Insurers' Underwriting Policies

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Keywords: Insurance underwriting; insurance companies; coal mining; carbon emissions

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1 Introduction

Insurers increasingly use underwriting policies to restrict coverage for business activities that they view as creating elevated reputational risks. Such policies span a range of activities, including controversial weapons (Allianz, 2025a), tobacco (AXA, 2018), and, more recently, carbon-intensive sectors such as coal, oil, and gas.[1] Some insurers also restrict coverage in response to sanctions, for example with respect to insuring the shipment of Russian or Iranian oil (e.g., Smith and Dempsey, 2022; Triebert et al., 2024), or have introduced underwriting policies on conduct-based grounds, for example for firms with poor human rights records (Generali, 2026). Yet it remains unclear whether these policies, especially when adopted voluntarily, are more than symbolic, that is, whether insurers follow through in their underwriting practices and whether they translate into real effects in the affected sectors.

Insurers may adopt such policies when non-actuarial costs driven by stakeholder pressure and reputational concerns are sufficiently strong to affect underwriting decisions beyond considerations of actuarial risk.[2] If implemented and binding, these underwriting commitments can constrain firm behavior because insurance is often legally required. However, if non-actuarial costs vary across insurers, firms may substitute toward insurers facing weaker pressure, thereby limiting the real effects of underwriting policies. In this paper, we provide the first systematic evidence on insurers' underwriting policies, examining their design, determinants, implementation, and real effects. Our analysis uncovers a novel mechanism through which the financial sector influences firm behavior, rationalized by an insurance-supply model that extends Koijen and Yogo (2023a) with heterogeneous non-actuarial costs.

An empirical analysis of underwriting policies and their effects faces three major challenges, which explain why systematic evidence remains scarce. First, underwriting policies are a recent phenomenon and lack a standardized format, making a systematic assessment difficult. Second, insurance contracts are not publicly disclosed, which obscures both whether underwriting restrictions are implemented in line with public commitments and whether policyholders that lose coverage can replace it with other insurers. Third, comprehensive data on insured projects and their operations are necessary to assess the real effects of underwriting

[1] For example, Allianz, a global insurance group headquartered in Germany, introduced a policy stating that from 2018 onward, it no longer provides stand-alone insurance for the operation of thermal coal mines, covering both new and renewed contracts (Allianz, 2025b). Internet Appendix A describes it in more detail.

[2] As non-actuarial costs, we consider factors that enter the decision problem of an insurer *on top of* actuarial factors related to risk-based pricing and expected losses (see Koijen and Yogo, 2023a). These costs can arise, for example, in response to pressure from retail customers, investors, or the broader public. Though non-actuarial costs do not operate through the insured risk itself, they may nonetheless generate financial consequences for an insurer.

policies, but such data are difficult to obtain.

We exploit unique data linking insurers' underwriting policies for coal projects to coal-mining activity, an empirical setting that allows us to make substantial progress on each of these three challenges. To address the lack of standardization in underwriting policies, the first challenge, we rely on scorecards from Insure Our Future (IOF), a coalition of NGOs. These scorecards provide consistent and comparable measures of the presence, scope, and stringency of coal underwriting policies across the world's major Property & Casualty (P&C) insurers.[3] To overcome the opacity of insurance contracting, the second challenge, we filed Freedom of Information Act (FOIA) requests to obtain insurance certificates for coal mines in the United States. These certificates reveal the full set of insurers covering each mine, allowing us to test whether insurers' underwriting practices align with public commitments and whether mines replace coverage lost to policy-adopting insurers. To examine real effects, the final challenge, we match insurers' underwriting decisions to granular information on U.S. coal mines from the Mine Safety and Health Administration (MSHA). This allows us to study whether coal underwriting policies affect coal production and abandonment of operations.

We present four main findings. First, we study the design and determinants of coal underwriting policies. Such policies have become more common and stringent since 2017, but remain highly heterogeneous across insurers. Coal policies are often vague or contain exemptions (e.g., some insurers apply them only to new, not existing projects). We show that the cross-insurer variation in the adoption of coal policies reflects tradeoffs related to stakeholder pressure. On the one hand, insurers headquartered in countries with stronger domestic climate policies are more likely to adopt a policy, and if they do, they adopt more restrictive ones. On the other hand, specialty and unlisted insurers—both of which plausibly face weaker pressure from retail clients or public-market investors—have a lower propensity toward restrictive policies. This variation indicates that underwriting decisions not only reflect risk-based pricing but also heterogeneous non-actuarial costs arising from stakeholder pressure.[4]

Second, we examine how insurers adjust underwriting activity for U.S. coal mines around the adoption of coal underwriting policies to evaluate whether these voluntary commitments are actually implemented. We find that coal policy adoptions are associated with a reduction in insurers' coverage of coal projects: on average, policy-adopting insurers reduce the

[3] Green and Vallee (2025) use similar data on the exit policies of banks for fossil-fuel lending collected by Reclaim Finance, an NGO that is part of IOF.

[4] We also analyze the design and determinants of insurers' oil & gas underwriting policies, which are likewise covered by the IOF scorecards. These policies are similar to coal underwriting policies but were introduced several years later and remain less widespread. Because we lack data on insured oil & gas projects, our analyses of policy implementation and real effects focus on coal underwriting policies.

number of insured coal mines by 16% (about 3.7 mines) and the volume of insured coal by 66% (about 3.7 million short tons, MMst), relative to non-adopters.

To address the concern that some of these results reflect time-varying sorting effects between insurers and mines, rather than causal effects of policy adoption, we exploit that the typical mine obtains coverage from four different insurers over the sample period, of which on average 1.8 actively cover it at a given point in time. This allows us to compare how different insurers adjust coverage for the *same* mine around an insurer's policy adoption, in the spirit of Khwaja and Mian (2008). In our tightest empirical specification, which absorbs contemporaneous mine-level shocks, the probability that a mine-insurer relationship remains active falls by 12.7 percentage points (pp) after policy adoption, a 31% decrease relative to the unconditional probability of an active relationship (41%). Dynamic event-study estimates show no significant pre-trends and a sharp decline in active coverage of 8.2 pp in the second quarter after policy adoption. This decline reaches 17.3 pp within about a year, consistent with the standard one-year duration of insurance policies. These results support an interpretation in which policy adoption causally affects underwriting decisions and reduces insurers' willingness to maintain coverage for coal mines. The immediate onset of the decline also suggests that at least some insurers begin implementing their policies upon adoption.

We also study heterogeneity in policy implementation. Because coal policies are voluntary and often vague, it is not obvious that stronger stated commitments translate into deeper coverage cuts, nor which coverage insurers withdraw. We document two patterns. First, implementation is stronger for insurers with more stringent coal policies, consistent with stricter commitments being enforced more forcefully. Second, it varies across insurance lines: insurers are less likely to discontinue worker safety and compensation coverage than commercial general liability (covering third-party bodily injury and property damage arising from a mine's operations), indicating that coverage of core mining activity is more likely to be cut.

Third, we examine whether U.S. coal mines can replace insurers that stop covering them, to understand whether substitution across insurers offsets the withdrawal of policy-adopting insurers. We first establish that insurer-mine relationships are very persistent over time: a mine's current insurers are strongly predictable from past insurer-mine relationships, indicating that mines do not switch insurers easily. We then decompose the change in the number of insurers covering a mine around one insurer's policy adoption into the contributions of policy-adopting and non-adopting insurers. After one of a mine's insurers adopts a coal policy, other insurers replace only part of the withdrawn coverage: although the number of non-adopting insurers rises and they widen the insurance lines they write, about 36% of the relationships withdrawn are not replaced. Substitution is therefore incomplete, so the total number of insurers still falls. At the market level, coal insurance coverage migrates from policy-adopting toward non-adopting insurers.

Fourth, we analyze whether the adoption of coal policies has real effects on U.S. coal mines, which are legally required to have insurance coverage. To isolate the effect of policy adoptions, we classify a mine as policy-exposed if, at the beginning of our sample period, it is insured by at least one insurer that subsequently adopts a coal policy. Fixing exposure at the start of the sample ensures that treatment reflects preexisting insurance relationships rather than insurers' endogenous choices of which mines to drop. We then examine whether exposed mines are more likely to be abandoned following the first coal policy adoption by any of their insurers. Estimating dynamic effects, we find that the effect on the likelihood of abandonment emerges gradually, becoming statistically significant about a year after policy adoption and reaching 2.8 pp, equal to about 25% of the unconditional abandonment rate of 11%. These effects are consequential because mine abandonment is rarely reversed. Among mines that remain operational, we find some evidence of lower output, though we interpret these effects cautiously, as they are noisy. Hence, insurance affects coal mines primarily by determining whether they continue to operate, not how much they produce. Because insurance is a legal prerequisite to operate and replacement supply is limited by licensing and capital requirements, even an incomplete loss of coverage can force otherwise-viable mines to close.[5]

We also examine whether the abandonment effect concentrates among particular kinds of mines. It does not vary systematically with mine productivity or size, suggesting that how much a mine stands to lose from closing plays a limited role. It is also unlikely to reflect reverse causality: the effect does not concentrate among mines with worse safety records, and if anything it is stronger at mines facing higher coal prices, neither of which fits the alternative explanation that insurers withdraw coverage because the insured risk deteriorated or because mining became less profitable.

To quantify how much of the abandonment effect operates through the loss of coverage, we estimate two complementary two-stage least squares designs. The first design instruments an individual insurer's coverage of a mine with that insurer's coal policy adoption, isolating policy-induced losses of coverage from non-renewals of any cause. We estimate that policy-induced loss of an adopter's coverage raises a mine's abandonment probability by about 6 pp. Because this estimate averages over mines that do and do not replace the lost coverage, it is a lower bound. The second design therefore instruments a mine's net number of active

[5] We complement this analysis with a shift-share (Bartik) design. Rather than focusing on the first policy adoption, this approach exploits the repeated adoption of underwriting policies by additional insurers, which, for a given mine, generates variation in exposure over time. Based on this design, the effect on mine abandonment is similar, though estimated less precisely.

insurers, which already nets out substitution, with the mine's exposure to policy-adopting insurers. This design yields an even larger effect of about 12 pp. The gap between the two estimates reflects the coverage that substitution replaces, so the abandonment effect is concentrated among mines that cannot replace a departing insurer. Both tests confirm that policy-induced losses of coverage can push affected mines toward abandonment.

We complement these four main results with evidence on insurer-level outcomes around the adoption of coal policies. The total gross written premiums of insurers remain unchanged, reflecting either that coal-related underwriting revenues are relatively modest for the average insurer or that insurers find ways to replace lost revenue. Both annual return on assets and market-adjusted stock returns (over the two-day window surrounding adoption announcements) decline by about 0.5 pp, though these effects are not statistically significant. The number of yearly environmental incidents, as measured by RepRisk, decreases, suggesting that underwriting policies come with reputational benefits for insurers. Overall, while informative, these tests do not provide conclusive evidence given the small sample and the fact that insurer-level outcomes reflect many activities beyond coal underwriting.

Our empirical analysis is guided by a simple insurance-supply model presented in Internet Appendix B. We augment the standard actuarial pricing framework of Koijen and Yogo (2023a) with two non-actuarial costs of coal underwriting that operate on different margins, motivated by our evidence that reputational costs from stakeholder pressure correlate with policy adoption and stringency. The first is a fixed penalty for maintaining coal exposure once a policy is in place, capturing reputational losses from violating stated commitments. When this penalty is large relative to the profits from coal underwriting, insurers withdraw entirely through abrupt non-renewals or relationship terminations. The second is a marginal cost that scales with coal exposure. When the fixed penalty is not prohibitive, and this marginal cost dominates, insurers instead retrench selectively, scaling back coverage limits or exiting the most carbon-intensive lines.[6] Because some mines rely on a single insurer they cannot easily replace, withdrawal can push them below required coverage thresholds and trigger abandonment.

Our paper provides the first systematic evidence on insurers' underwriting policies, using the adoption of coal policies as a setting to discover a novel mechanism through which insurers affect firm outcomes. We document that coal underwriting policies have become more prevalent, with their adoption being driven in part by non-actuarial cost motives. However, the implementation of coal policies remains incomplete and heterogeneous across insurers. Notably,

[6] In our data, this selective retrenchment is visible in the insurance lines an insurer writes, but not in coverage limits, which vary little because minimum coverage levels are largely set by state law.

we show that coal policy adoptions can push affected mines toward abandonment, suggesting that insurers can influence firm outcomes through underwriting restrictions. This interpretation is supported by anecdotal reports of mine operators caught off guard by non-renewals from insurers that had adopted coal underwriting policies, as well as by regulatory filings in which mining companies cite the potential loss of insurance due to climate-related underwriting restrictions as a material threat to continued operations (e.g., CONSOL Energy, 2020; Arch Resources, 2021; NACCO Industries, 2022; Alliance Resource Partners, 2023). Although our analysis centers on coal mining, the mechanism we document is unlikely to be specific to it. Underwriting policies for oil & gas projects exhibit similar adoption patterns and determinants, and, more broadly, wherever insurance is a legal prerequisite to operate, insurers can shape firm behavior through underwriting restrictions. However, the effectiveness of such policies ultimately depends on whether coverage from other insurers is available, which limits the impact of individual insurers' actions. Assessing these effects more systematically requires greater transparency on underwriting practices and insured projects, particularly because the consequences of such policies are difficult to observe at the insurer level.

We contribute to two streams of literature. First, we add to the literature on the real effects of insurance. Prior work shows that insurance affects economic behavior primarily through risk-based pricing and coverage terms, with documented effects on household decisions such as housing market participation, post-disaster rebuilding, and precautionary investment (e.g., Meyer, 1990; Cohen and Dehejia, 2004; French and Jones, 2011; Karlan et al., 2014; Cai, 2016). Related work shows that insurers influence firms' environmental or operational risks primarily through responses to direct, near-term hazards (e.g., Yin et al., 2011) or by mitigating judgment-proof problems (e.g., Shavell, 1982, 2000, 2005; Boomhower, 2019). Legal scholars have debated whether insurers can function as a form of private regulation (e.g., Ben-Sahar and Logue, 2012; Rappaport, 2016; Talesh, 2016; Abraham and Schwarcz, 2022), but systematic evidence remains scarce, even as insurers extend underwriting restrictions to a widening range of activities. Using coal underwriting policies as a laboratory, we provide the first link between insurers, identifiable corporate policyholders, and their operational outcomes, enabling an analysis of how insurance affects firm behavior. We establish that insurance non-renewals following the adoption of underwriting policies are associated with real effects on corporate operations. Unlike prior settings in which insurers regulate risks borne by policyholders themselves, coal policies target risks borne by society, revealing a novel channel through which underwriting decisions shaped by insurers' non-actuarial considerations influence firm behavior and economic activity.

Our second contribution is to the growing body of research on how the financial sector addresses climate-related risks. Prior work has primarily examined providers of capital, including banks (e.g., Flammer, 2021; Kacperczyk and Peydró, 2022; Haushalter et al., 2023; Ivanov et al., 2024; Sastry et al., 2024; Berg et al., 2025; Giannetti et al., 2025; Green and Vallee, 2025; Morse and Sastry, 2025), shareholders (e.g., Dimson et al., 2015; Hartzmark and Sussman, 2019; Krueger et al., 2020; He et al., 2023), and investor alliances (e.g., Gasparini and Tufano, 2025; Hastreiter, 2025). Recent work shows that climate concerns can affect firms through a cost-of-capital channel, thereby incentivizing green investment (Gormsen et al., 2025). Related theoretical work characterizes when socially responsible capital can generate real effects by trading off financial returns against reductions in social costs (Oehmke and Opp, 2025). Scholars such as Acharya et al. (2023) have called for greater attention to the role of insurance companies, and a nascent body of research examines insurers' exposure to and pricing of climate risks (e.g., Ge, 2022; Jung et al., 2024; Keys and Mulder, 2024; Sastry et al., 2026; Boomhower et al., 2025; Ge et al., 2025; Kim et al., 2025; Ge et al., 2026; Oh et al., 2026). We provide the first evidence on how insurers affect the management of climate risks through underwriting restrictions on carbon-intensive projects. This mechanism differs fundamentally from the channels studied for capital providers such as banks. Whereas capital-market channels affect firms through financing conditions or investor mandates, underwriting restrictions withdraw coverage that is often a legal prerequisite for continued operation, so a loss that cannot be replaced can force a firm to halt operations entirely.

2 Design and Determinants of Coal Underwriting Policies

2.1 Data and Measurement

We use data on the underwriting policies of coal and oil & gas projects by the world's leading insurance groups in the Property and Casualty (P&C) business from 2017 to 2023.[7] The data are drawn from annual scorecards published by IOF, a global coalition of NGOs, and provide standardized, comparable measures of insurers' coal and oil & gas policies based on public disclosures and survey responses. During our sample period, IOF evaluated between 24 and 30 large insurance groups that represent leading underwriters of carbon-intensive

[7] The IOF scorecards are published annually with a lag, and 2023 is the most recent year available on a consistent basis at the time of data construction.

projects.[8] We present our measures and analyses for coal policies in the main text and defer the parallel oil & gas results to the end of this section and the Internet Appendix.

From these scorecards, we construct two variables for each insurer-year. First, an indicator variable for the presence of a coal policy. Second, a stringency score for coal policies ranging from 0 to 10, with higher values indicating more restrictive policies (i.e., more comprehensive and credible underwriting restrictions) and lower values reflecting non-binding or exception-laden commitments.[9] Coal stringency scores are available from 2018 onward.

We complement these data with hand-collected information on policy announcement dates from insurer websites and news articles. Although some insurers commit to gradual underwriting phase-outs, we treat the announcement dates as the relevant starting point for our analysis, as our objective is to test whether public commitments translate into changes in underwriting activity. We further add insurer-level characteristics from ORBIS and other hand-collected insurer-level information. Table IA.2 reports these hand-collected variables for the insurers in the IOF data.

2.2 Policy Adoption and Stringency

Coal underwriting policies emerge gradually over our sample period and exhibit substantial cross-sectional heterogeneity. Figure 1 shows that coal policies first appear in 2017, with an increasing number of insurers introducing formal restrictions on underwriting coal-related activities, and by the end of the sample period, a majority of insurers covered by IOF have adopted some form of policy. Adoption is staggered across insurers and years, generating variation in treatment timing that we exploit below. Figure 2 shows that the average coal

[8] According to IOF, the insurers covered by the scorecard are identified based on a market analysis of key providers of insurance coverage for carbon-intensive projects. IOF (2023) reports that global gross direct premiums from insuring fossil-fuel activities amounted to approximately $21 billion in 2022, based on analyses by Insuramore, a consultancy. The top 10 insurers account for up to 50% of this market, indicating substantial concentration, and seven of these insurers are included in the IOF scorecards. As an additional benchmark, a 2023 S&P Global study of the top 50 global P&C insurers by premium volume includes 25 insurers in our sample (S&P Global, 2023). Insurers in the S&P list but not in our sample typically focus on business lines unrelated to carbon-intensive underwriting, while insurers in our sample but absent from the S&P study are often specialty insurers with concentrated exposure to corporate and industrial risks.

[9] Stringency scores are constructed by IOF along five policy dimensions (see Table IA.1 for details).

policy stringency increases after 2020, with substantial dispersion across insurers.[10]

2.3 Determinants

The variation in the adoption and stringency of coal policies calls for an analysis of their determinants. We therefore construct an annual insurer panel and regress policy adoption and stringency on proxies reflecting stakeholder pressure and reputational concerns. To capture public pressure from local climate policies, we include the Climate Change Performance Index (CCPI) in an insurer's headquarters country. We include an indicator for whether an insurer is a member of the Net-Zero Insurance Alliance (NZIA) to capture peer pressure toward aligning underwriting portfolios with net-zero targets. To capture the absence of pressure from retail clients—who may prefer their insurers not to underwrite carbon-intensive projects because of green preferences—we include an indicator for whether an insurer is a specialty insurer focused on corporate business lines. To capture pressure from investors, we consider whether an insurer is a listed or unlisted entity. Unlisted insurers may face less pressure because their lower public visibility and lack of capital markets exposure make them relatively less sensitive to investor scrutiny, ESG ratings, and reputational risks. We further control for insurers' exposure to fossil fuel underwriting (the share of an insurer's gross written premium from insuring fossil fuels), insurer size, profitability, and time fixed effects. Descriptive statistics for this sample are reported in Table IA.4, and variable definitions in Table A.1.

Table 1 presents results. Column 1 analyzes the extensive margin—whether an insurer has a coal policy in place—over the 2017-2023 period. Three insights related to the role of stakeholder pressure emerge. First, adoption is significantly more common among insurers headquartered in countries with stronger climate policies. Second, specialty insurers are less likely to adopt a coal policy, possibly because they face less scrutiny from retail customers. Third, public-market investor pressure plays an important role, as unlisted insurers are significantly less likely to adopt coal policies. In addition, insurers that are more dependent on fossil-fuel revenues are less likely to adopt coal policies. Column 2 examines the intensive margin—policy stringency conditional on adoption—over the 2018-2023 period. The determinants in these regressions are broadly consistent with those found for adoption.

[10] Insurers also hold large investment portfolios and may respond to climate-related concerns through screening or divestment on the asset side of their balance sheets (see, e.g., Ellul et al., 2011; Ge and Weisbach, 2021; Koijen and Yogo, 2023b; Knox and Sørensen, 2024; Kubitza, 2026). However, underwriting and investment policies are imperfectly correlated. Table IA.3 reports positive but far from perfect correlations between insurers' underwriting and fossil-fuel investment policies, and Figure IA.3 shows substantial within-insurer variation in policy stringency across the asset and liability sides. This suggests that underwriting restrictions do not merely reflect ESG-related investment decisions but constitute a distinct channel. Moreover, our implementation analysis exploits within-mine variation in insurer relationships, helping to absorb coinciding mine-level shocks that could be related to insurers' investment behavior.

Figures IA.1 and IA.2 show that oil & gas policies remain less prevalent and less stringent than coal policies. Table IA.5 shows that their determinants are similar to those of coal policies. This parallel suggests that similar factors shape underwriting behavior across carbon-intensive sectors, so the mechanisms we document for coal may generalize beyond it.

In sum, our evidence indicates that adoption and stringency of underwriting policies covering coal as well as oil & gas are associated with insurer-specific non-actuarial costs related to stakeholder pressure and reputational concerns. Whereas standard insurance-pricing frameworks, such as Koijen and Yogo (2023a), assume that insurers weigh only actuarial costs, our model in Internet Appendix B augments this framework with such non-actuarial costs, providing a unified account of the implementation and withdrawal patterns we document.

3 U.S. Coal Mining Insurance

3.1 Motivation

The previous section documents the rise of coal underwriting policies across insurers. Yet it remains unclear whether these policies are implemented and whether they have real effects. On the implementation side, non-actuarial costs of underwriting coal may induce some insurers to reduce coverage following policy adoption, while others continue or start underwriting coal projects, because such costs are lower for them or outweighed by other considerations. On the consequences side, it remains unclear whether any resulting coverage reductions are sufficiently large and whether substitution across insurers is sufficiently limited to affect the operations of coal projects.

We address these questions in the context of coal mining in the United States, analyzing the real effects of globally adopted coal underwriting policies within a single-country setting. This provides several benefits. First, relative to oil & gas, coal policies emerged several years earlier, allowing for a longer sample period. Second, coal production continues to grow globally (Enerdata, 2025), represents a critical upstream activity for coal combustion, and constitutes the single largest source of human-induced climate change (IEA, 2021; ClientEarth, 2022). Third, while coal mining in North America has been in secular decline, the United States remains the world's fourth-largest coal producer, and insurance coverage is a legal prerequisite for mine operations. Fourth, the United States provides exceptionally detailed mine-level information, including insurance relationships and quarterly operating characteristics, enabling a direct link between policy adoptions and project-level outcomes.

3.2 Data

Data on U.S. coal mines come from the MSHA, which collects data on coal production, operating status, and other operational metrics at the mine-quarter level, and we obtain them from its Mine Data Retrieval System (e.g., Charles et al., 2022; Gilje and Wittry, 2022; Chen and Wittry, 2025; Qiu et al., 2025). We construct a quarterly panel dataset of all coal mines with at least one quarter of non-zero coal production between 2014Q1 and 2024Q2 in the MSHA data. By starting in 2014, we include data prior to the introduction of coal underwriting policies to compare mine behavior before and after policy adoption.

