Production and Externalities: The Role of Corporate Governance*

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Abstract

We study how corporate governance impacts social costs. Our parsimonious principal-agent model with production externalities predicts that firms adopt higher-powered incentives in response to increased monitoring costs. This shift in governance mechanisms boosts production, but also results in higher social costs. We confirm this prediction using asset-level data on production and workplace safety in the coal industry. To establish causality, we exploit plausibly exogenous increases in monitoring costs driven by politically motivated coal divestment initiatives imposed on prominent activist institutional investors. Our findings highlight that firms' choice of governance mechanisms can have important implications for social and environmental performance.

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

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

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1 Introduction

Production often creates negative externalities. While technological developments may help mitigate some social and environmental costs, the production decision itself is often the most effective way of managing negative externalities (Hart and Zingales, 2017; Morgan and Tumlinson, 2019). For example, pharmaceutical companies could limit the social and economic costs stemming from an opioid epidemic by producing only for the most responsible patients. Hence, firms' production decisions can have significant consequences for society.

In this context, we argue that a firm's corporate governance framework—the array of mechanisms it employs to mitigate agency problems—plays a pivotal role in shaping its production decisions and the resulting externalities. To illustrate this argument and guide our empirical analysis, we develop a parsimonious principal-agent model with two key features. First, production intensity beyond a certain threshold imposes additional negative externalities, creating what we term *socially costly production*. One salient example of such high production intensity is the Wells Fargo cross-selling scandal in which bank employees opened millions of unauthorized accounts in order to meet sales targets (Tayan, 2019).[1] This feature of production leads to a trade-off: stronger pay-for-production incentives discourage managers from living the "quiet life", but also encourage them to pursue socially costly production.

The second key feature is that the firm's owners only partially internalize its social costs through the pecuniary penalty. For example, carbon taxes may under-represent the economic damages of CO_2 emissions borne by society (Pastor et al., 2024).[2] In our model, the firm's owners mitigate managerial moral hazards with two broad categories of governance

[1] Other examples of high production intensity leading to socially costly production include cutting corners to rush product development (e.g., Kuratko et al., 2020), increasing the quantity of service at the expense of quality (e.g., Oliva and Sterman, 2001), misleading consumers to increase sales (e.g., Eaton et al., 2020; DeWeerdt, 2019), and exploiting vulnerable groups of the population (e.g., Padon et al., 2018; Struik et al., 2020; Braghieri et al., 2022).

[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, to date 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).

mechanisms: incentive pay, such as production bonuses, and monitoring tools, such as internal controls, independent audits, and board oversight. While the firm's shareholders choose a governance framework that maximizes firm value, their failure to fully internalize social costs means that their privately optimal governance choices may diverge significantly from those that would maximize social welfare.

These model features allow us to highlight two interconnected agency problems: one between the manager and the firm's owners, and another between the firm's owners and society. Higher monitoring costs exacerbate both problems. That is, they make it easier for the manager to shirk, and they make strong performance-based pay more appealing to shareholders despite its social costs. The model's main predictions revolve around how firms substitute governance mechanisms when relative costs change. Specifically, when monitoring-based mechanisms become more costly, firms shift toward greater use of performance-based pay, which in turn drives higher production and increased social costs.

The availability of alternative governance mechanisms can mitigate these adverse effects in several ways. First, mechanisms that address managerial moral hazard, such as dedicated institutional blockholders, independent boards of directors, or stock price monitoring, reduce the need to rely on stronger pay-for-performance incentives when monitoring becomes more costly. Second, market and regulatory mechanisms that increase the pecuniary cost of socially costly production—such as unions demanding hazard pay for unsafe conditions or regulators imposing penalties for negative externalities—make stronger pay-for-production less attractive to the firm's owners. These alternative governance tools become particularly important as monitoring costs rise, providing a countervailing force that dampens the increase in socially costly production.

We test these predictions using novel data from the U.S. coal mining industry.[3] This setting offers three significant advantages in studying governance and social costs. First, the Mine Safety and Health Administration (MSHA) collects and makes available standardized reports for *every* single establishment (mine) in the entire industry over a 40-year sample period. These reports provide us with mine-level data on production and employment, as

[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 emphasized in this paper.

well as mine safety violations, a quantifiable measure of an important externality—hazardous working conditions. The economic costs associated with workplace accidents are significant, totaling around 4% of GDP, or $3 trillion globally each year (Dorman, 2012). Importantly, a significant portion of these costs falls on society at large. For instance, nearly 20% of the direct economic costs (e.g., lost wages and medical expenses) are paid by social insurance programs (Leigh et al., 2000; Health and Safety Executive, 2023). Moreover, extended or permanent production stoppages following serious accidents have significant negative consequences for suppliers and customers, as well as the local community, that are difficult to fully quantify.[4]

Second, this empirical setting features a well-defined and well-understood trade-off between production and hazardous working conditions (Gowrisankaran et al., 2018). Safety maintenance often requires halting production entirely, creating a tension between generating output and protecting workers. One horrifying example of this trade-off comes from the period leading up to the Upper Big Branch (UBB) disaster that tragically claimed the lives of 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 that such a corporate policy manifested in a dramatic increase in production per miner hour at UBB in the two years prior to the disaster. These output gains, however, 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 makes progress on key endogeneity challenges. For example, firms in this industry use similar technologies to extract a commoditized good, which limits confounding factors related to technological differences, product differentiation, or market segmentation, allowing us to better identify the effects of different governance frameworks. Moreover, political concerns about climate change have prompted divestments by large activist institutional investors, creating plausibly exogenous ownership changes that make monitoring management more costly for coal mining firms.

[4]For an analysis of the devastating effects of accident-induced mine closures on the local economy, including dampened GDP and increased unemployment, see (Isikoff, 1984; Kent, 2016). Internet Appendix Section IA.1.1 includes additional discussion on the treatment of hazardous working conditions as an externality.

In the first part of our empirical analysis, we exploit asset-level data to utilize a high-dimensional fixed-effects structure to examine how production and workplace safety at individual mines respond to ownership changes, particularly private-to-public transitions.[5] Ownership dispersion drives increases in monitoring costs due to issues such as free-riding (e.g., Grossman and Hart, 1980) and coordination challenges (e.g., Shleifer and Vishny, 1986). Previous studies find that the controlling shareholder's stake drops significantly immediately following an IPO (Mikkelson et al., 1997; Helwege et al., 2007; Larrain et al., 2024). Our data confirms this pattern in cases where we can clearly measure the controlling shareholder's stake pre- and post-IPO. As a result, private-to-public transitions in the mining industry create a well-defined laboratory to study how a firm's governance framework affects its production and externalities.

We find that mines that are part of a private-to-public transition (e.g., those subject to increased monitoring cost due to ownership dispersion) experience a significant increase in production (11%) and safety violations (33%). Moreover, these increases are concentrated in the firms that rely on bonus contracting, consistent with our model's prediction that socially costly production arises from the substitution to high-powered incentives. Dynamic treatment effects suggest that the increases in production and safety violations happen in the year of the listing status change and not before it, and persist for at least five years.

We argue that the observed increases in output and externalities are an indication of socially costly production rather than a reflection of efficiency improvements in the production process. In particular, inconsistent with such an efficiency gain, our analysis reveals that transitions from private to public ownership correlate with increased safety violations *per unit* of production. Moreover, we find little evidence that public ownership simply increases mine scale by relieving financial frictions (e.g., Brav, 2009).

Our empirical findings are also consistent with the ancillary predictions of our model. We find the availability of alternative governance mechanisms at the firm-, market-, and regulatory-level attenuates the increase in socially costly production following an increase in monitoring costs due to the private-to-public transition. In particular, the presence of dedicated institutional blockholders, an independent board, and informative stock prices

[5]Though we analyze public-to-private transitions as well, we use private-to-public for ease of exposition.

at the time of a firm's IPO leads to smaller increases in production and safety violations compared to otherwise similar firms. In addition, stringent safety enforcement and strong labor unions also dampen the increase in socially costly production post-IPO.

To establish a causal interpretation of our empirical results, we examine the coal divestment initiatives imposed on Norges Bank Investment Management (NBIM) and the California Public Employees' Retirement System (CalPERS) by the Norwegian Ministry of Finance and the state of California in the mid-2010s. These politically motivated initiatives removed prominent activist institutional investors from affected firms. Because such institutions play a pivotal role in monitoring management (Chen et al., 2007), their absence increases the cost of direct oversight. We exploit the specific scope of the divestment initiatives, which applied to thermal coal producers but not to metallurgical coal producers, to implement a difference-in-difference analysis using metallurgical coal firms as a control group. Consistent with our framework, we show that production intensity and workplace safety violations increase following the divestment initiative, with the observed effects concentrated entirely in thermal coal firms. To provide additional evidence of our model's main mechanism, we hand-collect data on EBITDA thresholds for managerial bonuses. Consistent with a substitution to high-powered incentives following the increase in monitoring costs, we show that the bonus thresholds increase for thermal but not metallurgical coal producers.

Our study makes contributions to at least four strands of the literature. First, we highlight a fundamental tension between reducing agency costs and minimizing social costs arising from production externalities. This trade-off is particularly relevant in settings where even modest increases in production intensity can generate significant social costs, and firms internalize a smaller proportion of these costs, such as in the pharmaceutical, finance, and manufacturing industries. We demonstrate how the interaction between different governance mechanisms ultimately shapes a firm's production and externalities policies. Our study also helps illustrate how formal governance mechanisms (e.g., performance-based pay) can, in some instances, undermine informal norms (e.g., safety-first culture) by creating competing priorities that place output above workplace safety, as suggested by Graham et al. (2022).

Second, our findings help identify a potential mechanism underlying the results of Shive and Forster (2020), who show that stronger oversight by the board and institutional owners

reduces pollution in public firms. Importantly, we show that even when external governance mechanisms do not necessarily have a strong interest in reducing externalities—because they internalize only a small portion of the social costs—their presence nonetheless helps curb socially costly production by reducing the firm's reliance on stronger performance-based incentives. This effect 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 performances signal other organizational deficiencies within the firm (Edmans et al., 2024)—specifically, our framework suggests that socially costly production results from ineffective monitoring. More generally, we provide important context in 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; O'Hare, 2022; Strine et al., 2022).

Third, we contribute to a growing literature that analyzes how asset ownership structures impact society due to diverging interests (e.g., Bellon, 2024; Duchin et al., 2024; Cohn et al., 2021). In our framework, when ownership structures shift in a way that increases monitoring costs, firms respond by adjusting their governance framework towards stronger performance-based incentives, which result in socially costly production. Our findings suggest that the design of oversight regarding the social and environmental costs of production, such as ESG ratings and SEC disclosure mandates (e.g., see El-Hage, 2021; Karpoff et al., 2022) should account for an industry's production function and its firms' governance frameworks.

