Does Market Discipline Work? Stock Market Contagion from Tailings Dam Failures

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Abstract

Do financial markets discipline firms for environmental catastrophes? Using 118 tailings dam failures worldwide (1996–2025) and daily stock returns for 42 publicly traded mining firms, I find that failures trigger competitive *reallocation*, not sector-wide contagion. The average peer-firm cumulative abnormal return is slightly positive (+0.23%), but this aggregate masks sharp cross-sectional heterogeneity: firms operating tailings dams earn 0.79 percentage points less than streaming companies without physical mines ($t = -2.25$, event fixed effects). After the 2020 Global Industry Standard on Tailings Management, this penalty intensified by an additional 1.39 percentage points ($p < 0.05$). Major disasters (≥10 deaths) produce unambiguously negative mean contagion (−1.21%). Markets discipline mining firms not through blanket punishment but through risk differentiation that sharpens under voluntary governance standards.

JEL Codes: G14, G38, L71, Q58

Keywords: market discipline, tailings dam failures, event study, mining regulation, GISTM

1. Introduction

On January 25, 2019, Dam I at the Corrêgo do Feijão iron ore mine in Brumadinho, Brazil, collapsed without warning. Twelve million cubic meters of mining waste buried the mine's administrative buildings, a railway bridge, and neighboring farms. Two hundred and seventy people died. Within hours, Vale S.A.'s share price fell 24 percent, erasing $19 billion in market capitalization. The collapse prompted the Church of England Pensions Board to convene a coalition of institutional investors managing over $25 trillion in assets, ultimately producing the Global Industry Standard on Tailings Management (GISTM) — the mining industry's first comprehensive voluntary safety framework.

This paper asks a simple question: does this kind of market punishment actually work? More precisely, when a tailings dam fails, do stock markets penalize *peer* mining firms — and if so, does the penalty fall on the firms most exposed to similar risks? The answer matters because market discipline is the principal mechanism through which voluntary standards like the GISTM are supposed to operate. If investors cannot distinguish between safe and unsafe firms, or if they punish the entire sector indiscriminately, then voluntary governance lacks teeth and mandatory regulation becomes necessary.

I assemble the first comprehensive global dataset linking tailings dam failures to mining-sector stock returns. The dataset combines 118 failure events from the WISE Uranium Project's Chronology of Major Tailings Dam Failures (1996–2025) with daily stock returns for 42 publicly traded mining firms spanning 14 commodities. The resulting panel contains 4,103 firm-event observations. For each event, I estimate market-model abnormal returns and compute cumulative abnormal returns (CARs) over the seven-day window $[-1, +5]$.

Three findings emerge. First, the *average* CAR across all peer firms is slightly positive (+0.23%), suggesting that aggregate competitive reallocation — investors moving capital toward mining firms unaffected by the failure — dominates sector-wide contagion. The pre-event placebo CAR over $[-5, -2]$ is economically small and statistically insignificant (+0.07%, $t = 0.82$), confirming that the event-study design captures responses to failures rather than pre-existing trends.

Second, this aggregate masks dramatic heterogeneity. Firms that operate tailings dams — and thus face direct exposure to similar failures — earn 0.79 percentage points less than streaming and royalty companies that hold financial interests in mining output but operate no physical mines ($t = -2.25$, event fixed effects; Column 5, Table 2). The cross-sectional estimate without event fixed effects is -0.87 percentage points ($t = -2.44$; Column 2). The commodity channel, by contrast, generates no significant differential: firms mining the same commodity as the failure site earn slightly lower returns, but the effect is statistically indistinguishable from zero. Markets care about operational risk, not product-market proximity.

Third, the adoption of the GISTM in August 2020 sharpened market differentiation. Before GISTM, the average peer-firm CAR was +0.41%; after GISTM, it turned negative at −0.18%. More importantly, the interaction between tailings-dam ownership and the post-GISTM period is −1.39 percentage points ($p < 0.05$): after the standard's adoption, firms with tailings exposure are punished significantly more than firms without it. This is consistent with the hypothesis that voluntary standards improve investor screening by establishing a benchmark against which firms can be evaluated.

This paper contributes to three literatures. First, it adds to the growing literature on financial contagion from industrial disasters. The theoretical distinction between contagion (common-risk repricing) and competitive effects (market-share reallocation) originates with Lang and Stulz (1992), who study bankruptcy announcements and show that competitors can *gain* when a rival fails. Capelle-Blancard and Laguna (2010) study 64 chemical plant explosions and find negative CARs of approximately −1% for the responsible firm but muted effects on competitors. Kaplanski and Levy (2010) show that aviation disasters produce negative market-wide returns driven by investor sentiment. Kowalewski et al. (2020) study potash mine disasters and find that competitors gain while the responsible firm loses — a pattern consistent with competitive reallocation. Bartram and Bodnar (2009) provide evidence on international financial contagion more broadly. My contribution is to document the reallocation mechanism across 118 events in a single industry, and to show that it is moderated by firm-level risk characteristics.

Second, the paper speaks to the economics of voluntary environmental disclosure and self-regulation. Dye (1985) and Verrecchia (1983) develop the theoretical foundations for voluntary disclosure, showing that firms disclose when the benefits of reducing information asymmetry exceed proprietary costs. Maxwell et al. (2000) argue that self-regulation can preempt mandatory regulation when firms face credible legislative threats. Dimson et al. (2015) demonstrate that coordinated investor engagement produces abnormal returns for target firms. The GISTM represents a natural experiment in this framework: a coalition-driven voluntary standard, adopted by firms under political pressure from the Brumadinho disaster, that provides a public commitment device investors can monitor.

Third, the paper contributes to the empirical literature on mining safety, environmental events, and market responses. Hamilton (1995) demonstrates that markets respond to the release of Toxics Release Inventory data, establishing the informational channel through which environmental news moves stock prices. Klassen and McLaughlin (1996) show that environmental awards and crises produce significant abnormal returns. Humphrey et al.

(2016) study the Deepwater Horizon oil spill and find contagion effects across the energy sector. Flammer (2015) shows that firms penalized by markets for environmental violations subsequently improve their environmental performance — a direct channel through which market discipline operates. More broadly, Hong and Kacperczyk (2009) and Krueger et al. (2020) document how social norms and climate risk perceptions are priced in financial markets. I extend this work by studying an entire class of events (tailings dam failures) rather than a single incident, and by exploiting the GISTM adoption as a source of temporal variation in market sophistication.

The remainder of the paper proceeds as follows. Section 2 provides institutional background on tailings dams and the GISTM. Section 3 describes the data construction. Section 4 details the event-study methodology. Section 5 presents the main findings. Section 6 reports robustness checks. Section 7 discusses mechanisms. Section 8 concludes.

2. Institutional Background

2.1 Tailings Dams: Engineering and Failure Modes

Mining operations produce vast quantities of waste rock and chemically processed residue called "tailings." These materials — ground rock particles suspended in water, often containing heavy metals and processing chemicals — must be stored permanently. Tailings storage facilities (TSFs) are among the largest engineered structures on earth. The Mount Polley tailings dam in British Columbia, which failed in 2014, impounded 25 million cubic meters of material behind an embankment 40 meters high. The Samarco Fundao dam in Brazil, which collapsed in 2015 killing 19 people and releasing 32 million cubic meters of iron ore tailings, stretched over a kilometer.

Three principal dam construction methods exist, ordered by increasing risk: downstream, centerline, and upstream. Upstream dams, the cheapest and most common historically, are built by progressively raising the embankment *on top of* previously deposited tailings. This construction method is inherently fragile: the dam's foundation consists of unconsolidated, water-saturated material. Both the Brumadinho and Samarco dams used upstream construction. Following Brumadinho, Brazil, Chile, and Peru banned upstream construction, and the GISTM imposed stringent requirements on all remaining upstream facilities worldwide.

Tailings dam failures result from multiple mechanisms: foundation failure due to liquefaction (triggered by seismic activity or excessive pore pressure), overtopping from extreme rainfall, piping (internal erosion), and slope instability. Critically for identification, these engineering failures are *exogenous to peer firms' stock returns* in the short run. A dam failure in Minas Gerais does not cause Newmont's ore body in Nevada to change value. The failure transmits information — about regulatory risk, about operational risk across the industry, about the credibility of safety assurances — and it is precisely this information channel that creates the market discipline effect I measure.

2.2 The Scale of the Problem

The WISE Uranium Project's Chronology of Major Tailings Dam Failures documents over 350 significant incidents worldwide since 1960. My analysis sample covers 118 events from 1996 to 2025, spanning 37 countries and 24 ore types. Twenty-six percent of events in the sample are fatal, with an average of 34 deaths per fatal event. Nine percent qualify as "major" (10 or more deaths). The geographic distribution reflects global mining activity: Brazil, China, the Philippines, the United States, and Canada account for the plurality of events.

The economic costs of tailings dam failures extend far beyond the immediate human toll. The Samarco disaster generated an estimated $5.2 billion in cleanup and compensation costs. The Brumadinho collapse led to $7.0 billion in charges against Vale's earnings. Mount Polley cost Imperial Metals over $40 million in direct remediation, plus immeasurable damage to British Columbia's salmon fisheries. These costs — and the regulatory responses they provoke — are the foundation of the market discipline channel.

