J. Int. Financ. Markets Inst. Money 77 (2022) 101496

Contents lists available at ScienceDirect

Journal of International Financial Markets, Institutions & Money

journal homepage: www.elsevier.com/locate/intfin

Press freedom and operational losses: The monitoring role of the media

Edina Berlinger[a,*], Judit Lilla Keresztúri[a], Ágnes Lublóy[b], Zsuzsanna Vőneki Tamásné[c]

[a] Corvinus University of Budapest, Department of Finance, Fővám tér 8, Budapest 1093, Hungary
[b] Stockholm School of Economics in Riga, Department of Accounting and Finance, Strēlnieku iela 4a, Rīga 1010, Latvia
[c] OTP Bank Hungary, Operational Risk Management Department, Babér utca 9., Budapest 1131, Hungary

A R T I C L E I N F O

JEL codes:
G32
G38
D83

Keywords:
Corporate governance
Media
Press freedom
Operational losses
Frequency
Severity
Risk management
Reporting bias

A B S T R A C T

We investigate the monitoring role of the media, its detection and deterrence effects in corporate operational losses. Relying on our theoretical model, we analyze 8,144 loss events from 132 countries between 2008 and 2019. Controlling for factors related to governance, living standards, business cycles, and firm size, we find that press freedom has a significant positive effect both on the frequency and severity of the observed operational losses. An improvement of one standard deviation in press freedom yields around 43% more and 71% higher public losses. Our estimations on hidden losses indicate that the worldwide detection rate of operational losses might be smaller than 53% and 13% in terms of number and value, respectively. Furthermore, in countries with a tightly controlled media, hidden operational risks might be tremendous. We suggest using public databases more carefully, adjusting operational risk models for the reporting bias, and promoting press freedom to improve corporate governance structures.

1. Background and motivation

Journalists publish corporate news by obtaining information from companies' official websites designated for public relationship management, other public sources (press releases, databases, analysts, auditors, regulators, court actions), and their own investigations relying, in many cases, on the hints given by whistleblowers (employees or other insiders) (Dyck, Morse & Zingales, 2010; Miller, 2006). At the same time, companies may have strong incentives to hide unfavorable corporate events to prevent adverse market reactions (Cummins, Lewis, & Wei, 2006). For instance, the agrochemical company Monsanto Co. maintained a whole department similar to an intelligence center to control and mislead journalists and civil activists who investigated the company's weed-killer product Roundup (glyphosate) and its association with cancer (Levin, 2019). Similarly, WireCard, a German payment processor and financial services provider part of the DAX index, hired Rami El Obeidi, the former head of Libyan foreign intelligence, to conduct sting operations against journalists and public short sellers (Storbeck, 2020).

Investigative journalists are threatened not only by corporations but also by organized crime groups and governments. According to the worldwide barometer of Reporters Without Borders (RSF, 2020a), in 2020, 47 journalists and 4 media assistants were killed (the

* Corresponding author.
E-mail addresses: edina.berlinger@uni-corvinus.hu (E. Berlinger), lilla.kereszturi@uni-corvinus.hu (J. Lilla Keresztúri), agnes.lubloy@sseriga.edu (Á. Lublóy), tamasnevzs@otpbank.hu (Z. Vőneki Tamásné).

https://doi.org/10.1016/j.intfin.2021.101496
Received 23 May 2021; Accepted 21 December 2021
Available online 26 December 2021
1042-4431/

most in Mexico, Afghanistan, India, Iraq, Pakistan, Syria), while 384 journalists and 12 media assistants were imprisoned (the most in China, Egypt, Saudi Arabia, and Turkey). However, the media can be oppressed not only in the third world or in dictatorial regimes but also in developed democracies. In addition to physical atrocities against journalists, the oppression can manifest in legislations and market interventions as well, as witnessed in Hungary in the last decade (RSF, 2020b; Szeidl & Szucs, 2021).

In this paper, we investigate the role of the media in revealing and preventing operational loss events worldwide and show why not just rights defenders and civil activists but also investors, corporate risk managers, and financial regulators should be concerned about violations of press freedom.

Our paper can be linked to three lines of research. First, our research is related to the literature on *operational risk management*. Operational losses and their determinants were thoroughly investigated both at a firm level (Chernobai, Jorion, & Yu, 2011) and at a country level (Abdymomunov, Curti, & Mihov, 2020; Alifano et al., 2019; Cope et al., 2012; Curti & Mihov, 2018; Li & Moosa, 2015). The main contribution of this paper is the identification of the press freedom as a significant new explanatory variable and the quantification of the *reporting bias*. It has been recognized previously that not all loss events are detected, hence operational loss databases might be biased (Li & Moosa, 2015; Wei et al., 2018). For the first time in the literature, we trace reporting bias back to press freedom and estimate the size of the effect. We find that an improvement of one standard deviation in the press freedom results in at least 43% and 71% higher frequency and severity of public operational loss events, respectively. In the light of our findings, operation risk models should be adjusted for the reporting bias.

Second, applying a widely used methodology to assess the size of the *shadow economy* (Schneider & Enste, 2000; Schneider & Buehn, 2018), we are the first in the literature to estimate the frequency and the severity of *hidden operational losses* for each country. Hidden operational losses might vary greatly, similar to the size of the shadow economy which ranges from 8 to 68% (relative to GDP) (Schneider & Enste, 2018). According to our estimations, the detection rate of operational loss events ranges from 79% (in countries with a free press like Norway and Finland) to 18% (in countries with a tightly controlled press like China and Iran) in 2008–2019. We also document that while more than 85% of public losses belong to countries with high press freedom, they account only for less than 18% of hidden losses.

Third, our research is rooted in the vast body of literature on *corporate governance*, more specifically, on the monitoring role of the media. It has been recognized in the financial literature that the media plays an important role in corporate governance. On the one hand, journalists act as watchdogs (Miller, 2006) keeping an eye on firms' operation, revealing, processing, and broadcasting information that is relevant to their public (You, Zhang, & Zhang, 2018; Zingales, 2000). In this regard, the media acts as a passive monitor just like auditors, regulators, investment analysts, and rating agencies (Tirole, 2006). This *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 long-term reputation (You et al., 2018).

On the other hand, an intensive media coverage triggers active monitors (large shareholders, banks, and venture capitalists) to exercise their control rights and to intervene, for example, by enhancing the firm's operation, in extreme situations, by removing the incompetent management. Increased media attention can also provoke other stakeholders, such as consumers and employees, to put the firm under pressure, for example, by boycotting. Thus, indirectly, a well-functioning media functions as a deterrent improving managers' behavior and firms' value in the long run (Dyck, Volchkova, & Zingales, 2008; Dyck & Zingales, 2004; Wang & Li, 2019; You et al., 2018). Basically, this *deterrence effect* is realized through the career development channel of *managers*: their employment, compensation package, promotion, and reputation are threatened in the case of a negative media coverage (Dyck et al., 2008; Dyck et al., 2010; Dyck & Zingales, 2004; Jiang & Kim, 2020; Liu et al., 2017; Liu & McConnell, 2013; Vergne et al., 2018; Zingales, 2000; You et al., 2018).

In this research, we find evidence for both the detection and deterrence effect of the media, hence for the fundamental role of the free press in corporate governance. The detection effect is manifested in the reporting bias: in countries with freer media, significantly more and larger losses are reported. The deterrence effect is apparent in the distribution of hidden losses: in countries with freer media, the frequency and severity of total hidden operational losses are significantly lower.

We advance the previous literature on the monitoring role of the media by extending the single-country analysis on Russia (Dyck et al., 2008) and China (You et al., 2018) into a multi-country analysis. In particular, we perform a cross-country comparison (not just a country case study) focusing on a longer and more recent period (2008–2019). In addition, we characterize the media in several dimensions, such as the level of media independence, transparency, pluralism, self-censorship, and the number of abuses and acts of violence against journalists. To this end, we use the World Press Freedom (WPF) index as an explanatory variable. Previous literature only focused on some of its elements like newspaper diffusion (Dyck & Zingales, 2004), the extent of state control (You et al., 2018), or the role of the target audience of the media (Dyck et al., 2008). Finally, we also differ in the broadness of our sample as our output variable is the frequency or the severity of public operational losses in each country. Operational losses are a broad category comprising all corporate loss events derived from the operation (and not just frauds as underlined in Dyck et al., 2010), and we investigate all industries, both financial and non-financial. We use the most comprehensive public database of operational loss events: SAS OpRisk Global covering 132 countries and 8,144 large corporate loss events (above US$100,000) (SAS, 2020). As a result of the wider scope in terms of countries, media dimensions, and corporate loss events, this research can be considered as more general and thus its conclusions are more widely applicable.

The article is structured as follows. In the next section, we present the theoretical framework and develop our hypotheses. Afterwards, we introduce the variables used in the empirical analysis and describe our methodology. Then, we present and discuss the findings from the empirical investigations. The final section concludes by stressing the importance of press freedom in risk management and corporate governance.

2. Theoretical framework and hypotheses development

Operational risk is defined as "the risk of loss resulting from inadequate or failed internal processes, people, and systems, or from external events" (BCBS, 2017, p. 128). This definition includes legal risk but excludes strategic and reputational risk. Operational risk is the second most important source of risk for financial institutions measured by the size of the capital requirement set by the regulator (ECB, 2017).

In the financial sector, operational risk management was institutionalized and linked to good corporate governance by the Basel II regulations (BCBS, 2003; Hull, 2015). Concepts and methods have spilled over to other industries as well. Operational risks are more difficult to model, measure, or mitigate than credit risk or market risk. It is a necessary part of doing business and there is always a danger of realizing a huge operational loss emerging from a source that was not even recognized before (Hull, 2015).

2.1. Information asymmetry and operational losses

Corporate operational risk events are rooted in asymmetric information and can even increase the degree of information asymmetry (Barakat et al., 2014; Kölbel et al., 2017; Liu & McConnell, 2013). Information asymmetry can have two negative consequences: moral hazard (hidden action) and adverse selection (hidden characteristics). In this research, we focus on the first one; large operational losses can be viewed as manifestations of moral hazard and the corresponding corporate governance problems. Moral hazard arises when a principal entrusts an agent with a task but cannot fully observe the agent's effort, while the agent may gain private benefits during the implementation (insufficient efforts, self-dealing, etc.) (Tirole, 2006). Thus, the interests of a utility-maximizing agent may conflict with the interests of the principal. Moral hazard can be reduced by transparency, incentives, or monitoring; however, all these instruments are costly, so corporate governance is never perfect and operational risks are never fully controlled.

In a firm, principal-agent relationships, hence moral hazard, may appear in many forms. The most important relations are when (a) shareholders are the principals and the managers are the agents; (b) managers are the principals and employees are the agents; or (c) other stakeholders (lenders, consumers, civil society, state, regulators, environment, etc.) are the principals and shareholders are the agents. Operational losses are essentially the result of something not working properly in these relationships. Although there are random, exogenous shocks as well, the endogenous causes of damage can be traced back to these governance problems. Note that relations of types (a) and (b) correspond to *internal* information asymmetry (within the firm), while relations of type (c) to *external* information asymmetry (outside the firm). An active media coverage can reduce both types of asymmetries (Liu & McConnell, 2013).

The attitude of a player (shareholder, manager, employee, or other stakeholder) to an operational loss is far from being obvious. Shareholders, for example, have interest in revealing embezzlements and other misappropriations of assets committed by managers and employees; but may prefer to keep them confidential because of the reputational risks. In other cases, also shareholders are actively involved in the misconduct (e.g., tax evasion, market manipulation, bribery, pollution), so they are interested in neither the deterrence nor the detection of operational losses, especially if losses are realized by the company (in forms of supervisory fines, damages lawsuits, etc.) only if the misconduct becomes public.

