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Modelling Economic Policy Issues

Self-regulation, media pressure, and corporate catastrophes

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ABSTRACT

To formalize the monitoring role of the media in corporate finance, we propose a new model of corporate catastrophic risk combining two disciplining forces: corporate self-regulation and media pressure. We assume that optimizing firms have a strong interest in hiding large operational loss events to avoid reputational losses. When a loss is revealed, the operation is immediately restored to its equilibrium, due to higher media attention. The model explains why public losses depend heavily on media attention but seem to be unrelated to the quality of internal governance. Internal governance has high impact on the hidden part of losses. Using the SAS Global Oprisk database, we test the model predictions for the period of 2011–2022 covering 4,547 loss events attributed to firms in the MSCI World index. The results of the empirical analysis are consistent with the theoretical model: higher media attention increases public losses but decreases total (the sum of public and hidden) losses in terms of both frequency and severity. We also find evidence that it may be easier to hide the actual size of large corporate losses than the occurrence of the loss event itself, especially within the financial sector. Promoting press freedom and market liquidity, prerequisites for media and investor attention, can be highly effective policies for improving corporate governance.

1. Introduction

Corporate catastrophic risk is a subset of corporate operational risk, involving losses that severely impact the company's operations, financial stability, and reputation, even though such events occur infrequently. When managing catastrophic risk, organizations must consider not only routine or moderate disruptions but also extreme scenarios, requiring robust contingency plans, crisis management protocols, and disaster recovery strategies.

In this paper, we present a novel theoretical model to analyze the role of self-regulation and media attention in large operational losses. Using this theoretical model, we conduct simulations, formulate testable hypotheses, and investigate empirical data.

Operational risk exhibits several distinctive features when compared to market risk and credit risk. First, it is a risk category which encompasses many *different types of risk*. According to the Basel Committee, it is "the risk of loss resulting from inadequate or failed internal processes, people, and systems, or from external events" (BCBS, 2024, p. 1). Mapping operational risk precisely into event types (frauds, natural disasters, business process disruptions, work safety, client service, etc.) is a difficult task, and the detailed taxonomy of operational risk is constantly developing in practice. Most of the operational risks are closely related to corporate incomes (flow variable) instead of portfolio values (stock variable). From risk management perspective, loss frequencies and severities are

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modelled separately; and high-frequency and low-severity (HFLS) versus low-frequency and high-severity (LFHS) risks necessitate different approaches (Hull, 2015). In this paper, we model LFHS operational loss events called corporate catastrophes or disasters.

Second, operational risk events might occur due to both exogeneous and endogenous factors, though *endogenous factors are dominant*. In the SAS Global Oprisk database, 67 % of large corporate operational risk events (accounting for 77 % in total value) can be attributed to misconduct resulting from inappropriate self-regulation. In these cases, the company was explicitly held accountable for the misconduct by a court or regulator. Corporate catastrophes are viewed as negative signals leading to market punishment in forms of equity price overreactions (Cummins et al., 2006) and are associated with other losses, such as market, credit, reputational, and strategical losses (Kölbel, et al., 2017; Wei et al., 2017). In our model, corporate incidents are impacted by internal governance, hence the firm is responsible for them.

Third, due to the negative signals associated with operational loss events, firms' managers and even shareholders are highly motivated to *keep operational loss events in secret*, as a result of which public operational loss databases suffer heavily from reporting biases (Li and Moosa, 2015; Wei et al., 2018). Depending on the firm characteristics (ownership, size, industry, technology, etc.), the incentives and ability to hide losses may vary. For example, we can suspect that a significant part of *the losses remains hidden* if the shareholders have close ties to the government or organized crime, the company is large and profitable enough to afford hiring lawyers and security experts to intimidate and deter journalists, or information asymmetry is high for other reasons (Cameron, 2018; Levin, 2019; Storbeck, 2020). The more transparently and ethically a company operates, the lower the propensity to hide operational losses. A key assumption in our model is that firms have strong interests in hiding losses from the public.

Finally, operational risks can be *mitigated* by improving business processes and systems, which usually require significant investments, however, a full hedge is neither possible nor optimal (Fragniere et al., 2010; Hull, 2015; Mitra et al., 2015). *Operational risks are mostly idiosyncratic* (Chernobai et al. 2011; Berger et al., 2022), thus investors are typically not compensated for taking more operational risks by a risk premium. Furthermore, operational risk (sub)categories are strongly related to the environmental, social, and governance (ESG) aspects of the firm's operation, attracting significant investor attention (Naffa and Fain, 2022). The significance of operational risk is high and expected to grow in the future. In the financial sector, it is considered the second largest risk in terms of capital requirements (ECB, 2017), while in the non-financial sector its relevance is even higher. Environmental risks, geopolitical tensions, (de)globalization, and technological advances are expected to further increase both the diversity and the threat of operational risk events (Allen and Saunders, 2004; Berger et al., 2022). In our model, we assume a certain level of self-regulation to avoid large operational losses (both hidden and public); this level is a result of corporate optimization (cost-benefit analysis).

The proposed theoretical model of corporate catastrophes is based on a stochastic mean-reverting latent variable. Latent variable models are helpful in understanding operational risks (Cruz 2002; Reynolds et al., 2003; Mittnik and Yener, 2009; Dahen and Dionne, 2010), and operational risk management is widely seen as a stochastic control problem (Xu et al., 2020). Borgonovo et al. (2018) provided a general framework for operational risk while relying on the toolkit of decision theory. Building on these insights, the novelty of our model lies in its integration of *internal self-regulation* and *external media attention* as primary disciplining forces, while also recognizing the company's interest in hiding losses.

Previous literature documented that *self-regulation*, materialized in the quality of internal governance systems, influences the likelihood of corporate misconduct which can harm the interests of consumers, investors, workers, the environment, and other stakeholders. For example, the proportion of independent directors, the number of board meetings, and the tenure of the chairman are associated with the incidence of fraud (Chen et al., 2006; Jain and Zaman, 2020). Inappropriate management compensation systems might also serve as an incentive to engage in corporate fraud (Hass et al., 2015). The duality of the chairman and the general manager roles, as well as having the founder serve as a CEO, can also weaken the internal control and hence increase the likelihood of corporate catastrophes (Zaman et al., 2021).

In addition to firm characteristics, several *external factors* influence the likelihood of large operational loss events and whether they are revealed. For example, well-established laws, regulations, and other governance mechanisms inhibit the occurrence of corporate fraud and facilitates its detection (Zhang, 2018; Keresztúri et al., 2022). From an informal institutional perspective, the level of social trust is negatively associated with corporate misconduct (Dong et al., 2018). Moreover, external public pressure from the media significantly impacts corporate behavior. In particular, journalists closely monitor companies' activities, revealing, analyzing, and disseminating information that is relevant to the public (Dyck et al., 2008; You et al., 2018). In this role, the media functions as a passive monitor, similar to auditors, regulators, investment analysts, and rating agencies (Tirole, 2006). Negative media coverage and the resulting reputational losses can strongly deter managers from engaging in corporate misconduct as such exposure can significantly harm their personal careers. Public scrutiny can lead to loss of customer trust, investor confidence, and business partnerships, while also attracting regulatory attention and potential legal action. Managers, who are often held responsible for corporate governance, face the risk of dismissal, career damage, and personal liability (Dyck et al., 2008; Dyck and Zingales, 2004; Heese et al. 2022; You et al., 2018). This deterrence effect is stronger when the pressure from the media is higher: in countries with freer media significantly more and larger losses are reported (Berlinger et al., 2021).

The relevance of the proposed theoretical model can be evaluated based on its ability to capture all the important features of operational risks. The stochastic process of the latent variable can incorporate various types of random effects, encompassing different sources and types of operational risks. Additionally, the model captures operational risk events occurring due to both exogeneous (manifested in the volatility of the latent variable) and endogenous factors (related to the firm's effort to stabilize its operation). The model also considers the firm's the motivation to hide operational problems. The ability to hide incidents is hindered by self-interested journalists captured by the detection mechanism. Finally, the model assumes that both managers and shareholders have strong interests in mitigating catastrophic risk on their own (self-regulation). This can be justified, for example, by reputational considerations and the high cost of financial distress under asymmetric information. Therefore, self-regulation is of primary importance as operational loss events send negative signals to the investors, regulators, and other stakeholders.

Using the theoretical model that integrates self-regulation and media pressure, we simulate operational loss frequencies and severities in the function of the key model variables: the quality of governance and the level of media attention. The simulation results reveal that higher media attention increases both the number and severity of public losses, while it has an opposite effect on total loss encompassing both public and hidden losses. At the same time, the effect of governance quality on public losses is ambiguous, even if it is clearly negative for total losses.

To test model predictions, we perform empirical analyses covering 4547 large operational losses attributable to 1218 firms that are constituents of the MSCI World Index. While the incidents are linked to firms based in the 23 countries included in the MSCI World Index, they occurred across 36 different countries. The losses became public in the period of 2011–2022, as reported in SAS Global Oprisk, the most accurate and comprehensive database of operational losses. This database has been used, for example, by Eling and Wirfs (2019) focusing on the severity of cyber risk events and Berlinger et al. (2021 and 2022) examining the potential impact of the quality of governance and quantifying the reporting bias. In this paper, we analyze the frequency and severity of all types of *public* operational loss events in both the financial and non-financial industries with panel regression models. The empirical analysis confirms the predictions of the theoretical model, demonstrating its ability to capture the relevant features of large operational losses.

