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Modeling Operational Risk Incorporating Reputation Risk: An Integrated Analysis for Financial Firms

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MODELING OPERATIONAL RISK INCORPORATING REPUTATION RISK: AN INTEGRATED ANALYSIS FOR FINANCIAL FIRMS

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ABSTRACT

It has been shown in the empirical literature that operational losses of financial firms can cause severe reputational losses, which, however, are typically not taken into account when modeling and assessing operational risk. The aim of this paper is to fill this gap by assessing the consequences of operational risk for a financial firm including reputational losses. Toward this end, we extend current operational risk models by incorporating reputation losses. We propose three different models for reputation risk: a simple deterministic approach, a stochastic model using distributional assumptions, and an extension of the second model by taking into account a firm's ability to deal with reputation events. Our results emphasize that reputational losses can by far exceed the original operational loss and that neglecting reputational losses may lead to a severe underestimation of certain operational risk types and especially fraud events.

Keywords: Operational risk; reputation risk; Solvency II; Basel III; loss distribution approach; Value at Risk
JEL Classification: G20; G21; G22; G32

1. INTRODUCTION

Reputation risk is among the most relevant risks for firms (see, e.g., The Economist, 2005; ACE, 2013; Deloitte, 2014), and at the same time considered to be more difficult to manage than any other specific risk category (see, e.g., ACE, 2013). For example, while other risks may imply direct (real) costs, the extent of potential financial consequences of a damaged reputation typically depends on various moderating factors, such as the prior level of reputation or the ability of the firm to recover its reputation over time. In addition, due to the fact that reputation risk is a risk of risks, it takes a special role in risk management and should generally be managed in an integrated way by considering the underlying risks along with their effects on reputation (see, e.g., Tonello, 2007; Regan, 2008). Since reputational losses in

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financial firms are most often caused by underlying operational loss events,[1] especially in case of fraud (see, e.g., Cummins et al., 2006; Gillet et al., 2010; Fiordelisi et al., 2014), the aim of this paper is to present a model approach that extends existing models for operational risk by taking into account reputational losses, which to the best of our knowledge has not been done so far.[2] In particular, purely empirical event study approaches typically do not study operational and the resulting reputational losses at the same time, and they can also not be applied in model settings under Basel III or Solvency II, for instance. Providing a model thus does not only allow us assessing reputation risk caused by operational loss events, but it also allows a better and more holistic understanding of the actual consequences of operational losses (pure operational loss and resulting pure reputational loss), which is of high relevance when deciding about the type and extent of preventive measures regarding operational risks, for instance. The model and the numerical analysis are thus intended to offer first insight into the relation between operational losses and reputational losses by calibrating the model consistently based on results from the empirical literature. It can further be used for scenario and sensitivity analyses under Basel III or Solvency II, for instance, to identify general interrelations between operational and reputational losses. We also discuss limitations of the presented approach and point out the need for future research in regard to reputation risk.

A large part of the literature is concerned with the modeling of operational risk, including, for instance, McNeil et al. (2005), Chavez-Demoulin et al. (2006), Gourier et al. (2009), Chaudhury (2010), Shevchenko (2010), and Brechmann et al. (2014), while Gatzert and Kolb (2014) study operational risk from an enterprise perspective under Solvency II with focus on the insurance industry. Another part of the literature empirically analyzes operational loss data. While most of these studies examine empirical data from the banking sector (see, e.g., de Fontnouvelle et al., 2003; Moscadelli, 2004), Hess (2011b) also investigates operational loss data for insurance companies, whereas Hess (2011a) examines the impact of the financial crisis on operational risk.

In addition, a further strand of the literature empirically examines the impact of operational risk events on reputational losses based on event studies by examining stock market value reactions that exceed the pure operational loss. While some papers focus on the banking industry (Perry and de Fontnouvelle, 2005; Fiordelisi et al., 2013, 2014), others also include the insurance industry (Cummins et al., 2006; Cannas et al., 2009), consider the financial (ser-

[1] Examples of large operational loss events include, e.g., the involvement of the CEO of Banca Italease in the Danilo Coppola affair 2007 (see, e.g., Soprano et al., 2009; Young and Coleman, 2009), the Société Générale trading loss 2008 (see, e.g., Soprano et al., 2009) or the UBS rogue trader scandal 2011 (see, e.g., Fiordelisi et al., 2014).

[2] Note that we therefore only consider reputation risk caused by underlying operational losses. To assess reputation risk in its entirety, other underlying risk types such as, e.g., credit risk (see KPMG, 2012) also have to be taken into account, which can be done similarly.

vices) industry in general (Gillet et al., 2010; Biell and Muller, 2013; Sturm, 2013) or investigate the consequences of certain subsets of operational risk also in other industries than the financial (services) industry (see, e.g., Murphy et al., 2009; Johnson et al., 2014). Most authors thereby find significant negative stock market reactions to operational losses that exceed the announced operational loss size, thus indicating substantial reputational losses, and most find that these losses are especially pronounced for (internal) fraud events. Fiordelisi et al. (2014) further show that reputational losses of banks are higher in Europe than in North America. The consideration of reputational losses arising from operational risk events is thus of high relevance.

In general, the potential impact of a bad reputation on the financial situation of the company can be fatal (see Kamiya et al., 2013), and reputation is even more important in the financial industry, especially for banks and insurers, whose activities are based on trust. Thus, reputation is a key asset and therefore an adequate management of reputational risk is vital (see Fiordelisi et al., 2014). Reputation risk is becoming increasingly important for firms especially against the background of the increasing prominence of social media and the internet, where particularly bad news spread faster. Finally, reputation risk is also of high relevance in the context of Solvency II and Basel III, the new regulatory frameworks for European insurance companies and global banks, where all relevant risks must be adequately addressed qualitatively and quantitatively in a holistic and comprehensive way. In this context, while for operational losses different types of insurance policies are available for different event types, reputational risk insurance as a stand-alone product has only recently been introduced (see Gatzert et al., 2014).