Finally, our results also contribute to the recent literature on unintended consequences of sustainable investment strategies (e.g., divestment, exclusion, negative screening) meant to direct capital away from brown firms, and thus, hasten the green transition (e.g., see Shue and Hartzmark, 2024). We show that such initiatives may also weaken governance by removing key institutional blockholders who provide important oversight. In our empirical setting, divestment shocks triggered an increased reliance on performance-based incentives, resulting in higher production but worse workplace safety. These findings suggest that, absent alternative governance mechanisms, divestment initiatives may inadvertently amplify social and environmental risks rather than mitigate 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.[6] The model has two dates: $t = 0$ and $t = 1$. The firm's production technology generates an output Q at $t = 1$ that can be high ($Q = q_H$), low ($Q = q_L$), or zero ($Q = 0$). The output's probability distribution depends on the manager's effort $e \in \{0, 1\}$ and 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 shock results in lower output (i.e., $q_L < q_H$). When operating at high production intensity ($x = 1$), the firm's output does not depend on the productivity shock, with Q taking values q_H and 0 with probabilities p and $1 - p$, respectively. At $t = 0$, the manager can shirk ($e = 0$) and extract B in private benefits.[7] 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 (i.e., $\frac{p}{p_L} < \frac{p}{p_H}$). Table 1 summarizes the production technology.

To capture the idea that generating output 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.[8] This *socially costly production* increases the expected production of the firm but imposes an additional s in expected social costs and incurs m in 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

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

[7] The private benefits could take the form of living the quiet life (Bertrand and Mullainathan, 2001), empire building (Jensen and Meckling, 1976; Jensen, 1986), corporate perquisites (Yermack, 2006), or self-dealing (Décaire and Sosyura, 2022).

[8] Internet Appendix Section IA.1 further discusses this convex relationship between the firm's social costs and its production, such as the convexity costs of many abatement technologies, and the industries and externalities that likely feature such a relationship.

that trigger regulatory fines. In some cases, it leads to a mine collapse that precipitates lawsuits and reductions in future output. 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.

Our model aims to highlight the tension between lowering agency rents and mitigating social costs arising from the manager's ability to privately adjust production intensity. 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 contracting limitations on non-pecuniary goals (e.g., Hart and Zingales, 2017), we assume that the manager's compensation $W(Q)$ can only depend on the firm's output at $t = 1$.[9] The manager is protected by limited liability. For simplicity, we assume that the manager's participation constraint (IR) is always satisfied by setting the manager's outside option to zero.[10]

In addition to compensation contracting, the firm can engage in costly monitoring to mitigate the manager's moral hazard problem. Specifically, the firm can pay a monitoring cost of $\frac{c}{2}(\Delta_B)^2$ at $t = 0$ to lower 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 monetary costs of negative externalities, if any.

[9]For instance, when the probability that the negative externality realizes is small (i.e., $s = \epsilon S$ for small values of ϵ and large values of S), discouraging the manager from pursuing socially costly production while maintaining high-powered incentives can be prohibitively costly due to the manager's limited liability.

[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, which increases 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.

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	$1-p_H$

To emphasize the firm's choice of different 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 $(W_H, W_L, W_0, \Delta_B)$, the manager's incentive-compatibility (IC)

[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 uses neither governance mechanisms. When managerial effort becomes optimal, the firm uses some combination of both.

constraint can be expressed as

$$\begin{aligned} &\Big((1-\eta)+\eta x\Big)(p-p_H)W_H + \Big(\eta(1-x)\Big)(p-p_L)W_L \\ \geq\ &(B-\Delta_B) + \Big(p - \Big((1-\eta)+\eta x\Big)p_H - \Big(\eta(1-x)\Big)p_L\Big)W_0. \end{aligned} \tag{1}$$

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; it implies that managerial contracts with high-powered incentives, specifically $W_H > W_L$, result in socially costly production.

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 ($Q = q_H$).

Lemma 1 follows from standard optimal contracting arguments. The monotone likelihood ratio property implies that high output is associated with the maximum likelihood ratio. Consequently, 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 providing incentives using the high-powered compensation contract given in Lemma 1 can be expressed as

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

While high-powered incentives minimize the cost of providing incentives, they violate the manager's SC constraint (2), resulting in socially costly production ($x = 1$).

Lemma 2: The lowest-cost, IC and SC compensation contract 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 (*$Q = q_L$ *or* $Q = q_H$*).*

The firm minimizes incentive costs by maximally punishing the manager for generating no output. The manager's SC constraint (2) implies that any compensation contract that pays more for high output than for low output results in socially costly production. Consequently, limiting social costs restricts the firm to offering low-powered incentives, $W_H = W_L > 0$. The payment for generating positive output ($Q = q_H$ or $Q = q_L$) binds the manager's IC constraint (1). The expected cost of providing incentives using the low-powered compensation contract given in Lemma 2 can be expressed as

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

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 are governance mechanisms that mitigate the manager's moral hazard problem. Employing one 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 how the firm substitutes one governance mechanism with another when their relative costs change.

2.2 Optimal Governance Framework and Firm Policies

Our model generates clear predictions about how the relative costs of different governance mechanisms shape the firm's governance framework, with significant implications for managerial incentives and the firm's production and externalities policies. We begin by charac-

terizing the firm's optimal governance framework as a function of its monitoring costs.

Proposition 1: There exists a threshold $\bar{c} > 0$ *such that* $c > \bar{c}$ *implies that the firm's optimal monitoring and compensation policies are*

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

and $c \leq \bar{c}$ *implies that the firm's optimal monitoring and compensation policies are*

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

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

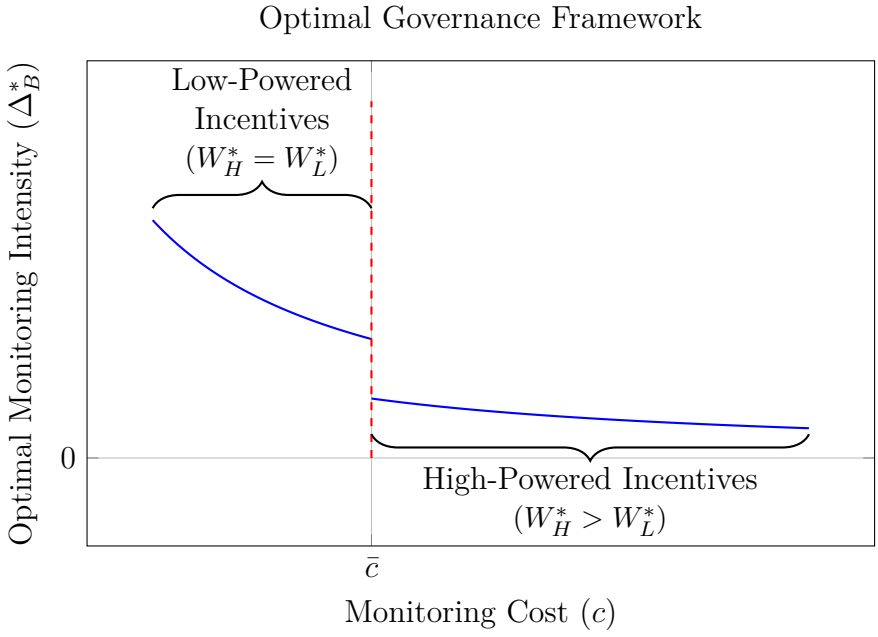


Figure 1: Optimal Governance Framework vs. Monitoring Cost. This figure illustrates the firm's optimal governance framework as a function of its monitoring cost (c). When monitoring costs are low ($c < \bar{c}$), the firm employs a low-powered managerial contract along with a high level of monitoring. 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, as in Piskorski and Westerfield (2016). This prediction is consistent with academic studies that document the increased use of contracts with strong incentives in publicly traded firms compared to 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 increase in high-powered incentives also results in more socially costly production—revealing an important but often overlooked consequence of changes in governance.

H1: An increase in the cost of monitoring is associated with an increase in socially costly production.

2.3 Other Governance Factors

Our main hypotheses examine how changes in the relative costs of internal governance tools affect the firm's governance framework and its subsequent production and externalities. Specifically, we posit that increased monitoring costs exacerbate the manager's moral hazard problem, making high-powered incentives more beneficial for the firm. This shift magnifies the divergence of interests between the firm's owners and its other stakeholders.

This section considers how other firm-, market-, and regulatory-level governance factors affect the firm's choice of governance framework in 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 the firm less likely to cross this critical boundary. For instance, the corporate governance literature often emphasizes how the cost of monitoring is reduced in the presence of large institutional blockholders (e.g., Shleifer and Vishny, 1986; Edmans, 2014), independent boards (e.g., Hermalin and Weisbach, 1998), and additional signals of managerial effort

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

(e.g., Ferreira et al., 2011). Hence, our model generates the following hypotheses:

H2a: The increase in socially costly production following shocks to monitoring costs is less pronounced for firms with large dedicated institutional shareholders.

H2b: The increase in socially costly production following shocks to monitoring costs is less pronounced for firms with independent boards.

H2c: The increase in socially costly production following shocks to monitoring costs is less pronounced for firms with more informative stock prices.

Second, we analyze how the pecuniary penalties imposed by market participants and regulators on the firm for its social costs influence the firm's governance framework decisions. Strong unions may demand additional hazard pay in response to deteriorating safety conditions at work. Regulators may impose monetary fines or suspect production when the firm adversely affects society. Other stakeholders may sue for relief. These external governance mechanisms create additional financial consequences for the firm's 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:* $\frac{d\bar{c}}{dm} > 0$.[13]

A larger pecuniary penalty compels the firm's owners to internalize more of its externalities. As a result, the firm is less likely to adopt high-powered incentives that result in socially costly production following an increase in monitoring costs. In other words, larger pecuniary penalties mitigate the agency problem between the firm's owners and its other stakeholders. Proposition 2 generates the following predictions 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.

[13]We also document empirical findings consistent with the model's other comparative statics. Because these results highlight the same economic forces, we omit them for brevity. See Internet Appendix Section IA.2.

3 Empirical Setup

3.1 Data

Our empirical setting offers an ideal laboratory for testing the implications of our model, as comprehensive data on both coal production quantities and the externality we focus on, workplace safety, are available for the universe of coal mines in the United States. These data are collected by the Mine Safety and Health Administration (MSHA) as part of the Code of Federal Regulation (30 CFR Part 50), which requires all coal mining operators to file reports with MSHA pertaining to coal production, safety violations, accidents, injuries, civil penalties, and employment, all at the mine level. Moreover, MSHA keeps historical records of MSHA inspection district assignments, mine operators, and ultimate mine ownership, among other details.