The paper is structured as follows. Section 2 introduces the theoretical model, while Section 3 presents the simulation results and derives the hypotheses. In Section 4, we perform an empirical analysis. Section 5 discusses the findings, elaborates on the policy implications and the limitations of the research. Finally, Section 6 contains some concluding remarks.

2. The model

We assume a latent variable X_t following a discrete-time, mean-reverting Ornstein-Uhlenbeck stochastic process:

$$\Delta X_t = a(b - X_t)\Delta t + \sigma \Delta W_t \tag{1}$$

where $0 < a < 1$ is the strength of the mean reversion, $b > 0$ is the long-term equilibrium, $\sigma > 0$ is the instantaneous volatility, and W_t is a Wiener process.

This latent variable characterizes the state of the firm's operation. If it is close to the long-term equilibrium b, the operation is safe. The further the latent variable deviates from its equilibrium level, either upward or downward, the more vulnerable the operation becomes (Cruz, 2002; Reynolds et al., 2003; Mittnik and Yener, 2009; Dahen and Dionne, 2010). For a manufacturing company, this latent variable can be interpreted as the internal temperature of the assembly plant; for an agricultural company, as the soil moisture; and for a service company, as the degree of autonomous decision-making by employees. The latent variable should be maintained at an optimal level for prudent operation, avoiding extremes. At a higher level of abstraction, this variable encompasses several factors that characterize the general state of the system at any given time.

The mean reversion parameter a in Eq. (1) represents the efforts the firm exerts to stabilize its operation under normal conditions, referred to as the quality of internal corporate governance *GOV*. We use the term of corporate governance broadly, including system of rules, practices, and processes by which a firm is directed and controlled which affects, among others, its internal IT processes and risk management policies (Chernobai et al., 2011). A high value of *GOV* (parameter a) indicates that the firm has effective self-regulation practices in place.

We assume that an operational loss event occurs at time t if the latent variable X_t is outside the critical thresholds $b \pm h$. The threshold parameter h and the volatility σ of the latent variable are supposed to be technology driven, and thus exogeneous and constant over the time horizon we investigate (Xu et al., 2020). The severity of the loss $S_t > 0$ is defined as the distance from the threshold (given that the latent variable is outside the safety range $b \pm h$, otherwise there is no loss).

$$S_t = \left\{ \begin{matrix} X_t - (b+h) \ \textit{if} \ X_t > (b+h) \\ (b-h) - X_t \ \textit{if} \ X_t < (b+h) \end{matrix} \right\} \tag{2}$$

Over a longer period, (average) severity S is the arithmetic average of loss severities, frequency F is the number of losses, and the total loss amount is the product of the two.

A key characteristic of our model is that operational loss events do not necessarily become public. We assume that firms have interest in hiding corporate misconducts in order to minimize the related reputational losses. We introduce journalists as important players who are motivated to reveal corporate scandals in order to increase journal readership, hence profits (Strömberg, 2004; You et al., 2018). The greater the damage, the bigger the scandal, the more it attracts investigative journalists, and the greater the likelihood of whistleblowing as well. Furthermore, it is reasonable to expect that journalists are more effective in detecting corporate loss events if the media is free (Szeidl and Szücs, 2021; You et al., 2018). Therefore, we assume that a loss event becomes public with probability p_t depending on the *severity of the loss* S_t and the level of the *media attention* denoted by *PRESS*:

$$p_t = 1 - e^{-S_t \cdot PRESS} \tag{3}$$

where $0 < PRESS \leq 1$ is supposed to be exogeneous and constant over time, and a higher value indicates higher media attention. Hence, some part of the loss events becomes public, while the rest remains hidden. As a result, the number of public losses (public frequency, *PF*) is less than the number of total losses (total frequency, *TF*) including both publicly revealed and hidden losses. Note that we do not allow the *PRESS* variable to be zero, because then there would be no public losses at all. Fig. 1 shows the probability of a loss to become public in the function of the media attention in line with assumption (3).

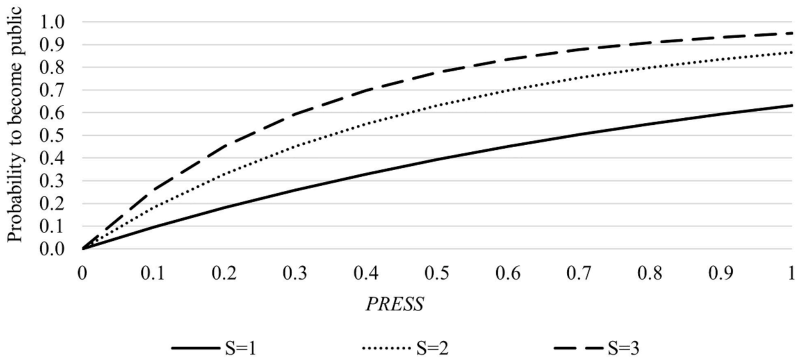

Fig. 1. Probability of a loss to become public.
Note: We assume that the probability of a loss to become public is a positive concave function of media attention (*PRESS*) and the severity of the loss *S*.

The severity of public operational losses can also be hidden. When a loss event is revealed, to reduce reputational losses, managers may try to hide some part of the loss. We can assume that the possibility of hiding the loss size depends on two factors again, the media attention denoted by *PRESS* and the size of the loss S_t, in a similar way as in Eq. (3). On the one hand, higher media attention makes it more difficult for managers to conceal the true size of the loss, resulting in a smaller underestimation of the loss severity. On the other hand, the size of the loss itself is also a significant factor. The larger the loss, the higher the attention from the media and the regulators, so the harder it is to hide the loss severity. Hence, the severity detection ratio, that is the ratio of public loss severity PS_t to the total loss severity S_t is given by

$$\frac{PS_t}{S_t} = 1 - e^{-S_t \cdot PRESS \cdot c} \tag{4}$$

Note that in Eq. (4), a new parameter *c* is introduced compared to Eq. (3). This new parameter *c* reflects the difficulty to hide the loss size relative to the difficulty to hide a loss event. If *c* is lower (higher) than 1, then it is less (more) difficult to hide the size of a loss than the loss event itself. In the specific case of $c = 1$, the difficulty to hide the loss is the same in the following cases: i) hiding one out of the two loss events, both in a value of one USD; 2) hiding half of a loss event in a value of two USD.

When a loss is detected and becomes public, active monitors (banks, shareholders) are assumed to intervene immediately. Their goal is to ensure prudent operations and to minimize reputational losses and other negative spillover effects as it is observed in several case studies (Dyck et al., 2008; Dyck and Zingales, 2004; Heese et al., 2022; You et al., 2018). In particular, the latent variable is expected to be reach the equilibrium in one step. Consequently, the stochastic process of the latent variable is modified at certain times through rapid interventions:

$$X_{t+1} = b \qquad \textit{if a loss is detected in time } t \tag{5a}$$

$$X_{t+1} = X_t + a(b - X_t)\Delta t + \sigma \Delta W_t \qquad \textit{if no loss is detected in time } t \tag{5b}$$

According to (5a), corporate scandals restore the system to its equilibrium point by imposing a strong additional mean-reverting effect. Hence, a drastic correction due to external pressure complements the self-regulation that occurs during normal operation. Fig. 2 shows two annual trajectories of the latent variable: one when media attention (*PRESS*) is high, and another one when it is low.

Fig. 1 suggests that in the case of low governance quality (a=*GOV*=0.1), the media can be an important external regulator. When media attention is relatively high (*PRESS*=0.9), losses are much smaller, and do not escalate (reach such high levels) as they do with low media attention (*PRESS*=0.1).

Note that in the theoretical model, we consistently refer to journalists as the sole external monitors capable of detecting operational incidents. However, in reality, other actors such as regulators, potential investors, short-sellers, whistleblowing employees, civil organizations, also play a role in uncovering corporate misconduct. Regardless of the exact source of the information, incidents gain widespread publicity through the press, underscoring the media's prominent role in the process.

To strike a balance between simplicity and realism, we assume that the *PRESS* variable represents all actors interested in revealing operational incidents but who have no direct influence over preventing or mitigating these. Similarly, the *GOV* variable represents all actors responsible for the damages and interested in mitigating them to some extent and preventing their public exposure.

3. Simulation of public losses

The frequency and the severity of operational loss events are usually modeled separately (Cornalba and Giudici, 2004; Eling and Wirfs, 2019). Using a Monte Carlo simulation based on the model described in Section 2, we examine first the impact of media attention (*PRESS)*, then the impact of governance (*GOV*) on the frequency and severity of public operational losses. Afterwards, we

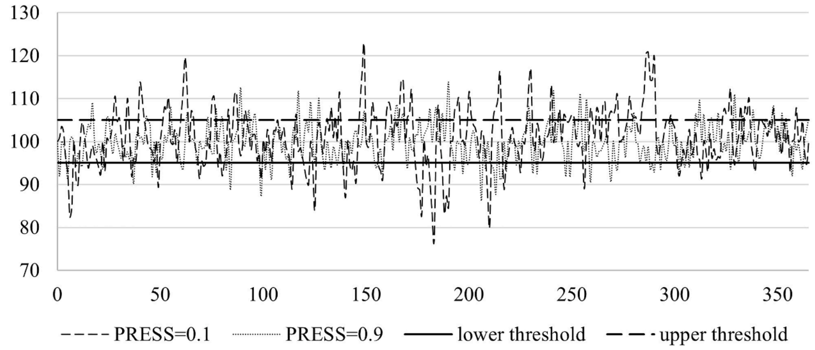

Fig. 2. Two trajectories of the latent variable (a=GOV=0.1, b = 100, σ=h = 5, Δt=1 day).
Note: The figure shows two random trajectories of the latent variable characterizing the state of the firm's operation in 365 days. The long-term equilibrium is 100, and loss events occur outside the safety thresholds (95 and 105). The severity of losses equals the distance from the closest safety threshold. In the case of low media attention (*PRESS*=0.1), losses are more frequent and severe.

look at the joint effect of media and governance. In each case, first we show the simulation results and then we form the related hypothesis to be tested in the empirical analysis.