Overall, the literature so far has thus studied various aspects of operational and reputational risk, but the models for operational risk generally do not take into account the resulting reputational losses, whereas the empirical literature does not focus on operational risk model frameworks, which can be used for risk assessment. Therefore, the aim of this paper is to combine both strands of the literature by extending current models for operational risk by incorporating resulting reputational losses as observed in the empirical literature for financial firms. We thereby propose three different ways of adding reputation risk that are generally based on the typical event study approaches, including a simple deterministic approach, a stochastic model using distributional assumptions, and by integrating a probability of a reputation loss that reflects a firm's ability to deal with reputation events (e.g., crisis communication). In a numerical analysis, we calibrate the model based on consistent empirical data, which allows a comprehensive assessment of the impact of operational and reputational risk. We thereby also study the impact of firm characteristics (market capitalization and total assets) by integrating a scaling approach (based on Dahen and Dionne, 2010) in the operational and reputational risk model.

Accounting for reputation risk is of high relevance as it represents a risk of risks and should thus be taken into account when assessing underlying risks such as operational risks that may result in reputational losses. By proposing a simple model framework, we aim to provide first insight into the quantitative effects of reputational losses resulting from operational risks and to thus obtain a more comprehensive picture of the impact of operational risk. The extended model allows a more precise analysis of operational risks and the relevance of individual risk types along with the possibility to conduct scenario and sensitivity analyses, which is vital for risk management decisions and to ensure an adequate allocation of resources for preventive measures, for instance. One main finding based on the consistently calibrated model is that reputational losses can by far exceed the original operational losses and that the distribution of losses among event types changes and shifts towards internal and external fraud events.

The paper is structured as follows. Section 2 discusses the relation between operational and reputation risk, while Section 3 introduces the model framework. Section 4 contains numerical analyses based on empirical results from the literature, and Section 5 summarizes and discusses implications.

2. Operational and Reputation Risks

2.1 Corporate reputation

While there is a substantial amount of literature regarding corporate reputation, the definitions vary. Literature reviews of definitions of reputation are thereby given in, e.g., Fombrun et al. (2000), Rindova et al. (2005), Barnett et al. (2006), Walker (2010), Helm (2011), and Clardy (2012). According to Wartick (2002) and Walker (2010), the definition of corporate reputation from Fombrun (1996) is used most often. Fombrun (1996, p. 72) defines corporate reputation as "a perceptual representation of a company's past actions and future prospects that describes the firm's overall appeal to all of its key constituents when compared with other leading rivals". Brown and Logsdon (1997) name three key elements of this definition, being 1) that corporate reputation is of perceptual nature, 2) that it is a net or aggregate perception by all stakeholders and 3) that it is comparative vis-à-vis some standard (see also Wartick, 2002). Recently, considering the above mentioned points, Fombrun (2012) proposed a new definition of corporate reputation in which he distinguishes between the stakeholder groups: "A corporate reputation is a collective assessment of a company's attractiveness to a specific group of stakeholders relative to a reference group of companies with which the company competes for resources" (Fombrun, 2012, p. 100).

2.2 Reputation risk

Reputation risk is generally defined as a risk of risks. For instance, in their work on Solvency II, the European regulatory framework for insurers, the Comité Européen des Assurances (CEA) and the Groupe Consultatif Actuariel Européen (2007) define reputation risk as the "risk that adverse publicity regarding an insurer's business practices and associations, whether accurate or not, will cause a loss of confidence in the integrity of the institution. Reputational risk could arise from other risks inherent in an organization's activities. The risk of loss of confidence relates to stakeholders, who include, inter alia, existing and potential customers, investors, suppliers, and supervisors." In a more recent consultation paper of the banking regulation framework Basel II, an updated definition of reputation risk states that „reputational risk can be defined as the risk arising from negative perception on the part of customers, counterparties, shareholders, investors or regulators that can adversely affect a bank's ability to maintain existing, or establish new, business relationships and continued access to sources of funding (e.g., through the interbank or securitization markets). Reputational risk is multidimensional and reflects the perception of other market participants. Furthermore, it exists throughout the organization and exposure to reputational risk is essentially a function of the adequacy of the bank's internal risk management processes, as well as the manner and efficiency with which management responds to external influences on bank-related transactions" (Basel Committee, 2009, p. 19). Other definitions of reputation risk additionally explicitly refer to the risk of a financial loss (see, e.g., Tonello, 2007).

Overall, reputation risk can thus be described by the causal chain of events in that an underlying crisis event (in our setting, we focus on an underlying operational risk event such as fraud or IT failures) leads to negative perceptions by a firm's stakeholders (e.g., consumers, counterparties, shareholders, employees, regulators), thus deteriorating corporate reputation. This in turn potentially implies a change in the behavior of stakeholders (e.g., customers do not buy products of the company, talented employees leave the firm), which can lead to financial losses for the firm that *exceed* the costs of the actual underlying (operational) risk event and which in what follows are interpreted as the relevant "reputational losses". The reputational losses thus have to be separately evaluated, namely as a *consequence* of the underlying operational risk / crisis event.

Since exactly measuring this financial loss is not possible, we follow previous empirical literature and approximate it by means of the market value loss that exceeds the loss from the underlying risk event (e.g. operational losses such as sanctions or penalties). We thus define reputation risk as a separate risk type, but due to its specific structure as a risk of risks, it requires a special role in risk management and should not be managed separately but in an integrated way together with the underlying risks, also to avoid a potential double counting.[3] Since in the financial industry reputational losses are most often caused by underling operational losses as discussed before, in this paper we focus on reputation risk caused by operational losses. Reputation risk caused by other risk types such as credit risks, for instance, can be treated in a similar way.

2.3 Operational loss events as triggers for reputational losses

Even though there are also other potential underlying risks (e.g., compliance, credit, liquidity, market, and strategic risks, see Basel Committee (1997), Basel Committee (2009), and KPMG (2012)), reputational losses in the financial industry most often occur due to underlying operational losses. Hence, we specifically focus on operational risk[4] events and their consequences regarding resulting reputational losses and follow the respective empirical literature (see, e.g., Perry and de Fontnouvelle, 2005; Gillet et al., 2010; Fiordelisi et al., 2013; Walter, 2013; Fiordelisi et al., 2014), where reputational loss is defined as the financial loss caused by an underlying (here: operational) risk event, which exceeds the actual (operational) loss of the underlying event. Reputational loss is thereby measured as the market value loss using cumulative abnormal returns (CAR) for a certain event window that exceeds the operational loss[5] and which reflects estimated financial effects in the sense of deteriorated future prospects.