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 coal divestment shock in Section 6, we supplement our main dataset with hand-collected information on the ownership of Norges Bank Investment Management (NBIM) and California Public Employee's Retirement System (CalPERS) from their annual investment reports, EBITDA performance targets from firm proxy filings, and whether the firms in our sample produce mainly thermal or metallurgical coal from various sources, including the Metallurgical Coal Producers Association website and public filings. Definitions and sources for all variables used in the analyses below can be found in Appendix Table A1.

3.2 Empirical Measure of Externalities

Prior research has typically focused on observable and measurable *environmental* externalities, such as toxic emissions (Shive and Forster, 2020). However, the emergence of cost-effective emissions abatement technology likely indicates that most firms can operate at relatively high levels of production while imposing relatively low levels of emissions. Our model predicts that an increase in monitoring costs will have little impact on such externalities, as the switch to high-powered incentives encourages additional production, but the resulting emissions can be abated at low costs. This prediction is consistent with 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, Internet Appendix Figure IA.1.2 suggests a 60-80% increase in safety violations when mines cross the 50th percentile of production per employee hour. Moreover, Gowrisankaran et al. (2018) note that progressive digging, a direct input into the production process, works to weaken roof support in underground mines over time, 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.[14] Specifically, we use the number of safety violations MSHA cites a firm for potential accidents. However, unlike OSHA violations, which mainly stem from infrequent and irregular inspections, safety violations in coal mining largely result from regular inspections by MSHA, which is mandated by Section 103(a) of the Federal Mine Safety and Health Act of 1977 to inspect underground mines at least four times per year and surface mines at least twice per year. This institutional detail significantly mitigates concerns arising

[14]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.

from the endogenous nature of irregular inspections.

Finally, the data include a unique dimension—MSHA classifies safety violations as having either a low probability or a high probability of an accident ultimately occurring.[15] This classification further validates the use of workplace safety in coal mining as an externality. In particular, MSHA reserves the high-probability classification for the most egregious infractions that often immediately suspend production, for example, inadequate ventilation systems in underground coal mines. 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.

3.3 Empirical Strategy

Our baseline empirical strategy uses private-to-public transitions as an instrument for discrete increases in monitoring costs driven by the dispersion of ownership (Grossman and Hart, 1980; Shleifer and Vishny, 1986; Pagano and Röell, 1998). For example, studies have found that the average stake of the controlling shareholder drops from around 70% to just over 40% immediately following an IPO (Mikkelson et al., 1997), and to around 20% within five years (Helwege et al., 2007). We find a similar reduction (from 60% to just over 30%) in a small subsample of our data where we can clearly measure the stake of the controller shareholder pre- and post-IPO. 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).

Our setting allows us to trace individual asset ownership that moves across listing status in a commodity setting, where producers obtain the same output prices and use similar production technologies. Moreover, we exploit high-dimensional fixed effects to control for unobservable heterogeneity that may impact public listing status, production, and externality generation simultaneously. First, county-by-year fixed effects absorb relevant variations in local coal prices and other time-varying unobservables, such as the local labor supply for

[15] 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).

different regions. Second, mine fixed effects hold constant 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 size and scale of the mine and its resources or reserves available. Finally, we also include firm-level fixed effects. Thus, our identification arises from firm IPOs or going-private transactions, acquisitions of privately held mines or firms, or the private acquisition of a public mine or firm, rather than from cross-sectional differences between public and private firms. Figure 3 displays the prevalence of each of these listing status changes throughout our sample period.[16]

4 Baseline Empirical Results

4.1 Summary Statistics

Table 3 displays the summary statistics for the main sample[17], which 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 over a sample period of 1983 through 2022 for production and employment, and 1994 through 2022 for safety violations.[18] The average (median) mine in our sample is cited for 52 (17) safety violations each year. Table 3 also reports that the average (median) mine produces just under 700,000 (125,000) short tons of clean coal across 116,560 (45,566) employee hours each year, 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 that are owned by a public firm.

[16]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.

[17]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.

[18]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.

4.2 Socially Costly Production (H1)

4.2.1 Production

First, we examine a mine's productive output as a function of its owner's listing status. 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. Model (2) adds the log of total mines owned by the firm and the log of the average number of mine employees. These covariates, while few, should parsimoniously control for the time-varying size and scale of both the mine and firm.

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* across both specifications are positive and statistically significant at the 1% level. 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 us to collapse 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 methodology (Gormley and Matsa, 2011), which Baker et al. (2022) argue is effective in recovering the true treatment path even under the most 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 not any 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. Finally, standard errors are clustered at the firm $\times$ cohort $\times$ event number level.

Panel A of Figure 4 depicts the estimated dynamic treatment effect for production and provides strong evidence that there is a discrete change in output for mines that experience a listing status change. Moreover, this figure eases concerns regarding two confounding mechanisms. First, any change in production for mines that eventually switch listing status happens during the year the change takes place and not before it. That is, the pre-trends for these listing status changes are flat, supporting the argument that our results are not driven by selection bias or reverse causality. Second, the increase in production is quite persistent, present even five years post-listing status change. This mitigates concerns that we are simply documenting features of a general ownership change, such as new capital investments that lead to a temporary disruption in safety standards 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.[19] 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, over three times as large as the increase in production. This is consistent with the argument that such mines operate on the convex component of the social costs function, e.g., above the output-externalities threshold (see Internet Appendix Figure IA.1.2). Moreover, Internet Appendix Table IA6 shows similar results when scaling safety violations by total productive output.

Next, we separate the dependent variable (safety violations) into those classified as either low or high probability of the accident ultimately occurring. 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 effect for high-probability violations is 50% larger than it is for low-probability violations. That is, mines increase high-probability safety violations by 45% upon a to-public change in listing status, and only by 29% for violations classified as low-probability. 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 ownership dispersion.

Panel B of Figure 4 depicts the dynamic treatment effects for safety violations us-

[19] 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).

ing 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 4 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 at the expense of long-term value. For instance, managers may exploit public investors' focus on short-term results by boosting immediate production while increasing the likelihood of future mine disasters (e.g., Caskey and Ozel, 2017). Moreover, if one views workplace safety as a type of long-term investment (Cohn et al., 2021), our finding that performance-based incentives encourage production at the expense of workplace safety also echoes the underinvestment dynamics documented by Asker et al. (2015).

However, several distinctions separate our governance-based framework from conventional corporate myopia frameworks. First, our framework does not require that the social costs manifest over a long time horizon—just that the firm's owners do not fully internalize them. 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. 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 doing so 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 group of stakeholders is "left holding the bag." Conventional myopia models emphasize the firm's future shareholders who 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 falls primarily on employees, the local community, and the state rather than future investors. This distinction has significant implications 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 and enhanced inspection—may be necessary for firms to internalize social costs.

5 Cross-Section Empirical Results

This section explores the cross-sectional empirical predictions generated by our model. 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 exclusively on public firms that IPO during the course of our sample. 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 the model, the trade-off between production and externalities is generated by a moral hazard problem. The firm increases its reliance on 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, limiting our ability to do so.[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 immediately following the IPO.

Table 5 reports the results of interacting the bonus indicator with the *Public owner* variable of interest. Consistent with the use of bonuses (e.g., high-powered incentives) playing an important role in the increase of socially costly production, Models (1) and (4) indicate that the entire impact of ownership dispersion on production and high-probability safety violations is concentrated in bonus-using firms.[21] While this test is imperfect, it is reassuring that our main effects are driven by firms that presumably rely on performance-based pay, which is 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 lessens the severity of the moral hazard problem and reduces the need for high-powered incentives. Thus, 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 first examine the role of other large shareholders as the firm's ownership disperses through the IPO. In our model, external shareholders such as institutions mitigate the agency problem only to the extent they lower monitoring costs. If dispersed institutions collectively hold a large percentage of shares, but each individual institution faces limited incentives to monitor,

[20] Section 6 provides a more 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 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.

the firm will still increase its reliance on high-powered incentives post-IPO. This shift toward stronger performance-based incentives subsequently encourages socially costly production.

Thus, we focus on the percentage of outstanding shares that are held by dedicated institutions (Bushee, 1998) at the time of their IPO. Chen et al. (2007) note that such institutions are much more likely than other investors (e.g., transient institutions) to perform the monitoring role by collecting information and attempting to influence managers, even with relatively small holdings. Panel A of Table 6 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 the percentage of shares held by dedicated institutions at the time of the firm's IPO is high. This is particularly true for safety violations deemed the most likely to occur.

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). Though our power in these tests is limited, the results using the total percentage of dedicated institutional ownership and 5% institutional blockholders are qualitatively similar to those in Table 6 Panel A. However, we find no attenuation effect on socially costly production when the firm has a higher percentage of total institutional ownership. We infer that high institutional holdings alone do not sufficiently lower monitoring costs.

5.2.2 Board Oversight (H2b)

Next, we explore the role of board oversight. A sufficiently effective board reduces the need for the firm's owners to rely on high-powered incentives. To test this prediction, we proxy for the effectiveness of the board's monitoring capabilities with the level of independence (Hermalin and Weisbach, 1998). In particular, Panel B of Table 6 interacts the *Public owner* variable 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 results for dedicated institutional ownership, the increase in socially costly production attenuates significantly in

the presence of a highly independent board. These results provide context 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)

Third, we examine the role of 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, lowering socially costly production in our framework. To test this prediction, we primarily rely on the relative price informativeness measure from Dávila and Parlatore (2024). Though there are potential issues interpreting Easley et al.'s (1996) probability of informed trading (PIN) (e.g., Duarte and Young, 2009), we show in Internet Appendix Table IA8 that using PIN leads to similar results. Panel C in Table 6 analyzes uses an indicator variable that equals one if relative price informativeness exceeds the sample 75th percentile (3.46%). 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 implies 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 other market-level governance provisions.

First, 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 the previous year $(t-1)$.[22] That is, we focus on the average number of spot inspec-

[22]Unlike Liang et al. (2023), we find no discernable differences in regulatory scrutiny between publicly and

tions 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 potential concern with our analysis in Section 4.2 is that the shocks to monitoring costs that coincide with the ownership dispersion during listing status changes may not be random. The most salient endogeneity issue is that firms choose the timing and nature of the going-public or going-private decision, and the decision likely depends on firm or managerial characteristics that may impact the outcomes we wish to study. For example, firms may decide to go public (IPO) precisely when the manager has revealed herself to be high quality, lowering the realized monitoring cost increase of ownership dispersion.

