition of its owner, a mine increases its coal production per employee hour by 10.5% relative to the sample mean. One way to benchmark the economic magnitude of this result is to consider the reallocation of safety shifts to production shifts required for the observed increase in output following the ownership transition. According to MSHA, the typical mine has one maintenance shift for every three production shifts. Hence, absent additional inputs, a newly public mine would need to reallocate about one in every four maintenance shifts to production to generate a 10.5% increase in output.

Because our identification focuses on within mine and firm changes in public listing status, our specifications are not immune to the criticisms of difference-in-differences specifications under treatment effect heterogeneity (e.g., see Baker et al., 2022; De Chaisemartin and d'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021). However, because our strategy exploits a mine-firm-year panel, implementing the Callaway and Sant'Anna (2021) or Sun and Abraham (2021) estimators would require collapsing the data into a firm-year panel, sacrificing both meaningful variation in the data and a critical part of our identification strategy. Instead, we use a stacked regression (Gormley and Matsa, 2011), which Baker et al. (2022) argue is effective in recovering the true treatment path even under extreme treatment heterogeneity assumptions.

Specifically, we estimate the annual coefficients in the ten-year period around a listing status change interacted with a *treat* variable that is equal to 1 for private-to-public changes and -1 for public-to-private changes, which gives the figure a private-to-public interpretation. We utilize the same specification as Model (1) of Table 4, including the full set of fixed effects, but no time-varying control variables that may also be affected by our treatment (Angrist and Pischke, 2008). Following Gormley and Matsa (2011), we interact the fixed effects from these models with a cohort indicator, as well as an event number indicator for mines that experience multiple listing status changes. Standard errors are clustered at the firm level.

Panel A of Figure 6 shows the estimated dynamic treatment effect for production, providing strong evidence of discrete output changes for mines that experience a listing status change. This figure eases concerns regarding two confounding mechanisms. First, production changes occur during the year of transition and not before—the flat pre-trends support the argument that our results are not driven by selection bias or reverse causality. Second, the production increase persists, even five years post-transition, mitigating concerns that we are simply documenting features of a general ownership change, such as new capital investments that temporarily disrupt operations as employees adjust to new equipment.

4.2.2 Externalities

Next, we analyze the social costs associated with monitoring cost increases. Because our measure of the externality, safety violations, creates a count-dependent variable, we follow the best practice in financial econometrics and use the Poisson-pseudo-maximum likelihood estimator. Cohn et al. (2022) argue that this approach produces consistent estimates under very general conditions, even when including high-dimensional fixed effects.[18] This methodology allows us to employ the full set of fixed effects we used in Models (1) and (2) of Table 4, as well as an additional fixed effect for the MSHA inspection district the mine is assigned to, which captures residual variation due to differences in enforcement across regional regulators. As before, we cluster standard errors at the firm level.

The second half of Table 4 reports the results. Model (3) displays the results with the full set of fixed effects but without additional time-varying control variables. The coefficient on *Public owner* is 0.224 and is significant at the 1% level. Model (4) adds the following additional control variables: the log of total mines owned by the ultimate parent, the log of the average number of mine employees, the log of the total employee hours worked in the mine, and the log of total inspections performed at the mine. The coefficient of interest increases to 0.284 in magnitude and remains significant at the 1% level. This suggests that mines that undergo a private-to-public listing status change experience a $(\exp(0.284) - 1) \times 100 = 33\%$ increase in safety violations. The effect is over three times as large as the increase in production, consistent with our model's prediction that mines crossing the output-externalities threshold experience disproportionately large increases in social costs (see Figure 4). Moreover, Internet Appendix Table IA6 shows similar results when scaling safety violations by total productive output.

Next, we separate the dependent variable (safety violations) by accident probability. Models (5) and (6) of Table 4 report the results for low- and high-probability violations, respectively. While the coefficients on *Public owner* are positive and significant in both models, the economic magnitude of the increase in high-probability violations is 50% larger than it is for low-probability violations (45% versus 29%). These results suggest that violations linked to the most extreme coal mining externalities (e.g., see Internet Appendix Table IA2) increase the most following ownership dispersion.

[18] Internet Appendix Table IA5 verifies that our results are robust to using an OLS model or scaling violations by either safety inspections or employee-hours in a linear rate regression (Cohn et al., 2022).

Panel B of Figure 6 depicts the dynamic treatment effects for safety violations using a Poisson-pseudo-maximum likelihood model inside the stacked regression methodology (Gormley and Matsa, 2011). That is, we follow the same procedure we used in Panel A, but we estimate the interacted annual coefficients around a listing status change with the PPML. Once again, we estimate the model with the full set of fixed effects and no time-varying control variables, as in Model (3) of Table 4. Consistent with the production result, Figure 6 Panel B shows a sharp increase in safety violations at time 0, suggesting the increase in externalities for publicly owned mines happens in the year of the listing status change and not before it. Moreover, there is little evidence of a reversion to the mean in the safety violations, as they remain elevated five years after the listing status change.

Our findings bear some resemblance to the corporate myopia literature, where managers of public firms prioritize short-term outcomes over long-term value. For instance, managers may exploit investor focus on short-term results by boosting immediate production while increasing the likelihood of future mine disasters (e.g., Caskey and Ozel, 2017). Moreover, viewing workplace safety as a type of long-term investment (Cohn et al., 2021), our finding that performance-based pay encourages production at the expense of workplace safety also echoes the underinvestment dynamics in Asker et al. (2015).

However, our governance-based framework differs from conventional corporate myopia frameworks in two important ways. First, our framework does not require that the social costs manifest over long time horizons—only that the firm's owners do not fully internalize them. Internet Appendix Figure IA1 shows that injuries and fatal accidents increase immediately following listing status changes, suggesting that social costs and pecuniary penalties are incurred over a short time horizon.[19] Second, while conventional myopia models typically attribute the firm's suboptimal decision-making to behavioral biases or distorted investor beliefs, our framework emphasizes an externality problem. The firm's owners *rationally* choose a governance framework that maximizes their private payoff, even when this choice increases social costs that are borne by workers, customers, suppliers, or the broader society.

Ultimately, the key distinction between myopia-driven inefficiencies and the governance-driven externalities in our framework is which stakeholders are "left holding the bag." Conventional myopia models emphasize that the firm's future shareholders suffer from its past short-termism (e.g., underinvestment in long-term projects). In contrast, our framework highlights a governance-induced externality, where the burden primarily falls on employees and society more broadly rather than future investors. This distinction has significant impli-

[19]Moreover, Internet Appendix Figure IA2 shows that thermal coal producers' propensity to meet or just beat earnings forecasts does not increase following the divestment of NBIM and CalPERS, which is examined in Section 6. This evidence is also inconsistent with corporate myopia.

cations for potential remedies: while myopia models suggest that firms should be encouraged to adopt a long-term perspective, our results indicate that regulatory intervention—such as stricter penalties—may be necessary for firms to internalize social costs.

5 Cross-Section Empirical Results

This section examines our model's cross-sectional predictions. Due to limited data availability for private firms, we take the following empirical approach for testing the firm-level cross-sectional predictions (Hypotheses *H2* and *H3*) in this section. First, we focus on public firms that IPO during the course of our sample (34 firms). Second, to make inferences regarding how socially costly production varies across different firm characteristics (e.g., external monitoring) before and after IPO, we extrapolate these characteristics to all firm observations (pre- and post-IPO) using the first observable characteristic of the newly public firm. For example, we use the institutional holdings data for the first available quarter after a firm's IPO to be its baseline (stationary) level of institutional ownership. Because we focus only on IPO firms, we include mine fixed effects *interacted* with firm fixed effects, rather than each separately, to fix ownership of each asset to the IPO firm. This approach strengthens our identification strategy by ruling out any confounders due to firm-mine matching effects.

5.1 Model Mechanism: Substitution to High-Powered Incentives

In our model, the trade-off between production and externalities is generated by a moral hazard problem: firms increase high-powered incentives to lower agency rents. Ideally, we would directly investigate this prediction by examining how incentive contracts adjust to post-IPO increases in monitoring costs. However, managerial compensation data are not available for the private firms in our sample.[20] As an alternative, we use managerial bonus contracting in the IPO firms as a proxy for increased reliance on high-powered incentives. Specifically, we create an indicator variable equal to one if the CEO has a non-zero bonus component of total compensation in Execucomp immediately following the IPO.

Table 5 reports the results of interacting the bonus indicator with *Public owner*. Consistent with bonuses (e.g., high-powered incentives) playing an important role in the increase of socially costly production, Models (1) and (4) indicate that ownership dispersion effects on production and high-probability safety violations are concentrated entirely in bonus-using firms.[21] While imperfect, this test reassuringly shows that our main effects are driven by

[20] Section 6 provides a direct test of the substitution to high-powered incentives when monitoring costs increase.

[21] A potential critique of this proxy variable is that it could also imply the firm's owners set the production bonus thresholds unattainably high (also reflecting high-powered incentives), such that the CEO did not

firms that rely on performance-based pay, consistent with the main mechanism in our model.

5.2 Alternative Forms of Monitoring

Hypothesis *H2* and *H3* imply that the increase in socially costly production is attenuated by alternative forms of monitoring, which lessen the severity of the moral hazard problem and reduce the need for high-powered incentives. This subsection analyzes how other firm-, market-, and regulatory-level corporate governance provisions interact with the effects of the monitoring cost increases documented above.

5.2.1 Dedicated Institutional Ownership (H2a)

We test Hypothesis *2a* by examining the role of other large shareholders as the ownership disperses through IPOs. In our model, external shareholders such as institutions mitigate agency problems only to the extent that they lower monitoring costs. If dispersed institutions collectively hold a large percentage of shares, but individually face limited incentives to monitor, the firm will still increase its reliance on high-powered incentives post-IPO, which subsequently encourages socially costly production.

Thus, we focus on dedicated institutional ownership (Bushee, 1998) at the time of IPO. Chen et al. (2007) note that such institutions are much more likely than other investors (e.g., transient institutions) to monitor management, even with relatively small holdings. Table 6 (Panel A) reports the results analyzing an indicator variable that takes a value of 1 if the percentage of dedicated ownership is greater than or equal to the sample 75th percentile (2.82%), and 0 otherwise. Consistent with Hypothesis *2a*, the increase in socially costly production for IPO firms is attenuated when dedicated institutional ownership is high at the time of the IPO, particularly for high-probability safety violations.

Internet Appendix Table IA7 reports results using two continuous measures—total institutional ownership and dedicated institutional ownership—as well as an indicator for any 5% institutional blockholder (Edmans, 2014). Despite limited power, the results for the continuous measure of dedicated institutional ownership and the 5% institutional blockholders indicator are qualitatively similar to those in Table 6 (Panel A). In contrast, we find no attenuation of socially costly production from higher total institutional ownership, suggesting that high institutional holdings alone do not sufficiently lower monitoring costs.

earn the bonus. Based on our readings of firm S-1s and 10-ks, this explanation seems less likely. Moreover, it seems counterintuitive to us that the entirety of production increases at IPO would be driven by firms with low bonus thresholds.

5.2.2 Board Oversight (H2b)

We test Hypothesis *2b* by examining the role of board oversight. Effective boards reduce the reliance on high-powered incentives. We proxy for the effectiveness of the board's monitoring capabilities using independence levels (Hermalin and Weisbach, 1998). In particular, Panel B of Table 6 interacts *Public owner* with an indicator variable that equals one if at least 50% of the board members are classified as independent, and zero otherwise. Consistent with the dedicated institutional ownership results, the increase in socially costly production attenuates significantly in the presence of a highly independent board. These results offer a potential mechanism for why many studies (e.g., Shive and Forster, 2020) find a significant link between measures of board oversight and environmental and social performance.

5.2.3 Informative Stock Price (H2c)

We test Hypothesis *2c* by examining the role of stock price informativeness. A more informative stock price can reduce monitoring costs by providing the board with an additional signal of manager quality and effort (e.g., Ferreira et al., 2011). Such a reduction in monitoring costs reduces the need for high-powered incentives, which can result in socially costly production in our framework. We use the relative price informativeness measure from Dávila and Parlatore (2024). Specifically, Panel C in Table 6 analyzes the interaction between public ownership and an indicator variable that equals one if relative price informativeness exceeds the sample 75th percentile (3.46%).[22] Consistent with Hypothesis *2c*, a more informative stock price significantly dampens socially costly production in our sample.

Overall, the results in Sections 5.2.1, 5.2.2, and 5.2.3 suggest that the interaction between ownership structure and other governance provisions has meaningful implications for the social costs of production.

5.2.4 Pecuniary Externality Costs (H3)

Finally, we explore Hypothesis *H3*, which predicts that the increase in socially costly production by public firms is less pronounced when the pecuniary costs of the externality are higher. Higher monetary penalties could reflect increases in reputation costs, heightened legal liability and hazardous pay, or additional scrutiny from stakeholders or regulators. We focus on two such sources of external governance: regulatory scrutiny and the presence of a strong labor union, which proxies for market-level governance provisions.

For regulatory scrutiny, we calculate the mean number of spot (nonroutine) inspections performed at mines in the MSHA inspection district *not* owned by the firm of interest over

[22] Internet Appendix Table IA8 reports similar results using the probability of informed trading (PIN).

the previous year ($t-1$).[23] That is, we focus on the average number of spot inspections at peer mines. Intuitively, this measure should track time-varying levels of enforcement across the inspection district. Furthermore, such a measure should reflect an unbiased measure of expected enforcement at the mine of interest at time t, without contamination from the production and externality policies of the mine's owner.

Panel A of Table 7 reports the results of the interaction between *Public owner* and *Mean spot inspections*. Consistent with Hypothesis *H3*, increased levels of mean spot inspections dampen socially costly production. For example, Model (2) suggests that an additional spot inspection per peer mine reduces the level of all safety violations cited to public firms by over 12%, an effect that is significant at the 1% level.

In Panel B of Table 7, we focus on scrutiny from one particularly strong labor union in the coal industry: United Mine Workers of America (UMWA) (e.g., see Morantz, 2013). Following Boal and Pencavel (1994), we hypothesize that the strength of UMWA should give workers additional bargaining power in wage negotiations, increasing the elasticity of wages with respect to safety and, thus, the monetary penalty of the externality. Specifically, we interact *Public owner* with an indicator variable equal to 1 if the mine is unionized by UMWA in year t, and 0 otherwise. Consistent with Hypothesis *H3*, these interacted coefficients are negative and statistically significant for both production and safety violations.

6 Coal Divestment Initiatives

A key concern with our baseline results is that monitoring cost increases during listing status transitions may not be random. For example, firms may decide to go public (IPO) precisely when they know they have high-quality managers, or in response to changing firm characteristics. To address this concern, we exploit plausibly exogenous shocks to monitoring costs induced by the politically motivated coal divestment initiatives imposed on two prominent institutional investors—California Public Employees' Retirement System (CalPERS) and Norges Bank Investment Management (NBIM).

CalPERS and NBIM are widely regarded as two of the most involved and influential institutions in the world.[24] For example, in 2023, CalPERS voted in 9,000 shareholder meetings (California Public Employees' Retirement System, 2024) and NBIM voted in nearly 12,000

[23]Unlike Liang et al. (2023), we find no discernible differences in regulatory scrutiny between publicly and privately owned mines.

[24]Moreover, the two funds have enormous portfolio footprints. In particular, CalPERS is the largest pension fund in the U.S., with just over \$500 billion in AUM as of June 2024, and NBIM is the manager of the world's largest sovereign wealth fund, the Government Pension Fund Global (GFPG) of Norway, with just under \$1.7 trillion in AUM as of February 2024. As of 2009, both CalPERS and NBIM had holdings in 92% of the public firms in our sample.

meetings and had over 3,000 meetings with its portfolio companies (Norges Bank Investment Management, 2024). Importantly, both institutions have long track records of activism on structural governance issues, such as executive compensation, board composition, and shareholder rights (e.g., see Smith, 1996; Wahal, 1996; Fahlenbrach et al., 2024; Aguilera et al., 2024). Hence, their forced exit represents a significant increase in the costs of managerial oversight, which is plausibly exogenous to the portfolio firms.

In the mid-2010s, both institutions faced mandates from their regulators—CalPERS from the state of California and NBIM from the Ministry of Finance in Norway—to liquidate their holdings in certain coal firms.[25] In particular, because these divestment initiatives were motivated by *environmental* concerns associated with climate change, rather than financial, governance, or social considerations, they focused only on producers of thermal coal.[26] Specifically, in May of 2015, Norwegian political parties agreed that NBIM would sell GPFG holdings in 122 firms worldwide that derive 30% or more of their income from thermal coal. Similarly, in September of 2015, California passed SB 185, which required CalPERS to divest its investments in coal companies generating at least 50% of total revenue from thermal coal. Importantly, metallurgical (met) coal firms were unaffected, creating a natural control group for our analysis.

Panel A of Figure 7 shows the average aggregate ownership of CalPERs and NBIM for the public firms in our sample from 2010 to 2020. The average holdings prior to 2015 hovered between 0.8% and 1.0%, in line with studies such as Wahal (1996) and Chiu et al. (2025). Consistent with the goal of the divestment initiatives, there is a sharp drop in these holdings starting in 2015. However, Panel B shows that the decline is driven nearly entirely by the average holdings in thermal coal producers. In contrast, the holdings in met coal producers remained elevated through 2020.[27]

We exploit the features of these divestment initiatives to employ two sets of difference-in-differences (DiD) estimators. First, because CalPERS and NBIM invested so thoroughly in the public firms in our sample prior to 2015 (92%), we use public listing status as the

[25]Though the mandates were not imposed until 2015, evidence suggests that both funds were aware of the pending regulations in 2014 (Siders and Ortiz, 2014). This is consistent with a small amount of divestment in late 2014 and early 2015 as the funds likely tried to avoid large losses due to price pressure.

[26]Thermal coal is significantly more harmful to the environment as it is burned in large quantities to produce energy. In addition to carbon dioxide (CO_2), the burning of thermal coal also releases high amounts of sulfur dioxide (SO_2), nitrogen oxide (NO_2), and particulate matter, contributing to air pollution and climate change. Metallurgical (coking) coal, in contrast, is used in relatively limited quantities to facilitate the smelting process in steel production.

[27]Internet Appendix Figure IA3 shows trends in aggregate institutional ownership for thermal coal firms relative to met coal firms and conglomerates in our sample. Consistent with the argument that the divestments removed monitoring institutions, dedicated ownership declines significantly. Transient and non-classified ownership, on the other hand, increase slightly, likely reflecting a reallocation among institutions.

treatment variable and interact it with an indicator variable equal to one if the year is greater than or equal to 2015. The intuition behind these DiD models is that the private firms in our sample were not affected by the CalPERS and NBIM divestments, and thus were subject to stable monitoring costs in this period.[28] We analyze both production and safety violations over a sample period of 2010 through 2022 and include mine-by-firm and county-by-year fixed effects. We continue to cluster our standard errors at the firm level.

Table 8 reports the results. Columns (1) and (3) indicate that both production and safety violations increase significantly for public firms following the coal divestment initiatives imposed on CalPERS and NBIM. In particular, the coefficients on *Public owner* $\times$ *I(Year* $\geq$ *2015)* in both models are significant at the level 1%. Figure 8 depicts the dynamic treatment effects for both production (Panel A) and safety violations (Panel B). Both panels show sharp increases in the year 2015 with flat pretrends in the early 2010s.

Second, to sharpen our identification and better exploit the nature of the divestment initiatives, Models (2) and (4) in Table 8 leverage a triple difference-in-differences setup by adding an interaction with an indicator variable equal to one if the firm is a thermal coal producer. Consistent with the divestment mandates from the state of California and the Norwegian Ministry of Finance, only public thermal coal producers experienced an increase in production and safety violations following 2015. Specifically, the coefficients on *Public owner* $\times$ *I(Year* $\geq$ *2015)* $\times$ *I(Thermal Coal Firm)* are both significant at the 5% level and represent large economic increases in production and safety violations for the affected firms.[29] Internet Appendix Table IA10 shows similar results using EBITDA as the measure of performance.

The main identifying assumption in our DiD models is that CalPERS and NBIM were forced to divest for environmental reasons, and that their exit represented a loss of active monitoring, rather than simply a deprioritization of workplace safety. Several facts and results support this assumption. First, both funds historically opposed divestment as a strategy. For example, CalPERS strongly opposed SB 185, stating "we firmly believe engagement is the first call of action, and results show that it is the most effective form of communicating concerns with the companies we own" (Siders and Ortiz, 2014). More generally, CalPERS is guided by the principle that "divestment conflicts with fiduciary duty" (California Public Employees Retirement System, 2017). Similarly, NBIM has called divestment a "last resort."

[28]While CalPERS likely had a small percentage of ownership in private firms through their private equity portfolio, NBIM is restricted from investing in private firms.

[29]Internet Appendix Table IA9 shows similar results when separately using the approximate holdings of CalPERS and NBIM that we construct from the combination of 13f data and investor reports published by the funds. Moreover, the findings indicate that the results are not driven by just one of the divestments, but rather both played a role in the increase in socially costly production.

Second, while both funds have long demonstrated interest in sustainable investment, their focus has been on environmental issues rather than social ones. To formalize the argument that NBIM and CalPERS had no apparent financial or social reasons for divesting from thermal coal producers, Internet Appendix Figure IA4 plots pre-trends for thermal vs. met coal producers leading up to the divestment in 2015. In particular, the figure analyzes trends in production, safety violations, operating performance, and investment opportunities, among other things. Each panel shows flat pre-trends and insignificant differences between thermal and met coal producers prior to the 2015 divestment. Moreover, we report cross-sectional analyses in Internet Appendix Table IA11 that show thermal coal producers do not significantly differ from met coal producers on any measurable safety dimensions, such as injuries or fatal accidents.

Third, the sum of post-2015 outcomes is consistent with a broad loss of monitoring rather than a narrow deemphasis of workplace safety. If the divestment simply led firms to neglect safety while maintaining other governance practices, we would expect safety violations to increase in isolation. Instead, Internet Appendix Table IA10 documents significant increases in discretionary accruals and self-reported internal control weaknesses for public thermal coal producers relative to their met coal counterparts, indicating a deterioration across broad governance dimensions following the forced exit of large governance-focused shareholders. While no set of evidence can unequivocally satisfy a model's identifying assumptions, these results provide reassurance that the divestment initiatives were driven primarily by environmental concerns and resulted in an exogenous increase in monitoring costs, rather than a weakening of workplace safety concerns.

Finally, we further test our model's mechanism using hand-collected EBITDA performance targets from proxy filings. Our model predicts substitution from monitoring to high-powered incentives following the shock. Panel A of Figure 9 shows that average thresholds remain stable around \$500 million from 2010 to 2020. Figure 9 Panel B plots log EBITDA targets for thermal versus metallurgical producers using firm and year fixed effects, and Internet Appendix Table IA10 Model (4) reports the DiD coefficient. Despite the small sample (22 firms), the results are striking: thermal coal producers show a sharp 60% increase in performance thresholds following divestment, consistent with our framework. This increase reflects intensive margin adjustments, as all sample firms employed EBITDA threshold bonuses both before and after divestment.

Taken together, these findings confirm our baseline analysis and strengthen the causal interpretation of our results. Moreover, they provide direct empirical support for our model's main mechanism: higher monitoring costs trigger a shift toward stronger performance-based incentives, resulting in more socially costly production.

7 Alternative Explanations and Robustness

The primary concern with our baseline empirical strategy is that private-to-public transitions often coincide with many changes that can impact both production decisions and externalities (e.g., the relaxation of financial constraints (Brav, 2009)). To further support our proposed mechanism—increased monitoring costs through ownership dispersion—and rule out potential alternatives, we conduct four sets of robustness tests.

First, we examine whether our results are concentrated in firms that arguably had the largest dispersion in ownership as a result of the IPO. Using managerial ownership data kindly provided by Fabisik et al. (2021), we assume that firms with lower initial managerial ownership (post-lockup period) had a greater dispersion of total ownership during the IPO process. To validate this assumption, we hand-collect the stake of the controlling shareholder pre- and post-IPO for the firms in our sample, where we cleanly observe both the form S-1 prior to the IPO and the firm's first proxy statement following the lockup period. The correlation between the controlling shareholder's stake reduction and the first observed managerial ownership is -0.61, suggesting that initial managerial ownership captures meaningful ownership dispersion. Panel B of Figure 3 reflects this relationship, as only firms with low initial managerial ownership experience a statistically significant dispersion in ownership.