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3 The potential problem of double counting can be illustrated when considering liquidity risk as a consequence of a deteriorated corporate reputation, for instance, as a deterioration of reputation can lead to an unexpected financial loss for the firm (e.g. a loss of a key business partner, strong reductions in revenues) and, at the same time, a bad reputation makes it more difficult to raise capital to cover such a liquidity shock. Approximating the (financial) reputational loss by means of market value losses may thereby lead to a double counting, since the higher liquidity risk may also be reflected in the market value. Nevertheless, we follow previous empirical literature and use the market value loss exceeding the actual operational loss as an approximation for the reputational loss. In particular, the higher liquidity risk should only be a small part of the resulting financial loss compared to the overall reputational loss (which inter alia includes a reduced revenue), and, furthermore, liquidity risk caused by reputational losses that are in turn caused by operational losses should only represent a small part of the whole liquidity risk that a firm is exposed to. However, future research regarding the effects of reputational losses caused by underlying operational losses on liquidity risk would be useful to disentangle the reputational loss from the liquidity risk. Note that a double counting with credit risk and market risk would not be the case in our setting as this would concern other firms holding bonds or shares of the firm that suffers the operational / reputational loss, while we focus on the reputational loss of the firm that suffers the operational loss. However, market and credit risks could indeed represent underlying risk sources that may cause reputation risk.

4 The Basel II Committee defines operational risk "as the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events. This definition includes legal risk, but excludes strategic and reputational risk" (Basel Committee, 2004, p. 137). Operational risk can be categorized in the following event types: 1) internal fraud, 2) external fraud, 3) employment practices & workplace safety, 4) clients, products & business practices, 5) damage to physical assets, 6) business disruption & system failures, 7) execution, delivery & process management.

5 This approach can thus only be applied to publicly traded companies. A detailed description is provided in Section 3.

Examining the consequences of a deteriorated reputation for fraud firms in the context of product markets, Johnson et al. (2014) show that this approach provides a reliable measure of reputational losses.

As described before, there are several empirical studies that investigate reputational losses caused by operational loss events in the financial services industry and that show significant stock market reactions that exceed the pure operational loss (Perry and de Fontnouvelle, 2005; Cummins et al., 2006; Cannas et al., 2009; Gillet et al., 2010; Biell and Muller, 2013; Fiordelisi et al., 2013; Sturm, 2013; Fiordelisi et al., 2014). Overall, one can conclude from the findings in the empirical literature that the consideration of resulting reputational losses is of high relevance when analyzing operational losses.

3. MODEL FRAMEWORK

Due to the fact that reputation risk can generally be considered as a risk of risks, it should be taken into account when assessing other (underlying) risks, which may imply reputational losses in case of their occurrence. This is especially relevant in case of operational losses as laid out in the previous section. By extending the current approaches used to quantify operational risk, we thus aim to gain a better understanding of the impact of reputation risk as a result of operational losses and, in addition, the model allows us to better assess the consequences of operational risks. Neglecting potential reputational losses may lead to an underestimation of certain operational risk types, which in turn may imply an inadequate allocation of resources in enterprise risk management and preventive measures regarding operational risk, for instance.

In what follows, we first present a model for quantifying operational and reputational losses for a single firm. In particular, focus is laid on how to integrate reputational losses (caused by operational losses) in an existing model for operational risk.

3.1 Modeling operational losses

The following model used to quantify operational losses only represents one way of modeling operational risk,[6] and in case other models appear more suitable for the respective situation of the firm, the inclusion of reputational risk can be done in the same way as presented in the following subsection. The total loss S^l resulting from operational risk[7] in a certain period (e.g., one year) for a certain firm l is given by

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6 See, e.g., Chaudhury (2010) for an overview of operational risk models.

7 Note that in the banking industry, for instance, the operational loss typically depends on the business line; in what follows, to keep the notation simple we omit a superscript for the respective business line.

$$S^l = \sum_{i=1}^{I} S_i^l = \sum_{i=1}^{I}\sum_{k=1}^{N_i^l} X_{i,k}^l \,, \tag{1}$$

where S_i^l denotes the operational loss of firm l resulting from event type $i = 1,\ldots,I$, N_i^l is the number of losses due to event type i during the considered period and $X_{i,k}^l$ represents the severity of the k-th loss of event type i in the considered period.

In what follows, we assume independence[8] between the respective losses $X_{i,k}^l$ (for all i) and between the severity $X_{i,k}^l$ and the frequency of losses N_i^l (see, e.g., Angela et al., 2008). Additionally, we assume for all i that the number of losses follows a Poisson process with intensity λ_i^l and that the severity of the loss $X_{i,k}^l$ follows a truncated lognormal distribution with truncation point T^l and parameters μ_i^l and σ_i^l.[9] These assumptions are very common when modeling operational risk (see, e.g., Chaudhury, 2010), and they allow keeping the model tractable; however, the model can as well be extended (e.g. by including dependencies etc.).

3.2 Modeling reputational losses as a consequence of operational losses

We define the reputational loss caused by a reputation risk event (here: operational loss) as the total financial loss due to, e.g., a loss of current or future customers or a loss of employees due to the damaged reputation (see Cummins et al., 2006). Assessing the financial consequences of a damaged reputation is thus generally rather complex, because the (real) costs may depend on various factors such as the ability of the firm to recover its reputation over time as well as other moderating factors. This is different from the direct observation of costs for the underlying operational loss event. However, the financial consequences of a damaged reputation resulting from a large operational risk event should still be taken into account when assessing operational risk types. To be able to measure these financial reputational losses, we follow the empirical literature for the financial industry (e.g., Perry and de Fontnouvelle, 2005; Cummins et al., 2006; Gillet et al., 2010; Fiordelisi et al., 2013, 2014) and assume that investors estimate these financial consequences, which are then reflected in the market value of the firm. The reputational loss is thus measured based on the market value loss that exceeds the announced operational loss using the cumulative abnormal return (CAR) for a given event window around the date of the operational loss event.[10,11] Empirically investigating the con-

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8 Dependencies between different event types can be modeled via copulas, for instance, (see, e.g., Angela et al., 2008).