Additionally, the IPO is a monumental moment in a firm's life-cycle. Many characteristics, policies, strategies, and cultural aspects of the firm evolve simultaneously. Such a

privately owned mines.

breadth of changes make disentangling the impact of the monitoring cost increase empirically challenging. To circumvent the combination of these issues, we exploit plausibly exogenous shocks to monitoring costs induced by the politically motivated coal divestment initiatives imposed on several prominent activist institutional investors.

We focus on California Public Employees' Retirement System (CalPERS) and Norges Bank Investment Management (NBIM), as both are widely regarded to be among the most involved and influential institutional investors in the world (e.g., see Smith, 1996; Wahal, 1996; Fahlenbrach et al., 2024; Aguilera et al., 2024).[23] For example, in 2023, CalPERS voted in 9,000 global meetings (California Public Employees' Retirement System, 2024). Similarly, over the same period, NBIM voted in nearly 12,000 shareholder meetings and had over 3,000 meetings with its portfolio companies (Norges Bank Investment Management, 2024).

Importantly, both funds emphasize good corporate governance practices, particularly the alignment of managerial interests with long-term investor goals. Over the past five years, CalPERS has maintained an average opposition rate of 50% for advisory votes on executive compensation (California Public Employees' Retirement System, 2024). NBIM has been similarly active in opposing high-powered incentive contracts for prominent companies such as Tesla (Rasmussen and Fouche, 2024) and Apple (Treloar, 2022), specifically when such contracts include bonus and short-term incentive schemes that prioritize short-term results (Baker, 2024).

Notably, both are regulated in part by governmental authorities—CalPERS by the state of California and NBIM by the Ministry of Finance in Norway—jurisdictions that have strongly advocated for environmental sustainability over the past two decades. As part of that broader agenda, both regulators imposed coal divestment initiatives in 2015.[24] Specifically, in May of 2015, Norwegian political parties agreed that NBIM would sell off GPFG holdings in 122 firms worldwide which derive 30% or more of their income from thermal coal.

[23]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.

[24]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.

Similarly, in September of 2015, California passed Senate Bill 185, which required CalPERS to divest their investments in coal companies generating at least 50% of total revenue from thermal coal.[25] Importantly, these divestment initiatives were plausibly exogenous to the coal firms themselves and removed major activist institutions from affected *thermal* coal firms, likely substantially increasing their monitoring costs. Metallurgical (met) coal firms and conglomerates, on the other hand, were unaffected by the divestments, thereby creating a natural control group for our analysis.

Figure 5 Panel A 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.

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 treatment variable and interact it with an indicator variable equal to one if the year is greater than or equal to 2015. The initiation 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 over the sample period.[26] 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

[25]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), nitrous 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. The California state bill also required the California State Teachers' Retirement System (CalSTRS) to liquidate from thermal coal, though their holdings in our sample firms are trivial.

[26]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.

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 6 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 (DiDiD) setup by adding an interaction with an indicator variable equal to one if the firm is a thermal coal producer. Consistent with the nature of the divestment mandates from the state of California and the Norwegian Ministry of Finance, only public thermal coal producers experience 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 changes to production and externalities policies for the affected firms.[27]

The main identifying assumption in our strategy is that CalPERS and NBIM did not pursue divestment for non-environmental reasons. Specifically, one may worry that coal firms were performing poorly on metrics that CalPERS and NBIM valued, such as financial returns or even social measures like workplace safety. First, the historical patterns of CalPERS and NBIM activism suggest that this is unlikely. 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 principal that "divestment conflicts with fiduciary duty" (California Public Employees Retirement System, 2017). Similarly, NBIM has called divestment a "last resort."

Second, while both CalPERS and NBIM have long demonstrated interest in sustainable investment, their focus has been predominantly on environmental issues rather than social ones. For example, AI summarizes NBIM's most recent sustainable investment reports to

[27]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.

be about 45-50% relating to environmental factors and only 1-2% relating to the workplace environment for employees (OpenAI, 2025; Norges Bank Investment Management, 2024). However, to further probe the possibility that NBIM or CalPERS may have had a social reason for divesting from thermal coal producers, we report cross-sectional analysis in Internet Appendix Table IA10 that shows thermal coal producers do not significantly differ from met coal producers on any measurable safety dimensions.

Finally, the nature of the shock allows us to further probe the underlying mechanism in the production and externality increases. In our model, the impact stems from a substitution from monitoring to incentive-based governance, particularly the use of high-powered incentives. To provide a direct test of this mechanism, we hand-collect EBITDA performance targets from the proxy filings of the public firms in our sample. Panel A of Figure 7 indicates that average thresholds remained stable at around $500 million over the 2010 through 2020 period. Panel B plots the dynamic trend of the log of EBITDA performance targets for thermal producers relative to met coal producers and conglomerates. Though the sample size is small (22 firms), the results are striking. Just as the model predicts, there is a sharp increase (60%) in the level of performance thresholds for thermal coal producers relative to met coal producers immediately following the divestment initiatives. We note that this increase is entirely driven by intensive margin adjustments, as all firms in our sample employed EBITDA threshold performance bonuses before and after the divestment.

In all, these findings confirm our baseline analysis based on listing status changes and suggest that the impact of increased monitoring costs on production and externalities is likely to be causal. 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 most salient concern in our baseline empirical strategy is that the transition from private to public ownership relieves financial constraints through greater access to capital markets (Brav, 2009). More generally, IPOs typically coincide with many changes in firm character-

istics and policies that could impact both production decisions and the resulting externalities. To pin down our proposed mechanism—increased monitoring costs through ownership dispersion—and rule out potential alternatives, we conduct four sets of robustness and subsample tests.

First, we examine if our results are concentrated in firms that arguably had the largest dispersion in ownership during the IPO process. 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, which suggests that our managerial ownership proxy is capturing meaningful ownership dispersion. 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%.[28] Consistent with our model's predictions, the results suggest that the increase in socially costly production is entirely concentrated in firms that presumably experienced the greatest ownership dispersion and, thus, the largest increase in monitoring costs through the IPO process.

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-

[28] 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 IA11). Moreover, Internet Appendix Table IA12 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).

externalities threshold. On the contrary, public firms with high output generate significantly 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 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 IA13 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 C shows results that are quantitatively and qualitatively similar to our baseline findings in Table 4.

Finally, it could be the case that recent productive output and the nature of workplace environments 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 portfolio of company 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 IA14 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 with low production-externalities thresholds, 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.

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.

Baker, S. 2024. World's largest sovereign wealth fund tells proxy advisers to favor longer-term U.S. CEO pay incentives. *Pensions & Investments* URL https://www.pionline.com/esg/norways-sovereign-wealth-fund-tells-proxy-advisers-favor-longer-term-us-ceo-pay-incen

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. 2001. Are CEOs Rewarded for Luck? The Ones Without Principals Are. *Quarterly Journal of Economics* 116:901–932.

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.

Braghieri, L., R. Levy, and A. Makarin. 2022. Social Media and Mental Health. *American Economic Review* 112:3660–93.

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

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

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. URL https://www.calpers.ca.gov/sites/default/files/spf/docs/forms-publications/calpers-and-divestment.pdf.

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. URL https://www.calpers.ca.gov/newsroom/calpers-news/2024/calpers-proxy-voting-global-company-accountability-for-climate-change-board-independe

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. URL https://www.sciencedirect.com/science/article/pii/S0304405X07001171.

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.

DeWeerdt, S. 2019. The Natural History of an Epidemic. *Nature* 573:S10–S11.

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

Duarte, J., and L. Young. 2009. Why is PIN Priced? *Journal of Financial Economics* 91:119–138.

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

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.

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.

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. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/fima.12413.

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

El-Hage, J. 2021. Fixing ESG: Are Mandatory ESG Disclosures the Solution to Misleading ESG Ratings? *Fordham Journal of Corporate and Financial Law* 26:359–390.

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.

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

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. *The Washington Post* URL https://www.washingtonpost.com/archive/politics/1984/12/27/community-faces-economic-impact-of-mine-disaster/341375ca-0a35-4a16-8dbc-aee3d29f7992/.

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

Jensen, M. C., and W. H. Meckling. 1976. Theory of the Firm: Managerial Behavior, Agency Costs, and Ownership Structure. *Journal of Financial Economics* 3:305–360.

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 to Dr. Emilia Istrate, Research Director for the National Association of Counties. URL https://www.marshall.edu/cber/files/2021/04/2016-09-Cruel_Coal.pdf.

Kuratko, D. F., H. L. Holt, and E. Neubert. 2020. Blitzscaling: The good, the bad, and the ugly. *Business Horizons* 63:109–119.

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

Larrain, B., P. Roosenboom, G. Sertsios, and F. Urzúa. 2024. Ownership Concentration and Firm Value: New Evidence from Owner Stakes in IPOs. *Management Science* 70:4167–4952.

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. URL https://www.nbim.no/en/publications/reports/2024/responsible-investment-2024/.

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

Oliva, R., and J. D. Sterman. 2001. Cutting corners and working overtime: Quality erosion in the service industry. *Management Science* 47:894–914.

OpenAI. 2025. ChatGPT 4.0. URL https://openai.com/chatgpt. Accessed: 2025-03-12.

Padon, A. A., R. N. Rimal, M. Siegel, W. DeJong, T. S. Naimi, and D. H. JernFigan. 2018. Alcohol Brand Use of Youth-Appealing Advertising and Consumption by Youth and Adults. *Journal of Public Health Research* 7:22–28.

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. Fama-Miller 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.

Rasmussen, L., and G. Fouche. 2024. Norway wealth fund to vote against Musk's $56 billion Tesla pay package. *Reuters* URL https://www.pionline.com/esg/norways-sovereign-wealth-fund-tells-proxy-advisers-favor-longer-term-us-ceo-pay-incen

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* URL https://www.sacbee.com/news/politics-government/article4502845.html. Accessed: 2025-03-12.

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.

Strine, L. E. J., J. L. Brooke, K. M. Diamond, and D. L. J. Parker. 2022. It's Time to Focus on the"G" in ESG. *Harvard Business Review* .

Struik, L. L., S. Dow-Fleisner, M. Belliveau, D. Thompson, and R. Janke. 2020. Tactics for Drawing Youth to Vaping: Content Analysis of Electronic Cigarette Advertisements. *Journal of Medical Internet Research* 22:e18943.

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

Tayan, B. 2019. The Wells Fargo Cross-Selling Scandal. Stanford University Graduate School of Business Research Paper No. 17-1.

Treloar, S. 2022. Norway's Wealth Fund to Vote Against Apple Executive Pay Package. *Bloomberg* URL https://www.bloomberg.com/news/articles/2022-02-28/norway-s-wealth-fund-to-vote-against-apple-executive-pay-package?embedded-checkout=true.

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.

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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.