3.1. The effects of media attention

In this subsection, we investigate the impact of media attention (*PRESS*) on the frequency and severity of public operational losses. In the first series of runs, we assume that the quality of governance is poor (*GOV*=0.1), while in the second series of runs we assume that it is high (*GOV*=0.9). As shown by Fig. 3a, independent from the quality of governance, the higher the media attention, the higher the frequency of public operational losses. In line with this observation, our first hypothesis is as follows:

H1: There is a significant positive relationship between the level of media attention and the *frequency* of public operational losses.

The hypothesized positive relationship between the level of media attention and the frequency of public losses highlights the importance of journalists writing freely. When journalists can articulate their opinions and ideas without fear of retaliation, censorship, or legal sanction they are expected to reveal more operational loss events. In the literature, it is argued that the *detection effect* of the media is realized through the career development channel of *journalists* who are motivated to produce high-impact news by direct financial incentives (such as performance-based compensation and promotion) and by long-term reputation (You et al., 2018; Berlinger et al., 2022).

Regarding loss severity, media attention has two effects of opposite signs. On the one hand, according to Eqs. (3) and (5a), higher

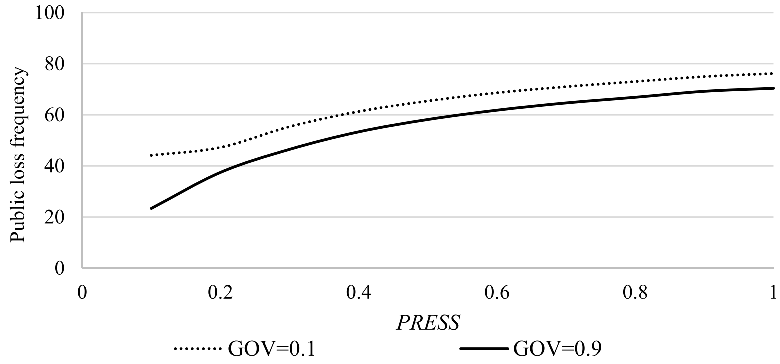

Fig. 3a. The impact of media attention (*PRESS*) on public loss ***frequency*** (b = 100, σ=h = 5, Δt=1 day).
Note: Results of the Monte Carlo simulation with 1000 annual trajectories. The frequency of public losses is positively associated with media attention (*PRESS*) regardless of the quality of governance (*GOV*).

media attention is coupled with more effective external monitoring, hence lower loss amounts (*deterrence effect*). On the other hand, according to (4) and (5), if media attention is higher, loss amounts are less underestimated, hence the severity of public losses *PS* is expected to be higher (*detection effect*). The outcome depends on the relative strength of these two opposing effects. Fig. 3b shows that the relationship between the level of media attention and the severity of public losses depends on the quality of governance *GOV* and the relative difficulty to hide the loss size *c*. If the quality of governance is low and the relative difficulty of hiding the loss size is high (e.g., *GOV*=0.1 and $c = 2$), there is a negative relationship between the level of media attention and the severity of losses, hence the deterrence effect is dominant. Contrary to this, if *GOV* is high and *c* is low (e.g., *GOV*=0.9 and $c = 0.5$), there is a positive relationship between the level of media attention and the severity of losses, hence the detection effect is dominant. As we have no a priori expectation about parameters *GOV* and *c*, we form the following two mutually exclusive hypotheses—one of these hypotheses shall be accepted while the other rejected:

H2a: The relationship between the level of media attention and the *severity* of public operational losses is negative due to the low quality of governance and/or the difficulty to hide the loss size.
H2b: The relationship between the level of media attention and the *severity* of public operational losses is positive due to the high quality of governance and/or the ease to hide the loss size.

3.2. The effects of governance

Second, we investigate the impact of governance (*GOV*) on the frequency and severity of public operational losses. In the first series of runs, we assume that the level of media attention is low (*PRESS*=0.1), while in the second series of runs we assume that it is high (*PRESS*=0.9).

When the level of media attention is low, good governance practices might play an important role and substitute the monitoring function of the media. In the absence of the disciplining effect of the media, the importance of insider monitors (governance) increases. As shown by Figs. 4a and 4b, the better the quality of the governance, the lower the frequency and severity of public operational losses.

When media attention is high, the quality of governance plays a less influential role in the frequency and severity of public operational losses; the slope of the curves is still negative but closer to zero. If the media (*PRESS*) function as strong monitors, many loss events are revealed which alert stakeholders to restore the system to its equilibrium. As a result, the mean reverting tendencies are strong, contributing to a safe operation. Under these conditions, internal governance may lose its significance.

In line with Figs. 4a and 4b, considering the negative slope of the curves in all cases, we formulate our hypotheses on the impact of governance as follows:

H3: There is a significant negative relationship between the quality of governance and the *frequency* of public operational losses.
H4: There is a significant negative relationship between the quality of governance and the *severity* of public operational losses.

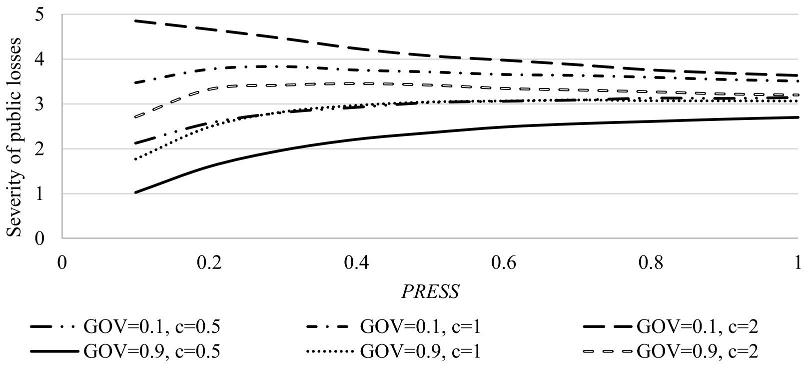

Fig. 3b. The impact of media attention (*PRESS*) on public loss ***severity*** ($b = 100$, σ=h = 5, Δt=1 day).
Note: Results of the Monte Carlo simulation with 1000 annual trajectories. The severity of public losses can be associated both positively and negatively with media attention (*PRESS*) depending on the quality of governance (*GOV*) and the relative difficulty to hide the loss size (*c*). If *c* is lower (higher) than 1, it is less (more) difficult to hide the true size of the loss than the occurrence of the loss.

3.3. The joint effects of media attention and governance

In the previous simulations, governance and media attention have been considered as exogenously given and independent of each other. In fact, it is more reasonable to assume that the governance parameter is a result of an optimization process similar to previous studies (Fragniere et al., 2010; Xu et al., 2020). Although better governance implies lower operational losses, operational risk cannot be eliminated completely; developing and operating more effective monitoring systems are costly with increasing marginal costs (Fragniere et al., 2010; Mitra et al., 2015). Therefore, we can assume that a company determines the optimal value of the governance parameter through a cost-benefit analysis. In our model, the optimum depends on many factors such as the volatility of the latent variable σ, the safety thresholds $b \pm h$, the cost of monitoring, the magnitude of the potential reputational loss, and the probability of a loss becoming public. Therefore, we assume that

$$a = GOV = f(PRESS) \tag{6}$$

and

$$\frac{\partial GOV}{\partial PRESS} > 0 \tag{7}$$

According to (7), if media attention is higher, ceteris paribus, the company is motivated to invest more in internal governance to avoid scandals, negative media coverage, and the associated reputational losses. Thus, assuming corporate optimization, higher media attention (*PRESS)* is associated with better internal governance systems, and hence with a higher level of parameter *GOV*. This assumption aligns with the studies by Dyck and Zingales (2004) and Dyck et al. (2008) which report that in countries with more widespread press and more powerful journalists, companies tend to be better governed. Mitra et al. (2015) found that in emerging countries, corporate operational risk management systems are significantly less developed; therefore, the less free media might partially explain this underinvestment.

To assess whether companies optimize their governance systems in line with Eq. (7), in the empirical model, we investigate the interaction between the level of media attention (*PRESS*) and the quality of governance (*GOV*). As shown by Fig. 5a, the interaction term *PRESS x GOV* is positively associated with the frequency of losses. As a result, in firms with lower media attention and consequently poorer governance (the interaction term is small), publicly revealed losses are *less frequent.* Conversely, in firms with higher media attention and better governance (interaction term is high), publicly revealed losses are more frequent. Accordingly, our fifth hypothesis can be formulated as follows:

H5: The $PRESS \times GOV$ interaction is significantly and positively associated with the *frequency* of public losses.