9 Note that the implementation of a truncation point is necessary in case the model is calibrated based on external empirical data, since such databases typically consider operational losses only above a certain threshold. In case internal data is used, a scaling model with truncation point is not needed.

10 Examples of such reputational losses are, e.g., the BP explosion and oil spill in 2010 (underlying operational loss size about \$28 billion, see BP, 2015), which led to market value losses of \$53.5 billion (Aon Oxford Metrica Reputation Review, 2011), or the UBS rogue trader scandal 2011 (underlying operational loss size

sequences of a damaged reputation for fraud firms, Johnson et al. (2014) thereby show that this approach indeed reflects the actual decrease in revenue of the firm due to customer reputational sanctions (including terminated business relationships, lower sales etc.), indicating that the market value loss exceeding the actual operational loss (here in terms of the CAR) represents a reliable measure of the financial reputational losses. The present approach is thus intended to obtain a more comprehensive understanding of the impact of operational risk by explicitly taking into account reputational losses resulting from operational loss events. The following description is based on Perry and de Fontnouvelle (2005) as well as Fiordelisi et al. (2014), and is intended to illustrate how the CARs can be measured empirically. However, in the numerical analysis (Section 4) we do not perform an event study ourselves but instead use existing results from the empirical literature (obtained using the presented event study approach) to calibrate the theoretical model with respect to reputational losses using one of the following three approaches.

The general model based on event study approaches

As we model the size of reputational losses by using assumptions regarding the CAR, we first describe the typical event study approaches that allow deriving the CAR (i.e. information regarding the mean or the distribution of the CAR). Here, stock markets are assumed to be efficient in that public information is incorporated into stock prices within a short period of time (McWilliams and Siegel, 1997). Based on an event study, stock return changes can be measured around the date of an operational loss announcement to account for the possibility of information leakage. The date of the announcement of the operational loss event is defined as day zero (t = 0) and the considered event window is the time window that takes into account τ_1 days before and τ_2 days after the date of the announcement (the largest event window typically ranges from 20 days before to 20 days after the date of the announcement). For each firm, the normal stock rate return R_t^l of a considered firm l at day t is measured by

$$R_t^l = \alpha^l + \beta^l \cdot R_{mkt,t} + \varepsilon_t^l,$$

where $R_{mkt,t}$ denotes the rate of return for selected benchmarks, α the excess return, β the beta coefficient of the share, and ε_t the idiosyncratic risk.[12] Using an ordinary least square regres-

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about \$2 billion, see Slater, 2011) with a market value loss of \$6.3 billion (Aon Oxford Metrica Reputation Review, 2012).

11 This assumption can be replaced with other measures of reputational loss (e.g., as related to lost revenues etc.). However, to the best of the authors' knowledge, empirical studies with such measures are not available.

12 Previous empirical literature (e.g., Fiordelisi et al., 2014) generally makes use of a standard CAPM model to estimate abnormal returns. Since we calibrate the model based on previous literature, we follow this approach and also use a CAPM model. However, our model can be easily extended to a richer factor model such as, e.g., 3-factor Fama French model, which can take into account further factors in the abnormal returns and

sion of R_t on $R_{mkt,t}$ for a (typically) 250-working day estimation period (e.g., from the 270th to the 21st day before the loss announcement in case of a +/- 20 day event window), the α and β coefficients are estimated for each firm. For each day t (unequal to day zero) the abnormal return ($AR_t^{l;i,k}$), given the k-th operational loss of type i in the considered time period, is defined as

$$AR_t^{l;i,k} = R_t^l - \alpha^l - \beta^l \cdot R_{mkt,t} .$$

To isolate the reputational effect, the abnormal return for day zero ($AR_0^{l;i,k}$) is defined as

$$AR_0^{l;i,k} = R_0^l - \alpha^l - \beta^l \cdot R_{mkt,0} - \frac{\hat{X}_{i,k}^l}{M_{0,i,k}^l},$$

where $\hat{X}_{i,k}^l$ is the announced loss from the k-th operational loss of event type i for firm l and $M_{0,i,k}^l$ denotes the market capitalization of the considered firm at the beginning of day 0 of this operational risk event, implying a corresponding cumulative abnormal return (CAR) for a given event window (τ_1, τ_2) for one firm l in the sample (where only one operational loss event is assumed to occur) of

$$CAR_{i,k}^l(\tau_1, \tau_2) = \sum_{t=\tau_1}^{\tau_2} AR_t^{l;i,k} . \tag{2}$$

We then define the reputational loss $Y_{i,k}^l$ following an operational loss $X_{i,k}^l$ as the product of market capitalization at the beginning of day 0 and the CAR (of the considered event window), i.e.[13]

$$Y_{i,k}^l = -M_{0,i,k}^l \cdot CAR_{i,k}^l(\tau_1, \tau_2) \cdot 1_{\{X_{i,k}^l \geq H_i^R\}}, \tag{3}$$

given that the operational loss $X_{i,k}^l$ exceeds a threshold H_i^R, above which reputational losses of size $-M_{0,i,k}^l \cdot CAR_{i,k}^l(\tau_1, \tau_2)$ occur. The thresholds H_i^R are introduced, since the empirical literature shows that only large operational losses exceeding a certain threshold (mostly \$1 million) cause significant reputational losses (see, e.g., Fiordelisi et al., 2014).

thus impact the measurement of reputational losses if a shock in one of the additional factors were to occur during the 40-day window around the reputational loss event.

13 Cummins et al. (2006) measure the market value response in a similar way, but use the market capitalization at the beginning of the event window. In general, it would be more precise to multiply the daily abnormal return with the market capitalization at the beginning of each day as is done in Karpoff et al. (2008).

Thus, the total reputational loss R^l of firm l resulting from operational risk in the considered period is given by

$$R^l = \sum_{i=1}^{I}\sum_{k=1}^{N_i^l} Y_{i,k}^l = \sum_{i=1}^{I}\sum_{k=1}^{N_i^l} -M_{0,i,k}^l \cdot CAR_{i,k}^l\left(\tau_1,\tau_2\right)\cdot 1_{\left\{X_{i,k}^l \geq H_i^R\right\}}. \tag{4}$$

The frequency of reputational losses is thus assumed to be equal to the frequency of operational losses. In case a certain operational loss event type does not imply a reputational loss, the reputational loss severity is set to zero when calibrating the model ($Y_{i,k}^l = 0$).