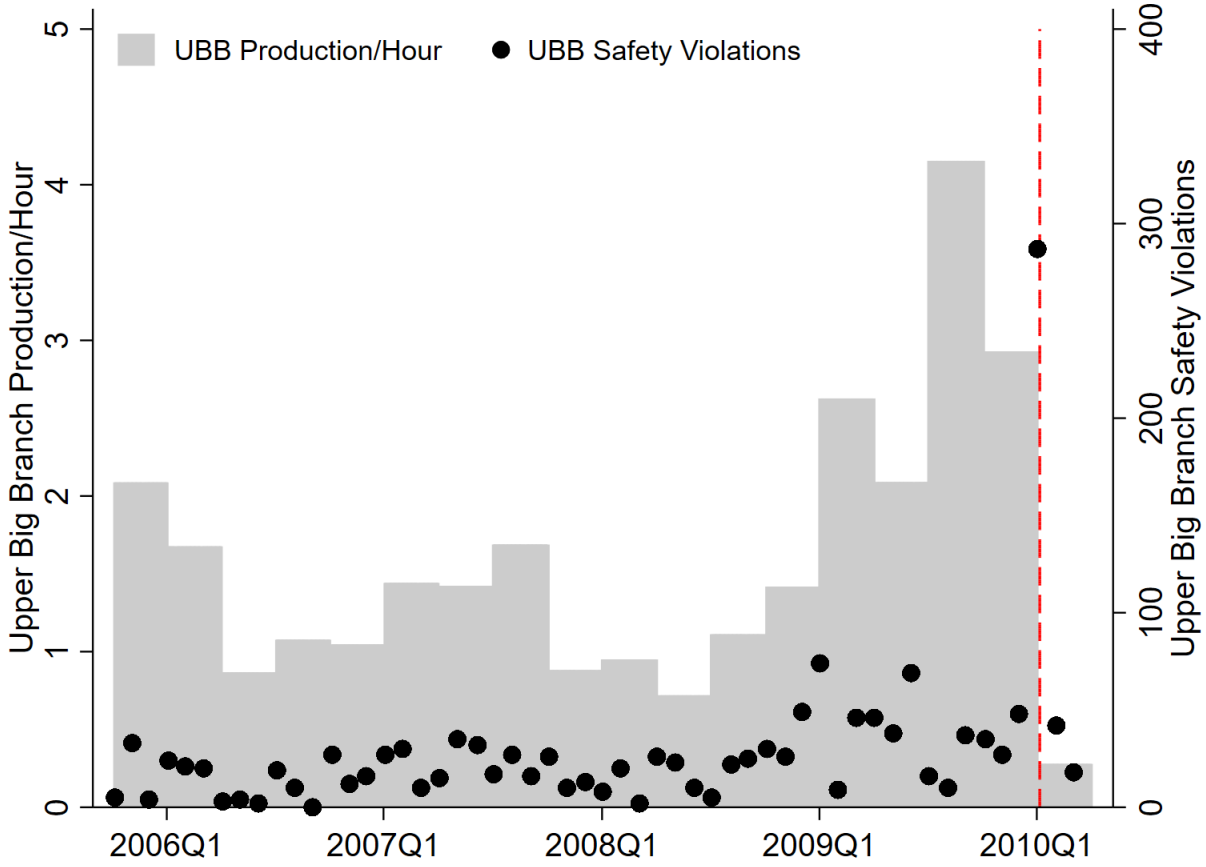


Figure 3: Annual Number of Mines Changing Listing Status. This figure displays the annual number of mines changing listing status over the sample period of 1983 through 2022. The blue bars depict mines that change listing status when the mine owner goes public through an IPO, the red bars depict mines 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.

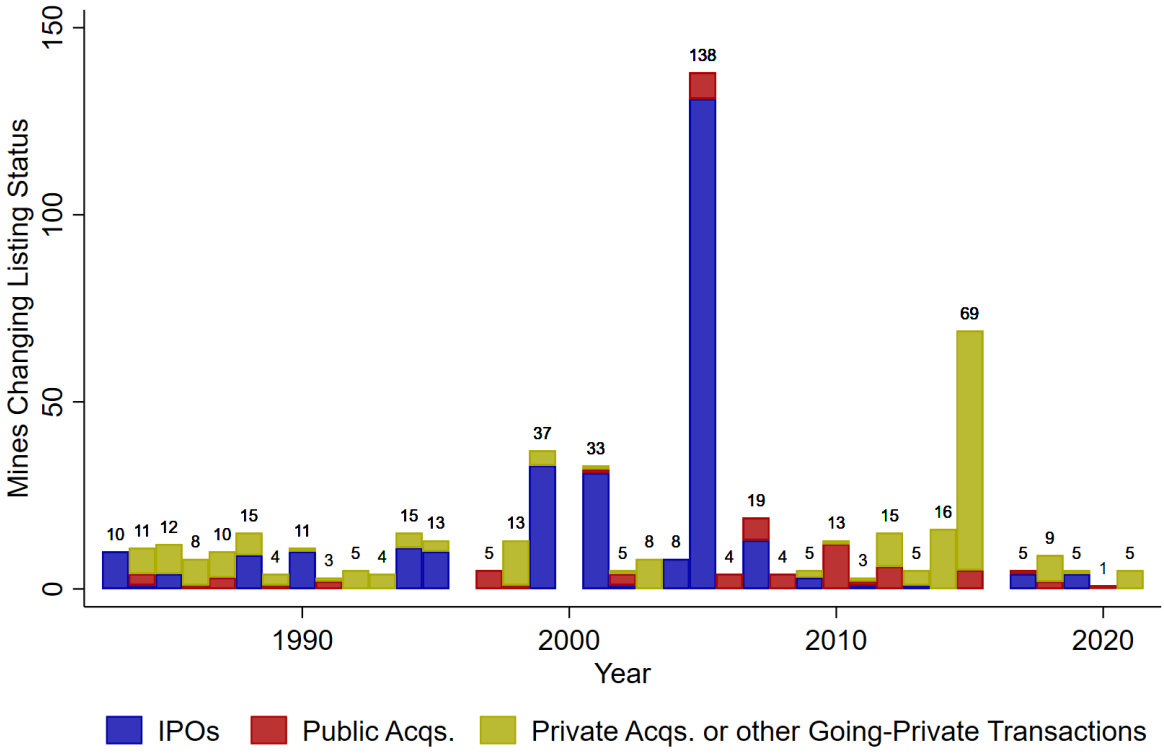
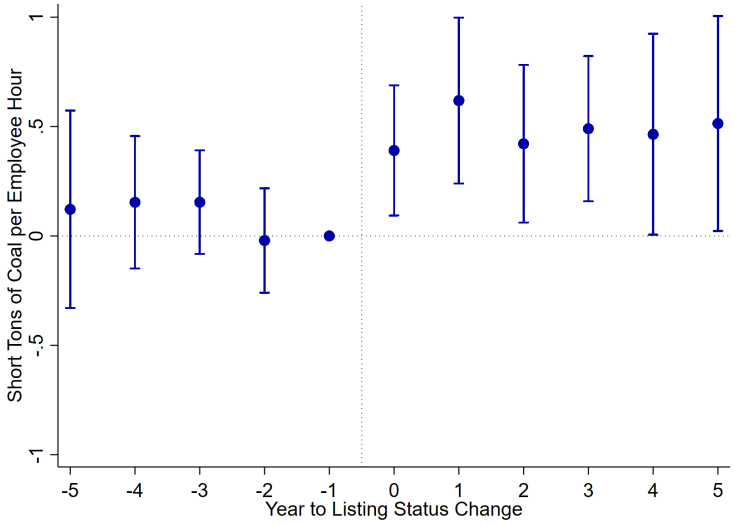


Figure 4: Stacked Regression Production and Externality Event-Time Trends around Listing Status Changes. These figures display the trends of mine-level production (Panel A) and safety violations (Panel B) around listing status changes (IPOs, public acquisitions, and private acquisitions or other going-private 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 × cohort × event number 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.

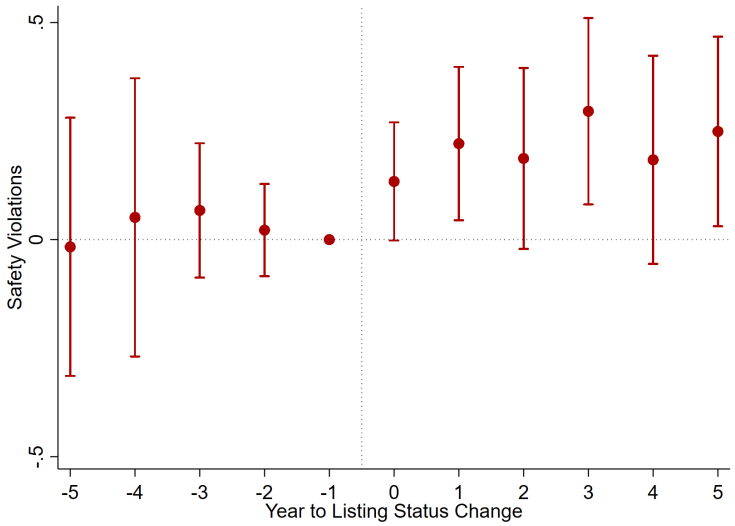
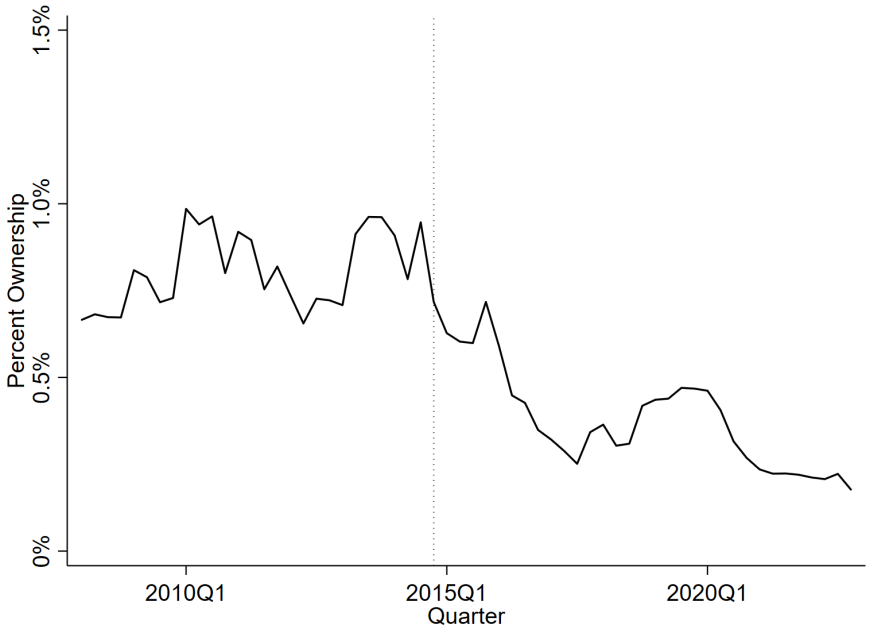


Figure 5: Coal Divestment Initiatives. These figures depict the total combined ownership percentages of Norges Bank Investment Management (NBIM), the manager of the sovereign wealth fund of Norway, and the California Public Employees' Retirement System (CalPERS) for the average firm in our sample (Panel 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.