Table 9 reports results that interact the *Public owner* variable with an indicator variable equal to one if the initial percentage of shares held by directors and officers is less than 25%.[30] Consistent with our model's predictions, the results suggest that the increase in socially costly production is entirely concentrated in firms that experienced the greatest ownership dispersion and, thus, the largest increase in monitoring costs through the IPO.

Second, we re-estimate our baseline models for safety violations with an interaction term between *Public owner* and the coal production per employee hour at mine i in year $t-1$. Table 10 reports the results. If ramping up production unequivocally leads to the generation of externalities, we would expect that all firms should experience more safety violations following high production. However, on average, production appears to have no general effect on externality creation. For example, the coefficient on *Production/hour* in Model (1) is 0.00 with a standard error of 0.007. Moreover, the effect for private firms is *negative*, though insignificant. These results are consistent with private firms operating below the output-externalities threshold. On the contrary, public firms with high output generate significantly

[30] 25% is, admittedly, ad hoc. However, the sample 75th percentile for managerial ownership is only 3.8%. Nonetheless, we verify that our results are robust to other cutoffs, e.g., 5% or 10%, or simply using a continuous measure of managerial ownership (Internet Appendix Table IA12). Moreover, Internet Appendix Table IA13 shows similar results for production and high-probability safety violations when analyzing the controlling shareholder stake reduction directly.

more safety violations, particularly those that are deemed most severe. These results suggest that a firm's ownership structure influences its imposition of negative externalities through the way it uses the production technology rather than its scale.

Third, Panel A of Table 11 interacts the public ownership indicator with an indicator for high initial leverage for firms that go public during our sample. In this context, the public firm's initial market leverage serves as a proxy for the financial constraints of the private firm (Cohn and Wardlaw, 2016; Lang et al., 1996; Denis and Denis, 1993). Model (1) shows a positive but insignificant additional effect on production for the group of firms that most likely experienced alleviation of financial constraints upon IPO, consistent with some marginal benefits of capital infusion generally. However, Models (2) through (4) suggest that the additional capital from equity markets leads to an improvement in workplace safety for the most constrained firms pre-IPO, which is consistent with Cohn and Wardlaw (2016), who show that financially constrained firms cut safety investment. Internet Appendix Table IA14 shows similar results using a continuous measure of market leverage. Panel B of Table 11 analyzes the subsample of only public-to-private ownership transitions. While it is natural to assume that private-to-public transitions alleviate financial constraints, the opposite is not necessarily true. That is, it is much less obvious that public-to-private transitions *create* financial constraints. Panel B shows results that are quantitatively and qualitatively similar to our baseline findings in Table 4.

Finally, recent productive output and the nature of workplace environments could influence the timing of ownership transitions. For example, firms may attempt to capitalize on periods of strong safety performance to maximize investor demand during road shows. However, each mine makes up only a portion of the company's assets and, thus, is unlikely to drive a listing status change or acquisition decision all on its own. This is particularly true for mines that make up very small portions of the firm's asset portfolio. Internet Appendix Table IA15 verifies our results remain strong and significant in a subsample with mines that account for less than 15% of the firm's total coal production.

8 Conclusion

We study the impact of corporate governance on production externalities. Our framework illustrates how firms respond to increases in the cost of monitoring-based mechanisms by increasing their reliance on strong performance-based incentives, which drive higher production but also elevate social costs. We document empirical evidence consistent with our model's predictions using granular asset-level data from the U.S. coal industry and an identification strategy based on private-public transitions and coal divestment initiatives imposed on prominent activist institutional investors.

These findings suggest that internal governance frameworks focused on firm value may not always result in production decisions that maximize societal welfare—particularly in industries where even modest increases in production intensity can result in significant social costs. While our results do not directly quantify the extent to which firms overproduce relative to the societal optimum, they do provide some policy guidance. For instance, our results suggest that regulators should recognize that governance structures influence not only firm value but also social welfare. Policies promoting stronger external oversight of management could also better align the interests of the firm's owners with those of the broader society. Additionally, regulators concerned with the firm's social costs should account for its incentives to shift costs onto other stakeholders, perhaps by strengthening penalties for violations or enhancing worker protections to ensure firms internalize a greater portion of their social costs.

By highlighting a fundamental tension between mitigating managerial moral hazards and limiting social costs, our work advances the understanding of the trade-offs between monitoring-based and incentive-based governance mechanisms and how corporate governance affects firms' production externalities. It provides important context for the recent trend in ESG-driven divestment initiatives. These policies, which are designed to improve environmental and social performance, may paradoxically induce governance changes that result in more negative externalities from production. Our findings suggest that concerned stakeholders should consider complementary strategies that ensure robust governance mechanisms remain in place even after divestment.

References

Aguilera, R. V., V. J. Bermejo, J. Capapé, and V. Cuñat. 2024. The systemic governance influence of expectation documents: evidence from a universal owner. *Review of Corporate Finance Studies*, Forthcoming.

Akey, P., and I. Appel. 2021. The Limits of Limited Liability: Evidence from Industrial Pollution. *Journal of Finance* 76 (1):5–55.

Almberg, K. S., L. S. Friedman, D. Swedler, and R. A. Cohen. 2018. Mine Safety and Health Administration's Part 50 program does not fully capture chronic disease and injury in the Illinois mining industry. *American Journal of Industrial Medicine* 61:436–443.

Angrist, J. D., and J.-S. Pischke. 2008. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Asker, J., J. Farre-Mensa, and A. Ljungqvist. 2015. Corporate investment and stock market listing: A puzzle? *Review of Financial Studies* 28:342–390.

Baker, A. C., D. F. Larcker, and C. C. Wang. 2022. How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics* 144:370–395.

Bellon, A. 2024. Does Private Equity Ownership Make Firms Cleaner? The Role Of Environmental Liability Risks. *Review of Financial Studies*, Forthcoming.

Bénabou, R., and J. Tirole. 2016. Bonus culture: Competitive pay, screening, and multitasking. *Journal of Political Economy* 124:305–370.

Bertrand, M., and S. Mullainathan. 2003. Enjoying the Quiet Life? Corporate Governance and Managerial Preferences. *Journal of Political Economy* 111:1043–1075.

Beyer, D. 2022. The Economic Toll of the Opioid Crisis Reached Nearly $1.5 Trillion in 2020. U.S. Congress Joint Economic Committee (JEC) Costs of Opiods Issue Brief. URL https://www.jec.senate.gov/public/index.cfm/democrats/2022/9/the-economic-toll-of-the-opioid-crisis-reached-nearly-1-5-trillion-in-2020.

Bias, D., B. Lochner, S. Obernberger, and M. Sevilir. 2023. Going Public and the Internal Organization of the Firm. Working paper, Vanderbilt University.

Boal, W. M., and J. Pencavel. 1994. The Effects of Labor Unions on Employment, Wages, and Days of Operation: Coal Mining in West Virginia. *Quarterly Journal of Economics* 109:267–298.

Borisov, A., A. Ellul, and M. Sevilir. 2021. Access to public capital markets and employment growth. *Journal of Financial Economics* 141:896–918.

Brav, O. 2009. Access to Capital, Capital Structure, and the Funding of the Firm. *Journal of Finance* 64:263–308.

Bushee, B. J. 1998. The Influence of Institutional Investors on Myopic R&D Investment Behavior. *The Accounting Review* 73:305–333.

California Public Employees Retirement System. 2017. CalPERS and Divestment: Reviewing Policy, Costs, and Impacts. Tech. rep.

California Public Employees' Retirement System. 2024. CalPERS Proxy Voting: Global Company Accountability for Climate Change, Board Independence, and Executive Compensation. Tech. rep., California Public Employees' Retirement System.

Callaway, B., and P. H. Sant'Anna. 2021. Difference-in-differences with multiple time periods. *Journal of Econometrics* 225:200–230.

Caskey, J., and N. B. Ozel. 2017. Earnings expectations and employee safety. *Journal of Accounting and Economics* 63:121–141.

Chen, A., D. Gupta, and J. Starmans. 2024. Sustainable Investing and Market Governance. Working paper, Stockholm School of Economics.

Chen, X., J. Harford, and K. Li. 2007. Monitoring: Which institutions matter? *Journal of Financial Economics* 86:279–305.

Chiu, T.-T., X. Li, R. Nandy, and S. Traini. 2025. The Value of Dissent: Market Reaction to Voting Intention Disclosures. Working paper, NHH Norwegian School of Economics.

Cohn, J., N. Nestoriak, and M. Wardlaw. 2021. Private Equity Buyouts and Workplace Safety. *Review of Financial Studies* 34:4832–4875.

Cohn, J. B., Z. Liu, and M. I. Wardlaw. 2022. Count (and count-like) data in finance. *Journal of Financial Economics* 146:529–551.

Cohn, J. B., and M. I. Wardlaw. 2016. Financing Constraints and Workplace Safety. *Journal of Finance* 71:2017–2058.

Cronqvist, H., and R. Fahlenbrach. 2008. Large shareholders and corporate policies. *The Review of Financial Studies* 22:3941–3976.

Dávila, E., and C. Parlatore. 2024. Identifying Price Informativeness. *Review of Financial Studies*, Forthcoming.

De Chaisemartin, C., and X. d'Haultfoeuille. 2020. Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review* 110:2964–2996.

Décaire, P. H., and D. Sosyura. 2022. Self-Dealing in Corporate Investment. Working paper, Arizona State University.

Denis, D. J., and D. K. Denis. 1993. Managerial discretion, organizational structure, and corporate performance: A study of leveraged recapitalizations. *Journal of Accounting and Economics* 16:209–236.

Dorman, P. 2012. Estimating the economic costs of occupational injuries and illnesses in developing countries: Essential information for decision-makers. ILO.

Duchin, R., J. Gao, and Q. Xu. 2024. Sustainability or Greenwashing: Evidence From the Asset Market for Industrial Pollution. *Journal of Finance*, Forthcoming.

Edmans, A. 2014. Blockholders and Corporate Governance. *Annual Review of Financial Economics* 6:23–50.

Edmans, A. 2023. The end of ESG. *Financial Management* 52:3–17.

Edmans, A., T. Gosling, and D. Jenter. 2024. Sustainable investing: Evidence from the field. European Corporate Governance Institute - Finance Working Paper No. 1028/2024.

Fabisik, K., R. Fahlenbrach, R. M. Stulz, and J. P. Taillard. 2021. Why are firms with more managerial ownership worth less? *Journal of Financial Economics* 140:699–725.

Fahlenbrach, R., N. Rudolf, and A. Wegerich. 2024. Leading by Example: Can One Universal Shareholder's Voting Pre-Disclosure Influence Voting Outcomes? European Corporate Governance Institute - Finance Working Paper No. 958/2024.

Ferreira, D., M. A. Ferreira, and C. C. Raposo. 2011. Board Structure and Price Informativeness. *Journal of Financial Economics* 99:523–545.

Filer, R. K., and D. L. Golbe. 2003. Debt, Operating Margin, and Investment in Workplace Safety. *Journal of Industrial Economics* 51:359–381.

Gao, H., and K. Li. 2015. A comparison of CEO pay–performance sensitivity in privately-held and public firms. *Journal of Corporate Finance* 35:370–388.

Goodchild, M., N. Nargis, and E. Tursan d'Espaignet. 2018. Global economic cost of smoking-attributable diseases. *Tobacco Control* 27:58–64.

Goodman-Bacon, A. 2021. Difference-in-differences with variation in treatment timing. *Journal of Econometrics* 225:254–277.

Gormley, T. A., and D. A. Matsa. 2011. Growing out of trouble? Corporate responses to liability risk. *Review of Financial Studies* 24:2781–2821.

Gowrisankaran, G., C. He, E. A. Lutz, and J. L. Burgess. 2018. Productivity, safety, and regulation in underground coal mining: Evidence from disasters and fatalities. NBER Working Paper No. 21129.

Graham, J. R., J. Grennan, C. R. Harvey, and S. Rajgopal. 2022. Corporate culture: Evidence from the field. *Journal of Financial Economics* 146:552–593.

Green, D., and B. Vallee. 2024. Measurement and Effects of Bank Exit Policies. *Journal of Financial Economics*, Forthcoming.

Grossman, S. J., and O. D. Hart. 1980. Takeover bids, the free-rider problem, and the theory of the corporation. *The Bell Journal of Economics* pp. 42–64.

Hart, O., and L. Zingales. 2017. Companies Should Maximize Shareholder Welfare Not Market Value. *Journal of Law, Finance, and Accounting* 2:247–275.

Hartzell, J. C., and L. T. Starks. 2003. Institutional Investors and Executive Compensation. *Journal of Finance* 58:2351–2374.

He, Y. E., B. Kahraman, and M. Lowry. 2023. ES Risks and Shareholder Voice. *Review of Financial Studies*, Forthcoming.

Helwege, J., C. Pirinsky, and R. Stulz. 2007. Why Do Firms Become Widely Held? An Analysis of the Dynamics of Corporate Ownership. *Journal of Finance* 62:995–1028.

Hermalin, B. E., and M. S. Weisbach. 1998. Endogenously chosen boards of directors and their monitoring of the CEO. *American Economic Review* pp. 96–118.

Holmstrom, B., and P. Milgrom. 1991. Multitask principal–agent analyses: Incentive contracts, asset ownership, and job design. *Journal of Law, Economics, and Organization* 7:24–52.

Isikoff, M. 1984. Community Faces Economic Impact Of Mine Disaster. *Washington Post* .

Jensen, M. 1986. Agency Cost of Free Cash Flow, Corporate Finance, and Takeovers. *American Economic Review* 76:323–32.

Karpoff, J. M., R. Litan, C. Schrand, and R. L. Weil. 2022. What ESG-Related Disclosures Should the SEC Mandate? *Financial Analysts Journal* 78:9–18.

Ke, B., K. Petroni, and A. Safieddine. 1999. Ownership Concentration and Sensitivity of Executive Pay to Accounting Performance Measures: Evidence from Publicly and Privately-Held Insurance Companies. *Journal of Accounting and Economics* 28:185–209.

Kent, C. A. 2016. *The Cruel Coal Facts: The Impact on West Virginia Counties from the Collapse of the Coal Economy*. Report for the National Association of Counties. URL https://www.marshall.edu/cber/files/2021/04/2016-09-Cruel_Coal.pdf.

Kothari, S., A. Leone, and C. Wasley. 2005. Performance matched discretionary accrual measures. *Journal of Accounting and Economics* 39:163–197.

Lang, L., E. Ofek, and R. M. Stulz. 1996. Leverage, investmcmt, and firm growth. *Journal of Financial Economics* 40:3–29.

Leigh, J. P., S. Markowitz, M. Fahs, and P. Landrigan. 2000. *Costs of Occupational Injuries and Illnesses*. University of Michigan Press.

Liang, C. Y. C., Y. Qi, R. A. Zhang, and H. Zhu. 2023. Does Sunlight Kill Germs? Stock Market Listing and Workplace Safety. *Journal of Financial and Quantitative Analysis* 58:1645–1674.

McAteer, J. D., K. Beall, J. A. Beck, Jr., P. C. McGinley, C. Monforton, D. C. Roberts, B. Spence, and S. Weise. 2011. *Upper Big Branch: The April 5, 2010, Explosion: A Failure of Basic Coal Mine Safety Practices*. Report to the Governor. Governor's Independent Investigation Panel. URL https://media.npr.org/documents/2011/may/giip-massey-report.pdf.

Mikkelson, W. H., M. Megan Partch, and K. Shah. 1997. Ownership and operating performance of companies that go public. *Journal of Financial Economics* 44:281–307.

Morantz, A. D. 2013. Coal Mine Safety: Do Unions Make a Difference? *Industrial and Labor Relations Review* 66:88–116.

Morgan, J., and J. Tumlinson. 2019. Corporate Provision of Public Goods. *Management Science* 65:4489–4504.

Norges Bank Investment Management. 2024. Responsible Investment 2024. Tech. rep., Government Pension Fund Global, Oslo, Norway.

O'Hare, J. 2022. Don't Forget the "G" in ESG: The SEC and Corporate Governance Disclosure. *Arizona Law Review* 64:417–462.

Pagano, M., and A. Röell. 1998. The Choice of Stock Ownership Structure: Agency Costs, Monitoring, and the Decision to Go Public. *Quarterly Journal of Economics* 113:187–225.

Pastor, L., R. F. Stambaugh, and L. A. Taylor. 2024. Carbon Burden. Working Paper.

Piskorski, T., and M. M. Westerfield. 2016. Optimal Dynamic Contracts with Moral Hazard and Costly Monitoring. *Journal of Economic Theory* 166:242–281.

Shive, S. A., and M. M. Forster. 2020. Corporate Governance and Pollution Externalities of Public and Private Firms. *Review of Financial Studies* 3:1296–1330.

Shleifer, A., and R. W. Vishny. 1986. Large Shareholders and Corporate Control. *Journal of Political Economy* 94:461–488.

Shleifer, A., and R. W. Vishny. 1997. A Survey of Corporate Governance. *Journal of Finance* 52:737–783.

Shue, K., and S. Hartzmark. 2024. Counterproductive Sustainable Investing: The Impact Elasticity of Brown and Green Firms. Working Paper, Boston College.

Siders, D., and J. Ortiz. 2014. California Senate leader calls for pension funds to pull out of coal. *The Sacramento Bee* .

Smith, M. P. 1996. Shareholder Activism by Institutional Investors: Evidence from CalPERS. *Journal of Finance* 51:227–252.

Strey, D. M. 2020. With Public and Private Firms Competing for Talent, Have Executive Pay Packages Changed? Aon Total Compensation Measurement Survey.

Sun, L., and S. Abraham. 2021. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics* 225:175–199.

Wahal, S. 1996. Pension Fund Activism and Firm Performance. *Journal of Financial and Quantitative Analysis* 31:1–23.

Watkins, T. R. 2020. Citation and Order Writing Handbook Number PH20-I-3.

Wittry, M. D. 2021. (Debt) Overhang: Evidence from Resource Extraction. *Review of Financial Studies* 34:1699–1746.

Yermack, D. 2006. Flights of Fancy: Corporate Jets, CEO Perquisites, and Inferior Shareholder Returns. *Journal of Financial Economics* 80:211–242.

.

Figure 2: Upper Big Branch Production and Safety Violations. This figure displays the quarterly production per employee hour (shown in the gray bars), and the monthly safety violations (shown in the black dots) for the Upper Big Branch Mine, over a period of January 1, 2006 through June 30, 2010. The dashed red vertical line depicts April 5, 2010, the date of the explosion at Upper Big Branch Mine, which tragically claimed the lives of 29 miners. Data on production, employment, and safety violations for Upper Big Branch Mine are from the Mine Safety and Health Administration (MSHA) published through an Open Government Initiative.

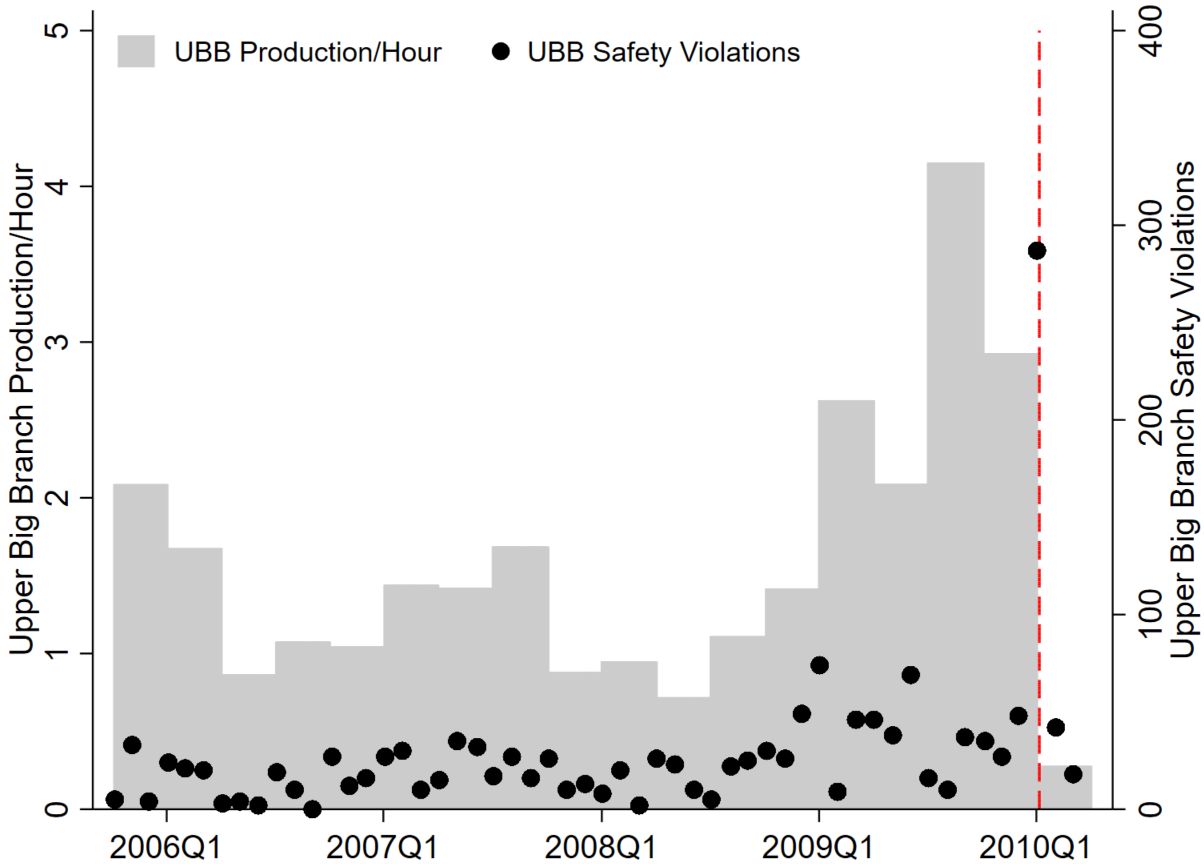
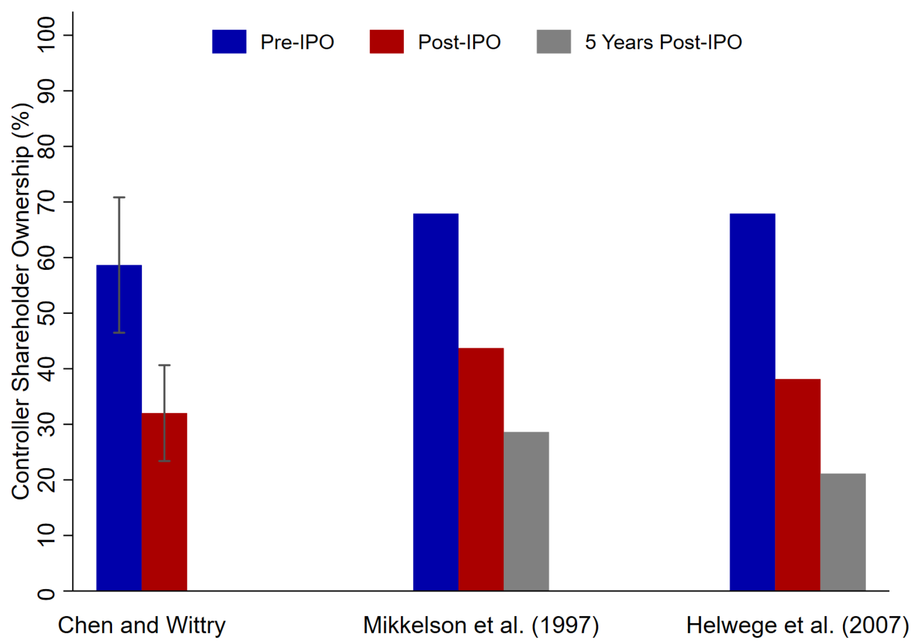


Figure 3: Ownership Dispersion in IPOs. These figures display the level of ownership dispersion in IPOs, both in our data, and for comparison, in previous studies. In particular, Panel A shows the pre-IPO stake of the controller shareholder as documented in the S-1 for 16 of our coal firms' IPOS (blue bars), and the post-IPO stake of the controlling shareholder as documented in the first 10k post-lockup period (red bars). Similarly, we document the pre- and post-IPO D&O ownership for IPOs studied by Mikkelson et al. (1997) and Helwege et al. (2007). Panel B displays the same ownership dispersion in our study, but also separates by whether we classify the firm as having high or low initial managerial ownership using data from Fabisik et al. (2021). The gray bars indicated 90% confidence intervals.

(A) Full Sample Comparison with Previous Studies.



(B) Split by High and Low Initial Managerial Ownership.