In theory, principals are interested in uncovering operational problems, while agents are interested in hiding them. Real life situations, however, are more complicated. On the one hand, a particular player (shareholder or manager) can be both a principal and an agent at the same time in different relationships. On the other hand, even principals may prefer secrecy if other risks (credit, market, reputational, strategical) associated with operational losses are high (Kölbel, et al., 2017; Wei et al., 2017).

Depending on the situation, shareholders, managers, employees, and even outside stakeholders might have an interest in initiating, committing, or hiding operational misconducts; or just the opposite, they might have strong incentives to avoid, reveal or even whistle blow these cases to the media. When deciding which action to take, they perform a specific cost-benefit analysis considering their tangible (shareholder value, income, bonus, career development, etc.) and intangible (reputation, health, integrity, etc.) interests (Wei et al., 2017; Zingales, 2000).

2.2. The detection and the deterrence effects of the media

The media has two effects on operational losses: detection (revealing more losses) and deterrence (retaining players from corporate misconducts), notions borrowed from criminology. These effects can act through different channels. The two most important channels are (1) the career incentives for journalists to investigate events and report them (You et al., 2018; Zingales, 2000), and (2) the career incentives for managers to ensure prudent operation (Dyck et al., 2008; Dyck et al., 2010; Dyck & Zingales, 2004; Jiang & Kim, 2020; Liu et al., 2017; Vergne et al., 2018; Zingales, 2000; You et al., 2018). There are many prerequisites for these career development channels (both for journalists and managers) to function properly: the media should be *widespread*; it should be *independent* from both governments and corporations; *incentives* should be set properly; *institutions* should ensure the rule of law; and last but not least, the *audience* should be interested in corporate stories and despise abuses.

Empirical evidence shows that these prerequisites do not always hold resulting in weaker detection and deterrence effects. For example, in countries where newspapers are less *widespread*, larger investors have larger private benefits making small investors more vulnerable (Dyck & Zingales, 2004). At the same time, a direct or indirect state control undermines both the *independence* of the media and the performance-based *incentive systems* with serious implications on monitoring effectiveness. Analyzing news articles on non-financial firms traded on Chinese exchanges, You et al. (2018) found that the state-controlled media was less critical, less accurate, less comprehensive, and slower in response to corporate events than the market-oriented independent media. Moreover, the state-controlled media lagged far behind the market-oriented media in terms of price impact, information on fundamentals, and effects on CEO turnovers as well. The importance of solid *institutions* and the rule of law was demonstrated, for example, by Dyck et al. (2010) who found that in the United States, a developed market economy, the media was more successful in revealing corporate frauds than designated monitors (regulators, auditors, etc.). Finally, the importance of the *audience* was emphasized, for example, by Dyck et al. (2008) who showed that in Russia, the local media targeting powerless or unconcerned domestic readers had no deterrence effect on the managers, while Anglo-American newspapers targeting international investors were highly effective even in reverting abusive corporate decisions of Russian firms.

In this research, we investigate the extent to which the detection and deterrence effects of the media are present in each country.

2.3. Model of public and hidden information

We introduce a simple model of public and hidden information which provides a theoretical framework for the empirical analysis. Supposing an investor who plans to invest in a country, and thus intends to estimate the country-specific operational risk, we define the expected total operational risk (in percentage) TR as

$$TR = \frac{TL}{IC} \tag{1}$$

where TL is the expected total operational loss in dollars, and IC is the invested capital in dollars.

The total operational loss is the sum of the public operational loss (PL) and the hidden operational loss (HL):

$$TL = PL + HL \tag{2}$$

The detection rate, defined as the ratio of PL to TL, is an important measure showing the proportion of losses becoming public. Rearranging (1), the public operational loss (PL) is

$$PL = \frac{PL}{TL} \times TR \times IC \tag{3}$$

According to (3), the observable part of the operational losses is the product of three factors: the detection rate, the total operational risk, and size of the invested capital. Taking the natural logarithm of both sides of (3) yields an additive model:

$$lnPL = ln\frac{PL}{TL} + lnTR + lnIC \tag{4}$$

As public loss is the product of the observed frequency F (the number of public loss events in a given period) and severity S (the average loss size, i.e., the total amount of public loss in a given period divided by the number of public loss events), we get:

$$lnPL = lnF + lnS \tag{5}$$

Thus, using (4) for the total public loss and (5) for the additivity of log frequency and log severity, we can write two separate equations, one for log frequency and another one for log severity:

$$lnF = a_F + b_F ln\frac{PL}{TL} + c_F lnTR + d_F lnIC \tag{6}$$

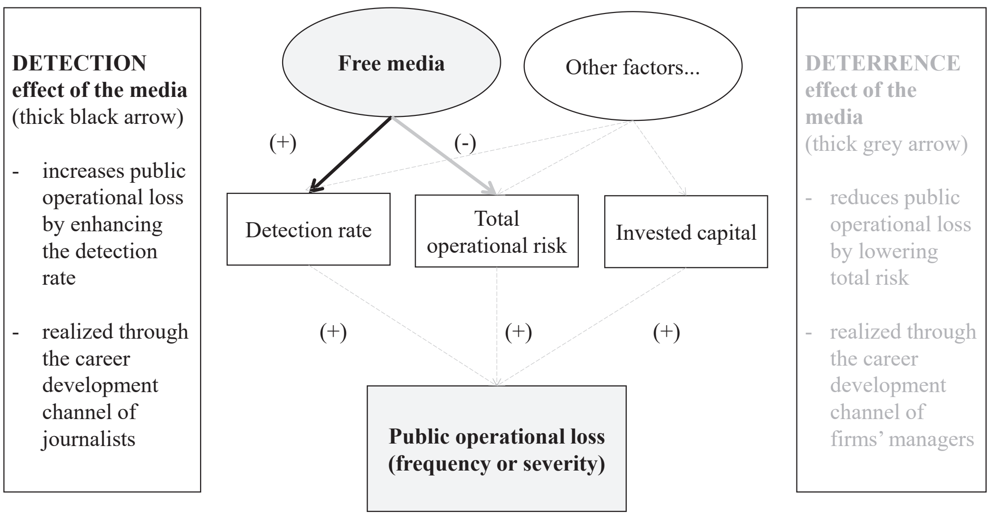

Fig. 1. Detection and deterrence effects of the media.

$$lnS = a_S + b_S ln\frac{PL}{TL} + c_S lnTR + d_S lnIC \tag{7}$$

where $a_F + a_S = 0$, $b_F + b_S = c_F + c_S = d_F + d_S = 1$.

Clearly, (6) and (7) imply (4). Equations (6) and (7) are worth investigating separately, similar to advanced risk models where frequency and severity are modelled separately.

Equations (6) and (7) provide a theoretical framework for modeling public operational loss events.

The *detection* effect of the media (revealing more losses) is reflected in the first terms in (6) and (7). In general, a more intensive media attention (realized through the career development channel of journalists) can lead to a higher detection rate (PL/TL), which in turn causes either *higher* frequency (F), or *higher* severity (S), or both. The *deterrence* effect of the media is manifested in the total risk TR components in (6) and (7). A more intensive media attention can lead to a lower level of total operational risk (revealed or hidden), which in turn causes either *lower* frequency (F), or *lower* severity (S), or both. Fig. 1 summarizes the key effects investigated in this research.

Fig. 1 presents that the media might influence the frequency and severity of public operational losses adversely. On the one hand, when journalists can write freely, they are expected to reveal more and larger operational loss events (detection effect). On the other hand, in countries with independent press publicizing facts and forming the public opinion, market players are expected to be more disciplined resulting in fewer and smaller loss events (deterrence effect).

In line with Fig. 1, we formulate two testable hypotheses:

H1: Press freedom has a *positive* effect both on the frequency and severity of *public* operational losses (detection effect).

H2: Press freedom has a *negative* effect both on the frequency and severity of *total* (public and hidden) operational losses (deterrence effect).

3. Data and method

3.1. Sample

Public operational loss data are retrieved from the SAS OpRisk Global database, the world's most comprehensive and accurate repository of external loss events (SAS, 2015; Wei et al., 2018). The database includes all publicly reported operational losses higher than US$100,000 across all industries worldwide, see some typical cases and country-level statistics in the Online Supplementary material Table S1 and Figure S1, respectively. Data are retrieved for the period of 2008–2019, covering 132 countries and 8,144 loss events. Countries are included in the sample if at least one operational loss event occurred in that country during the sample period. Assuming that a loss event is highly dependent on the local environment, losses are assigned to countries according to the place of the incident.

3.2. Variables

The *dependent variable* is either the frequency or the severity of operational losses. Frequency is the number of public operational loss events in a particular country in a given year, and severity is the average loss size. Both are expressed in natural logarithm in line with (6) and (7).

Independent variables, as suggested by (6) and (7), include variables to explain the detection rate, the total operational risk, and the size of the invested capital. Table 1 matches the variables from the theoretical model with the variables in the empirical analysis. For the empirical investigation, we first define the potential explanatory variables and then we infer them from other directly measurable indicators. Table 1 also shows the expected sign of the coefficients in the regression analysis, both for frequency and severity of losses, based on our theoretical model and/or previous literature.

First, a proxy for the *detection rate* (PL/TL), the key variable of interest in this research, is introduced: the PRESS variable derived

Table 1
Model variables and expected signs.

Model variables	Empirical analysis		Expected signs	
	Potential explanatory variables/determinants	Indicators	Frequency	Severity
Detection rate	press freedom	PRESS	+	+
Total risk	macro-level governance (development of institutions)	GOV	+	
	financial institutions information asymmetry	FIE index	–	–
	financial markets information asymmetry	FME index	–	–
	micro-level governance (internal information asymmetry)	internal fraud to total loss	+	+
	financial regulation (external information asymmetry)	finance loss to total loss	–	–
	living standards	GNI per capita	–	+
	business cycle (expansion versus recession)	GDP growth	–	–
Size	size of the economy, macro-level net income	GDP	+	+
	average size of companies with loss	total assets	+	+
	average size of companies with loss	net income	+	+
	average size of companies with loss	number of employees	+	+

from the *Word Press Freedom* (WPF) index.

$$ln\frac{PL}{TL} = \mathrm{f}(PRESS) \tag{8}$$

where f is a linear function.

The detection rate is expected to be higher in countries with higher freedom of speech, where individuals can articulate their opinions and ideas without fear of retaliation, censorship, or legal sanction. The *World Press Freedom* index, measuring the freedom of speech, is published annually by an international non-governmental organization, Reporters Without Borders (in French, Reporters Sans Frontières, RSF) for 180 countries (RSF, 2020b). The World Press Freedom index has been published since 2002, and it aggregates the most relevant qualitative and quantitative dimensions characterizing the conditions the media operates in: pluralism, media independence, environment and self-censorship, legislative framework, transparency, and infrastructure (RSF, 2020b). The scores for the qualitative dimensions are based on media professionals', lawyers', and sociologists' answers to an online questionnaire. Additionally, 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.

Total operational risk TR, the second component in (6) and (7) is the most difficult part to model. According to the literature, operational risk can be explained by a couple of variables (Table 1). These variables shall be considered as potential explanatory variables or determinants of operational risk.

$$lnTR = g\left(GOV,\ FIE\ index,\ FME\ index,\ internal\ loss,\ finance\ loss,\ ln\ GNI\ per\ capita,\ GDP\ growth\right) \tag{9}$$

where g is assumed to be a linear (increasing or decreasing) function in each variable. Variables in (9) are detailed in the following paragraphs.