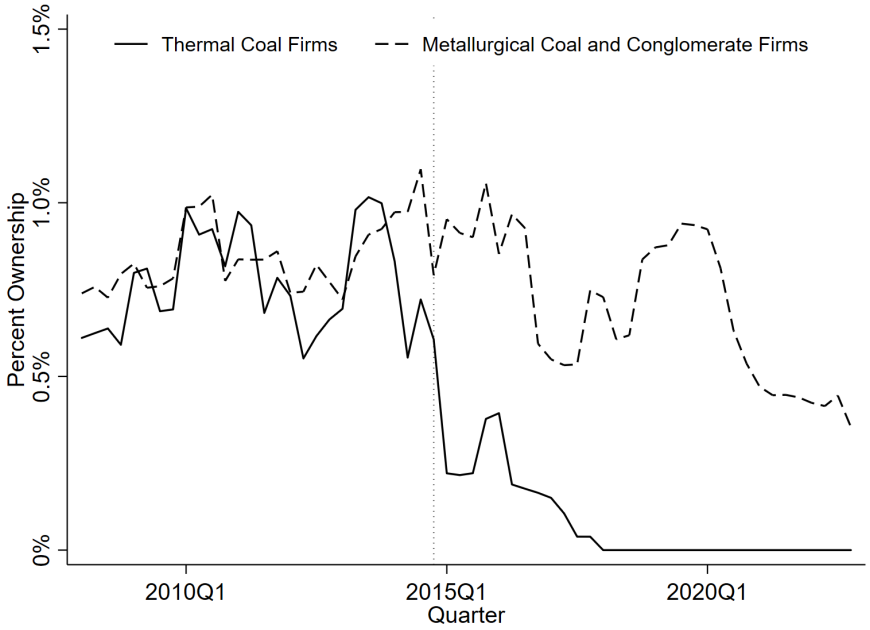
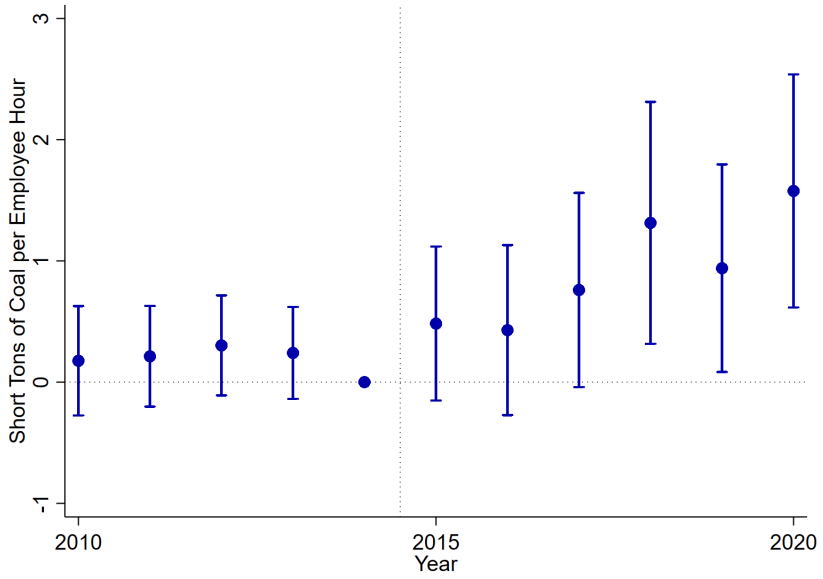


Figure 6: Production, Externalities, and Coal Divestment Initiatives. These figures display the trends of mine-level production (Panel A) and safety violations (Panel B) around the 2015 coal divestment announcements by Norges Bank Investment Management (NBIM) and California Public Employees Retirement 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.

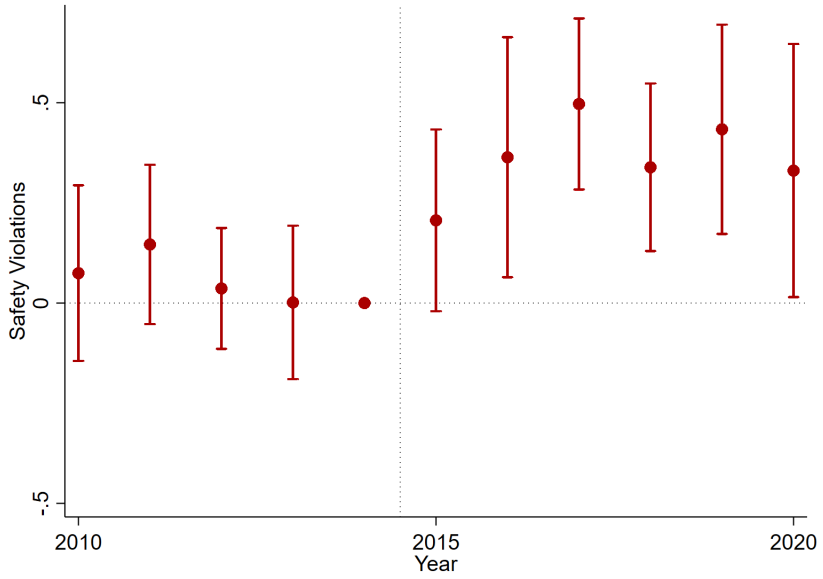
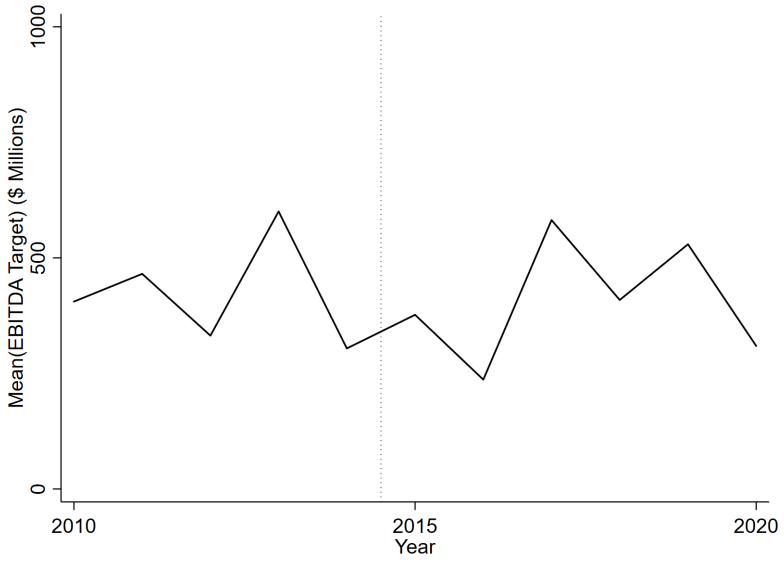


Figure 7: Performance Targets and Coal Divestment Initiatives. These figures display the trends of EBITDA performance targets for the average public firm in our sample from 2010 through 2020 (Panel A) and the log levels of the EBITDA performance targets differentially for thermal and metallurgical coal 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.

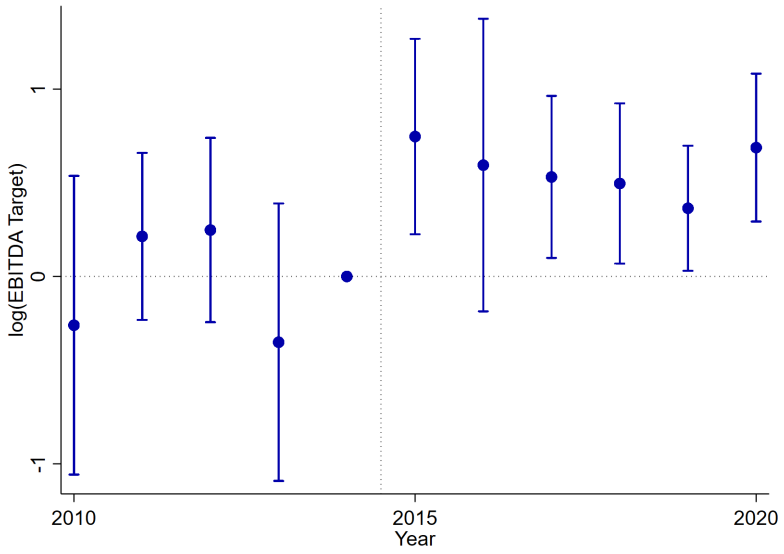


Table 3: Summary Statistics. This table reports summary statistics for all publicly and privately owned U.S. coal mines over a sample period of 1983 through 2022. A mine-year observation is included in our sample if it satisfies the following requirements: (1) the mine is actively producing coal and 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 =	$\frac{\text{Production}}{\text{Hours}}_{ist}$	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$_{ist}$× I(Year$_t \geq 2015$)	0.647**	-0.309	0.418***	-0.191
	(0.317)	(0.280)	(0.125)	(0.253)
Public owner$_{ist}$× I(Year$_t \geq 2015$)× 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$_{ist}$× I(Thermal Coal Firm$_s$)		-0.113		0.076
		(0.396)		(0.213)
I(Year$_t \geq 2015$)× I(Thermal Coal Firm$_s$)		-0.383		-0.032
		(0.259)		(0.073)
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	2,737	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$_{ist}$× 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 × 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: 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: 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. Source: MSHA https://www.msha.gov/mine-data-retrieval-system.
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. Source: MSHA https://www.msha.gov/mine-data-retrieval-system.
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 $\tau_\pi^{R,s}$	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.
PIN_s (%)	The probability of informed training (Easley et al., 1996) from Brown and Hillegeist (2007), measured in percent at the first available quarter after firm s's initial public offering. Source: https://terpconnect.umd.edu/~stephenb/pinsdatanew.html.

High PIN_s	An indicator variable equal to 1 if PIN_s measured at the first available quarter after firm s's initial public offering is above the sample's 75th percentile, equal to PIN_s of 26.32%. Source: https://terpconnect.umd.edu/~stephenb/pinsdatanew.html.
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).
$\tau_\pi^{R,s}$ (%)	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 $\tau_\pi^{R,s}$	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.
PIN_s (%)	The probability of informed training (Easley et al., 1996) from Brown and Hillegeist (2007), measured in percent at the first available quarter after firm s's initial public offering. Source: https://terpconnect.umd.edu/~stephenb/pinsdatanew.html.
High PIN_s	An indicator variable equal to 1 if PIN_s measured at the first available quarter after firm s's initial public offering is above the sample's 75th percentile, equal to PIN_s of 26.32%. Source: https://terpconnect.umd.edu/~stephenb/pinsdatanew.html.