Finally, Fig. 5b reveals that the impact of the interaction term $PRESS \times GOV$ on the severity of public losses is ambiguous, and it is heavily influenced by the relative difficulty to hide the loss size c. If it is very difficult the hide the loss size (c is high), we can expect a negative relationship between the level of press freedom and the severity of losses. Higher media attention results not only in stronger external monitoring but also more effective internal monitoring, leading to an even stronger *deterrence* effect. Nevertheless, if it is

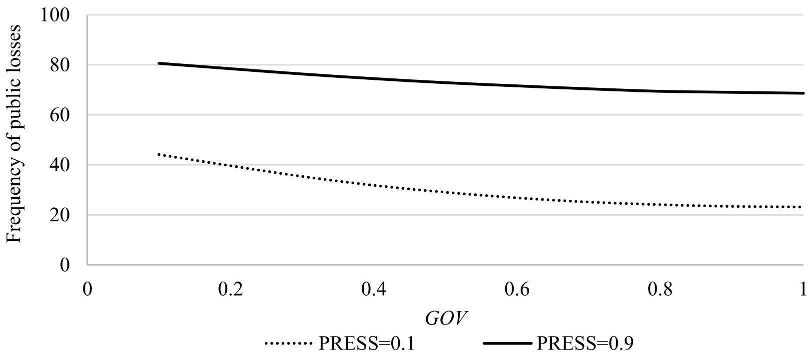

Fig. 4a. The impact of governance (*GOV*) on the *frequency* of public losses (b = 100, σ=h = 5, Δt=1 day).
Note: Results of the Monte Carlo simulation with 1000 annual trajectories. The frequency of public losses is negatively associated with the quality of governance (*GOV*) regardless of the level of media attention (*PRESS*).

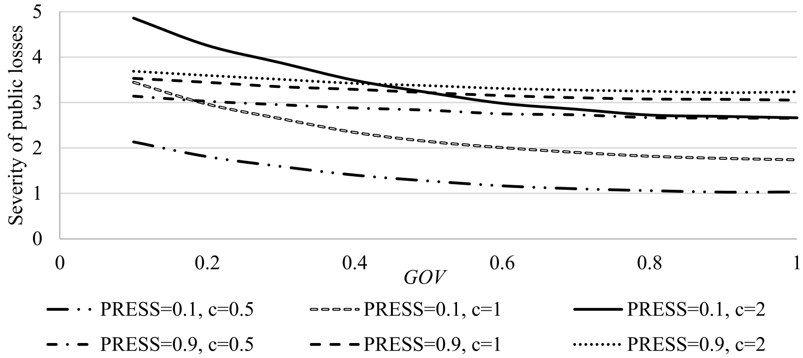

Fig. 4b. The impact of governance (*GOV*) on the *severity* of public losses ($b = 100$, σ=h = 5, Δt=1 day).
Note: Results of the Monte Carlo simulation with 1000 annual trajectories. The severity of public losses is negatively associated with the quality of governance (*GOV*) regardless of media attention (*PRESS*) and the relative difficulty to hide the loss size (*c*). In the case of high media attention (*PRESS*=0.9), the slopes of the curves are close to zero. If *c* is lower (higher) than 1, it is less (more) difficult to hide the true size of the loss than the occurrence of the loss.

much easier to hide the true size of the loss than the occurrence of the loss (*c* is low), then some part of the loss remains hidden depending on the level of media attention. In this case, the *detection* effect of the media can dominate the deterrence effect, so overall, there can be a positive relationship between the level of media attention and the severity of losses. As we have no a priori expectation on the relative difficulty to hide the loss size *c*, we form the following two mutually exclusive hypotheses—one of these hypotheses shall be accepted while the other rejected:

H6a: The *PRESS* × *GOV* interaction is significantly and negatively associated with the *severity* of public losses due to difficulty to hide the loss size.
H6b: The *PRESS* × *GOV* interaction is significantly and positively associated with the *severity* of public losses due to the ease to hide the loss size.

4. Empirical analysis

In this section, we aim to test the hypotheses derived from the simulation results.

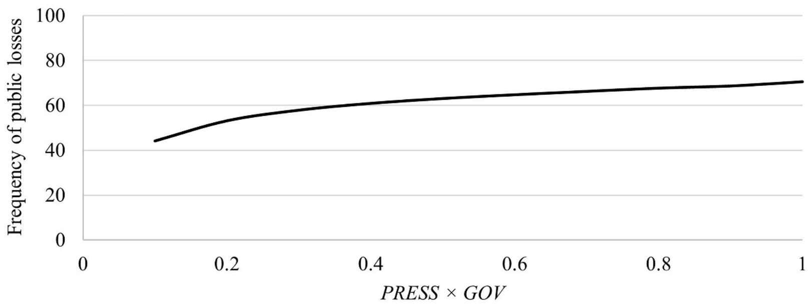

Fig. 5a. The effects of *PRESS* × *GOV* on the *frequency* of public losses.
Note: Results of the Monte Carlo simulation with 1000 annual trajectories. The frequency of public losses is positively associated with the interaction of the quality of governance (*GOV*) and media attention (*PRESS*).

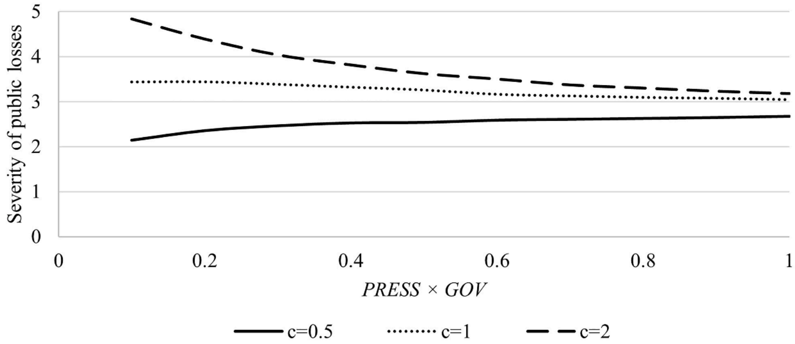

Fig. 5b. The effects of *PRESS* × *GOV* on the *severity* of public losses.
Note: Results of the Monte Carlo simulation with 1000 annual trajectories. The severity of public losses can be both positively and negatively associated with the interaction of the quality of governance (*GOV*) and media attention (*PRESS*) depending on the relative difficulty to hide the loss size (c). If c is lower (higher) than 1, it is less (more) difficult to hide the true size of the loss than the occurrence of the loss.

4.1. Data and method

Economic activities can be investigated at various levels of aggregation, such as projects, business units, firms, countries, and regions. In principle, the model of catastrophic risk introduced in Section 2 can be interpreted at each of these levels. When testing the empirical relevance of a theoretical model, the key challenge is to identify suitable, measurable proxy variables that correspond to the selected level of aggregation.

In this paper, we conduct a *firm-level* empirical analysis. The key variables of interest, such as the frequency and severity of operational loss events (*F* and *S*), governance (*GOV*), and media attention (*PRESS*), can be proxied by country- and firm-level variables extracted from databases maintained by professional providers. The time scale is one year. If a firm experiences multiple losses within a year, these losses are aggregated. In case of multinational companies, each subsidiary is treated as a separate firm.

Public operational loss data are retrieved from the SAS OpRisk Global database, the world's most comprehensive and accurate repository of low-frequency and high-severity operational loss events (SAS, 2021; Wei et al., 2018). The database includes all publicly reported operational losses higher than US$100,000 across all industries worldwide. Data are extracted for the period of 2011–2022 covering 4547 loss events attributable to firms included in the MSCI World Index. The MSCI World Index includes 1218 large and mid-cap stocks from 23 developed market economies, representing about 85 % of each country's free float-adjusted market capitalization. Although the incidents are associated with firms headquartered in the 23 countries of the MSCI World Index, they took place in 36 different countries. In line with the spirit of the simulation model, we consider only endogenous risk events: incidents where the firm's responsibility has been established by a legal court or regulatory body. For characteristic cases, see Table S1 in the online Supplementary Material. Assuming that a loss event is highly dependent on the local environment, losses are assigned to countries based on the location of the incident, rather than the firm's headquarters. We assign losses to the settlement year, as this can be regarded as the year the loss is revealed to the public.

We define two *dependent variables*: frequency and severity of operational losses. Frequency is the number of public operational loss events occurring within a specific firm over a given year. Severity is the average loss amount incurred by a firm in a given year. Both frequency and severity are expressed in natural logarithms.

The two *independent variables* of particular interest are the intensity of media attention (*PRESS*) and the quality of governance (*GOV*). In the empirical model, each of the variables *PRESS* and *GOV* has country-specific and firm-specific components. The *country-specific governance* (*C_GOV*) is measured by the Worldwide Governance Indicator which is retrieved from the database of the World Bank (World Bank, 2024a). This indicator aggregates six dimensions of a country's governance: 1) voice and accountability; 2) political stability and absence of violence; 3) government effectiveness; 4) regulatory quality; 5) rule of law; and 6) control of corruption (Kaufmann et al., 2011). The *firm-specific quality of governance* (*F_GOV*) is measured by the Governance pillar score of the firm's ESG rating, as provided by Refinitiv. This pillar score, among other factors, assesses the independence and the diversity of the board, the compensation structure, the existence of various committees, and the CSR strategy. In case of a multinational firm with several subsidiaries, we use the subsidiary's Governance pillar scores. If this is not available, we rely on the parent company's assessment.

The *country-specific media attention* (*C_PRESS*) is measured by the Word Press Freedom (WPF) index. In general, this index assesses the freedom of speech, the extent to which individuals can articulate their opinions and ideas without fear of retaliation, censorship, or legal sanction. The index has been published since 2002 annually for 180 countries by an international non-governmental organization, Reporters Without Borders (in French, Reporters Sans Frontières, RSF) (RSF, 2020). The index aggregates the most relevant qualitative and quantitative dimensions characterizing the conditions in which the media operates: pluralism, media independence, environment and self-censorship, legislative framework, transparency, and infrastructure (RSF, 2020). The scores are based on media professionals', lawyers', and sociologists' answers to an online questionnaire. Quantitative dimensions consider seven different types of abuses and acts of violence against journalists such as murder, imprisonment, firing, ruining media, exile, arrest, and aggression. The *firm-specific media attention* (*F_PRESS*) is measured by the stock market liquidity of the firm (average bid-ask spread in year t). We can assume that in case of more liquid stocks, firms are more closely monitored by journalists, analysts, auditors, regulators, potential investors, short sellers, civil organizations, leading to higher media attention.