Coal mine operators in the United States are required to maintain liability insurance as a condition for obtaining or renewing their operating permits. This mandate is enforced by state mine regulators under the Surface Mining Control and Reclamation Act of 1977 and Title 30 of the Code of Federal Regulations. Operators must also meet minimum coverage standards set by relevant state agencies, typically covering workplace injuries, third-party claims, and environmental risks. Because proof of adequate coverage is a legal prerequisite for continued operation, insurers hold substantial influence over coal mines: by choosing whether to issue or renew policies, they effectively determine whether a mine is allowed to operate.

As part of the permitting process, state regulators maintain detailed records of mine-level insurance coverage. To access these data, we filed FOIA requests with the relevant agencies, requesting Certificates of Liability Insurance for all mines in the MSHA database since 2014. These mines span 25 states, of which nine states supplied comprehensive certificate data in the form of standardized ACORD 25 filings.[11] Though not all states provided data, our sample of 698 mines accounts for 79% of U.S. coal production from 2014Q1 to 2024Q2. The mines are concentrated in major coal-producing regions: West Virginia (44% of sampled mines), Pennsylvania (34%), Virginia (10%), Illinois (4%), Wyoming (3%), Utah (2%), Colorado (1%), Montana (1%), and North Dakota (1%).

Figure IA.4 shows the ACORD 25 insurance certificate for the Black Butte Coal Mine in Wyoming. The top section lists the insurance broker ("producer"), the insured entity

[11] Maryland and New Mexico are not included in our sample because they only provided the most recent certificates, despite follow-up efforts. From Alaska, Arizona, Arkansas, Kansas, Louisiana, Missouri, Mississippi, Oklahoma, and Tennessee—states that each have five or fewer mines—we did not receive a response to the FOIA requests. We exclude Ohio, Kentucky, and Texas because their agencies do not use standardized certificate forms, making their data difficult to compare with that of other states. Indiana did not provide any information. Our request in Alabama is still pending (we requested data in February 2025).

("insured"), and the insurers ("insurer(s) affording coverage").[12] The middle section details policy-level information, including the coverage start and end dates. Insurance policies are categorized into four insurance lines: commercial general liability, automobile liability, workers' compensation and employer's liability, and umbrella/excess liability. The bottom section identifies the responsible regulatory agency.

Our dataset comprises 13,935 insurance policies across the 698 sampled mines. We define an insurance policy as a unique insurer-insurance line combination listed on a certificate. A mine may hold multiple policies from different insurers, even for the same insurance line. Around 40% of policies cover commercial general liability, 33% umbrella/excess liability, 14% automobile liability, and 13% workers' compensation and employer's liability. Roughly 95% of all policies have a duration of one year. We do not observe policy-level premium amounts, as the certificates do not report pricing information. The certificates do report coverage limits, but these display little variation across policies because minimum coverage levels are largely set by state law. Our analysis therefore focuses on policy non-renewals. Although insurers could adjust premiums, doing so often requires modifications to their filed rates and must remain actuarially defensible under review by state insurance departments. By contrast, non-renewals represent a more direct margin of adjustment.

3.3 Linking Mines to Insurer-Level Underwriting Policies

We link mine-level data from the MSHA with insurer-level coal underwriting policies using the Certificates of Liability Insurance to create a mine-quarter-insurance policy panel. This task requires mapping the insurers listed on the certificates to their corresponding insurance groups.[13] Although the certificates specify start and end dates for each policy, the MSHA data are at the mine-quarter level. To merge these data, we assume a mine is covered by a given underwriting policy in a quarter if the policy covers the start date of that quarter.[14]

The 698 coal mines in our dataset are insured by 56 insurance groups between 2014Q1

[12] Mining companies may opt for self-insurance ("captive insurance"). We identify such cases either when the top section of the certificate explicitly mentions a captive insurer or when it explicitly states that the mine is self-insured. Fewer than 20 certificates in our sample indicate self-insurance. This low number may reflect substantial costs and regulatory requirements associated with establishing and maintaining captive insurers.

[13] We perform this mapping using the 5-digit NAIC company codes provided on the certificates, cross-referenced with group affiliations from NAIC's semiannual publication *Listing of Companies* as of June 2017, before the announcement of any coal policies. We evaluate the possibility of ownership changes after 2017 (e.g., through mergers and acquisitions) and find these to be rare. In fact, only one coal mine-insuring subsidiary changes group affiliation after this date. Policies that cannot be matched to an insurance group are excluded, though such cases are rare (fewer than 2% of all policies).

[14] This rule effectively lags mine-level outcomes by up to one quarter relative to changes in insurance coverage, since coverage is assigned based on whether the quarter's start date falls within the coverage period.

and 2024Q2. Among these insurers, 16 appear in the IOF scorecards, with 12 introducing a coal policy during the sample period. We assume that the 40 insurance groups not covered by IOF do not adopt such policies, an assumption supported by extensive news searches and discussions with IOF. Hence, 44 insurance groups do not have a coal policy (four covered by IOF and 40 uncovered). While this sample omits some insurers from the IOF scorecards, either because they insure coal mines outside the U.S. or implement underwriting restrictions differently in other markets, it reliably captures the primary actors in U.S. coal mine insurance.

3.4 Summary Statistics

Table 2 reports descriptive statistics for the sample at different levels of aggregation. The raw dataset is at the mine-quarter-policy level, identifying for a given mine-quarter which insurance policies are active and which insurance group provides coverage.

Panel A reports statistics at the mine-quarter-insurance level, enabling us to track mine-insurer relationships. For each mine, we include all observed mine–insurer relationships and populate inactive quarters. Specifically, for each insurer that appears on a mine's certificate at least once, we retain that mine–insurer pair for all quarters with available certificate data, coding periods without coverage as inactive. The average relationship lasts 14.3 quarters, or roughly 3.5 years. In 50% of observations, the insurer has a coal policy in place, and in 41% of observations, the relationship is active (i.e., the mine is insured by the respective insurer).

Panel B provides statistics at the insurer-quarter level, which we use to study insurer-level changes around policy adoptions. On average, an insurer underwrites about 22 coal mines, corresponding to 5.6 MMst of coal production per quarter. A coal policy is in place in 25% of insurer-quarter observations.

Panel C presents statistics at the mine-quarter level, which is used to study substitution across insurers and the operational outcomes of coal mines. In 11% of mine-quarters, a mine is classified as abandoned. In our data, abandonment is rarely reversed. Thus, it is effectively an absorbing state. On average, a mine produces 0.4 MMst of coal. A mine is insured by about four different insurers over the sample period, of which 1.8 actively cover it in a given quarter, split almost evenly between insurers that have and have not adopted a coal policy, with about 0.64 active insurance lines per insurer.

4 Implementation of Coal Underwriting Policies

We now examine whether insurers' coal underwriting policies translate into actual changes in their underwriting of coal mines. Anecdotal evidence suggests that they do. Coal mine operators report being caught off guard as insurers begin to withdraw their coverage, and several member companies of the Lignite Energy Council, a coal-industry trade association, received non-renewal notices from their insurers (Guidehouse Inc., 2022).

4.1 Trends in Insurance Coverage by Coal Policy Status

Initial evidence on changes in insurance coverage following the adoption of coal underwriting policies is provided in Figure 3. We plot the number of coal mines insured by insurers that introduced a coal policy during our sample period (Panel A), and by insurers that never did (Panel B).[15] In Panel A, for policy-adopting insurers, the number of insured mines stands at around 200 at the beginning of our sample period, rises close to 400 by the last quarter of 2016, just before the first coal policy adoptions in 2017, and falls back to around 250 thereafter. However, there is considerable heterogeneity within this group. AIG, which dominates the market in the early sample years alongside Chubb, insures fewer mines over time, while Zurich emerges as one of the main insurers in later years.

In contrast, Panel B shows that among insurers that never adopt a coal policy, the number of insured mines increases steadily over time, from about 200 at the start of the sample period to around 600 by the end. Houston, BrickStreet, and Argonaut are the primary underwriters in this group. However, there is also heterogeneity within non-adopters. Berkshire Hathaway, for example, reduced its coverage considerably. The contrasting trends across the two panels suggest that insurers adopting coal policies reduce their exposure to coal mining, while those without such policies expand their activity, though there is heterogeneity within each group.[16]

4.2 Insurer-Level Effects of Coal Policy Adoption

To formally test whether coal underwriting activity declines following the adoption of coal policies, we estimate the following OLS regression at the insurer-quarter level:

$$\textit{Coal insurance}_{i,t} = \beta \times \textit{Post coal policy}_{i,t} + \alpha_i + \alpha_t + \epsilon_{i,t}, \tag{1}$$

[15] Figure IA.5 reports analogous patterns using the volume of insured coal production. Among policy-adopting insurers, insured coal volume falls even more steeply than the number of insured mines they cover, indicating that their retrenchment is not confined to small mines. This underscores the heterogeneity in how underwriting policies are implemented, which we analyze in detail below.

[16] As we show in Section 5, this expansion partly reaches the mines that lose a policy-adopting insurer: non-adopting insurers replace part of this lost coverage, leaving a net reduction in coverage.

where i indexes an insurer and t a quarter. *Coal insurance* denotes the log of either the number of insured coal mines (*# Coal mines insured*) or the volume of produced coal across insured mines (*Coal volume insured*). *Post coal policy* equals one for insurer-quarters after a coal underwriting policy is introduced, and zero otherwise. α_i and α_t are insurer and time fixed effects, respectively. We use robust standard errors. β captures the change in coal underwriting activity among insurers that adopt a coal policy, relative to those that do not, at the same point in time. If insurers adjust underwriting activity in line with public commitments, we expect β to be negative.

Table 3 reports results. In Column 1 for *# Coal mines insured*, the β estimate is negative and statistically significant, indicating that insurers, on average, reduce the number of insured coal mines by about 16% ($\approx e^{-0.178} - 1$) or 3.7 mines following policy adoption. In Column 2 for *Coal volume insured*, the estimate continues to be negative and significant, implying a reduction in the volume of insured coal by about 66% ($\approx e^{-1.066} - 1$) or 3.7 MMst after policy adoption. Hence, coal underwriting activity is reduced following policy adoption.

A limitation of this analysis is that we do not observe *why* insurance coverage ends. In particular, we cannot distinguish whether it ends due to insurer-level factors, such as coal policies, or due to mine-level factors, such as operational or financial difficulties. As a first step toward addressing this limitation, Columns 3 and 4 restrict the sample to mines that remain operationally active throughout the sample period. The continued negative and significant β estimates suggest that results are not driven by changes in mine operating status.

4.3 Mine-Insurer Relationship Effects of Coal Policy Adoption

The results in the previous subsection do not allow for a causal interpretation. First, they do not account for the endogenous matching of mines to insurers, so we cannot rule out that insurers adopt coal policies because of the mines they insure. Second, they do not control for time-varying mine characteristics that could influence insurers' renewal decisions (e.g., deteriorating performance or rising operational risk), or adverse shocks that affect a mine's financial conditions (e.g., tighter bank credit). To address these concerns, we exploit that the typical mine obtains coverage from four insurers over the sample period, of which on average 1.8 actively cover it at a given point in time, allowing us to compare how different insurers adjust coverage for the same mine around an insurer's policy adoption. This approach, in the spirit of Khwaja and Mian (2008), identifies off mines insured by adopting and non-adopting insurers, holding constant the mine-insurer match and time-varying mine characteristics.[17]

We implement this identification strategy using a stacked difference-in-differences (DiD) design (e.g., Gormley and Matsa, 2011; Baker et al., 2022, 2026). A stack is defined as one policy-adopting insurer and all coal mines it insures. For each mine-insurer pair in a stack, we construct a balanced panel of 13 quarterly observations around treatment. These mine-insurer pairs constitute the treated observations in the stack. Control observations are all other mine-insurer pairs involving the same mines but insurers that never adopt a coal policy, thereby avoiding anticipatory effects. Each stack tracks how mine-insurer relationships evolve around the adoption of a policy by one insurer, comparing changes in coverage between the adopting insurer and insurers that never adopt a policy within the same mine and quarter. We repeat this procedure for each of the 12 policy-adopting insurers and stack the samples to estimate the average effect of coal policies on insurers' active coverage of coal mines. Specifically, we estimate the following dynamic DiD regression with OLS:

$$Active\ insurance_{s,m,i,t} = \sum_{t=-6}^{t=6} \beta_t \times Coal\ policy_i \times Event\ quarter_{s,t} + \alpha_{s,m,i} + \alpha_{s,m,t} + \epsilon_{s,m,i,t}, \tag{2}$$

where s indexes a stack, m a mine, i an insurer, and t a quarter. *Active insurance* equals one if an insurer insures a mine in a given quarter, and zero otherwise. *Coal policy* equals one for policy-adopting insurers, and zero otherwise. *Event quarter* are dummy variables indicating quarters relative to treatment, where treatment is the first quarter after policy adoption. $\alpha_{s,m,i}$ are stack-mine-insurer fixed effects, while $\alpha_{s,m,t}$ are stack-mine-time fixed effects. These fixed effects ensure that we compare the evolution of mine-insurer relationships across insurers within the same mine and quarter, thereby controlling for the match of mines to insurers, the concern that policy adoptions could be driven by specific insurer-mine relationships, and unobservable time-varying mine characteristics. Standard errors are clustered at the insurer-stack level. If insurers adjust underwriting in line with public commitments,

[17]This within-mine comparison assumes that, absent its coal policy, an adopting insurer would have adjusted its coverage of a mine like that mine's other insurers, so that any divergence reflects the policy rather than insurer-specific factors (e.g., Degryse et al., 2019). Moreover, because mines must carry insurance, the withdrawal of one insurer induces the mine's others to substitute, so the relationships we compare are not independent (a violation of the stable unit treatment value assumption, SUTVA) and such spillovers can overstate treatment effects in difference-in-differences designs (e.g., Berg et al., 2021). Estimates from this comparison therefore capture how much more adopting insurers withdraw than the mine's other insurers, not a single insurer's withdrawal in isolation and not the net change in a mine's coverage. We measure that net change directly in Section 5.2 with a mine-level analysis that aggregates across all of a mine's insurers, does not rely on a within-mine comparison, and internalizes substitution across insurers. Our real-effects analysis in Section 6 relies on this net measure and is therefore also unaffected by the within-mine interference.

we expect β_t to be indistinguishable from zero prior to treatment and negative afterwards.

Figure 4 presents the estimated quarterly coefficients relative to treatment, with the adoption quarter (t=-1) as the omitted baseline. In the quarters leading up to adoption and in event quarter 0, there are no significant differences in the probability of active coverage, supporting the parallel trends assumption. Starting in the first event quarter, however, relationships between mines and policy-adopting insurers are significantly less likely to remain active. This decline grows steadily, from 8.2 pp in the first event quarter to 17.3 pp by the third event quarter, by which point most of the effect has materialized. This pattern is consistent with the typical one-year duration of insurance policies, as most non-renewals will have taken effect within a year. The effect continues to rise more gradually thereafter, reaching 23 pp by the sixth event quarter. The sharp discontinuity around policy adoption provides evidence that coal policies drive changes in underwriting activity, and it suggests that at least some insurers begin to implement their policies upon introduction.[18] Consistent with this evidence, our model shows that policy adoption reflects non-actuarial costs that are sufficiently high to make continued coal underwriting suboptimal, leading insurers to withdraw coverage.

To complement the dynamic DiD estimates, we define a post-adoption indicator (*Post*) that equals one for the quarters after the introduction of a coal policy, and interact it with *Coal policy*. We then estimate the following static DiD regression with OLS:

$$Active\ insurance_{s,m,i,t} = \beta \times Coal\ policy_i \times Post_{s,t} + \alpha_{s,m,i} + \alpha_{s,m,t} + \epsilon_{s,m,i,t}. \tag{3}$$

Table 4 reports results. In Column 1, the coefficient on the interaction term indicates that, in the quarters following adoption, relationships between a mine and a policy-adopting insurer are 12.7 pp less likely to be active, about a 31% decrease relative to the unconditional active probability of 41%. In Column 2, among mines that remain active throughout the sample, the decline is similar at 12.3 pp. These results confirm earlier evidence that non-renewals reflect changes in insurer behavior driven by coal policy adoptions rather than changes in mine characteristics. Consistent with this argument, Table IA.6 shows that insurers do not selectively drop low-quality or low-performing mines: the reduction in coverage is not systematically related to mine productivity, size, accident numbers, or the coal price.

[18] Our estimates are identified off mines insured by multiple insurers, which differ from single-insurer mines along observable characteristics. Such level differences do not threaten our design, which identifies off changes within mines, but they raise the question of whether our results extend to single-insurer mines. In a robustness test, we therefore re-estimate Eq. 2 on the full sample of mines, replacing the stack-mine-time fixed effects with stack-time fixed effects, so that mines insured by a single insurer contribute to identification. Figure IA.6 reports the dynamic estimates. Results are virtually unchanged, indicating that our findings are not specific to mines insured by multiple insurers.

4.4 Heterogeneity in Implementation

The preceding results show that insurers adopting a coal policy are, on average, more likely to terminate their insurance relationships with coal mines. Because the estimated effects remain well below full cancellation, we examine two dimensions along which implementation varies: the stringency of the insurer's policy and the type of insurance line.

First, if a more stringent policy reflects a stronger commitment to exit coal projects, then insurers with more stringent policies should terminate coverage more often. To test this prediction, we adjust Eq. 3 by interacting the post-adoption indicator with *First coal policy score*, the insurer's policy score at adoption, and *Max coal policy score*, the highest policy score observed for an insurer during the sample period. Table 5, Columns 1 and 2, show that the coefficients on both interaction terms are negative and statistically significant, indicating that implementation intensity increases with policy stringency. In Column 1, a one-standard-deviation increase in the stringency score is associated with about a 5 pp larger reduction in the probability of active coverage after policy adoption. Hence, insurers with broader and more credible underwriting restrictions are more likely to terminate coverage.

Second, if the cost of maintaining a line rises with how directly it covers coal mining, insurers should discontinue more coal-exposed lines (commercial general liability, umbrella and excess liability, and automobile liability) at higher rates than less coal-exposed lines (workers' compensation). To test this prediction, we first replicate the stacked DiD specification at the insurance line level. The static estimates in Table 5, Column 3, and the dynamic estimates in Figure IA.7 indicate that the aggregate pattern holds across insurance lines. Next, we add interaction terms with dummies for specific lines. Table 5, Column 4, shows that relationships involving workers' compensation insurance are significantly more likely to remain active than those covering commercial general liability (the omitted category). While the baseline post-policy effect of coal policy adoption is negative (-0.128), the triple interaction for workers' compensation (0.137) offsets this effect. This suggests that insurers retain coverage related to worker safety and compensation.[19]

Overall, the findings show that coal policies lead to substantial reductions in insurance

[19]This finding is confirmed by a joint significance test. These results are consistent with anecdotal evidence. In its coal underwriting policy, SCOR explicitly carved out exceptions for coverage related to worker and community protection: "*SCOR will not issue insurance or facultative reinsurance that would specifically encourage new greenfield thermal coal mines or stand-alone lignite mines or plants. The only exception to this rule would be the implementation of cover for the benefit of the local community or workers.*" (SCOR, 2017). Similarly, Zurich's latest coal underwriting policy explicitly exempts "*workers' compensation, other employee protections, or considerations, which have a positive impact on human health and the environment.*" (Zurich, 2025).

coverage for coal mines, especially among insurers with stronger policy commitments. The effects also vary systematically across insurance lines: insurers cut the coverage most directly tied to core mining while retaining worker safety and compensation lines. These heterogeneities align with our model, which predicts that insurers with more stringent policies withdraw more aggressively, in particular from insurance lines with higher reputational exposure.

5 Substitution in Coal Mine Insurance

Any potential real effects of coal underwriting policies depend on whether mines can substitute withdrawn coverage. If substitution across insurers were frictionless, policy adoptions would merely reshuffle market shares without affecting insured mines. However, two sets of frictions can make it costly for a mine to replace a lost insurer. At the relationship level, although insurance contracts are largely standardized and typically run for one year, a mine's incumbent insurers accumulate match-specific information (Cohen, 2012). This is information that prospective insurers lack and makes incumbents costly to replace. At the insurer level, the supply of replacement coverage is limited and slow to adjust, because the market is highly concentrated and entry is slow. At the start of our sample period in 2014, only 32 insurance groups underwrite coal risks, and six of these, insuring 50.5% of mines in our sample, eventually adopt a coal policy. Their withdrawal therefore removes coverage from a large share of mines, raising the question of whether remaining insurers can absorb it. Moreover, new capacity, whether from existing insurers expanding their underwriting or from entry by domestic or foreign insurers, can arrive only slowly because it requires licenses and regulatory capital (e.g., Doherty and Posey, 1997; Froot, 2001; Koijen and Yogo, 2015). At the same time, a mine that loses coverage must replace it quickly to continue operating.[20]

5.1 Persistence in Insurer-Mine Relationships

We begin the substitution analysis by examining the persistence of insurer-mine relationships. This analysis parallels the bank-firm relationship literature, with a mine's insurers playing the role of a firm's lenders (e.g., Petersen and Rajan, 1994; Ongena and Smith, 2001). Insurer-mine relationships are relatively long-lived: Table 2, Panel A, shows that the average relationship lasts 14.3 quarters (about 3.5 years), with a median of 12 quarters. As most

[20] Insurance is regulated at the state level, so an insurer must hold a certificate of authority (in some states, a license) from each state in which it writes coverage, which it obtains only after meeting that state's capital and securities-deposit requirements and passing a regulatory review. This requirement applies to any insurer not already admitted in the state, whether a U.S. insurer expanding from another state or a non-U.S. insurer, with the latter facing additional requirements before admission. Replacement capacity therefore cannot enter a state quickly.

policies have a one-year term, the typical relationship spans two or more renewals, implying that mines do not re-shop insurance coverage annually. This persistence is consistent with switching costs (e.g., Sharpe, 1990; von Thadden, 2004).

Next, we examine stickiness in insurer-mine relationships more formally. If relationships embody match-specific information and switching costs, a mine's current insurers should be predictable from relationships formed in the past, after absorbing mine- or insurer-specific factors (Chodorow-Reich, 2014). We test this prediction with the following OLS regression at the mine-insurer-quarter level:

$$\textit{Active insurance}_{m,i,t} = \beta \times X_{m,i,t} + \alpha_{i,t} + \alpha_{m,t} + \epsilon_{m,i,t}, \tag{4}$$

where *Active insurance* is a dummy indicating an active relationship between mine m and insurer i at time t, X is a measure of past relationship activity at the insurer-mine level. $\alpha_{i,t}$ and $\alpha_{m,t}$ are insurer-time and mine-time fixed effects, which absorb both time-varying insurer characteristics (e.g., shifts in underwriting capacity or risk appetite) and time-varying mine characteristics (e.g., variation in profitability or riskiness).[21]

Results are reported in Table 6, Panel A. In Column 1, a relationship that was active at any point since the start of our sample is 57 pp more likely to be active in the current quarter. In Column 2, a relationship that was active in the past four quarters is 72 pp more likely to be active, and in Column 3, current activity rises strongly with the share of past quarters in which the relationship was active. Estimates are similar in Columns 4 to 6, which absorb time-varying mine characteristics. That the estimates are large and significant across specifications indicates that persistence is a property of insurer-mine relationships, not a mine or insurer characteristic. Overall, the evidence shows that insurer-mine relationships are long-running and sticky, consistent with the presence of frictions in replacing incumbent insurers.

5.2 Substitution on the Extensive Margin: Number of Insurers

To understand the role of frictions in insurer substitution, we first examine the extensive margin, that is, whether and how mines replace insurers that withdraw under coal policies with other insurers. [22] This test mirrors an analysis of how firms substitute across banks (e.g., Amiti and Weinstein, 2018; Huber, 2018). Because coal policies are adopted at the

[21] Because X is a lagged measure of the dependent variable, the within estimator with fixed effects is subject to Nickell bias (Nickell, 1981), which attenuates the coefficient toward zero in panels with a short time dimension. This bias works against persistence, so our estimates, if anything, understate the stickiness of insurer-mine relationships.