Internet Appendix
for
"Production and Externalities: The Role of Ownership Structure"

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 one figure 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. Table IA1: Public Listing Status and Fatalities and Injuries

   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 14)

3. 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)

4. 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)

5. 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.,

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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 16)

6. 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 19)

7. 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)

8. 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)

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

   Reference in the main paper: "Though there are potential issues interpreting Easley et al.'s (1996) probability of informed trading (PIN) (e.g., see Duarte and Young, 2009), we show in Internet Appendix Table IA8 that using PIN leads to similar results." (Section 5.2.3)

10. 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 27)

11. Table IA10: Are Thermal Coal Firms More Dangerous?

    Reference in the main paper: "However, to further probe the possibility that NBIM or CalPERS may have had a social reason for divesting from thermal coal producers, we report cross-sectional analysis in Internet Appendix Table IA10 that shows thermal coal producers do not significantly differ from met coal producers on any measurable safety dimensions." (Section 6)

12. Table IA11: 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 IA11). Moreover, Internet Appendix Table IA12 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)

13. Table IA12: 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 IA11). Moreover, Internet Appendix Table IA12 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)

14. Table IA13: Public Listing Status, Production, Externalities, and Financial Constraints.

    Reference in the main paper: "Internet Appendix Table IA13 shows similar results using a continuous measure of market leverage." (Section 7)

15. Table IA14: Public Listing Status, Production, Externalities, and Mines Producing Less Than 15% of Total Firm Coal

    Reference in the main paper: "Internet Appendix Table IA14 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.

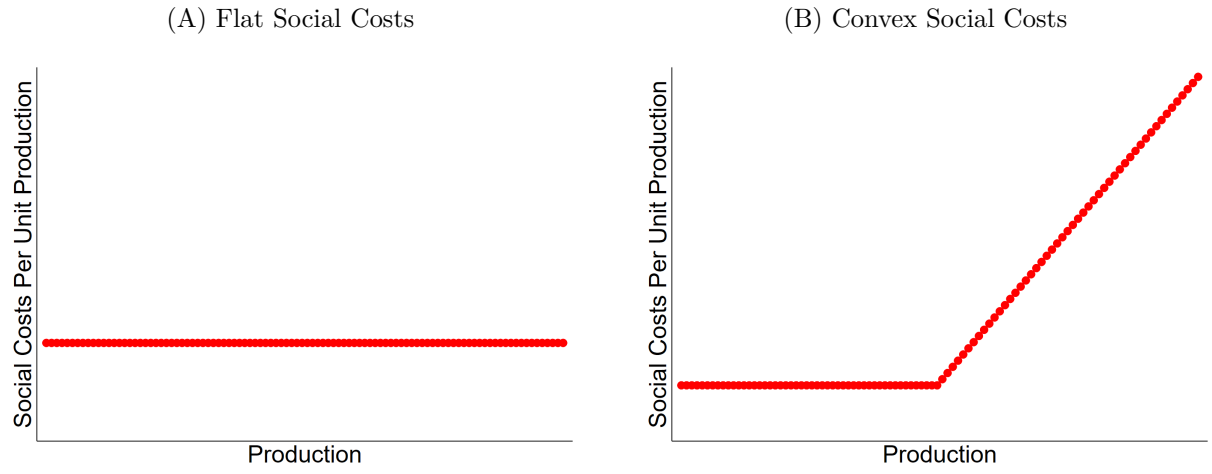


Figure IA.1.1 displays two hypothetical social cost functions. Panel A shows an externality that does not become increasingly costly as production increases. The most common example of an externality with such a social cost structure is industrial emissions. Factories and power plants emit pollutants 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. 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.

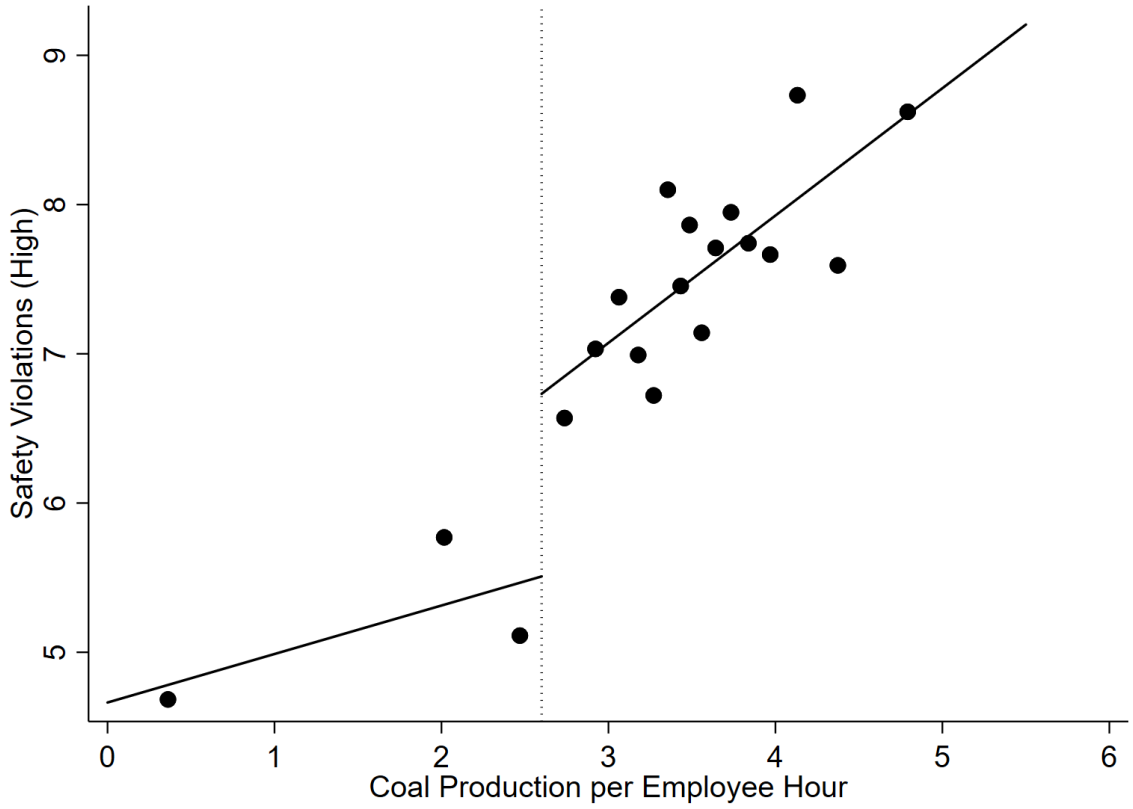
The production technology in coal mining makes it extremely difficult to extract additional coal per hour without sacrificing miner-hours spent on other activities, e.g., safety and maintenance (Rittenberg and Manuel, 1986). In other words, workers cannot simultaneously extract coal from a tunnel that is being maintained. As noted above in Section IA.1, we view production stoppages for maintenance and safety as

[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.

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.

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.



While mapping out the entire social costs function for coal mining is not feasible, Figure IA.1.2 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

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

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

$$\Delta B^* = \frac{1}{(1-\phi_H^{-1})c}.$$

In this case, 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

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

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

$$\Delta B^* = \frac{1}{(1-\phi_L^{-1})c}.$$

In this case, 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

$$\begin{aligned} \Pi_1^* &> \Pi_0^* \\ (\bar{Q}_1 - \bar{Q}_0) - m + B\left(\tfrac{1}{1-\phi_L^{-1}} - \tfrac{1}{1-\phi_H^{-1}}\right) &> \tfrac{1}{2c}\left(\tfrac{1}{(1-\phi_L^{-1})^2} - \tfrac{1}{(1-\phi_H^{-1})^2}\right) \\ c &> \frac{1}{2}\left(\frac{\frac{1}{(1-\phi_L^{-1})^2} - \frac{1}{(1-\phi_H^{-1})^2}}{p\eta(q_H - q_L) - m + B\left(\frac{1}{1-\phi_L^{-1}} - \frac{1}{1-\phi_H^{-1}}\right)}\right) = \bar{c}. \end{aligned}$$

Proof of Proposition 2. From Proposition 1, $\bar{c}$ can be expressed as

$$\bar{c} = \frac{1}{2}\left(\frac{\frac{1}{(1-\phi_L^{-1})^2} - \frac{1}{(1-\phi_H^{-1})^2}}{p\eta(q_H - q_L) - m + B\left(\frac{1}{1-\phi_L^{-1}} - \frac{1}{1-\phi_H^{-1}}\right)}\right)$$

Taking the derivatives of $\bar{c}$ 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: Punishment for Negative Externality

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 section examines how relaxing those frictions affects the trade-off between deterring private benefits and limiting social costs. Specifically, we assume that shareholders can contract a penalty of $\kappa \geq 0$ for the manager for socially costly production. A higher κ indicates reduced contracting frictions. The baseline specification of the model corresponds to $\kappa = 0$. In the limit as $\kappa \to \infty$, the firm's owners can effectively offer a "forcing contract" that specifies no socially costly production.

Consider a managerial compensation contract (W_H, W_L, W_0, κ) paired with the firm's monitoring policy Δ_B. The manager avoids socially costly production ($x = 0$) if and only if

$$\begin{aligned} (1-\eta)pW_H + \eta p W_L \geq\ & pW_H - \kappa \\ W_H - W_L \leq\ & \frac{\kappa}{\eta p}. \end{aligned} \tag{3}$$

The revised social-compatibility constraint (3) implies that when the firm's owners cannot punish the manager for the negative externality ($\kappa = 0$), paying the manager more for high output than for low output results in socially costly production as in the main specification of the model. When punishment for the negative externality is possible ($\kappa > 0$), the firm's owners can offer the manager some high-powered incentives while still deterring socially costly production (i.e., $W_H - W_L \in (0, \frac{\kappa}{\eta p}]$). When κ is sufficiently large, the constraint on the power of incentives in the contract is not binding (i.e., $\kappa \geq \eta \left(\frac{B-\Delta_B}{1-\phi_H^{-1}}\right)$ and the lowest-cost IC contract identified by Lemma 1 also deters socially costly production if it includes the punishment term κ for socially costly production.