Empirical evidence shows that good *governance* (GOV) has a strong negative effect on severity of operational loss events not only at a firm level (Chernobai, Jorion, & Yu, 2011), but also at a country level (Alifano et al., 2019; Cope et al., 2012; Curti & Mihov, 2018; Li & Moosa, 2015). As argued by Li and Moosa (2015), good governance reduces the number of low-frequency and high-severity (LFHS) loss events at the cost of increasing high-frequency and low-severity (HFLS) events. The quality of a country's governance can be measured by the Worldwide Governance Indicator which is retrieved from the database of the World Bank (World Bank, 2021a). The Worldwide Governance Indicator aggregates six dimensions of a country's governance: voice and accountability; political stability and absence of violence; government effectiveness; regulatory quality; rule of law; and control of corruption (Kaufmann, Kraay, & Mastruzzi, 2011).

Although the World Press Freedom index is a subcomponent of the Worldwide Governance Indicator and the correlation between the two is high ($\rho = 0.64$), we include both variables separately in the empirical model for several reasons. First, press freedom is only one of the several hundred components included in the Worldwide Governance Indicator and the correlation is not perfect. Second, the Worldwide Governance Indicator is an explanatory variable for the total operational risk (TR), while press freedom is a proxy for the detection rate (PL/TL). Third, these two variables affect the number of operational loss events adversely and thus their coefficients are expected to have opposite signs. In better governed countries with sound institutions, the deterrence effect of the media is expected to be stronger, hence, operational risk is lower. In contrast, in better governed countries with higher freedom in mass media reporting, it is reasonable to assume that journalists will reveal more and larger loss events (detection effect). Finally, their interactions can be examined only if press freedom and governance are introduced separately.

In addition to the quality of a country's governance, *information asymmetry* may also explain total operational risk. The higher the information asymmetry, the higher the probability and severity of operational loss events. In the empirical analysis, we define four variables for information asymmetry. The first two variables capturing a broader perspective of information asymmetry in the financial system include the Financial Institutions Efficiency (FIE) index and the Financial Markets Efficiency (FME) index. It is reasonable to assume that the more efficient financial institutions and financial markets are, the lower the level of information asymmetry. The Financial Institutions Efficiency (FIE) index complies data on the banking sector's net interest margin, lending-deposits spread, non-interest income to total income, and overhead costs to total assets, while the Financial Markets Efficiency (FME) index complies data on the stock market's turnover ratio (stock traded to capitalization) (Svirydzenka, 2016). Data are extracted from the IMF Financial Development Index Database (IMF, 2021). These broad indicators capture the two most widely used information asymmetry measures in the literature: bid-ask spread and trading volume (Leuz & Verrecchia, 2000; Yoon, Zo, & Ciganek, 2011). The third variable shows the ratio of losses resulting from internal fraud to total loss (*internal fraud to total loss*). Intuitively, among the Basel II event type categories, internal fraud is the most dependent on the *internal* information asymmetry and the quality of firm-level corporate governance. A high ratio in a given country signals severe deficiencies in firm-level corporate governance. In general, firms with weaker governance structures (e.g., lower board independence ratios, lower equity incentives of executive directors, and lower levels of institutional ownership) are associated with more internal fraud events, and thus exposed to higher risk (Barakat, Chernobai, & Wahrenburg, 2014). The fourth variable, the ratio of operational losses incurring at financial institutions to total losses (*finance loss to total loss*) considers the weight of the highly regulated and controlled financial sector (in terms of operational losses). If the ratio is high, then firms are tightly monitored due to the considerable weight of the financial sector in the economy. As a result of the tight monitoring, which is associated with higher transparency and appropriate incentives as well, the *external* information asymmetry shall be lower in all industries as sophisticated risk management practices might spill over from the financial sector to other sectors.

Economic, societal, and political factors might also be considered as determinants of total operational risk (Table 1). For example, the standard of living, measured by the per capita GNI (World Bank, 2021b) was identified as a country-specific explanatory variable of operational risk by Li and Moosa (2015). The authors showed that the higher the standard of living, the lower the frequency of losses due to higher concentration of low frequency-high severity events. At the same time, the higher the standard of living, the more severe the losses are due to the higher wealth. In addition to the standard of living, the phase of the business cycle (expansion versus recession), proxied by the GDP growth rate, might also be related to operational risk with more and larger loss events occurring during economic downturns (Abdymomunov, Curti, & Mihov, 2020).

Finally, the *size of the invested capital IC* in a country is proxied by the size of the economy expressed as its gross domestic product (GDP) in current USD (World Bank, 2021c) and other firm-level size variables.

$$lnIC = h(ln\ GDP,\ total\ assets,\ net\ income,\ number\ of\ employees) \tag{10}$$

where h is assumed to be a linear function in each variable.

The GDP can be considered as a macro-level income measure, it shows the total income generated by the production of economic goods and services in a country. In the empirical analysis, we also include three firm-level size measures. We control for the average size of the sample firms in each country measured by the total assets, net income, and number of employees given the moderate correlation (0.31–0.57) among the variables (Online Supplementary Material, Table S3). Based on our theoretical model, we expect that the frequency and severity of losses are positively associated with the size of the economy and the average size of the sample firms (Table 1).

3.3. Panel regression model

Introducing (8), (9), and (10) to (6) and relying on the Durbin–Wu–Hausman test, we specify the following (country and year) *fixed effects panel regression model* for the frequency of operational losses:

$$\begin{aligned} lnF_{i,t} = {} & \alpha_i + \beta PRESS_{i,t} + \gamma GOV_{i,t} + \delta FIE_{i,t} + \zeta FME_{i,t} + \zeta Internal\ fraud_{i,t} + \eta Finance\ loss_{i,t} + \theta \ln GNI_{i,t} + \kappa GDP\ growth_{i,t} + \lambda lnGDP_{i,t} \\ & + \mu Total\ assets_{i,t} + \nu Net\ income_{i,t} + \xi Employees_{i,t} + \sum_t \tau_t YEAR_t + \varepsilon_{i,t} \end{aligned} \tag{11}$$

where

- $F_{i,t}$ is the number of public operational loss events in country i in year t;
- α_i is the country-specific intercept;
- PRESS is the World Press Freedom index multiplied by minus one and scaled between 0 and 100 (a larger value means higher press freedom);
- GOV is the aggregate Worldwide Governance Indicator scaled between 0 and 100 (a larger value means better governance);
- FIE is the Financial Institutions Efficiency Index to characterize information asymmetry at financial institutions;
- FME the Financial Markets Efficiency Index to characterize information asymmetry in financial markets;
- Internal fraud is the ratio of internal fraud to total loss as documented in the SAS OpRisk Global database to characterize internal information asymmetry (within the firm);
- Finance loss is the ratio of the loss in the financial sector to the total loss as documented in the SAS OpRisk Global database to characterize external information asymmetry;
- GNI is the gross national income per capita;
- GDPgrowth is the GDP growth rate compared to the previous year;
- GDP is the gross domestic product in current USD;
- Total assets, Net income and Employees are the average size of the sample firms as reported in the SAS OpRisk Global;
- $YEAR_t$ is a binary variable for year t;
- ε_{it} is the error term.

The reason for multiplying the World Press Freedom index by minus one is that in this way the higher values of the PRESS variable are associated with a more favorable situation (similarly to the GOV variable). The variables PRESS and GOV were scaled between 0 and 100 by using the min–max normalization method. Year dummies are introduced to account for the general trend in the number of loss events over the sample period. Online Supplementary Material Table S2 shows the data source used for each variable.

To expand the understanding of the relationship between the variables PRESS and GOV, we first add them separately to the regressions. Afterwards, we include both variables together in the model. Finally, we add their interaction terms (GOV × PRESS) to the regression model as well. In the same specification, following an exploratory approach, we include all plausible interactions with the PRESS variable. Although we try all plausible interactions, we only keep the statistically significant and economically relevant ones in the end.

In the second round of the specifications, in line with (7), we run fixed effect panel regression models with the same independent variables as in (11) for loss severity (average loss size) as well.

In all specifications, we use the size of countries' GDP as weights in the analysis acknowledging that larger countries in which the number and size of the firms are larger are more important observations than smaller ones. Standard errors are adjusted for heteroscedasticity and country-level clustering.

To test the robustness of the findings, we run a set of alternative model specifications for both dependent variables (frequency and severity). *First,* due to the high frequency and severity of losses in the financial sector, panel regressions are run separately for the financial sector and for all other industries. *Second,* we exclude the US as an outlier from the analysis. In the US, 4,218 operational loss events occurred in the period of 2008–2019, which is 8.21 and 9.95 times higher than the number of loss events in India (ranked as top 2) and United Kingdom (ranked as top 3), respectively. *Third,* the panel data analysis is performed on a subsample of 51 countries with the largest GDP; these countries are responsible for 95% of the sample countries' GDP. *Fourth*, we run the regressions on countries with the highest number of operational loss events; the 41 countries in this subsample are responsible for 95% of the number of loss events. *Fifth,* the panel data analysis is performed on a subsample of countries with the largest operational losses; we include 48 countries responsible for 95% of the total loss.

Note that in our analysis, *endogeneity* is less of a concern when testing causality between the freedom of press and the number (or the severity) of public operational loss events. Basically, endogeneity can emerge from three sources: measurement errors in the variables, simultaneous causality, and omitted variables (Bascle, 2008). First, neither the dependent variables (frequency and severity of public operational losses) nor the key variables of interest (press freedom, governance) are supposed to be systemically biased due to *measurement errors.* These variables are computed from data provided by independent organizations specialized on information gathering and processing; hence, self-selection bias can be excluded. Second, neither loss frequency nor severity is supposed to have a backward effect on press freedom, so *simultaneous causality* can also be excluded in this context. Therefore, only *omitted variables* can be a source of endogeneity. Country and year fixed effects inherently control for several potentially omitted, unobserved country characteristics that are unchanged over time (regions, cultural differences, etc.) and time trends. Nevertheless, as a final robustness check, we address omitted variable bias by implementing a two-stage least squares (2SLS) model with instrumental variables (Bascle, 2008). We specify three instrumental variables: individuals using the internet (% of population), the index of democracy, and the age dependency ratio (% of working age population) (Economist Intelligence Unit, 2020; World Bank, 2021d; World Bank, 2021e). Logically, these variables are expected to correlate with the freedom of press (relevance), while they are expected to be independent of the control variables and thus can affect operational risk only through press freedom (exogeneity).