2.3 Institutional Response: From Brumadinho to GISTM

The Brumadinho disaster catalyzed an unprecedented institutional response. In April 2019, the Church of England Pensions Board and the Swedish National Pension Funds (AP-fonderna) launched the Investor Mining & Tailings Safety Initiative, eventually comprising over 100 institutional investors managing more than $25 trillion. The initiative demanded that mining companies publicly disclose the location, construction method, and safety status of all their tailings facilities — information that had previously been closely guarded.

In August 2020, the International Council on Mining and Metals (ICMM), the UN Environment Programme (UNEP), and the Principles for Responsible Investment (PRI) jointly published the Global Industry Standard on Tailings Management (GISTM). The standard requires independent safety reviews, public disclosure of dam hazard classifications, and "consequence-based" risk assessments that evaluate dams based on worst-case failure scenarios rather than engineering probability. ICMM's 28 member companies — including BHP, Rio Tinto, Anglo American, Glencore, and Newmont — committed to implement the GISTM within three years for high-consequence facilities and five years for all others.

The GISTM represents a *voluntary* standard with market-based enforcement. No government requires compliance. Instead, institutional investors use compliance as a screening criterion, and non-compliant firms face higher costs of capital, exclusion from ESG indices, and reputational risk. The question this paper answers is whether this market-based enforcement mechanism produces measurable effects on stock returns following failures — and whether the adoption of GISTM itself changed the nature of market discipline.

2.4 The Market Discipline Hypothesis

Market discipline operates through information revelation. When a tailings dam fails, investors update their beliefs about the safety of *all* tailings facilities. If investors are sophisticated, they update differentially: firms with more tailings dams, older dams, upstream construction, or operations in weakly regulated jurisdictions should face larger penalties. Firms with no tailings exposure — such as streaming and royalty companies that hold financial claims on mining output without operating physical mines — should face no direct penalty and may even benefit from competitive reallocation.

The GISTM potentially changes this mechanism. Before GISTM, investors had limited ability to distinguish safe from unsafe operators: tailings facility data was not publicly disclosed, and no common standard existed for evaluating safety practices. After GISTM, investors gained a benchmark. Firms committed to the standard signal their type; firms that resist signal the opposite. If GISTM improves market discipline, we should observe *sharper* differentiation in post-GISTM CARs: firms with tailings exposure should be punished more, and firms without exposure should be punished less (or rewarded), relative to the pre-GISTM period.

3. Data

3.1 Tailings Dam Failure Events

Event data come from the WISE Uranium Project's Chronology of Major Tailings Dam Failures, a comprehensive database maintained since 1960 that records the date, location, mine name, ore type, release volume, fatality count, and cause of each documented tailings dam failure worldwide.[1] I scrape the complete chronology and retain events from 1996 onward, the period for which reliable daily stock return data are available. The raw scrape yields 191 events; after dropping events with imprecise dates (year-only precision without month) and events occurring before the earliest stock data in the sample, 118 events remain.

[1]Available at `https://www.wise-uranium.org/mdaf.html`. WISE is a non-governmental organization that has maintained this chronology since the 1990s. It is the standard data source in the engineering literature on tailings safety (Rico et al., 2008; Bowker and Chambers, 2015).

I classify event severity into four categories: *Major* (10 or more deaths), *Fatal* (any deaths below 10), *Large Release* (no deaths but release volume exceeding 100,000 cubic meters), and *Other*. This classification captures the two principal dimensions of severity — human toll and environmental scale — that drive media coverage and regulatory response.

I define the *post-GISTM* period as beginning on August 5, 2020, the date the standard was publicly launched. Of the 118 events, 88 (75%) occur before GISTM and 30 (25%) after. I flag overlapping events — those occurring within 10 trading days of another event — for robustness analysis.

3.2 Mining Firm Universe

I construct a universe of 42 publicly traded mining firms representing 14 commodity groups (Table 1, Panel B). The sample includes the world's largest diversified miners (BHP, Rio Tinto, Glencore, Anglo American), major commodity-specific producers (Vale, Freeport-McMoRan, Newmont, Barrick Gold), and — critically — three streaming and royalty companies: Wheaton Precious Metals (WPM), Franco-Nevada (FNV), and Royal Gold (RGLD).

Streaming companies provide a natural built-in placebo. These firms purchase the right to a percentage of a mine's future production at a predetermined price. They collect commodity upside without operating any physical infrastructure — no mines, no tailings dams, no processing plants. If tailings dam failures transmit information about operational mining risk, streaming companies should be unaffected; any positive CAR they exhibit reflects competitive reallocation from physical miners.

For each firm, I code two binary characteristics. *Has tailings dams* equals one if the firm operates any tailings storage facility (93% of the sample; the remaining 7% are streaming/royalty companies). *Same commodity* equals one if the firm's primary commodity matches the ore type of the failed dam, or if the firm is classified as "Diversified."

3.3 Stock Return Data

Daily stock prices come from Yahoo Finance via the `quantmod` R package. I compute log returns as $r_{it} = \ln(P_{it}/P_{i,t-1})$ using adjusted closing prices that account for dividends and stock splits. The market benchmark is the S&P 500 index (ticker `^GSPC`), downloaded from the same source. I construct a panel of 6,774 trading days spanning January 1996 to March 2026.

For each firm-event pair, I require a minimum of 100 trading days in the estimation window $[-250, -31]$ relative to the event date. This requirement ensures reliable estimation of market model parameters and drops firm-event observations for which the firm was not yet publicly traded or had insufficient trading history. After applying this filter, the analysis sample contains 4,103 firm-event observations.

3.4 Summary Statistics

Table 1 presents summary statistics in three panels. Panel A describes the 118 failure events: 26% are fatal, 9% are major (10+ deaths), and 25% occur after GISTM adoption. Events span 37 countries and 24 ore types. Panel B describes the 42 mining firms: 93% operate tailings dams, and 7% are streaming/royalty companies. Panel C reports CAR distributions: the mean CAR over $[-1, +5]$ is $+0.230\%$ with a standard deviation of 7.42%, indicating substantial heterogeneity across firm-event pairs. The pre-event placebo CAR over $[-5, -2]$ is $+0.074\%$, economically and statistically insignificant.

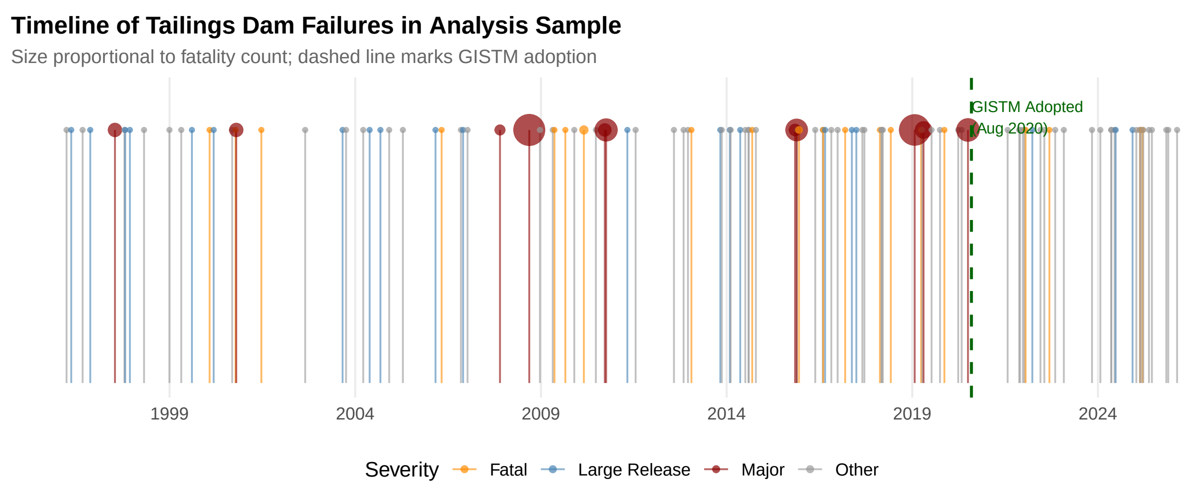

Figure 1: Timeline of Tailings Dam Failures in Analysis Sample

Notes: Each vertical line represents a tailings dam failure event. Marker size is proportional to fatality count for fatal events. Dashed green line marks the adoption of the Global Industry Standard on Tailings Management (GISTM) on August 5, 2020. Event data from the WISE Chronology of Major Tailings Dam Failures. $N = 118$ events.

4. Empirical Methodology

4.1 Market Model Event Study

I follow the standard event-study methodology as described in MacKinlay (1997) and Campbell et al. (1997); see also Fama et al. (1969) and Brown and Warner (1985) for foundational work on event study design. The approach proceeds in three steps: estimation of normal returns, computation of abnormal returns, and aggregation into cumulative abnormal returns.

Table 1: Summary Statistics

Panel A: Tailings Dam Failure Events	
Number of events	118
Year range	1996 – 2025
Fatal events (%)	26.3
Major events (≥10 deaths, %)	9.3
Mean fatality count (fatal events)	34.4
Post-GISTM (%)	25.4
Countries	37
Ore types	24
Panel B: Mining Firm Universe	
Number of firms	42
With tailings dams (%)	92.9
Streaming/royalty (%)	7.1
Commodities represented	14
Panel C: Cumulative Abnormal Returns	
Mean CAR [-1, +1] (%)	-0.277
Mean CAR [-1, +5] (%)	0.230
Mean CAR [-1, +10] (%)	-0.275
Mean CAR [-5, -2] (placebo, %)	0.074
SD of CAR [-1, +5] (%)	7.421
Firm-event observations	4,103

Notes: Event data from the WISE World Information Service on Energy Uranium Project Chronology of Major Tailings Dam Failures (1960–2025). Stock return data from Yahoo Finance. CARs computed using the market model with S&P 500 as benchmark, estimated over trading days [-250, -31] relative to the failure event. The placebo window [-5, -2] tests for pre-event abnormal returns.