[22] We measure substitution through the number of insurers and the insurance lines they write. As the certificates report neither premiums nor meaningful variation in coverage limits (see Section 3), we cannot analyze substitution through prices or limits.

insurer level and coverage is terminated within insurer-mine relationships, analyzing substitution at the mine level requires a mine-level measure of treatment. We classify a mine as *Coal policy exposed* if, between 2014 and 2016 (before any coal policies were in place), it was insured by at least one insurer that subsequently adopted a coal policy. Defining exposure from pre-period relationships makes treatment predetermined relative to policy adoption and controls for the selection of mines into policy adopters' portfolios. Pre-adoption exposure remains relevant because insurer-mine relationships are persistent, so a mine exposed in the pre-period is typically still insured by an insurer when the policy takes effect. Using OLS, we then estimate at the mine-quarter level:

$$\# \; Active\ insurers_{m,t} = \beta \times Post\ coal\ policy\ exposed_{m,t} + \alpha_m + \alpha_t + \epsilon_{m,t}, \tag{5}$$

where the dependent variable is (i) the number of active insurers (*# Active insurers*), (ii) the number of active policy-adopting insurers (*# Active insurers w/ coal policy*), or (iii) the number of active non-adopting insurers (*# Active insurers w/o coal policy*). *Post coal policy exposed* equals one for mine-quarters after the first coal policy adoption by any insurer that covered the mine in the pre-period. α_m are coal mine fixed effects, α_t are time fixed effects, and we cluster standard errors at the mine level. The estimation sample comprises the same mines as the relationship-level analysis in Section 4.3, making the two sets of results directly comparable. The coefficient on the total number of active insurers captures the net change in a mine's coverage, while the split into policy-adopting and non-adopting insurers reveals whether substitution occurs: it shows up as a decline among policy-adopting insurers that is partly offset by an increase among non-adopting insurers.

Results are reported in Table 6, Panel B. Column 1 shows that after policy adoption, the number of active insurers covering an exposed mine falls by 0.13, which is about 7% of the sample mean of 1.8 insurers. This net decline reflects two offsetting changes. The number of policy-adopting insurers, in Column 2, falls by 0.35, about 38% of the mean of 0.9 such insurers, while the number of non-adopting insurers, in Column 3, rises by 0.22, about 25% of the mean of 0.9. Substitution is therefore incomplete: non-adopting insurers replace only 0.221 of the 0.345 relationships withdrawn, so about 36% are not replaced, leaving the typical exposed mine with fewer insurers than before. This within-mine substitution mirrors the market-wide expansion of non-adopting insurers over the sample period shown in Figure 3.

5.3 Substitution on the Intensive Margin: Number of Insurance Lines

The previous results show a net decline in the number of insurers covering exposed mines. For these mines to keep satisfying their legal insurance requirements, the insurers that remain would have to take on the lines that policy-adopting insurers dropped. We therefore examine the intensive margin, that is, the scope of coverage each insurer provides at a mine. This test also mirrors the bank-firm literature (e.g., Degryse and Van Cayseele, 2000; Jiménez et al., 2014). We re-estimate Eq. 5 with *Mean # active lines* as the dependent variable.[23] This variable is the average number of active insurance lines of insurers covering mine m in quarter t. We compute this average across all insurers, across all policy-adopting insurers, and across all non-adopting insurers. Intensive-margin substitution would imply an increase in the average number of lines per non-adopting insurer at exposed mines after adoption.

Results are reported in Panel C of Table 6. In Column 1, the average number of lines per insurer at an exposed mine is unchanged after policy adoption. This stability masks two offsetting and statistically significant changes. Among policy-adopting insurers, in Column 2, average lines per insurer fall by 0.23, from a mean of 0.58 (about 39%), while among non-adopting insurers, in Column 3, they rise by 0.19, from a mean of 0.70 (about 27%). The insurers that keep insuring a mine, therefore, widen their coverage, absorbing much of the scope that policy-adopting insurers shed. With the number of insurers falling and average lines per insurer unchanged, however, a mine's total coverage still declines.

Overall, this section documents that coal mine insurance is sticky and that insurer substitution after policy adoptions is incomplete. The result is a residual decline in a mine's coverage. Because this net change aggregates across all of a mine's insurers, it is unaffected by the within-mine substitution that complicates the relationship-level estimates, and it is the coverage measure on which our real-effects analysis builds. This decline matters because insurance, unlike the financing channels of banks and other capital providers, is a legal prerequisite to operate. Even an incomplete loss of coverage can therefore force a mine to close that would otherwise continue operating. Both features appear in our model, in which a mine operates only if its total coverage clears a mandated minimum and substitution is incomplete because absorbing dropped coverage raises a remaining insurer's non-actuarial cost.

[23] The number of active insurers and the average number of active lines per insurer are non-negative, count-like variables. Our extensive- and intensive-margin results are robust to estimating these regressions as Poisson models (Cohn et al., 2022), as reported in Table IA.7, Panels A and B.

6 Real Effects of Coal Underwriting Policies

Having established that insurers reduce their underwriting activity after adopting coal policies and that mines only partly replace the lost coverage, we now examine the consequences for insured projects. Anecdotal evidence suggests they can be severe: coal mine operators themselves treat the loss of insurance as a threat to survival. In their filings with the Securities and Exchange Commission, mining companies point to challenging insurance markets driven by ESG considerations and cite the potential inability to obtain coverage as a material risk to continued operations (e.g., CONSOL Energy, 2020; Arch Resources, 2021; NACCO Industries, 2022; Alliance Resource Partners, 2023). We proceed in three steps: we first estimate how exposure to policy-adopting insurers affects mine outcomes, then examine whether deteriorating mine fundamentals can explain these effects, and finally quantify how much of the abandonment effect operates through the loss of coverage.

6.1 Effects of Coal Underwriting Policies on Mine Outcomes

To capture the implications of coal underwriting policies, we test how outcomes of coal-policy-exposed mines change around policy adoption relative to non-exposed mines. We use three designs: (i) a two-way fixed-effects panel regression that exploits the staggered timing of mines' first exposure to a policy-adopting insurer over the full sample period, (ii) a stacked DiD design around this first exposure with never-exposed mines as controls, and (iii) a shift-share design that exploits the repeated adoption of policies by a mine's insurers. Throughout this subsection, the treatment is a mine's exposure to policy-adopting insurers, not the loss of coverage itself. Because a policy adoption affects a mine only if the insurer actually terminates coverage and the mine cannot replace it, these designs estimate the average effect of exposure across mines whose coverage does or does not survive. Hence, this intent-to-treat effect understates the effect of an actual loss of coverage.

6.1.1 Two-Way Fixed-Effects Regressions

Our first design provides a benchmark that uses the full mine-quarter panel. We estimate the following two-way fixed-effects regression at the mine-quarter level:

$$\textit{Coal mine outcome}_{m,t} = \beta \times \textit{Post coal policy exposed}_{m,t} + \alpha_m + \alpha_t + \epsilon_{m,t}, \tag{6}$$

where m indexes a mine and t a quarter. *Coal mine outcome* is either a dummy for whether a mine is abandoned (*Abandoned*) or the (log of) volume of coal produced (*Production*). *Post coal policy exposed* equals one for mine-quarters after the first coal policy adoption by any insurer that covered the mine in the pre-period. α_m are mine fixed effects and α_t are time fixed effects. We cluster standard errors at the mine level.

Table 7, Columns 1 and 2, report the results. Exposed mines are 4.2 pp more likely to be abandoned once one of their insurers adopts a coal policy, significant at the 5% level and equal to about 38% of the unconditional abandonment rate of 11% (Column 1), while the estimate for production is negative but insignificant (Column 2). Because treatment is defined by a mine's first exposure and remains in place for the rest of the sample period, this estimate captures the cumulative effect of exposure over the full horizon, a period in which many mines lose additional insurers to later adoptions.

6.1.2 Stacked DiD Regressions

Our second design addresses that the two-way fixed-effects estimates can be biased under staggered treatment timing, because the comparisons underlying them use already-treated mines as controls (e.g., Baker et al., 2026). To avoid these comparisons, we adopt a stacked DiD approach, which also provides a well-defined event date around which we can trace dynamic effects and assess pre-trends. For each group of insurers adopting a coal policy in the same quarter, we construct a stack comprising all their mines at the first coal policy adoption by any of their insurers, observed over a 13-quarter window around treatment. Control observations are drawn from mines that, at the beginning of the period, are insured exclusively by insurers that never adopt a policy (i.e., control status is predetermined relative to policy adoption). We estimate the following dynamic DiD regression with OLS:

$$\begin{aligned} \textit{Coal mine outcome}_{s,m,t} = \sum_{t=-6}^{t=6} \beta_t \times \textit{Coal policy exposed}_{s,m} \times \textit{Event quarter}_{s,t} \; + \\ \alpha_{s,m} + \alpha_{s,t} + \epsilon_{s,m,t}, \end{aligned} \tag{7}$$

where s indexes a stack, m a mine, and t a quarter. *Coal mine outcome* is again either *Abandoned* or (log of) *Production*. *Coal policy exposed* identifies mines with a pre-period insurer that subsequently adopts a coal policy. *Event quarter* are dummy variables indicating quarters relative to treatment, where treatment is the first quarter after coal policy adoption. $\alpha_{s,m}$ are stack-mine fixed effects and $\alpha_{s,t}$ are stack-time fixed effects. These fixed effects ensure that we study within-mine variation and compare changes in mine outcomes with non-exposed mines at the same point in time. Notably, the stack-time fixed effects account for common trends in the secular decline of U.S. coal production and other time-varying factors that affect all mines. Standard errors are clustered at the mine-stack level. If coal policies constrain operations, β_t should be zero prior to treatment and positive for abandonment or negative for production thereafter.

Figure 5 plots the dynamic estimates relative to treatment, with the adoption quarter (t=−1) as the omitted baseline. Panel A documents the absence of pre-trends for abandonment. Post-treatment, the effect emerges gradually, becomes significant in the fourth event quarter, reaching 2.8 pp, and rises to 3.1 pp by the sixth event quarter. Hence, this increase suggests that reduced insurance availability can push some mines below the regulatory coverage threshold, inducing exit. Panel B reveals no consistent pattern for production. Overall, our evidence indicates that coal policies reduce mine viability, primarily by raising the likelihood of exit. These dynamics align with our model, where mines must satisfy a regulatory minimum and insurer withdrawal induces exit once total coverage falls below it.[24]

To complement this dynamic specification, we run a static DiD regression with OLS in which we replace the event-time indicators with a single post-treatment indicator (*Post*):

$$Coal\ mine\ outcome_{s,m,t} = \beta \times Coal\ policy\ exposed_{s,m} \times Post_{s,t} + \alpha_{s,m} + \alpha_{s,t} + \epsilon_{s,m,t}. \quad (8)$$

Table 7, Columns 3 and 4, report the results. Column 3 points to a 2.4 pp higher abandonment probability for policy-exposed mines, though this point estimate is not statistically significant at conventional levels. The lack of significance for this average effect is consistent with our dynamic estimates: because the effect emerges only from the fourth event quarter, *Post* averages it over the entire window, diluting the large late-quarter effects with the near-zero early ones and yielding a modest, imprecise static estimate. The point estimate is smaller than its full-horizon counterpart in Column 1 because the stack measures the effect within a ±6-quarter window around treatment, whereas the abandonment effect matures late and continues to build as additional insurers adopt. Column 4 examines production, restricting the sample to continuously active mines, and suggests that production declines by about 24% ($\approx e^{-0.270} - 1$) post-adoption. We interpret this intensive-margin estimate cautiously, as production is noisy and heavily skewed. Overall, we conclude that the effect of coverage loss concentrates on the extensive margin of whether a mine continues to operate, consistent with insurance acting as a discrete operating requirement rather than a marginal cost.

6.1.3 Shift-Share Regressions

The two previous designs define a mine's exposure by the first coal policy adoption among its insurers. In our third design, we implement a shift-share (Bartik) strategy (Goldsmith-

[24]Figure IA.8 reports estimates from the staggered event-study estimator of de Chaisemartin and d'Haultfœuuille (2026), which is robust to treatment-effect heterogeneity. The effects are similar in magnitude to the estimates reported above, with weaker pre-trends, but estimated with lower precision.

Pinkham et al., 2020), which exploits repeated treatments, that is, additional insurers of the same mine adopting policies later. This design mirrors the approach Green and Vallee (2025) use to study banks' exit from fossil-fuel lending. We estimate the following OLS regression, using the mine-quarter panel described in Table 2, Panel C:

$$\textit{Coal mine outcome}_{m,t} = \beta \times \textit{Share coal policy exposed}_{m,t} + \alpha_m + \alpha_t + \epsilon_{m,t}, \tag{9}$$

where *Coal mine outcome* is one of the two outcomes used above, α_m are mine fixed effects, and α_t are time fixed effects. To capture mine m's share of insurers ($w_{m,i}$) that provided coverage between 2014 and 2016 and have adopted a coal policy by quarter t (i.e., insurers for which $\textit{Post coal policy}_{i,t} = 1$), we calculate $\textit{Share coal policy exposed}_{m,t} = \sum_i w_{m,i} \times \textit{Post coal policy}_{i,t}$. A mine's exposure thus increases with each additional policy-adopting insurer, generating shift-share variation in treatment intensity across mines and over time.[25] Relative to the stacked event study, which relies on a single first-adoption event and a constructed control group of never-exposed mines, this design exploits the full sequence of adoptions and continuous variation in exposure intensity within a mine over time.

The results in Table IA.8 continue to point to an increase in the abandonment likelihood (Column 1), although the effect is not statistically significant at conventional levels, consistent with the intent-to-treat interpretation above. As in the stacked design, we do not overinterpret the estimates for production in Column 2, which turn significant. Taken together, the three designs consistently point to a higher abandonment likelihood for mines exposed to policy-adopting insurers, with the largest estimates over horizons that accumulate repeated adoptions, while production exhibits no robust response. Because all three designs measure exposure rather than actual loss of coverage, these estimates are conservative.

6.2 Alternative Explanation: Deteriorating Mine Fundamentals

Our interpretation is that coal policy adoptions cause insurers to withdraw coverage, which can push affected mines toward abandonment. An alternative explanation reverses this chain: mines first deteriorate in value, riskiness, or profitability, and insurers then withdraw coverage, with policy adoptions merely coinciding with withdrawal. Two features of our design make these alternatives unlikely. As our regressions include time fixed effects, we already absorb common movements in coal prices, demand, or regulation. In addition, our relationship-

[25] This measure relies on two assumptions. First, due to the lack of information on the relative importance of insurers for a given mine, we assume that all insurers contribute equally to a mine's exposure (assigning equal weights $w_{m,i}$). Second, we limit the set of mines and insurers to insurer-mine relationships lasting at least eight quarters between 2014 and 2016, ensuring that exposure reflects sustained ties. The dynamic post-treatment effects become cleaner when using the refined 8-quarter relationship definition (Figure IA.9), supporting the notion that longer-lasting insurer ties capture more meaningful exposure.

level results in Section 4.3 compare insurers within the same mine and quarter, absorbing all mine-level shocks, including those to riskiness and profitability. We nonetheless address the three alternative channels—deterioration in value, riskiness, or profitability—directly.

First, if the effect reflected mines closing for their own value-related reasons, it would concentrate among mines with the least to lose. While we do not observe mine-level profitability, we can classify mines into those that have more to lose from abandonment as they operate at above-median productivity (*Productive mine*, average output per working hour) or above-median size (*Large mine*, total production). Table 8, Column 1, shows that more productive mines are generally less likely to close after policy adoption, but this difference does not vary with exposure to coal policies. Column 2 shows no significant difference in the abandonment effect between large and small mines. Mine value, if proxied by productivity and size, therefore does not shape the abandonment response.

Second, suppose insurers withdraw coverage because the insured risk itself deteriorated. Under this explanation, the abandonment effect would need to concentrate among riskier mines. We test this prediction using mine-level safety incidents reported to the MSHA, interacting exposure with an indicator for an above-median number of accidents. Column 3 shows that the coefficient on this interaction term is insignificant, implying that there is no evidence that mines with worse safety records are differentially abandoned. This finding is difficult to reconcile with risk-driven withdrawals. In fact, it complements the pattern across insurance lines documented in Section 4.4: an insurer responding to deteriorating mine risk would reduce exposure across all lines, including workers' compensation, whereas we find that adopting insurers retain precisely those lines.

Third, insurers might drop mines because mining has become less profitable. Because time fixed effects do not absorb regional differences in coal prices, we interact exposure with an indicator for above-median coal shipment prices. Profitability-driven withdrawal would predict a stronger abandonment effect at mines facing lower prices, where mining is least profitable. In Column 4, we find the opposite: the interaction is positive and significant, so the effect is, if anything, stronger at higher-price mines. These results suggest that coal policies, rather than deteriorating mine fundamentals, drive the loss of coverage and its real effects.[26]

[26] The same holds for the withdrawal of coverage itself. As Table IA.6 reports, the policy-driven reduction in coverage does not vary with mine productivity, size, accident number, or coal price. If deteriorating fundamentals drive insurers to exit, coverage should instead fall the most at the least productive, smallest, least safe, or lowest-priced mines.

6.3 Effects of Policy-Induced Coverage Loss on Mine Abandonment

Our evidence shows that exposure to policy-adopting insurers affects mine outcomes. These intent-to-treat estimates average over exposed mines that keep or replace their coverage. To quantify the effect of the coverage actually lost, we combine the termination and exposure effects in a two-stage least squares (2SLS) framework that uses policy adoption as an instrument for the loss of coverage.[27] The system is estimated with a first stage:

$$Active\ insurance_{i,m,t} = \pi \times Post\ coal\ policy_{i,t} + \alpha_{i,m} + \alpha_t + u_{i,m,t}, \tag{10}$$

and the following second stage:

$$Abandoned_{m,t} = \beta \times \widehat{Active\ insurance}_{i,m,t} + \alpha_{i,m} + \alpha_t + \epsilon_{i,m,t}, \tag{11}$$

where i indexes an insurance group, m a mine, and t a quarter. *Active insurance* equals one if insurer i covers mine m in quarter t, and zero otherwise, and $\widehat{Active\ insurance}$ is its first-stage fitted value. *Post coal policy* equals one for relationships with a policy-adopting insurer in the quarters after that insurer's adoption, and *Abandoned* indicates whether mine m is abandoned in quarter t. $\alpha_{i,m}$ are insurance group-coal mine fixed effects and α_t are time fixed effects. We double-cluster standard errors at the mine and insurance group level. Because abandonment is measured at the mine level while the unit of observation is the insurer-mine relationship, mine outcomes are repeated across a mine's relationships, and the estimates implicitly weight mines by their number of insurers. The evidence in the previous subsection that neither the withdrawal of coverage nor the abandonment response is related to mine fundamentals supports the validity of the instrument: policy adoptions do not appear to respond to the condition of the mines insurers cover.

Results are reported in Table 9. For the first stage in Column 1, the probability that a policy-adopting insurer covers an affected mine falls by 20 pp after that insurer adopts a coal policy, significant at the 1% level with an F-statistic of 8.87. The second-stage estimate in Column 2 indicates that a policy-induced loss of an adopter's coverage raises a mine's abandonment probability by about 6 pp, significant at the 5% level and more than half of the unconditional abandonment rate of 11% (Panel C of Table 2).[28] Although this estimate captures the average effect of losing an insurer, regardless of whether it is replaced,

[27] The resulting estimate is a local average treatment effect (LATE) that applies to relationships that lapse because of a coal policy adoption: those involving insurers with more stringent policies and coal-exposed insurance lines (Section 4.4). Although other insurers partly offset these withdrawals (Section 5.2), the lapsed relationships on average still represent a net loss of coverage.

[28] Given the moderate strength of the instruments, we read these magnitudes as indicative.

it suggests that even the loss of a single insurer can threaten a mine's survival.

This estimate is a lower bound because the endogenous variable is a single insurer's coverage, while abandonment is measured at the mine level. A withdrawal that another insurer absorbs leaves the mine's total coverage, and therefore its operations, largely intact. This pulls the second-stage coefficient toward zero. This test thus underestimates the effect of an unreplaced coverage loss. To isolate this net effect, we move to the mine-quarter level and instrument the number of insurers actively covering a mine—a measure that is net of substitution—with the mine's exposure to policy-adopting insurers.[29]

In the first stage, reported in Column 3, exposure reduces the number of active insurers at a mine by 0.33, statistically significant at the 1% level, with an F-statistic of 12.4. The second-stage estimate in Column 4 indicates that the net loss of an active insurer raises the abandonment probability by about 12 pp, significant at the 10% level. Because this design instruments a mine's net coverage after substitution rather than an individual relationship, the estimate is larger than its relationship-level counterpart, consistent with the attenuation just described. Taken together, both designs confirm that policy-induced loss of coverage can push affected mines toward abandonment.

The comparison of the two approaches also isolates the role of alternative insurers. The relationship-level estimate in Column 2 (about 6 pp) is about half the mine-level estimate in Column 4 (about 12 pp) because it averages over withdrawals that other insurers absorb and withdrawals that leave a net loss of coverage, whereas the mine-level design captures only the net loss. The difference therefore reflects how much substitution buffers a withdrawal. When a mine can replace a departing insurer, the loss does not translate into abandonment, and when it cannot, abandonment rises by the larger mine-level magnitude. These estimates also reconcile the magnitudes across designs: the full-horizon exposure effect of 4.2 pp is approximately the product of the first-stage decline in the number of active insurers (0.33) and the per-insurer abandonment effect (12.1 pp). Access to alternative insurers thus mitigates the real effects of coal policies, a consequence of the incomplete and slow substitution documented in Section 5 rather than of any mine's insurer count.[30]

Overall, this section shows that coal underwriting policies affect coal mines primarily by

[29]Relative to the sample underlying Table 6, this analysis includes mine-quarter pairs in which the mine is not covered by any insurer, thereby allowing us to account for cases in which mines halt production as they fail to meet the legally required minimum insurance coverage.

[30]A mine's number of insurers is itself an equilibrium outcome that may reflect its anticipation of coverage risk and its access to insurers, so it is not a clean source of cross-sectional variation. We therefore identify the role of alternative coverage from the policy-induced change in a mine's net number of insurers rather than from differences in insurer counts across mines.

raising the likelihood of abandonment. Exposure to policy-adopting insurers is linked to a higher likelihood of abandonment, with weaker, noisier signs of lower output. Because abandonment is rarely reversed, these effects are effectively permanent. The effect size increases with exposure to policy-adopting insurers, pointing to a role for insurers' underwriting decisions in shaping coal mine activity. While abandonment decisions do not vary systematically with mine characteristics such as productivity or size, they depend on whether a mine can replace the coverage it loses. Isolating the coverage that mines actually lose, the loss of an insurer that is not replaced raises the abandonment probability by about 12 pp, well above the diluted effect of exposure alone. Because few insurers underwrite coal and substitution is incomplete, a withdrawal can push a mine toward abandonment only when the lost coverage cannot be replaced, so market structure shapes the real impact of individual insurer actions.

7 Effects of Coal Underwriting Policies on Insurer Outcomes

Our finding that insurers adjust underwriting behavior following the adoption of coal underwriting policies raises the question of whether such policies meaningfully affect insurer-level outcomes. For insurers, adopting coal policies entails trade-offs. On the one hand, reduced underwriting activity may lead to lower income. On the other hand, such policies may decrease non-actuarial costs and generate reputational benefits that may enhance franchise value. Assessing these trade-offs comprehensively is challenging because coal-related activities account for only a small share of insurers' overall business, our sample of adopting insurers is limited, and any effects may take time to materialize. With these caveats in mind, we examine changes in five insurer-level outcomes around adoptions of coal underwriting policies: gross written premiums as a measure of operating income (*GWP (log)*), return on assets as a measure of profitability (*ROA (%)*), abnormal stock returns around the announcement of coal policy adoptions as a forward-looking measure of shareholder wealth (*CAR[0,1]*), an insurer's solvency ratio as a measure of riskiness (*Solvency ratio*), and the number of environmental incidents to capture reputational risks (*# RepRisk incidents*).