4. Results

4.1. Descriptive statistics

The final sample includes 132 countries and 8,144 loss events with a total loss of almost $490 billion adjusted for inflation. Online supplementary material Figure S1 shows the distribution of the number of loss events for the 132 countries during the sample period. The smallest loss amount in the sample is $0.1 million, while the largest is $23,449 million. The mean loss amount is $60.2 million. The most frequent operational loss events are caused by business processes (clients, products, and business practices) and frauds (internal and external). The highest amount of total losses is attributable to business processes and damages to physical assets. The financial sector is responsible for 38% of the total losses followed by the mining industry (24%), manufacturing (18%), and utilities (11%). The

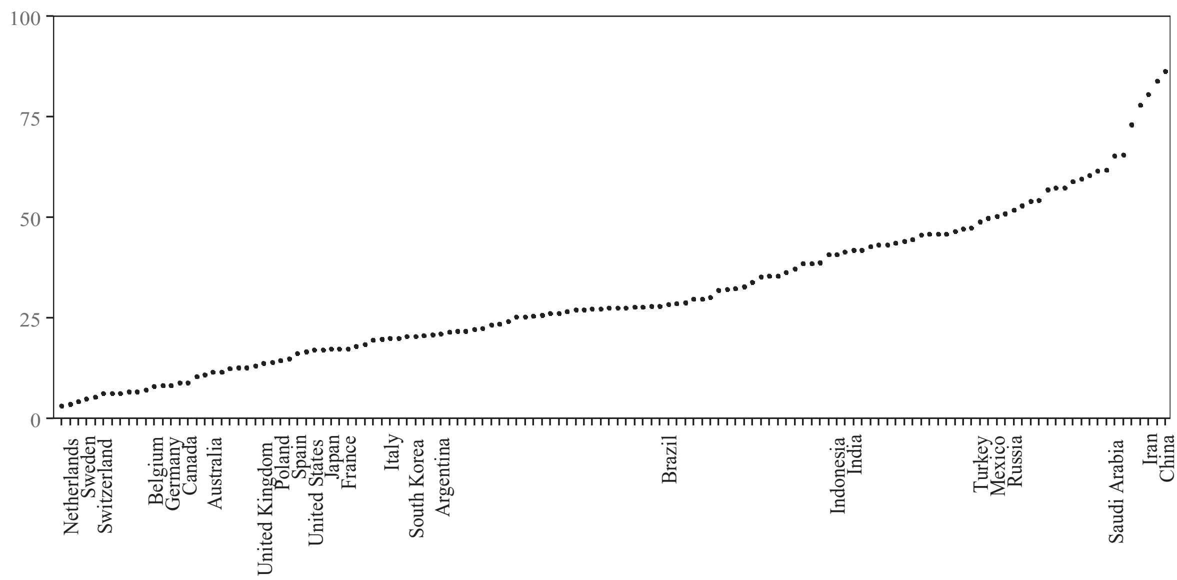

Fig. 2. World Press Freedom index, average values for 2008–2019. The points represent the average *World Press Freedom index* in the 132 sample countries. Norway has the lowest value (3.26), while China the highest (86.31). Larger values correspond to lower freedom of press. On the *x-axis* the names of the 25 countries with the largest GDP, averaged across the sample period, are shown. The *World Press Freedom index* varies in a wide range across the countries. Although larger economies are concentrated mostly at the lower end, some of them can be found at the upper end.

sample is dominated by loss events occurring in the United States; more than half of the loss events (50.77%) were recorded here. Countries with the highest number of operational loss events include the United States (4,135), India (497), the United Kingdom (424), Australia (218), Russia (215), Italy (180), China (160), Canada (150), France (135), and Brazil (117). The top 10 countries are responsible for 76.51% of the number of loss events. 95% of the loss events occur in only 41 countries, roughly one-third of the sample countries. 99% of the loss events were documented in 84 countries, roughly two-thirds of the sample countries.

The *freedom of the press* varies greatly across countries as well. Fig. 2 presents the distribution of the average World Press Freedom index for the 132 sample countries over the period 2008–2019. The figure indicates the top 25 countries with the largest GDP. Online supplementary material Figure S2 provides more detailed information on this distribution for 2019, the last year of the sample period.

Fig. 3 shows the evolution of the key variables over time. In the period of 2008–2019, there was a declining trend both in the number and the size of loss events as well as in the value of the freedom of the press (PRESS). Note that the lower values of the PRESS variable indicate a less favorable situation (tighter control of the media).

Figs. 4a and 4b show the cross-sectional relationship between two variables: the PRESS variable (*y* axis) and either the frequency or the severity of operational losses (both relative to the GDP) (*x* axis), respectively.

Fig. 4a demonstrates that a high number of public losses are reported only in those countries where the press is free, at least to some extent. For example, in the United States, far more loss events are recorded than in China though their GDPs are comparable. However, above a certain threshold, higher freedom of press is not always associated with a higher number of losses. For example, in Germany, operational risks events are less frequent (relative to the GDP) than in the United States. Note that small countries (e.g., Bissau Guinea) might be outliers due to the uneven distribution of the loss events (small sample bias). Fig. 4b shows that loss severity is also positively associated with press freedom, however, this relationship is not driven by the US-China dichotomy, and the interaction with the GDP is less clear.

Online supplementary material Table S2 summarizes the most important descriptive statistics of the dependent and independent variables. We can see a great variation in the explanatory variables, which makes estimations more reliable.

4.2. Regression results

In all specifications, we run panel data regressions with country and year fixed effects. Throughout the analysis, we use countries' GDP as weights; we assign larger weights to larger countries as leading world economies, such as the US, China, and Germany can be considered more important observations than smaller countries, such as Bissau Guinea (see the highlighted observations in Fig. 4a).

Table 2 shows the results from the regression analyses for the total sample (132 countries, 8,144 loss events); we use the loss frequency as a dependent variable. To fully understand the impact of press freedom (PRESS) and the quality of governance (GOV) on the frequency of losses, we run four specifications. As argued previously, although the PRESS and GOV variables correlate, they may affect the number of operational loss events adversely. In *Model 1*, the press freedom (PRESS) is included, while the quality of governance (GOV) is excluded. In *Model 2* we exclude the PRESS variable, but we include the GOV variable. In *Model 3*, both variables are included. In *Model 4*, we add interactions (PRESS × lnGDP) and (PRESS × GOV) as well.

As shown in Table 2, in the model with the PRESS variable only (*Model 1*), the coefficient of the press freedom (PRESS) is positive and statistically significant. The higher the freedom of the press, the more risk events are published by the journalists. The coefficient

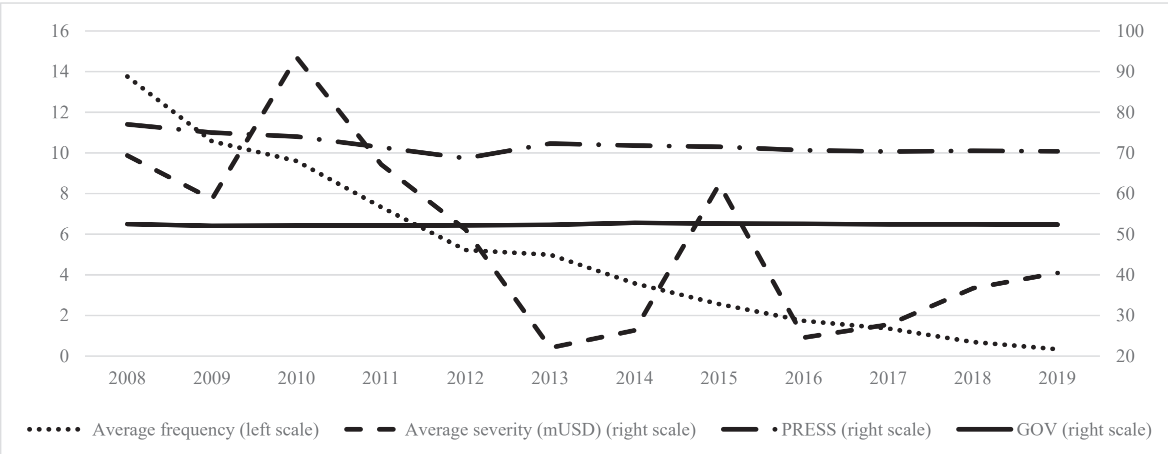

Fig. 3. Frequency and severity of losses, freedom of press, and quality of governance 2008–2019, average values. Variables are averaged across the sample countries for each year. *Frequency*: average values of the frequency of loss events (left-hand scale). *Severity*: average values of the severity of loss events in million US dollar (right-hand scale). *PRESS:* average values of the PRESS variable (right-hand scale). The PRESS variable is the transformation of the World Press Freedom index (scaled between 0 and 100 so that larger values indicate higher freedom). *GOV*: average values of the GOV variable (right-hand scale) which is the transformation of the aggregate Worldwide Governance Indicator (scaled between 0 and 100 so that larger values indicate better governance).

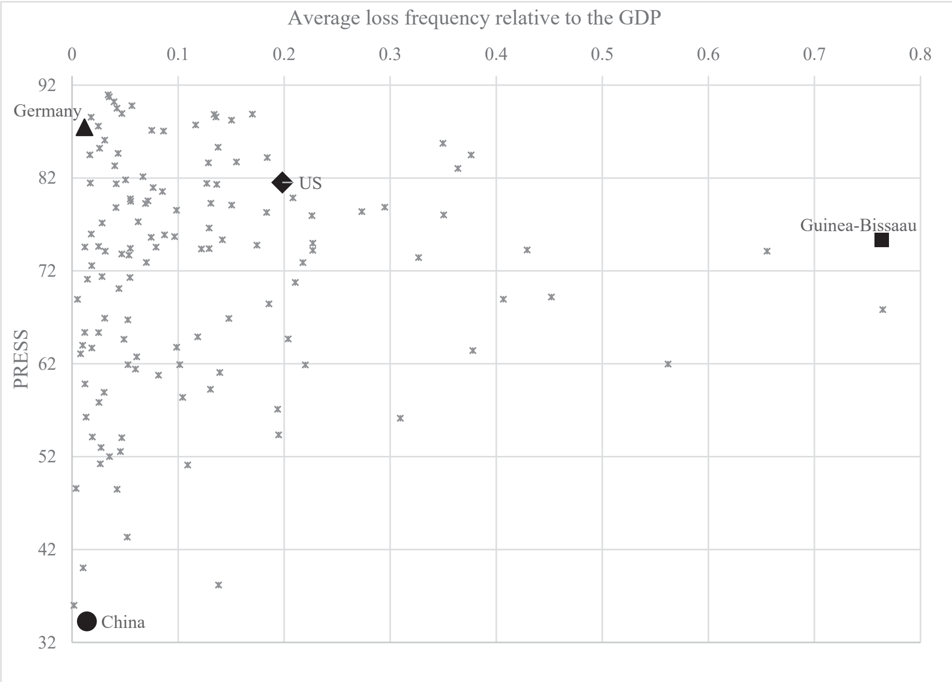

Fig. 4a. Frequency-to-GDP versus press freedom. The *x-axis* shows the loss frequency relative to GDP for each country; both the loss frequency and the GDP are averaged for each country across the sample period (2008–2019). The *y-axis* shows the average PRESS variable for each country in 2008–2019.

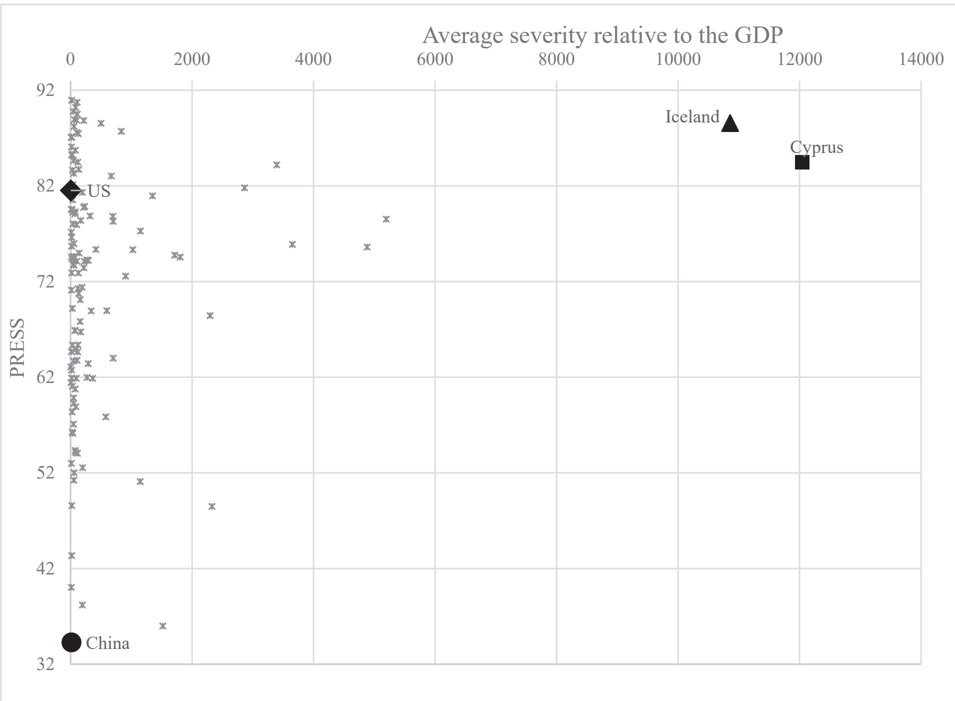

Fig. 4b. Severity-to-GDP versus press freedom. The *x-axis* shows the loss severity relative to GDP for each country; both the loss severity and the GDP are averaged for each country across the sample period (2008–2019). The *y-axis* shows the average PRESS variable for each country for 2008–2019.

shows that if the PRESS variable is higher by one point, then the observed loss frequency is higher by exp(0.026)-1 = 2.63%. In *Model 1*, the financial institutions efficiency (FIE), the living standards (GNI per capita), and the GDP growth are significant with negative signs, the size of the economy (GDP) with a positive sign, while year dummies (not shown) are insignificant with negative sign reflecting the global tendency of decreasing loss frequencies during the sample period.