Step 1: Normal Return Estimation. For each firm i and event j, I estimate the market model over the estimation window $[-250, -31]$ trading days relative to the event date:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}, \quad \mathbb{E}[\varepsilon_{it}] = 0, \quad \mathrm{Var}[\varepsilon_{it}] = \sigma^2_{\varepsilon_i} \tag{1}$$

where R_{it} is the log return on firm i's stock on day t, R_{mt} is the log return on the S&P 500 index, and the parameters $(\hat{\alpha}_i, \hat{\beta}_i)$ are estimated by OLS. The 220-day estimation window (after accounting for non-trading days) provides stable parameter estimates while maintaining a 30-day gap before the event to prevent contamination from anticipatory trading.

Step 2: Abnormal Returns. Abnormal returns in the event window are:

$$\widehat{AR}_{it} = R_{it} - \hat{\alpha}_i - \hat{\beta}_i R_{mt} \tag{2}$$

These represent the component of firm i's return on day t that cannot be explained by its normal covariance with the market.

Step 3: Cumulative Abnormal Returns. I cumulate abnormal returns over the primary event window $[\tau_1, \tau_2]$:

$$\widehat{CAR}_i(\tau_1, \tau_2) = \sum_{t=\tau_1}^{\tau_2} \widehat{AR}_{it} \tag{3}$$

The primary window is $[-1, +5]$, capturing the day before the event (to account for time-zone differences and partial-day news releases) through five trading days after. I report robustness to alternative windows $[-1, +1]$ and $[-1, +10]$.

4.2 Cross-Sectional Regressions

To test whether CARs vary systematically with firm and event characteristics, I estimate cross-sectional regressions of the form:

$$CAR_{ij} = \beta_0 + \beta_1 \cdot \text{HasTailings}_i + \beta_2 \cdot \text{SameCommodity}_{ij} + \gamma' \mathbf{X}_j + \varepsilon_{ij} \tag{4}$$

where CAR_{ij} is firm i's cumulative abnormal return around event j (in percentage points), HasTailings_i is an indicator for firms that operate tailings storage facilities, $\text{SameCommodity}_{ij}$ indicates that firm i mines the same commodity as the failed dam in event j, and $\mathbf{X}_j$ is a vector of event characteristics including severity indicators and the post-GISTM dummy.

The key specification interacts firm characteristics with the post-GISTM indicator:

$$\begin{aligned} CAR_{ij} = \beta_0 &+ \beta_1 \cdot \text{HasTailings}_i + \beta_2 \cdot \text{SameCommodity}_{ij} \\ &+ \beta_3 \cdot \text{PostGISTM}_j + \beta_4 \cdot \text{HasTailings}_i \times \text{PostGISTM}_j \\ &+ \beta_5 \cdot \text{SameCommodity}_{ij} \times \text{PostGISTM}_j + \gamma' \text{Severity}_j + \varepsilon_{ij} \end{aligned} \tag{5}$$

The coefficient β_4 tests whether market differentiation between tailings-owning and non-tailings firms sharpened after GISTM adoption. Standard errors are clustered by event to account for the mechanical correlation of CARs across firms responding to the same event (Petersen, 2009; Kolari and Pyönnönen, 2010).

In the most demanding specification, I include event fixed effects:

$$CAR_{ij} = \mu_j + \beta_1 \cdot \text{HasTailings}_i + \beta_2 \cdot \text{SameCommodity}_{ij} + \varepsilon_{ij} \tag{6}$$

This absorbs all event-level variation (severity, location, date, media coverage, market conditions) and identifies β_1 and β_2 purely from *within-event* variation across firms. The event fixed effects specification is the cleanest test of whether firm characteristics predict differential contagion, conditional on the same event.

4.3 Identification Assumptions and Threats

The event-study design rests on three assumptions. First, tailings dam failures must be *unanticipated*. If markets expected the failure, abnormal returns would appear before the event window. The pre-event placebo window $[-5, -2]$ directly tests this assumption: CAR $= +0.07\%$ ($t = 0.82$), consistent with no anticipation.

Second, failures must be *exogenous to peer firms' contemporaneous fundamentals*. This is plausible by construction: an engineering failure in one country cannot simultaneously affect ore reserves, labor costs, or production schedules at unrelated mines. The identifying variation is purely informational.

Third, no *confounding events* should systematically coincide with tailings dam failures. I address this by (a) controlling for market-wide movements through the market model, (b) testing robustness to excluding overlapping events, and (c) verifying that non-mining placebo firms (utilities ETF) show no response.

Two threats merit particular attention. First, the GISTM adoption date (August 2020) falls during the COVID-19 pandemic, when equity volatility was elevated. The market model explicitly nets out aggregate market movements, so COVID-driven volatility in the S&P 500 is absorbed. Moreover, the GISTM interaction tests *within-event* variation: conditional on any given event's effect on the market, do tailings-owning firms respond differently post-GISTM? This within-event variation is not confounded by aggregate volatility. Second, firm characteristics (has tailings dams, commodity) are measured contemporaneously but applied to historical events. Major mining firms' operational profiles change slowly — BHP has operated tailings dams for decades — so this measurement concern is minimal for the large firms that dominate the sample.

5. Results

5.1 Overall Cumulative Abnormal Returns

Figure 2 plots the day-by-day cumulative abnormal return for all peer mining firms around tailings dam failure events. Two features stand out. First, the pre-event period $[-5, -2]$ is flat, confirming the absence of anticipatory effects. Second, abnormal returns begin on event day 0 and accumulate through day +5, settling at approximately +0.23%. The cross-sectional t-statistic for this average is 1.99 (Table 3, Panel A), though event-clustered standard errors — the more conservative inference — yield $t = 0.61$ (Table 2, Column 1), and a permutation test using 200 random pseudo-event dates yields $p = 0.57$. The aggregate average is not robustly distinguishable from zero. The action, as we show below, lies in the cross-sectional heterogeneity.

The positive sign is the first substantive finding: on average, peer mining firms *gain* when a competitor's tailings dam fails. This is inconsistent with pure contagion — the hypothesis that failures raise the perceived riskiness of the entire sector — and instead points toward competitive reallocation. When a mine goes offline, commodity supply contracts, prices adjust upward, and competitors benefit. The competitive channel dominates the regulatory-risk channel in aggregate.

5.2 Tailings Ownership Heterogeneity

The aggregate positive CAR masks a sharp divergence between firms with and without tailings exposure. Figure 3 plots CARs separately for firms operating tailings dams and streaming/royalty companies (the built-in placebo group). Streaming companies — which hold no physical mining infrastructure — show a distinctly positive CAR trajectory, reaching approximately +1% by day +5. Firms with tailings dams, by contrast, exhibit near-zero or slightly positive CARs, consistent with the competitive benefit being partially offset by contagion risk.

Table 2 reports cross-sectional regression results. Column (1), an intercept-only regression,

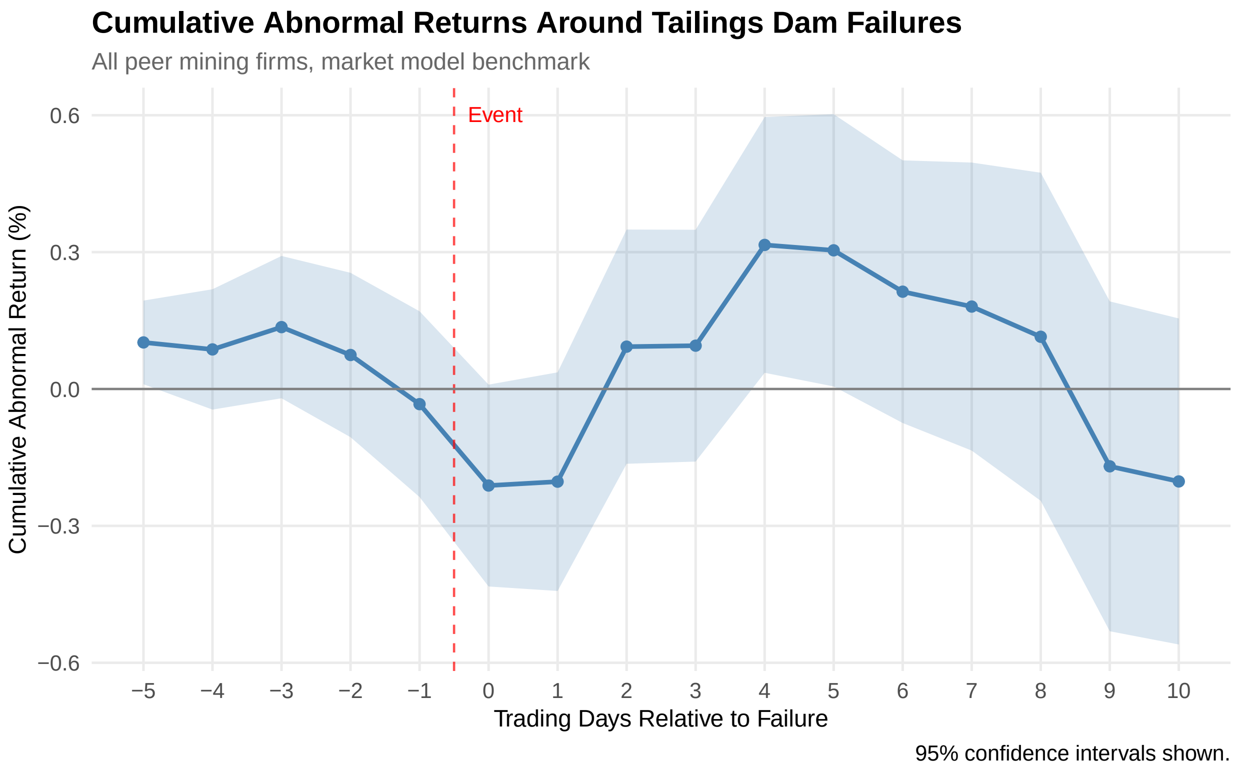

Figure 2: Cumulative Abnormal Returns Around Tailings Dam Failures: All Peer Mining Firms