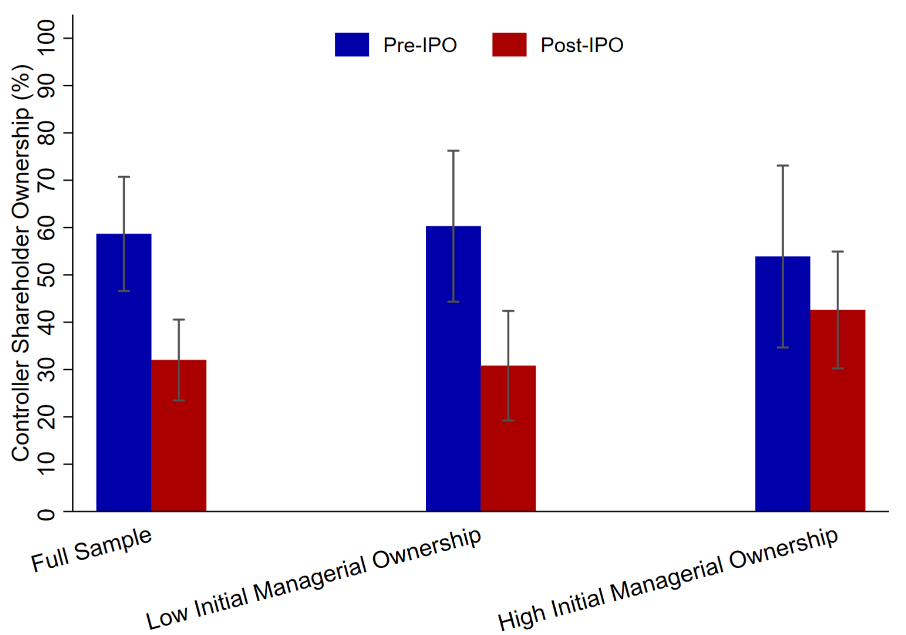


Figure 4: Output-Externalities Threshold. This figure displays a binscatter plot of high-probability safety violations as a function of coal production per employee hour at U.S. coal mines over a sample period of 1994 through 2022. A vertical dashed line depicts the 50th percentile for production per employee hour over the course of the sample. The figure highlights a low threshold of production before steep increases in the measurable externality, suggesting a convex relationship between abatement and per unit production. Data on mine-level production, safety violations, and employee hours are from the Mine Safety and Health Administration (MSHA) published through an Open Government Initiative.

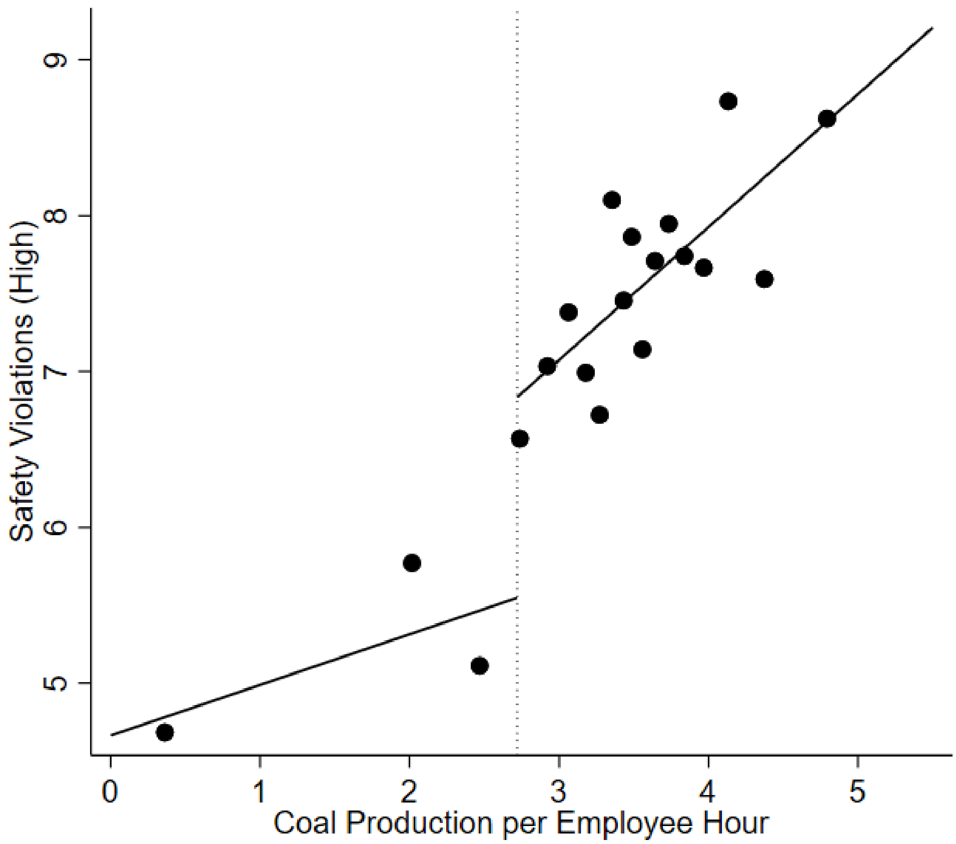


Figure 5: Annual Number of Mines Changing Listing Status. This figure displays the annual number of mines changing listing status over the sample period of 1983 through 2022. The blue bars depict mines that change listing status when the mine owner goes public through an IPO, the red bars depict mines that change status when a public firm acquires a privately owned mine (or in most cases, the entire private firm), the yellow bars depict mines that change status when a private firm acquires a publicly owned mine, or the mine owner goes private through other going-private transactions. Data on mine ownership and mining acquisitions are from the Mine Safety and Health Administration (MSHA) published through an Open Government Initiative. Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website.

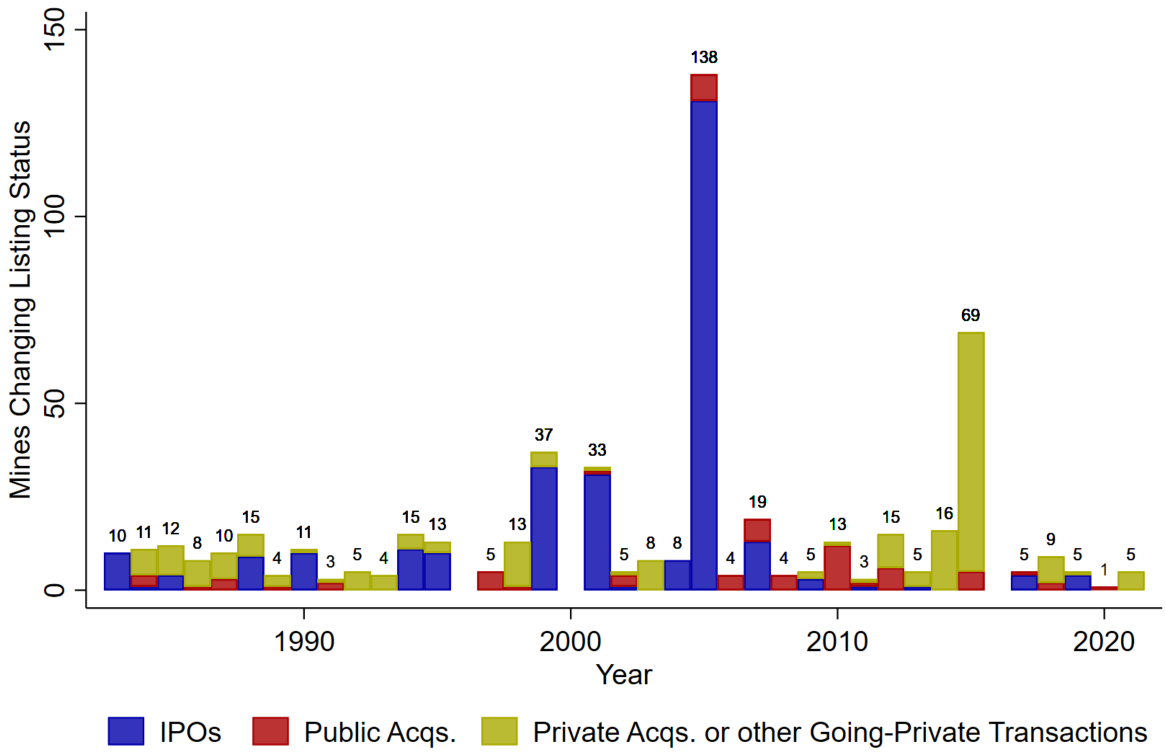
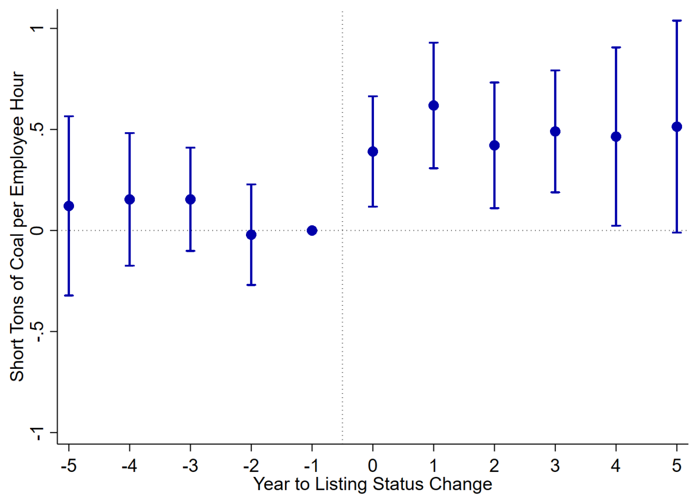


Figure 6: Stacked Regression Production and Externality Event-Time Trends around Listing Status Changes. These figures display the trends of mine-level production (Panel A) and safety violations (Panel B) around listing status changes (IPOs, public acquisitions, and private acquisitions or other going-private transactions) for U.S. coal mines over a sample period of 1983 through 2022 for production and 1994 through 2022 for safety violations. We use an OLS model (Panel A) and a Poisson pseudo-maximum-likelihood model (Panel B) within stacked regression methodology to estimate the dynamic effects (Baker et al., 2022; Gormley and Matsa, 2011). The figures plot annual coefficients for each time (year $t = -5$ through year $t = 5$) directly around a listing status change interacted with an indicator (*treat*) that is equal to 1 for to-public listing status changes, and -1 for to-private listing status changes. We use the same fixed effects as our baseline specifications in Table 4, and following Gormley and Matsa (2011), we interact the fixed effects from these models with a cohort indicator, as well as an event number indicator for mines that experience multiple listing status changes. Standard errors are clustered at the firm level. Data on mine-level production and employee hours, safety violations, and ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration (MSHA) published through an Open Government Initiative. Data on firms' public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website.

(A) Production.



(B) Safety Violations.

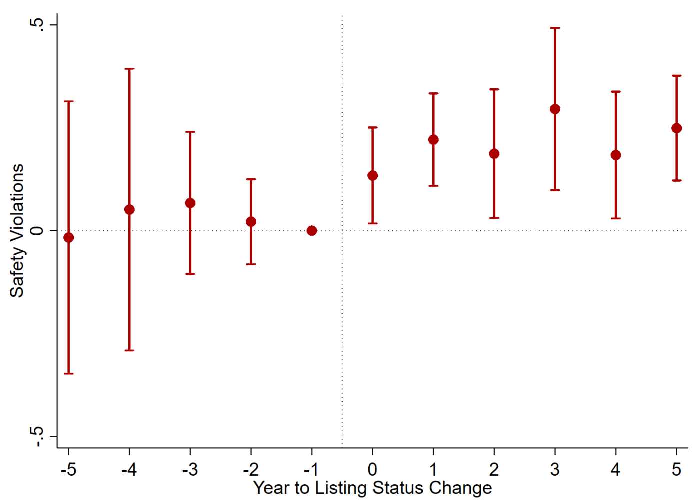
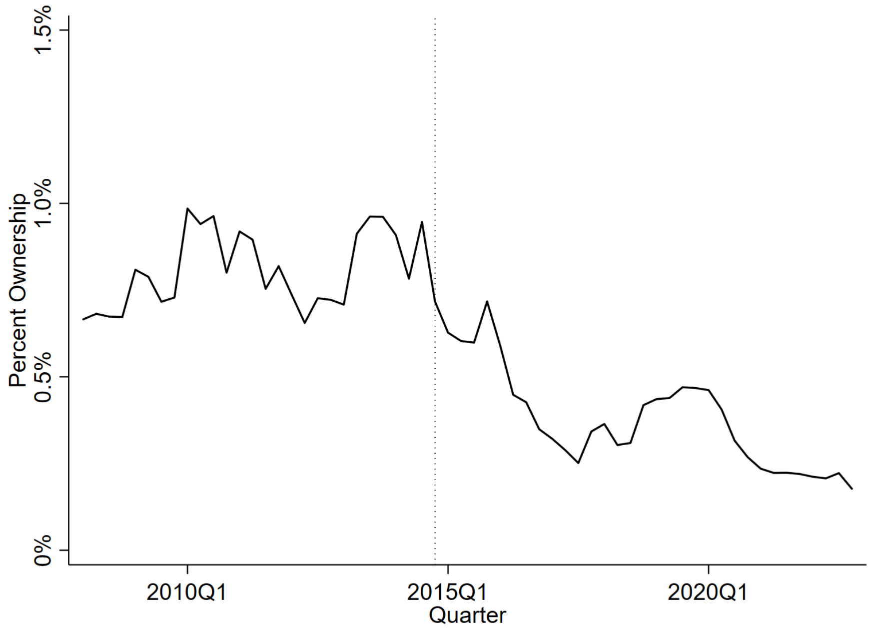


Figure 7: Coal Divestment Initiatives. These figures depict the total combined ownership percentages of Norges Bank Investment Management (NBIM), the manager of the sovereign wealth fund of Norway, and the California Public Employees' Retirement System (CalPERS) for the average firm in our sample (Panel A), and separately for the average thermal coal firm and metallurgical coal firm in our sample (Panel B). We assemble the ownership percentages from three sources. First, we start with data on 13f institutional holdings from Thomson/Refinitiv. We cross-reference and fix some substantial mistakes using the annual investment reports published by CalPERS and NBIM. Because of the granularity differences (e.g., quarterly in Thomson and annual in the reports), we are unable to precisely identify the true ownership numbers. For example, at times, 13f data understates the ownership shares by an order of magnitude. Thus, this figure should be interpreted mostly as an illustrative example of the divestment, but likely understates the true ownership percentages.

(A) NBIM and CalPERS Ownership Percentages in Sample Firms.



(B) NBIM and CalPERS Ownership in Thermal Coal versus Metallurgical Coal and Conglomerates.

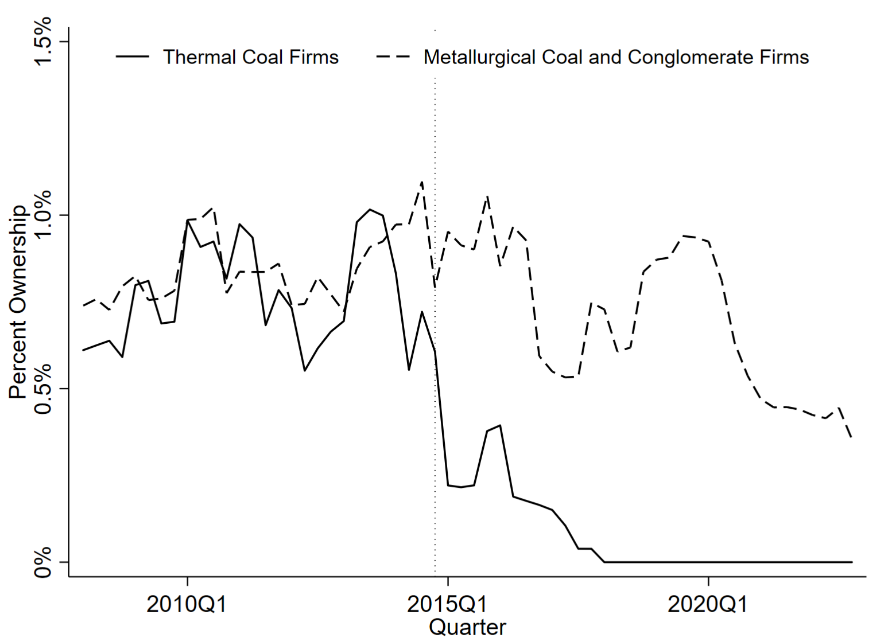
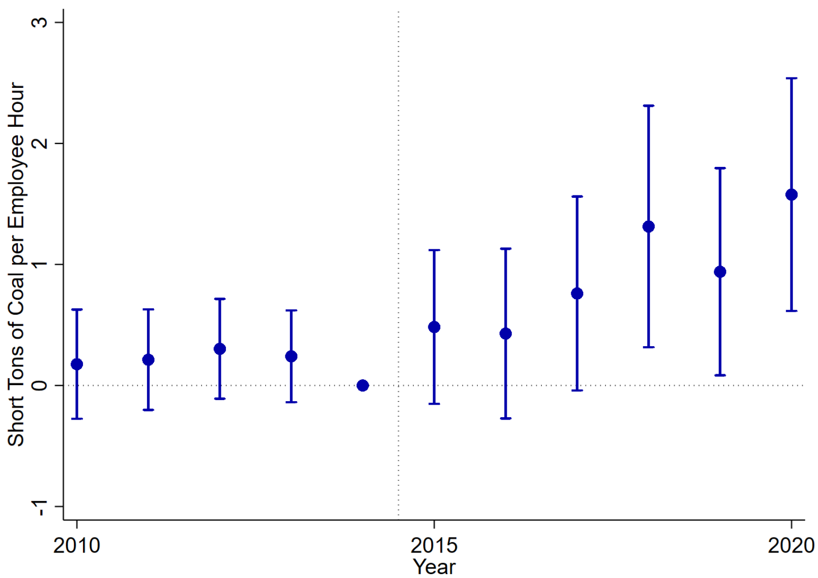


Figure 8: Production, Externalities, and Coal Divestment Initiatives. These figures display the trends of mine-level production (Panel A) and safety violations (Panel B) around the 2015 coal divestment announcements by Norges Bank Investment Management (NBIM) and California Public Employees Retirement System (CalPERS). We use an OLS model (Panel A) and a Poisson pseudo-maximum-likelihood model (Panel B) estimate the dynamic effects. The figures plot annual coefficients for each time (year 2010 through 2020) around the divestment initiative interacted with an indicator (*treat*) that is equal to 1 for public firms. We use the same fixed effects as our baseline specifications in Table 8, and cluster standard errors at the firm level. Data on mine-level production and employee hours, safety violations, and ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration (MSHA) published through an Open Government Initiative.

(A) Production for Public vs. Private Firms.



(B) Safety Violations for Public vs. Private Firms.

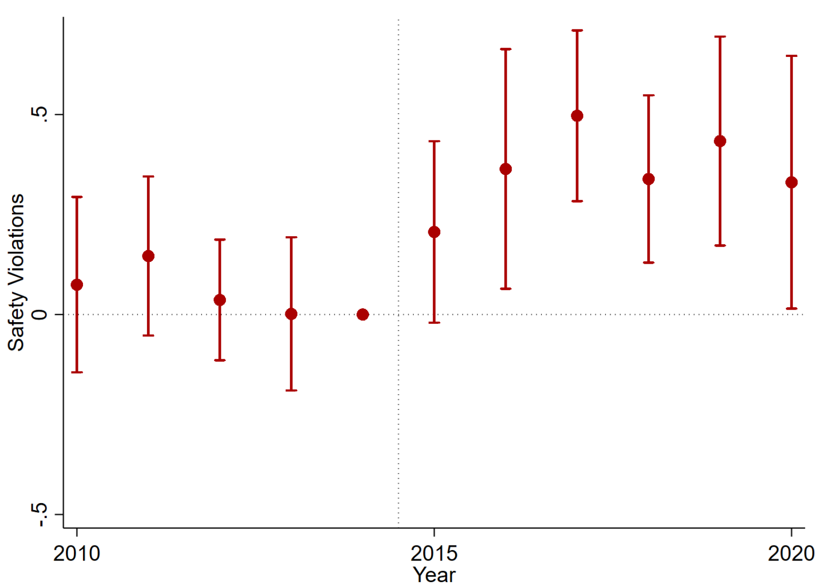
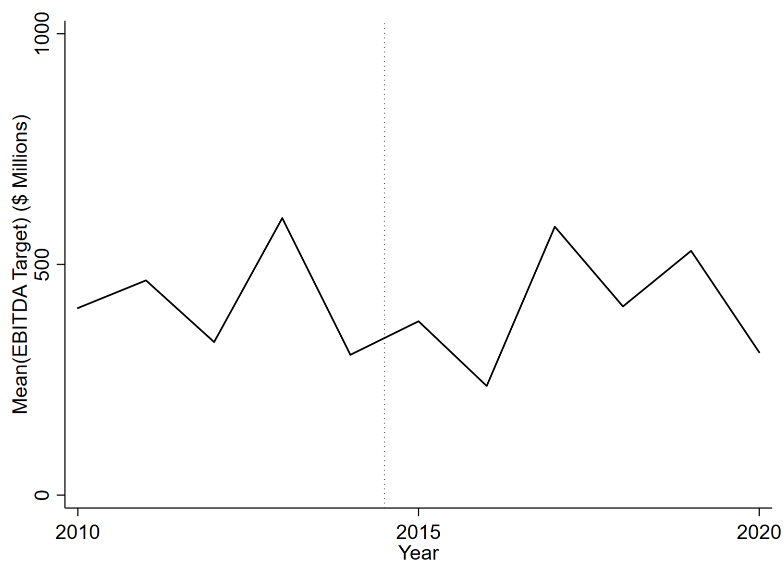


Figure 9: Performance Targets and Coal Divestment Initiatives. These figures display the trends of EBITDA performance targets for the average public firm in our sample from 2010 through 2020 (Panel A) and the log levels of the EBITDA performance targets differentially for thermal and metallurgical coal firms in our sample around the 2015 coal divestment announcements by Norges Bank Investment Management (NBIM) and California Public Employees Retirement System (CalPERS) (Panel B). In particular, we use an OLS model to estimate the dynamic effects in Panel B. The figure plots annual coefficients for each time (year 2010 through 2020) around the divestment initiative interacted with an indicator (*treat*) that is equal to 1 for thermal coal firms. We use year and firm fixed effects and cluster standard errors at the firm level. Data on mine-level production and employee hours, safety violations, and ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration (MSHA) published through an Open Government Initiative. Data on whether coal firms are thermal or metallurgical are collected via the Metallurgical Coal Producers Association and through various firm filings. Data on firms' EBITDA performance targets are hand-collected from firm proxy filings.

(A) Average EBITDA Performance Targets for All Public Firms.



(B) log(EBITDA Performance Targets) for Public Thermal Coal Firms vs. Public Metallurgical or Conglomerate Coal Firms.

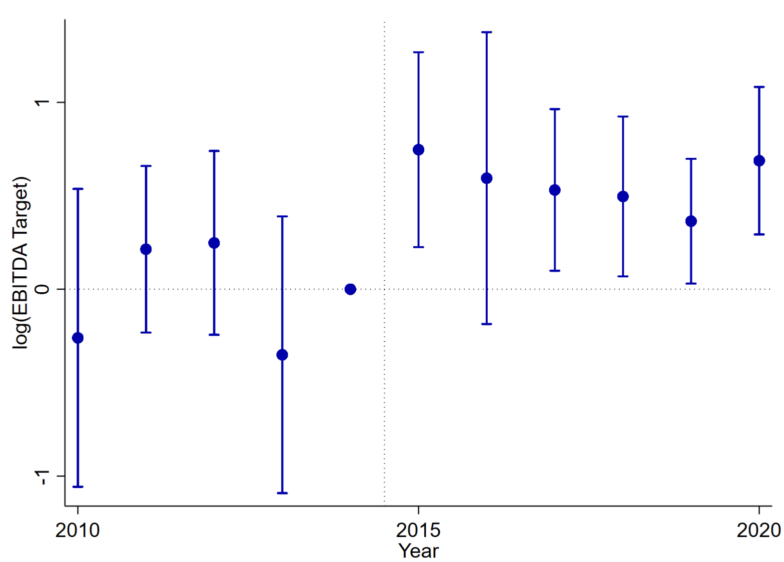


Table 3: Summary Statistics. This table reports summary statistics for all publicly and privately owned U.S. coal mines over a sample period of 1983 through 2022. A mine-year observation is included in our sample if it satisfies the following requirements: (1) the mine is actively producing coal and employs at least 10 workers, (2) the mine produces bituminous (not anthracite) coal, and (3) the owner of the mine is not foreign, not part of a joint venture, not structured as a sole proprietorship or a partnership, and owns at least one other mine. All variable definitions appear in Appendix Table A1. Data on mining production and employment, safety violations, as well as mine ownership and mining acquisitions, are from the Mine Safety and Health Administration (MSHA) published through an Open Government Initiative. Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website.