When including the quality of governance (GOV) instead of the freedom of press (PRESS) in the regressions (*Model 2*), we document an insignificant coefficient for GOV. Thus, in spite of the positive correlation among these two variables, they cannot be used interchangeably. When both variables are included in the analysis (*Model 3*), the coefficient of press freedom (PRESS) is significant with a *p*-value of 0.000, while the coefficient of the GOV is still insignificant. All in all, the coefficient of the PRESS variable is always significant, while the coefficient of the GOV variable is never significant, irrespective of the specification.

When adding interaction terms to the regressions (*Model 4*), we document a positive coefficient for both PRESS × GOV and PRESS × lnGDP, but only the second one is significant in statistical terms (p-values are 0.221 and 0.000, respectively). Thus, PRESS has a larger positive effect on the frequency of losses in larger countries, but the interaction between press freedom and country-level governance is not clear. Note that in the specification with interactions, the coefficients of the PRESS, GOV, and lnGDP variables cannot be interpreted in themselves.

To test the reliability of the findings reported in Table 2, we run a series of robustness checks. In each robustness check, both PRESS and GOV are included. First, we split the 8,144 operational loss events into two subsamples: loss events occurring in financial sector (*Model 5*) and loss events in the nonfinancial sector (*Model 6*). The former specification includes 4,973 loss events, while the latter 3,171 events. Afterwards, we exclude the United States as an outlier from the analysis *(Model 7)*; run the regression on the subsample of the 51 countries with the largest GDP *(Model 8)*, on the subsample of 41 countries with the highest number of operational losses *(Model 9)*, and on the subsample of only 23 countries with the highest amount of total losses *(Model 10)*. Finally, we address the omitted variable problem and implement a 2SLS model with instrumental variables *(Model 11)*.

As shown in Table 3, the coefficient of press freedom (PRESS) is positive and significant in all these robustness checks (*Models 5–11*). The higher the freedom of press, the more risk events are published by the journalists. The freedom of the media affects the number of loss events revealed by journalist both in the financial and non-financial sector (*Models 5–6)*. *Models 8–10* show that the PRESS coefficient is stable to the removal of a significant proportion of the sample countries; in *Model 10* less than one fifth (17.42%) of the 132 sample countries were included. In the 2SLS specification *(Model 11)*, the coefficient of the PRESS variable is much higher than in the basic model (*Model 3*) and in other robustness checks.

Table 4 presents the results from the regression analysis for the dependent variable of severity S (average loss amount). Severity shall be interpreted as a conditional value: the average loss amount when there is a loss event.

In the regression analyses with the PRESS variable but without interactions (*Models 12 and 14*), the coefficient of the press freedom (PRESS) is positive and statistically significant. The coefficient shows that if the PRESS variable increases by one point, then the observed severity of losses increases by exp(0.039)-1 = 3.98%. As in the case of frequency, PRESS is significant for severity, while GOV

Table 2
Regression results on loss frequency F for the full sample (132 countries, 8,144 loss events).

		Model 1		Model 2		Model 3		Model 4	
		β	p-value	β	p-value	β	p-value	β	p-value
Detection rate	**PRESS**	0.027	0.000 ***			0.026	0.000 ***	−0.161	0.000 ***
Total risk	**GOV**			0.031	0.228	0.022	0.337	0.013	0.646
	FIE	−0.031	0.003 **	−0.035	0.002 **	−0.031	0.002 **	−0.025	0.003 **
	FME	−0.003	0.278	−0.003	0.287	−0.003	0.352	0.000	0.963
	Internal fraud to total loss	−0.078	0.469	−0.147	0.174	−0.077	0.485	−0.027	0.819
	Finance loss to total loss	0.104	0.523	0.097	0.493	0.105	0.497	0.110	0.506
	ln GNI per capita	−1.674	0.002 **	−1.673	0.026 *	−1.899	0.009 **	−1.764	0.015 *
	GDP growth	−0.036	0.021 *	−0.044	0.015 *	−0.038	0.022 *	−0.038	0.021 *
Size	**ln GDP**	1.629	0.000 ***	1.787	0.001 **	1.732	0.000 ***	0.793	0.083
	Total asset	0.000	0.899	0.000	0.852	0.000	0.893	0.000	0.716
	Net income	0.000	0.153	0.000	0.347	0.000	0.151	0.000	0.109
	Employees	0.000	0.715	0.000	0.401	0.000	0.608	0.000	0.191
Interactions	**PRESS × GOV**							0.000	0.221
	PRESS × ln GDP							0.012	0.000 ***
constant		−3.552	0.275	−5.624	0.105	−4.409	0.117	7.858	0.014 *
	R-sq within	0.707		0.690		0.709		0.720	
	R-sq between	0.323		0.478		0.407		0.453	
	R-sq overall	0.275		0.379		0.332		0.363	
	n	1584		1584		1584		1584	

* p < 0.05; ** p < 0.01; *** p < 0.001
Model 1: Full sample, PRESS included, GOV excluded
Model 2: Full sample, PRESS excluded, GOV included
Model 3: Full sample, with PRESS and GOV
Model 4: Full sample, with PRESS, GOV, and interactions.

Table 3
Robustness checks on loss frequency F.

		Model 5		Model 6		Model 7		Model 8		Model 9		Model 10		Model 11	
		β	p-value	β	p-value	β	p-value	β	p-value	β	p-value	β	p-value	β	p-value
Detection rate	**PRESS**	0.026	0.000 ***	0.023	0.000 ***	0.019	0.000 ***	0.026	0.000 ***	0.024	0.000 ***	0.027	0.000 ***	0.230	0.000 ***
Total risk	**GOV**	0.021	0.442	0.030	0.286	−0.015	0.297	0.028	0.271	0.049	0.068	0.056	0.076	−0.084	0.304
	FIE	−0.033	0.006 **	−0.034	0.003 **	−0.006	0.346	−0.031	0.001 **	−0.030	0.000 ***	−0.028	0.001 **	0.023	0.285
	FME	−0.002	0.691	−0.007	0.066	0.001	0.699	−0.003	0.323	−0.001	0.851	0.002	0.616	−0.003	0.791
	Internal fraud to total loss	0.032	0.784	−0.156	0.305	0.019	0.798	−0.068	0.560	−0.074	0.559	−0.089	0.551	0.967	0.142
	Finance loss to total loss	0.488	0.008 **	−0.696	0.000 ***	0.235	0.051	0.119	0.452	0.154	0.357	0.190	0.313	−0.010	0.978
	ln GNI per capita	−1.223	0.094	−2.128	0.006 **	−1.375	0.006 **	−2.011	0.024 *	−1.914	0.063	−2.307	0.064	−3.315	0.258
	GDP growth	−0.037	0.041 *	−0.028	0.072	−0.025	0.041 *	−0.056	0.010 *	−0.057	0.038 *	−0.080	0.036 *	0.027	0.272
Size	**ln GDP**	1.087	0.011 *	1.312	0.010 *	1.783	0.000 ***	1.744	0.002 **	1.624	0.017 *	1.898	0.024 *	1.911	0.359
	Total asset	0.000	0.093	0.000	0.447	0.000	0.438	0.000	0.948	0.000	0.883	0.000	0.779	0.000	0.356
	Net income	0.000	0.208	0.000	0.075	0.000	0.342	0.000	0.100	0.000	0.198	0.000	0.177	0.000	0.215
	Employees	0.000	0.001 **	0.000	0.806	0.000	0.739	0.000	0.513	0.000	0.315	0.000	0.589	0.000	0.643
constant		−2.331	0.480	3.867	0.259	−9.422	0.001	−3.858	0.195	−4.661	0.100	−6.110	0.062		
	R-sq within	0.668		0.761		0.597		0.733		0.763		0.785			
	R-sq between	0.415		0.097		0.423		0.424		0.465		0.499			
	R-sq overall	0.341		0.126		0.319		0.391		0.428		0.435			
	n	1332		1260		1572		612		492		276		1584	

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Model 5: Subsample of operational loss events in the financial sector (n = 4,973 loss events).

Model 6: Subsample of operational loss events for all industries excluding the financial sector (n = 3,171 loss events).

Model 7: The US is excluded from the analysis (outlier).

Model 8: Subsample of countries with the largest GDP (51 countries, 95% of total GDP).

Model 9: Subsample of countries with the highest number of operational losses (41 countries, 95% of the total number of operational loss events).

Model 10 Subsample of countries with the highest amount of total losses (23 countries, 95% of the total loss).

Model 11: Full sample, with PRESS and GOV (2SLS). Statistical test results on instrument relevance and exogeneity: number of instruments: 3; first-stage F-statistics (p value in parentheses): 3.92 (p = 0.0102); Hansen J-test (Chi-sq. p-value in parentheses): 2.780 (0.2491); difference-in-Sargan statistics: each instrument is exogenous; Moreira's conditional likelihood ratio test (p-value in parentheses): [-0.0052539 –0.0112807] (0.04658).

Table 4
Regression results on loss severity S for the full sample (132 countries, 8,144 loss events).

		Model 12		Model 13		Model 14		Model 15	
		β	p-value	β	p-value	β	p-value		p-value
Detection rate	**PRESS**	0.039	0.018 *			0.039	0.02 *	−0.132	0.197
Total risk	**GOV**			0.027	0.540	0.018	0.731	0.140	0.031 *
	FIE	0.029	0.06	0.024	0.104	0.030	0.062	0.027	0.082
	FME	−0.001	0.923	−0.001	0.869	0.000	0.960	−0.001	0.923
	Internal fraud to total loss	−0.498	0.102	−0.617	0.103	−0.497	0.100	−0.359	0.231
	Finance loss to total loss	−0.601	0.112	−0.599	0.089	−0.601	0.110	−0.580	0.115
	ln GNI per capita	1.607	0.417	2.058	0.197	1.429	0.444	1.714	0.304
	GDP growth	−0.072	0.036 *	−0.081	0.014 *	−0.074	0.034 *	−0.095	0.004 **
Size	**ln GDP**	−2.093	0.237	−2.109	0.154	−2.018	0.218	−2.957	0.027 *
	Total asset	0.000	0.155	0.000	0.032 *	0.000	0.154	0.000	0.392
	Net income	0.000	0.982	0.000	0.618	0.000	0.992	0.000	0.689
	Employees	0.000	0.259	0.000	0.186	0.000	0.257	0.000	0.154
Interactions	**PRESS × GOV**							−0.002	0.010 *
	PRESS × ln GDP							0.018	0.001 **
constant		15.832	0.245	13.204	0.213	15.116	0.224	22.757	0.025 *
	R-sq within	0.290		0.000		0.290		0.320	
	R-sq between	0.100		0.268		0.084		0.128	
	R-sq overall	0.040		0.043		0.032		0.036	
	n	637		637		637		637	

* p < 0.05; ** p < 0.01; *** p < 0.001
Model 12: Full sample, PRESS included, GOV excluded
Model 13: Full sample, PRESS excluded, GOV included
Model 14: Full sample, with PRESS and GOV
Model 15: Full sample, with PRESS, GOV, and interactions

has no effect on severity in any specifications, including the one without PRESS (*Model 13*).