In what follows, we compare three approaches to specify the CAR in Equation (4) and to derive reputational losses based on different assumptions.

Approach 1: Deterministic integration of reputational losses using the average observed CAR

In a first approach, we deterministically integrate the reputational loss by using the average cumulative abnormal returns $\overline{CAR_i}\left(\tau_1,\tau_2\right)$ for event type i, assumed to be the same for each occurring operational loss event k of type i, where the mean is derived for the sample of firms considered in the event study (this assumption is relaxed in the second approach). The average CAR is thereby estimated based on event studies (e.g., Fiordelisi et al., 2014) and thus depends on the event type, i.e. in Equation (4), we use

$$Y_{i,k}^l = -M_{0,i,k}^l \cdot \overline{CAR_i}\left(\tau_1,\tau_2\right)\cdot 1_{\left\{X_{i,k}^l \geq H_i^R\right\}}.$$

While this model does not imply a stochastic behavior for reputational losses, it allows first insight regarding the expected (mean) operational and reputational loss depending on the event type, which is especially helpful against the background of difficult data availability (which already arises for operational loss data). Moreover, due to its simplicity, we are able to calibrate the model consistently based on the empirical literature.

Approach 2: Stochastic integration of reputational losses using distributional assumptions for the CAR

The first approach can be extended by assuming a probability distribution for the CAR and by assuming independence between the $CAR_{i,k}^l\left(\tau_1,\tau_2\right)$ for all k and for all i,[14] and between the $CAR_{i,k}^l\left(\tau_1,\tau_2\right)$ and the frequency (number) of operational losses of event type i, N_i^l (for all k and for all i), as well as between the $CAR_{i,k}^l\left(\tau_1,\tau_2\right)$ and the severity of the operational loss

[14] We use this assumption for simplification purposes. However, the CARs caused by two operational losses occurring within a short period of time might even exhibit a certain degree of dependence.

$X_{i,k}^{l}$ (for all k and for all i). To estimate the severity of reputational losses for the considered firm l, one could thus estimate the distribution of the CAR based on the whole event study sample (using Equation (2)). Hence, in contrast to the first approach, the second approach allows a risk assessment of reputational risk based on stochastic reputational loss amounts. However, even though there are a few papers that empirically study reputational losses as a consequence of operational losses, only Cannas et al. (2009) fit a severity distribution for reputational losses for a small sample of 20 bank and insurance company events and, based on this, derive the "reputational value at risk". They assume that the cumulative abnormal returns are independent of the severity of the underlying operational losses and state that the cumulative abnormal returns following an internal fraud event exceeding \$20 million are well fitted using a logistic distribution. However, they do not focus on other operational loss event types than internal fraud and there is currently still only very little research in this regard.

To obtain a first impression of the impact of randomness in regard to reputational losses, we assume in this second approach that the cumulative abnormal return $CAR_{i,k}^{l}\left(\tau_1,\tau_2\right)$ in Equation (4) follows a logistic distribution with parameters α_i and β_i. Logistically distributed random variables can assume any real number, implying that in contrast to the first approach, an operational loss does not need to lead to additional losses in market capitalization and that even gains are possible. This is also consistent with Fiordelisi et al. (2014), who find that only about 50% to 57% (depending on the event window) of the considered operational losses lead to negative cumulative abnormal returns.

Furthermore, closed-form expressions for estimating the expected loss and variance of reputational losses are derived in the Appendix whenever possible. We thereby assume a fixed market capitalization M^l for ease of representation and calculation. While we can derive closed-form expressions for the expected operational and reputational loss and the variance of the operational and reputational loss for the first and second approach, this is not possible for risk measures such as the value at risk, for instance, without further assumptions regarding the distribution of operational losses.

Approach 3: Stochastic integration of reputational losses using distributional assumptions for the CAR and a probability of occurrence

In a third approach, we further extend the second approach and explicitly take into account the probability with which reputational losses occur, which also allows taking into consideration, e.g., firm characteristics or the ability for crisis management and crisis communication after a reputation risk event. Toward this end, we adapt the approach in Fiordelisi et al. (2013), who sort the observed CARs in their sample according to size and only consider a CAR in the lowest third as "reputational damage" and all other cases as "no reputational damage". They then estimate the probability of suffering a reputational damage (i.e., a CAR in the lowest third) depending on firm and other characteristics using an ordered logit model and a partial proportional odds model.

In what follows, we integrate these considerations as a third possible method to address reputational losses, which are weighted by a probability that reflects the firm's ability to deal with reputation risk events, by first splitting the distribution of the $CAR_{i,k}^{l}$ in two parts, the one below the critical level x (e.g., $x = q_{i,1/3}$ the 1/3-quantile of $CAR_{i,k}^{l}$ in case of Fiordelisi et al., 2013), which is then considered as a "reputational damage", and the CAR values above this level. Thus, for the CAR following an operational loss event of type i, let $L\left[CAR_{i,k}^{l}\right]$ denote the distributional law of this random variable and let the new random variables $U_{i,k,x}^{l}$ and $V_{i,k,x}^{l}$ have distributional laws

$$L\left[U_{i,k,x}^{l}\right] = L\left[CAR_{i,k}^{l} \middle| CAR_{i,k}^{l} \leq x\right]$$

and

$$L\left[V_{i,k,x}^{l}\right] = L\left[CAR_{i,k}^{l} \middle| CAR_{i,k}^{l} > x\right],$$

whereby the first random variable represents the case of a reputational damage for a given level x. To take into account that the probability of a reputational damage (i.e. that the CAR falls below the level x) may differ depending on the firm's ability, we introduce another random variable $P_{i,k,x}^{l}$, which is equal to 1 with probability $p_{i,x}^{l}$ and 0 with probability $1 - p_{i,x}^{l}$ and assume that the $P_{i,k,x}^{l}$ are independent for all i and for all k.