Results are reported in Table 10. Gross written premiums in Column 1 remain unchanged around the adoption of coal policies. Return on assets in Column 2 declines by about 0.5 pp, though the effect is not statistically significant. Similarly, abnormal announcement returns around adoptions are negative, around -0.5 pp, but also not statistically significant. Solvency ratios, shown in Column 4, exhibit no systematic change. However, the number of yearly environmental incidents in Column 5 decreases by about 1 incident or 38% relative to the sample mean. This result indicates some reputational benefits associated with the adoption of coal policies. Overall, given the small samples, limited time period, and the fact that insurer-level outcomes reflect many activities beyond coal underwriting, we can provide only limited evidence of insurer-level consequences. Nevertheless, our analysis highlights that coal policies have discernible effects within insurers' coal business and their relationships with coal mines.

8 Conclusion

Underwriting policies have become an increasingly important tool through which insurers manage reputational risks. In this paper, we provide the first systematic analysis of the design, determinants, implementation, and real effects of such policies, using policies covering coal projects as a setting. While such policies have become increasingly common and stringent, their design, adoption, and implementation remain highly heterogeneous. Using novel mine-level insurance data, we show that coal underwriting policies reduce coverage of U.S. coal mines, lower insured coal volumes, and make it less likely that existing mine-insurer relationships continue. Other insurers replace only part of this lost coverage, leaving a net reduction. Mines affected by changes in coverage are more likely to be abandoned, suggesting that underwriting decisions provide a viable channel through which the financial sector can influence decarbonization. Our findings underscore that their effectiveness depends on policy design and implementation. We illustrate how a simple insurance-supply model with non-actuarial costs can rationalize these empirical patterns. Our results also point to the role of market structure. Because few insurers underwrite coal and substitution is incomplete, an insurer's withdrawal can push a mine toward abandonment only when the lost coverage cannot be replaced, leaving mines with fewer alternatives more exposed. More broadly, mandatory insurance is pervasive across the economy, so the lever we document is unlikely to be specific to coal. In cases where firms cannot operate without coverage, underwriting decisions give insurers influence over firm behavior that is distinct from the financing channels of banks and other capital providers. How insurers use this influence beyond the climate context is a promising avenue for future research.

Table A.1: Variable definitions

Variable	Definition	Source
	Panel A: Insurer characteristics	
Post coal policy	Equals one for policy-adopting insurers after adoption, and zero otherwise	IOF scorecards
Coal policy score	Score ranging from 0 to 10 to reflect the stringency of a coal underwriting policy of an insurer in a year. Higher values indicate stricter policies	IOF scorecards
First coal policy score	An insurer's *Coal policy score* at adoption of the policy. For insurers that adopted a policy in 2017, we use the 2018 stringency scores.	IOF scorecards
Max coal policy score	Maximum of *Coal policy score* for an insurer	IOF scorecards
Post oil & gas policy	Equals one for oil & gas policy-adopting insurers after adoption, and zero otherwise	IOF scorecards
Oil & gas policy score	Score ranging from 0 to 10 to reflect the stringency of an oil & gas underwriting policy of an insurer in a year. Higher values indicate stricter policies	IOF scorecards
Post coal investment policy	Equals one for coal investment policy-adopting insurers after adoption, and zero otherwise	IOF scorecards
Coal investment score	Score ranging from 0 to 10 to reflect the stringency of a coal investment policy of an insurer in a year. Higher values indicate stricter policies	IOF scorecards
Post oil & gas investment policy	Equals one for oil & gas investment policy-adopting insurers after adoption, and zero otherwise	IOF scorecards
Oil & gas investment score	Score ranging from 0 to 10 to reflect the stringency of an oil & gas investment policy of an insurer in a year. Higher values indicate stricter policies	IOF scorecards
CCPI	Yearly Climate Change Performance Index score of an insurer's headquarters country. Insurers headquartered in the Bermuda territory are given the United Kingdom score.	CCPI website
NZIA	Equals one if an insurer (parent company of an insurance group) is a member of the Net Zero Insurance Alliance (NZIA) in a year, and zero otherwise	NZIA website
Specialty insurer	Equals one if an insurer (parent company of an insurance group) is a specialty insurer, and zero otherwise	Online searches
Unlisted insurer	Equals one if the parent company of an insurance group is unlisted, and zero otherwise	Orbis
High fossil fuel GWP share	Equals one if an insurer has a gross written premium to fossil fuels over 2022 total gross written premium above the median, and zero otherwise	IOF scorecards
Total assets	Consolidated total assets of the insurer in a year	Orbis
ROA (%)	Consolidated pre-tax return on assets of the insurer in a year	Orbis
GWP (log)	Gross written premiums of the insurer in a year	Orbis
CAR[0,1]	Sum of daily abnormal returns on the day of the announcement of the adoption of a coal underwriting policy and the following trading day, where daily abnormal returns equal an insurer's stock return minus the market return	Compustat Global and Kenneth French Data Library
Solvency ratio	Solvency capital in a year, computed as the sum of capital and surplus, claims equalization reserve, and unrealized gains on investments, over total assets	Orbis
# RepRisk incidents	Number of environmental incidents in a year	RepRisk
# Coal mines insured	Number of unique coal mines insured in a quarter	Certificates of Liability Insurance

Coal volume insured	Million short tons (MMst) of coal produced by the mines insured in a quarter	Certificates of Liability Insurance
	Panel B: Policy characteristics	
Commercial general liability	Equals one if a policy covers commercial general liability, and zero otherwise	Certificates of Liability Insurance
Automobile	Equals one if a policy covers automobile liability, and zero otherwise	Certificates of Liability Insurance
Umbrella & excess	Equals one if a policy covers Umbrella or excess liability, and zero otherwise	Certificates of Liability Insurance
Workers compensation	Equals one if a policy covers workers compensation and employers' liability, and zero otherwise	Certificates of Liability Insurance
	Panel C: Insurer-mine relationship characteristics	
Coal policy	Equals one for policy-adopting insurers, and zero otherwise	IOF scorecards and Certificates of Liability Insurance
Active insurance	Equals one for quarters in which the insurer insures the mine, and zero otherwise	Certificates of Liability Insurance
Length active insurance	Time in quarters since which the insurer insures the mine	Certificates of Liability Insurance
Past active insurance	Equals one if the insurer insured the mine in any quarter since the beginning of the sample period until the previous quarter, and zero otherwise	Certificates of Liability Insurance
Past year active insurance	Equals one if the insurer insured the mine in any of the previous four quarters, and zero otherwise	Certificates of Liability Insurance
Prob. past active insurance	Share of quarters in which the insurer insured the mine since the beginning of the sample period until the previous quarter	Certificates of Liability Insurance
	Panel D: Mine characteristics	
Coal policy exposed	Equals one if, between 2014 and 2016, a mine is insured by an insurer that subsequently adopted a coal underwriting policy, and zero otherwise	IOF scorecards and Certificates of Liability Insurance
Share coal policy exposed	Equals $\sum_i w_{m,i} \times \mathit{Post\ coal\ policy}_{i,t}$ for a mine-quarter, where i indexes an insurer, m a mine and t a quarter. w are equal weights allocated to each insurer with at least eight quarters of active insurance relationship with a mine between 2014 and 2016, and *Post coal policy* equals one for insurer-quarters after a coal underwriting policy is introduced, and zero otherwise.	IOF scorecards and Certificates of Liability Insurance
Abandoned	Equals one if mine status in a quarter is either abandoned or abandoned and sealed, and zero otherwise	MSHA
Production	Million short tons (MMst) of coal produced by a mine in a quarter	MSHA
# Active insurers	Number of insurers actively covering a mine in a quarter. The corresponding variables for insurers with and without a coal policy count insurers that have, respectively have not, adopted a coal underwriting policy	Certificates of Liability Insurance
Mean # active lines	Average number of active insurance lines of each mine's insurers in a given quarter. The corresponding variables for insurers with and without a coal policy restrict to insurers that have, respectively have not, adopted a coal underwriting policy	Certificates of Liability Insurance
Productive mine	Equals one if a mine has an above-median average quarterly output per working hour between 2014 and 2016, and zero otherwise	MSHA

Large mine	Equals one if a mine has an above-median total coal production between 2014 and 2016, and zero otherwise	MSHA
High accident number	Equals one if a mine has an above-median total number of accidents between 2014 and 2016, and zero otherwise	MSHA
High coal shipment price	Equals one if a mine is in a state with an above-median average price of coal shipped to power plants between 2014 and 2016, and zero otherwise	EIA

References

Abraham, Kenneth S, and Daniel Schwarcz, 2022, The limits of regulation by insurance, *Indiana Law Journal* 98, 215–275.

Acharya, Viral, Richard Berner, Robert Engle, Hyeyoon Jung, Johannes Stroebel, Xuran Zeng, and Yihao Zhao, 2023, Climate stress testing, *Annual Review of Financial Economics* 15, 291–326.

Alliance Resource Partners, 2023, 10-k, *EDGAR,* Available at: https://www.sec.gov/Archives/edgar/data/1086600/000155837023002034/arlp-20221231x10k.htm (Accessed: May 26, 2025).

Allianz, 2025a, Allianz sustainability integration framework, October 2025. https://www.allianz.com/content/dam/onemarketing/azcom/Allianz_com/sustainability/documents/Allianz_ESG_Integration_Framework.pdf (Accessed: July 16, 2026).

Allianz, 2025b, Statement on coal-based business models, Available at: https://www.allianz.com/content/dam/onemarketing/azcom/Allianz_com/responsibility/documents/allianz-statement-on-coal-2025.pdf (Accessed: July 2, 2026).

Allianz, 2025c, Statement on oil and gas business models, Available at: https://www.allianz.com/content/dam/onemarketing/azcom/Allianz_com/responsibility/documents/allianz-statement-on-oil-and-gas-2025.pdf (Accessed: July 2, 2026).

Allianz, 2025d, Statement on oil sands business models, Available at: https://www.allianz.com/content/dam/onemarketing/azcom/Allianz_com/responsibility/documents/allianz-statement-on-oil-sands-2025.pdf (Accessed: July 2, 2026).

Amiti, Mary, and David E Weinstein, 2018, How much do idiosyncratic bank shocks affect investment? Evidence from matched bank-firm loan data, *Journal of Political Economy* 126, 525–587.

Arch Resources, 2021, 10-k, *EDGAR,* Available at: https://www.sec.gov/Archives/edgar/data/1037676/000155837021000957/arch-20201231x10k.htm (Accessed: May 26, 2025).

AXA, 2018, AXA signs the tobacco free finance pledge, September 26, 2018. https://www.axa.com/en/news/axa-signs-the-tobacco-free-finance-pledge (Accessed: July 16, 2026).

Baker, Andrew, Brantly Callaway, Scott Cunningham, Andrew Goodman-Bacon, and Pedro H. C. Sant'Anna, 2026, Difference-in-Differences Designs: A Practitioner's Guide, *Journal of Economic Literature* 64, 498–557.

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

Ben-Sahar, Omri, and Kyle Logue, 2012, Outsourcing regulation: How insurance reduces moral hazard, *Michigan Law Review* 111, 197–248.

Berg, Tobias, Markus Reisinger, and Daniel Streitz, 2021, Spillover effects in empirical corporate finance, *Journal of Financial Economics* 142, 1109–1127.

Berg, Tobias, Robin Röttling, Xander Hut, and Wolf Wagner, 2025, Do voluntary initiatives make loans greener? Evidence from project finance, SSRN Working Paper 4781649.

Boomhower, Judson, 2019, Drilling like there's no tomorrow: Bankruptcy, insurance, and environmental risk, *American Economic Review* 109, 391–426.

Boomhower, Judson, Meredith Fowlie, Jacob Gellman, and Andrew Plantinga, 2025, How are insurance markets adapting to climate change? Risk classification and pricing in the market for homeowners insurance, NBER Working Paper w32625.

Cai, Jing, 2016, The impact of insurance provision on household production and financial decisions, *American Economic Journal: Economic Policy* 8, 44–88.

Charles, Kerwin Kofi, Matthew S. Johnson, Melvin Stephens Jr., and Do Q. Lee, 2022, Demand conditions and worker safety: Evidence from price shocks in mining, *Journal of Labor Economics* 40, 47–94.

Chen, Alvin, and Michael Wittry, 2025, Production and externalities: How corporate governance shapes social costs, SSRN Working Paper 5177020.

Chodorow-Reich, Gabriel, 2014, The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis, *Quarterly Journal of Economics* 129, 1–59.

ClientEarth, 2022, Fossil fuels and climate change: The facts, Available at: https://www.clientearth.org/latest/news/fossil-fuels-and-climate-change-the-facts/ (Accessed: May 26, 2025).

Cohen, Alma, 2012, Asymmetric learning in repeated contracting: An empirical study, *The Review of Economics and Statistics* 94, 419–432.

Cohen, Alma, and Rajeev Dehejia, 2004, The effect of automobile insurance and accident liability laws on traffic fatalities, *Journal of Law and Economics* 47, 357–393.

Cohn, Jonathan B., Zack Liu, and Malcolm I. Wardlaw, 2022, Count (and count-like) data in finance, *Journal of Financial Economics* 146, 529–551.

CONSOL Energy, 2020, 10-k, *EDGAR,* Available at: https://www.sec.gov/Archives/edgar/data/1710366/000171036620000006/ceix-12312019form10xk.htm (Accessed: May 26, 2025).

de Chaisemartin, Clément, and Xavier d'Haultfœuuille, 2026, Difference-in-differences estimators of intertemporal treatment effects, *Review of Economics and Statistics* forthcoming.

de Chaisemartin, Clément, Diego Ciccia, Xavier D'Haultfœuille, Felix Knau, Mélitine Malézieux, and Doulu Sow, 2025, Event-study estimators and variance estimators computed by the `did_multiplegt_dyn` command, SSRN Working Paper 4953691.

Degryse, Hans, Olivier De Jonghe, Sanja Jakovljević, Klaas Mulier, and Glenn Schepens, 2019, Identifying credit supply shocks with bank-firm data: Methods and applications, *Journal of Financial Intermediation* 40, 1–15.

Degryse, Hans, and Patrick Van Cayseele, 2000, Relationship lending within a bank-based system: Evidence from european small business data, *Journal of Financial Intermediation* 9, 90–109.

Dimson, Elroy, Oğuzhan Karakaş, and Xi Li, 2015, Active ownership, *Review of Financial Studies* 22, 3225–3268.

Doherty, Neil, and Lisa Posey, 1997, Availability crises in insurance markets: optimal contracts with asymmetric information and capacity constraints, *Journal of Risk and Uncertainty* 15, 55–80.

Ellul, Andrew, Chotibhak Jotikasthira, and Christian T. Lundblad, 2011, Regulatory pressure and fire sales in the corporate bond market, *Journal of Financial Economics* 101, 596–620.

Enerdata, 2025, World energy & climate statistics—Yearbook of world energy statistics, https://yearbook.enerdata.net/ (Accessed: July 16, 2026).

Flammer, Caroline, 2021, Corporate green bonds, *Journal of Financial Economics* 142, 499–516.

French, Eric, and John Bailey Jones, 2011, The effects of health insurance and self-insurance on retirement behavior, *Econometrica* 79, 693–732.

Froot, Kenneth A., 2001, The market for catastrophe risk: A clinical examination, *Journal of Financial Economics* 60, 529–571.

Gasparini, Matteo, and Peter Tufano, 2025, An empirical examination of business climate alliances: Effective and/or harmful?, Harvard Business School Working Paper 25-060.

Ge, Shan, 2022, How do financial constraints affect product pricing? Evidence from weather and life insurance products, *Journal of Finance* 77, 449–503.

Ge, Shan, Stephanie Johnson, and Nitzan Tzur-Ilan, 2026, The effect of rising insurance premiums on mortgage delinquency and household relocation, SSRN Working Paper 4992281.

Ge, Shan, Ammon Lam, and Ryan Lewis, 2025, The effect of insurance premiums on the housing market and climate risk pricing, SSRN Working Paper 4192699.

Ge, Shan, and Michael S. Weisbach, 2021, The role of financial conditions in portfolio choices: The case of insurers, *Journal of Financial Economics* 142, 803–830.

Generali, 2026, Human rights statement, January 30, 2026. https://www.generali.com/sustainability/our-rules/respecting-human-rights (Accessed: July 11, 2026).

Giannetti, Mariassunta, Martina Jasova, Maria Loumioti, and Caterina Mendicino, 2025, "Glossy green'' banks: The disconnect between environmental disclosures and lending activities, *Management Science* forthcoming.

Gilje, Erik, and Michael Wittry, 2022, Is public equity deadly? Evidence from workplace safety and productivity tradeoffs in the coal industry, SSRN Working Paper 3810655.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift, 2020, Bartik instruments: What, when, why, and how, *American Economic Review* 110, 2586–2624.

Gormley, Todd A., and David A. Matsa, 2011, Growing out of trouble? Corporate responses to liability risk, *Review of Financial Studies* 24, 2781–282.

Gormsen, Niels Joachim, Kilian Huber, and Sangmin Oh, 2025, Climate capitalists, NBER Working Paper 32933.

Green, Daniel, and Boris Vallee, 2025, Measurement and effects of bank exit policies, *Journal of Financial Economics* 172, 104129.

Guidehouse Inc., 2022, North Dakota insurance reserve fund insurance study, Available at: https://ndlegis.gov/files/committees/67-2021/23_5148_02000presentation1130.pdf (Accessed: May 26, 2025).

Hartzmark, Samuel M., and Abigail B. Sussman, 2019, Do investors value sustainability? A natural experiment examining ranking and fund flows, *Journal of Finance* 74, 2789–2837.

Hastreiter, Nikolaus, 2025, Can investor coalitions drive corporate climate action?, Working Paper, London School of Economics.

Haushalter, David, Joseph Henry, and Peter Iliev, 2023, Can banks save mountains?, *Review of Corporate Finance Studies* 12, 761–791.

He, Yazhou Ellen, Bige Kahraman, and Michelle Lowry, 2023, ES risks and shareholder voice, *Review of Financial Studies* 36, 4824–4863.

Huber, Kilian, 2018, Disentangling the effects of a banking crisis: Evidence from German firms and counties, *American Economic Review* 108, 868–898.

IEA, 2021, It's critical to tackle coal emissions, Available at: `https://www.iea.org/commentaries/it-s-critical-to-tackle-coal-emissions` (Accessed: May 26, 2025).

IOF, 2023, Fifty years of climate failure, Available at: `https://global.insure-our-future.com/wp-content/uploads/2023/11/IOF-2023-Scorecard.pdf` (Accessed: December 14, 2025).

Ivanov, Ivan T., Mathias S. Kruttli, and Sumudu W. Watugala, 2024, Banking on carbon: Corporate lending and cap-and-trade policy, *Review of Financial Studies* 37, 1640–1684.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina, 2014, Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking?, *Econometrica* 82, 463–505.

Jung, Hyeyoon, Robert Engle, Shan Ge, and Xuran Zeng, 2024, Physical climate risk factors and an application to measuring insurers' climate risk exposure, SSRN Working Paper 4510592.

Kacperczyk, Marcin, and José-Luis Peydró, 2022, Carbon emissions and the bank-lending channel, SSRN Working Paper 3915486.

Karlan, Dean, Robert Osei, Isaac Osei-Akoto, and Christopher Udry, 2014, Agricultural decisions after relaxing credit and risk constraints, *Quarterly Journal of Economics* 129, 597–652.

Keys, Benjamin J., and Philip Mulder, 2024, Property insurance and disaster risk: New evidence from mortgage escrow data, NBER Working Paper w32579.

Khwaja, Asim Ijaz, and Atif Mian, 2008, Tracing the impact of bank liquidity shocks: Evidence from an emerging market, *American Economic Review* 98, 1413–1442.

Kim, Minjoo, Prateek Mahajan, and Zirui Wang, 2025, The rise in insurance costs for commercial properties: Causes, effects on rents, and the role of owners, SSRN Working Paper 5175451.

Knox, Benjamin, and Jakob Ahm Sørensen, 2024, Insurers' investments and insurance prices, SSRN Working Paper 4394474.

Koijen, Ralph S.J., and Motohiro Yogo, 2015, The cost of financial frictions for life insurers, *American Economic Review* 105, 445–475.

Koijen, Ralph S.J., and Motohiro Yogo, 2023a, *Financial Economics of Insurance* (Princeton University Press).

Koijen, Ralph S.J., and Motohiro Yogo, 2023b, Understanding the ownership structure of corporate bonds, *American Economic Review: Insights* 5, 73–92.

Krueger, Philipp, Zacharias Sautner, and Laura T. Starks, 2020, The importance of climate risks for institutional investors, *Review of Financial Studies* 33, 1067–1111.

Kubitza, Christian, 2026, Investor-driven corporate finance: Evidence from insurance markets, *Review of Financial Studies* forthcoming.

Meyer, Bruce D., 1990, Unemployment insurance and unemployment spells, *Econometrica* 58, 757–782.

Morse, Adair, and Parinitha Sastry, 2025, The economics of net zero banking, *Annual Review of Financial Economics* 17, 343–361.

NACCO Industries, 2022, 10-k, *EDGAR,* Available at: https://www.sec.gov/Archives/edgar/data/789933/000078993323000016/nacco-20221231.htm (Accessed: May 26, 2025).

Nickell, Stephen, 1981, Biases in dynamic models with fixed effects, *Econometrica* 49, 1417–1426.

Oehmke, Martin, and Marcus M. Opp, 2025, A theory of socially responsible investment, *Review of Economic Studies* 92, 1193–1225.

Oh, Sangmin, Ishita Sen, and Ana-Maria Tenekedjieva, 2026, Pricing of climate risk insurance: Regulation and cross-subsidies, *Journal of Finance* 81, 1161–1215.

Ongena, Steven, and David C. Smith, 2001, The duration of bank relationships, *Journal of Financial Economics* 61, 449–475.

Petersen, Mitchell A., and Raghuram G. Rajan, 1994, The benefits of lending relationships: Evidence from small business data, *Journal of Finance* 49, 3–37.

Qiu, Yue, Aaron Sojourner, and Paolo Volpin, 2025, M&A and workplace safety: Evidence from mines, SSRN Working Paper 4952912.

Rappaport, John, 2016, How private insurers regulate public police, *Harvard Law Review* 130, 1539–1614.

Sastry, Parinitha, Ishita Sen, and Ana-Maria Tenekedjieva, 2026, When insurers exit: Climate losses, fragile insurers, and mortgage markets, *Quarterly Journal of Economics* forthcoming.

Sastry, Parinitha, Emil Verner, and David Marques-Ibanez, 2024, Business as usual: Bank climate commitments, lending, and engagement, ECB Working Paper 2024/2921.

SCOR, 2017, Scor announces further environmental sustainability initiatives, Available at: https://www.scor.com/sites/default/files/23_-_coal_disengagement_veng.pdf (Accessed: May 26, 2025).

Sharpe, Steven A., 1990, Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships, *Journal of Finance* 45, 1069–1087.

Shavell, Steven, 1982, On liability and insurance, *Bell Journal of Economics* 13, 120–132.

Shavell, Steven, 2000, On the social function and the regulation of liability insurance, *Geneva Papers on Risk and Insurance* 25, 166–179.

Shavell, Steven, 2005, Minimum asset requirements and compulsory liability insurance as solutions to the judgment-proof problem, *RAND Journal of Economics* 36, 63–77.

Smith, Ian, and Harry Dempsey, 2022, Insurance ban to tighten squeeze on russian oil shipments, *Financial Times,* Available at: https://www.ft.com/content/0c62b2d6-315f-43bf-abd2-674753b27cbe (Accessed: May 8, 2025).

S&P Global, 2023, The world's largest P&C insurers, 2023, Available at: https://www.spglobal.com/marketintelligence/en/news-insights/blog/the-worlds-largest-p-and-c-insurers-2023 (Accessed: May 26, 2025).

Talesh, Shauhin A, 2016, Insurance companies as corporate regulators: The good, the bad, and the ugly, *DePaul Law Review* 66, 463–502.

Triebert, Christiaan, Blacki Migliozzi, Neil Bedi, and Alexander Cardia, 2024, The $2.8 billion hole in U.S. sanctions on Iran, *The New York Times,* Available at: https://www.nytimes.com/interactive/2024/02/16/world/middleeast/iran-oil-tankers-sanctions.html (Accessed: May 26, 2025).

von Thadden, Ernst-Ludwig, 2004, Asymmetric information, bank lending and implicit contracts: The winner's curse, *Finance Research Letters* 1, 11–23.

Yin, Haitao, Howard Kunreuther, and Matthew White, 2011, Risk-based pricing and risk-reducing effort: Does the private insurance market reduce environmental accidents?, *Journal of Law and Economics* 54, 325–363.