When adding interaction terms to the regressions (*Model 14*), we document significant coefficients for both interactions. The interaction term PRESS × GOV is significant with a negative sign, while the interaction term PRESS × lnGDP is significant with a positive sign. Thus, PRESS has a larger positive effect on the severity of losses if the quality of governance is lower and the GDP is higher.

To test the reliability of the findings on severity, we run a series of robustness checks, see Table 5. In particular, we run the regression on the subsample of the financial sector (*Model 16*); on the subsample of the nonfinancial sector (*Model 17*); we exclude the United States as an outlier (*Model 18*); run the regression on the subsample of countries with the largest GDP (*Model 19*), the highest number of operational losses (*Model 20*), and the highest amount of total losses (*Model 21*). The estimation results from the 2SLS regression using instrumental variables are shown in the last two columns of Table 5 (*Model 22)*.

As shown in Table 5, the press freedom is significant in all but one specifications the coefficient is insignificant when losses in the financial sector are examined (*Model 16*). In the 2SLS estimation the coefficient of the PRESS variable is much higher than in the other models. In addition to the press freedom, only some year dummies (not shown) are consistently significant across all the specifications (*Models 16–22*).

5. Discussion

The coefficients of the press freedom variable are significant with positive signs for both the frequency and severity of public losses, so we can accept hypothesis H1. In addition to press freedom, only a few other explanatory variables proved to be significant with the same signs as the theoretical model suggested: financial institutions efficiency (-), living standards (-), GDP growth (-), and GDP (+) for frequency; and GDP growth (-) for severity. In the following, we discuss our key findings in relation to the literature.

5.1. The detection effect of the media

Table 6 summarizes the most important findings of this research: the effects of press freedom on operational losses.

For the basic model of *loss frequency*, for the full sample (*Model 3*), the estimated PRESS coefficient is 0.026. Across all specifications, the estimated PRESS coefficients are between 0.019 and 0.027 (Table 6). Therefore, a one-point increase in the PRESS variable *ceteris paribus* improves the detection rate of the loss events by 1.92%–2.74%. For the full sample, we can estimate that one standard deviation (13.83 points) improvement in the press freedom results in exp(0.06*13.83)-1 = 43.27% more losses revealed. The effect of press freedom is thus both statistically significant and economically relevant.

For *severity*, the estimated PRESS coefficient is 0.039 in the total sample (*Model 13*). Across all specifications, the estimated PRESS coefficients are between 0.036 and 0.060 (Table 5). Therefore, a one-point increase in the PRESS variable *ceteris paribus* improves the observed severity of the loss events by 3.67%-6.18%. For the full sample, we can estimate that one standard deviation (13.83 points) improvement in the press freedom results in exp(0.039*13.83)-1 = 71.49% more severe losses revealed. Thus, the effect of press

Table 5
Robustness checks on loss severity S.

		Model 16		Model 17		Model 18		Model 19		Model 20		Model 21		Model 22	
		β	p-value		p-value	β	p-value	β	p-value	β	p-value	β	p-value	β	p-value
Detection rate	**PRESS**	0.036	0.133	0.060	0.000 ***	0.043	0.013 *	0.040	0.018 *	0.040	0.022 *	0.047	0.004 **	0.126	0.033 *
Total risk	**GOV**	0.022	0.762	−0.071	0.121	0.028	0.634	0.021	0.713	0.013	0.825	0.011	0.873	−0.055	0.616
	FIE	0.030	0.093	0.053	0.000 ***	0.031	0.204	0.032	0.062	0.031	0.067	0.041	0.033 *	0.045	0.045 *
	FME	−0.004	0.725	−0.010	0.228	−0.004	0.548	0.000	0.961	−0.004	0.566	0.004	0.643	0.003	0.814
	Internal fraud to total loss	−0.587	0.118	−1.060	0.005 **	−0.586	0.055	−0.526	0.094	−0.540	0.098	−0.650	0.091	1.037	0.008 **
	Finance loss to total loss	2.137	0.000 ***	−2.626	0.000 ***	−0.282	0.427	−0.615	0.115	−0.582	0.143	−0.688	0.131	−1.058	0.013 *
	ln GNI per capita	−2.556	0.281	0.085	0.965	1.794	0.354	1.527	0.426	1.242	0.524	1.646	0.425	−1.558	0.568
	GDP growth	−0.048	0.344	−0.108	0.028 *	−0.076	0.036 *	−0.079	0.045 *	−0.105	0.008 **	−0.118	0.022 *	−0.006	0.907
Size	**ln GDP**	0.482	0.791	0.370	0.837	−2.672	0.148	−2.207	0.191	−1.886	0.273	−2.609	0.153	−0.917	0.637
	Total asset	0.000	0.019 *	0.000	0.232	0.000	0.151	0.000	0.178	0.000	0.039 *	0.000	0.255	0.000	0.983
	Net income	0.000	0.054	0.000	0.787	0.000	0.998	0.000	0.906	0.000	0.392	0.000	0.471	0.000	0.228
	Employees	0.000	0.009 **	0.000	0.043 *	0.000	0.295	0.000	0.249	0.000	0.216	0.000	0.141	0.000	0.275
constant		16.074	0.318	−2.254	0.855	19.652	0.113	16.769	0.198	15.947	0.225	21.800	0.114		
	R-sq within	0.466		0.544		0.315		0.301		0.315		0.350			
	R-sq between	0.185		0.014		0.095		0.118		0.210		0.121			
	R-sq overall	0.011		0.077		0.039		0.013		0.017		0.000			
	n	495		398		625		408		388		233		637	

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Model 16: Subsample of operational loss events in the financial sector (n = 4,973 loss events).

Model 17: Subsample of operational loss events for all industries excluding the financial sector (n = 3,171 loss events).

Model 18: The US is excluded from the analysis (outlier).

Model 19: Subsample of countries with the largest GDP (51 countries, 95% of total GDP).

Model 20: Subsample of countries with the highest number of operational losses (41 countries, 95% of the total number of operational loss events).

Model 21: Subsample of countries with the highest amount of total losses (23 countries, 95% of the total loss)

Model 22: Full sample, with PRESS, GOV (2SLS). Statistical test results on instrument relevance and exogeneity: number of instruments: 3; first-stage F-statistics (p value in parentheses): 4.94 (p = 0.0031); Hansen J-test (Chi-sq. p-value in parentheses): 1.533 (0.4645); difference-in-Sargan statistics: each instrument is exogenous; Moreira's conditional likelihood ratio test (p-value in parentheses): [-96.31–−52.368] (0.05722).

Table 6
Summary of PRESS coefficients.

Specification	Output variable	Description	Explanatory variable of interest	Coefficient	Confidence interval −95%
Model 1	Frequency	Full sample, with PRESS	PRESS	0.027 ***	0.017–0.037
Model 2	Frequency	Full sample, with GOV			
Model 3	Frequency	Full sample, with PRESS and GOV	PRESS	0.026 ***	0.017–0.035
Model 4	Frequency	Full sample, with interactions	PRESS x GOV	0.000	0.000–0.001
			PRESS x ln GDP	0.012 ***	0.008–0.016
Model 5	Frequency	Finance sector.	PRESS	0.026 ***	0.016–0.037
Model 6	Frequency	Non-finance sector.	PRESS	0.023 ***	0.000–0.000
Model 7	Frequency	The US is excluded.	PRESS	0.019 ***	0.010–0.029
Model 8	Frequency	Countries with the largest GDP (95%).	PRESS	0.026 ***	0.016–0.036
Model 9	Frequency	Countries with the highest number of losses (95%).	PRESS	0.024 ***	0.014–0.035
Model 10	Frequency	Countries with the largest total losses (95%).	PRESS	0.027 ***	0.017–0.038
Model 11	Frequency	Full sample, 2SLS	PRESS	0.23 ***	0.105–0.355
Model 12	Severity	Full sample, with PRESS	PRESS	0.039 *	0.007–0.071
Model 13	Severity	Full sample, with GOV			
Model 14	Severity	Full sample, with PRESS and GOV	PRESS	0.039 *	0.006–0.071
Model 15	Severity	Full sample, with interactions	PRESS x ln GDP	−0.002 *	− 0.004-(-0.001)
			PRESS x GOV	0.018 **	0.007–0.029
Model 16	Severity	Finance sector.	PRESS	0.036	−0.011–0.084
Model 17	Severity	Non-finance sector.	PRESS	0.060 ***	0.034–0.086
Model 18	Severity	The US is excluded.	PRESS	0.043 *	0.009–0.078
Model 19	Severity	Countries with the largest GDP (95%).	PRESS	0.040 *	0.007–0.072
Model 20	Severity	Countries with the highest number of losses (95%).	PRESS	0.040 *	0.006–0.074
Model 21	Severity	Countries with the largest total losses (95%).	PRESS	0.047 **	0.017–0.077
Model 22	Severity	Full sample, 2SLS	PRESS	0.126 *	0.010–0.243

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

freedom is both statistically significant and economically relevant for severity as well.

Overall, we find that in countries with tightly controlled media, the number and severity of publicly reported operational loss events are significantly lower than in countries with free media. This finding is robust across various model specifications. The coefficient of the PRESS variable is significant both with and without the GOV variable for both the frequency and severity of operational losses (Table 2, Table 4). The coefficient is also significant for various subsamples (Table 3, Table 5). Investments in a country with tight media control, however, do not carry less risk. Instead, journalists reveal and report less misconduct due to intense censorship, tight editorial control, and the harassment of journalists, which by weakening managerial incentives might even increase total operational risk and uncertainties.

According to You et al. (2018), the effectiveness of free media in monitoring operational risk events is realized through the operating efficiency and independency of the news agencies. As a result, in countries with free media, journalists are expected to reveal more operational loss events. Our results are consistent with a strong *detection* effect of the media (more press freedom leading to more and larger public losses). The coefficients of press freedom are significant and positive in all specifications for the frequency, and in all but one specifications for the severity of losses, so results are robust.

As far as *omitted variables* are concerned, the instrumental variable models based on the two-step least squares method (*Models 11 and 22*) give much higher (positive) PRESS coefficients. These results indicate that omitted variables have opposite effects on press freedom and operational risks. Variables that make a country a better place to live (culture, efficiency, risk management systems, education level, risk awareness, public safety, etc.) typically increase press freedom and decrease operational risks at the same time. Consequently, PRESS coefficients estimated in the basic models are biased downward (can be considered as lower bounds). Hence, in reality the detection effect of the media can be even larger than suggested in this research.

There are a few plausible explanations why free media affects positively not only the frequency, but also the severity of loss events revealed by journalist. First, journalists prefer publishing articles that are interesting to a wide audience, resulting in higher subscription revenues and a larger reader base associated with higher advertising revenues (Strömberg, 2004; Baron, 2006, You et al., 2018). In addition, the press will attempt to increase future readership by publishing sensations and stories readers find remarkable (Mullainathan & Shleifer, 2005; Baron, 2006). As a result, the more severe a loss event is, the more eager journalists are to publish it—high operational losses can definitely be considered as sensations. The eagerness of journalists can be linked to their career development opportunities; direct financial incentives (e.g., performance-based compensation and promotion) motivates them to produce high-impact news (You et al. 2018). Second, it might well be the case that in developed economies with free media, the law provides a higher level of protection to their citizens which in turn is associated with more and larger compensatory damages for the citizens, and thus, larger losses for the companies. Compensatory damages are typically awarded in civil court cases where loss has occurred as a result of the negligence or unlawful conduct of another party. For example, in our sample, the penalty for the largest operational loss event in the mining industry in the US was 109 times higher than in China (20,800 versus 191 US$M), while the magnitudes of the environmental degradation were comparable (both were oil spilling into the sea), see supplementary Table S1. Last but not least, in countries with tightly controlled media operational loss amounts can be significantly underestimated given the intense censorship, tight editorial control, harassment, and absence of direct financial incentives (You et al., 2018). As a result, in countries with tightly controlled media, the actual size of the loss events might be considerably higher than the registered value in the SAS OpRisk Global database. Presumably, the underestimation of the losses is less feasible in a highly regulated environment—a potential explanation as to why the PRESS coefficient is insignificant on the financial subsample (*Model 15*).