Thus, the total reputational loss R^l of firm l resulting from operational risk in the considered period is then given by replacing the CAR in Equation (4) by the conditional distribution of the CAR, i.e. the severity of the reputational loss, which is weighted with a random variable that expresses the risk (probability) of actually experiencing a reputational damage, i.e. that the CAR falls below the critical level x, e.g., using the same distributional assumptions for the CAR as in the second approach. Thus, Equation (4) becomes

$$R^{l} = \sum_{i=1}^{I} \sum_{k=1}^{N_i^l} Y_{i,k}^{l} = \sum_{i=1}^{I} \sum_{k=1}^{N_i^l} -M_{0,i,k}^{l} \cdot \left(P_{i,k,x}^{l} \cdot U_{i,k,x}^{l} + \left(1 - P_{i,k,x}^{l}\right) \cdot V_{i,k,x}^{l}\right) \cdot 1_{\left\{X_{i,k}^{l} \geq H_i^R\right\}}. \tag{5}$$

Note that this approach allows changing the actual probability of occurrence of reputational damages, which can be higher or lower than the one actually associated with the CAR. If the critical level x is set to the 1/3-quantile of CAR and the probability of occurrence is also set to 1/3 $(p_{i,x}^{l} = 1/3)$, Equation (5) corresponds to Equation (4). In case $p_{i,x}^{l}$ is set to a lower value, the probability of a reputational damage, i.e. that the CAR falls below the 1/3-quantile, is reduced due to actions taken by the firm (adequate crisis management etc.).

The $p_{i,x}^{l}$ can thus be interpreted as the ability of the firm to handle crisis communication or the strength of the brand and can be estimated, e.g., by means of historical data, by expert surveys or by means of an ordered logit model or a partial proportional odds model as done in Fiordelisi et al. (2013). The severity of the reputational loss may also depend on firm characteristics in addition to the characteristics of the underlying operational risk event (see Sturm, 2013; Fiordelisi et al., 2014), which can implicitly be taken into account here using scenario analysis or if sufficient data is available for calibrating the model. Following Fiordelisi et al. (2013) one could further model the probability (and extent) of a reputational damage depending on various firm and event characteristics, as they take into account firm characteristics (e.g., price-book value ratio, equity capital, bank size), event characteristics (the business line in which the operational loss occurred and the size of the operational loss) and other characteristics (GDP, inflation).

Limitations

The presented simplified approaches to measure reputational losses are associated with several restrictions and limitations. In particular, a stock company is needed when using the event study approach, which is based on the very stringent assumption of efficient markets (see McWilliams and Siegel, 1997) and we assume that reputational losses can be described by the cumulative abnormal returns as is done in the empirical literature. In this regard, choosing the appropriate event window is not entirely straight forward, which is why empirical studies typically compare different event windows (mostly up to 20 days around the event window). Furthermore, the task of disentangling reputation from operational losses is complex, and losses in market capitalization used for approximating reputational losses could also be impacted by other aspects, e.g., an initial misestimation of the operational loss size. However, as Johnson et al. (2014) show and as described before, the market value loss is highly consistent with actual reputational losses resulting from an adverse change in customer behavior, for instance. In general, more research is necessary regarding the probability distribution of the cumulative abnormal returns used in the second and third approach. The assumption of a logistic distribution is based on only few observations and only internal fraud events. Overall, the lack of data represents one main limitation, as operational losses are already rare despite growing databases. Given that only large operational losses cause reputation risk, the databases become smaller, and severity distributions are very difficult to estimate.

In general, we are not aware of other empirical or theoretical literature to date that aims to quantify reputational losses in the present setting, and applying the proposed approaches is especially relevant against the background of difficult data availability in order to allow first relevant insight into reputation risks resulting from operational losses, e.g. by using scenario and sensitivity analyses.

4. Numerical Analysis

4.1 Input parameters

There are only a few papers that provide empirical estimates for operational losses depending on the event type and the bank's business line (e.g., Moscadelli, 2004; Angela et al., 2008; Basel Committee, 2008; Dahen and Dionne, 2010; Cummins et al., 2012), and even fewer papers on the empirical quantification of reputational losses resulting from operational losses (e.g., Cannas et al., 2009; Fiordelisi et al., 2013, 2014). Thus, in order to calibrate our model and to obtain first insight into the central effects of the interaction of operational and reputational losses, we use input parameters based on empirical estimates from the literature that ensure a mostly consistent and empirically realistic calibration.

The calibration regarding operational losses is described in the Appendix and makes use of a scaling approach based on Dahen and Dionne (2010), who estimate mean and standard deviation of the severity as well as the intensity of the frequency of operational losses exceeding $1 million for all event types and business lines in case of banks, where we assume a lognormal distribution with truncation point T = $1 million for the operational loss severity and a Poisson distribution for the frequency of the different event types. Reputational losses are added based on the results by Fiordelisi et al. (2014), who are the only ones to explicitly estimate the CAR depending on the event type and business line. Dahen and Dionne (2010) and Fiordelisi et al. (2014) both use Algo OpData. Moreover, their data bases are mostly comparable in regard to the time periods (1994-2003 and 1994-2008) and the number and country of operational loss events, as Dahen and Dionne (2010) include 300 operational losses of U.S. bank holding companies exceeding $1 million and Fiordelisi et al. (2014) use 430 operational losses of European and North American banks exceeding $1 million.

We follow Dahen and Dionne (2010) and consider an illustrative U.S. bank l with market capitalization M^l, total assets A^l, bank capitalization B^l, mean salary S^l and real GDP growth G^l as shown in Table 1 (needed for scaling the external operational losses to the individual firm; note that input parameters for the bank are later varied and are subject to sensitivity analyses). For simplicity we assume that these parameters are constant over time (in the considered period) and then conduct robustness tests. Since information on the market capitalization is not available in Dahen and Dionne (2010), we set this value based on empirical results of Cummins et al. (2006) and ensure that the parameter fits the remaining assumptions.[15] The impact of market capitalization and total assets as well as all other input parameters will be studied in detail later.

In particular, even though the input parameters are calibrated based on mostly consistent data from comparable empirical studies, the distributional assumptions require additional assumptions. We therefore conduct extensive sensitivity analyses in order to assess and illustrate the impact of potentially misestimated input parameters on the results, which also emphasizes the usefulness of the model.