Furthermore, we add both country- and firm- specific *control variables*. Country-specific control variables include the size of the economy, the concentration of the firms, and the living standards. The *size of the economy* is measured by the gross domestic product (*GDP*) in current USD (World Bank, 2024b). The *concentration of the firms* is measured by the normalized Herfindahl-Hirschman index (*HHI*) retrieved from the World Bank database (World Bank, 2024c). Finally, we control for the *living standards* measured by the *GNI* per capita (World Bank, 2024d). According to Li and Moosa (2015), this country-specific variable may explain the cross-country variation of operational risk. Firm-specific control variables include proxies for profitability, growth, liquidity, leverage, and beta, among others, retrieved from Datastream (Datastream, 2024). The definitions of the control variables are provided in online Supplementary Material Table S2.

We specify the following (industry- and year) *fixed effects panel regression model* for the frequency of public operational loss events:

$$lnPF_{i,y} = \alpha + \beta\, C\_PRESS_{i,y} + \gamma\, F\_PRESS_{i,y} + \delta\, C\_GOV_{i,y} + \zeta\, F\_GOV_{i,y} + \sum_k \mu_k C_{i,y}^{(k)} + \lambda_{industry} + \theta_y + \varepsilon_{i,y} \tag{8}$$

$$lnPS_{i,y} = \alpha + \beta\, C\_PRESS_{i,y} + \gamma\, F\_PRESS_{i,y} + \delta\, C\_GOV_{i,y} + \zeta\, F\_GOV_{i,y} + \sum_k \mu_k C_{i,y}^{(k)} + \lambda_{industry} + \theta_y + \varepsilon_{i,y} \tag{9}$$

where $PF_{i,y}$ is the number of public operational loss events at firm i in year y; α is the intercept; $C\_PRESS_{i,y}$ is the country-specific press freedom index; $F\_PRESS_{i,y}$ is the firm-specific media attention variable proxied by stock market liquidity (average bid ask spread); $C\_GOV_{i,y}$ is the country-specific governance indicator; $F\_GOV_{i,y}$ is the firm-specific governance indicator proxied by the Governance pillar score from Refinitiv; $C_{i,y}^{(k)}$ is the kth country- or firm-specific control variable; $\lambda_{industry}$ is the industry fixed effect; θ_y is the time fixed effect, and $\varepsilon_{i,y}$ is the error term. When estimating the basic regression model (8), we apply robust cluster standard errors for industry, winsorize observations at 1 % and 99 %, and impute the missing control variables using chained equations.

In another series of specifications, we change the dependent variable, and estimate (9) for the severity of public losses $PS_{i,y}$ which is the average loss amount of firm i in year y if there was a loss. Note that in this case, we estimate unbalanced panel regressions considering only non-zero aggregate losses.

To better understand the relationship between the *PRESS* and *GOV,* we first add both variables together in the model. Afterwards, we include them separately. Finally, we estimate (8) and (9) with interaction terms (*PRESS* × *GOV*) as well.

When estimating models (8) and (9), endogeneity issues may arise due to reverse causality, measurement errors, or omitted variables. To exclude reverse causality, we estimate the models with lagged independent variables as well. Measurement errors can result in identification problems if data on public operational losses, as well as the variables of media attention, governance, and the controls are systematically biased. Indicators aggregating several variables (e.g., country indices, ESG pillar scores) are prone to methodological errors due to arbitrary weighting and the specific multivariate interdependence structure of the components (Treier and Jackman, 2008). However, the measurement error can be minimized if a large number of factors are considered in the index calculation, data collection is systematic, and data processing is standardized. We used comprehensive, standardized, and highly professional databases that have served both academic and business research community for many decades. Therefore, the measurement error shall be minimal, if not completely eliminated. Finally, the fixed effects (FE) model helps mitigate the omitted variable bias to some extent by controlling for time-invariant unobserved heterogeneity across industries and years. Furthermore, we include a wide range of observed time-varying control variables that are suspected to correlate with both the dependent variable and the independent variables. As long as these controls are properly specified, they can help reduce the omitted variable bias.

As a robustness check, we estimate the basic model without imputation, without winsorization, and with lagged dependent variables as well. Robustness checks help mitigate the omitted variable problem and ensure the reliability of estimated coefficients in fixed effects panel regressions. To better understand the role of media attention and the quality of governance, we also perform heterogeneity analyses by cutting the sample into two subsets according to some firm characteristics. Specifically, we estimate coefficients separately for firms operating outside the USA, in the top 50 % versus the bottom 50 % (measured by market capitalization), and separately for financial and non-financial firms.

4.2. Results

The descriptive statistics of the variables in the regression are displayed in online Supplementary Material Table S2. The regression results and the robustness checks can be seen in Table 1 for the frequency and in Table 3 for the severity of public losses. Tables 2 and 4 display the results of the heterogeneity analyses for the frequency and severity of public losses, respectively.

As shown in Table 1, the coefficients of both the country and firm-specific media attention variables (*C_PRESS, F_PRESS*) are positive and statistically significant in *Models 1, 2 and 3.* (Note that in *Models 4, 5, and 6,* we do not interpret the coefficients *PRESS* and *GOV* as their interactions are included.) Consequently, the higher the media attention, the more risk events are published by journalists. In the basic model *F1*, the coefficient indicates that if the *C_PRESS* variable is by one percentage point higher, then the observed loss frequency is by 0.14 % higher. The coefficient of *F_PRESS* is almost the same (0.13 %). *PRESS* coefficients are roughly the same when we include the country- and firm-specific *PRESS* and *GOV* variables separately, see models *F2* and *F3*.

The coefficients of the variables capturing the quality of country and firm-specific governance (*C_GOV, F_GOV*) are insignificant for loss frequency in models *F1-F3*. The interaction terms (*PRESS* × *GOV*) are also insignificant in models *F4, F5*, and *F6*.

The coefficients of the country- and firm-specific controls are intuitive and align with our expectations.

Overall, the results from the robustness checks (models *F7-F9*) and heterogeneity analyses (models *F10-F14*) confirm the findings from the basic model. The only exception is the subsample of smaller firms (bottom 50 %) in model *F12*, where the country and firm-specific media attention variables are insignificant. However, firm-specific governance may have an impact in the subsample of smaller firms; when the quality of governance is higher, more losses are revealed and disclosed.

Table 3 presents the results from the regression analysis and robustness check for the dependent variable of severity. Loss severity shall be interpreted as a conditional value: the average loss amount if there is a loss event.

The coefficients of media attention (*C_PRESS, F_PRESS*) are positive and statistically significant in Models *S1-S3*. In the basic model *S1*, the coefficient shows that if the C_PRESS variable is by one percentage point higher, then the observed severity of losses is by 1.17 % higher. The coefficient of the variable capturing media attention at the firm-level (*F_PRESS)* is roughly the same (1.99 %) as at the country-level (C_PRESS). These coefficients are quite robust in models *S2* and *S3*. (In models *S4, S5,* and *S6*, the coefficients are not interpreted on their own due to the interaction term.)

The quality of country-specific governance (*C_GOV*) is significantly associated with loss severity in the basic models *S1*. If the *C_GOV* variable is by one percentage point higher, then the observed loss amount is by 2.78 % lower. Model *S3* yields similar results. At the same time, for loss severity, the coefficient of the firm-specific governance (*F_GOV*) variable is not significant in any specifications.

It is notable, however, that the *C_PRESS* $\times$ *C_GOV* interaction term is significant and positive in model *S4*. Therefore, if both *PRESS* and *GOV* are higher, the severity of losses is expected to be higher. In line with Fig. 5b, this suggests that the parameter c in the theoretical model tends to be smaller than 1, indicating that the real size of the loss can be easier to hide than the occurrence of loss event itself. When estimating models *S4, S5*, and *S6* for the financial sector separately, the coefficient of the interaction term is significant, positive, and even higher in value. In contrast, for the non-financial sector, it is insignificant. Therefore, this result ($c < 1$, meaning that it might be easier to conceal the loss size than the occurrence of the loss) is likely to be driven by the financial sector.

Overall, findings from the basic model are corroborated by the results of the robustness checks (models *S7-S9*) and heterogeneity analyses (models *S10-S14*). However, when all independent variables are lagged by one year (model *S9*), the role of country-specific media attention (press freedom) is replaced by firm-specific investor attention. In addition, the country-specific governance also loses its significance. Smaller firms (model *S12*) are also an exception; in this specification, all country and firm-specific media attention variables are insignificant.

5. Discussion

In this section, we contrast the simulation results with the findings from the empirical analysis and discuss the implications and limitations of the research.

5.1. Simulation versus empirical results

Table 5 summarizes the effects of the variables of particular interest (*PRESS, GOV, PRESS* $\times$ *GOV*) on the two dependent variables (*frequency* and *severity of public loss events*). The table compares the slope of the curves from the simulations with the coefficients from the regression analysis.

The empirical results are consistent with the predictions of the simulation model, which suggests that the proposed theoretical model might capture relevant patterns. Most importantly, *media attention,* free media at country-level and highly liquid stocks at firm-level, can have a large positive effect on both the frequency and the severity of public losses. Coefficients are significant also in economic terms. If county-level media attention, proxied by the freedom of press, is one point higher on a scale of 100, it is associated with 0.14 % more and 1.17 % larger public losses. If firm-level media attention, proxied by the bid-ask spread on the stock market, is one point higher on a scale of 100, it is associated with 0.13 % more and 1.99 % larger public losses. MSCI index companies are subject to intense media scrutiny in the US both due the high level of press freedom (capturing country-level media attention) and the high level of liquidity (capturing firm-level media attention), which provides a plausible explanation for the very high number of loss events in the US, as recorded in the SAS Global Oprisk database.