5.2. The deterrence effect of the media

To illustrate the size effect of the press freedom in a more intuitive way, we estimate for each country the number of additional loss events that could be detected if the media were as free as in Norway (the country with the highest PRESS value which is 100) keeping all observed controls unchanged. Hence, the formula for the estimation of the number of hidden losses for country i for the sample period of 2008–2019 is

$$HL_i \geq PL_i \times \left(e^{0.026(100-PRESS_i)} - 1\right) \quad (12)$$

The estimation method of hidden losses is similar to the currency demand approach widely used for the assessment of the shadow economies (Tanzi, 1983, Schneider & Enste, 2000, Schneider & Buehn, 2018). Note that we can give an estimate only for the upper bound of the detection rate as there might be some hidden loss events in countries with the highest press freedom as well. Using (12), the estimated number of *hidden losses* is relatively high for those countries where the average press freedom $PRESS_i$ is low and the total number of public losses PL_i is high. At a global level, it would mean 7,157 more loss events in the sample period (2008–2019). Given that the number of public loss events is only 8,144, the detection rate might be smaller than 8,144/(8,144 + 7,157) = 53%.

Continuing the above thought experiment, if the PRESS variable jumped to its maximal value (100, just like in Norway in years 2009 and 2010) in all countries, according to our model estimations, there would be 1.88 times more public operational loss events and 4.01 times larger losses worldwide. Thus, the total value of public losses would be 1.88*4.01 = 7.54 times larger, hence, the global detection rate (in value) might be smaller than 1/7.54 = 13.27%. To illustrate differences in operational losses at a large scale, we divide countries into two groups: those with relatively low or high press freedom (total GDPs being approximately the same). Estimating the value of public and the hidden losses for the two groups of countries, we get the results summarized in Table 7.

Table 7 shows that countries with high press freedom account for 82% of public losses, while only 28% of hidden losses (in value). Regarding all losses (public and hidden), however, around twice as much loss is realized in countries with less free media. Similarly, according to our estimates, all losses in China can be more than twice larger than in the United States, even if public losses in the United States are more than ten times larger than those in China. All this can be interpreted as the global manifestation of the strong deterrence effect of the media; more press freedom leading to less frequent or less severe total losses. This is consistent with the findings of the financial literature documented in local contexts. In particular, a negative media coverage increases the cost of misbehavior vis-a-vis a relevant audience (Dyck et al., 2008; Dyck et al., 2010; Dyck & Zingales, 2004; Jiang & Kim, 2020; You et al., 2018; Zingales, 2000). Hence, free media is associated with the strong disciplining effects on managers, which reduces the overall operational risk.

5.3. Press freedom and the size of the economy

In line with the expectations, the size of the economy (GDP) is positively associated with the frequency of losses in each specification. In contrast, the size of the economy does not influence the severity of losses; the coefficient is insignificant in each model run.

The detection effect of the media is, however, more pronounced in *larger economies*, which is reflected in the positive and statistically significant coefficient of the interaction term PRESS × lnGDP for both the frequency and severity of losses (Table 6). In larger economies, journalists not only reveal more loss events, but also more severe ones. One plausible explanation for the stronger detection effect of the free media in larger economies could be related to economies of scale and scope. In larger economies, the target audience is larger, which is associated with higher reader and advertising revenues. The higher revenues, in turn, attract more and/or better qualified journalists who reveal and report a higher number of misconducts. In an industry with fierce competition, journalists can stand out with their motivation and desire to report shocking sensations (You et al. 2018).

The GDP growth rate is negatively associated with the frequency and severity of losses in all but one specifications. Thus, the lower the growth of the GDP from one year to another, the higher the frequency and the severity of losses. In recession, more losses might be incurred due to the decreased spending on internal controls and the higher number of firms defaulting on their payment obligations. This finding is consistent with the procyclical behavior of operational risk reported in the literature: operational losses are more frequent and more severe during economic downturns (Abdymomunov, Curti, & Mihov, 2020; Chernobai, Jorion, & Yu, 2011; Moosa 2011).

Table 7
Estimated values of hidden losses between 2008 and 2019.

	Public loss (M US$)	Hidden loss (M US$)	Total loss (M US$)	Public loss (%)	Hidden loss (%)	Total loss (%)
Countries with low press freedom	86 730	2 316 901	2 403 631	18%	72%	65%
Countries with high press freedom	403 198	886 148	1 289 346	82%	28%	35%
All the 132 countries	489 928	3 203 049	3 692 977	100%	100%	100%

5.4. Press freedom and governance

We find no evidence that in better governed countries the operational risk is lower. In all specifications, the coefficient of the variable measuring the quality of a country's governance (GOV) is insignificant. The country-level governance thus affects neither the frequency nor the severity of operational losses. At the same time, the press freedom is significant in all but one specifications. Thus, press freedom carries fundamentally different information, nonetheless the two indicators are correlated. This result supports the argument that the two measures must be introduced in economic models separately. Our findings are in line with Wang and Li (2019) who investigated how public disclosure of corporate social irresponsibility (CSI) can damage reputation-based firm-specific advantages of multinational companies (MNCs) and how foreign subsidiary governance can subsequently be used as strategic responses. The authors argued that press freedom and regulatory quality, two country-level characteristics should be separated as they require the MNCs to utilize different governance mechanisms as responses to CSI disclosure.

At the same time, our results reveal that the effect of press freedom on the severity of losses is less pronounced in countries with better governance, see the significant and negative coefficient of the interaction term GOV × PRESS in *Model 15*. Thus, when comparing countries with good and bad governance, all other factors being equal, the effect of press freedom is higher in the latter. It might well be the case that if other monitors (regulators, civil society, etc.) are weak, the media can replace them in their functions, so its detection effect can be even more pronounced.

5.5. Financial sector

For the financial sector, we find that in countries with free media the frequency of publicly reported operational loss events is significantly higher than in countries with tightly controlled media. However, we find no empirical evidence for a similar relationship for the severity of losses. It means that financial institutions may be successful in hiding operational misconduct, especially if the media is not free. However, once a case is detected, its real value cannot be hidden, which can be due to the stricter regulation. Beyond the more prudent regulation, the large weight of the financial sector in operational losses indicates that journalists are attracted more to financial stories (larger sums, larger scandals, and higher interest from the public), and managers in the financial sector are also in a more leveraged position regarding their career opportunities, reputation, but also the private benefits they can gain through misbehavior.

It is worth noting that for operational risk, the new Basel regulation eliminates the application of existing capital calculation methodologies, especially, the internal models relying on comprehensive operational loss databases (Advanced Measurement Approach, AMA) under the first pillar. From January 2023, banks shall use a new methodology, the Standardized Measurement Approach (SMA) when calculating the minimum capital requirement for operational risk (BCBS, 2017). The capital requirement under the first pillar will be determined by multiplying the bank's income by a bank-specific factor that is solely a function of the bank's own historical operational losses above a given threshold. The threshold is set at €20,000 which can be increased to €100,000 at the discretion of the national supervisors (BCBS, 2017). Thus, eventually, a large loss raises the bank's capital requirement for several years. This new regulation will further motivate banks to hide their losses or at least to keep them below the threshold. We can, therefore, expect that the monitoring role of the media in the financial sector will be further strengthened in the future.

5.6. Policy implications

The findings of this study carry important *implications for many stakeholders*. Most importantly, the frequency and severity of operational loss events are of high importance to *investors* who are primarily interested in the risk-return trade-off of their portfolio. Once an operational loss event is detected, negative market reaction occurs; there is typically a strong, statistically significant negative stock price reaction to announcements of operational loss events (Cummins et al., 2006). Hidden operational loss events pose additional risk to investors as they may alter the anticipated risk-return trade-off. For *policy makers*, the study indicates that assuring high level of press freedom is important in making operational risk more transparent, which in turn might improve corporate governance systems, hence foster competitiveness, economic growth, and sustainability. The findings of this study are relevant for the *regulators* as well; they have interest in preventing and revealing risk events. Finally, the findings bear important implications for the *analysts using publicly reported operational loss data.* Commercial databases (for example, Algo OpData, Algo FIRST, SAS OpRisk Global Data, WTW database, OpBase (Wei, Li, & Zhu, 2018)) may be significantly biased when estimating the total operational risk, especially in countries with tightly controlled media.

6. Limitations

The estimation of PRESS coefficients has several limitations. First, we matched the model variables of public and hidden information with measurable indicators. The detection rate was proxied by the level of press freedom, the total operational risk was captured by a couple of variables drawn from previous literature, and the size of the invested capital was proxied by the income generated by the economy (GDP) and some firm-level size variables. Measurable indicators, however, might only partially capture the essence of the model variables. Second, although SAS OpRisk Global database is the world's most comprehensive and accurate repository of external loss events (SAS, 2015; Wei et al., 2018), the database includes operational losses higher than US$100,000. Thus, loss events smaller than this threshold are excluded from the analysis. Third, operational risk might be influenced by market and firm related factors we could not control for. These potentially omitted variables might have a downward bias on the press coefficients.

Thus, the effect of free press might be even larger than our model estimations suggest. This argument is supported by the results of the two-step least squares model relying on instrumental variables where we get much higher coefficients for the PRESS variable. In this research, we had only limited information about the patterns of market organization, ownership and industry structure, and firm characteristics in different countries. Fourth, we investigated the effects of domestic media on domestic events. Evidence shows, however, that foreign media can also have strong effects on home events (Dyck et al., 2008). Fifth, we captured a 12-year period, from 2008 to 2019, a period including the impact of the subprime crisis. Future research might aim at confirming our findings for other time periods.

The estimation of hidden losses has several limitations as well. The methodology we use, the currency demand approach, was borrowed from the shadow banking literature, we just reinterpreted it for operational risks. Hence, the criticisms of the original method summarized by Schneider & Buehn (2018) apply to our case as well. On the one hand, we cannot be sure that press freedom has a linear effect on operational losses even for large changes. On the other hand, we assume that the detection rate depends only on the freedom of the press. If other variables also affect the detection rate (like governance or GDP), then these other variables may also change when the PRESS variable increases to 100 and influence the detection rate. Nevertheless, this thought experiment highlights that we can only see the tip of the iceberg. In countries where the media is not free, total losses can be much larger than public losses in terms of both frequency and severity.

7. Conclusions

We develop a theoretical model of public and hidden information, and based on this, we investigate the effects of press freedom on operational losses. We find that the level of press freedom is positively associated with both the number and the size of operational loss events revealed by journalists. Thus, in our sample, we can accept hypotheses H1.

The tighter the control, the lower the number and severity of operational losses published in the press. Several commercial vendors offer databases that contain publicly reported operational loss events. For countries where the mass media is directly or indirectly controlled and censored, these databases typically include only a few observations, and the loss amounts also tend to be smaller. Therefore, these databases are seriously biased, which might mislead investors and risk analysts; they might perceive the level of operational risk as low.