Zurich, 2025, Zurich has implemented positions for its investment and underwriting portfolios to restrict support of new fossil fuel developments, Available at: https://www.zurich.com/sustainability/governance-and-positions/our-positions/fossil-fuels (Accessed: May 26, 2025).

Figure 1: Prevalence and design of coal underwriting policies over time

The figure shows the number of insurers whose coal underwriting policies incorporate specific policy features. The sample is based on annual scorecards compiled by Insure Our Future (IOF) and includes up to 25 insurers with coal underwriting policies in place.

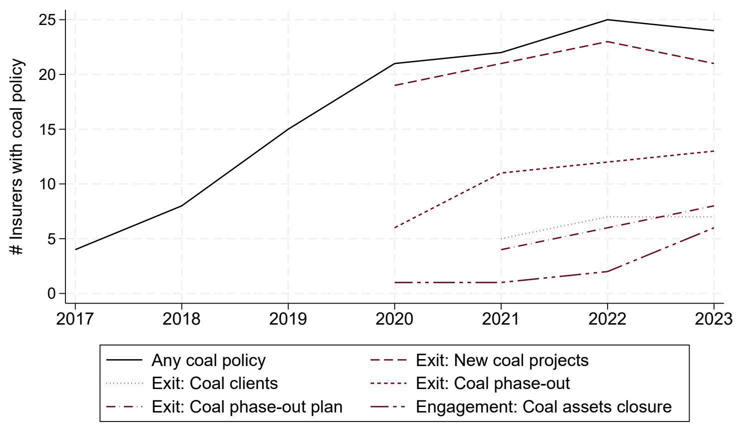


Figure 2: Stringency of coal underwriting policies over time

The figure displays scores capturing the stringency of coal underwriting policies over time. Scores range from 0 to 10, with higher values indicating more restrictive policies. Each dot represents an individual insurer in a given year. The solid line connects average scores by year. The two insurers with the highest and lowest overall coal policy scores in the final sample year (2023) are highlighted with colored dots. The sample is based on annual scorecards compiled by Insure Our Future (IOF) and includes 25 insurers with coal underwriting policies in place.

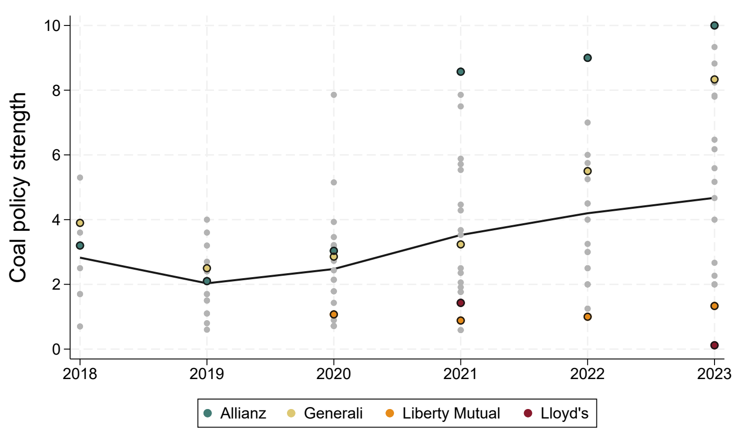
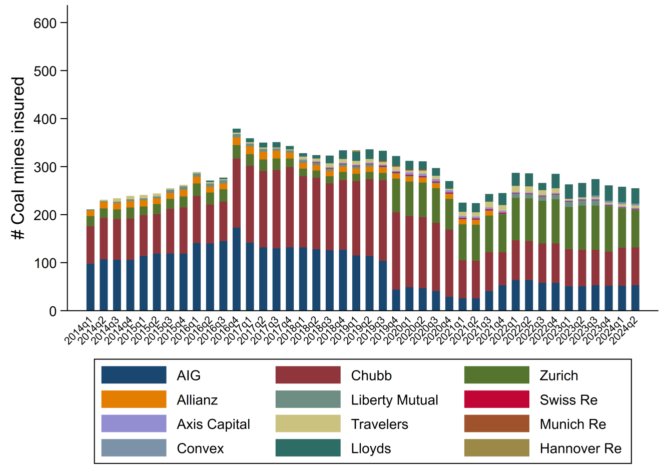


Figure 3: Number of insured coal mines over time

The figure displays the number of insured coal mines over time. For each insurer-quarter, we count the number of unique mines insured by that insurer. Panel A presents this information for insurers that adopted a coal underwriting policy at any point during the sample period, while Panel B presents this information for those that never did. The sample includes all coal mines that appear in MSHA's Mine Data Retrieval System between 2014Q1 and 2024Q2, provided they report at least one quarter of non-zero production, and for which we successfully obtained Certificates of Liability Insurance on ACORD 25 forms from state-level agencies. Table A.1 provides descriptions of all variables.

Panel A: Insurers adopting a coal underwriting policy



Panel B: Insurers never adopting a coal underwriting policy

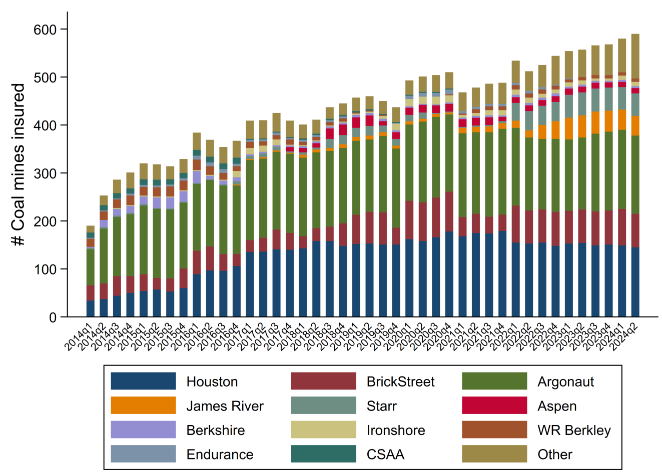


Figure 4: Coal mines' insurance status and underwriting policies

This figure displays coefficient estimates and 90% confidence intervals from the following OLS regression:

$$Active\ insurance_{s,m,i,t} = \sum_{t=-6}^{t=6} \beta_t \times Coal\ policy_i \times Event\ quarter_{s,t} + \alpha_{s,m,i} + \alpha_{s,m,t} + \epsilon_{s,m,i,t},$$

where s indexes a stack, m indexes a mine, i an insurer, and t a quarter. The dependent variable, *Active insurance*, equals one if an insurer insures a mine in a given quarter, and zero otherwise. *Coal policy* equals one for policy-adopting insurers, and zero otherwise. *Event quarter* are dummy variables indicating quarters relative to treatment, where treatment is the first quarter after coal policy adoption. $\alpha_{s,m,i}$ are stack-mine-insurer fixed effects, while $\alpha_{s,m,t}$ are stack-mine-time fixed effects. The initial sample includes all coal mines that appear in MSHA's Mine Data Retrieval System between 2014Q1 and 2024Q2, report at least one quarter of non-zero production, and have insurance certificate data available for those quarters. For each insurer that adopts a coal underwriting policy, we identify all mines it insures and construct a balanced sample of 13 quarterly observations per mine-insurance pair, whenever information on the liability insurance certificates of a given mine is available. These mine-insurer pairs form the treated relationships in the stack. As a control group, we include all other relationships that the same mines have with insurers that never adopt a coal underwriting policy. Standard errors are clustered at the insurer-stack level. Table A.1 provides descriptions of all variables.

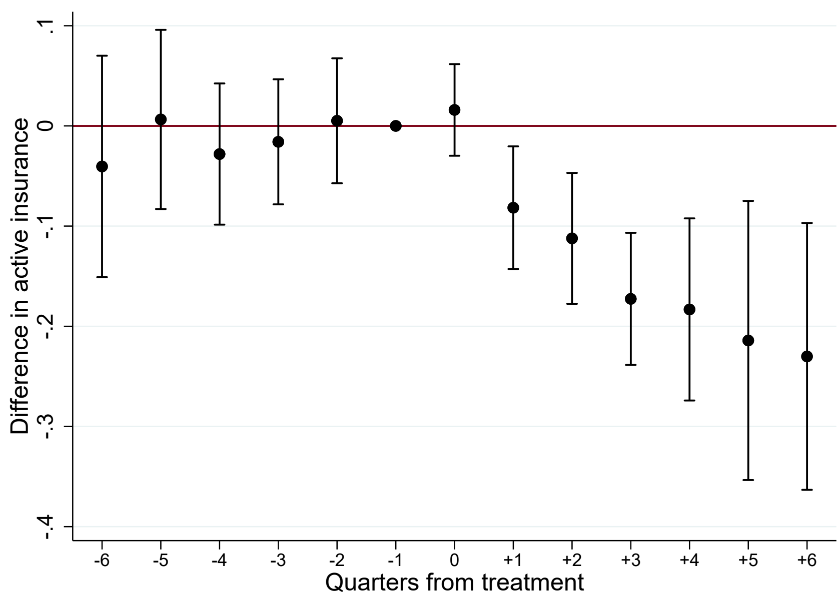


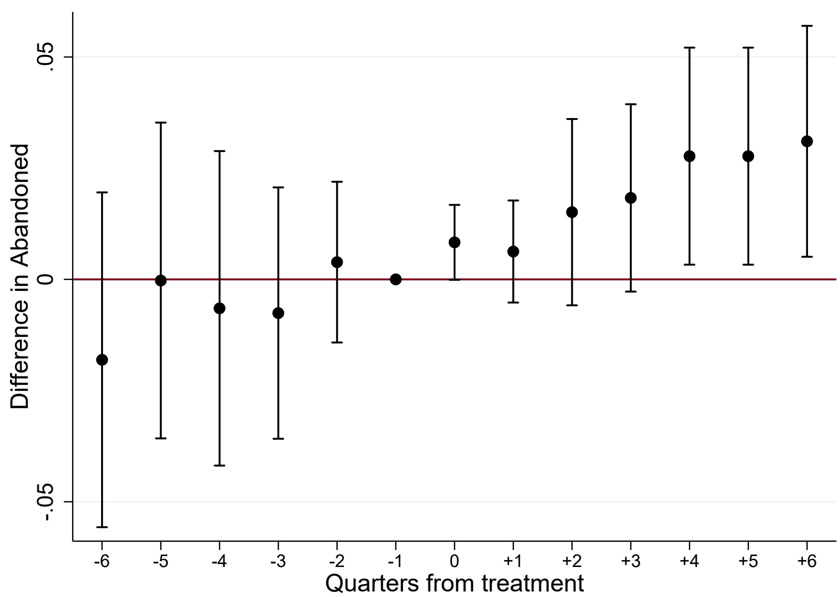
Figure 5: Coal mine outcomes and underwriting policies

This figure displays coefficient estimates and 90% confidence intervals from the following OLS regression:

$$\textit{Coal mine outcome}_{s,m,t} = \sum_{t=-6}^{t=6} \beta_t \times \textit{Coal policy exposed}_{s,m} \times \textit{Event quarter}_{s,t} \; + \alpha_{s,m} + \alpha_{s,t} + \epsilon_{s,m,t},$$

where s indexes a stack, m a mine, and t a quarter. The dependent variable, *Coal mine outcome*, is a dummy variable indicating whether a mine is abandoned (Panel A) or the (log of) volume of coal produced (Panel B). *Coal policy exposed* equals one for mines that, between 2014 and 2016, are insured by an insurer that subsequently adopted a coal underwriting policy, and zero otherwise. *Event quarter* are dummy variables indicating quarters relative to treatment, where treatment is the first quarter after the earliest coal policy adoption. If a mine is exposed to multiple such adoptions, only the first instance is used to define treatment. The sample includes all mines from Table 4, provided that we successfully obtained Certificates of Liability Insurance on ACORD 25 forms from state-level agencies between 2014 and 2016. In Panel B, the sample includes only mines that are active throughout the entire sample period. Standard errors are clustered at the mine-stack level. Table A.1 provides descriptions of all variables.

Panel A: Abandoned



Panel B: Production

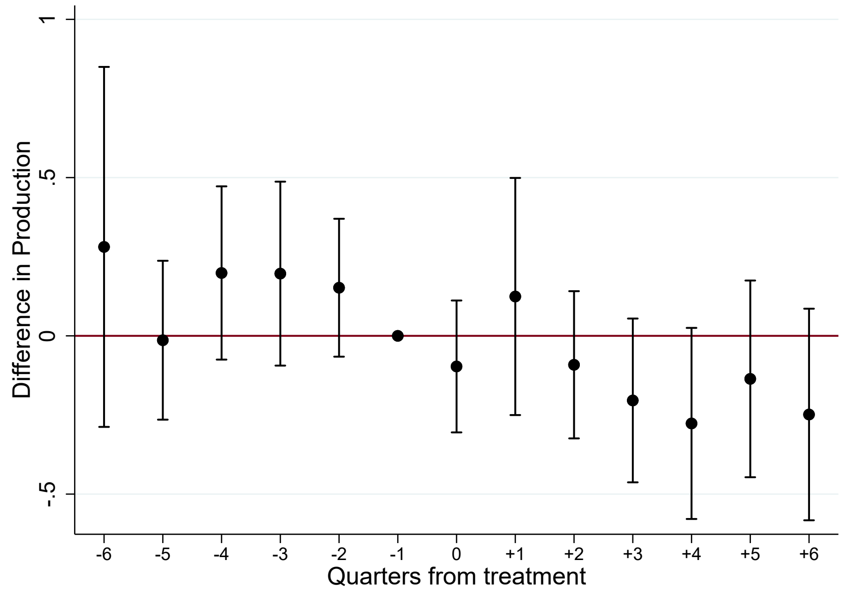


Table 1: Determinants of coal underwriting policies

This table presents results from the following OLS regression:

$$Y_{i,t} = \beta \times X_{i,t-1} + \alpha_t + \epsilon_{i,t},$$

where i indexes an insurer and t a year. In Column 1, the dependent variable, Y, is *Post coal policy*, which equals one for policy-adopting insurers after adoption, and zero otherwise. In Column 2, Y is *Coal policy score*, which is a score ranging from 0 to 10, with higher scores indicating stricter coal underwriting policies. X is a vector of insurer-level characteristics. The sample is based on annual scorecards compiled by Insure Our Future (IOF); Column 2 additionally conditions on insurers with a policy in place. Standard errors are clustered at the insurer level and reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. Table A.1 provides descriptions of all variables.

	Post coal policy	*Coal policy score*
	(1)	(2)
CCPI	0.009**	0.077***
	(0.004)	(0.022)
NZIA	0.013	1.935**
	(0.092)	(0.708)
Specialty insurer	-0.313**	-0.518
	(0.146)	(0.969)
Unlisted insurer	-0.419***	-2.403*
	(0.137)	(1.243)
High fossil fuel GWP share	-0.222**	0.454
	(0.094)	(0.735)
Total Assets (log)	-0.005	-0.201
	(0.050)	(0.336)
ROA	-0.037*	-0.242*
	(0.019)	(0.141)
Time FE	Yes	Yes
Obs.	180	115
Adj. R^2	0.404	0.477
# Insurers in sample	32	25

Table 2: Descriptive statistics on coal mines and underwriting policies

This table presents descriptive statistics on coal mines and underwriting policies. The sample includes all coal mines that appear in MSHA's Mine Data Retrieval System between 2014Q1 and 2024Q2, provided they report at least one quarter of non-zero coal production, and for which we successfully obtained Certificates of Liability Insurance on ACORD 25 forms from state-level agencies. In Panel A, the sample is at the mine-quarter-insurer level. In Panel B, the sample is collapsed at the insurer-quarter level. In Panel C, the sample is collapsed at the mine-quarter level. Table A.1 provides descriptions of all variables.

	Obs.	Mean	Std.	25th	Median	75th
Panel A: Insurer-mine-quarter sample						
Coal policy	53,407	0.50				
Active insurance	53,407	0.41				
Length active insurance (quarters)	53,407	14.29	9.14	8.00	12.00	19.00
Past active insurance	52,444	0.70				
Past year active insurance	52,444	0.31				
Prob. past active insurance	52,444	0.33	0.33	0.00	0.22	0.56
Panel B: Insurer-quarter sample						
Coal policy	1,353	0.25				
# Coal mines insured	1,353	22.46	42.27	2.00	4.00	15.00
Coal volume insured (MMst)	1,353	5.56	11.34	0.00	0.50	4.35
Panel C: Mine-quarter sample						
Coal policy exposed	13,222	0.89				
Share coal policy exposed	7,342	0.25	0.40	0.00	0.00	0.50
# Active insurers	10,249	1.80	0.85	1.00	2.00	2.00
# Active insurers w/ coal policy	10,249	0.90	0.74	0.00	1.00	1.00
# Active insurers w/o coal policy	10,249	0.90	0.81	0.00	1.00	1.00
Mean # active lines all insurers	10,249	0.64	0.36	0.33	0.60	0.90
Mean # active lines insurers w/ coal policy	10,249	0.58	0.62	0.00	0.50	1.00
Mean # active lines insurers w/o coal policy	10,249	0.70	0.75	0.00	0.50	1.00
Abandoned mine	13,222	0.11				
Production (MMst)	13,222	0.40	1.74	0.00	0.01	0.14
Productive mine	12,055	0.49				
Large mine	13,222	0.51				
High accident number	12,852	0.49				
High coal shipment price	13,222	0.58				

Table 3: Insurers' coal underwriting activity and underwriting policies

This table presents results from the following OLS regression:

$$Coal\ insurance_{i,t} = \beta \times Post\ coal\ policy_{i,t} + \alpha_i + \alpha_t + \epsilon_{i,t},$$

where i indexes an insurer and t a quarter. In Columns 1 and 3, the dependent variable, *Coal insurance*, is *# Coal mines insured*, which is the (log of) number of mines insured by an insurer in a given quarter. In Columns 2 and 4, *Coal insurance* is *Coal volume insured*, which is the (log of) volume of insured coal that is produced. *Post coal policy* equals one for policy-adopting insurers after adoption, and zero otherwise. The sample includes all coal mines that appear in MSHA's Mine Data Retrieval System between 2014Q1 and 2024Q2, provided they report at least one quarter of non-zero coal production, and for which we successfully obtained Certificates of Liability Insurance on ACORD 25 forms from state-level agencies. In Columns 3 and 4, the sample includes only mines that are active throughout the entire sample period. Robust standard errors are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. Table A.1 provides descriptions of all variables.

	# Coal mines insured (log)	*Coal volume insured* (log)	*# Coal mines insured* (log)	*Coal volume insured* (log)
	All coal mines		Active coal mines	
	(1)	(2)	(3)	(4)
Post coal policy	-0.178**	-1.066***	-0.428***	-0.761***
	(0.074)	(0.190)	(0.080)	(0.166)
Insurance group FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Obs.	1,353	1,044	788	740
Adj. R^2	0.856	0.827	0.808	0.802
# Insurance groups	56	48	33	32

Table 4: Coal mines' insurance status and underwriting policies

This table presents results from the following OLS regression:

$$Active\ insurance_{s,m,i,t} = \beta \times Coal\ policy_i \times Post_{s,t} + \alpha_{s,m,i} + \alpha_{s,m,t} + \epsilon_{s,m,i,t},$$

where s indexes a stack, m a mine, i an insurer, and t a quarter. The dependent variable, *Active insurance*, equals one if an insurer insures a mine in a given quarter, and zero otherwise. *Coal policy* equals one for policy-adopting insurers, and zero otherwise. *Post* equals one for the first quarter after adoption of a coal policy and all quarters thereafter, and zero otherwise. The initial sample includes all coal mines that appear in MSHA's Mine Data Retrieval System between 2014Q1 and 2024Q2, report at least one quarter of non-zero production, and have insurance certificate data available for those quarters. For each insurer that adopts a coal underwriting policy, we identify all mines it insures and construct a balanced sample of 13 quarterly observations per mine-insurance pair, whenever information on the liability insurance certificates of a given mine is available. These mine-insurer pairs form the treated observations in the stack. As control observations, we include all other mine-insurer pairs that include the same mines but insurers that never adopt a coal underwriting policy. In Column 2, the sample includes only mines that are active throughout the entire sample period. Standard errors are clustered at the insurer-stack level and reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. Table A.1 provides descriptions of all variables.

	Active insurance	
	All coal mines	Active coal mines
	(1)	(2)
Coal policy × *Post*	-0.127**	-0.123*
	(0.054)	(0.066)
Stack × Insurance group × Coal mine FE	Yes	Yes
Stack × Coal mine × Time FE	Yes	Yes
Obs.	27,628	5,206
Adj. R^2	0.582	0.570
# Insurance groups	51	28

Table 5: Cross-sectional variation in implementation

In Columns 1 and 2, this table presents variants of the following OLS regression:

$$Active\ insurance_{s,m,i,t} = \beta \times Coal\ policy\ score_i \times Post_{s,t} + \alpha_{s,m,i} + \alpha_{s,m,t} + \epsilon_{s,m,i,t},$$

while Columns 3 and 4 present variants of the following OLS regression:

$$\begin{aligned} Active\ insurance_{s,m,l,i,t} = & \beta_1 \times Coal\ policy_i \times Post_{s,t} \times Insurance\ line_l + \beta_2 \times Coal\ policy_i \times Post_{s,t} \\ & + \beta_3 \times Post_{s,t} \times Insurance\ line_l + \alpha_{s,m,l,i} + \alpha_{s,m,t} + \epsilon_{s,m,l,i,t}, \end{aligned}$$

where s indexes a stack, m a mine, l an insurance line, i an insurer, and t a quarter. The dependent variable, *Active insurance*, equals one if an insurer insures a mine in a given quarter, and zero otherwise. *Coal policy* equals one for policy-adopting insurers, and zero otherwise. *Post* equals one for the first quarter after adoption of a coal policy and all quarters thereafter, and zero otherwise. The initial sample of mines includes all coal mines that appear in MSHA's Mine Data Retrieval System between 2014Q1 and 2024Q2, provided they report at least one quarter of non-zero coal production, and for which we successfully obtained Certificates of Liability Insurance on ACORD 25 forms from state-level agencies. For Columns 1 and 2, we define the unit of observation as a mine-insurer pair. For each insurer that adopts a coal underwriting policy, we identify all mines it insures and construct a balanced sample of 13 quarterly observations per pair, whenever liability insurance certificate data are available. These mine-insurer pairs form the treated observations in the stack. As controls, we include all other mine-insurer pairs involving the same mines but insurers that never adopt a coal underwriting policy. Standard errors are clustered at the insurer-stack level. For Columns 3 and 4, we repeat this procedure at the finer level of mine-insurance line-insurer triplets. That is, we construct balanced panels of 13 quarterly observations per triplet and stack them analogously. As the first IOF scorecard, published in 2017, does not include stringency scores, we use the 2018 stringency scores for insurers that adopted a policy in 2017. Standard errors are clustered at the insurer-insurance line-stack level and reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. Table A.1 provides descriptions of all variables.