Panel A: Data Description

	Total Distinct Mines	Total Distinct Firms
Full Sample	5,332	1,614
Public Firms	875	67
Private Firms	4,682	1,570

Panel B: Summary Statistics

	No. Obs.	Mean	Std. Dev.	25^{th} Pct.	Median	75^{th} Pct.
Externality Measures						
Total safety violations	10,282	52	99	25	17	52
Low-probability violations	10,282	33	66	3	10	31
High-probability violations	10,282	18	36	1	6	17
Total safety inspections	26,151	12.1	15.2	4	7	15
Production and Employment						
Tons of clean coal produced	26,151	694,056	4,145,557	38,073	125,514	364,347
Number of employee hours	26,151	116,560	225,433	18,062	45,566	109,048
Short tons of clean coal per employee hour	26,151	3.45	3.19	1.83	2.77	4.11
Cross-Sectional Measures						
Initial bonus contracting (indicator)	3,803	0.87	0.34	1	1	1
Initial dedicated institutional ownership (%)	3,735	0.6	1.0	0.0	0.0	1.1
Initial board independence (indicator)	4,957	0.28	0.45	0	0	1
Initial price informativeness (%)	4,774	2.53	3.32	0.38	0.38	3.46
Mean spot inspections (district-level)	23,729	1.3	1.9	0.2	0.5	1.7
Unionized (Indicator)	24,569	0.15	0.36	0	0	0
Initial managerial ownership (%)	5,218	4.9	13.2	0.2	1.4	2.9
Ownership						
Public owner (%)	26,151	0.18				

Table 4: Public Listing Status, Production, and Externalities. This table reports the results of linear regression models (Models (1) and (2)) in which the dependent variable is the total short tons of clean coal produced divided by employee hours, or Poisson pseudo-maximum-likelihood (PPLM) models (Models (3) through (6)) in which the dependent variable is the total number of safety violations at mine i, owned by firm s, during year t. The sample consists of publicly and privately owned U.S. coal mines over a sample period of 1983 through 2022 for production and 1994 through 2022 for safety violations. The independent variable of interest is *Public owner*$_{ist}$. All variable definitions appear in Appendix Table A1. Data on mining production and employment, safety violations, as well as mine ownership and mining acquisitions, are from the Mine Safety and Health Administration (MSHA) published through an Open Government Initiative. Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	$\frac{\text{Production}}{\text{Hours}}_{ist}$		Safety Violations$_{ist}$			
MSHA Prob. of Accident =			All		Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
Public owner$_{ist}$	0.394***	0.362***	0.224***	0.284***	0.257***	0.370***
	(0.143)	(0.139)	(0.082)	(0.085)	(0.089)	(0.094)
log(Mines$_{st}$)		0.009		0.055	0.044	0.067
		(0.091)		(0.072)	(0.092)	(0.067)
log(Employees$_{ist}$)		0.375***		0.073	0.078	0.056
		(0.058)		(0.047)	(0.059)	(0.045)
log(Hours$_{ist}$)				0.709***	0.714***	0.735***
				(0.037)	(0.041)	(0.046)
log(Safety inspections$_{ist}$)				0.257***	0.242***	0.278***
				(0.020)	(0.024)	(0.025)
Mine FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Inspection District FE	No	No	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Model	OLS	OLS	PPML	PPML	PPML	PPML
Observations	26,151	26,151	10,069	10,069	9,971	9,892
R^2 or Pseudo-R^2	0.853	0.856	0.859	0.907	0.896	0.835

Table 5: Public Listing Status, Production, Externalities, and Bonus Contracting. This table reports the results of linear regression models (Model (1)) in which the dependent variable is the total short tons of clean coal produced divided by employee hours, or Poisson pseudo-maximum-likelihood (PPLM) models (Models (2) through (4)) in which the dependent variable is the total number of safety violations at mine i, owned by firm s, during year t. The sample consists of publicly and privately owned U.S. coal mines over a sample period of 1983 through 2022 for production and 1994 through 2022 for safety violations. The independent variable of interest is $Public\ owner_{ist}$ interacted with an indicator variable that equals one if an IPO firm utilizes bonus contracting in the first year after going public. All variable definitions appear in Appendix Table A1. Data on mining safety violations, safety inspections, production, and employment, as well as ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration published through an Open Government Initiative. Data on the bonus contracting is taken from Execucomp. Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	$\frac{\text{Production}}{\text{Hours}}_{ist}$	Safety Violations$_{ist}$		
MSHA Prob. of Accident =		All	Low	High
	(1)	(2)	(3)	(4)
Public owner$_{ist}$	-0.218	0.209***	0.131	0.086
	(0.215)	(0.075)	(0.103)	(0.144)
Public owner$_{ist}$× I(Bonus Contracting$_s$)	0.767***	0.282*	0.338*	0.515***
	(0.252)	(0.170)	(0.205)	(0.181)
Controls	Yes	Yes	Yes	Yes
Mine × Firm FE	Yes	Yes	Yes	Yes
Inspection District FE	No	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Model	OLS	PPML	PPML	PPML
Observations	3,342	1,597	1,579	1,557
R^2 or Pseudo-R^2	0.960	0.934	0.921	0.891

Table 6: Public Listing Status, Production, Externalities, and Alternative Firm-Level Monitoring. This table reports the results of linear regression models (Model (1)) in which the dependent variable is the total short tons of clean coal produced divided by employee hours, or Poisson pseudo-maximum-likelihood (PPLM) models (Models (2) through (4)) in which the dependent variable is the total number of safety violations at mine i, owned by firm s, during year t. The sample consists of publicly and privately owned U.S. coal mines over a sample period of 1983 through 2022 for production and 1994 through 2022 for safety violations. The independent variables of interest are *Public owner*$_{ist}$ interacted with (i) an indicator variable equal to 1 if an IPO firms' initial dedicated institutional ownership is greater than or equal to the 75th percentile (Panel A), (ii) an indicator variable equal to 1 if an IPO firms' initial board independence is greater or equal to 50% (Panel B), and (iii) an indicator variable equal to 1 if an IPO firms' relative price informativeness ($\tau_{\pi}^{R,s}$) is greater than or equal to the 75th percentile over the first 40 quarters after the firm has IPO'ed (Panel C). See Dávila and Parlatore (2024) for details on the construction of $\tau_{\pi}^{R,s}$. All variable definitions appear in Appendix Table A1. Data on mining safety violations, safety inspections, production, and employment, as well as ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration published through an Open Government Initiative. Data on institutional holdings is from Thomson Reuters Institutional (13F) Holdings Database, and we identify dedicated institutions using data from Brian Bushee's website. Data on $\tau_{\pi}^{R,s}$ is taken from the authors' Github website: https://github.com/edavila/identifying_price_informativeness. Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	$\frac{\text{Production}}{\text{Hours}}_{ist}$	Safety Violations$_{ist}$		
MSHA Prob. of Accident =		All	Low	High
	(1)	(2)	(3)	(4)
Panel A: Dedicated Institutional Ownership				
Public owner$_{ist}$	0.463*	0.468***	0.418***	0.602***
	(0.264)	(0.108)	(0.122)	(0.092)
Public owner$_{ist}$ × High dedicated IO$_s$	-0.796*	-0.104	0.257	-0.569***
	(0.412)	(0.135)	(0.167)	(0.130)
Controls	Yes	Yes	Yes	Yes
Mine × Firm FE	Yes	Yes	Yes	Yes
Inspection District FE	No	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Model	OLS	PPML	PPML	PPML
Observations	3,260	2,463	2,457	2,436
R^2 or Pseudo-R^2	0.934	0.913	0.898	0.864
Panel B: Board Oversight				
Public owner$_{ist}$	0.728**	0.455***	0.444***	0.526***
	(0.291)	(0.097)	(0.110)	(0.088)
Public owner$_{ist}$ × Majority Independent Board$_s$	-0.785**	-0.219**	-0.305***	-0.195*
	(0.317)	(0.087)	(0.107)	(0.118)
Controls	Yes	Yes	Yes	Yes
Mine × Firm FE	Yes	Yes	Yes	Yes
Inspection District FE	No	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Model	OLS	PPML	PPML	PPML
Observations	4,456	2,636	2,616	2,600
R^2 or Pseudo-R^2	0.919	0.918	0.904	0.870
Panel C: Informative Stock Price				
Public owner$_{ist}$	1.087***	0.510***	0.463***	0.685***
	(0.270)	(0.117)	(0.139)	(0.059)
Public owner$_{ist}$ × High $\tau_{\pi}^{R,s}$	-0.848**	-0.459***	-0.330	-0.565***
	(0.412)	(0.131)	(0.205)	(0.117)
Controls	Yes	Yes	Yes	Yes
Inspection District FE	No	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Model	OLS	PPML	PPML	PPML
Observations	4,262	2,097	2,081	2,059
R^2 or Pseudo-R^2	0.925	0.916	0.904	0.863

Table 7: Public Listing Status, Production, Externalities, and Alternative Market-Level Monitoring. This table reports the results of linear regression models (Model (1)) in which the dependent variable is the total short tons of clean coal produced divided by employee hours, or Poisson pseudo-maximum-likelihood (PPLM) models (Models (2) through (4)) in which the dependent variable is the total number of safety violations at mine i, owned by firm s, during year t. The sample consists of publicly and privately owned U.S. coal mines over a sample period of 1983 through 2022 for production and 1994 through 2022 for safety violations. The independent variable of interest is $Public\ owner_{ist}$ interacted with the average number of spot safety inspections at other firms' mines in the inspection district over the preceding year (Panel A) and an indicator equal to 1 if the mine is unionized by United Mine Workers of America in year t (Panel B). All variable definitions appear in Appendix Table A1. Data on mining production and employment, safety violations, and inspections, as well as mine ownership and mining acquisitions, are from the Mine Safety and Health Administration (MSHA) published through an Open Government Initiative. Data on the unionization is from the U.S. Energy Information Administration (EIA) and is limited in the early part of our sample. Thus, for Model (1) in Panel B, we focus on the 1994 through 2022 period. Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	$\left(\frac{\text{Production}}{\text{Hours}}\right)_{ist}$	Safety Violations$_{ist}$		
MSHA Prob. of Accident =		All	Low	High
	(1)	(2)	(3)	(4)
Panel A: Inspection District Spot Inspections				
Public owner$_{ist}$	0.485***	0.329***	0.304***	0.407***
	(0.161)	(0.084)	(0.086)	(0.102)
Mean spot inspections$_{d,-s,t-1}$	0.056**	0.010	0.019	-0.013
	(0.028)	(0.050)	(0.059)	(0.063)
Public owner$_{ist}$× Mean spot inspections$_{d,-s,t-1}$	-0.145***	-0.132***	-0.109**	-0.170**
	(0.046)	(0.049)	(0.053)	(0.085)
Controls	Yes	Yes	Yes	Yes
Mine FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Inspection District FE	No	Yes	Yes	Yes
County × Year	Yes	Yes	Yes	Yes
Model	OLS	PPML	PPML	PPML
Observations	23,063	9,802	9,688	9,636
R^2 or Pseudo-R^2	0.873	0.908	0.897	0.836
Panel B: Unionization Status				
Public owner$_{ist}$	0.231	0.340***	0.303***	0.459***
	(0.184)	(0.086)	(0.083)	(0.104)
United Mine Workers of America$_{ist}$ (UMWA)	0.212	0.051	0.067	0.053
	(0.329)	(0.069)	(0.063)	(0.089)
Public owner$_{ist}$× UMWA$_{ist}$	-0.450**	-0.151***	-0.132*	-0.217**
	(0.225)	(0.056)	(0.075)	(0.095)
Controls	Yes	Yes	Yes	Yes
Mine FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Inspection District FE	No	Yes	Yes	Yes
County × Year	Yes	Yes	Yes	Yes
Model	OLS	PPML	PPML	PPML
Observations	9,685	9,656	9,565	9,492
R^2 or Pseudo-R^2	0.929	0.907	0.896	0.836

Table 8: Production, Externalities, and Coal Divestment Initiatives. This table reports the results of linear regression models (Models (1) and (2)) in which the dependent variable is the total short tons of clean coal produced divided by employee hours, or Poisson pseudo-maximum-likelihood (PPLM) models (Models (3) and (4)) in which the dependent variable is the total number of safety violations at mine i, owned by firm s, during year t. The sample consists of publicly and privately owned U.S. coal mines over a sample period of 2010 through 2022. The independent variable of interest is $Public\ owner_{ist}$ interacted with an indicator variable equal to 1 for all years post-2015, when Norges Bank Investment Management (NBIM) and California Public Employees Retirement System (CalPERS) announced coal divestment initiatives. Further, Models (2) and (4) and a triple interaction term: an indicator variable equal to 1 if firm s is a thermal coal firm. The remaining interaction terms are omitted for brevity. All variable definitions appear in Appendix Table A1. Data on mining safety violations, safety inspections, production, and employment, as well as ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration published through an Open Government Initiative. Data on whether coal firms are thermal or metallurgical is collected via the Metallurgical Coal Producers Association and through various firm filings. Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively..

Dependent variable =	$\frac{\text{Production}}{\text{Hours}}_{ist}$		Safety Violations$_{ist}$	
MSHA Prob. of Accident =			All	
	(1)	(2)	(3)	(4)
Public owner$_{ist}$	-0.041	0.037	0.076	0.028
	(0.182)	(0.364)	(0.108)	(0.210)
Public owner$_{ist}\times$ I(Year$_t \geq 2015$)	0.647**	-0.309	0.418***	-0.191
	(0.317)	(0.280)	(0.125)	(0.253)
Public owner$_{ist}\times$ I(Year$_t \geq 2015$)$\times$ I(Thermal Coal Firm$_s$)		1.170**		0.552**
		(0.464)		(0.247)
I(Thermal Coal Firm$_s$)		0.511		0.200
		(0.352)		(0.124)
Public owner$_{ist}\times$ I(Thermal Coal Firm$_s$)		-0.113		0.076
		(0.396)		(0.213)
I(Year$_t \geq 2015$)$\times$ I(Thermal Coal Firm$_s$)		-0.383		-0.032
		(0.259)		(0.073)
Controls	No	No	No	No
Mine $\times$ Firm FE	Yes	Yes	Yes	Yes
Inspection District FE	No	No	Yes	Yes
County $\times$ Year FE	Yes	Yes	Yes	Yes
Model	OLS	OLS	PPML	PPML
Observations	2,737	2,737	2,731	2,731
R^2 or Pseudo-R^2	0.939	0.939	0.892	0.892

Table 9: Public Listing Status, Production, Externalities, and Managerial Ownership. This table reports the results of linear regression models (Model (1)) in which the dependent variable is the total short tons of clean coal produced divided by employee hours, or Poisson pseudo-maximum-likelihood (PPLM) models (Models (2) through (4)) in which the dependent variable is the total number of safety violations at mine i, owned by firm s, during year t. The sample consists of publicly and privately owned U.S. coal mines over a sample period of 1983 through 2022 for production and 1994 through 2022 for safety violations. The independent variable of interest is *Public owner*$_{ist}$ interacted with an indicator variable equal to 1 if an IPO firms' initial managerial ownership is less than 25%. All variable definitions appear in Appendix Table A1. Data on mining safety violations, safety inspections, production, and employment, as well as ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration published through an Open Government Initiative. Data on managerial ownership was kindly shared by Fabisik et al. (2021). Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	$\frac{\text{Production}}{\text{Hours}}_{ist}$	Safety Violations$_{ist}$		
MSHA Prob. of Accident =		All	Low	High
	(1)	(2)	(3)	(4)
Public owner$_{ist}$	0.017	0.168	0.305	0.071
	(0.349)	(0.118)	(0.210)	(0.069)
Public owner$_{ist}$ × Low managerial ownership$_s$	0.622*	0.276***	0.110	0.510***
	(0.315)	(0.064)	(0.135)	(0.094)
Controls	Yes	Yes	Yes	Yes
Mine × Firm FE	Yes	Yes	Yes	Yes
Inspection District FE	No	No	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Model	OLS	PPML	PPML	PPML
Observations	4,736	2,568	2,556	2,532
R^2 or Pseudo-R^2	0.929	0.919	0.905	0.873

Table 10: Public Listing Status and Externalities in Productive Mines. This table reports the results of Poisson pseudo-maximum-likelihood (PPLM) models in which the dependent variable is the total number of safety violations at mine i, owned by firm s, during year t. The sample consists of publicly and privately owned U.S. coal mines over a sample period of 1994 through 2022. The independent variable of interest is *Public owner*$_{ist}$ interacted with short tons of coal produced per employee hour in the previous quarter. All variable definitions appear in Appendix Table A1. Data on mining production and employment, safety violations, as well as mine ownership and mining acquisitions, are from the Mine Safety and Health Administration (MSHA) published through an Open Government Initiative. Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	Safety Violations$_{ist}$					
MSHA Prob. of Accident =	All		Low		High	
	(1)	(2)	(3)	(4)	(5)	(6)
Public owner$_{ist}$	0.308***	0.216**	0.289***	0.238**	0.377***	0.202*
	(0.089)	(0.098)	(0.095)	(0.104)	(0.096)	(0.121)
Production/hour$_{is,t-1}$	0.000	-0.015	-0.005	-0.013	0.011	-0.018
	(0.007)	(0.010)	(0.009)	(0.010)	(0.007)	(0.014)
Public owner$_{ist}\times$ Production/hour$_{is,t-1}$		0.025**		0.014		0.046***
		(0.012)		(0.011)		(0.017)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mine FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Inspection District FE	Yes	Yes	Yes	Yes	Yes	Yes
County $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Model	PPML	PPML	PPML	PPML	PPML	PPML
Observations	8,425	8,425	8,361	8,361	8,293	8,293
Pseudo-R^2	0.910	0.910	0.900	0.900	0.841	0.841

Table 11: Public Listing Status, Production, Externalities, and Financial Constraints. This table reports the results of linear regression models (Model (1)) in which the dependent variable is the total short tons of clean coal produced divided by employee hours, or Poisson pseudo-maximum-likelihood (PPLM) models (Models (2) through (4)) in which the dependent variable is the total number of safety violations at mine i, owned by firm s, during year t. The sample consists of publicly and privately owned U.S. coal mines over a sample period of 1983 through 2022 for production and 1994 through 2022 for safety violations. The independent variable of interest is $Public\ owner_{ist}$ interacted with an indicator that is equal to 1 if the firm has high leverage immediately after the IPO (Panel A). Panel B restricts the sample to only going-private transactions. All variable definitions appear in Appendix Table A1. Data on mining safety violations, safety inspections, production, and employment, as well as ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration published through an Open Government Initiative. Data on leverage is from Compustat. Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	$\frac{\text{Production}}{\text{Hours}}_{ist}$	Safety Violations$_{ist}$		
MSHA Prob. of Accident =		All	Low	High
	(1)	(2)	(3)	(4)
Panel A: High Financial Leverage				
Public owner$_{ist}$	0.272*	0.463***	0.437***	0.558***
	(0.159)	(0.093)	(0.091)	(0.098)
Public owner$_{ist}$ × High leverage$_s$	0.189	-0.304***	-0.303***	-0.296*
	(0.561)	(0.069)	(0.102)	(0.178)
Controls	Yes	Yes	Yes	Yes
Mine × Firm FE	Yes	Yes	Yes	Yes
Inspection District FE	No	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Model	OLS	PPML	PPML	PPML
Observations	5,471	2,907	2,885	2,869
R^2 or Pseudo-R^2	0.935	0.917	0.901	0.869
Panel B: Public-to-Private Transactions				
Public owner$_{ist}$	0.474**	0.202	0.087	0.409***
	(0.220)	(0.141)	(0.183)	(0.119)
Controls	Yes	Yes	Yes	Yes
Mine FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Inspection District FE	No	Yes	Yes	Yes
County × Year	Yes	Yes	Yes	Yes
Model	OLS	PPML	PPML	PPML
Observations	3,702	2,275	2,271	2,248
R^2 or Pseudo-R^2	0.939	0.902	0.887	0.844

Appendix: Variable Definitions

Table A1: Variable Definitions

Subscript i indicates a specific mine, s indicates a specific firm, t indicates a year, d indicates a MSHA inspection district, and j indicates a state.

Variable	Definition
Safety Violations$_{ist}$	The total number of safety violations mine i is cited for potential accidents when owned by firm s during year t. Source of all safety violations, including low- and high-probability: MSHA https://www.msha.gov/mine-data-retrieval-system.
Low-Probability Safety Violations$_{ist}$	The total number of safety violations mine i is cited for potential accidents that MSHA considers "unlikely to occur" when owned by firm s during year t.
High-Probability Safety Violations$_{ist}$	The total number of safety violations mine i is cited for potential accidents that MSHA considers "reasonably likely or highly likely to occur" when owned by firm s during year t.
Safety Inspections$_{ist}$	The total number of safety inspections performed by MSHA at mine i owned by firm s during year t. Source: MSHA https://www.msha.gov/mine-data-retrieval-system.
Spot Inspections$_{ist}$	The number of spot (non-routine) inspections performed by MSHA at mine i owned by firm s during year t. Source: MSHA https://www.msha.gov/mine-data-retrieval-system.
Coal Production$_{ist}$	The total short tons of clean coal produced at mine i owned by firm s during year t. Source: MSHA https://www.msha.gov/mine-data-retrieval-system.
Employees$_{ist}$	The average number of employees at mine i owned by firm s during year t. Source: MSHA https://www.msha.gov/mine-data-retrieval-system.
Employee hours$_{ist}$	The total number of hours worked at mine i owned by firm s during year t. Source: MSHA https://www.msha.gov/mine-data-retrieval-system.
Production/Hours$_{ist}$	The total short tons of clean coal produced per employee hour at mine i owned by firm s during year t. Winsorized at the 1st and 99th percentile. Source: MSHA https://www.msha.gov/mine-data-retrieval-system.
Mean Spot Inspections$_{d,-s,t-1}$	The average number of spot (non-routine) inspections performed by MSHA at all mines in mine i's MSHA inspection district d during year t-1 expect those owned by firm s. Source: MSHA https://www.msha.gov/mine-data-retrieval-system.

United Mine Workers of America$_{ist}$	Indicator variable equal to 1 if mine i owned by firm s is unionized by United Mine Workers of America during year t. Source: EIA https://www.eia.gov/coal/data.php.
I(Bonus Contracting$_s$)	An indicator variable equal to 1 if the CEO has non-zero bonus-based compensation in the first year after firm s's initial public offering. Source: Execucomp
Dedicated Institutional Ownership$_s$ (%)	The percentage of shares outstanding that are held by dedicated institutions in the first quarter after firm s's initial public offering, measured in percent. We use the Bushee classification data to identify dedicated institutions (e.g., see Bushee, 1998). Source: Thomson Reuters Institutional (13F) Holdings Database and https://accounting-faculty.wharton.upenn.edu/bushee/.
High Dedicated Institutional Ownership$_s$ (Indicator)	An indicator variable equal to 1 if the percentage of shares outstanding that are held by dedicated institutions in the first quarter after firm s's initial public offering is above the sample's 75th percentile, equal to dedicated ownership of 1.05%. Source: Thomson Reuters Institutional (13F) Holdings Database and https://accounting-faculty.wharton.upenn.edu/bushee/.
Majority Independent Board$_s$	An indicator variable equal to 1 if the board is made up of at least 50% independent members in the first year after firm s's initial public offering. Source: BoardEx
$\tau_\pi^{R,s}$ (%)	The relative price informativeness proxy from Dávila and Parlatore (2024), which is computed over a rolling window of 40 quarters, measured in percent at the first available quarter after firm s's initial public offering. Source: https://github.com/edavila/identifying_price_informativeness.
High $\tau_\pi^{R,s}$ (Indicator)	An indicator variable equal to 1 if the price informativeness proxy from Dávila and Parlatore (2024) measured at the first available quarter after firm s's initial public offering is above the sample's 75th percentile, equal to $\tau_\pi^{R,s}$ of 3.46%. Source: https://github.com/edavila/identifying_price_informativeness.
Managerial Ownership$_s$ (%)	The percentage of shares outstanding that are held by directors and officers in the first year after firm s's initial public offering, measured in percent. Source: Fabisik et al. (2021).
Low Managerial Ownership$_s$ (Indicator)	An indicator variable equal to 1 if the percentage of shares outstanding that are held by directors and officers in the first year after firm s's initial public offering is less than 25%. Source: Fabisik et al. (2021).