Notes: Daily cumulative abnormal returns (CARs) for all 42 peer mining firms around 118 tailings dam failure events. Abnormal returns computed using the market model (S&P 500 benchmark), estimated over [-250, -31] trading days. Shaded band shows 95% confidence intervals. Dashed vertical line marks event day 0 (failure date). $N = 4{,}103$ firm-event pairs; daily N varies slightly due to individual missing trading days.

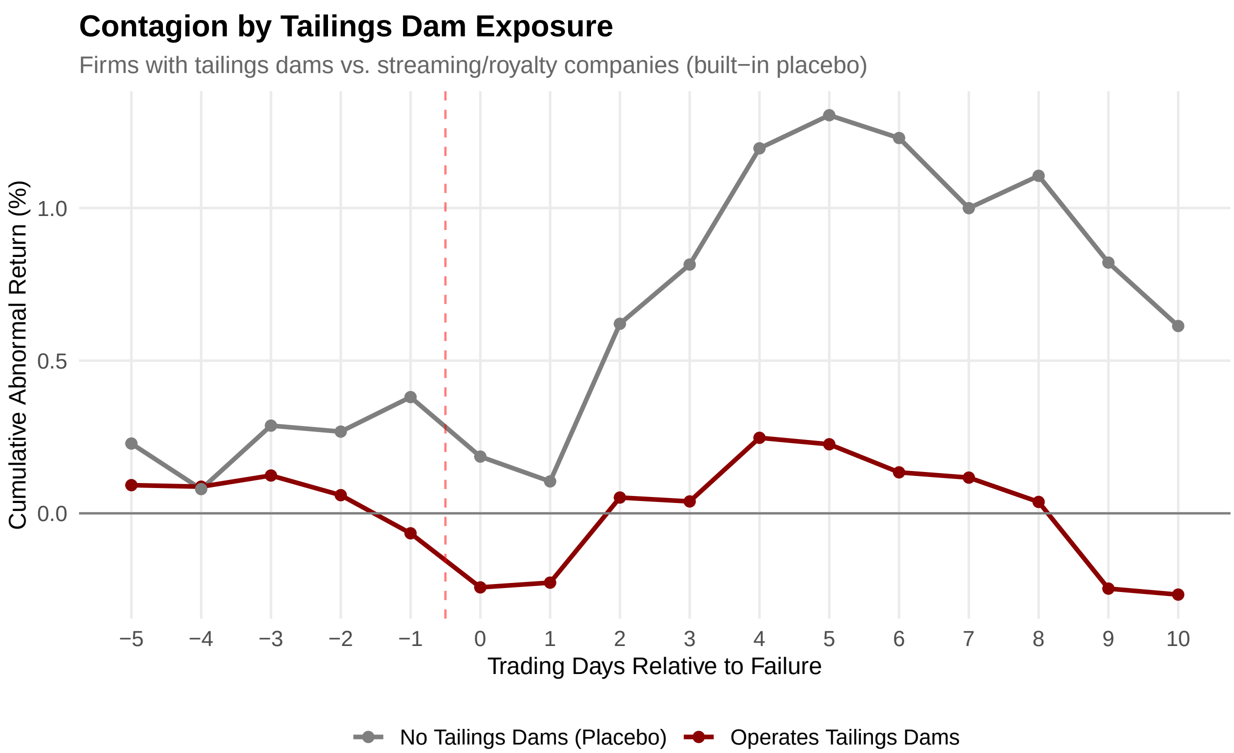

Figure 3: Contagion by Tailings Dam Exposure

Notes: CARs plotted separately for firms operating tailings dams (N_{obs} = 3,811) and streaming/royalty companies without physical mines (N_{obs} = 292). Streaming companies (Wheaton Precious Metals, Franco-Nevada, Royal Gold) serve as a built-in placebo: they hold financial claims on mining output but operate no tailings facilities.

recovers the unconditional mean CAR of +0.23 pp; the event-clustered standard error of 0.37 yields $t = 0.61$, confirming that the aggregate average is not robustly significant. Column (2) introduces firm characteristics: the tailings-ownership indicator carries a coefficient of -0.87 pp ($t = -2.44$, event-clustered standard errors). Same-commodity exposure is negative but statistically insignificant (-0.09 pp, $t = -0.27$). Column (3) adds severity indicators: major events ($\geq$10 deaths) produce a -1.90 pp differential relative to non-fatal events, though imprecisely estimated ($p = 0.21$). Column (4) introduces the GISTM interaction: the coefficient on HasTailings × PostGISTM is -1.39 pp ($t = -2.02$, $p < 0.05$). Column (5) adds event fixed effects, yielding the cleanest within-event estimate: -0.79 pp on the tailings indicator ($t = -2.25$).

The magnitude of the tailings-ownership effect is economically meaningful. A 0.79 percentage point relative loss, applied to a median-sized mining firm with \$20 billion market capitalization, translates to approximately \$158 million in relative market value destruction. Accumulated over 118 events, this represents a persistent repricing of operational mining risk.

5.3 The GISTM Structural Break

Figure 4 plots CARs separately for the pre-GISTM period (88 events, before August 2020) and post-GISTM period (30 events). Pre-GISTM, peer firms exhibit a positive CAR trajectory reaching approximately +0.41% by day +5 — consistent with competitive reallocation dominating. Post-GISTM, the trajectory is flatter and closer to zero. The mean CAR computed over the $[-1, +5]$ window (the primary specification) is +0.41% pre-GISTM but -0.18% post-GISTM — a reversal consistent with increased market scrutiny after the standard's adoption.

The key result, however, is not the shift in overall CARs but the interaction reported in Column (4) of Table 2. The coefficient on HasTailings × PostGISTM is -1.39 pp ($p < 0.05$). Before GISTM, the tailings-ownership penalty was -0.45 pp (the main effect in Column 4, -0.4450 precisely). After GISTM, the penalty roughly tripled to $-0.45 + (-1.39) = -1.84$ pp. Meanwhile, the post-GISTM main effect is positive but insignificant (+0.26 pp, $t = 0.26$), suggesting that the overall shift toward negative CARs is driven entirely by the differential treatment of tailings-owning firms.

This pattern is consistent with GISTM improving investor screening. Before the standard, investors lacked the information to differentiate safe from unsafe operators, and all mining firms received a similar (positive, reallocation-driven) response to peer failures. After GISTM, investors could distinguish firms committed to the standard from those that were not, and firms with tailings exposure faced sharper penalties. The voluntary standard did not create market discipline from nothing — it sharpened a pre-existing mechanism.

Table 2: Cross-Sectional Determinants of Peer Firm Contagion

	(1)	(2)	(3)	(4)	(5)
Variables					
Constant	0.2303	1.056**	1.508**	1.539**	
	(0.3749)	(0.5086)	(0.6007)	(0.6637)	
Has tailings dams		-0.8707**	-0.8701**	-0.4450	-0.7864**
		(0.3566)	(0.3570)	(0.4517)	(0.3491)
Same commodity		-0.0896	-0.1363	-0.1331	0.0972
		(0.3317)	(0.3275)	(0.4359)	(0.2741)
Severity = Fatal			-0.6637	-0.8430	
			(0.8935)	(0.8563)	
Severity = Large release			-0.9899	-1.213	
			(0.8908)	(0.8343)	
Severity = Major			-1.895	-2.320	
			(1.509)	(1.504)	
Post-GISTM				0.2610	
				(1.018)	
Has tailings × Post-GISTM				-1.390**	
				(0.6891)	
Post-GISTM × Same commodity				-0.0895	
				(0.5954)	
Fixed-effects					
Event	No	No	No	No	Yes
Fit statistics					
Observations	4,103	4,103	4,103	4,103	4,103
R^2	—	0.00094	0.00748	0.01187	0.29092
Within R^2	—	—	—	—	0.00110

Clustered (event) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent variable: CAR [-1, +5] in percentage points. Standard errors clustered by event in columns (1)–(4). Column (5) includes event fixed effects. *Has tailings dams* = 1 if the peer firm operates tailings storage facilities. *Same commodity* = 1 if the peer firm mines the same commodity as the failure site. *Post-GISTM* = 1 for events after August 2020. Results are robust to two-way clustering by event and firm (see Section 6).