Table 5: (continued)

	Active insurance			
	(1)	(2)	(3)	(4)
First coal policy score × Post	-0.042*			
	(0.023)			
Max coal policy score × Post		-0.026***		
		(0.010)		
Coal policy × Post			-0.094**	-0.128**
			(0.044)	(0.051)
Coal policy × Post × Automobile				0.027
				(0.075)
Coal policy × Post × Umbrella & excess				0.060
				(0.090)
Coal policy × Post × Workers compensation				0.137*
				(0.075)
Post × Automobile				-0.007
				(0.073)
Post × Umbrella & excess				-0.024
				(0.058)
Post × Workers compensation				0.035
				(0.060)
Stack × Insurance group × Coal mine FE	Yes	Yes		
Stack × Coal mine × Time FE	Yes	Yes		
Stack × Insurance group × Coal mine × Insurance type FE			Yes	Yes
Stack × Coal mine × Time FE			Yes	Yes
Obs.	27,628	27,628	47,199	47,199
Adj. R^2	0.580	0.580	0.617	0.619
# Insurance groups	51	51	51	51

Table 6: Persistence and substitution in coal mine insurance

Panel A presents results on the persistence of insurer-mine relationships, from the following OLS regression estimated at the mine-quarter-insurance level:

$$Active\ insurance_{m,i,t} = \beta \times X_{m,i,t} + \alpha_{i,t} + \alpha_{m,t} + \epsilon_{m,i,t},$$

where m indexes a mine, i an insurer, and t a quarter. The dependent variable, *Active insurance*, equals one if an insurer insures a mine in a given quarter, and zero if it does not. X is a mine-insurer level variable. In Columns 1 and 4, X is equal to 1 if the mine-insurance relationship is active anytime in the past (i.e., any t before and including $t-1$). In Columns 2 and 5, X is equal to 1 if the mine-insurance relationship is active in the previous 4 quarters (i.e., from $t-1$ to $t-4$). In Columns 3 and 6, X is the probability of the mine-insurance relationship being active anytime in the past (i.e., any t before and including $t-1$). Panels B and C present results on the substitution of insurers and of insurance lines, from OLS regressions estimated at the mine-quarter level:

$$\#Active\ insurers_{m,t} = \beta \times Post\ coal\ policy\ exposed_{m,t} + \alpha_m + \alpha_t + \epsilon_{m,t}.$$

In Panel B, the dependent variable, *# Active insurers*, is the number of insurers actively covering a mine in a given quarter, counting all insurers in Column 1, only insurers that have adopted a coal underwriting policy in Column 2 (*# Active insurers w/ coal policy*), and only insurers that have not in Column 3 (*# Active insurers w/o coal policy*). In Panel C, we use a variant of the regression in Panel B where the dependent variable is the corresponding average number of active insurance lines of the mine's insurers (*Mean # active lines*). *Post coal policy exposed* equals one for mines that, between 2014 and 2016, are insured by an insurer that subsequently adopted a coal underwriting policy, in the first quarter after the earliest adoption of such policy and all quarters thereafter, and zero otherwise. The sample includes all mines from Table 4, and quarters in which we successfully obtained Certificates of Liability Insurance on ACORD 25 forms from state-level agencies. For each mine, we retain every observed mine-insurer pair for all quarters with available certificate data, coding quarters without coverage as inactive. In all panels, standard errors are clustered at the mine level and reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. Table A.1 provides descriptions of all variables.

Panel A: Persistence in insurer-mine relationships

	Active insurance					
	(1)	(2)	(3)	(4)	(5)	(6)
Past active insurance	0.569***			0.666***		
	(0.011)			(0.014)		
Past year active insurance		0.725***			0.766***	
		(0.007)			(0.008)	
Prob. past active insurance			0.660***			0.695***
			(0.012)			(0.012)
Coal mine × Time FE	No	No	No	Yes	Yes	Yes
Insurance group × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	52,444	52,444	52,444	52,444	52,444	52,444
Adj. R^2	0.349	0.575	0.336	0.364	0.574	0.307
# Insurance groups	50	50	50	50	50	50

Panel B: Substitution on the extensive margin

	# Active insurers	*# Active insurers w/ coal policy*	*# Active insurers w/o coal policy*
	(1)	(2)	(3)
Post coal policy exposed	-0.125*	-0.345***	0.221***
	(0.069)	(0.066)	(0.083)
Coal mine FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Obs.	10,249	10,249	10,249
Adj. R^2	0.399	0.440	0.496
# Coal mines	296	296	296

Panel C: Substitution on the intensive margin

	Mean # active lines	*Mean # active lines of insurers w/ coal policy*	*Mean # active lines of insurers w/o coal policy*
	(1)	(2)	(3)
Post coal policy exposed	0.006	-0.227***	0.187***
	(0.028)	(0.059)	(0.068)
Coal mine FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Obs.	10,249	10,249	10,249
Adj. R^2	0.512	0.386	0.478
# Coal mines	296	296	296

Table 7: Coal mine outcomes and underwriting policies

This table presents results from two OLS regressions. Columns 1 and 2 are estimated at the mine-quarter level:

$$\textit{Coal mine outcome}_{m,t} = \beta \times \textit{Post coal policy exposed}_{m,t} + \alpha_m + \alpha_t + \epsilon_{m,t}$$

Columns 3 and 4 are estimated at the stack-mine-quarter level:

$$\textit{Coal mine outcome}_{s,m,t} = \beta \times \textit{Coal policy exposed}_m \times \textit{Post}_{s,t} + \alpha_{s,m} + \alpha_{s,t} + \epsilon_{s,m,t}$$

where s indexes a stack, m a mine, and t a quarter. The dependent variable, *Coal mine outcome*, is a dummy variable indicating whether a mine is abandoned (Columns 1 and 3) or the (log of) volume of coal produced (Columns 2 and 4). *Post coal policy exposed* equals one for mines that, between 2014 and 2016, are insured by an insurer that subsequently adopted a coal underwriting policy, in the first quarter after the earliest adoption of such policy and all quarters thereafter, and zero otherwise. *Coal policy exposed* equals one for mines that, between 2014 and 2016, are insured by an insurer that subsequently adopted a coal underwriting policy, and zero otherwise. *Post* equals one for the first quarter after adoption of a coal policy and all quarters thereafter, and zero otherwise. If a mine is exposed to multiple such adoptions, only the first instance is used to define treatment. The sample includes all mines from Table 4. In Columns 2 and 4, the sample includes only mines that are active throughout the entire sample period. Standard errors are clustered at the mine-level (Columns 1 and 2) or at the mine-stack level (Columns 3 and 4) and are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. Table A.1 provides descriptions of all variables.

	Abandoned	*Production (log)*	*Abandoned*	*Production (log)*
	(1)	(2)	(3)	(4)
Post coal policy exposed	0.042**	-0.135		
	(0.020)	(0.118)		
Coal policy exposed × *Post*			0.024	-0.270*
			(0.017)	(0.138)
Coal mine FE	Yes	Yes		
Time FE	Yes	Yes		
Stack × Coal mine FE			Yes	Yes
Stack × Time FE			Yes	Yes
Obs.	13,222	2,766	6,461	1,107
Adj. R^2	0.546	0.924	0.821	0.938
# Coal mines	317	69	317	67

Table 8: Cross-sectional variation in changes in coal mine outcomes

This table presents results from the following OLS regression estimated at the mine-quarter level:

$$\begin{aligned}Coal\ mine\ outcome_{s,m,t} = \beta_1 \times Coal\ policy\ exposed_m \times Post_{s,t} + \\ \beta_2 \times Coal\ policy\ exposed_m \times Post_{s,t} \times X_m + \beta_3 \times Post_{s,t} \times X_m + \alpha_{s,m} + \alpha_{s,t} + \epsilon_{s,m,t}\end{aligned}$$

where s indexes a stack, m a mine, and t a quarter. The dependent variable, *Coal mine outcome*, is a dummy variable indicating whether a mine is abandoned. *Coal policy exposed* and *Post* are defined as in Table 7. X is a mine-level dummy variable. In Column 1, X is *Productive mine*, defined as one if the mine has above-median average productivity (output per working hour) between 2014 and 2016. In Column 2, X is *Large mine*, defined as one if the mine has above-median total coal production between 2014 and 2016. In Column 3, X is *High accident number*, defined as one if the mine has an above-median number of safety incidents reported to MSHA between 2014 and 2016. In Column 4, X is *High coal shipment price*, defined as one if the mine faces an above-median coal shipment price between 2014 and 2016. The sample includes all mines from Table 4. Standard errors are clustered at the mine-stack level and reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. Table A.1 provides descriptions of all variables.

	Abandoned			
	(1)	(2)	(3)	(4)
Coal policy exposed × Post	0.001	0.000	0.010	-0.014
	(0.023)	(0.027)	(0.024)	(0.023)
Post × Productive mine	-0.046***			
	(0.018)			
Coal policy exposed × Post × Productive mine	0.038			
	(0.030)			
Post × Large mine		0.018		
		(0.016)		
Coal policy exposed × Post × Large mine		0.030		
		(0.029)		
Post × High accident rate			0.038**	
			(0.018)	
Coal policy exposed × Post × High accident number			0.013	
			(0.029)	
Post × High coal shipment price				-0.049***
				(0.017)
Coal policy exposed × Post × High coal shipment price				0.069**
				(0.028)
Stack × Coal mine FE	Yes	Yes	Yes	Yes
Stack × Time FE	Yes	Yes	Yes	Yes
Obs.	5,759	6,461	6,461	6,461
Adj. R^2	0.829	0.822	0.823	0.822
# Coal mines	288	317	317	317

Table 9: Coal mine outcomes, insurance coverage, and underwriting policies

This table presents results from two 2SLS specifications that instrument the loss of insurance coverage with the adoption of coal underwriting policies. Columns 1 and 2 are estimated at the insurer-mine-quarter level and instrument an insurer's active coverage of a mine with that insurer's own coal policy adoption:

$$\text{First stage: } \textit{Active insurance}_{m,i,t} = \pi_1 \times \textit{Post coal policy}_{i,t} + \alpha_{m,i} + \alpha_t + \epsilon_{m,i,t}$$

$$\text{Second stage: } \textit{Abandoned}_{m,t} = \beta \times \widehat{\textit{Active insurance}}_{m,i,t} + \alpha_{m,i} + \alpha_t + \mu_{m,i,t}$$

Columns 3 and 4 are estimated at the mine-quarter level and instrument the number of insurers actively covering a mine with the mine's exposure to policy-adopting insurers:

$$\text{First stage: } \#\ \textit{Active insurers}_{m,t} = \pi_1 \times \textit{Post coal policy exposed}_{m,t} + \alpha_m + \alpha_t + \epsilon_{m,t}$$

$$\text{Second stage: } \textit{Abandoned}_{m,t} = \beta \times \#\ \widehat{\textit{Active insurers}}_{m,t} + \alpha_m + \alpha_t + \mu_{m,t}$$

where m indexes a mine, i an insurance group, and t a quarter. *Active insurance* equals one if insurer i covers mine m in quarter t, and zero otherwise. *# Active insurers* is the number of insurers actively covering mine m in quarter t. *Abandoned* is a dummy variable indicating whether a mine is abandoned. *Post coal policy* equals one for policy-adopting insurers after adoption, and zero otherwise. *Post coal policy exposed* equals one for mines that, between 2014 and 2016, are insured by an insurer that subsequently adopted a coal underwriting policy, in the first quarter after the earliest adoption of such policy and all quarters thereafter, and zero otherwise. The sample includes all mines from Table 4. Relative to the sample underlying Table 6, Columns 3 and 4 include mine-quarter pairs in which the mine is not covered by any insurer, thereby including cases of abandoned mines as they fail to meet the legally required minimum insurance coverage. In Columns 1 and 2, standard errors are clustered at the mine and insurer level; in Columns 3 and 4, at the mine level. Standard errors are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. Table A.1 provides descriptions of all variables.

	Active insurance	*Abandoned*	*# Active insurers*	*Abandoned*
	First stage	Second stage	First stage	Second stage
	(1)	(2)	(3)	(4)
Post coal policy	-0.205***			
	(0.069)			
$\widehat{\textit{Active insurance}}$		-0.064**		
		(0.031)		
Post coal policy exposed			-0.326***	
			(0.093)	
$\#\ \widehat{\textit{Active insurers}}$				-0.121*
				(0.072)
Insurance group × Coal mine FE	Yes	Yes		
Coal mine FE			Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Obs.	53,407	53,407	12,363	12,363
First-stage F-statistic	8.9		12.4	
# Insurance groups	51	51		
# Coal mines	375	375	296	296

Table 10: Insurer-level outcomes and coal underwriting policies

This table presents results from the following OLS regression:

$$Y_{i,t} = \beta_1 \times Post\ coal\ policy_{i,t-1} + \alpha_i + \alpha_t + \epsilon_{i,t},$$

where i indexes an insurer and t year. The dependent variable, Y, is gross written premiums (Column 1), return on assets (Column 2), two-day cumulative abnormal returns around the announcement of policy adoptions (Column 3), solvency ratio (Column 4), or the number of RepRisk environmental incidents (Column 5). *Post coal policy* equals one for policy-adopting insurers after adoption, and zero otherwise. α_i are insurer fixed effects and α_t are year fixed effects. The sample in Columns 1, 2, 4, and 5 is a firm-year panel based on annual scorecards compiled by Insure Our Future (IOF), while the sample in Column 3 includes all 19 insurers that adopt a coal underwriting policy. Standard errors in Columns 1, 2, 4, and 5 are clustered at the insurer level and reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. Table A.1 provides descriptions of all variables.

	GWP (log)	*ROA*	*CAR[0,1]*	*Solvency ratio*	*# RepRisk incidents*
	(1)	(2)	(3)	(4)	(5)
Post coal policy	-0.002	-0.471		-0.156	-0.963**
	(0.030)	(0.395)		(0.476)	(0.427)
Constant			-0.520		
			(0.425)		
Time FE	Yes	Yes	No	Yes	Yes
Insurance group FE	Yes	Yes	No	Yes	Yes
Obs.	130	133	19	133	146
Adj. R^2	0.993	0.363	0.000	0.983	0.749
# Insurance groups	28	29	19	29	29

Internet Appendix to

Insurers' Underwriting Policies

A. Example of a Coal Underwriting Policy

To make concrete what a coal underwriting policy can involve, we describe the coal policy of Allianz, a global insurance group headquartered in Germany. The policy of Allianz records among the highest coal-policy stringency scores in our sample period from 2021 to 2023 (Figure 2). It is therefore an example of a relatively stringent policy rather than a representative one, as policies vary widely in scope and stringency and are often vaguer or contain more exemptions. Allianz first restricted coal in its proprietary investments in 2015 and extended these restrictions to its P&C underwriting in 2018, the coal-policy adoption date we assign to Allianz, and tightened it in 2021 (Allianz, 2025b).

The restriction has two parts. Its project-level component withdraws stand-alone P&C insurance for the construction or operation of thermal coal mines, as well as coal-fired power plants and related infrastructure, for both new and renewed contracts. A separate company-level component restricts coverage of firms whose coal share exceeds evolving thresholds, subject to exemptions for firms with credible transition plans. The policy applies to thermal coal, not to metallurgical coal used in steel or cement production. Our mine-insurer data capture the project-level component directly, and the company-level component insofar as a restricted firm's mines lose coverage.

Allianz states that the policy reflects its commitment to "*limiting global warming to 1.5° C*" and its participation in initiatives such as the UN-convened Net-Zero Asset Owner Alliance. As with the other policies we study, it is a voluntary commitment rather than a regulatory requirement, and its scope and stringency are recorded in the Insure Our Future scorecards that underlie our measures. Allianz maintains separate statements for its oil & gas and oil sands underwriting (Allianz, 2025c,d).

B. Insurance Supply Model with Non-actuarial Costs

B.1 Motivation

Our empirical analysis in Section 2.3 indicates that the adoption and stringency of underwriting policies covering coal as well as oil & gas are positively associated with proxies for pressure from various stakeholder groups, such as retail customers, employees, peers, investors, or the broader public. Rationalizing these patterns requires modeling insurance supply in a way that goes beyond the standard framework of Koijen and Yogo (2023a), in which the underwriting decision of insurers is modeled to reflect expected losses, regulatory reserves, the marginal cost of capital, and other standard pricing components such as markups. Specifically, it appears that in the context of carbon-intensive assets, insurers face additional non-actuarial costs resulting from stakeholder pressure that shape their willingness to underwrite risks.[31] Examples of non-actuarial costs not reflected in the risk-based underwriting decision include reputational damage, brand erosion, "loss of license to operate," or talent attraction and retention problems, all of which arise in response to pressure by various stakeholders.

To guide our empirical analysis and understand the implications of these additional costs, we augment the standard insurance-supply model with (i) a fixed non-actuarial penalty for maintaining any coal exposure (fixed cost) and (ii) a per-unit non-actuarial cost of underwriting coal-related risks (marginal cost).[32] The first cost type is not a cost of adopting a climate policy *per se*, but arises when underwriting behavior contradicts an insurer's own publicly stated climate policy or commitment. Once an insurer underwrites any coal-related coverage in violation of such a commitment, the fixed penalty is incurred, independent of the scale of the underwriting exposure (one can think of it as a fixed cost of greenwashing). Instead, the second cost type reflects costs associated with stakeholder pressure that increase with an insurer's overall coal exposure, as greater coal involvement attracts more sustained attention and pressure from stakeholders (one can think of it as a rising fraction of retail customers with green preferences who shy away from an insurer as the coal exposure

[31] As "non-actuarial" costs, we consider factors that enter into the decision problem of an insurer *on top of* factors related to risk-based pricing and expected losses, following the modeling approach of Koijen and Yogo (2023a). In our framework, expected losses, regulatory reserves, capital requirements, and other standard pricing components, such as markups, capture actuarial costs of underwriting decisions that are directly tied to the actuarial risk of the insured object and priced through the underwriting contract. By contrast, the costs we label non-actuarial do not reflect the insured risk itself and do not operate through expected losses or capital requirements, even though they may ultimately have financial consequences for the insurer.

[32] A unit of coverage can be interpreted broadly. For example, it may correspond to an insured mine-insurance line combination (e.g., a general liability insurance certificate for mine A or a workers' compensation certificate for mine B), but it could also represent finer or coarser measures of insured exposure, such as coverage volume or mine size. The precise definition of a unit is not material for the model's qualitative predictions.

increases). Notably, both types of costs can have financial consequences for insurers and should therefore affect their decision-making.

This adjusted model delivers several key mechanisms relevant to our empirical setting. First, insurer-specific differences in these two types of non-actuarial costs imply heterogeneous withdrawal intensities across insurers. Second, the fixed non-actuarial penalty associated with maintaining any coal exposure (once a policy is in place) can generate abrupt non-renewals or full relationship terminations, rather than gradual retrenchment. Third, the per-unit non-actuarial cost raises the marginal cost of insuring lines more directly tied to core coal extraction activities, producing selective reductions in coverage. Fourth, because mines require a minimum level of liability coverage to operate, reductions in coverage can trigger mine abandonment when total available coverage falls below a regulatory threshold required to operate a mine. Fifth, the extent to which withdrawal translates into real effects depends on the availability of alternative insurers. The reason is that mines that rely heavily on a single insurer are most exposed to coverage losses because insurance supply is not perfectly elastic. Replacing withdrawn coverage requires costly underwriting, and, while insurers without underwriting policies partly absorb it, substitution remains incomplete, leaving mines that depend on few insurers exposed even in the absence of strategic interaction.

B.2 The model

1. Insurers and coal mines. Coal mines $j \in J$ require liability insurance to operate and may obtain coverage from multiple insurers.

Insurers $i \in I$ choose premiums P_{ij} and coverage quantities Q_{ij}. Demand for insurer i's coverage is downward sloping,

$$Q_{ij} = Q_{ij}(P_{ij}), \qquad \frac{\partial Q_{ij}}{\partial P_{ij}} < 0,$$

and total available coverage for mine j is

$$Q_j^{\text{total}} = \sum_i Q_{ij}(P_{ij}).$$

Competition matters because $Q_{ij}(P_{ij})$ depends on the prices charged by alternative insurers through the elasticity of substitution across insurers (this elasticity reflects any unmodeled reduced-form limits to substitution in insurance supply).

2. Losses, reserves, and capital requirements. Insurers are risk-neutral but face regulatory reserve requirements and costly risk-based capital, which act as reduced-form representations of risk considerations and generate effective risk aversion at the underwriting margin. Losses follow the random variable ℓ_{ij} with mean μ_{ij} and standard deviation σ_{ij}.

Regulatory reserves for insuring coal mine j by insurer i are

$$R_{ij} = \mu_{ij} + \kappa_i \sigma_{ij},$$

where $\kappa_i > 0$ reflects prudence in reserve setting.

Underwriting Q_{ij} units of exposure requires risk-based capital K_i for insurer i:

$$K_i = \sum_j \alpha_i R_{ij} Q_{ij},$$

where $\alpha_i > 0$ is a risk-based capital coefficient. Insurer i incurs a convex cost of capital,

$$\Phi_i(K_i), \qquad \Phi_i'(K_i) > 0, \qquad \Phi_i''(K_i) > 0,$$

and we denote the marginal cost of capital by $\lambda_i \equiv \Phi_i'(K_i)$. The convexity of $\Phi_i(\cdot)$ captures that the marginal cost of capital increases with the scale of underwriting. These reserve and capital requirements embed the effect of risk without requiring explicit curvature in insurers' utility functions.

3. Non-actuarial costs. We extend the model of Koijen and Yogo (2023a) to our setting by incorporating two forms of non-actuarial costs that arise from underwriting coal-mining-related insurance lines: a fixed penalty that is incurred whenever an insurer maintains any coal underwriting exposure and a marginal cost that scales with coal exposure. As mentioned above, these terms capture costs beyond standard risk-based underwriting costs associated with coal underwriting.

- *Fixed non-actuarial penalty.* Maintaining any coal exposure may trigger a fixed cost, reflecting stakeholder pressure unrelated to expected losses or capital requirements, such as fixed costs from reputational or credibility losses as a result of breaching public zero-coal underwriting commitments:

$$\Omega_i = \begin{cases} 0, & Q_{ij} = 0 \ \forall j, \\ F_i, & \exists j : Q_{ij} > 0. \end{cases}$$

Here, $F_i > 0$ is increasing in the stringency of the insurer's public underwriting commitment, as captured by the policy score: insurers with stricter and more visible commitments to exit coal face larger reputational or credibility losses if those commitments are violated, operating as a fixed cost of maintaining any coal exposure.

- *Marginal non-actuarial cost.* Let j index insured exposure units (e.g., all mine-line combinations), and let e_j denote the coal-exposure intensity of unit j, reflecting how directly it is tied to core mining activities (e.g., commercial general liability coverage of the mine operations has high exposure intensity, and workers' compensation insurance of a mine has low exposure intensity). Insurer i's total coal-related exposure is

$$E_i = \sum_j e_j Q_{ij}.$$

Non-actuarial costs from incremental coal exposure are captured by a convex cost function $\Psi_i(E_i)$ with $\Psi_i'(E_i) > 0$. This function reflects any costs related to stakeholder pressure that increase with exposure.

4. Heterogeneity in coal exposure and policy stringency. Insurers differ in their non-actuarial cost functions $\Psi_i(\cdot)$ and in the fixed penalty F_i, reflecting variation in public commitments, regulatory pressure, stakeholder preferences, and existing carbon exposure. These differences imply heterogeneous marginal costs of underwriting identical lines. They also interact with competition: when insurers with high non-actuarial costs withdraw, remaining insurers face higher E_i if they replace lost coverage, making substitution incomplete and potentially amplifying the real effects of insurance coverage.

5. Insurer's problem. We express profits relative to a baseline in which the insurer underwrites no coal-related lines. Baseline profits from all non-coal business are normalized to zero, so Π_i represents the incremental profit from underwriting coal.

Each insurer chooses $\{P_{ij}\}$ to maximize profits:

$$\Pi_i = \sum_j (P_{ij} - \mu_{ij}) Q_{ij}(P_{ij}) \; - \; \Phi_i(K_i) \; - \; \Psi_i(E_i) \; - \; \Omega_i,$$

where $\Omega_i = F_i$ if the insurer underwrites any coal-related line and $\Omega_i = 0$ otherwise.

Let $\varepsilon_{ij} > 1$ denote the (absolute) elasticity of demand for insurer i's coverage for line j. For any line with strictly positive coverage ($Q_{ij} > 0$), the first-order condition yields a

Lerner-type pricing rule:

$$\frac{P_{ij} - MC_{ij}}{P_{ij}} = \frac{1}{\varepsilon_{ij}},$$

where marginal cost is

$$MC_{ij} = \mu_{ij} + \lambda_i \alpha_i R_{ij} + \Psi_i'(E_i)\, e_j.$$

The premium therefore satisfies $P_{ij} = m(\varepsilon_{ij})\, MC_{ij}$, where $m(\varepsilon) \equiv \varepsilon/(\varepsilon - 1)$ denotes the markup factor. The fixed penalty F_i does not affect the marginal cost once the insurer has entered the coal market, because Ω_i is constant for all $Q_{ij} > 0$.

Entry condition. Relative to a baseline with no coal underwriting, entry requires

$$\Pi_i^{\text{enter}} \geq 0 \quad \Leftrightarrow \quad \sum_j (P_{ij} - \mu_{ij}) Q_{ij}(P_{ij}) \; - \; \Phi_i(K_i) \; - \; \Psi_i(E_i) \; - \; F_i \geq 0.$$

This implies that a sufficiently large fixed penalty F_i deters entry into coal underwriting entirely, leading the insurer to set $Q_{ij} = 0$ for all coal-related lines.