With the proposed theoretical model, we can explain another puzzle as well: why the quality of *governance* is less relevant for public losses. As Figs. 4a and 4b indicate, better governance is associated with fewer and lower losses; however, the slopes of the curves are much closer to zero when compared to the slope of the curves of media attention shown by Figures 3. The positive impact of better governance can hence be masked by the strong detection effect of the media, especially if press freedom is high. Therefore, it is understandable why the regression coefficient of governance for loss frequency and severity did not prove significant in most of the specifications.

If companies optimize their internal governance systems, greater media attention is associated with better governance. In particular, enhanced media attention motivates improvements in internal self-regulatory mechanisms to avoid potential scandals and large reputational losses. However, the *joint effect of PRESS and GOV* is uncertain as it is the result of two opposing effects. While greater press freedom increases the frequency and severity of public losses, better internal governance clearly acts in the opposite direction and decreases them. Regression results indicate that both effects are strong and nearly equal in magnitude, more or less offsetting each other. For frequency, the coefficient of the interaction term is insignificant; while for severity, it is significant with a positive coefficient. This positive coefficient indicates that the true size of large corporate losses can be easier to hide than the loss event itself. This result is even more pronounced in the financial sector.

Overall, we can conclude that the empirical analysis confirms the theoretical predictions in all important aspects.

Table 1
Regression results and robustness checks for the frequency of public losses (PF).

Variable names		F1		F2		F3		F4		F5		F6		F7		F8		F9	
														Without imputation		Without winsorization		Lagged independent variables	
		Beta	p	Beta	P	Beta	p	Beta	p	Beta	p	Beta	p	Beta	p	Beta	p	Beta	p
Country-specific variables	C_PRESS	0.0014	0.000***	0.0014	0.000***			0.0017	0.003**			0.0017	0.004**	0.0007	0.001**	0.0013	0.000***	0.0013	0.000***
	C_GOV	−0.0003	0.313	−0.0004	0.198			−0.0001	0.808			0.0000	0.940	0.0001	0.710	−0.0003	0.279	0.0002	0.400
	C_PRESS × C_GOV							0.0000	0.623			0.0000	0.601						
Firm-specific variables	F_PRESS	0.0013	0.000***			0.0014	0.000***			0.0015	0.042*	0.0013	0.084	0.0003	0.275	0.0014	0.000***	0.0011	0.001**
	F_GOV	0.0002	0.067			0.0002	0.058			0.0003	0.279	0.0002	0.396	0.0004	0.000***	0.0003	0.012*	0.0002	0.145
	F_PRESS × F_GOV									0.0000	0.794	0.0000	0.975						
Country-specific controls	GDP	0.0343	0.000***	0.0337	0.000***	0.0338	0.000***	0.0338	0.000***	0.0337	0.000***	0.0344	0.000***	0.0192	0.000***	0.0330	0.000***	0.0367	0.000***
	GNI per capita	0.0136	0.010*	0.0141	0.007**	0.0221	0.000***	0.0140	0.008**	0.0220	0.000***	0.0134	0.011*	0.0030	0.565	0.0134	0.011*	0.0057	0.292
	HHI	−0.0002	0.432	−0.0002	0.238	−0.0001	0.608	−0.0002	0.274	−0.0001	0.608	−0.0001	0.485	−0.0002	0.233	−0.0002	0.283	−0.0003	0.092
Firm controls	Revenue	0.0385	0.000***	0.0442	0.000***	0.0376	0.000***	0.0442	0.000***	0.0377	0.000***	0.0385	0.000***	0.0380	0.000***	0.0369	0.000***	0.0385	0.000***
	Growth (3 years)	−0.0011	0.000***	−0.0011	0.000***	−0.0010	0.000***	−0.0011	0.000***	−0.0010	0.000***	−0.0011	0.000***	−0.0006	0.005**	−0.0001	0.075	−0.0007	0.001**
	Capex/Asset	0.1568	0.077	0.1630	0.066	0.1510	0.090	0.1633	0.066	0.1507	0.090	0.1570	0.077	0.1656	0.023*	0.1259	0.099	0.1190	0.192
	ROA	−0.0006	0.181	−0.0005	0.197	−0.0005	0.204	−0.0005	0.205	−0.0005	0.204	−0.0006	0.189	−0.0004	0.237	−0.0008	0.014*	−0.0010	0.024*
	CF to sales	0.0004	0.020*	0.0005	0.002**	0.0004	0.023*	0.0005	0.002**	0.0004	0.022*	0.0004	0.020*	0.0005	0.011*	0.0000	0.999	0.0007	0.000***
	Leverage	0.0000	0.046*	0.0000	0.064	0.0000	0.038*	0.0000	0.064	0.0000	0.039*	0.0000	0.047*	0.0000	0.516	0.0000	0.817	0.0000	0.035*
	Funding liquidity	0.0029	0.324	0.0028	0.347	0.0025	0.393	0.0027	0.353	0.0026	0.389	0.0029	0.331	0.0003	0.909	0.0029	0.145	0.0026	0.366
	Beta	−0.0158	0.002**	−0.0129	0.013*	−0.0154	0.003**	−0.0129	0.013*	−0.0155	0.003**	−0.0158	0.002**	−0.0159	0.002**	−0.0106	0.024*	−0.0159	0.003**
	Market-to book	−0.0017	0.003**	−0.0014	0.012*	−0.0017	0.003**	−0.0014	0.012*	−0.0017	0.003**	−0.0017	0.003**	−0.0008	0.152	0.0000	0.543	−0.0016	0.008**
	EV/EBITDA	0.0005	0.084	0.0007	0.028*	0.0004	0.169	0.0007	0.027*	0.0004	0.169	0.0005	0.083	0.0010	0.007**	0.0000	0.349	0.0006	0.052
No. of observations		22 320		22 320		22 320		22 320		22 320		22 320		14 846		22 320		20 460	
Industry fixed effect		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Time fixed effect		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Cluster-robust standard error		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Note: The dependent variable is the natural logarithm of the frequency (number) of public losses. *C_PRESS (F_PRESS)* is the country (firm) specific media attention; *C_GOV (F_GOV)* is the quality of country (firm) specific governance (scaled between 0 and 100 where a higher value indicates a more favorable situation). Specifications *F7-F9* are robustness checks for the basic model. *F7*: we apply no imputation; *F8:* we apply no winsorization; *F9:* independent variables are lagged by one year.

Table 2
Heterogeneity analysis for the frequency of public losses (PF).

Variable names		F10		F11		F12		F13		F14	
		Without USA		Top50 %		Bottom 50 %		Non-financial firms		Financial firms	
		Beta	p	Beta	p	Beta	p	Beta	p	Beta	P
Country-specific variables	C_PRESS	0.0014	0.000***	0.0022	0.000***	0.0002	0.349	0.0006	0.003**	0.0029	0.000***
	C_GOV	−0.0003	0.313	−0.0011	0.002**	−0.0002	0.531	0.0000	0.932	−0.0012	0.070
	C_PRESS × C_GOV										
Firm-specific variables	F_PRESS	0.0013	0.000***	0.0011	0.015*	0.0003	0.291	0.0006	0.048*	0.0040	0.000***
	F_GOV	0.0002	0.067	0.0000	0.895	0.0002	0.013*	0.0003	0.002**	−0.0001	0.705
	F_PRESS × F_GOV										
Country-specific controls	GDP	0.0343	0.000***	0.0457	0.000***	0.0062	0.000***	0.0170	0.000***	0.0720	0.000***
	GNI per capita	0.0136	0.010*	0.0202	0.003**	−0.0031	0.607	0.0060	0.227	0.0481	0.000***
	HHI	−0.0002	0.432	−0.0004	0.179	−0.0001	0.437	−0.0002	0.342	−0.0008	0.077
Firm-specific controls	Revenue	0.0385	0.000***	0.0481	0.000***	0.0150	0.000***	0.0350	0.000***	0.0487	0.000***
	Growth (3 years)	−0.0011	0.000***	−0.0018	0.000***	0.0001	0.406	−0.0006	0.000***	−0.0025	0.000***
	Capex/Asset	0.1568	0.077	0.1545	0.275	0.0617	0.299	0.1203	0.065	0.2615	0.622
	ROA	−0.0006	0.181	−0.0009	0.147	−0.0003	0.355	−0.0005	0.189	−0.0016	0.405
	CF to sales	0.0004	0.020*	0.0003	0.216	−0.0002	0.165	0.0005	0.003**	0.0003	0.305
	Leverage	0.0000	0.046*	0.0000	0.072	0.0000	0.361	0.0000	0.630	0.0001	0.033*
	Funding liquidity	0.0029	0.324	0.0050	0.257	0.0008	0.681	0.0026	0.198	0.0029	0.742
	Beta	−0.0158	0.002**	−0.0317	0.000***	0.0121	0.002**	−0.0183	0.000***	0.0107	0.466
	Market-to book	−0.0017	0.003**	−0.0021	0.008**	−0.0002	0.677	−0.0008	0.144	−0.0036	0.241
	EV/EBITDA	0.0005	0.084	0.0005	0.276	0.0004	0.096	0.0007	0.041*	0.0007	0.329
No. of observations		14 424		15 444		6 876		16 116		6 204	
Industry fixed effect		Yes		Yes		Yes		Yes		Yes	
Time fixed effect		Yes		Yes		Yes		Yes		Yes	
Cluster-robust standard error		Yes		Yes		Yes		Yes		Yes	

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.
Note: The dependent variable is the natural logarithm of the frequency (number) of public losses. *C_PRESS (F_PRESS)* is the country (firm) specific media attention; *C_GOV* (*F_GOV*) is the quality of country (firm) specific governance (scaled between 0 and 100 where a higher value indicates a more favorable situation). Specifications *F10-F14* are heterogeneity analyses for the basic model *F1*. *F10:* incidents in the USA are excluded; *F11:* the top 50 % of the firms (by market capitalization) are considered; *F12:* the bottom 50 % of the firms (by market capitalization) are considered; *F13:* only non-financial firms are included; *F14:* only financial firms are included.