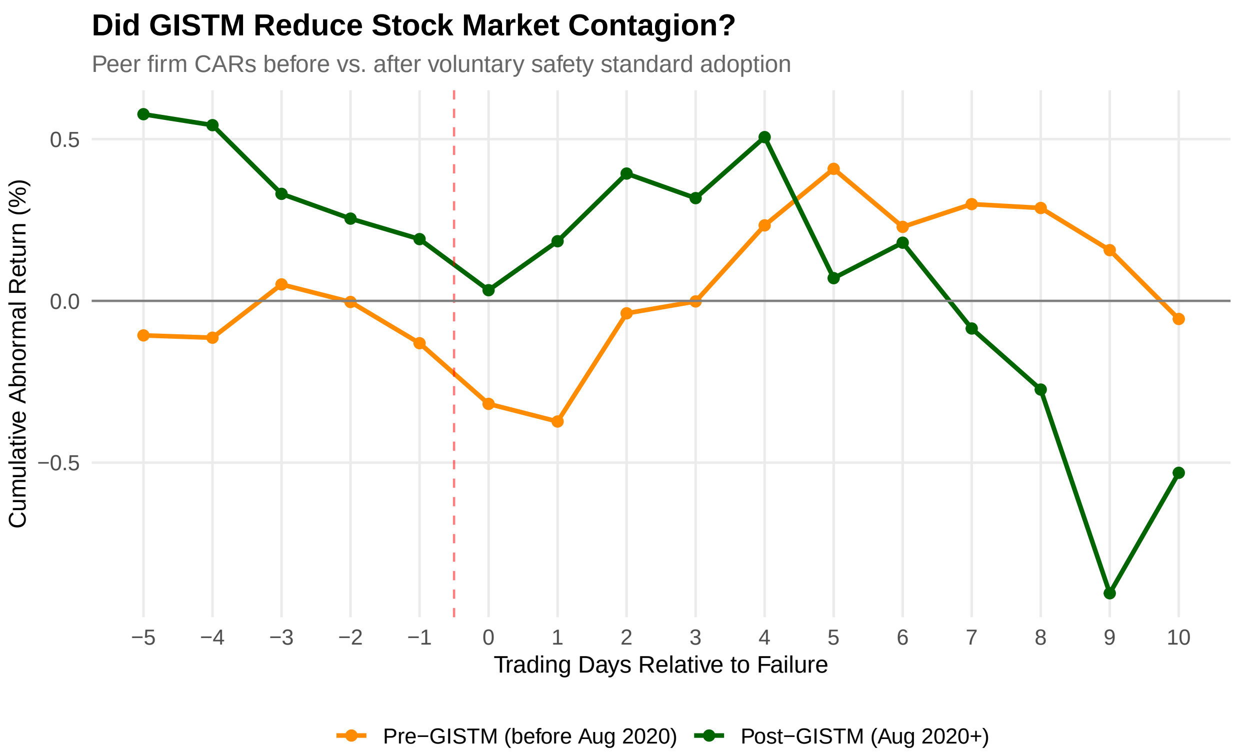

Figure 4: Cumulative Abnormal Returns Before and After GISTM Adoption

Notes: CARs plotted separately for events before August 2020 (pre-GISTM, $N = 88$ events) and after (post-GISTM, $N = 30$ events). GISTM = Global Industry Standard on Tailings Management, launched August 5, 2020.

5.4 Severity Gradient

Figure 5 plots CARs by event severity. Major events (≥10 deaths) produce an unambiguously negative *unconditional mean* CAR of −1.21% by day +5, consistent with severe disasters overwhelming the competitive reallocation channel. (The regression coefficient on the major-severity indicator in Column 3 of Table 2 is −1.90 pp, which measures the differential relative to non-fatal events *conditional on* firm characteristics.) Fatal events (below 10 deaths) produce near-zero CARs. Non-fatal events produce positive CARs (+0.67%), where the competitive benefit dominates.

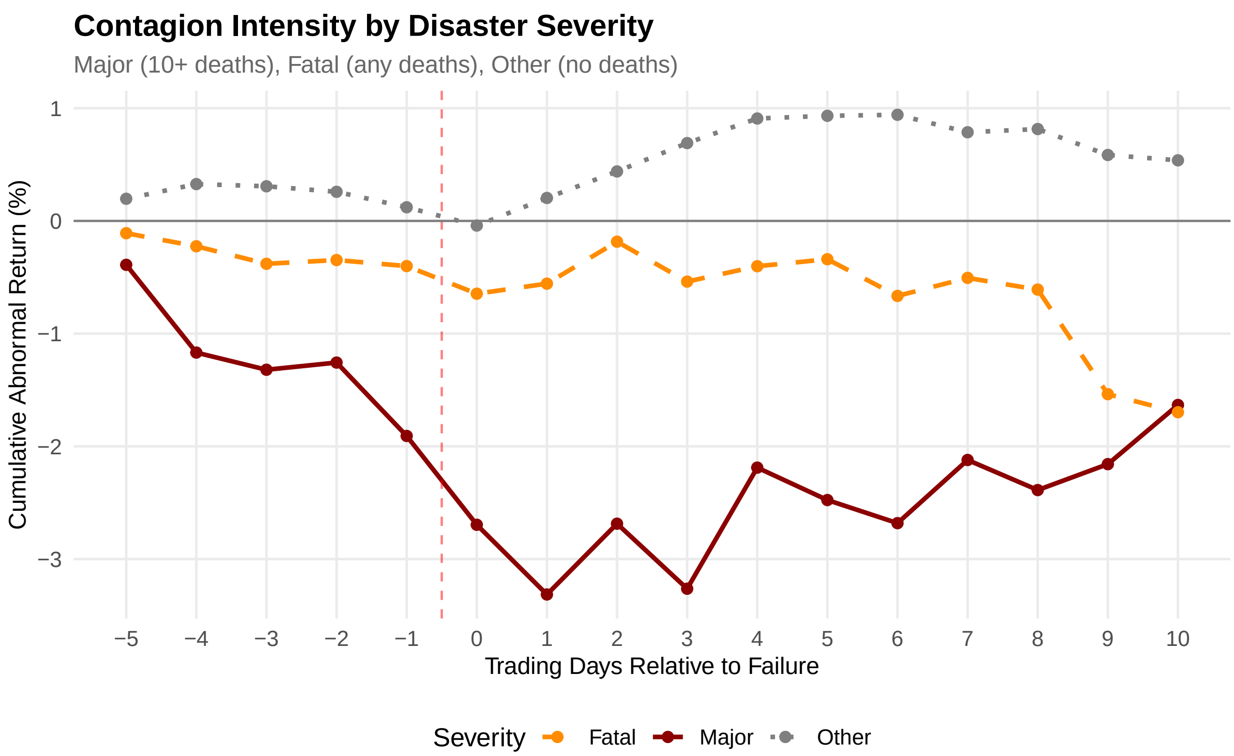

Figure 5: Contagion Intensity by Disaster Severity

Notes: CARs plotted separately by event severity classification. Major = 10+ deaths; Fatal = any deaths below 10; Other = no deaths. Severity classification based on fatality count from the WISE database.

The severity gradient provides further evidence for the market discipline interpretation. Market punishment is not uniform — it scales with the salience and severity of the failure. This is exactly what a rational updating model predicts: a non-fatal spill reveals little about systemic risk (and competitors benefit from supply disruption), while a catastrophe with dozens of deaths signals that the industry's safety assurances are unreliable.

5.5 Commodity Channel

Figure 6 plots CARs separately for firms mining the same commodity as the failure site and firms mining different commodities. The commodity channel is weak: same-commodity firms earn slightly lower CARs than different-commodity firms, but the difference is economically small and statistically insignificant across all specifications in Table 2. This null result is informative: it suggests that markets do not view tailings dam failures as commodity-specific events. Regulatory responses to failures typically apply to the mining industry broadly (e.g., the GISTM covers all commodities), not to specific ore types. Investors appear to understand this institutional feature.