Internet Appendix for "Production and Externalities: How Corporate Governance Shapes Social Costs"

ALVIN CHEN[1] and MICHAEL D. WITTRY[2]

This Internet Appendix reports results that are mentioned but not tabulated in the main paper. In Section IA.1, we discuss externalities with convex abatement costs and the argument that workplace safety in coal mining is an externality. Section IA.2 provides the proofs for Section 2. Section IA.3 considers a model extension in which shareholders can contract a penalty for the manager when the firm's production generates negative externalities. Section IA.4 provides examples of executive compensation plans from the coal industry. Section IA.5 discusses the implications of our paper for private equity. Finally, in Section IA.7 we report four figures and 14 tables, as outlined below:

1. Figure IA1: Stacked Regression Injuries and Fatalities Event-Time Trends around Listing Status Changes.

   Reference in the main paper: "Internet Appendix Figure IA1 shows that realized injuries and fatal accidents increase immediately following a listing status change, suggesting that social costs and pecuniary penalties are incurred over a short time horizon." (Section 4.2.2)

2. Figure IA2: Myopia and Earnings Pressure around the Divestment Shock.

   Reference in the main paper: "Moreover, Internet Appendix Figure IA2 shows that thermal coal producers' propensity to meet or just beat earnings forecasts does not increase following the divestment of NBIM and CalPERS, which is examined in Section 6 below. This evidence is also inconsistent with corporate myopia." (Section 4.2.2 Footnote 19)

3. Figure IA3: Aggregate Institutional Ownership around the Divestment Shock.

   Reference in the main paper: "Internet Appendix Figure IA3 shows trends in aggregate institutional ownership for thermal vs. met coal firms in our sample. Consistent with the argument that the divestments removed monitoring institutions, dedicated ownership declines significantly. Transient, quasi-indexer, and non-classified ownership, on the other hand, increase slightly, likely reflecting a reallocation among institutions." (Section 6 Footnote 27)

4. Figure IA4: Pre-trends in Production, Externalities, and Public Firm Characteristics prior to the Divestment Shock.

   Reference in the main paper: "However, to further probe the possibility that NBIM or CalPERS may have had financial or social reasons for divesting from thermal coal producers, Internet Appendix Figure IA4 plots pre-trends for thermal vs. met coal producers leading up to the divestment in 2015." (Section 6)

5. Table IA1: Public Listing Status and Fatalities and Injuries

[1]Stockholm School of Economics, Email: alvin.chen@hhs.se

[2]Fisher College of Business, Ohio State University, Email: wittry.2@osu.edu, and ECGI.

Reference in the main paper: "While accidents are almost certainly correlated with ex-ante firm policies, they include a random component that may muddle inferences. Moreover, injuries are often under-reported (Almberg et al., 2018). We nonetheless show consistent results using such ex-post measures in Internet Appendix Table IA1." (Section 3.2 Footnote 13)

6. Table IA2: Safety Violations and the Probability of a Fatal Accident

   Reference in the main paper: "Internet Appendix Table IA2 shows that only such high-probability violations are associated with fatal accidents, which are arguably the most pressing externality associated with coal mining." (Section 3.2)

   Reference in the main paper: "These results suggest the violations linked to the most extreme coal mining externality (e.g., see Internet Appendix Table IA2) are those that increase the most following an ownership dispersion." (Section 4.2.2)

7. Table IA3: Public Listing Status, Labor, and Organizational Structure

   Reference in the main paper: "Moreover, unlike other industries (e.g., Borisov et al., 2021; Bias et al., 2023), the coal sector provides a production-based setting where firms' labor and organizational structures remain relatively stable across listing status changes (e.g., see Internet Appendix Table IA3)." (Section 3.3)

8. Table IA4: Public Listing Status, Production, Externalities, and Listing Status Change Clusters

   Reference in the main paper: "While some listing status changes cluster in a handful of years (e.g., ICG's IPO and its acquisition of Horizon Natural Resources, both in 2005), there is significant variation in listing statuses across the sample. Internet Appendix Table IA4 verifies that our results remain similar if we (a) exclude 2005, or (b) exclude all mine-year observations for ICG and Horizon Natural Resources." (Section 3.3 Footnote 15)

9. Table IA5: Public Listing Status and Mine-Level Safety Violations.

   Reference in the main paper: "Internet Appendix Table IA5 verifies that our results are robust to using an OLS model or scaling violations by either safety inspections or employee-hours in a linear rate regression (Cohn et al., 2022)." (Section 4.2.2 Footnote 18)

10. Table IA6: Public Listing Status, Production, Externalities, and Production-Externality Threshold.

    Reference in the main paper: "Moreover, Internet Appendix Table IA6 shows similar results when scaling safety violations by total productive output." (Section 4.2.2)

11. Table IA7: Public Listing Status, Production, Externalities, and Production-Externality Threshold.

    Reference in the main paper: "In Internet Appendix Table IA7, we also report results using two continuous measures: the percentage of outstanding shares that are held by any institution and the percentage of outstanding shares that are held by institutions classified as dedicated, as well as an indicator for any 5% institutional blockholder (Edmans, 2014)." (Section 5.2.1)

12. Table IA8: Public Listing Status, Production, Externalities, and Price Informativeness Using PIN

    Reference in the main paper: "Internet Appendix Table IA8 reports similar results using the probability of informed trading (PIN)." (Section 5.2.3 Footnote 22)

13. Table IA9: Production, Externalities, and Coal Divestment Initiatives Robustness.

Reference in the main paper: "Internet Appendix Table IA9 shows similar results when separately using the approximate holdings of CalPERS and NBIM that we construct from the combination of 13f data and investor reports published by the funds. Moreover, the findings indicate that the results are not driven by just one of divestments, but rather both played a role in the increase in socially costly production." (Section 6 Footnote 29)

14. Table IA10: EBITDA, Earnings Quality, Bonus Thresholds, and Coal Divestment Initiatives Robustness.

    Reference in the main paper: "Internet Appendix Table IA10 shows similar results using EBITDA as the measure of performance." (Section 6)

    Reference in the main paper: "To formalize the argument that NBIM and CalPERS had no apparent financial or social reasons for divesting from thermal coal producers, Internet Appendix Figure IA4 plots pre-trends for thermal vs. met coal producers leading up to the divestment in 2015." (Section 6)

    Reference in the main paper: "Panel B plots log EBITDA targets for thermal versus metallurgical producers using firm and year fixed effects, and Internet Appendix Table IA10 Model (4) reports the DiD coefficient." (Section 6)

15. Table IA11: Are Thermal Coal Firms More Dangerous?

    Reference in the main paper: "Moreover, we report cross-sectional analyses in Internet Appendix Table IA11 that show thermal coal producers do not significantly differ from met coal producers on any measurable safety dimensions, such as injuries or fatal accidents." (Section 6)

16. Table IA12: Public Listing Status, Production, Externalities, and Managerial Ownership.

    Reference in the main paper: "25% is, admittedly, ad hoc. However, the sample 75th percentile for managerial ownership is only 3.8%, which strikes us as too low to associate with other firms we define as having a small reallocation of shares through the IPO. Nonetheless, we verify that our results are robust to other cutoffs, e.g., 5% or 10%, or simply using a continuous measure of managerial ownership (Internet Appendix Table IA12). Moreover, Internet Appendix Table IA13 shows similar results for production and high-probability safety violations when analyzing the controlling shareholder stake reduction directly in the reduced IPO sample (16 IPOs)." (Section 7 Footnote 30)

17. Table IA13: Public Listing Status, Production, Externalities, and Controlling Shareholder Stake Reductions.

    Reference in the main paper: "25% is, admittedly, ad hoc. However, the sample 75th percentile for managerial ownership is only 3.8%, which strikes us as too low to associate with other firms we define as having a small reallocation of shares through the IPO. Nonetheless, we verify that our results are robust to other cutoffs, e.g., 5% or 10%, or simply using a continuous measure of managerial ownership (Internet Appendix Table IA12). Moreover, Internet Appendix Table IA13 shows similar results for production and high-probability safety violations when analyzing the controlling shareholder stake reduction directly in the reduced IPO sample (16 IPOs)." (Section 7 Footnote 30)

18. Table IA14: Public Listing Status, Production, Externalities, and Financial Constraints.

    Reference in the main paper: "Internet Appendix Table IA14 shows similar results using a continuous measure of market leverage." (Section 7)

19. Table IA15: Public Listing Status, Production, Externalities, and Mines Producing Less Than 15% of Total Firm Coal

    Reference in the main paper: "Internet Appendix Table IA15 verifies our results remain strong and significant in a subsample with mines that account for less than 15% of the firm's total coal production." (Section 7)

IA.1 Externalities with Convex Social Costs

Our model highlights a central tension between minimizing agency costs and addressing the social costs arising from production externalities when these costs are convex. This section discusses the type of production externalities that fit our model.

When the social cost curve is convex, the marginal cost of mitigating one additional unit of the externality increases as the level of production increases. This relationship implies that production imposes proportionally higher social costs at higher levels of production.

Figure IA.1.1: Social Cost Functions. These figures display hypothetical social costs functions. Panel A displays a cost function that is flat in productive output, while Panel B displays a convext social costs function—one in which the costs increase at an increasing rate after some threshold.

(A) Flat Social Costs (B) Convex Social Costs

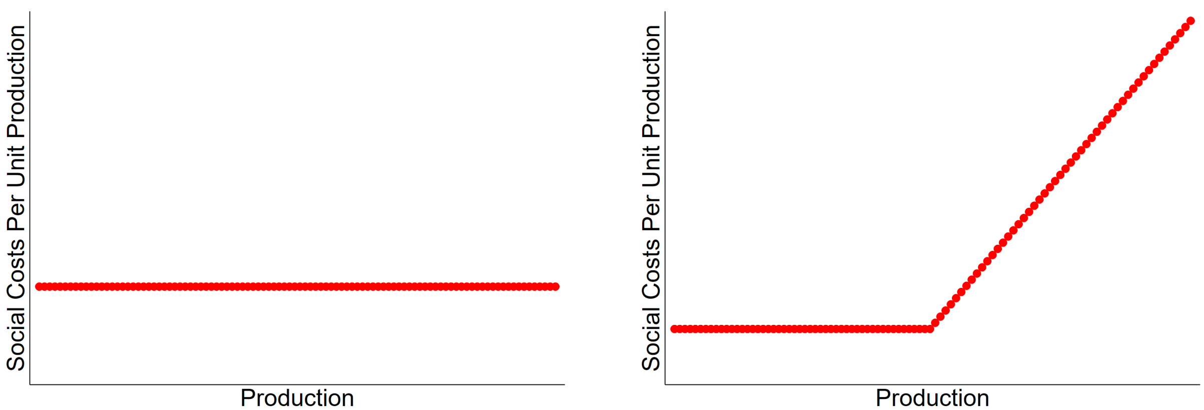


Figure IA.1.1 displays two hypothetical social cost functions. Panel A shows an externality that does not become increasingly costly as production increases. The most common example of an externality with such a social cost structure is industrial emissions. Factories and power plants emit pollutants such as sulfur dioxide (SO2), nitrogen oxides (NOx), and particulate matter. It seems likely, however, that firms can implement basic pollution control technologies (like filters and scrubbers) at low costs, and that these costs remain relatively flat throughout the range of productive outputs. That is, social costs per unit of production is fixed.

Panel B of Figure IA.1.1 illustrates an externality characterized by convex social costs, where the costs to mitigate the externality increase at an accelerating rate beyond a certain production threshold. A typical example of such costs involves the maintenance and safety improvements required as machinery experiences wear and tear, which often increases disproportionately with usage intensity. This type of social cost structure is common in industries that must frequently halt production to conduct maintenance and safety upgrades, e.g., most types of manufacturing. Additionally, many social externalities likely display this cost function. For example, opioids, cigarettes, alcohol, and even social media products are often marketed towards vulnerable groups of the population (e.g., minors), which almost certainly creates convexity in the social costs.

Section IA.1.1 discusses how coal mining fits this description. It should be noted that if production must be stopped in order to maintain and replace industrial filters and smokestack scrubbers, and if higher levels of production necessitate more frequent updates to the abatement equipment, even industrial emissions may have a convex social cost function at very high levels of production.

A second class of externalities that likely displays the social cost function depicted in Figure IA.1.1 Panel B is social health externalities. For example, tobacco, alcohol, recreational drugs, opioids, and firearms likely have limited abatement needs when the sales of these items are limited to the most responsible consumers. However, when overall sales exceed such a threshold, the costs of health and violence epidemics increase dramatically as overdoses and fatal accidents become more prevalent.

IA.1.1 Workplace Safety as an Externality

Classical economists (e.g., Smith, 1776) argue that the workplace environment, including safety conditions, is simply a function of the wage-setting process. Consistent with this view, much of the social and economic costs of hazardous working conditions (nearly $3 trillion annually worldwide (Dorman, 2012)) are internalized by the direct parties of the employment relationship, employers and employees (e.g., see Leigh et al., 2000). However, we contend, both below and in the main text, that poor working conditions also impose societal costs. For example, empirical studies have estimated that society at large bears around 20% of the direct costs stemming from hazardous working conditions, such as lost wages and medical costs (Leigh et al., 2000; Health and Safety Executive, 2023). Moreover, these estimates do not account for the economic costs to suppliers and customers that may arise from potential production stoppages.

This section argues that (1) coal mining is a setting in which the internalization of the social costs of hazardous working conditions due to wage pressures and regulatory enforcement is limited, (2) unsafe working conditions create convex social costs like the examples above. First, workers compensation and insurance are nearly always insufficient to cover the medical costs incurred by workplace accidents. This insufficiency leaves substantial costs to taxpayers, who must bear the burden through Medicare, Medicaid, disability, and social security payments to maintain the physical and emotional well-being of affected workers.

The estimates of 20% are likely a lower bound in the coal mining sector because of strong labor monopsony and low employee education levels. First, coal mining is the quintessential example of firm labor monopsony (e.g., Berger et al., 2022; Ashenfelter et al., 2010; Boyd, 1994). Such labor market power offers the firm the upper hand in labor negotiations, particularly with respect to wages and benefits, including workers compensation and insurance. Second, empirical research suggests that wages and benefits are inelastic to extreme working conditions such as fatality risk. For example, in a meta-analysis, Viscusi and Aldy (2003) report that the median wage elasticity with respect to the value of a statistical life is under 0.6. Importantly, this inelasticity is exacerbated by poor education (Maestas et al., 2023), a prominent feature of the coal industry, where generational miners have few other employment options.[3] Combined, these features impose more costs on society than other industries.

Importantly, the estimates of societal costs in these studies include only medical costs borne by taxpayers, ignoring several other important costs not borne by the firm or the miners themselves. For example, the costs of hazardous working conditions may be imposed on consumers in the form of higher energy prices (Leigh et al., 2000). Moreover, accident-induced mine closures often have devastating effects on the local economy (Isikoff, 1984; Kent, 2016). These effects can include dampened GDP, increased unemployment, and dramatic increases in opioid use (Boslett and Hill).

We note that the exact terminology is not critical to our results. We view the distinction of an externality not as binary but as a matter of degree, depending on the extent to which firms internalize the costs they impose.[4] Furthermore, we demonstrate that our results attenuate in mines where the elasticity of wages with respect to safety is presumably higher, such as unionized mines. Finally, to the extent that firms and workers internalize hazardous working conditions more than other externalities, our empirical results potentially provide a lower bound on the magnitude of the trade-off firms face between socially costly production and negative externalities.

IA.1.2 Socially Costly Production in Coal Mining

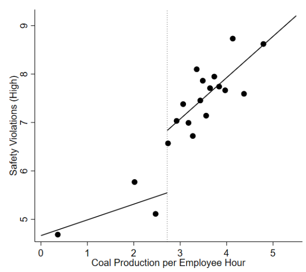
In this section, we build on the evidence that hazardous working conditions likely impose substantial societal costs that are not internalized by the direct parties to the employment relationship, that is, the employers and employees. Specifically, we argue that the technology for production and externality abatement in coal mining makes coal production at a mine increasingly socially costly at higher levels of production.

The production technology in coal mining makes it extremely difficult to extract additional coal per

[3] For example, after the Upper Big Branch explosion, one of the surviving miners, a 34 year-old father of four communicated his plans to return to work in a mine as soon as possible. "It's the only thing I know how to do," he said, "I don't read or write (Dwyer, 2010)."

[4] For example, polluting firms often face private lawsuits (Seba, 2017), and employee wages and home prices are not perfectly inelastic to firms' emissions (e.g., see Bajari et al., 2012; Cole et al., 2009; Goodwin et al., 2021), nor are prices that consumers are willing to pay for retail goods (Meier et al., 2023). These findings suggest that firms internalize some fraction of the costs imposed by even some of the most classical examples of externalities.

Figure IA.1.2: Production-Externality Threshold in Coal Mining Safety Violations. This figure displays a binscatter plot of high-probability safety violations as a function of coal production per employee hour at U.S. coal mines over a sample period of 1994 through 2022. A vertical dashed line depicts the 50th percentile for production per employee hour over the course of the sample. The figure highlights a low threshold of production before steep increases in the measurable externality, suggesting a convex relationship between abatement and per unit production. Data on mine-level production, safety violations, and employee hours are from the Mine Safety and Health Administration (MSHA) published through an Open Government Initiative.



hour without sacrificing miner-hours spent on other activities, e.g., safety and maintenance (Rittenberg and Manuel, 1986). In other words, workers cannot simultaneously extract coal from a tunnel that is being maintained. As noted above in Section IA.1, we view production stoppages for maintenance and safety as a major driver of convex social costs. Such stoppages have become increasingly common in coal mines, particularly underground ones, as firms increase coal production. For instance, as more and more coal is extracted from a mine, the tunnels become increasingly unstable. To adequately prevent the mine from collapsing, production must be stopped to reinforce the structure (e.g., installing additional support systems, backfilling, grouting). Combined, these factors suggest the likelihood that high production in coal mining is socially costly is significantly higher than in other industries.

While mapping out the entire social costs function for coal mining is not feasible, Figure IA.1.2 (which also appears in the main text) plots the observed externality with respect to productive output. In particular, the figure displays the observed safety violation rate as a function of coal production per employee hour for the firms in our sample. While the figure does not depict the actual social costs of working conditions in dollar terms, they do suggest that firms increase safety violations at an increasing rate as production increases, particularly after the 50th percentile of the production per employee hour, which we interpret as the “output-externality” threshold from our model.

IA.2 Proofs

Proof of Proposition 1. The firm maximizes its expected output net of wage costs and monetary penalties, if any. Suppose the firm allows for high production intensity ($x = 1$), then for any level of monitoring (Δ_B), the optimal contract to offer is given by Lemma 1: $W_H^* = \frac{1}{p}\left(\frac{B-\Delta_B}{1-\phi_H^{-1}}\right) > W_L^* = W_0^* = 0$. The optimal amount of monitoring solves

$$\underset{\Delta_B}{\text{maximize}} \quad \Pi_1 = \bar{Q}_1 - m - \tfrac{B-\Delta_B}{1-\phi_H^{-1}} - \tfrac{c\Delta_B^2}{2},$$

where $\bar{Q}_1$ is the firm's expected output when operating with high production intensity and managerial effort ($e = 1$). The first-order condition implies that $\Delta B^* = \frac{1}{(1-\phi_H^{-1})c}$. The firm's expected payoff is $\Pi_1^* = \bar{Q}_1 - m - \frac{B}{1-\phi_H^{-1}} + \frac{1}{2c}\frac{1}{(1-\phi_H^{-1})^2}$. Similarly, if the firm decides to enforce standard production intensity ($x = 0$), then for any level of monitoring (Δ_B), the optimal contract to offer is given by Lemma 2: $W_H^* = W_L^* = \frac{1}{p}\left(\frac{B-\Delta_B}{1-\phi_L^{-1}}\right) > W_0^* = 0$. The optimal amount of monitoring solves

$$\underset{\Delta_B}{\text{maximize}} \quad \Pi_0 = \bar{Q}_0 - \tfrac{B-\Delta_B}{1-\phi_L^{-1}} - \tfrac{c\Delta_B^2}{2},$$

where $\bar{Q}_0$ is the firm's expected output when operating with standard production intensity and managerial effort ($e = 1$). The first-order condition implies that $\Delta B^* = \frac{1}{(1-\phi_L^{-1})c}$. The firm's expected payoff is $\Pi_0^* = \bar{Q}_0 - \frac{B}{1-\phi_L^{-1}} + \frac{1}{2c}\frac{1}{(1-\phi_L^{-1})^2}$.

The firm's expected payoff is larger with less monitoring and high-powered incentives if and only if $\Pi_1^* > \Pi_0^*$, which corresponds to

$$\begin{aligned}(\bar{Q}_1 - \bar{Q}_0) - m + B\left(\tfrac{1}{1-\phi_L^{-1}} - \tfrac{1}{1-\phi_H^{-1}}\right) &> \tfrac{1}{2c}\left(\tfrac{1}{(1-\phi_L^{-1})^2} - \tfrac{1}{(1-\phi_H^{-1})^2}\right)\\ c &> \frac{1}{2}\left(\frac{\frac{1}{(1-\phi_L^{-1})^2} - \frac{1}{(1-\phi_H^{-1})^2}}{p\eta(q_H - q_L) - m + B\left(\frac{1}{1-\phi_L^{-1}} - \frac{1}{1-\phi_H^{-1}}\right)}\right) = \bar{c}.\end{aligned}$$

Proof of Proposition 2. Taking the derivatives of $\bar{c}$ from the proof of Proposition 1 with respect to m, B, and η yield $\frac{d\bar{c}}{dm} > 0$, $\frac{d\bar{c}}{dB} < 0$, and $\frac{d\bar{c}}{d\eta} < 0$.

The comparative statistics for the severity of the manager's moral hazard problem (B) and the probability of the negative productivity shock (η) also generate predictions that are consistent with our empirical results (see Table IA6).

IA.3 Model Extension: Contracting on the Firm's Social Cost

The baseline specification of our model captures the contracting frictions that limit the ability of shareholders to express non-pecuniary goals by assuming that compensation contracts can only specify pay contingent on the firm's output. This extension relaxes this assumption by introducing a noisy verifiable signal of the firm's social cost. Specifically, S takes values Ψ and 0 with probabilities ϵ and $1-\epsilon$, respectively. The expected social cost s in the main specification of the model corresponds to $s = \epsilon\Psi$. In this extension, a feasible compensation contract specifies the payment $W(Q, S)$ to the manager contingent on the firm's output (Q) and social cost (S) at $t = 1$. For notational convenience, let $W(q_i, S) = W_{iS}$.

As in the baseline model, standard arguments imply that the optimal contract does not pay the manager when the firm generates no output (i.e., $W_{0S} = 0$). When the manager does not shirk, her social compatibility (SC) constraint can be expressed as

$$\begin{aligned} (1-\eta)pW_{H0} + \eta p W_{L0} \geq&\ p(1-\epsilon)W_{H0} + p\epsilon W_{H\Psi} \\ W_{L0} \geq&\ W_{H0}\left(1 - \tfrac{\epsilon}{\eta}\right) + p\epsilon W_{H\Psi}. \end{aligned} \tag{3}$$

Note that for small values of ϵ (i.e., the firm's social cost is noisy), condition (3) well approximates the social compatibility constraint in the main body of the paper. When the firm's social cost is sufficiently noisy, (3) implies a lower bound for the payment to the manager when the firm's output is low, limiting how high-powered the compensation contract can be without violating the manager's social compatibility constraint. As a result, the firm continues to face a trade-off between minimizing agency costs and preventing socially costly production. It can be shown that the lowest-cost IC and SC compensation contract is given by

$$W^*_{0\Psi} = W^*_{00} = W^*_{L\Psi} = W^*_{H\Psi} = 0,$$

$$W^*_{H0} = \frac{B - \Delta B^*}{(1-\eta)(p-p_H) + \eta(1-\frac{\epsilon}{\eta})(p-p_L)}$$

and

$$W_{L0} = \left(1 - \tfrac{\epsilon}{\eta}\right) W^*_{H0} < W^*_{H0}.$$

In this case, the agency cost associated with this contract is given by $A_\epsilon = \frac{B}{1-\phi_\epsilon^{-1}}$, where ϕ_ϵ^{-1} is the inverse weighted average of the likelihood ratios for low and high output:

$$\phi_\epsilon^{-1} = \frac{(1-\eta)p_H + \eta(1-\frac{\epsilon}{\eta})p_L}{p(1-\eta) + p\eta(1-\frac{\epsilon}{\eta})}.$$

The monotone likelihood ratio property (MLRP) of the firm's production technology implies that $\phi_\epsilon^{-1} > \phi_H^{-1}$

for $\epsilon < \eta$. Hence, the adoption of high-powered incentives that pays a bonus only for high output (i.e., $W_H^* > W_L^* = 0$) results in agency cost savings relative to the socially-compatible, lower-powered incentives that also reward the manager for low output (i.e., $W_{H0}^* > W_{L0}^* > 0$). Hence, as long as the measure of the firm's social cost is sufficiently noisy, the firm continues to face a trade-off between minimizing agency costs and limiting the social costs of production.