Table 3
Regression results for the severity of public losses (PS).

Variable names		S1		S2		S3		S4		S5		S6		S7		S8		S9	
														Without imputation		Without winsorization		Lagged independent variables	
		Beta	p	Beta	p	Beta	p	Beta	p	Beta	p	Beta	p	Beta	p	Beta	p	Beta	p
Country-specific variables	C_PRESS	0.0117	0.002**	0.0117	0.002**			−0.0283	0.006**			−0.0290	0.005**	0.0112	0.027*	0.0115	0.002**	−0.0038	0.419
	C_GOV	−0.0278	0.000***	−0.0286	0.000***			−0.0627	0.000***			−0.0626	0.000***	−0.0155	0.029*	−0.0272	0.000***	−0.0012	0.834
	C_PRESS × C_GOV							0.0006	0.000***			0.0006	0.000***						
Firm-specific variables	F_PRESS	0.0199	0.000***			0.0213	0.000***			0.0426	0.007**	0.0419	0.008**	0.0183	0.016*	0.0189	0.000***	0.0217	0.000***
	F_GOV	0.0004	0.860			0.0000	0.993			0.0070	0.187	0.0077	0.146	0.0022	0.396	0.0007	0.724	0.0002	0.943
	F_PRESS × F_GOV									−0.0003	0.151	−0.0003	0.146						
Country-specific controls	GDP	0.1125	0.000***	0.0985	0.000***	0.1511	0.000***	0.0892	0.002**	0.1516	0.000***	0.1040	0.000***	0.2282	0.000***	0.1067	0.000***	0.1339	0.000***
	GNI per capita	0.5583	0.000***	0.5682	0.000***	0.2232	0.000***	0.5890	0.000***	0.2189	0.000***	0.5776	0.000***	0.1110	0.373	0.5511	0.000***	0.3170	0.002**
	HHI	−0.0150	0.000***	−0.0173	0.000***	−0.0187	0.000***	−0.0197	0.000***	−0.0186	0.000***	−0.0172	0.000***	−0.0114	0.060	−0.0153	0.000***	−0.0158	0.000***
Firm-specific controls	Revenue	0.0911	0.029*	0.1600	0.000***	0.0899	0.032*	0.1662	0.000***	0.0962	0.023*	0.1004	0.016*	0.1167	0.026*	0.0996	0.014*	0.0987	0.028*
	Growth (3 years)	−0.0154	0.000***	−0.0169	0.000***	−0.0158	0.000***	−0.0161	0.000***	−0.0158	0.000***	−0.0145	0.000***	−0.0112	0.040*	−0.0149	0.000***	−0.0177	0.000***
	Capex/Asset	−0.2594	0.894	−0.3287	0.866	−0.3853	0.844	−0.6392	0.743	−0.4959	0.800	−0.6841	0.725	−0.5626	0.790	−0.6613	0.732	−0.3906	0.856
	ROA	−0.0068	0.478	−0.0064	0.507	−0.0069	0.479	−0.0084	0.383	−0.0065	0.501	−0.0085	0.375	−0.0144	0.175	−0.0079	0.334	−0.0126	0.225
	CF to sales	−0.0020	0.469	−0.0008	0.768	−0.0016	0.568	−0.0006	0.813	−0.0016	0.549	−0.0019	0.472	0.0068	0.236	−0.0004	0.812	0.0005	0.880
	Leverage	0.0005	0.044*	0.0004	0.071	0.0004	0.083	0.0004	0.086	0.0004	0.090	0.0004	0.058	0.0006	0.178	0.0000	0.985	0.0003	0.294
	Funding liquidity	0.0630	0.317	0.0605	0.338	0.0650	0.305	0.0632	0.315	0.0688	0.279	0.0703	0.264	0.0499	0.604	0.0249	0.554	0.0605	0.330
	Beta	0.1432	0.133	0.1759	0.064	0.1455	0.129	0.1964	0.038*	0.1411	0.141	0.1589	0.095	−0.0016	0.992	0.1676	0.057	0.1379	0.181
	Market-to book	−0.0031	0.806	0.0010	0.937	−0.0019	0.88	0.0009	0.943	−0.0015	0.904	−0.0029	0.815	−0.0012	0.939	0.0011	0.617	−0.0089	0.509
	EV/EBITDA	−0.0052	0.310	−0.0035	0.488	−0.0057	0.268	−0.0034	0.505	−0.0062	0.233	−0.0056	0.278	−0.0175	0.256	−0.0012	0.273	0.0002	0.968
No. of observations		2 485		2 485		2 485		2 485		2 485		2 485		1 258		2 485		2 205	
Industry fixed effect		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Time fixed effect		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Cluster-robust standard error		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.
Note: The dependent variable is the natural logarithm of the frequency (number) of public losses. *C_PRESS (F_PRESS)* is the country (firm) specific media attention; *C_GOV* (*F_GOV*) is the quality of country (firm) specific governance (scaled between 0 and 100 where a higher value indicates a more favorable situation). Specifications *S7-S9* are robustness checks for the basic model. *S7:* we apply no imputation; *S8:* we apply no winsorization; *S9:* independent variables are lagged by one year.

Table 4
Heterogeneity analysis for the severity of public losses (PS).

Variable names		S10		S11		S12		S13		S14	
		Without USA		TOP50 %		Bottom 50 %		Non-financial firm		Financial firms	
		Beta	p	Beta	p	Beta	p	Beta	p	Beta	P
Country-specific variables	C_PRESS	0.0117	0.002**	0.0110	0.005**	0.0202	0.104	0.0138	0.013*	0.0102	0.044*
	C_GOV	−0.0278	0.000***	−0.0293	0.000***	−0.0129	0.504	−0.0381	0.000***	−0.0152	0.032*
	C_PRESS × C_GOV										
Firm-specific variables	F_PRESS	0.0199	0.000***	0.0182	0.003**	0.0176	0.368	0.0200	0.026*	0.0176	0.023*
	F_GOV	0.0004	0.860	0.0001	0.97	0.0069	0.315	0.0007	0.840	0.0005	0.844
	F_PRESS × F_GOV										
Country-specific controls	GDP	0.1125	0.000***	0.1184	0.000***	0.0999	0.364	0.0513	0.171	0.2261	0.000***
	GNI per capita	0.5583	0.000***	0.6030	0.000***	−0.2353	0.533	0.9362	0.000***	0.1174	0.345
	HHI	−0.0150	0.000***	−0.0144	0.000***	−0.0373	0.043*	−0.0158	0.002**	−0.0096	0.113
Firm-specific controls	Revenue	0.0911	0.029*	0.0768	0.094	0.3378	0.073	0.0670	0.342	0.1063	0.051
	Growth (3 years)	−0.0154	0.000***	−0.0131	0.004**	−0.0394	0.001**	−0.0151	0.023*	−0.0151	0.006**
	Capex/Asset	−0.2594	0.894	−1.1827	0.578	1.0467	0.841	−1.4109	0.753	0.2273	0.915
	ROA	−0.0068	0.478	−0.0019	0.86	−0.0451	0.119	−0.0094	0.784	−0.0109	0.296
	CF to sales	−0.0020	0.469	−0.0027	0.345	0.0214	0.066	−0.0023	0.466	0.0031	0.573
	Leverage	0.0005	0.044*	0.0005	0.048*	0.0003	0.744	0.0003	0.440	0.0007	0.073
	Funding liquidity	0.0630	0.317	0.0580	0.384	0.0565	0.802	−0.0228	0.788	0.2294	0.004**
	Beta	0.1432	0.133	0.2204	0.032*	−0.3495	0.217	0.1967	0.139	−0.0324	0.824
	Market-to book	−0.0031	0.806	−0.0053	0.687	0.0313	0.644	−0.0128	0.754	−0.0013	0.933
	EV/EBITDA	−0.0052	0.310	−0.0073	0.184	0.0175	0.321	−0.0051	0.422	−0.0203	0.130
No. of observations		1 219		2 261		224		1 206		1 279	
Industry fixed effect		Yes		Yes		Yes		Yes		Yes	
Time fixed effect		Yes		Yes		Yes		Yes		Yes	
Cluster-robust standard error		Yes		Yes		Yes		Yes		Yes	

**p* < 0.05; ***p* < 0.01; ****p* < 0.001.

Note: The dependent variable is the natural logarithm of the frequency (number) of public losses. *C_PRESS (F_PRESS)* is the country (firm) specific media attention; *C_GOV* (*F_GOV*) is the quality of country (firm) specific governance (scaled between 0 and 100 where a higher value indicates a more favorable situation). Specifications *S10-S14* are heterogeneity analyses for the basic model S*1*. *S10:* incidents in the USA are excluded; *S11:* the top 50 % of the firms (by market capitalization) are considered; *S12:* the bottom 50 % of the firms (by market capitalization) are considered; *S13:* only non-financial firms are included; *S14:* only financial firms are included.