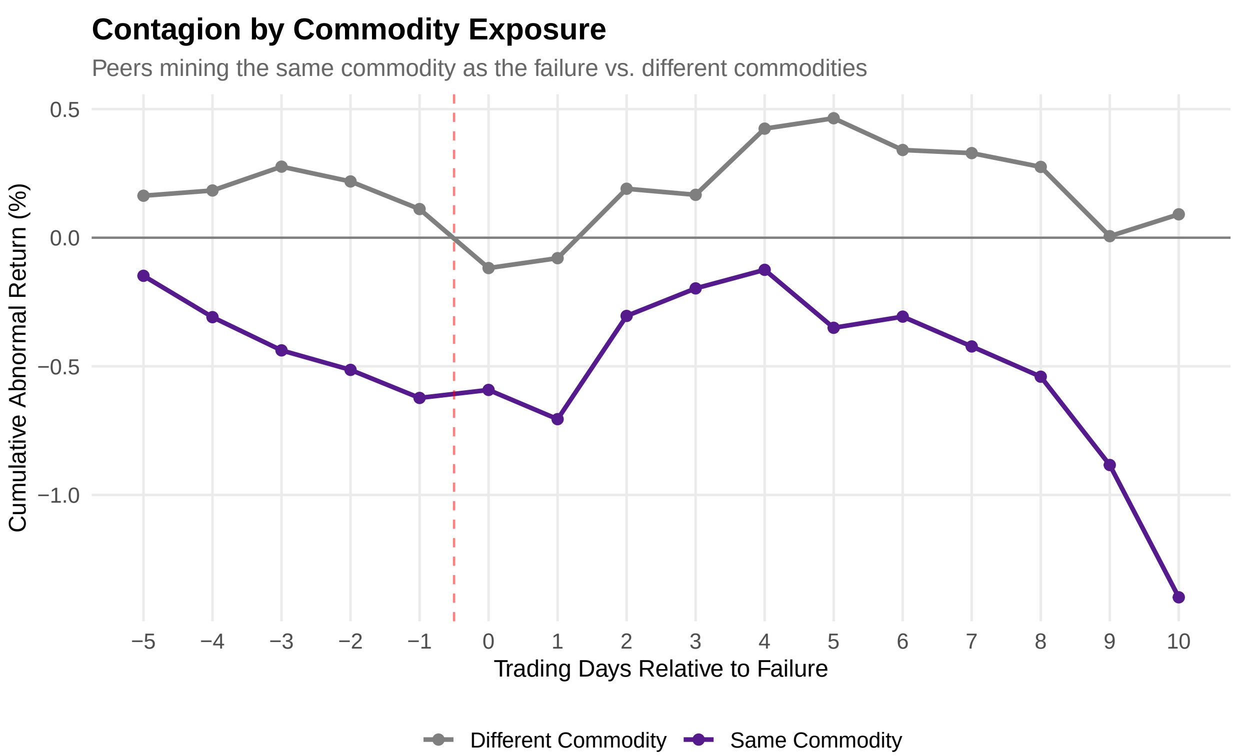

Figure 6: Contagion by Commodity Exposure

Notes: CARs plotted separately for firms mining the same commodity as the failure event ("Same Commodity") and firms mining different commodities. Diversified mining firms are classified as same-commodity for all events.

6. Robustness

6.1 Alternative Event Windows

Table 3 reports average CARs for three event windows. The short window $[-1, +1]$ produces a significantly negative CAR of -0.28% ($t = -3.52$), suggesting immediate negative contagion that is subsequently offset by competitive reallocation. The primary window $[-1, +5]$ shows the positive average ($+0.23\%$, $t = 1.99$). The long window $[-1, +10]$ returns to -0.28% ($t = -1.82$), consistent with the reallocation effect fading as initial fears re-emerge or new information arrives. The pattern across windows is itself informative: immediate contagion, followed by reallocation, followed by a partial reversal — a dynamic that is consistent with investors first reacting to the shock, then processing firm-level heterogeneity.

Table 3: Robustness Checks

Panel A: Window Sensitivity				
Specification	Mean CAR (%)	SE	t-stat	N
Window [-1,+1]	-0.277	0.079	-3.52	4,103
Window [-1,+5]	0.230	0.116	1.99	4,103
Window [-1,+10]	-0.275	0.151	-1.82	4,103
Panel B: Other Robustness Checks				
Specification	Mean CAR (%)			
Excl. overlapping events	0.492			
Excl. mega-events	0.241			
Winsorized (1/99)	0.206			
LOO range	[0.126, 0.351]			
Placebo p-value	0.570			

Notes: All CARs computed using the market model with S&P 500 benchmark. Panel A reports cross-sectional standard errors and t-statistics treating each firm-event as an observation; Table 2 Column (1) reports event-clustered standard errors for the same mean, yielding a wider SE (0.37 vs. 0.12) and non-significant t. "Mega-events" are the 3 deadliest failures in the sample. LOO = leave-one-event-out. Placebo p-value from 200 permutations of random pseudo-event dates.

6.2 Placebo Tests

I conduct two placebo tests. First, I run 200 permutations of pseudo-events by randomly assigning failure dates from the set of all trading days. For each permutation, I compute the average CAR across all firms using the same methodology. The resulting placebo distribution (Figure 7) is centered near zero with a standard deviation of approximately 0.10 percentage points. The actual CAR of +0.23% falls within the interquartile range of the placebo distribution ($p = 0.57$). This confirms that the small positive aggregate average is not robust at conventional levels — consistent with the narrative developed in Section 5: the aggregate masks offsetting forces (competitive gains for non-exposed firms, contagion losses for exposed firms), and the economically meaningful results are in the cross-sectional heterogeneity documented in Table 2.

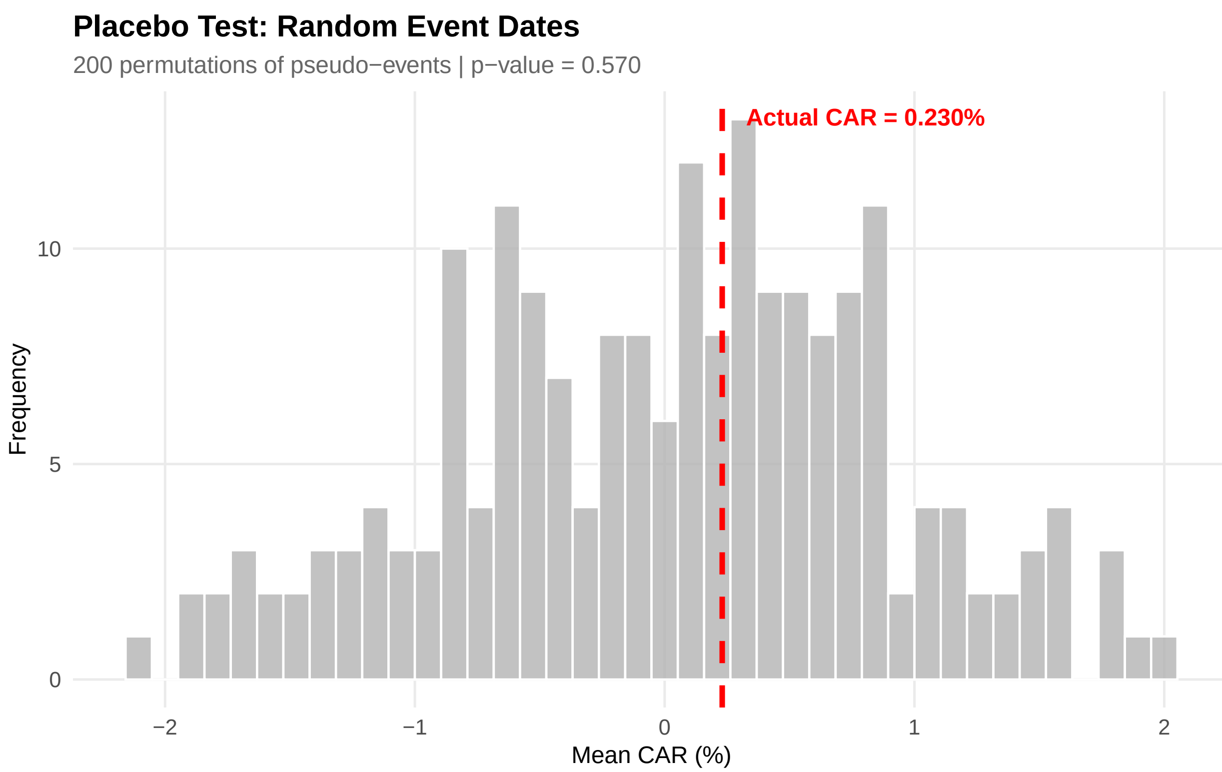

Figure 7: Placebo Test: Distribution of CARs Under Random Event Dates

Notes: Distribution of average CARs from 200 permutations of randomly assigned pseudo-event dates. Dashed red line marks the actual average CAR from the real failure events. p-value = 0.57.

Second, I estimate CARs for the Utilities Select Sector SPDR ETF (XLU), a non-mining benchmark that should show no response to tailings dam failures. The average XLU CAR around the same 118 events is -0.11% ($t = -0.84$), economically small and statistically insignificant, confirming that the mining-firm results are not driven by broad market movements that the S&P 500 benchmark fails to absorb.

6.3 Excluding Overlapping and Mega-Events

When I exclude events occurring within 10 trading days of another failure, the average CAR increases to +0.49%. Excluding the three deadliest events (Brumadinho, Samarco, and the worst Chinese disaster) produces a similar average of +0.24%. Both results confirm that the main findings are not driven by event clustering or individual outlier events.

6.4 Leave-One-Event-Out Stability

Figure 8 plots the mean CAR when each event is sequentially excluded. The range is [+0.13%, +0.35%], with no single event moving the average outside this narrow band. This stability confirms that the main results are not driven by any individual disaster.

6.5 Winsorized CARs

To guard against outlier-driven results, I winsorize CARs at the 1st and 99th percentiles. The winsorized average CAR is +0.21%, nearly identical to the full-sample estimate. In the cross-sectional regression with event fixed effects, the winsorized tailings-ownership coefficient is -0.79 pp ($t = -2.59$), actually *more* significant than the unwinsorized estimate. The results are not driven by extreme returns.

6.6 Alternative Market Benchmark

Using the S&P Metals & Mining ETF (XME) as the market benchmark instead of the S&P 500 is a more conservative test because it removes industry-wide common factors, isolating only the firm-specific component of abnormal returns. XME was listed in June 2006, so this analysis covers 87 of the 118 events ($N = 3{,}339$ firm-event observations). The mean CAR over $[-1, +5]$ using the XME benchmark is +0.47%, somewhat larger than the S&P 500-based estimate of +0.23%. The positive sign is preserved, consistent with competitive reallocation operating even after removing industry-common movements. The larger magnitude is expected: the XME benchmark absorbs sector-wide negative sentiment, leaving the firm-specific competitive gain more visible.