Table 1: Input parameters for the considered firm at time t = 0 (base case)

Market capitalization M^l	\$9 billion
Total assets A^l	\$100 billion
Total average assets in external database A^E	\$38.617 billion
Bank capitalization B^l	0.1
Mean salary S^l	\$50,000
Real GDP growth G^l	3.7

Notes: Parameters (except market capitalization) are based on the parameters of an illustrative firm considered in Dahen and Dionne (2010, p. 1494, Table 9); market capitalization is based on empirical results from Cummins et al. (2006) and calibrated to fit the remaining parameters.

The input data for the (external) operational loss events used to scale the considered firm l are also based on empirical results from Dahen and Dionne (2010) and laid out in Table 2.[16] Reputational losses resulting from operational risk events in the banking industry are based on Fiordelisi et al. (2014) using the mean CAR depending on the event type in percent of the market capitalization (right column of Table 2). The mean CAR is based on the event window (-10,10)[17] for every event type, where Fiordelisi et al. (2014) only consider events without obvious confounding events to ensure that market value losses are attributable to one event only.

15 Cummins et al. (2006) provide statistics of U.S. banks, where the median of the market capitalization is \$11,818 million and the median of the total assets is \$133,381 million. Following Dahen and Dionne (2010), we consider a firm with total assets of \$100,000 million. To approximately ensure the same ratio between total assets and market capitalization as in Cummins et al. (2006), we set the market capitalization to \$9,000 million.

16 Due to a lack of observations, we do not include the two event types “damage to physical assets” and “business disruption and system failures”.

17 Cummins et al. (2012) found this event window to be appropriate for U.S. banks. In addition, we note that the mean CAR for “Execution delivery & process management” (to measure reputational losses) is not significant for the event window (-10,10), but for the event windows (0,10) and (0,20). For consistency reasons, however, the mean CAR is taken for the even window (-10,10) for all event types. We also conducted robustness tests using alternative event windows as shown later.

Table 2: Input parameters of external operational loss data and reputational losses depending on the event type

		*Severity of op. loss in \$ million**		*Intensity of op. loss**	*Severity of rep. loss***
i	*Event type*	*Mean*	*Standard deviation*	*λ_i (see Eq. (9))*	*Mean CAR in % of market capitalization*
1	Internal fraud	9.413	17.855	0.0220	-3.222%
2	External fraud	16.640	31.253	0.0314	-2.519%
3	Employment practices & work-place safety	8.917	15.338	0.0072	-1.617%
4	Clients, products & business practices	31.469	67.281	0.0581	-1.048%
5	Execution delivery & process management	13.869	18.011	0.0072	-0.652%

*Notes: *Dahen and Dionne (2010, p. 1488): estimates for the entire external database; basis for scaling; **Fiordelisi et al. (2014)*

Fiordelisi et al. (2014) consider operational losses exceeding \$1 million and find that operational losses of every event type they consider (on average) cause significant reputational losses, i.e. $H_i^R = 1$. In addition, Dahen and Dionne (2010) also consider only operational losses exceeding \$1 million. Therefore, to obtain the mean operational and reputational losses considering only operational losses exceeding \$1 million as well as the variance of these losses, we do not need any distributional assumptions regarding the severity distribution of the operational losses, as the exceedance probability (Equation (16)) can be omitted since the data is consistent with only taking into account operational losses above \$1 million (see also Equations (15) and (17) in the Appendix for details). However, to determine risk measures such as the value at risk, distributional assumptions are needed.

Given the parameters in Table 1 and the empirical results in Dahen and Dionne (2010) as given in Table 2, using the scaling approaches we obtain the parameters μ_i^l and σ_i^l in Table 3 for a lognormal distribution with truncation point T = \$1 million (severity). Where closed-form solutions (see Appendix) cannot be applied, we use Monte Carlo simulation with 10 million runs, whereby for comparability the random numbers are fixed for all examples. In addition, we ensured the robustness of our results by using different sets of random numbers.

Table 3: Input parameters for the lognormal distribution of operational losses with truncation point T = \$1 million (severity) scaled to firm l (see Table 1) depending on the event type

i	*Event type*	*Lognormal (severity)*	
		μ_i	σ_i
1	Internal fraud	1.497	1.272
2	External fraud	2.168	1.245
3	Employment practices & workplace safety	1.517	1.214
4	Clients, products & business practices	2.733	1.318
5	Execution delivery & process management	2.291	0.999

Notes: The empirical results from Table 2 regarding mean and standard deviation of the severity of operational losses (depending on the event type i) are scaled to the size of firm l in Table 1 (see Appendix for details). Based on these means and standard deviations, we obtain the parameters μ_i and σ_i of the associated lognormal distribution in Table 3 with truncation point T=\$1 million as follows: $E[X]=\exp\left(\mu+\sigma^2/2\right)\Phi(\sigma-a)/\Phi(-a)$ *and* $Var[X]=\exp\left(2\mu+2\sigma^2\right)\Phi(2\sigma-a)/\Phi(-a)-E[X]^2$, *where* $a=(\ln T-\mu)/\sigma$.

4.2 Assessing operational losses incorporating reputational losses using the average reputational loss (mean CAR) – Approach 1

Studying the mean loss

Based on the mostly consistent and realistic input parameters for the base case, we apply the first approach by integrating reputational losses using the average cumulative abnormal returns (CAR) as shown in Table 2. Results are displayed in Table 4 including the mean operational and reputational loss depending on the event type in the base case (Tables 1 and 2), which are derived based on the closed-form expressions (see Appendix for details). As can be seen, the expected reputational loss considerably exceeds the operational loss, which holds for every event type (total reputational loss: \$20.45 million; total operational loss: \$3.23 million).

Table 4: Mean annual operational and reputational loss depending on the *event type* (values in million \$) based on Tables 1 and 2 (see Equations (11) and (15) in the Appendix)

	Operational loss		*Reputational loss*		*Total loss*	
Operational risk event type	Mean	% of total	Mean	% of total	Mean	% of total
Internal fraud	0.25	7.6%	6.39	31.3%	6.64	28.0%
External fraud	0.62	19.2%	7.11	34.8%	7.73	32.6%
Employment practices & workplace safety	0.08	2.4%	1.05	5.1%	1.13	4.8%
Clients, products & business practices	2.17	67.2%	5.48	26.8%	7.65	32.3%
Execution delivery & process management	0.12	3.7%	0.42	2.1%	0.54	2.3%
Sum	3.23	100%	20.45	100%	23.68	100%

While these results appear extreme at a first glance, they are also consistent with findings in Karpoff et al. (2008), for instance, who investigate reputational losses of firms “cooking their books” as a subset of internal fraud and who find that the reputational loss is on average 7.5 times the size of the operational loss. This can also be explained by the fact that the financial reputational loss may consist of several components that accumulate, such as, e.g., a loss of revenue due to a reduced demand by customers or talented employees leaving the firm.