Table 5
Simulations versus regression results for public losses.

Independent variable	Dependent variable	Simulation: slope of the curve	Regression: country-specific coefficient	Regression: firm-specific coefficient	Hypothesis
PRESS	frequency	strongly positive	+ 0.0014***	+0.0013***	H1 accepted
PRESS	severity	negative/positive	+ 0.0117**	+0.0199***	H2a rejected H2b accepted
GOV	frequency	slightly negative	insignificant	insignificant	H3 rejected
GOV	severity	slightly negative	−0.0278***	insignificant	H4 accepted
PRESS × *GOV*	frequency	slightly positive	insignificant	insignificant	H5 rejected
PRESS × *GOV*	severity	negative/positive	+0.0006***	insignificant	H6a rejected H6b accepted

5.2. Policy implications

If we accept the theoretical model as a simplified, but valid description of the reality, we can have an idea not only about public but also about hidden losses. In Figs. 6a and 6b, we summarize the effects of parallel improvements in media attention *PRESS* and governance *GOV* on the total loss frequency and severity in line with the simulation model.

As shown by Fig. 6a, the interaction of media attention and the quality of governance has an opposite effect on the frequency of total (public and hidden) losses than on public losses. If both media attention and the quality of governance are higher, paradoxically, we can observe more public losses (detection effect of the media), while the number of total losses is massively decreasing (joint deterrence effect of the media and internal governance).

The severity of total losses displays a more complex pattern. Public losses might increase or decrease in the function of the *PRESS* × *GOV* interaction depending on the relative difficulty of hiding the loss size c, see Fig. 6b. Note that the empirical analysis provides an indication that the value of the parameter c might be smaller than 1, especially in the financial sector. If we accept that it is easier to hide the loss size than the occurrence of the loss ($c < 1$), then we can expect a large difference between public and total loss severities similar to the large differences between public and total frequencies. Higher media attention and better internal governance are associated with higher public loss severity (detection effect of the media) and lower total severity (joint deterrence effect of the media and internal governance).

For operational risk management, the key policy implication is that it can be very misleading to examine public losses unless we control for the *reporting bias*. Risk managers, company leaders and business practitioners should keep in mind that if a company is less exposed to media attention (e.g., private equity firms) or it operates in a country with low press freedom, then a significant part of the losses remains hidden. Recently, *private equity firms* have been found to engage in abusive practices, including misallocating expenses, manipulating portfolio company valuations, and collecting undisclosed fees (Batt and Appelbaum, 2021). *Multinational companies* are keen to outsource some of their activities to developing countries because of the cheap labor and less stringent regulatory environment. In addition, low press freedom can also be a *motivation to outsource* the most polluting and controversial corporate activities to developing countries where they do not have to fear the press (Baumert et al., 2019).

If both media attention and the quality of governance are low, that is, the product of *PRESS* × *GOV* is low, then public operational losses are expected to exhibit LFHS (low-frequency and high-severity) characteristics. In contrast, if we often hear about corporate scandals in the media but loss sizes are relatively low, then the firm seems to operate under the HFLS regime (high-frequency and low-severity). Therefore, we can expect that the corporate misconducts are detected, processes are controlled, internal governance is improved, and the overall loss is smaller, as minor operational problems are fixed in time, so they are less likely to escalate into Chernobyl-like catastrophes. Media attention is, therefore, a key factor which determines whether a firm (or a country) operates under a *LFHS or a HFLS regime* (in terms of public losses). This is particularly true when the quality of governance is tailored to it due to firms' optimization. Thus, media attention not only has a direct impact on businesses through the scandals but also indirectly drives the improvement of internal governance structures. Improving *press freedom* and *market liquidity* can, therefore, be a highly effective policy tool to promote corporate sustainability.

Figs. 6a and 6b also suggest that the variables of *PRESS* and *GOV* not only complement, but also *substitute* each other. On the one hand, if corporate governance is weak, media can act as an effective monitor, disciplining firms' operation. On the other hand, if media attention in general, press freedom in particular, along with other relevant institutions, are weak in a country, then corporate social responsibility is of major importance (Tirole, 2006; He, Du, Yo, 2022). Furthermore, media attention and internal governance enhance

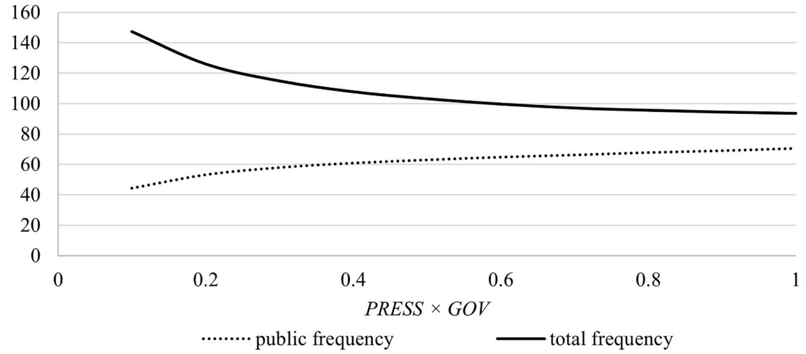

Fig. 6a. The effects of *PRESS* × *GOV* on the *total frequency* of losses.
Note: Results of the Monte Carlo simulation with 1000 annual trajectories. The frequency of total losses is negatively associated with the interaction of the quality of governance (*GOV*) and media attention (*PRESS*).

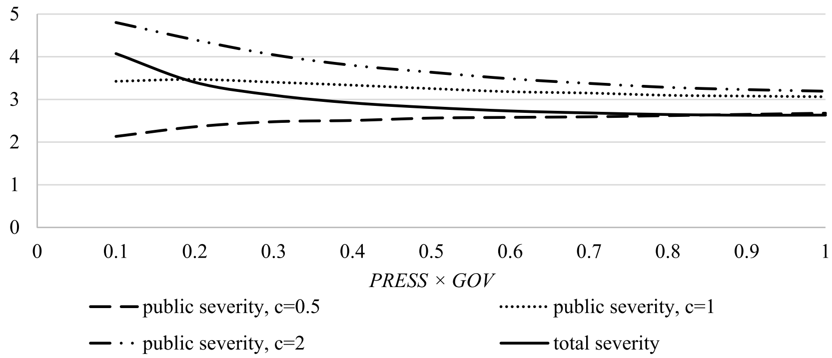

Fig. 6b. The effects of *PRESS* × *GOV* on the *total severity* of the losses.
Note: Results of the Monte Carlo simulation with 1000 annual trajectories. The severity of total losses is negatively associated with the interaction of the quality of governance (*GOV*) and media attention (*PRESS*).

each other, creating a *positive feedback loop* where a regulatory intervention may trigger a larger positive (or negative) multiplicative effect. For example, requirements to increase transparency (going public, ESG rating, reporting, disclosures, etc.) facilitate the access to information, thereby enhancing media attention. This, in turn, positively impacts internal governance as firms improve their corporate governance systems, including transparency, to avoid reputational and other types of losses.

5.3. Limitations and future research

The proposed theoretical model has several limitations. First, for simplicity, the latent variable follows an Ornstein-Uhlenbeck process that is complemented with conditional jumps to the equilibrium. Consequently, the loss distribution does not exhibit the well-documented fait tail characteristics (Cornalba and Giudici, 2004; Eling and Wirfs, 2019). This shortcoming could be addressed by assuming more complex stochastic processes. For example, the instantaneous volatility could increase as a function of the distance from the equilibrium, especially beyond a certain threshold. The model can be further developed, for example, by including more latent variables and/or path-dependent adaptive learning, where the parameters evolve according to the loss history.

Regarding the empirical analysis, not all endogeneity issues might be fully mitigated. While fixed effects panel regression models, complemented with extensive robustness checks and heterogeneity analyses, effectively mitigate the potential omitted variable bias, measurement bias—especially in the independent variables—remains a more serious threat. Further research may investigate the effects of using alternative proxies for media attention and governance, the key variables of interest, and the inclusion of additional control variables.

6. Conclusions

We propose a new integrated model of corporate catastrophic risk based on a latent variable following a stochastic mean reversion process. The novelty of the model lies in combining two disciplinary mechanisms: self-regulation (internal governance) and media pressure (external governance). The model is able to reproduce important stylized facts on large public operational loss events.

First, if the media is freer and media attention is higher, more and larger losses come to light. Second, while internal governance has a strong effect on total losses, this is not necessarily reflected in public losses. Therefore, it is easy to erroneously conclude that investing in internal governance systems is not worthwhile. The simulation model provides an explanation for why it is not true and enables us to estimate the hidden losses as well.

We conclude that media attention has strong but opposite effects on total (-) and public (+) losses both in terms of frequency and severity. Therefore, the media has significant deterrence (decreasing total losses) and detection effects (increasing public losses) at the same time.

If a firm performs a cost-benefit analysis when determining the optimal level for the quality of its internal governance systems, then we can expect that corporate governance systems are more advanced in publicly traded firms operating in countries where the media is freer. In this case, media attention has an indirect effect on operational losses through making internal governance better, hence reducing total losses (both frequency and severity). Moreover, the media scandals contribute directly to improving the processes as well. Thus, promoting press freedom can be a highly effective policy in improving governance and risk management systems, hence corporate sustainability.

CRediT authorship contribution statement

Edina Berlinger: Conceptualization, Funding acquisition, Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing. **Judit Lilla Keresztúri:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – review & editing. **Ágnes Lublóy:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

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