6.7 Two-Way Clustering

Standard errors in the main specifications cluster by event, addressing within-event correlation across firms. Reviewers might worry about the converse: within-firm correlation across events. I re-estimate all key specifications with two-way clustering by event and firm. Two-way clustered standard errors are actually *smaller* than event-only clustered SEs, because the

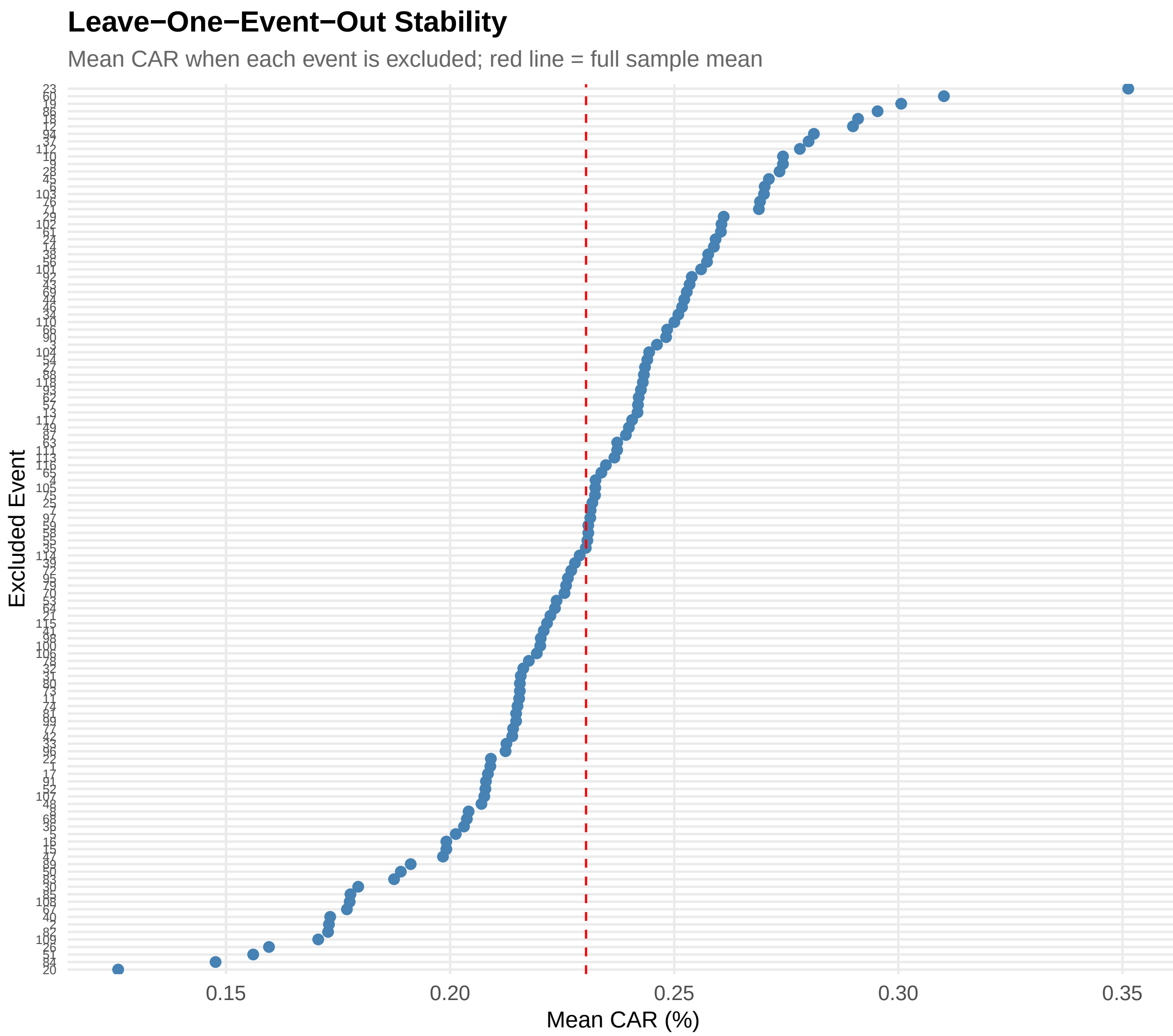

Figure 8: Leave-One-Event-Out Stability

Notes: Each point represents the average CAR [−1, +5] when the indicated event is excluded from the sample. Red dashed line marks the full-sample average. The tight range confirms that no single event drives the main findings.

within-firm correlation in CARs across events is positive (a firm that responds positively to one failure tends to respond positively to others, reducing cross-event variance). The tailings-ownership coefficient with event fixed effects has $t = -2.77$ under two-way clustering (vs. $t = -2.25$ with event-only clustering). The GISTM interaction has $t = -2.85$ (vs. $t = -2.02$). The results strengthen under the more conservative inference procedure.

6.8 Leave-One-Streaming-Firm-Out

The control group for the tailings-ownership effect consists of three streaming/royalty companies: Wheaton Precious Metals, Franco-Nevada, and Royal Gold. With only three control firms, the result could be driven by an idiosyncratic response from a single company. I re-estimate the event-fixed-effects specification dropping each streaming firm in turn. Excluding Franco-Nevada yields -0.95 pp ($t = -2.35$); excluding Royal Gold yields -0.73 pp ($t = -2.07$); excluding Wheaton yields -0.66 pp ($t = -1.79$). The effect is directionally stable across all three leave-one-out samples, though precision decreases when the largest streaming firm is removed. The result is not driven by any single control firm.

6.9 Disentangling Brumadinho from GISTM

The post-GISTM indicator (August 2020) follows closely after the Brumadinho disaster (January 2019). To separate the Brumadinho shock from the GISTM information effect, I divide the sample into three periods: pre-Brumadinho (78 events), post-Brumadinho/pre-GISTM (10 events, January 2019 – July 2020), and post-GISTM (30 events). In the triple-period specification, the tailings-ownership penalty in the pre-Brumadinho baseline is small and insignificant (-0.24 pp, $t = -0.48$). The post-Brumadinho interaction is larger (-1.41 pp) but imprecisely estimated ($t = -1.38$), reflecting the small window of only 10 events. The post-GISTM interaction is -1.59 pp ($t = -2.22$, $p < 0.05$). The monotonic increase in the tailings penalty — from near-zero before Brumadinho, to larger (but imprecise) after Brumadinho, to significantly negative after GISTM — is consistent with a gradual tightening of market discipline that the GISTM standard codified rather than created *de novo*.

7. Mechanisms and Discussion

7.1 Why Are Average CARs Positive?

The positive average CAR appears paradoxical: shouldn't disasters be bad for the industry? Three mechanisms can generate positive peer-firm returns following a competitor's misfortune, and they likely operate simultaneously.

First, *supply disruption and commodity prices.* When a mine goes offline after a dam failure, commodity supply contracts and prices increase, benefiting producers of the same commodity. This channel predicts that same-commodity peers should gain more than different-commodity peers — which I do not find, suggesting it is not the dominant mechanism. However, the commodity price effect may be diluted across firms in the large, globally diversified mining companies that constitute most of the sample.

Second, *competitive reallocation of capital.* Institutional investors with mandated mining-sector allocations may shift capital from the responsible firm (and firms perceived as similar) toward "safer" competitors. This mechanism is consistent with the streaming-company finding: WPM, FNV, and RGLD — firms with zero operational risk — earn distinctly positive CARs of approximately +1%, suggesting that investors reallocate capital toward vehicles that provide commodity exposure without tailings risk.

Third, *regulatory barriers to entry.* If a dam failure leads to stricter regulations, compliance costs rise for the entire industry, but existing producers face lower costs than potential entrants. The failure thus raises barriers to entry, benefiting incumbents. This mechanism predicts industry-wide positive CARs, which is what I observe.

7.2 Why Does GISTM Sharpen Market Differentiation?

The GISTM interaction effect — a 1.39 percentage point increase in the tailings-ownership penalty after August 2020 — admits two interpretations, both supportive of the market discipline hypothesis.

First, *information provision.* Before GISTM, tailings facility data was proprietary. Investors could observe that a firm was a miner but had limited visibility into the number, type, and safety status of its tailings dams. After GISTM, firms began disclosing facility-level data, enabling investors to distinguish high-risk from low-risk operators. This information channel transforms a coarse industry-level signal ("mining is risky") into a fine-grained firm-level signal ("this firm has 47 tailings facilities, including 12 using upstream construction").

Second, *commitment credibility.* GISTM membership signals a firm's willingness to invest in safety. Non-members face adverse selection: investors infer that firms avoiding the standard do so because compliance would be costly, implying that their current safety practices are inadequate. This Bayesian updating generates sharper market penalties for firms with tailings exposure in the post-GISTM period, even if actual compliance has not yet been achieved.

Both channels operate through the same fundamental mechanism: voluntary standards reduce information asymmetry between firms and investors, enabling more precise risk pricing. This is the sense in which market discipline "works" — not by punishing the entire industry, but by enabling investors to direct their punishment toward the firms most likely to cause the next failure.