IA.3.1 Contracting on Workplace Safety: An Empirical Investigation

This section empirically examines the impact of safety-based incentive compensation contracts for coal mining firms in our sample. The above model extension suggests that our results should weaken in the presence of such incentive contracts for the CEOs.

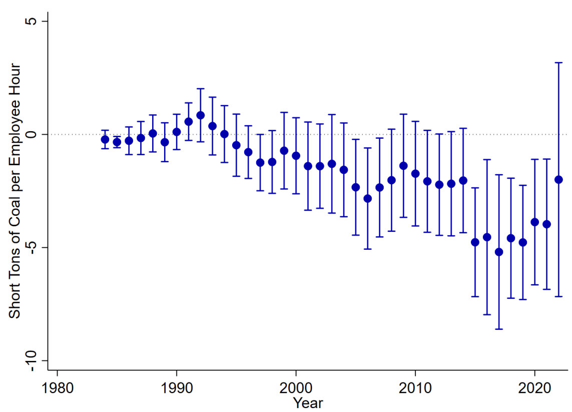
We collect data on safety-based performance incentives from ISS Incentive Lab's Absolute Performance Goals Data. Unfortunately, the coverage on these provisions is incredibly sparse, with almost no coverage until the mid 2010s. More problematic, even when the coverage does improve late in the sample, the vast majority of firms that eventually add a safety-based incentive do so in one single year: 2018. While such a discrete jump in firms using safety incentives is technically possible, it leaves open the possibility that data collection procedures changed at that time instead.

To circumvent these data issues, we employ a relatively crude approach. First, we restrict our analysis to public firms as ISS Incentive Lab does not cover private firms. Next, we construct an indicator variable, *I(Safety contract)*, that equals 1 if a firm uses a safety incentive at any point in our sample. There are 28 such firms. Finally, we interact this indicator variable with year dummy variables, given we do not know the true initiation year for such provisions. We plot the estimates of these coefficients in Table IA.3.1.

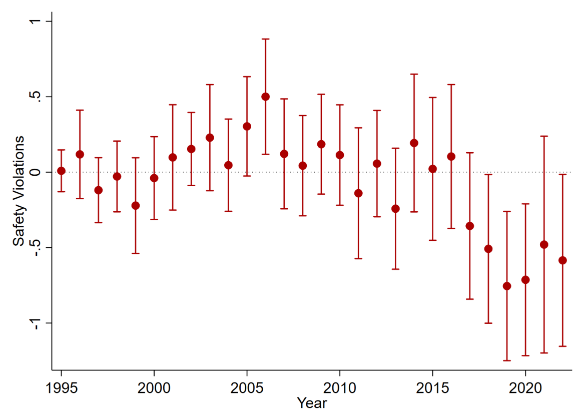
Panel A plots the coefficients for production, while Panel B plots the coefficients for safety violations. In general, both plots show a consistent decline, at least post-2005, indicating that such firms may have started incentivizing safety much earlier than 2018. Moreover, both Panels show a fairly dramatic drop starting around 2015 or 2016, which is consistent with a general increase in the use of worker-safety pay incentives across the S&P 500 at that time (Massa and Ritcey, 2015). More importantly, these results—production and externalities decreasing with the use of safety-based incentive contracting—are consistent with the model extension above.

Figure IA.3.1: Production, Externalities, and Safety-based Incentive Contracts. These figures display the trends of mine-level production and safety violations for U.S. coal mines owned by *public* firms over a sample period of 1985 through 2022 for production and 1994 through 2022 for safety violations. We use an OLS model for production and a Poisson pseudo-maximum-likelihood model for safety violations. These figures plot annual coefficients for each time interacted with an indicator that is equal to 1 for public firms that award performance compensation to their executives based on safety goals at any point in our sample. Data on performance compensation is from ISS Incentive Lab. Data on mine-level production and safety violations, as well as ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration (MSHA) published through an Open Government Initiative. Data on firms' public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website.

(A) Production



(B) All safety violations.



IA.4: Coal Industry Compensation Plans

This section displays snippets for executive compensation plans for coal firms that IPO during our sample.

The snippets are taken from either the firms' form 10-ks or the firms' form S-1s/S-4s.

Figure IA.4.1: Warrior Met Coal Summary Compensation Table from 2019 Form 10-k. This figure displays the Summary Compensation Table for executive officers at Warrior Met Coal as reported in its 2019 Form 10-k. Warrior Met Coal went public in April, 2017. This figure highlights large increases in the non-equity incentive plan compensation following the IPO, even while base salary stayed constant or decreased.

SUMMARY COMPENSATION TABLE

The following table summarizes the total compensation earned by each of the Company's NEOs for the fiscal years ended December 31, 2018, December 31, 2017 and December 31, 2016.

Name and Principal Position[1]	Year	Salary ($)[2]	Bonus ($)[3]	Stock Awards ($)[4]	Option Awards ($)	Non-Equity Incentive Plan Compensation ($)[5]	Change in Pension Value and Nonqualified Deferred Compensation Earnings ($)	All Other Compensation ($)[6]	Total ($)
Walter J. Scheller, III[7]	2018	643,477	—	596,824	—	1,184,963	—	817,283	3,242,547
Chief Executive Officer	2017	614,539	—	1,125,738	—	1,097,013	—	724,999	3,562,289
	2016	634,231	—	1,225,463	—	480,000	—	46,916	2,386,610
Jack K. Richardson	2018	410,731	—	209,484	—	756,361	—	414,442	1,791,018
Chief Operating Officer	2017	353,848	—	562,902	—	631,654	—	372,798	1,921,202
	2016	242,656	75,000	612,768	—	280,000	—	92,550	1,302,974
Dale W. Boyles[8]	2018	389,808	—	197,169	—	717,831	—	111,815	1,416,623
Chief Financial Officer	2017	336,539	555,000	804,208	—	600,755	—	133,630	2,430,132
Kelli K. Gant[9]	2018	288,076	—	147,846	—	397,869	—	259,997	1,093,788
Chief Administrative Officer and Secretary	2017	239,289	—	333,552	—	320,366	—	231,035	1,124,242
Phillip C. Monroe[10] General Counsel	2018	228,655	—	142,956	—	315,801	—	114,522	801,934
Michael T. Madden[11]	2018	185,719	—	162,455	—	256,501	—	745,611	1,350,286
Chief Commercial Officer	2017	327,755	—	333,552	—	438,807	—	234,125	1,334,239
	2016	328,380	35,000	363,100	—	192,000	—	38,952	957,432

Figure IA.4.2: Change in Foundation Coal's Compensation Structure Post-IPO. This figure displays excerpts from Foundation Coal's form S-4 prior to its IPO in December, 2004, as well as from its form 10-k filed one year after its IPO. Prior to going public, Foundation Coal's CEO, James Roberts earned no performance bonus. However, just one year after Foundations' IPO, he was nearly doubling his base salary in performance incentives.

(A) Foundation Coal Form S-4 filed in 2004.

Summary Compensation Table

		Annual Compensation			
Name and Principal Position	Year	Salary ($)	Bonus ($)	Other Annual Compensation ($)	All Other Compensation ($)
James F. Roberts President and Chief Executive Officer	2003	540,000	—	—	47,186(1)
John R. Tellmann Senior Vice President, Sales and Marketing	2003	252,144	100,000	—	—
Greg A. Walker Senior Vice President, General Counsel and Secretary	2003	225,879	90,000	—	—
James A. Bryja Senior Vice President, Eastern Operations	2003	225,000	54,000	82,159	—
Thomas J. Lien Senior Vice President, Western Operations	2003	220,000	70,000	—	—

(B) Foundation Coal Form 10-k filed in 2006.

Summary Compensation Table:

	Annual Compensation					
Name and Principal Position	Year	Salary ($)	Performance Bonus ($)	Other Annual Compensation ($)	LTIP-Payouts	All Other Compensation
James F. Roberts President and Chief Executive Officer	2004 2005	$ 571,388 $ 615,024	$ 450,000 $ 1,033,135	$ 1,118,550(a)	$ 1,190,919	$ 253,293(f) $ 6,103(g)
James J. Bryja	2004 2005	$ 229,509 $ 235,247	$ 75,000 $ 294,048	$ 289,865(b)	$ 260,294	$ 16,009(h) $ 5,293(i)
Frank J. Wood Senior Vice President and Chief Financial Officer	2004 2005	$ 204,875 $ 270,010	$ 200,000 $ 337,500	$ 513,185(c)	$ 396,974	$ 201,112(j) $ 6,000(k)
Greg A. Walker Senior Vice President, General Counsel and Secretary	2004 2005	$ 230,406 $ 236,166	$ 175,000 $ 295,196	$ 453,185(d)	$ 396,974	$ 147,479(l) $ 6,300(m)
John R. Tellmann Former, Senior Vice President, Sales and Marketing (p)	2004 2005	$ 257,197 $ 280,049	$ 170,000 $ 362,500	$ 443,050(e)	$ 396,974	$ 77,231(n) $ 6,033(o)

Figure IA.4.3: Change in Ramaco Resources' Compensation Structure Post-IPO. This figure displays excerpts from Ramaco Resources' form S-1 prior to its IPO in February, 2017, as well as from its form 10-k filed one year after its IPO, and its form 10-k filed three years after its IPO. Ramaco's executives earned just $25,000 in performance bonuses two years prior to the IPO and $125,000 in the year directly prior to going public. However, during the year after Ramaco's IPO, the performance incentives were up to $340,000, before leveling off at over $600,000 in 2019-2020.

(A) Ramaco Resources Form S-4 filed in 2015.

2015 Summary Compensation Table

The following table summarizes the compensation awarded to, earned by or paid to our principal executive officer and our next two most highly compensated executive officers (our "Named Executive Officers") for the fiscal year ended December 31, 2015.

Name and Principal Position	Year	Salary($)	Bonus($) (1)	Total($)
Michael Bauersachs *(President and Chief Executive Officer)*	2015	81,250	25,000	106,250
Randall Atkins *(Executive Chairman)*	2015	81,250	25,000	106,250
Mark Clemens *(Chief Operating Officer)*	2015	56,833	20,000	76,833

(B) Ramaco Resources Form 10-k filed in 2018.

Summary Compensation Table for 2017

Name and Principal Position	Year	Salary ($)	Bonus(1) ($)	Stock Awards(2) ($)	Option Awards(3) ($)	Total ($)
Randall W. Atkins	2017	391,167	340,000	800,000	—	1,531,167
Executive Chairman, Director and Chairman of the Board	2016	300,000	125,000	—	1,222,088	1,647,088
Michael D. Bauersachs	2017	391,667	340,000	800,000	—	1,531,667
President, Chief Executive Officer and Director	2016	300,000	125,000	—	1,222,088	1,647,088
Mark A. Clemens	2017	295,833	191,250	450,000	—	937,083
Chief Commercial Officer	2016	250,000	100,000	—	—	350,000

(C) Ramaco Resources Form 10-k filed in 2021.

Summary Compensation Table for 2020

Name and Principal Position	Year	Salary ($)	Bonus(1) ($)	Stock Awards(2) ($)	Option Awards(3) ($)	Other(4) ($)	Total ($)
Randall W. Atkins	2020	540,000	620,000	1,350,000	—	11,400	2,521,400
Chief Executive Officer, Executive Chairman, Director and Chairman of the Board(5)	2019	500,000	625,000	1,273,991	—	11,200	2,410,191
Michael D. Bauersachs	2020	540,000	540,000	1,350,000	—	11,400	2,441,400
Former President, Chief Executive Officer and Director(6)	2019	500,000	625,000	1,273,991	—	11,200	2,410,191
Christopher L. Blanchard	2020	378,000	435,000	567,000	—	11,400	1,391,400
Chief Operating Officer	2019	350,000	438,000	531,523	—	11,200	1,330,723

Figure IA.4.4: Change in Contura Energy's Compensation Structure Post-IPO. This figure displays excerpts from Contura Energy's form S-1 prior to its IPO in July, 2017, as well as from its form 10-k filed one year after its IPO. Prior to going public, Contura had performance metrics based on Free Cash Flow for its executives. The maximum payout of 200% of base salary could be obtained with a CIB FCF of $46 million. However, just one year after its IPO, the performance metric changed to EBITDA, which incentives higher production relative to costs savings. Moreover, the maximum payout could only be obtained with an EBITDA of $247 million, over 40% higher than the realized EBITDA in 2016.

(A) Contura Form S-1 filed in 2017.

Performance Metrics

For 2016, the compensation committee approved a mix of performance measures based on financial metrics and operational metrics, as shown in the table below. Additional information regarding the performance metrics are included in the footnotes to the table below, including reconciliation of the non-GAAP measurements to the most closely-related GAAP measurements.

The compensation committee approved the following metrics, the respective weighting of each metric and the performance thresholds for the executives' 2016 annual bonuses under the Bonus Plan. The metrics were intended to align annual incentive compensation for 2016 with the goals and objectives set forth in the company's business plan. If the threshold level of performance for any of our metrics is not achieved, the resulting payout as a percentage of target is 0%, and no payouts are made under the metric.

The table below sets forth the performance metrics and their respective weightings and thresholds as well as the actual achievement of each metric based on the company's financial and operational results for the period from July 26, 2016 to December 31, 2016:

	Metric Goals & Performance						
Performance Metric	**Weighting (A)**	**Threshold (Payout - 50%)**	**Target (Payout - 100%)**	**Maximum (Payout - 200%)**	**Actual Performance**	**Payout as % of Target (B)**	**As % of Target Bonus Opportunity (AxB)**
CIB Free Cash Flow [1]	35.00%	$38.0M	$42.0M	$46.0M	$102.6M	200.00%	70.00%
CIB Cost of Coal Sales per Ton Sold [2]	25.00%	$17.70	$16.10	$14.50	$17.14	67.50%	16.88%
CIB SG&A [3]	20.00%	$15.0M	$13.5M	$12.0M	$12.0M	200.00%	40.00%
NFDL [4]	10.00%	3.03	2.76	2.48	2.50	192.86%	19.29%
Environmental Compliance [5]	10.00%	10.28	8.94	8.04	16.67	0.00%	0.00%
Total	**100%**						**146.16%**

(B) Contura Form 10-k filed in 2019.

Performance Metrics

In establishing 2018 performance goals, the compensation committee considered the economic environment and challenges to be faced during the fiscal year. The compensation committee designed the performance goals to ensure that performance significantly in excess of the target performance goals would be rewarded with above target payout levels, up to the cap established by the compensation committee. In setting the target goals, the compensation committee sought to establish challenging but attainable goals that would motivate and reward the NEOs for strong performance without encouraging excessive risk taking.

For 2018, the compensation committee approved a mix of performance measures based on financial metrics and operational metrics, as shown in the table below. Additional information regarding the performance metrics are included in the footnotes to the table below.

The compensation committee approved the following metrics, the respective weighting of each metric and the performance thresholds for the executives' 2018 annual bonuses under the Bonus Plan. The metrics were intended to align annual incentive compensation for 2018 with the goals and objectives set forth in the Company's business plan, specifically a focus on safety, environmental compliance and financial performance, especially with respect to costs. If the threshold level of performance for any of our metrics is not achieved, the resulting payout as a percentage of target is 0%, and no payouts are made under the metric.

The table below sets forth the performance metrics and their respective weightings and thresholds as well as the performance under each metric:

	2018 Metric Goals				2018 Performance		
Performance Metric	**Weighting**	**Threshold Payout (50%)**	**Target Payout (100%)**	**Maximum Payout (200%)**	**Performance**	**Payout as % of Target**	**Aggregate Target Bonus % Earned**
EBITDA [1]	30.00%	$202.16M	$224.62M	$247.09M	$327.06M	200.00%	60.000%
Cost of Coal Sales per Ton Sold – CAPP [2]	15.00%	$76.36	$72.36	$68.36	$74.34	75.25%	11.287%
Cost of Coal Sales per Ton Sold - NAPP [2]	10.00%	$34.14	$32.14	$30.14	$39.15	0.00%	0.000%
SG&A Expense [3]	15.00%	$38.00M	$35.96M	$32.50M	$32.80M	191.33%	28.699%
Safety – NFDL [4]	20.00%	3.22	2.93	2.64	2.94	98.28%	19.655%
Environmental Compliance [5]	10.00%	42	32	22	16	200.00%	20.000%
Total	**100%**						**139.641%**

Figure IA.4.5: Change in Cloud Peak's Compensation Structure Post-IPO. This figure displays excerpts from Cloud Peak's form S-1 prior to its IPO in November, 2009, as well as from its form 10-k filed one year after its IPO. Prior to going public, Cloud Peak had no performance incentive program for its executives. However, just one year after its IPO, the CEO, Colin Marshall, could earn more than double his base salary in performance incentives by hitting the maximum EBIDTA of $323 million, nearly 40% higher than the EBITDA the company realized in 2007.

(A) Cloud Peak Form S-1 filed in 2009.

Short-Term Incentives

We expect to adopt a Short-Term Incentive Plan, or STIP, to provide rewards for achieving annual operating and financial performance objectives. We expect the STIP will have a one-year performance period and awards under the plan will be paid based on actual performance against pre-established performance targets that are approved in advance by our compensation committee.

We expect to determine annual incentive compensation under the STIP after the completion of each fiscal year and we intend for it to be based on mine site operational performance and company-wide operational and financial performance.

Long-Term Equity-Based Awards

We believe that long-term performance is enhanced through an "ownership culture." Accordingly, we expect that a significant part of our executive compensation program will consist of equity-based compensation.

We expect to establish a Long-Term Incentive Plan, or LTIP, that will provide for the grant of share-based compensation including share based awards and options. We will make awards under the

(B) Cloud Peak Form 10-k filed in 2011.

Metric	Threshold	Objective	Maximum	Actual 2010 Result
EBITDA(4)	$216 million	$268 million	$323 million	$311 million
Safety (AIFR)(5)	0.77	0.62 (+ zero fatalities)	0.46 (+ zero fatalities)	0.52
SOX Multiplier (CFO)	50%(1)	100%(2)	125%(3)	125%
SOX Multiplier (All other NEOs)	75%(1)	100%(2)	110%(3)	110%

(1) Material Weakness Identified

(2) No Material Weakness Identified

(3) No Significant Deficiencies

(4) Refer to our Form 10-K for additional information regarding EBITDA.

(5) See below for a discussion of the differences between our AIFR calculation for the Annual Incentive Plan compared to the MSHA methodology.

Annual Incentive Compensation

Our Annual Incentive Plan has one-year performance periods. Awards under the plan are paid based on actual performance against pre-established company and personal performance targets that are approved in advance by the Compensation Committee. In accordance with the plan, annual incentive compensation is determined after the completion of each fiscal year and is based on operational and financial performance during the year, as well as personal performance measurements.

The target bonus percentage amounts ("target") under the Annual Incentive Plan awards for 2010 were based on a multiple of each executive's base salary for 2010. In its review of the 2010 executive compensation program, the Compensation Committee determined that no changes to the target multiple were necessary for the 2010 compensation program since the target in effect for each executive officer at the end of 2009 was still appropriate. After consulting with Aon Hewitt and considering the market data provided by Aon Hewitt, the Compensation Committee determine no changes to the target multiple were needed with regard to the 2011 compensation program.

The following table provides the 2010 target multiple, as well as theoretical payments which could have been made upon the achievement of a threshold, objective or maximum award determination. The table also provides for comparison purposes the actual award each of the named executive officers earned during 2010.

Name	2010 Target Award (% of Base Salary)	2010 Threshold Award (50% of Target Award) ($)	2010 Objective (100% of Target Award) ($)	2010 Maximum Award (200% of Target Award) ($)	Actual 2010 Award ($)
Colin Marshall	100	325,000	650,000	1,300,000	1,202,500
Michael Barrett	75	140,625	281,250	562,500	562,500
Gary Rivenes	75	140,625	281,250	562,500	523,200
James Orchard	60	90,000	180,000	360,000	333,000
Bryan Pechersky	60	90,000	180,000	360,000	311,500

The measurement objectives for the plan were established at the beginning of 2010 by the Compensation Committee. There are three components that determined 2010 awards under the Annual Incentive Plan: EBITDA, safety and a discretionary component for personal performance. Although personal performance is discretionary at the sole determination of the Compensation Committee, with respect to the senior executive officers other than the CEO, the CEO provided his recommendations for these amounts to the Compensation Committee for its consideration.

IA.5 Private Equity

We note that our paper is tangentially related to a growing literature on the effects of private equity buyouts on various stakeholders of the firm in a variety of industries, such as employees (Cohn et al., 2021; Agrawal and Tambe, 2016; Antoni et al., 2019; Garcia-Gomez et al., 2022), healthcare patients (Gupta et al., 2021; Liu, 2022; Gao et al., 2021), consumers (Eaton et al., 2020; Bernstein and Sheen, 2016; Howell et al., 2023), and the local community Bellon (2024). See Gupta et al. (2021) for a more complete list of references on the impacts of PE in the healthcare industry. Thus, we contribute to this growing literature that analyzes how asset ownership impacts society due to differing economic incentives.

However, we caution readers from making strong inferences from our paper regarding private equity ownership for several reasons. First, the transition from being closely held or publicly listed to PE-backed status often involves significant governance changes that are not captured by our model. For instance, our model assumes that the firm sets its policies to maximize shareholder welfare subject to agency frictions. PE buyouts often target poorly governed firms with policies that enrich some insiders (Kaplan and Schoar, 2005; Acharya et al., 2012). Hence, a PE buyout may be associated with not only a change in feasible governance mechanisms but also in the firm's objective itself.

Second, our empirical setting (coal mining) simply features very little private equity ownership, at least that we can verify. For example, when we match our data to Preqin, we find only six unique private equity buyouts of coal mining firms in our sample. Each of these buyouts is associated with relatively small private coal firms with few producing mines. We remove these observations from our sample. Though we do not observe non-buyout related PE investments and ownership for the private firms in our sample, we have strong reason to believe such ownership is quite small. First, when exploring the ownership of controlling shareholders pre- and post-IPO for the firms that go public in our sample, the form S-1s suggest that these coal firms are very closely held and without PE owners. Second, and consistent with this observation, Fickling (2022) presents data from Bloomberg that shows trivial private equity investment in coal M&A since the early 2000s. Combined, these factors suggest that our results do not readily apply to private equity buyouts of either public or private firms.

Internet Appendix References

[IA1] Acharya, V. V., O. F. Gottschalg, M. Hahn, and C. Kehoe. 2012. Corporate Governance and Value Creation: Evidence from Private Equity. *The Review of Financial Studies* 26:368–402.

[IA2] Agrawal, A., and P. Tambe. 2016. Private equity and workers career paths: The role of technological change. *Review of Financial Studies* 29:2455–2489.

[IA3] Antoni, M., E. Maug, and S. Obernberger. 2019. Private equity and human capital risk. *Journal of Financial Economics* 133:634–657.

[IA4] Ashenfelter, O. C., H. Farber, and M. R. Ransom. 2010. Labor Market Monopsony. *Journal of Labor Economics* 28:203–210.

[IA5] Bajari, P., J. C. Fruehwirth, K. I. Kim, and C. Timmins. 2012. A Rational Expectations Approach to Hedonic Price Regressions with Time-Varying Unobserved Product Attributes: The Price of Pollution. *American Economic Review* 102:1898–1926.

[IA7] Bellon, A. 2024. Does Private Equity Ownership Make Firms Cleaner? The Role Of Environmental Liability Risks. *Review of Financial Studies*, Forthcoming.

[IA7] Berger, D., K. Herkenhoff, and S. Mongey. 2022. Labor Market Power. *American Economic Review* 112:1147–93. URL `https://www.aeaweb.org/articles?id=10.1257/aer.20191521`.

[IA8] Bernstein, S., and A. Sheen. 2016. The Operational Consequences of Private Equity Buyouts: Evidence from the Restaurant Industry. *Review of Financial Studies* 29:2387–2418.