6. Mine continuation condition. Mines operate only if they meet the regulatory minimum insurance coverage requirement. Formally, mine j continues operating if

$$Q_j^{\text{total}} = \sum_i Q_{ij}(P_{ij}) \geq L_j,$$

where L_j denotes the mandated coverage threshold. The parameter L_j serves as a reduced-form representation of mines' operational need for insurance, rather than reflecting risk aversion.

The availability of alternative coverage matters because the effect of one insurer's withdrawal depends on the mine's access to other insurers: if few insurers offer coverage, mine j is more likely to fall below L_j when one insurer withdraws.

B.3 Model predictions

The model yields several predictions that map directly into our empirical findings:

- *Policy adoption and enforcement.* Differences in $\Psi_i(\cdot)$ and F_i imply that insurers with more stringent public commitments to exit coal, captured by higher policy scores, implement these policies more stringently. This is because higher F_i raises the likelihood of full exit from coal underwriting, while higher $\Psi_i'(E_i)$ increases the marginal cost of maintaining coal exposure.
- *Heterogeneity across insurers.* Conditional on adoption, variations in $\Psi_i'(E_i)$ and F_i

generate systematic differences in withdrawal intensity across insurers.

- *Selective withdrawal.* Coal-policy stringency enters marginal cost through $\Psi_i'(E_i)e_j$, so increases in $\Psi_i'(E_i)$ disproportionately raise the cost of insuring high-exposure lines:

$$\frac{\partial P_{ij}}{\partial e_j} = m(\varepsilon_{ij})\Psi_i'(E_i).$$

  This leads insurers to reduce coverage for high-exposure lines, such as commercial general liability, while maintaining coverage for lines with lower exposure, such as workers' compensation.
- *Mine exit and real effects.* The continuation condition $\sum_i Q_{ij} \geq L_j$ links insurer withdrawal directly to mine abandonment: operations cannot continue when available coverage falls below the regulatory threshold L_j.
- *Incomplete substitution and entry deterrence.* Although the model does not explicitly model insurer coordination or strategic interaction, the continuation condition implies that the real effects of withdrawal depend on the availability of alternative insurers: mines that rely heavily on a small number of insurers are most vulnerable to falling below required coverage once one insurer withdraws. Insurers with low non-actuarial costs can absorb the withdrawn coverage, but this substitution is incomplete: taking on coal exposure raises E_i and, given the convexity of $\Psi_i(\cdot)$, the marginal non-actuarial cost of further coal exposure, so mines dependent on few insurers are only partially re-covered.

C. Additional Figures and Tables

C.1 Additional Figures

Figure IA.1: Prevalence and design of oil & gas underwriting policies over time

The figure shows the number of insurers whose oil & gas underwriting policies incorporate specific policy features. The sample is based on annual scorecards compiled by Insure Our Future (IOF) and includes up to 22 insurers with oil & gas underwriting policies in place.

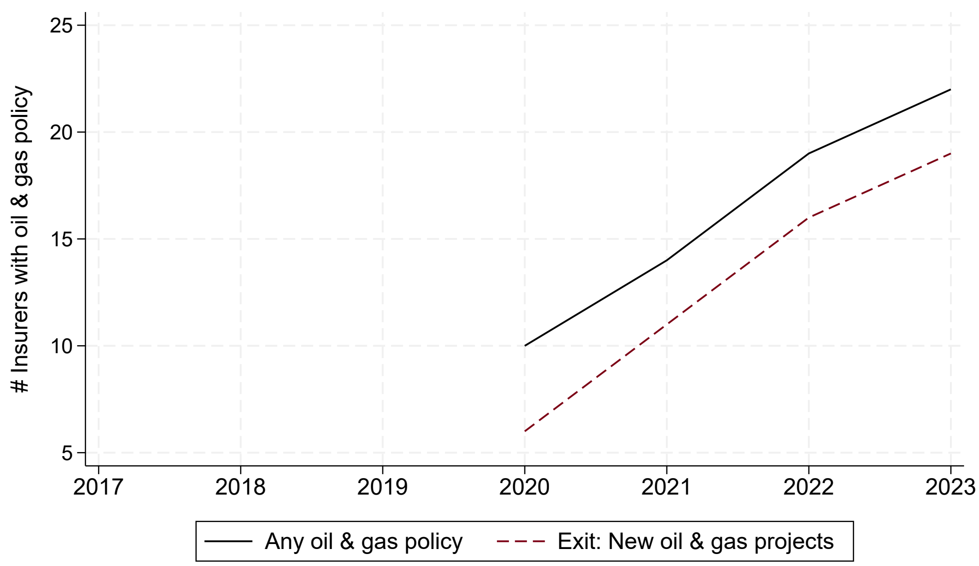


Figure IA.2: Stringency of oil & gas underwriting policies over time

The figure displays scores capturing the stringency of oil & gas underwriting policies over time. Scores range from 0 to 10, with higher values indicating more restrictive policies. Each dot represents an individual insurer in a given year. The solid line connects average scores by year. The two insurers with the highest and lowest overall underwriting policy scores in the final sample year (2023) are highlighted with colored dots. The sample is based on annual scorecards compiled by Insure Our Future (IOF) and includes 22 insurers with oil & gas underwriting policies in place.

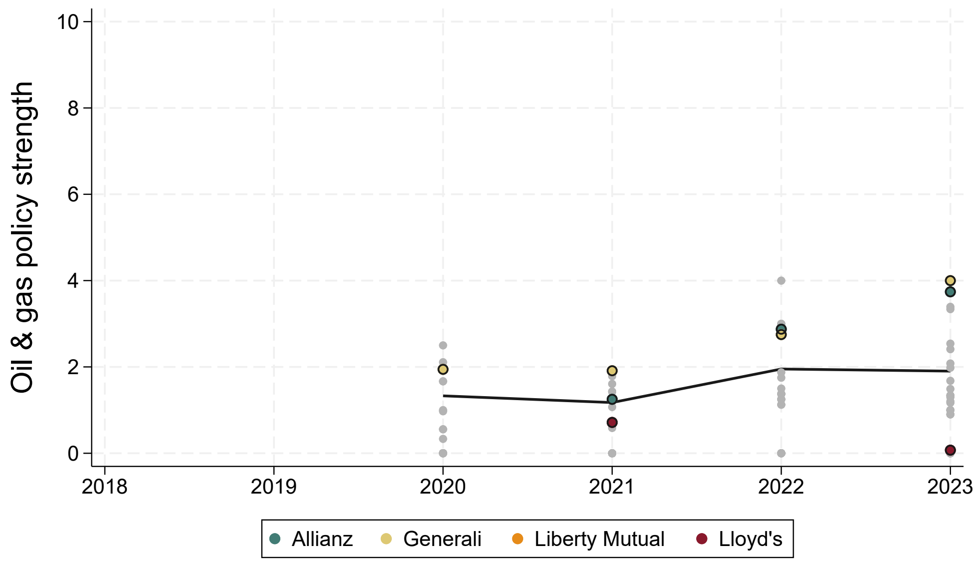
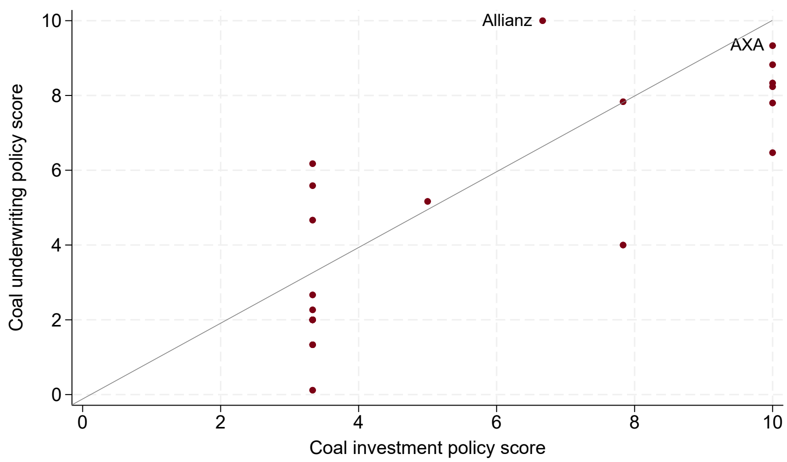


Figure IA.3: Alignment of underwriting and investment policy stringency

The figure shows the relationship between the stringency of underwriting and investment policies covering coal as well as oil & gas for the sample year 2023. Each dot represents the combination of underwriting and investment policies of an insurer. Panel A shows the relationship for coal policies, while Panel B shows the relationship for oil & gas policies. The sample is based on annual scorecards compiled by Insure Our Future (IOF) and comprises 25 insurers with underwriting policies in place.

Panel A: Coal underwriting policies



Panel B: Oil & gas underwriting policies

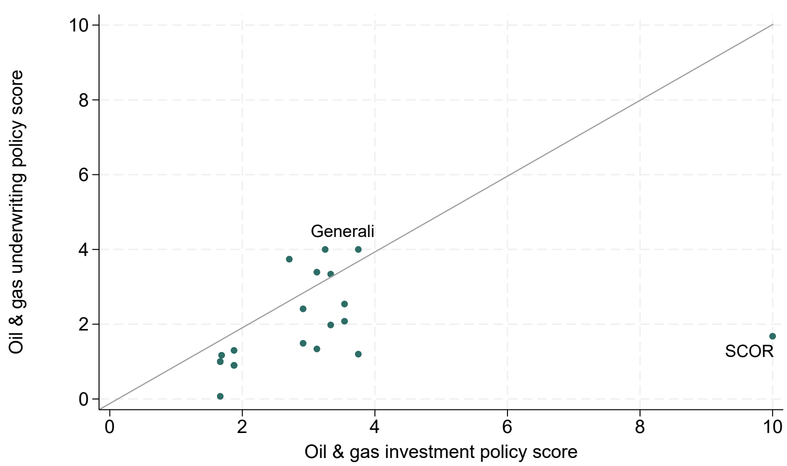


Figure IA.4: Certificate of Liability Insurance of Black Butte Coal Mine

The figure shows the Certificate of Liability Insurance of Black Butte Coal Mine dated September 26, 2018, on a standardized ACORD 25 form filed with the Wyoming Department of Environmental Quality.

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ACORD®

CERTIFICATE OF LIABILITY INSURANCE

DATE (MM/DD/YYYY) 09/26/2018

THIS CERTIFICATE IS ISSUED AS A MATTER OF INFORMATION ONLY AND CONFERS NO RIGHTS UPON THE CERTIFICATE HOLDER. THIS CERTIFICATE DOES NOT AFFIRMATIVELY OR NEGATIVELY AMEND, EXTEND OR ALTER THE COVERAGE AFFORDED BY THE POLICIES BELOW. THIS CERTIFICATE OF INSURANCE DOES NOT CONSTITUTE A CONTRACT BETWEEN THE ISSUING INSURER(S), AUTHORIZED REPRESENTATIVE OR PRODUCER, AND THE CERTIFICATE HOLDER.

IMPORTANT: If the certificate holder is an ADDITIONAL INSURED, the policy(ies) must have ADDITIONAL INSURED provisions or be endorsed. If SUBROGATION IS WAIVED, subject to the terms and conditions of the policy, certain policies may require an endorsement. A statement on this certificate does not confer rights to the certificate holder in lieu of such endorsement(s).

PRODUCER
Willis of Illinois, Inc.
c/o 26 Century Blvd
P.O. Box 305191
Nashville, TN 372305191 USA

CONTACT NAME:
PHONE (A/C, No, Ext): 1-877-945-7378 FAX (A/C, No): 1-888-467-2378
E-MAIL ADDRESS: certificates@willis.com

INSURER(S) AFFORDING COVERAGE		NAIC #
INSURER A :	American Guarantee and Liability Insurance	26247
INSURER B :	Zurich American Insurance Company	16535
INSURER C :	ACE Property & Casualty Insurance Company	20699
INSURER D :		
INSURER E :		
INSURER F :		

INSURED
Black Butte Coal Company
101 Black Buttes Road
Point Of Rocks, WY 82942 USA

COVERAGES CERTIFICATE NUMBER: W8113289 REVISION NUMBER:

THIS IS TO CERTIFY THAT THE POLICIES OF INSURANCE LISTED BELOW HAVE BEEN ISSUED TO THE INSURED NAMED ABOVE FOR THE POLICY PERIOD INDICATED. NOTWITHSTANDING ANY REQUIREMENT, TERM OR CONDITION OF ANY CONTRACT OR OTHER DOCUMENT WITH RESPECT TO WHICH THIS CERTIFICATE MAY BE ISSUED OR MAY PERTAIN, THE INSURANCE AFFORDED BY THE POLICIES DESCRIBED HEREIN IS SUBJECT TO ALL THE TERMS, EXCLUSIONS AND CONDITIONS OF SUCH POLICIES. LIMITS SHOWN MAY HAVE BEEN REDUCED BY PAID CLAIMS.

INSR LTR	TYPE OF INSURANCE	ADDL INSD	SUBR WVD	POLICY NUMBER	POLICY EFF (MM/DD/YYYY)	POLICY EXP (MM/DD/YYYY)	LIMITS	
A	X COMMERCIAL GENERAL LIABILITY			GLO 5851797-06	10/01/2018	10/01/2019	EACH OCCURRENCE	$ 1,000,000
	CLAIMS-MADE X OCCUR						DAMAGE TO RENTED PREMISES (Ea occurrence)	$ 1,000,000
							MED EXP (Any one person)	$ 10,000
							PERSONAL & ADV INJURY	$ 1,000,000
	GEN'L AGGREGATE LIMIT APPLIES PER:						GENERAL AGGREGATE	$ 2,000,000
	X POLICY PRO-JECT LOC						PRODUCTS - COMP/OP AGG	$ 2,000,000
	OTHER:							$
B	AUTOMOBILE LIABILITY			BAP 5851796-06	10/01/2018	10/01/2019	COMBINED SINGLE LIMIT (Ea accident)	$ 1,000,000
	X ANY AUTO						BODILY INJURY (Per person)	$
	OWNED AUTOS ONLY / SCHEDULED AUTOS						BODILY INJURY (Per accident)	$
	HIRED AUTOS ONLY / NON-OWNED AUTOS ONLY						PROPERTY DAMAGE (Per accident)	$
								$
C	X UMBRELLA LIAB X OCCUR			G2790869A 004	10/01/2018	10/01/2019	EACH OCCURRENCE	$ 5,000,000
	EXCESS LIAB CLAIMS-MADE						AGGREGATE	$ 5,000,000
	DED X RETENTION $ 10,000							$
	WORKERS COMPENSATION AND EMPLOYERS' LIABILITY Y/N						PER STATUTE / OTH-ER	
	ANYPROPRIETOR/PARTNER/EXECUTIVE OFFICER/MEMBER EXCLUDED? (Mandatory in NH)	N/A					E.L. EACH ACCIDENT	$
	If yes, describe under DESCRIPTION OF OPERATIONS below						E.L. DISEASE - EA EMPLOYEE	$
							E.L. DISEASE - POLICY LIMIT	$

DESCRIPTION OF OPERATIONS / LOCATIONS / VEHICLES (ACORD 101, Additional Remarks Schedule, may be attached if more space is required)
Re: Black Butte Coal Co. Permit #467 and all subsequent renewals.

05-14-2019
PT0467

CERTIFICATE HOLDER
Wyoming Dept. of Environmental Quality
200 West 17th Street
Cheyenne, WY 82002

CANCELLATION
SHOULD ANY OF THE ABOVE DESCRIBED POLICIES BE CANCELLED BEFORE THE EXPIRATION DATE THEREOF, NOTICE WILL BE DELIVERED IN ACCORDANCE WITH THE POLICY PROVISIONS.

AUTHORIZED REPRESENTATIVE
Rudi Harwood

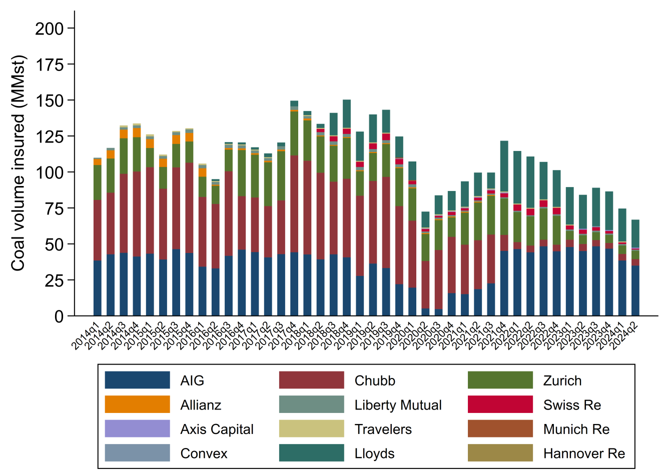
ACORD 25 (2016/03) The ACORD name and logo are registered marks of ACORD
SR ID: 16780344 BATCH: 882111

TFN6 6/339
RECD OCT 10 2018

Figure IA.5: Volume of coal insured over time

The figure displays the volume of coal insured over time. For each insurer-quarter, we aggregate coal production across all mines insured by that insurer. Panel A presents this information for insurers that adopted a coal underwriting policy at any point during the sample period, while Panel B presents this information for those that never did. The sample includes all coal mines that appear in MSHA's Mine Data Retrieval System between 2014Q1 and 2024Q2, provided they report at least one quarter of non-zero production, and for which we successfully obtained Certificates of Liability Insurance on ACORD 25 forms from state-level agencies. Table A.1 provides descriptions of all variables.

Panel A: Insurers adopting a coal underwriting policy



Panel B: Insurers never adopting a coal underwriting policy

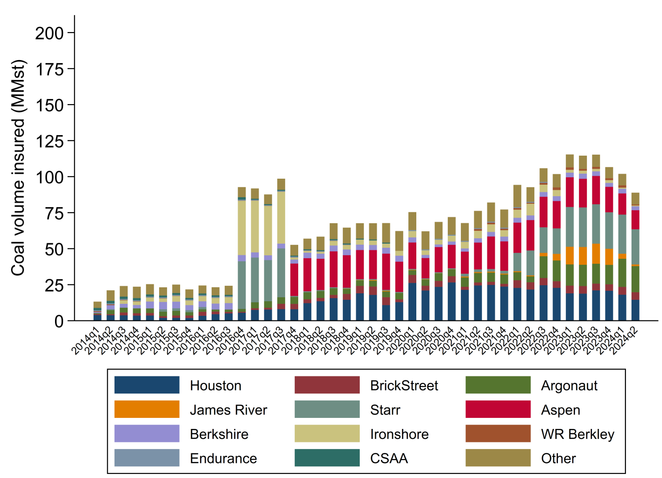


Figure IA.6: Coal mines' insurance status and underwriting policies

This figure displays coefficient estimates and 90% confidence intervals from the following OLS regression:

$$Active\ insurance_{s,m,i,t} = \sum_{t=-6}^{t=6} \beta_t \times Coal\ policy_i \times Event\ quarter_{s,t} + \alpha_{s,m,i} + \alpha_{s,t} + \epsilon_{s,m,i,t},$$

where s indexes a stack, m indexes a mine, i an insurer, and t a quarter. The dependent variable, *Active insurance*, equals one if an insurer insures a mine in a given quarter, and zero otherwise. *Coal policy* equals one for policy-adopting insurers, and zero otherwise. *Event quarter* are dummy variables indicating quarters relative to treatment, where treatment is the first quarter after coal policy adoption. $\alpha_{s,m,i}$ are stack-mine-insurer fixed effects, while $\alpha_{s,t}$ are stack-time fixed effects. The initial sample includes all coal mines that appear in MSHA's Mine Data Retrieval System between 2014Q1 and 2024Q2, report at least one quarter of non-zero production, and have insurance certificate data available for those quarters. For each insurer that adopts a coal underwriting policy, we identify all mines it insures and construct a balanced sample of 13 quarterly observations per mine-insurance pair, whenever information on the liability insurance certificates of a given mine is available. These mine-insurer pairs form the treated relationships in the stack. As a control group, we include all other relationships that the same mines have with insurers that never adopt a coal underwriting policy. In contrast to Figure 4, the estimation sample comprises all mines, including those insured by a single insurer. Standard errors are clustered at the insurer-stack level. Table A.1 provides descriptions of all variables.

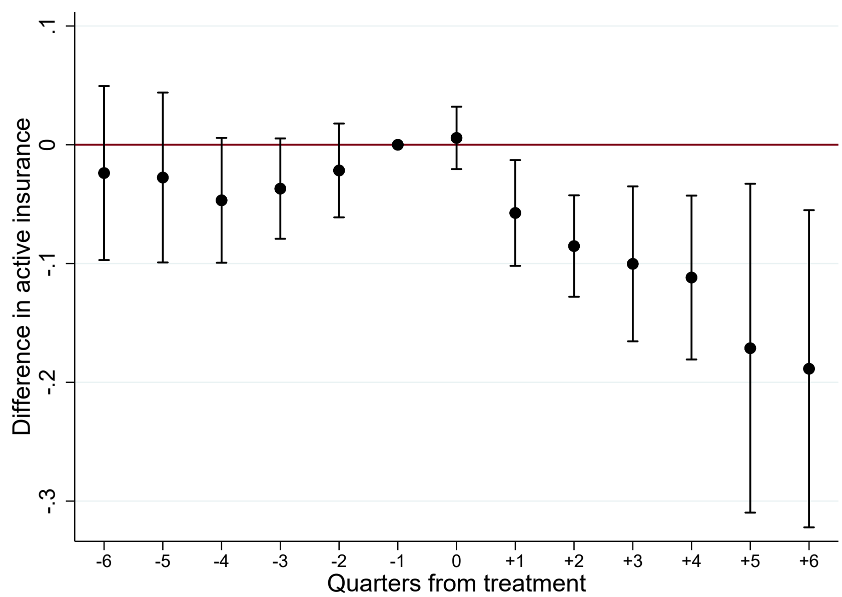


Figure IA.7: Coal mines' insurance status and underwriting policies by insurance line

This figure displays 90% confidence intervals and coefficient estimates from the following OLS regression:

$$Active\ insurance_{s,m,l,i,t} = \sum_{t=-6}^{t=6} \beta_t \times Coal\ policy_i \times Event\ quarter_{s,t} + \alpha_{s,m,l,i} + \alpha_{s,m,t} + \epsilon_{s,m,l,i,t},$$

where s indexes a stack, m a mine, l an insurance line, i an insurer, and t a quarter. The dependent variable, *Active insurance*, equals one if an insurer insures a mine in a given quarter, and zero otherwise. *Coal policy* equals one for policy-adopting insurers, and zero otherwise. *Event quarter* are dummy variables indicating quarters relative to treatment, where treatment is the first quarter after coal policy adoption. $\alpha_{s,m,l,i}$ are stack-mine-insurance line-insurer fixed effects, while $\alpha_{s,m,t}$ are stack-mine-time fixed effects. The initial sample of mines includes all coal mines that appear in MSHA's Mine Data Retrieval System between 2014Q1 and 2024Q2, provided they report at least one quarter of non-zero production, and for which we successfully obtained Certificates of Liability Insurance on ACORD 25 forms from state-level agencies. For each insurer that adopts a coal underwriting policy, we identify all mines it insures and construct a balanced sample of 13 quarterly observations per mine-insurance line-insurer triplet, whenever information on the liability insurance certificates of a given mine is available. These mine-insurance line-insurer triplets form the treated observations in the stack. As control observations, we include all other mine-insurance line-insurer triplets that include the same mines but insurers that never adopt a coal underwriting policy. Standard errors are clustered at the insurance group-insurance line-stack level. Table A.1 provides descriptions of all variables.