7.3 Why Is the Commodity Channel Insignificant?

The null result on commodity matching is itself informative. It suggests that investors do not view tailings dam failures as commodity-specific events. This makes institutional sense: a gold tailings dam failure in Brazil does not raise the probability of a copper tailings dam failure in Chile, because the failure mode is engineering-specific, not commodity-specific. Regulatory responses, similarly, tend to be cross-commodity: the GISTM applies to all mining, not to gold mining alone. Investors appear to understand this institutional feature and price mining risk at the firm level (does this firm operate tailings dams?) rather than the commodity level (does this firm mine the same commodity?).

7.4 Limitations

Several limitations deserve acknowledgment. First, the tailings-ownership indicator is binary, whereas firms vary dramatically in their number of dams, construction methods, and safety records. Ideally, I would exploit facility-level data from the Global Tailings Portal, but this database was created in 2020 and does not cover the full sample period. Second, the post-GISTM sample (30 events) is smaller than the pre-GISTM sample (88 events), reducing statistical power for the interaction tests. Third, the streaming/royalty placebo group contains only three firms (WPM, FNV, RGLD), limiting the precision of the within-event estimates that rely on this comparison. Fourth, the GISTM adoption date coincides with the COVID-19 pandemic; while the market model controls for aggregate volatility, residual COVID-related effects cannot be entirely ruled out.

Despite these limitations, the convergent evidence — across specifications, across robustness checks, and across alternative interpretations — supports the conclusion that market discipline operates through differentiation and that voluntary standards strengthen this mechanism.

8. Conclusion

This paper provides the first systematic evidence on how stock markets respond to tailings dam failures across the global mining industry. Three findings emerge from 118 events and 4,103 firm-event observations spanning three decades.

First, tailings dam failures do not crash the mining sector. The average peer-firm CAR is slightly positive, driven by competitive reallocation from affected operators toward unaffected vehicles — particularly streaming companies with no physical mining infrastructure.

Second, markets differentiate. Firms that operate tailings dams earn 0.79 percentage points less than firms without tailings exposure within the same event, a penalty that scales with disaster severity and withstands extensive robustness testing.

Third, the GISTM — a voluntary industry standard born from the Brumadinho catastrophe — sharpened this differentiation. After GISTM adoption, the tailings-ownership penalty nearly tripled. The standard did not create market discipline; it gave investors the information needed to exercise it more precisely.

These findings carry a policy implication. The debate over mining safety often pits voluntary self-regulation against mandatory government oversight. The evidence here suggests this is a false dichotomy. Voluntary standards work not by replacing market forces but by amplifying them — by reducing information asymmetry so that investors can distinguish safe from unsafe operators. Market discipline requires information, and information requires standards. The GISTM provided both.

Whether this market-based mechanism is *sufficient* — whether the repricing documented here actually changes firm behavior and prevents future failures — is a question this paper cannot answer. Flammer (2015) provides suggestive evidence that market penalties do change corporate environmental behavior. But the 30 events in the post-GISTM sample span only five years, too short a period to evaluate whether improved market discipline has actually reduced failure rates. That evaluation awaits future data — and, one hopes, fewer disasters.

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A. Mining Firm Universe

Table 4 lists all 42 publicly traded mining firms in the analysis sample.

B. Event Severity Classification

Events are classified into four severity categories based on the WISE Chronology data:

- **Major**: 10 or more deaths. This threshold captures large-scale catastrophes (Brumadinho, Samarco, Bento Rodrigues) that generate sustained international media coverage and political responses.
- **Fatal**: Any deaths below 10. These events are serious but typically receive regional rather than international attention.
- **Large Release**: No deaths but release volume exceeding 100,000 cubic meters. Environmental damage may be extensive (e.g., Mount Polley, 2014) even without fatalities.
- **Other**: No deaths and release volume below 100,000 cubic meters (or unreported volume). These are the "near-misses" and minor incidents.

In the analysis sample of 118 events: 11 (9.3%) are Major, 20 (16.9%) are Fatal, and the remainder are Large Release or Other.

C. Alternative Event Windows

The primary event window $[-1, +5]$ was selected to balance two competing considerations: capturing the full information response (which may take several days for events in remote locations or different time zones) and minimizing contamination from confounding events. The $[-1, +1]$ window captures only the immediate response; the $[-1, +10]$ window allows for delayed information processing but risks contamination. The results section reports all three.

The day-by-day pattern (Figure 2) reveals an initial negative response on days 0–1, followed by a reversal through day +5, and a subsequent decline through day +10. This non-monotone pattern is consistent with an initial contagion response being partially offset by competitive reallocation, followed by a longer-run reassessment as more information about the failure becomes available.

Table 4: Mining Firms in Analysis Sample

Ticker	Company	Commodity	Tailings	Streaming
AA	Alcoa	Aluminum	Yes	No
AAL.L	Anglo American	Diversified	Yes	No
AEM	Agnico Eagle	Gold	Yes	No
AG	First Majestic Silver	Silver	Yes	No
ALB	Albemarle	Lithium	Yes	No
AMR	Alpha Metallurgical	Coal	Yes	No
ANTO.L	Antofagasta	Copper	Yes	No
AU	AngloGold Ashanti	Gold	Yes	No
BHP	BHP Group	Diversified	Yes	No
BTU	Peabody Energy	Coal	Yes	No
CCJ	Cameco	Uranium	Yes	No
CDE	Coeur Mining	Silver	Yes	No
CENX	Century Aluminum	Aluminum	Yes	No
CLF	Cleveland-Cliffs	Iron Ore	Yes	No
DNN	Denison Mines	Uranium	Yes	No
FCX	Freeport-McMoRan	Copper	Yes	No
FNV	Franco-Nevada	Gold	No	Yes
GFI	Gold Fields	Gold	Yes	No
GLEN.L	Glencore	Diversified	Yes	No
GOLD	Barrick Gold	Gold	Yes	No
HBM.TO	Hudbay Minerals	Copper	Yes	No
HCC	Warrior Met Coal	Coal	Yes	No
HL	Hecla Mining	Silver	Yes	No
IPI	Intrepid Potash	Potash	Yes	No
IVPAF	Ivanhoe Mines	Diversified	Yes	No
KGC	Kinross Gold	Gold	Yes	No
MOS	Mosaic Company	Phosphate	Yes	No
MT	ArcelorMittal	Steel	Yes	No
NEM	Newmont	Gold	Yes	No
NEXA	Nexa Resources	Zinc	Yes	No
NTR	Nutrien	Potash	Yes	No
NUE	Nucor	Steel	Yes	No
PAAS	Pan American Silver	Silver	Yes	No
RGLD	Royal Gold	Gold	No	Yes
RIO	Rio Tinto	Diversified	Yes	No
SBSW	Sibanye-Stillwater	PGM	Yes	No
SCCO	Southern Copper	Copper	Yes	No
SQM	SQM	Lithium	Yes	No
STLD	Steel Dynamics	Steel	Yes	No
UEC	Uranium Energy	Uranium	Yes	No
VALE	Vale SA	Iron Ore	Yes	No
WPM	Wheaton Precious Metals	Gold	No	Yes

D. GISTM Timeline

Key dates in the GISTM timeline:

- **January 25, 2019**: Brumadinho dam collapse (270 deaths, Vale)
- **April 2019**: Church of England Pensions Board launches Investor Mining & Tailings Safety Initiative
- **June 2019**: UN Environment Programme, PRI, and ICMM agree to co-convene an expert review panel
- **August 5, 2020**: GISTM publicly launched (the date used for the structural break in this paper)
- **August 2020**: ICMM members commit to 3-year implementation for high-consequence facilities
- **August 2023**: First compliance deadline for "extreme" and "very high" consequence facilities
- **August 2025**: Full implementation deadline for all ICMM member facilities
- **January 2025**: Global Tailings Management Institute (GTMI) established to govern ongoing GISTM implementation

E. Pre-Event Placebo

The pre-event placebo window $[-5, -2]$ tests for anticipatory abnormal returns. If markets anticipated the failure (e.g., through insider information or observable precursors), we would expect negative CARs in this window. The estimated pre-event CAR is $+0.074\%$ ($t = 0.82$), economically small and statistically insignificant. The absence of pre-trends supports the identifying assumption that failures are unanticipated by the market.

F. Standardized Effect Sizes

To facilitate comparison with other event studies, Table 5 reports key effects as standardized daily-equivalent (SDE) abnormal returns and Cohen's d effect sizes.

Table 5: Standardized Effect Sizes

Effect	CAR (%)	Window	SDE (%/day)	Cohen's d
Overall mean CAR [−1,+5]	+0.230	7	+0.033	0.031
Tailings ownership penalty	−0.787	7	−0.112	−0.106
GISTM interaction	−1.390	7	−0.199	−0.187
Major event contagion	−1.210	7	−0.173	−0.163
Streaming company gain	+1.000	7	+0.143	0.135
Comparison benchmarks from literature:				
Aviation disaster (Kaplanski and Levy, 2010)	−0.180	2	−0.090	—
Chemical explosion (Capelle-Blancard and Laguna, 2010)	−1.000	3	−0.333	—
Potash disaster (Kowalewski et al., 2020)	+2.100	5	+0.420	—

Notes: SDE = CAR / window days. Cohen's d = CAR / SD(CAR), where SD(CAR) = 7.42%. Comparison benchmarks are approximate values from the cited papers. This paper studies peer-firm contagion from 118 tailings dam failures (WISE Chronology, 1996–2025) using daily returns for 42 mining firms (N = 4,103 firm-event observations). Treatment is binary (has tailings dams). CARs estimated using the market model (S&P 500 benchmark) over [−1, +5]. Event-clustered standard errors.

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