[IA9] Boslett, A., and E. Hill. Mortality during Resource Booms and Busts. *Journal of Environmental Economics and Management* 115.

[IA10] Boyd, L. W. 1994. The Economics of the Coal Company Town: Institutional Relationships, Monopsony, and Distributional Conflicts in American Coal Towns. *The Journal of Economic History* 54:426–427.

[IA11] Brown, S., and S. A. Hillegeist. 2007. How Disclosure Quality Affects the Level of Information Asymmetry. *Review of Accounting Studies* 12:443–477.

[IA23] Cohn, J., N. Nestoriak, and M. Wardlaw. 2021. Private Equity Buyouts and Workplace Safety. *Review of Financial Studies* 34:4832–4875.

[IA13] Cole, M. A., R. J. Elliott, and J. K. Lindley. 2009. Dirty Money: Is There a Wage Premium for Working in a Pollution Intensive Industry? *Journal of Risk and Uncertainty* 39:161–180.

[IA31] Dorman, P. 2012. Estimating the economic costs of occupational injuries and illnesses in developing countries: Essential information for decision-makers. ILO.

[IA15] Dwyer, D. 2010. Craving Coal Dust 'Like Nicotine': Why Miners Love the Work. *ABC News* URL `https://abcnews.go.com/US/Mine/west-virginia-coal-miners-allure-dangerous-profession/story?id=10305839`.

[IA16] Easley, D., N. M. Kiefer, M. O'Hara, and J. B. Paperman. 1996. Liquidity, Information, and Infrequently Traded Stocks. *Journal of Finance* 51:1405–1436.

[IA17] Eaton, C., S. T. Howell, and C. Yannelis. 2020. When Investor Incentives and Consumer Interests Diverge: Private Equity in Higher Education. *Review of Financial Studies* 33:4024–4060.

[IA18] Fickling, D. 2022. Why Private Equity Won't Be the Savior of Fossil Fuels. *Bloomberg* URL https://www.bloomberg.com/opinion/articles/2022-01-05/why-private-equity-won-t-be-the-savior-of-fossil-fuels.

[IA19] Gao, J., M. Sevilir, and Y. Kim. 2021. Private Equity in the Hospital Industry. European Corporate Governance Institute – Finance Working Paper No. 787/2021.

[IA20] Garcia-Gomez, P., E. G. Maug, and S. Obernberger. 2022. Private equity buyouts and employee health. European Corporate Governance Institute - Finance Working Paper No. 680/2020.

[IA21] Goodwin, M. B., M. Fontenla, and F. Gonzalez. 2021. Estimating the Impact of Pollution on Wages and Housing Prices Using Satellite Imagery. *Applied Economics Letters* 28:1750–1753.

[IA22] Gupta, A., S. T. Howell, C. Yannelis, and A. Gupta. 2021. Owner Incentives and Performance in Healthcare: Private Equity Investment in Nursing Homes. NBER Working Paper No. 28474.

[IA23] Health and Safety Executive. 2023. Costs to Britain of workplace fatalities and self-reported injuries and ill health, 2021/22.

[IA24] Howell, S., Y. Jang, H. Kim, and M. S. Weisbach. 2023. All Clear for Takeoff: Evidence from Airports on the Effects of Infrastructure Privatization. NBER Working Paper No. 30544.

[IA54] Isikoff, M. 1984. Community Faces Economic Impact Of Mine Disaster. *Washington Post* .

[IA26] Kaplan, S. N., and A. Schoar. 2005. Private Equity Performance: Returns, Persistence, and Capital Flows. *Journal of Finance* 60:1791–1823.

[IA58] Kent, C. A. 2016. *The Cruel Coal Facts: The Impact on West Virginia Counties from the Collapse of the Coal Economy*. Report for the National Association of Counties. URL https://www.marshall.edu/cber/files/2021/04/2016-09-Cruel_Coal.pdf.

[IA61] Leigh, J. P., S. Markowitz, M. Fahs, and P. Landrigan. 2000. *Costs of Occupational Injuries and Illnesses*. University of Michigan Press.

[IA29] Liu, T. 2022. Bargaining with Private Equity: Implications for Hospital Prices and Patient Welfare. Working paper, MIT Sloan School of Management.

[IA30] Maestas, N., K. J. Mullen, D. Powell, T. Von Wachter, and J. B. Wenger. 2023. The Value of Working Conditions in the United States and Implications for the Structure of Wages. *American Economic Review* 113:2007–2047.

[IA31] Massa, A., and A. Ritcey. 2015. Do CEO Bonuses for Worker Safety Do Any Good? Massey Trial Begins. *Bloomberg* URL https://www.bloomberg.com/news/articles/2015-10-01/doubt-cast-on-ceo-safety-bonuses-as-mine-disaster-trial-starts.

[IA32] Meier, J.-M., H. Servaes, J. Wei, and S. C. Xiao. 2023. Do Consumers Care About ESG? Evidence from Barcode-Level Sales Data. ECGI Finance Working Paper No. 926/2023.

[IA33] Rittenberg, L., and E. H. Manuel, Jr. 1986. A Case Study of Decline in Labor Productivity: Underground Coal Mining Industry, 1960-1976. *Quarterly Journal of Business and Economics* 25:38–55.

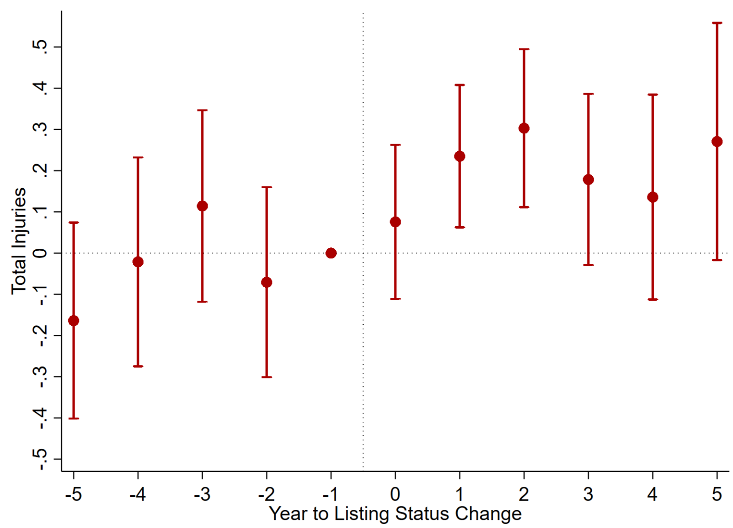
[IA34] Seba, E. 2017. Judge says Exxon Owes $19.95 Million for Texas Refinery Pollution. *Reuters* URL https://www.reuters.com/article/refinery-pollution-exxon-penalty/judge-says-exxon-owes-19-95-million-for-texas-refinery-pollution-idUSL1N1HZ26P.

[IA35] Smith, A. 1776. *The Wealth of Nations*. University of Chicago Press, Chicago.

[IA36] Viscusi, W. K., and J. E. Aldy. 2003. The Value of a Statistical Life: A Critical Review of Market Estimates Throughout the World. *Journal of Risk and Uncertainty* 27:5–76.

Figure IA1: Stacked Regression Injuries and Fatalities Event-Time Trends around Listing Status Changes. These figures display the trends of mine-level injuries (Panel A) and fatal accidents (Panel B) around listing status changes (IPOs, public acquisitions, and private acquisitions or other going-private transactions) for U.S. coal mines over a sample period of 1983 through 2022. We use a Poisson pseudo-maximum-likelihood model (Panel A) and an OLS model (Panel B) within stacked regression methodology to estimate the dynamic effects (Baker et al., 2022; Gormley and Matsa, 2011). The figures plot annual coefficients for each time (year $t = -5$ through year $t = 5$) directly around a listing status change interacted with an indicator (*treat*) that is equal to 1 for to-public listing status changes, and -1 for to-private listing status changes. We use the same fixed effects as our baseline specifications in Table 4, and following Gormley and Matsa (2011), we interact the fixed effects from these models with a cohort indicator, as well as an event number indicator for mines that experience multiple listing status changes. Standard errors are clustered at the firm level. Data on mine-level injuries, accidents, and ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration (MSHA) published through an Open Government Initiative. Data on firms' public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website.

(A) Injuries.



(B) I(Fatal Accident)

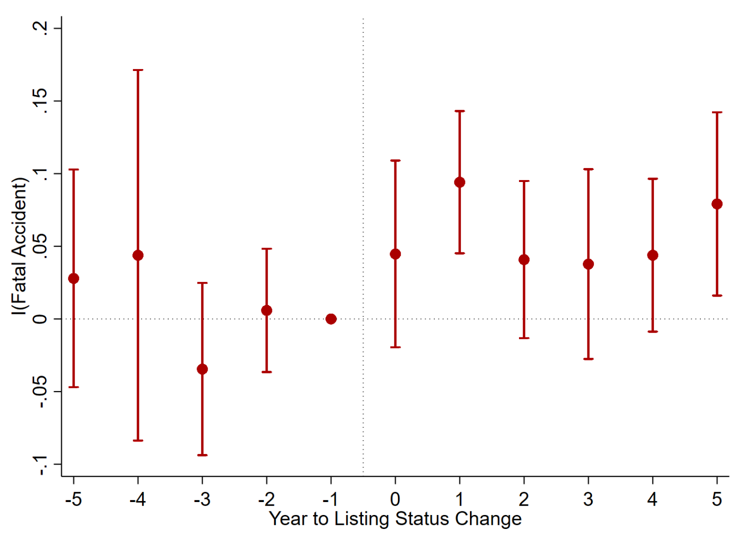


Figure IA2: Myopia and Earnings Pressure around the Divestment Shock. This figure displays the trends in public firms' propensity to meet or just beat analysts' consensus earnings forecasts. In particular, the figure plots annual coefficients for each time (year $t = -5$ through year $t = 5$) directly around the divestment shock in 2015 interacted with an indicator (*treat*) that is equal to 1 for thermal coal producers, and 0 for met coal producers. The dependent variable is an indicator variable equal to 1 if a firm's realized earnings are equal to, are greater than or equal to (up to \$0.01) the consensus forecast among analysts of one-year ahead EPS. Data on forecasted and realized EPS is from IBES.

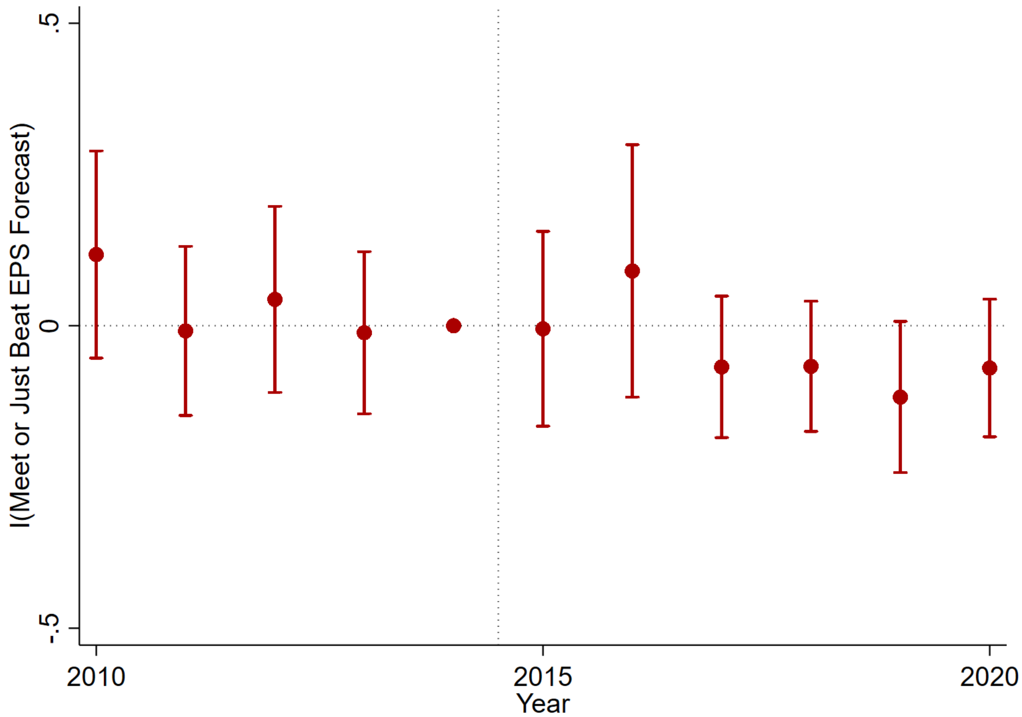


Figure IA3: Aggregate Institutional Ownership around the Divestment Shock. These figures display the trends in public firms' aggregate institutional ownership. In particular, the figure plots annual coefficients for each time (year $t = -5$ through year $t = 5$) directly around the divestment shock in 2015 interacted with an indicator (*treat*) that is equal to 1 for thermal coal producers, and 0 for met coal producers. The dependent variables are various types of institutional ownership, including all (Panel A), dedicated ownership (Panel B), transient ownership (Panel C), quasi-indexer ownership (Panel D), and non-classified ownership (Panel E). Each model contains firm and year fixed effects. Standard errors are clustered at the firm level. The confidence interval bars reflect the 95% level. Data on institutional holdings is from Thomson Reuters Institutional (13F) Holdings Database, and we identify institutions using data from Brian Bushee's website.

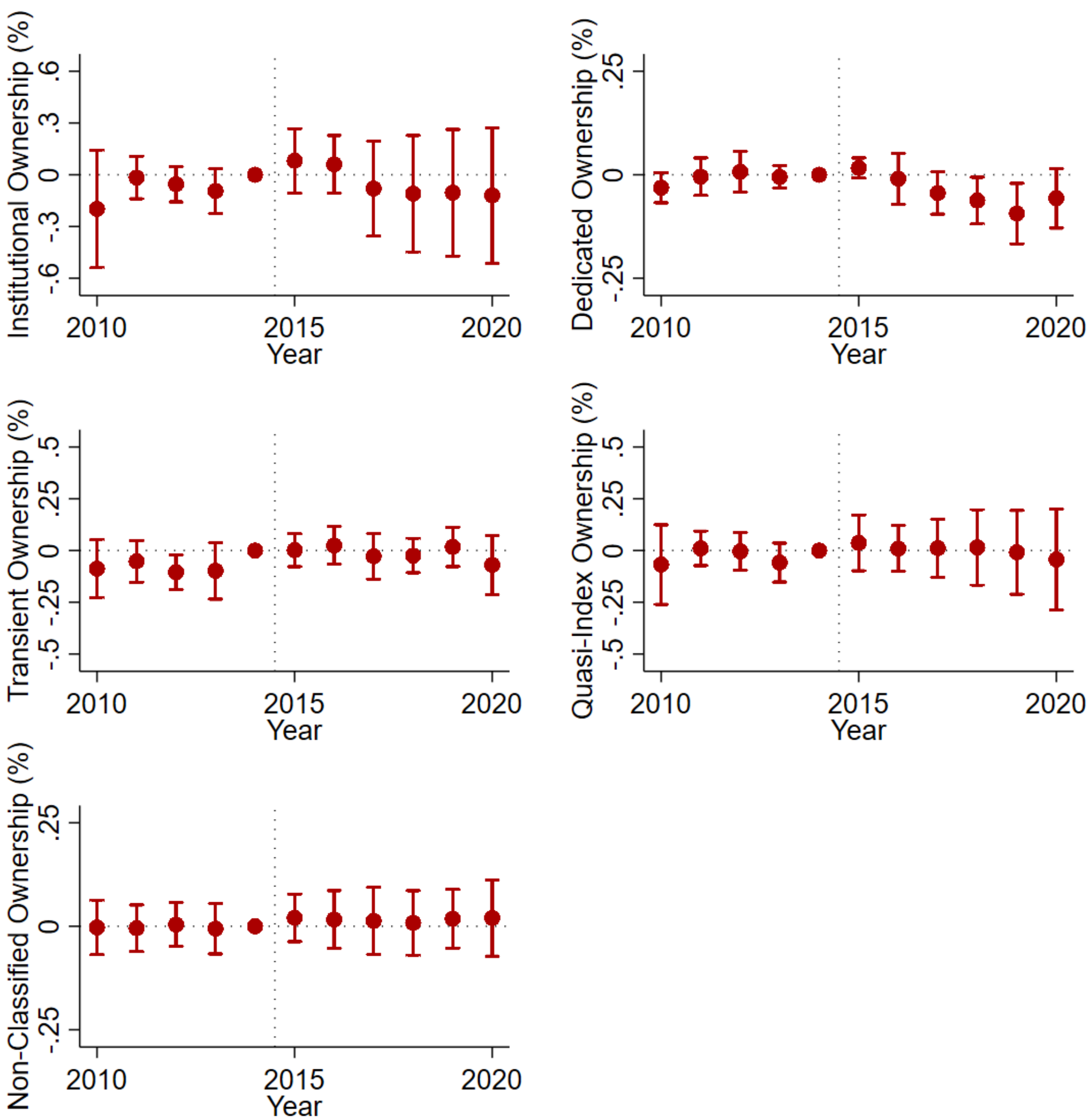


Figure IA4: Pre-trends in Production, Externalities, and Public Firm Characteristics prior to the Divestment Shock. This figure displays various firm characteristics in the years leading up to the divestment shock. Each model employs thermal coal firms as the treated group and met coal firms as the control group. Panels A (production) and B (safety violations) include all firms and use mine-, firm-, and count-by-year fixed effects. The remaining panels examine only public firms and include firm- and year-fixed effects. All standard errors are clustered at the firm level. The confidence interval bars reflect the 95% level. Data on mine-level production, employment, and safety violations are from the Mine Safety and Health Administration (MSHA) published through an Open Government Initiative. Firm-level accounting data is from Compustat.

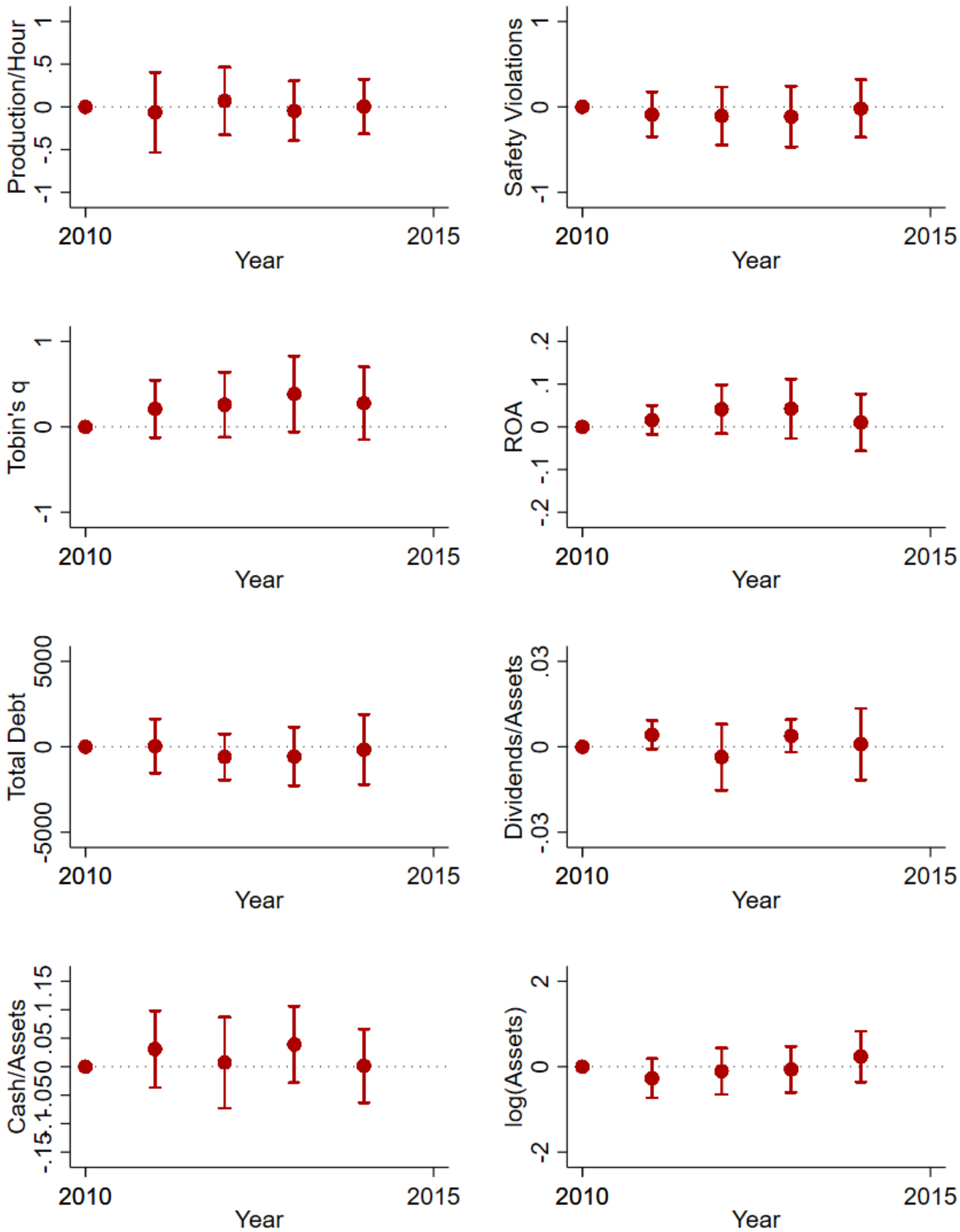


Table IA1: Public Listing Status and Fatalities and Injuries. This table reports the results of linear regression models (Model (1) and (2)) in which the dependent variables are the number of fatalities or an indicator for any fatalities, respectively, at mine i, owned by firm s, during year t, or Poisson pseudo-maximum-likelihood (PPLM) models (Models (3) and (4)) in which the dependent variables are the total number of injures and days lots, respectively, at mine i, owned by firm s, during year t. The sample consists of publicly and privately owned U.S. coal mines over a sample period of 1983 through 2022 for production and 1994 through 2022 for safety violations. The independent variable of interest is *Public owner*$_{ist}$. All variable definitions appear in Appendix Table A1. Data on mining fatalities, injuries, and days lost, as well as ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration published through an Open Government Initiative. Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	Fatalities$_{ist}$	I(Fatalities$_{ist}$)	Injuries$_{ist}$	Days lost$_{ist}$
	(1)	(2)	(3)	(4)
Public owner$_{ist}$	0.047	0.030	0.210***	0.309***
	(0.030)	(0.022)	(0.072)	(0.118)
log(Mines$_{st}$)	-0.008	-0.006	-0.021	-0.140**
	(0.015)	(0.007)	(0.053)	(0.068)
log(Hours$_{ist}$)	0.003	0.004**	0.862***	0.864***
	(0.005)	(0.002)	(0.032)	(0.054)
log(Employees$_{ist}$)	0.017	0.008***	0.058	0.209***
	(0.014)	(0.003)	(0.050)	(0.077)
Mine FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Model	OLS	OLS	PPML	PPML
Observations	26,151	26,151	21,621	20,865
R^2 or Pseudo-R^2	0.202	0.285	0.774	0.838

Table IA2: Safety Violations and the Probability of a Fatal Accident. This table reports the results of linear regression models in which the dependent variable is an indicator for a fatal accident at mine i, owned by firm s, during year t. The sample consists of publicly and privately owned U.S. coal mines over a sample period of 1994 through 2022. The independent variables of interest are the number of safety violations at mine i, owned by firm s, during year t. All variable definitions appear in Appendix Table A1. Data on mining fatalities and safety violations, as well as ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration published through an Open Government Initiative. Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	I(Fatal Accident$_{ist}$)			
	(1)	(2)	(3)	(4)
Safety violations$_{ist}$	0.031***			
	(0.005)			
Safety violations$_{ist}$ (High)		0.073***		
		(0.013)		
Safety violations$_{ist}$ (Low)		0.008		
		(0.009)		
Safety violations$_{ist}$ (High)/Safety Inspections$_{ist}$			0.156***	
			(0.048)	
Safety violations$_{ist}$ (Low)/Safety Inspections$_{ist}$			-0.001	
			(0.001)	
Safety violations$_{ist}$ (High)/Employee Hours$_{ist}$				0.915***
				(0.311)
Safety violations$_{ist}$ (Low)/Employee Hours$_{ist}$				0.017*
				(0.009)
log(Mines$_{st}$)	-0.024**	-0.025*	-0.023*	-0.024*
	(0.012)	(0.013)	(0.013)	(0.013)
log(Hours$_{ist}$)	0.007**	0.007**	0.012***	0.011***
	(0.003)	(0.003)	(0.004)	(0.003)
log(Employees$_{ist}$)	-0.002	0.000	0.006	0.008
	(0.006)	(0.006)	(0.007)	(0.007)
Mine FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Inspection District FE	No	No	No	No
County × Year FE	Yes	Yes	Yes	Yes
Model	OLS	OLS	OLS	OLS
Observations	10,105	10,105	9,992	10,105
R^2	0.338	0.339	0.334	0.333