When $\kappa < \eta \left(\frac{B-\Delta_B}{1-\phi_H^{-1}}\right)$, the manager's SC constraint binds. Hence, a contract that satisfies the manager's SC pays $W_H^* = W_L^* + \frac{\kappa}{\eta p}$. Additionally, binding the manager's IC implies that

$$\begin{aligned} (1-\eta)p(W_L^* + \tfrac{\kappa}{\eta p}) + \eta p W_L^* =\ & (B - \Delta_B) + (1-\eta)p_H(W_L^* + \tfrac{\kappa}{\eta p}) + \eta p_L W_L^* \\ W_L^* =\ & \underbrace{\frac{1}{p}\frac{B-\Delta_B}{1-\phi_L^{-1}}}_{\text{from Lemma 2}} - \frac{1}{p}\left(\frac{(1-\eta)(p-p_H)}{1-\phi_L^{-1}}\right)\frac{\kappa}{\eta p}. \end{aligned}$$

Note that W_L^* declines to 0 as κ increases towards the threshold. Moreover, the expected compensation cost in this case $A_\kappa < A_L$ because the compensation contract is higher-powered, paying more for high output which is associated with a higher likelihood ratio.

Additionally, A_κ decreases in κ, which implies that an increase in κ reduces the relative agency cost

savings of the high-powered incentives identified in Lemma 1. Hence, the firm is less likely to switch to high-powered incentives that result in socially costly production following an increase in monitoring costs when κ is larger (i.e., $\frac{d\bar{c}}{d\kappa} > 0$).

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.

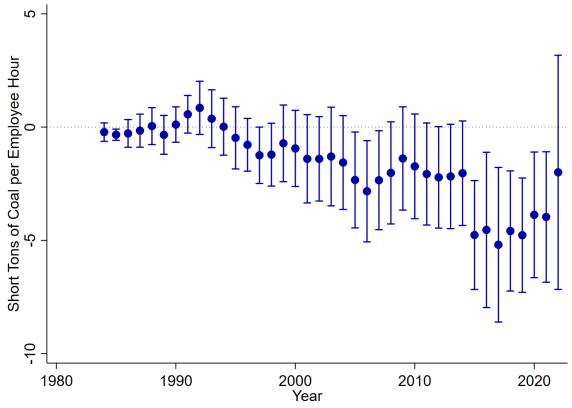
We collect data on safety-based performance incentives from ISS Incentive Lab's Absolute Performance Goals Data. Unfortunately, the coverage on these provisions is incredibly sparse, with almost no coverage until the mid 2010s. More problematic, even when the coverage does improve late in the sample, 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.

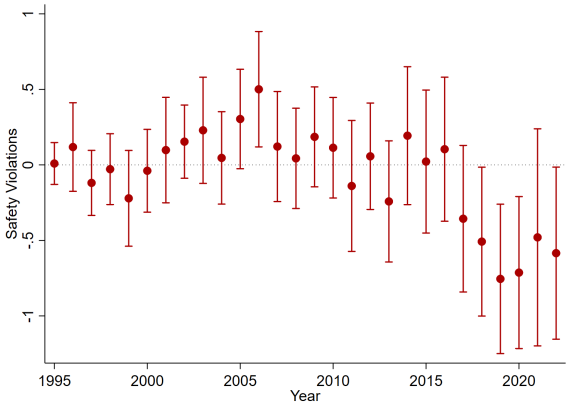
Panel A plots the coefficients for production, while Panel B plots the coefficients for safety violations. In general, both plots show a consistent decline, at least post-2005, indicating that such firms may have started incentivizing safety much earlier than 2018. Moreover, both Panels show a fairly 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]	2018	228,655	—	142,956	—	315,801	—	114,522	801,934
General Counsel									
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

Name and Principal Position	Year	Annual Compensation: Salary ($)	Annual Compensation: Bonus ($)	Annual Compensation: 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:

Name and Principal Position	Year	Annual Compensation: Salary ($)	Annual Compensation: Performance Bonus ($)	Annual Compensation: Other Annual Compensation ($)	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 Novermber, 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.

[IA25] Cohn, J., N. Nestoriak, and M. Wardlaw. 2021. Private Equity Buyouts and Workplace Safety. *Review of Financial Studies* 34:4832–4875.

[IA12] 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.

[IA34] Dorman, P. 2012. Estimating the economic costs of occupational injuries and illnesses in developing countries: Essential information for decision-makers. International Labour Organization.

[IA14] 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.

[IA38] 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.

[IA16] 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.

[IA17] Gao, J., M. Sevilir, and Y. Kim. 2021. Private Equity in the Hospital Industry. European Corporate Governance Institute – Finance Working Paper No. 787/2021.

[IA18] 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.

[IA19] 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.

[IA20] 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.

[IA58] Health and Safety Executive. 2023. Costs to Britain of workplace fatalities and self-reported injuries and ill health, 2021/22.

[IA22] 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.

[IA62] Isikoff, M. 1984. Community Faces Economic Impact Of Mine Disaster. *The Washington Post* URL https://www.washingtonpost.com/archive/politics/1984/12/27/community-faces-economic-impact-of-mine-disaster/341375ca-0a35-4a16-8dbc-aee3d29f7992/.

[IA24] Kaplan, S. N., and A. Schoar. 2005. Private Equity Performance: Returns, Persistence, and Capital Flows. *Journal of Finance* 60:1791–1823.

[IA67] Kent, C. A. 2016. *The Cruel Coal Facts: The Impact on West Virginia Counties from the Collapse of the Coal Economy*. Report to Dr. Emilia Istrate, Research Director for the National Association of Counties. URL https://www.marshall.edu/cber/files/2021/04/2016-09-Cruel_Coal.pdf.

[IA71] Leigh, J. P., S. Markowitz, M. Fahs, and P. Landrigan. 2000. *Costs of Occupational Injuries and Illnesses*. University of Michigan Press.

[IA27] Liu, T. 2022. Bargaining with Private Equity: Implications for Hospital Prices and Patient Welfare. Working paper, MIT Sloan School of Management.

[IA28] 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.

[IA29] 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.

[IA30] 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.

[IA31] 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.

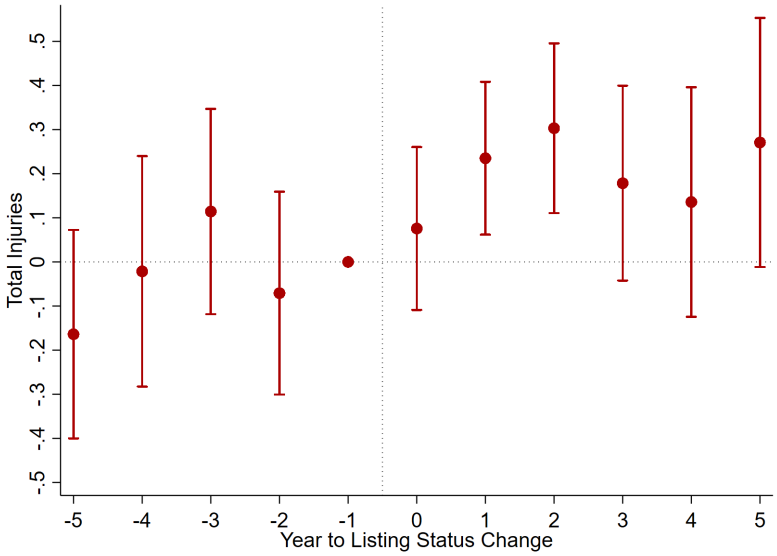
[IA32] Seba, E. 2017. Judge says Exxon Owes $19.95 Million for Texas Refinery Pollution. *Reuters* URL https://www.reuters.com/article/refinery-pollution-exxon-penalty/judge-says-exxon-owes-19-95-million-for-texas-refinery-pollution-idUSL1N1HZ26P.

[IA33] Smith, A. 1776. *The Wealth of Nations*. University of Chicago Press, Chicago.

[IA34] 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 × cohort × event number 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)

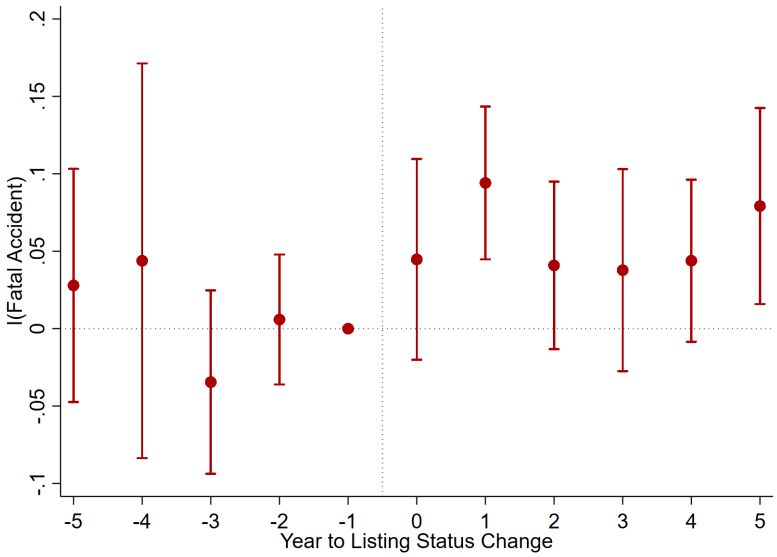


Table IA1: Public Listing Status and Fatalities and Injuries. This table reports the results of linear regression models (Model (1) and (2)) in which the dependent variables are the number of fatalities or an indicator for any fatalities, respectively, at mine i, owned by firm s, during year t, or Poisson 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 $Public\ owner_{st}$. 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 *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 ultimate parent level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	Safety Violations$_{ist}$			$\frac{\text{Safety Violations}}{\text{Inspections}}_{ist}$	$\frac{\text{Safety Violations}}{\text{1,000 Hours}}_{ist}$
	(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)
log(Safety inspections$_{ist}$)		0.257***	21.008***		0.085***
		(0.020)	(3.886)		(0.022)
log(Mines$_{st}$)		0.055	2.852	0.301	0.022
		(0.072)	(4.724)	(0.304)	(0.022)
log(Hours$_{ist}$)		0.709***	-0.062	0.525***	
		(0.037)	(2.904)	(0.096)	
log(Employees$_{ist}$)		0.073	36.315***	1.443***	-0.098***
		(0.047)	(5.539)	(0.153)	(0.019)
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$_{ist}$× 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$_{ist}$× 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$_{ist}$× 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) during the first quarter after the firm has IPO'ed. 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. 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 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	OLSS	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: 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 Associated 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 IA11: 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$_{ist}$× 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 × 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		0.919	0.905	0.873
R^2 or Pseudo-R^2	0.929			

Table IA12: 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 shareholders stake reduction following an 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 shareholders 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$_{ist}$ × 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 IA13: 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 =	$\frac{\text{Production}}{\text{Hours}}_{ist}$	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$_{ist}$ × 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 IA14: 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