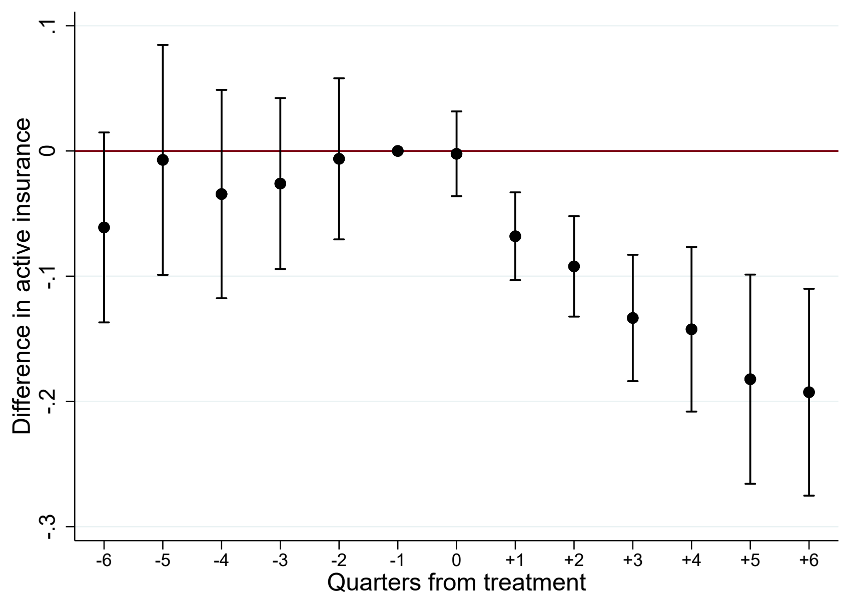
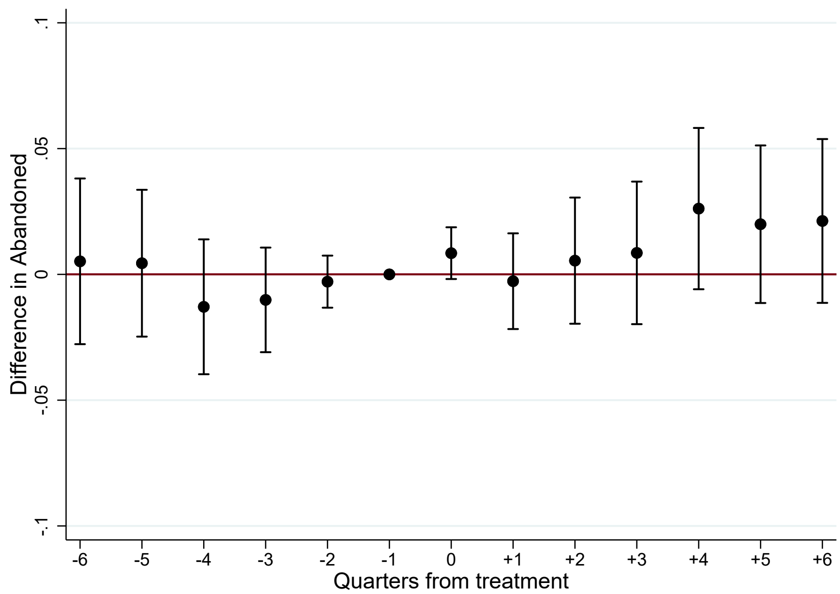


Figure IA.8: Coal mine outcomes and underwriting policies

This figure reports dynamic treatment effect estimates with 90% confidence intervals computed using the cohort-aggregated event-study estimator of de Chaisemartin and d'Haultfœuuille (2026), implemented via `did_multiplegt_dyn` as described in de Chaisemartin et al. (2025). We apply the estimator without modification. *Event quarter* are dummy variables indicating quarters relative to treatment, where treatment is the first quarter after the earliest coal policy adoption. If a mine is exposed to multiple such adoptions, only the first instance is used to define treatment. A mine is *Coal-policy exposed* if, between 2014 and 2016, it maintained an insurance relationship lasting at least eight quarters with an insurer that subsequently adopted a coal underwriting policy. The dependent variable is a dummy for mine abandonment (Panel A) or the (log of) volume of coal produced (Panel B). The sample comprises all mines underlying the analyses reported in Table 4; Panel B further restricts to mines active throughout the full period. Standard errors are clustered at the mine level. See Table A.1 for variable definitions.

Panel A: Abandoned



Panel B: Production

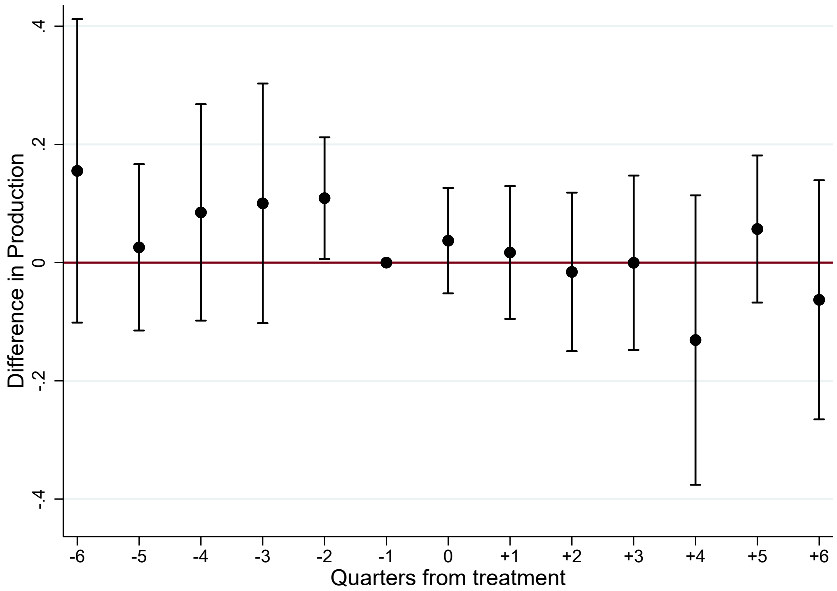


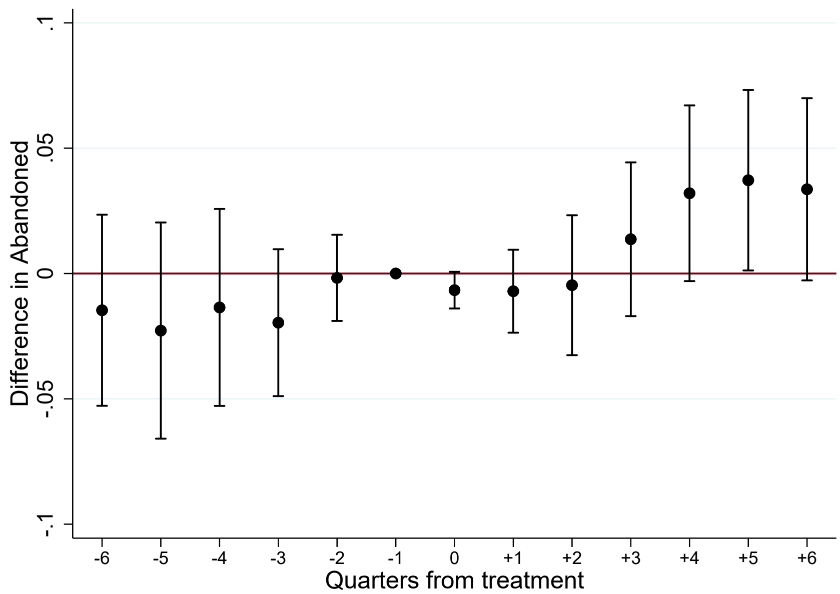
Figure IA.9: Coal mine outcomes and underwriting policies

This figure displays coefficient estimates and 90% confidence intervals from the following OLS regression:

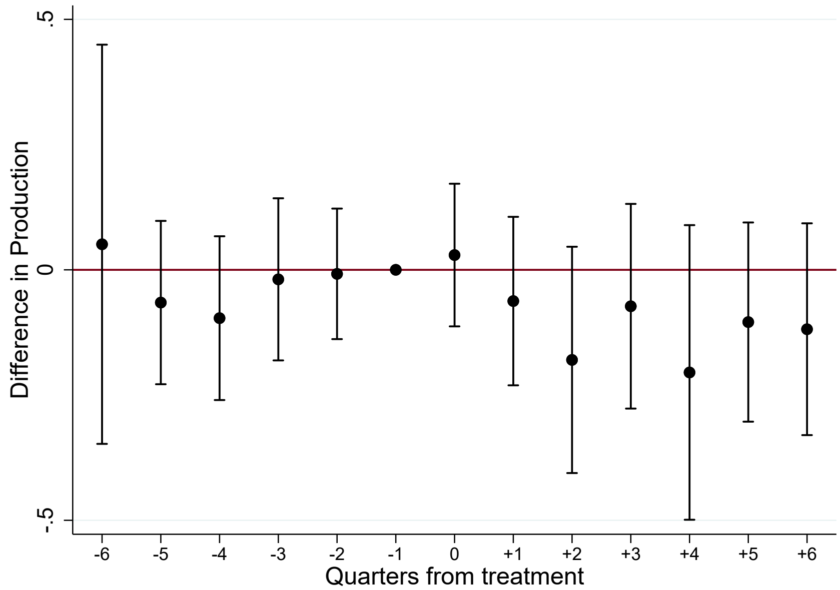
$$Coal\ mine\ outcome_{s,m,t} = \sum_{t=-6}^{t=6} \beta_t \times Coal\ policy\ exposed_{s,m} \times Event\ quarter_{s,t} + \alpha_{s,m} + \alpha_{s,t} + \epsilon_{s,m,t},$$

where s indexes a stack, m a mine, and t a quarter. The dependent variable, *Coal mine outcome*, is either a dummy variable indicating whether a mine is abandoned (Panel A) or the (log of) volume of coal produced (Panel B). *Coal policy exposed* equals one for mines that, between 2014 and 2016, have a relationship lasting at least eight quarters with at least one insurer that subsequently adopted a coal underwriting policy. *Event quarter* are dummy variables indicating quarters relative to treatment, where treatment is the first quarter after the earliest coal policy adoption. If a mine is exposed to multiple such adoptions, only the first instance is used to define treatment. The sample includes all mines from Table 4, provided that we successfully obtained Certificates of Liability Insurance on ACORD 25 forms from state-level agencies between 2014 and 2016. In Panel B, the sample includes only mines that are active throughout the entire sample period. Standard errors are clustered at the mine-stack level. Table A.1 provides descriptions of all variables.

Panel A: Abandoned



Panel B: Production



C.2 Additional Tables

Table IA.1: Assessment of underwriting policies

This table reports the five dimensions over which underwriting policies for coal as well as oil & gas are assessed by IOF and the respective description.

IOF scoring dimension	Description
Scope	Does an underwriting policy rule out insurance for (i) all types of new coal infrastructure (including mines and power plants as well as transport facilities); (ii) extreme fossil fuels such as tar sands, associated pipelines, Arctic and ultra-deepwater drilling; and (iii) any oil & gas expansion projects that drive increased production?
Types of cover	Does an underwriting policy apply to all lines of business for new and existing projects and companies, except cover for protecting workers, ringfenced renewable energy projects, and existing mine reclamation surety bonds?
	Does an underwriting policy of a reinsurer apply to treaty as well as facultative reinsurance?
Fossil fuel companies	Does an underwriting policy apply comprehensive criteria to define companies operating in coal, oil & gas, and tighten cover over time in line with the need to phase out these fossil fuels completely?
	Does an underwriting policy immediately exclude new customers from the fossil fuel sector not aligned with a 1.5°C pathway and phase out all insurance services within two years for existing fossil fuel company customers not aligned with such a pathway?
Emissions reduction targets	Does an insurer set emissions reduction targets for new projects as well as ongoing operations which they insure, and define short- and medium-term targets across their entire commercial property & casualty portfolio?
	Do the targets cover the Scope 3 emissions of all carbon-intensive sectors, including energy and power, and aim for a reduction of insured emissions of at least 43% by 2030, in line with IPCC findings?
Human rights	Does an underwriting policy include robust due diligence to ensure that clients fully respect all human rights, including a requirement that they obtain and document the Free, Prior, and Informed Consent of impacted Indigenous Peoples?

Table IA.2: Insurer characteristics

This table reports insurance characteristics for all insurers in IOF's scorecard. *Adoption date* is constructed via manual online news searches of each insurer's earliest coal underwriting policy adoption date. For XL Catlin, the variable refers to the period prior to its acquisition by AXA. *Unlisted insurer* and *Specialty insurer* are header variables. While *NZIA* is time-varying, this table only reports the maximum value per insurer.

Name	Adoption date	Region (Country)	Unlisted insurer	Specialty insurer	NZIA
AIG	01-03-2022	U.S. (United States)	0	0	0
AXA	12-12-2017	Europe (France)	0	0	1
Allianz	04-05-2018	Europe (Germany)	0	0	1
Aviva	N/A (unknown adoption date)	Europe (United Kingdom)	0	0	1
Axis Capital	16-10-2019	RoW (Bermuda)	0	1	0
Berkshire Hathaway	No policy adoption	U.S. (United States)	0	0	0
Chubb	01-07-2019	U.S. (United States)	0	0	0
Convex	01-02-2022	RoW (Bermuda)	1	1	0
Everest Re	No policy adoption	RoW (Bermuda)	0	1	0
FM Global	No policy adoption	U.S. (United States)	1	1	0
Generali	21-02-2018	Europe (Italy)	0	0	1
HDI	18-04-2019	Europe (Germany)	1	0	0
Hannover Re	18-04-2019	Europe (Germany)	0	1	1
Legal and General	No policy adoption	Europe (United Kingdom)	0	0	0
Liberty Mutual	13-12-2019	U.S. (United States)	1	0	0
Lloyd's	16-12-2020	Europe (United Kingdom)	1	1	1
MS&AD	30-09-2020	Asia (Japan)	0	0	0
Mapfre	11-03-2019	Europe (Spain)	0	0	1
MetLife	No policy adoption	US (United States)	0	0	0
Munich Re	06-08-2018	Europe (Germany)	0	0	1
PICC	No policy adoption	Asia (China)	0	0	0
Ping An	N/A (unknown adoption date)	Asia (China)	0	0	0
Prudential	No policy adoption	U.S. (United States)	0	0	0
QBE	01-04-2019	RoW (Australia)	0	0	1
SCOR	06-09-2017	Europe (France)	0	1	1
Samsung FM	12-11-2020	Asia (Korea, Rep.)	0	0	0
Sinosure	No policy adoption	Asia (China)	1	0	0
Sompo	23-09-2020	Asia (Japan)	0	0	1
Starr	No policy adoption	U.S. (United States)	1	1	0
Swiss Re	02-07-2018	Europe (Switzerland)	0	0	1
TIAA	No policy adoption	U.S. (United States)	1	0	0
The Hartford	20-12-2019	U.S. (United States)	0	0	0
Tokio Marine	28-09-2020	Asia (Japan)	0	0	1
Travelers	07-02-2022	U.S. (United States)	0	0	0
WR Berkley	No policy adoption	U.S. (United States)	0	1	0
XL Catlin	No policy adoption	Europe (Ireland)	0	1	0
Zurich	13-11-2017	Europe (Switzerland)	0	0	1

Table IA.3: Correlations between underwriting and investment policies

This table reports correlations between underwriting and investment policies. In Panel A, the table reports the correlations between dummy variables equal to one for underwriting policy-adopting insurers after adoption and investment policy-adopting insurers after adoption, for coal as well as oil & gas. The sample comprises 32 insurers and spans the period from 2017 to 2023. In Panel B, the table reports the correlations between the scores assigned to the underwriting policies and investment policies of insurers. The sample comprises 25 insurers with underwriting policies in place and spans the period from 2018 to 2023.

Panel A: Prevalence of policies

	Coal policy	*Oil & gas policy*	*Coal inv. policy*	*Oil & gas inv. policy*
Coal policy	1.00			
Oil & gas policy	0.62	1.00		
Coal investment policy	0.79	0.65	1.00	
Oil & gas investment policy	0.59	0.87	0.62	1.00

Panel B: Stringency of policies

	Coal score	*Oil & gas score*	*Coal inv. score*	*Oil & gas inv. score*
Coal score	1.00			
Oil & gas score	0.55	1.00		
Coal investment score	0.81	0.34	1.00	
Oil & gas investment score	0.36	0.33	0.55	1.00

Table IA.4: Descriptive statistics on underwriting policies

This table presents descriptive statistics on underwriting policies for coal as well as oil & gas. The sample is based on annual scorecards compiled by Insure Our Future (IOF). Table A.1 provides descriptions of all variables.

	Obs.	Mean	Std.	25th	Median	75th
Panel A: Insurer-year sample						
Post coal policy	181	0.66				
Coal policy score	162	2.44	2.59	0.00	1.85	3.60
Post oil & gas policy	117	0.55				
Oil & gas policy score	117	0.90	1.09	0.00	0.59	1.43
CCPI	181	47.82	15.81	37.39	52.20	60.85
NZIA	181	0.13				
Specialty insurer	181	0.23				
Unlisted insurer	181	0.15				
High fossil fuels GWP share	181	0.54				
Total assets (billion $)	180	299.98	350.52	61.31	148.14	437.56
ROA (%)	180	1.51	1.83	0.70	1.27	2.23
GWP (billion $)	130	44.98	32.17	20.00	37.48	63.68
Solvency ratio (%)	130	17.04	10.75	8.71	14.48	22.01
# RepRisk incidents	146	2.53	3.31	0.00	1.00	4.00
Panel B: Listed insurer sample						
CAR[0,1]	19	-0.52	1.58	-1.34	-0.42	-0.14

Table IA.5: Determinants of oil & gas underwriting policies

This table presents results from the following OLS regression:

$$Y_{i,t} = \beta \times X_{i,t-1} + \alpha_t + \epsilon_{i,t},$$

where i indexes an insurer and t a year. In Column 1, Y is *Post oil & gas policy*, which equals one for oil & gas policy-adopting insurers after adoption, and zero otherwise. In Column 2, Y is *Oil & gas policy score*, which is a score ranging from 0 to 10, with higher scores indicating stricter oil & gas underwriting policies. X is a vector of insurer-level characteristics. The sample is based on annual scorecards compiled by Insure Our Future (IOF); Column 2 additionally conditions on insurers with a policy in place. Standard errors are clustered at the insurer level and reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. Table A.1 provides descriptions of all variables.

	Post oil & gas policy	*Oil & gas policy score*
	(1)	(2)
CCPI	0.010**	0.029***
	(0.005)	(0.008)
NZIA	0.275*	0.406
	(0.136)	(0.265)
Specialty insurer	-0.270	-0.823*
	(0.195)	(0.444)
Unlisted insurer	-0.392*	-1.088**
	(0.200)	(0.453)
High fossil fuel GWP share	-0.212	-0.631**
	(0.162)	(0.236)
Total Assets (log)	-0.049	0.015
	(0.073)	(0.105)
ROA	-0.009	-0.059
	(0.023)	(0.084)
Time FE	Yes	Yes
Obs.	117	64
Adj. R^2	0.312	0.452
# Insurers in sample	31	22

Table IA.6: Cross-sectional variation in coverage termination

This table reports cross-sectional heterogeneity in the termination of insurance coverage following coal policy adoptions, from the following OLS regression:

$$Active\ insurance_{s,m,i,t} = \beta_1 \times Coal\ policy_i \times Post_{s,t} + \beta_2 \times Coal\ policy_i \times Post_{s,t} \times X_m + \alpha_{s,m,i} + \alpha_{s,m,t} + \epsilon_{s,m,i,t}$$

where s indexes a stack, m a mine, i an insurer, and t a quarter. The dependent variable, *Active insurance*, equals one if an insurer insures a mine in a given quarter, and zero otherwise, so a negative coefficient on *Coal policy* × *Post* reflects a loss of coverage. *Coal policy* and *Post* are defined as in Table 4. X is a mine-level dummy variable. In Column 1, X is *Productive mine*, defined as one if the mine has above-median average productivity (output per working hour) between 2014 and 2016. In Column 2, X is *Large mine*, defined as one if the mine has above-median total coal production between 2014 and 2016. In Column 3, X is *High accident number*, defined as one if the mine has an above-median number of safety incidents reported to MSHA between 2014 and 2016. In Column 4, X is *High coal shipment price*, defined as one if the mine faces an above-median coal shipment price between 2014 and 2016. Standard errors are clustered at the insurer-stack level and reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. Table A.1 provides descriptions of all variables.

	Active insurance			
	(1)	(2)	(3)	(4)
Coal policy × *Post*	-0.158***	-0.125***	-0.123**	-0.102**
	(0.045)	(0.045)	(0.057)	(0.044)
Coal policy × *Post* × *Productive mine*	0.048			
	(0.045)			
Coal policy × *Post* × *Large mine*		-0.016		
		(0.038)		
Coal policy × *Post* × *High accident number*			-0.019	
			(0.045)	
Coal policy × *Post* × *High coal shipment price*				-0.038
				(0.063)
Stack × Insurance group × Coal mine FE	Yes	Yes	Yes	Yes
Stack × Coal mine × Time FE	Yes	Yes	Yes	Yes
Obs.	22,730	25,230	25,230	27,628
Adj. R^2	0.594	0.589	0.589	0.582
# Insurance groups	47	49	49	51

Table IA.7: Substitution in coal mine insurance: Poisson estimates

This table re-estimates Panels B and C of Table 6 as Poisson regressions at the mine-quarter level:

$$\#Active\ insurers_{m,t} = \beta \times Post\ coal\ policy\ exposed_{m,t} + \alpha_m + \alpha_t + \epsilon_{m,t}.$$

In Panel A, the dependent variable, *# Active insurers*, is the number of insurers actively covering a mine in a given quarter, counting all insurers in Column 1, only insurers that have adopted a coal underwriting policy in Column 2 (*# Active insurers w/ coal policy*), and only insurers that have not in Column 3 (*# Active insurers w/o coal policy*). In Panel B, we use a variant of the regression in Panel A where the dependent variable is the corresponding average number of active insurance lines of the mine's insurers (*Mean # active lines*). *Post coal policy exposed* equals one for mines that, between 2014 and 2016, are insured by an insurer that subsequently adopted a coal underwriting policy, in the first quarter after the earliest adoption of such policy and all quarters thereafter, and zero otherwise. The sample includes all mines from Table 4, and quarters in which we successfully obtained Certificates of Liability Insurance on ACORD 25 forms from state-level agencies. For each mine, we retain every observed mine-insurer pair for all quarters with available certificate data, coding quarters without coverage as inactive. In all panels, standard errors are clustered at the mine level and reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. Table A.1 provides descriptions of all variables.

Panel A: Substitution on the extensive margin

	# Active insurers	*# Active insurers w/ coal policy*	*# Active insurers w/o coal policy*
	(1)	(2)	(3)
Post coal policy exposed	-0.075*	-0.352***	0.304***
	(0.039)	(0.095)	(0.083)
Coal mine FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Obs.	10,249	10,249	10,249
# Coal mines	296	296	296

Panel B: Substitution on the intensive margin

	Mean # active lines	*Mean # active lines of insurers w/ coal policy*	*Mean # active lines of insurers w/o coal policy*
	(1)	(2)	(3)
Post coal policy exposed	0.008	-0.390***	0.274***
	(0.044)	(0.121)	(0.091)
Coal mine FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Obs.	10,249	10,249	10,249
# Coal mines	296	296	296

Table IA.8: Coal mine outcomes and share of underwriters with policies

This table presents results from the following shift-share (Bartik) regression, estimated with OLS at the mine-quarter level:

$$Coal\ mine\ outcome_{m,t} = \beta \times Share\ coal\ policy\ exposed_{m,t} + \alpha_m + \alpha_t + \epsilon_{m,t}$$

where m indexes a mine and t a quarter. The dependent variable, *Coal mine outcome*, is either a dummy variable indicating whether a mine is abandoned (Column 1) or the (log of) volume of coal produced (Column 2). We define $Share\ coal\ policy\ exposed_{m,t} = \sum_i w_{m,i} \times Post\ coal\ policy_{i,t}$, where i indexes an insurer, w are equal weights allocated to each insurer with at least eight quarters of active insurance relationship with a given mine between 2014 and 2016, and *Post coal policy* equals one for insurer-quarters after a coal underwriting policy is adopted, and zero otherwise. The sample includes all mines from Table 4, excluding those that do not have an active insurance relationship with the same insurer for at least eight quarters between 2014 and 2016. In Column 2, the sample includes only mines that are active throughout the entire sample period. Standard errors are clustered at the mine level and reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. Table A.1 provides descriptions of all variables.

	Abandoned	*Production (log)*
	(1)	(2)
Share coal policy exposed	0.033	-0.160**
	(0.033)	(0.079)
Coal mine FE	Yes	Yes
Time FE	Yes	Yes
Obs.	8,938	1,886
Adj. R^2	0.558	0.929
# Coal mines	213	47

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