Investments in a country with tightly controlled media, however, do not carry less risk; the contrary is true. Under these conditions, the disciplining effect of the media cannot be realized either, so the total operational risk can be much larger as indicated by the country-specific estimations of hidden losses. Thus, we accept hypothesis H2 as well. Similar to detected damage, undetected damage (pollution of the environment, consumer abuses, exploitation of the employees etc.) can also pose a serious threat to sustainability.

Therefore, investors and risk analysts should model the hidden part of operational risk as well. Our findings suggest that using press freedom indicators might be helpful in this modelling. Moreover, improving press freedom can reduce not only operational risks and uncertainties, but also sustainability risks.

In this study, we emphasize the importance of press freedom when modelling operational risks, but our approach might be generalized to other types of risks as well. Future research might aim at conceptualizing and investigating the association between the level of press freedom and some other risk components.

CRediT authorship contribution statement

Edina Berlinger: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Supervision. **Judit Lilla Keresztúri:** Conceptualization, Methodology, Software, Formal analysis, Validation, Investigation, Data curation, Visualization. **Ágnes Lublóy:** Conceptualization, Methodology, Investigation, Data curation, Writing – original draft, Writing – review & editing. **Zsuzsanna Vőneki Tamásné:** Conceptualization, Data curation, Writing – original draft.

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.

Acknowledgement

The data for this paper was generated using SAS® OpRisk Global Data. Copyright, SAS Institute Inc. Cary, NC, USA. All Rights Reserved. This research was funded under the TKP2021-NVA program of the National Office for Research, Development, and Innovation. Edina Berlinger thanks funding from National Research, Development and Innovation Office - NKFIH, K-138826.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.intfin.2021.101496.

References

Abdymomunov, A., Curti, F., Mihov, A., 2020. US banking sector operational losses and the macroeconomic environment. Journal of Money, Credit and Banking 52 (1), 115–144. https://doi.org/10.1111/jmcb.12661.

Alifano, D., Corradi, V., Distaso, W., 2019. The determinants of operational risk losses. Available at SSRN 3407863. https://doi.org/10.2139/ssrn.3407863.

Barakat, A., Chernobai, A., Wahrenburg, M., 2014. Information asymmetry around operational risk announcements. Journal of Banking & Finance 48, 152–179. https://doi.org/10.1016/j.jbankfin.2014.06.029.

Baron, D.P., 2006. Persistent media bias. Journal of Public Economics 90 (1–2), 1–36. https://doi.org/10.1016/j.jpubeco.2004.10.006.

Bascle, G., 2008. Controlling for endogeneity with instrumental variables in strategic management research. Strategic Organization 6 (3), 285–327. https://doi.org/10.1177/1476127008094339.

BCBS. 2003. *Sound practices for the management and supervision of operational risk. Basel* Committee on Banking Supervision. Bank for International Settlements. February 2003 https://www.bis.org/publ/bcbs96.pdf Accessed 14 July 2021.

BCBS. 2017. Basel III: Finalising post-crisis reforms, Basel Committee on Banking Supervision, December 2017 https://www.bis.org/bcbs/publ/d424.htm Accessed 27 June 2021.

Chernobai, A., Jorion, P., Yu, F., 2011. The determinants of operational risk in U.S. financial institutions. Journal of Financial and Quantitative Analysis 46 (6), 1683–1725. https://doi.org/10.1017/S0022109011000500.

Cope, E.W., Piche, M.T., Walter, J.S., 2012. Macroenvironmental determinants of operational loss severity. Journal of Banking & Finance 36 (5), 1362–1380. https://doi.org/10.1016/j.jbankfin.2011.11.022.

Cummins, J.D., Lewis, C.M., Wei, R., 2006. The market value impact of operational loss events for US banks and insurers. Journal of Banking & Finance 30 (10), 2605–2634. https://doi.org/10.1016/j.jbankfin.2005.09.015.

Curti, F., Mihov, A., 2018. Fraud recovery and the quality of country governance. Journal of Banking & Finance 87, 446–461. https://doi.org/10.1016/j.jbankfin.2017.11.009.

Dyck, A., Morse, A., Zingales, L., 2010. Who blows the whistle on corporate fraud? Journal of Finance 65 (6), 2213–2253. https://doi.org/10.1111/j.1540-6261.2010.01614.x.

Dyck, A., Volchkova, N., Zingales, L., 2008. The corporate governance role of the media: Evidence from Russia. Journal of Finance 63 (3), 1093–1135. https://doi.org/10.1111/j.1540-6261.2008.01353.x.

Dyck, A., Zingales, L., 2004. Private benefits of control: An international comparison. Journal of Finance 59 (2), 537–600. https://doi.org/10.1111/j.1540-6261.2004.00642.x.

[dataset] ECB, 2017. Supervisory Banking Statistics. https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.supervisorybankingstatistics_fourth_quarter_2017_201804.en.pdf. Accessed 16 June 2018.

[dataset] Economist Intelligence Unit, 2020. Democracy index. https://www.gapminder.org/data/documentation/democracy-index/ Accessed 10 October 2021.

Hull, John C., 2015. Operational Risk. Risk Management and Financial Institutions, 4th. John Wiley & Sons, New Jersey.

Jiang, F., Kim, K.A., 2020. Corporate governance in China. Review of Finance 24 (4), 733–772. https://doi.org/10.1093/rof/rfaa012.

Kaufmann, D., Kraay, A., Mastruzzi, M., 2011. The worldwide governance indicators: Methodology and analytical issues. Hague Journal on the Rule of Law 3 (2), 220–246. https://doi.org/10.1017/S1876404511200046.

Kölbel, J.F., Busch, T., Jancso, L.M., 2017. How media coverage of corporate social irresponsibility increases financial risk. Strategic Management Journal 38 (11), 2266–2284. https://doi.org/10.1002/smj.2647.

[dataset] IMF, 2021. International Monetary Fund, Financial Development Index Database. https://data.imf.org/?sk=F8032E80-B36C-43B1-AC26-493C5B1CD33B. Accessed 10 September 2021.

Levin, S. 2019. Revealed: How Monsanto's 'intelligence center' targeted journalists and activists. *The Guardian*, 8 August. https://www.theguardian.com/business/2019/aug/07/monsanto-fusion-center-journalists-roundup-neil-young Accessed 10 January 2020.

Leuz, C., Verrecchia, R.E., 2000. The economic consequences of increased disclosure. Journal of Accounting Research 91–124.

Li, L., Moosa, I., 2015. Operational risk, the legal system, and governance indicators: A country-level analysis. Applied Economics 47 (20), 2053–2072. https://doi.org/10.1080/00036846.2014.1000533.

Liu, B., McConnell, J.J., 2013. The role of the media in corporate governance: Do the media influence managers' capital allocation decisions? Journal of Financial Economics 110 (1), 1–17. https://doi.org/10.1016/j.jfineco.2013.06.003.

Liu, B., McConnell, J.J., Xu, W., 2017. The power of the pen reconsidered: The media, CEO human capital, and corporate governance. Journal of Banking & Finance 76, 175–188. https://doi.org/10.1016/j.jbankfin.2016.12.004.

Miller, G.S., 2006. The press as a watchdog for accounting fraud. Journal of Accounting Research 44 (5), 1001–1033. https://doi.org/10.1111/j.1475-679X.2006.00224.x.

Moosa, I., 2011. Operational risk as a function of the state of the economy. Economic Modelling 28 (5), 2137–2142. https://doi.org/10.1016/j.econmod.2011.05.011.

Mullainathan, S., Shleifer, A., 2005. The market for news. American Economic Review 95 (4), 1031–1053. https://doi.org/10.1257/0002828054825619.

RSF. 2020a. Violations of press freedom barometer. Reporters without Border (RSF). https://rsf.org/en/barometer?year=2020&type_id=233#list-barometre Accessed 29 December 2020.

RSF. 2020b. 2019 World Press Freedom Index. Detailed methodology. Reporters without Borders (RSF). https://rsf.org/en/detailed-methodology Accessed 30 August 2020.

[dataset] SAS. 2015. SAS® OpRisk Global Data. https://www.sas.com/content/dam/SAS/en_us/doc/productbrief/sas-oprisk-global-data-101187.pdf Accessed 16 June 2020.

[dataset] SAS. 2020. OpRisk Global Data software. SAS Institution Kft.

Schneider, F., Enste, D.H., 2000. Shadow economies: Size, causes, and consequences. Journal of Economic Literature 38 (1), 77–114. https://doi.org/10.1257/jel.38.1.77.

Schneider, F., Buehn, A., 2018. Shadow economy: Estimation methods, problems, results and open questions. Open Economics 1 (1), 1–29. https://doi.org/10.1515/openec-2017-0001.

Storbeck, O. 2020. Germany to overhaul accounting regulation after Wirecard collapse. Financial Times, 28 June 2020. https://www.ft.com/content/e037d830-cfd8-4bca-853d-d49f48e67f13 Accessed 10 September 2020.

Strömberg, D., 2004. Mass media competition, political competition, and public policy. The Review of Economic Studies 71 (1), 265–284. https://doi.org/10.1111/0034-6527.00284.

Svirydzenka, K. 2016. Introducing a new broad-based index of financial development. IMF Working Paper 16/5. International Monetary Fund.

Szeidl, A., Szucs, F., 2021. Media capture through favor exchange. Econometrica 89 (1), 281–310. https://doi.org/10.3982/ECTA15641.

Tirole, J. 2006. *The Theory of Corporate Finance*, Princeton. NJ: Princeton University Press.

Vergne, J.P., Wernicke, G., Brenner, S., 2018. Signal incongruence and its consequences: A study of media disapproval and CEO overcompensation. Organization Science 29 (5), 796–817. https://doi.org/10.1287/orsc.2018.1209.

Wang, S.L., Li, D., 2019. Responding to public disclosure of corporate social irresponsibility in host countries: Information control and ownership control. Journal of International Business Studies 50 (8), 1283–1309. https://doi.org/10.1057/s41267-019-00224-w.

Wei, L., Li, J., Zhu, X., 2018. Operational loss data collection: A Literature Review. Annals of Data Science 5 (3), 313–337. https://doi.org/10.1007/s40745-018-0139-2.

Wei, J., Ouyang, Z., Chen, H.A., 2017. Well known or well liked? The effects of corporate reputation on firm value at the onset of a corporate crisis. Strategic Management Journal 38 (10), 2103–2120. https://doi.org/10.1002/smj.2639.

[dataset] World Bank. 2021a. The World Bank Data Bank, World Governance Indicators. https://databank.worldbank.org/source/worldwide-governance-indicators Accessed 20 March 2021.
[dataset] World Bank. 2021b. The World Bank Data Bank, GNI per capita, Atlas method (current US$). https://data.worldbank.org/indicator/NY.GNP.PCAP.CD Accessed 20 March 2021.
[dataset] World Bank. 2021c. The World Bank Data Bank, GDP (current US$). https://data.worldbank.org/indicator/NY.GDP.MKT Accessed 20 March 2021.
[dataset] World Bank. 2021d. The World Bank Data Bank, Individuals using the Internet (% of population). https://data.worldbank.org/indicator/IT.NET.USER.ZS Accessed 10 October 2021.
[dataset] World Bank. 2021e. The World Bank Data Bank, Age dependency ratio (% of working-age population). https://data.worldbank.org/indicator/SP.POP.DPND Accessed 10 October 2021.
You, J., Zhang, B., Zhang, L., 2018. Who captures the power of the pen? Review of Financial Studies 31 (1), 43–96. https://doi.org/10.1093/rfs/hhx055.
Yoon, H., Zo, H., Ciganek, A.P., 2011. Does XBRL adoption reduce information asymmetry? Journal of Business Research 64 (2), 157–163.
Zingales, L., 2000. In search of new foundations. Journal of Finance 55 (4), 1623–1653. https://doi.org/10.1111/0022-1082.00262.