Table IA3: Public Listing Status, Labor, and Organizational Structure. This table reports the results of Poisson pseudo-maximum-likelihood (PPLM) models in which the dependent variables are total employee hours, total number of mines, total number of operators, and total number of counties operated in at firm s during year t. The sample consists of publicly and privately owned U.S. coal mines over a sample period of 1983 through 2022. The independent variable of interest is $\textit{Public owner}_{st}$. All variable definitions appear in Appendix Table A1. Data on employment, as well as ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration published through an Open Government Initiative. Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	Employee hours$_{st}$	No. of mines$_{st}$	No. of operators$_{st}$	No. of counties$_{st}$
	(1)	(2)	(3)	(4)
Public owner$_{st}$	0.080	-0.021	-0.127	0.176
	(0.151)	(0.185)	(0.162)	(0.163)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Model	PPML	PPML	PPML	PPML
Observations	5,841	5,838	5,836	5,841
Pseudo-R^2	0.954	0.773	0.583	0.320

Table IA4: Public Listing Status, Production, Externalities, and Listing Status Change Clusters. This table reports the results of linear regression models (Model (1)) in which the dependent variable is the total short tons of clean coal produced divided by employee hours, or Poisson pseudo-maximum-likelihood (PPLM) models (Models (2) through (4)) in which the dependent variable is the total number of safety violations at mine i, owned by firm s, during year t. The sample consists of publicly and privately owned U.S. coal mines over a sample period of 1983 through 2022 for production and 1994 through 2022 for safety violations. The independent variable of interest is $\textit{Public owner}_{ist}$. All variable definitions appear in Appendix Table A1. Panel A excludes observations from the year 2005 and Panel B excludes observations in which the ultimate owners is either ICG or Horizon Natural Resources. Data on mining safety violations, safety inspections, production, and employment, as well as ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration published through an Open Government Initiative. Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	$\frac{\text{Production}}{\text{Hours}}_{ist}$	Safety Violations$_{ist}$		
MSHA Prob. of Accident =		All	Low	High
	(1)	(2)	(3)	(4)
Panel A: Excluding 2005				
Public owner$_{ist}$	0.366***	0.290***	0.267***	0.370***
	(0.139)	(0.083)	(0.087)	(0.092)
Controls	Yes	Yes	Yes	Yes
Mine FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Inspection District FE	No	Yes	Yes	Yes
County × Year	Yes	Yes	Yes	Yes
Model	OLS	PPML	PPML	PPML
Observations	25,724	9,641	9,529	9,458
R^2 or Pseudo-R^2	0.854	0.908	0.898	0.836
Panel B: Excluding ICG and Horizon Natural Resources				
Public owner$_{ist}$	0.375***	0.291***	0.259***	0.389***
	(0.141)	(0.087)	(0.092)	(0.095)
Controls	Yes	Yes	Yes	Yes
Mine FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Inspection District FE	No	Yes	Yes	Yes
County × Year	Yes	Yes	Yes	Yes
Model	OLS	PPML	PPML	PPML
Observations	25,743	9,763	9,643	9,591
R^2 or Pseudo-R^2	0.857	0.907	0.896	0.837

Table IA5: Public Listing Status and Mine-Level Safety Violations. This table reports the results of linear regression models in which the dependent variable is the number of safety violations divided by the number of safety inspections at mine i, owned by ultimate parent s, during year t. The sample consists of publicly and privately owned U.S. coal mines over a sample period of 1993 through 2018. The independent variable of interest is *Public owner*$_{ist}$. In Columns (3) through (8), the safety violations for constructing the dependent variables are split by the probability of an accident actually occurring, as deemed by the Mine Safety and Health Administration (MSHA) at the time of the citation for the safety violation. All variable definitions appear in Appendix Table A1. Data on mining safety violations, safety inspections, production, and employment, as well as ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration published through an Open Government Initiative. Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	Safety Violations$_{ist}$			$\left(\frac{\text{Safety Violations}}{\text{Inspections}}\right)_{ist}$	$\left(\frac{\text{Safety Violations}}{\text{1,000 Hours}}\right)_{ist}$
	(1)	(2)	(3)	(4)	(5)
Public owner$_{ist}$	0.224***	0.284***	29.578**	0.720**	0.078***
	(0.082)	(0.085)	(15.020)	(0.352)	(0.025)
Mine FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Inspection District FE	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes
Model	PPML	PPML	OLS	OLS	OLS
Observations	10,069	10,069	10,101	10,101	10,101
R^2 or Pseudo-R^2	0.859	0.907	0.784	0.749	0.749

Table IA6: Public Listing Status, Production, Externalities, and Production-Externality Threshold. This table reports the results of linear regression models in which the dependent variable is total number of safety violations scaled by the total short tons of clean coal produced at mine i, owned by firm s, during year t. The sample consists of publicly and privately owned U.S. coal mines over a sample period of 1994 through 2022. The independent variable of interest is $Public\ owner_{ist}$. The table reports the results for the full sample, for the age subsamples , and for the mine-type subsamples. All variable definitions appear in Appendix Table A1. Data on mining production and employment, safety violations, as well as mine ownership and mining acquisitions, are from the Mine Safety and Health Administration (MSHA) published through an Open Government Initiative. Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	$\frac{\text{Safety Violations}}{\text{100,000 Short Tons of Coal}}_{ist}$						
MSHA Prob. of Accident =	All	Low	High	All			
Sample =		Full		Young	Old	Surface	Underground
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Public owner$_{ist}$	1.594**	0.670*	0.647**	0.692	1.728**	-0.094	1.738
	(0.709)	(0.391)	(0.257)	(1.809)	(0.780)	(0.691)	(1.199)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mine FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inspection District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Observations	9,825	9,825	9,825	4,879	4,414	5,104	4,193
R^2	0.844	0.841	0.786	0.874	0.867	0.782	0.824

Table IA7: Public Listing Status, Production, Externalities, and Alternative Firm-Level Monitoring. This table reports the results of linear regression models (Model (1)) in which the dependent variable is the total short tons of clean coal produced divided by employee hours, or Poisson pseudo-maximum-likelihood (PPLM) models (Models (2) through (4)) in which the dependent variable is the total number of safety violations at mine i, owned by firm s, during year t. The sample consists of publicly and privately owned U.S. coal mines over a sample period of 1983 through 2022 for production and 1994 through 2022 for safety violations. The independent variables of interest are $Public\ owner_{ist}$ interacted with (i) continuous institutional ownership immediately follow a firm's IPO (Panel A), (ii) continuous dedicated institutional ownership immediately follow a firm's IPO (Panel B), and (iii) an indicator variable equal to 1 if the firm has any 5% blockholder immediately follow a firm's IPO (Panel C). All variable definitions appear in Appendix Table A1. Data on mining safety violations, safety inspections, production, and employment, as well as ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration published through an Open Government Initiative. Data on institutional holdings is from Thomson Reuters Institutional (13F) Holdings Database, and we identify dedicated institutions using data from Brian Bushee's website. Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	$\frac{\text{Production}}{\text{Hours}}_{ist}$	Safety Violations$_{ist}$		
MSHA Prob. of Accident =		All	Low	High
	(1)	(2)	(3)	(4)
Panel A: Continuous Institutional Ownership				
Public owner$_{ist}$	0.157	0.248	0.287	0.277**
	(0.316)	(0.179)	(0.241)	(0.141)
Public owner$_{ist}\times$ Institutional Ownership$_s$	0.009	0.006	0.003	0.008*
	(0.011)	(0.004)	(0.005)	(0.005)
Controls	Yes	Yes	Yes	Yes
Mine × Firm FE	Yes	Yes	Yes	Yes
Inspection District FE	No	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Model	OLS	PPML	PPML	PPML
Observations	4,863	2,771	2,759	2,740
R^2 or Pseudo-R^2	0.937	0.916	0.900	0.869
Panel B: Continuous Dedicated Institutional Ownership				
Public owner$_{ist}$	0.495*	0.444***	0.321**	0.663***
	(0.280)	(0.138)	(0.155)	(0.135)
Public owner$_{ist}\times$ Dedicated Institutional Ownership$_s$	-0.114	0.016	0.111	-0.112*
	(0.128)	(0.062)	(0.070)	(0.059)
Controls	Yes	Yes	Yes	Yes
Mine × Firm FE	Yes	Yes	Yes	Yes
Inspection District FE	No	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Model	OLS	PPML	PPML	PPML
Observations	3,260	2,463	2,457	2,436
R^2 or Pseudo-R^2	0.934	0.913	0.898	0.864
Panel C: 5% Institutional Blockholders				
Public owner$_{ist}$	0.421*	0.411***	0.388***	0.507***
	(0.221)	(0.107)	(0.124)	(0.089)
Public owner$_{ist}\times$ I(Blockholder$_s$)	-1.010***	-0.173	-0.257	-0.328
	(0.249)	(0.160)	(0.192)	(0.206)
Controls	Yes	Yes	Yes	Yes
Mine × Firm FE	Yes	Yes	Yes	Yes
Inspection District FE	No	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Model	OLS	PPML	PPML	PPML
Observations	4,863	2,771	2,759	2,740
R^2 or Pseudo-R^2	0.937	0.916	0.900	0.869

Table IA8: Public Listing Status, Production, Externalities, and Price Informativeness Using PIN. This table reports the results of linear regression models (Model (1)) in which the dependent variable is the total short tons of clean coal produced divided by employee hours, or Poisson pseudo-maximum-likelihood (PPLM) models (Models (2) through (4)) in which the dependent variable is the total number of safety violations at mine i, owned by firm s, during year t. The sample consists of publicly and privately owned U.S. coal mines over a sample period of 1983 through 2022 for production and 1994 through 2022 for safety violations. The independent variable of interest is *Public owner*$_{ist}$ interacted with the firm's probability of informed trading (PIN_s) (e.g., see Easley et al., 1996) during the first quarter after the firm has IPO'ed. *High PIN* is an indicator variable equal to 1 if PIN_s is above the sample's 75th percentile, equal to PIN_s of 26.32%. All variable definitions appear in Appendix Table A1. Data on mining safety violations, safety inspections, production, and employment, as well as ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration published through an Open Government Initiative. Data on PIN_s is taken from Stephen Brown's website: https://terpconnect.umd.edu/~stephenb/pinsdatanew.html (Brown and Hillegeist, 2007). Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	$\left(\frac{\text{Production}}{\text{Hours}}\right)_{ist}$	Safety Violations$_{ist}$		
MSHA Prob. of Accident =		All	Low	High
	(1)	(2)	(3)	(4)
Panel A: Continuous Measure				
Public owner$_{ist}$	1.406**	0.581***	0.397**	0.937***
	(0.576)	(0.164)	(0.187)	(0.144)
Public owner$_{ist}\times$ PIN_s (%)	-0.057**	-0.009	-0.000	-0.021***
	(0.023)	(0.007)	(0.009)	(0.006)
Controls	Yes	Yes	Yes	Yes
Mine × Firm FE	Yes	Yes	Yes	Yes
Inspection District FE	No	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Model	OLS	PPML	PPML	PPML
Observations	5,210	2,779	2,765	2,741
R^2 or Pseudo-R^2	0.936	0.919	0.904	0.873
Panel B: Discrete Measure				
Public owner$_{ist}$	0.636**	0.453***	0.390***	0.644***
	(0.273)	(0.099)	(0.111)	(0.066)
Public owner$_{ist}\times$ High PIN_s	-0.983***	-0.141	-0.004	-0.339***
	(0.365)	(0.093)	(0.128)	(0.081)
Controls	Yes	Yes	Yes	Yes
Mine × Firm FE	Yes	Yes	Yes	Yes
Inspection District FE	No	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Model	OLS	PPML	PPML	PPML
Observations	5,210	2,779	2,765	2,741
R^2 or Pseudo-R^2	0.936	0.919	0.904	0.873

Table IA9: Production, Externalities, and Coal Divestment Initiatives Robustness. This table reports the results of linear regression models (Models (1) and (2)) in which the dependent variable is the total short tons of clean coal produced divided by employee hours, or Poisson pseudo-maximum-likelihood (PPLM) models (Models (3) through (4)) in which the dependent variable is the total number of safety violations at mine i, owned by firm s, during year t. The sample consists of publicly and privately owned U.S. coal mines over a sample period of 1983 through 2022 for production and 1994 through 2022 for safety violations. The independent variable of interest is either the holdings of CalPERS or of NBIM. All variable definitions appear in Appendix Table A1. Data on mining safety violations, safety inspections, production, and employment, as well as ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration published through an Open Government Initiative. Data on CalPERS and NBIM ownership is from the combination of Thomson Reuters 13f filings data and annual investor reports published by the funds. Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	$\frac{\text{Production}}{\text{Hours}}_{ist}$		Safety Violations$_{ist}$	
MSHA Prob. of Accident =			All	
	(1)	(2)	(3)	(4)
NBIM Ownership$_{st}$ (%)	-0.482**		-0.235**	
	(0.218)		(0.109)	
CalPERS Ownership$_{st}$ (%)		-0.154		-0.127**
		(0.181)		(0.059)
Public owner$_{ist}$	0.745**	0.888*	0.366***	0.397***
	(0.335)	(0.470)	(0.128)	(0.145)
Controls	No	No	No	No
Mine × Firm FE	Yes	Yes	Yes	Yes
Inspection District FE	No	No	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Model	OLS	OLS	PPML	PPML
Observations	2,737	2,570	2,731	2,564
R^2 or Pseudo-R^2	0.939	0.927	0.892	0.891

Table IA10: EBITDA, Earnings Quality, Bonus Thresholds, and Coal Divestment Initiatives Robustness. This table reports the results of linear regression models in which the dependent variable is the log of realized EBITDA (Model (1)), discretionary accruals (Model (2)), an indicator variable equal to one if a firm reports at least one internal control weakness (Model (43)), and the log of EBITDA bonus thresholds (Model (4)). The sample consists of publicly owned U.S. coal mining firms over a sample period of 2010 through 2022. The independent variable of interest is the interaction between an indicator variable that equals one if the coal firm produces a majority of thermal—rather than metallurgical—coal and an indicator variable equal to one if the year is greater than or equal to 2015—the year that NBIM and CAlPERS divested from thermal coal firms. All variable definitions appear in Appendix Table A1. Discretionary accruals are calculated using a three-year rolling window pooled across all public firms in our sample following the methodology of Kothari et al. (2005). Data on EBITDA and accruals is from Compustat, data on internal control weakness is from Audit Analytics, data on EBITDA performance targets is hand-collected from firms' proxy filings, and data on whether the firm produces thermal or metallurgical coal is from the Metallurgical Coal Producers Association and various public filings. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	log(EBITDA)	Discretionary Accruals	I(Internal Control Weakness)	log(EBITDA Target)
	(1)	(2)	(3)	(4)
I(Year$_t \geq$ 2015)$\times$ I(Thermal Coal Firm$_s$)	1.233***	0.012***	0.096*	0.607***
	(0.241)	(0.003)	(0.053)	(0.119)
Controls	No	No	No	No
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Model	OLS	OLS	OLS	OLS
Observations	227	202	229	129
R^2	0.945	0.614	0.182	0.883

Table IA11: Are Thermal Coal Firms More Dangerous? This table reports the results of Poisson pseudo-maximum-likelihood (PPLM) models (Models (1) through (4)) or linear regression models (Model (5)) in which the dependent variable is the total number of safety violations, injuries, or fatal accidents at mine *i*, owned by firm *s*, during year *t*. The sample consists of publicly and privately owned U.S. coal mines over a sample period of 1983 through 2022 for injuries and fatalities and 1994 through 2022 for safety violations. The independent variable of interest is *I(Thermal Coal Firm*$_{ist}$*)*. All variable definitions appear in Appendix Table A1. Data on mining safety violations, injuries and fatalities, as well as ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration published through an Open Government Initiative. Data on whether the firm produces thermal or metallurgical coal is from the Metallurgical Coal Producers Association and various public filings. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	Safety Violations$_{ist}$			Injuries	I(Fatal Accident)
MSHA Prob. of Accident =	All	Low	High		
	(1)	(2)	(3)	(4)	(5)
I(Thermal Coal Firm$_s$)	-0.006	-0.059	0.108	-0.043	-0.004
	(0.116)	(0.116)	(0.129)	(0.070)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes
Mine × Firm FE	No	No	No	No	No
Inspection District FE	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes
Model	PPML	PPML	PPML	PPML	OLS
Observations	10,017	9,999	9,980	24,733	25,002
R^2 or Pseudo-R^2	0.783	0.779	0.704	0.736	0.125

Table IA12: Public Listing Status, Production, Externalities, and Managerial Ownership. This table reports the results of linear regression models (Model (1)) in which the dependent variable is the total short tons of clean coal produced divided by employee hours, or Poisson pseudo-maximum-likelihood (PPLM) models (Models (2) through (4)) in which the dependent variable is the total number of safety violations at mine i, owned by firm s, during year t. The sample consists of publicly and privately owned U.S. coal mines over a sample period of 1983 through 2022 for production and 1994 through 2022 for safety violations. The independent variable of interest is $Public\ owner_{ist}$ interacted with a continuous measure of an IPO firms' initial managerial ownership. All variable definitions appear in Appendix Table A1. Data on mining safety violations, safety inspections, production, and employment, as well as ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration published through an Open Government Initiative. Data on managerial ownership was kindly shared by Fabisik et al. (2021). Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	$\frac{\text{Production}}{\text{Hours}}_{ist}$	Safety Violations$_{ist}$		
MSHA Prob. of Accident =		All	Low	High
	(1)	(2)	(3)	(4)
Public owner$_{ist}$	0.652**	0.460***	0.429***	0.602***
	(0.245)	(0.093)	(0.105)	(0.068)
Public owner$_{ist}\times$ Managerial ownership$_s$ (%)	-0.017*	-0.010***	-0.006	-0.017***
	(0.009)	(0.002)	(0.004)	(0.003)
Controls	Yes	Yes	Yes	Yes
Mine $\times$ Firm FE	Yes	Yes	Yes	Yes
Inspection District FE	No	No	Yes	Yes
County $\times$ Year FE	Yes	Yes	Yes	Yes
Model	OLS	PPML	PPML	PPML
Observations	4,736	2,568	2,556	2,532
R^2 or Pseudo-R^2	0.929	0.919	0.905	0.873

Table IA13: Public Listing Status, Production, Externalities, and Controlling Shareholder Stake Reductions. This table reports the results of linear regression models (Model (1)) in which the dependent variable is the total short tons of clean coal produced divided by employee hours, or Poisson pseudo-maximum-likelihood (PPLM) models (Models (2) through (4)) in which the dependent variable is the total number of safety violations at mine i, owned by firm s, during year t. The sample consists of publicly and privately owned U.S. coal mines over a sample period of 1983 through 2022 for production and 1994 through 2022 for safety violations. The independent variable of interest is *Public owner*$_{ist}$ interacted with the absolute size of the controlling shareholder's stake reduction following an IPO. The controlling stakeholder's stake reduction is measured using the S-1s and 10-ks from 16 IPOs in our sample where we can clearly measure the controlling shareholder's stake both pre- and post-IPO. All variable definitions appear in Appendix Table A1. Data on mining safety violations, safety inspections, production, and employment, as well as ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration published through an Open Government Initiative. Data on the controlling shareholder's stake reduction is hand-collected from S-1 forms pre-IPO, and proxy filings and 10-k forms post-IPO. Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	$\frac{\text{Production}}{\text{Hours}}_{ist}$	Safety Violations$_{ist}$		
MSHA Prob. of Accident =		All	Low	High
	(1)	(2)	(3)	(4)
Public owner$_{ist}$	0.235	0.330	0.314	0.546***
	(0.266)	(0.704)	(0.800)	(0.089)
Public owner$_{ist}\times$ CS stake reduction$_s$	2.874*	1.367	1.353	0.949***
	(1.459)	(2.681)	(3.023)	(0.353)
Controls	Yes	Yes	Yes	Yes
Mine × Firm FE	Yes	Yes	Yes	Yes
Inspection District FE	No	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Model	OLS	PPML	PPML	PPML
Observations	1,543	1,282	1,280	1,254
R^2 or Pseudo-R^2	0.956	0.936	0.922	0.900

Table IA14: Public Listing Status, Production, Externalities, and Financial Constraints. This table reports the results of linear regression models (Model (1)) in which the dependent variable is the total short tons of clean coal produced divided by employee hours, or Poisson pseudo-maximum-likelihood (PPLM) models (Models (2) through (4)) in which the dependent variable is the total number of safety violations at mine i, owned by firm s, during year t. The sample consists of publicly and privately owned U.S. coal mines over a sample period of 1983 through 2022 for production and 1994 through 2022 for safety violations. The independent variable of interest is $Public\ owner_{ist}$ interacted with the firm's market leverage in the year following its IPO. All variable definitions appear in Appendix Table A1. Data on mining safety violations, safety inspections, production, and employment, as well as ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration published through an Open Government Initiative. Data on leverage is from Compustat. Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	$\left(\frac{\text{Production}}{\text{Hours}}\right)_{ist}$	Safety Violations$_{ist}$		
MSHA Prob. of Accident =		All	Low	High
	(1)	(2)	(3)	(4)
Public owner$_{ist}$	0.301	0.537***	0.415***	0.728***
	(0.285)	(0.122)	(0.105)	(0.180)
Public owner$_{ist}\times$ Leverage$_s$ (%)	0.001	-0.004**	-0.001	-0.006*
	(0.009)	(0.002)	(0.003)	(0.003)
Controls	Yes	Yes	Yes	Yes
Mine × Firm FE	Yes	Yes	Yes	Yes
Inspection District FE	No	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Model	OLS	PPML	PPML	PPML
Observations	4,801	2,771	2,759	2,740
R^2 or Pseudo-R^2	0.937	0.916	0.900	0.870

Table IA15: Public Listing Status, Production, Externalities, and Mines Producing Less Than 15% of Total Firm Coal. This table reports the results of linear regression models (Model (1)) in which the dependent variable is the total short tons of clean coal produced divided by employee hours, or Poisson pseudo-maximum-likelihood (PPLM) models (Models (2) through (4)) in which the dependent variable is the total number of safety violations at mine i, owned by firm s, during year t. The sample consists of publicly and privately owned U.S. coal mines over a sample period of 1983 through 2022 for production and 1994 through 2022 for safety violations. The independent variable of interest is *Public owner*$_{ist}$. All variable definitions appear in Appendix Table A1. This table limits observations to only mine-years in which the production is no more than 15% of the firm's total coal production during that year. Data on mining safety violations, safety inspections, production, and employment, as well as ultimate mine ownership and mining acquisitions, are from the Mine Safety and Health Administration published through an Open Government Initiative. Data on public listing status are hand-collected from firm filings, CRSP, CapitalIQ, and data on IPO dates from Jay Ritter's website. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	$\frac{\text{Production}}{\text{Hours}}_{ist}$	Safety Violations$_{ist}$		
MSHA Prob. of Accident =		All	Low	High
	(1)	(2)	(3)	(4)
Public owner$_{ist}$	0.316*	0.254***	0.196***	0.425***
	(0.176)	(0.053)	(0.053)	(0.085)
Controls	Yes	Yes	Yes	Yes
Mine FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Inspection District FE	No	Yes	Yes	Yes
County × Year	Yes	Yes	Yes	Yes
Model	OLS	PPML	PPML	PPML
Observations	10,716	5,053	5,001	4,923
R^2 or Pseudo-R^2	0.776	0.907	0.893	0.843

about ECGI

The European Corporate Governance Institute has been established to improve *corporate governance through fostering independent scientific research and related activities.*

The ECGI will produce and disseminate high quality research while remaining close to the concerns and interests of corporate, financial and public policy makers. It will draw on the expertise of scholars from numerous countries and bring together a critical mass of expertise and interest to bear on this important subject.

The views expressed in this working paper are those of the authors, not those of the ECGI or its members.

Electronic Access to the Working Paper Series

The full set of ECGI working papers can be accessed through the Institute's Web-site (www.ecgi.global/content/working-papers) or SSRN:

Finance Paper Series	http://www.ssrn.com/link/ECGI-Fin.html
Law Paper Series	http://www.ssrn.com/link/ECGI-Law.html