Furthermore, one needs to take into account that we only consider operational losses exceeding $1 million, since in general it is shown that only larger operational losses lead to reputational losses (see, e.g., Fiordelisi et al., 2014). Hence, the ratio of the mean operational loss to the mean reputational loss will presumably change (size of overall mean operational loss will increase, while reputational losses would remain unchanged), when taking into account operational losses below $1 million. According to the Basel Committee (2008, Annex E, p. 8), such smaller operational losses account for 27% to 40% of the total mean operational losses. Another reason for a potential overestimation of reputational losses (relative to the operational losses) could be that the calibration of operational losses (due to lack of alternative data) is based on empirical results for U.S banks, while the calibration of reputational losses is based on empirical results of Fiordelisi et al. (2014) for North American and European banks. According to Fiordelisi et al. (2014), operational losses of European banks are generally higher than North American banks,[18] which also holds for reputational losses. Further analyses in this regard showed that this would generally imply a lower ratio, which however still involves a substantial reputational loss.[19] On the other hand, Fiordelisi et al. (2014) show that small operational losses (between $1 and $10 million) on average lead to similar reputational effects as large operational losses (greater or equal than $10 million), which would imply that the lower average operational loss in our base case (Dahen and Dionne, 2010) would not distort the general results.

Finally, choosing the length of the event window to determine reputational losses also influences the results. In the base case, the length of the event window is 20 days (10 days before to 10 days after the operational loss event), which is appropriate according to the literature (see, e.g., Cummins et al., 2012; Biell and Muller, 2013), leading to a mean reputational loss

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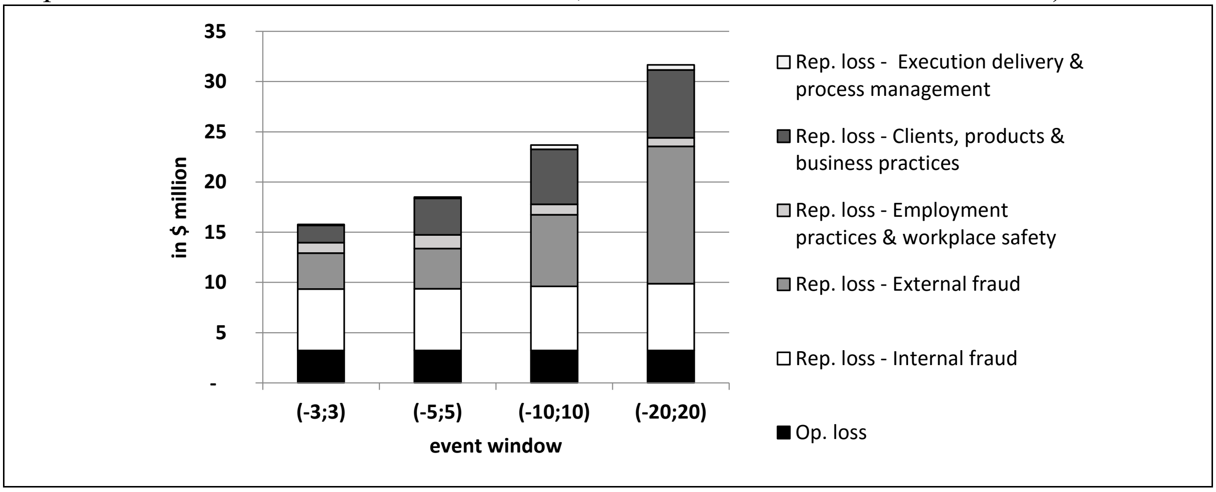
[18] In particular, the observed mean operational loss size in Fiordelisi et al. (2014) for the whole dataset consisting of North American banks and European banks is considerably higher ($83.36 million) than the one used in our base case ($25.79 million), which is calibrated to the firm in Table 1 based on Dahen and Dionne (2010) for U.S. banks.

[19] Without distinguishing between the event types, Fiordelisi et al. (2014) provide separate estimates for reputational losses of European and U.S. banks. Using their aggregate estimates for reputational losses for U.S. banks and the aggregate estimates for operational losses presented in Dahen and Dionne (2010) for U.S. banks, we obtain a mean operational loss of $3.23 million and a mean reputational loss of $11.74 million. Despite the fact that the ratio is much smaller, the mean reputational loss is still considerably higher than the mean operational loss.

of $20.45 million and a total loss of $23.68 million when including the mean operational loss. Choosing a much smaller event window (3 days before to 3 days after the event), for instance, leads to a mean reputational loss of only $12.94 million, which is still considerably higher than the operational loss. As can be seen in Figure 1, smaller event windows lead to a lower mean reputational loss, while a larger event window generally implies higher average losses, whereby the strongest deviations can be seen in case of “external fraud” and “clients, products & business practices”, while “internal fraud” losses remain relatively stable on average. This is consistent with findings in Biell and Muller (2013), who focus on European firms and observe that market reactions due to internal fraud events appear rather quickly, and it suggests that the market model is well specified since larger time windows do not affect the results and only add zeros to the cumulative abnormal returns. Furthermore, regarding other operational loss event types such as “clients, products & business practices”, the market reaction takes a longer time and one does not capture the whole extent of the loss when considering smaller event windows, which is also in line with Biell and Muller (2013). Overall, it seems necessary to at least use a time window of 10 days before to 10 days after the event in order to capture the entire reputational loss (see also Biell and Muller (2013), who find that time windows consisting of 25 days are sufficient, even though larger time windows also increase the probability that other previous events affect the results, and Cummins et al. (2012), who find that a time window of 10 days before to 10 days after the announcement is most appropriate for banks).

In regard to suitable event windows for reputational loss caused by external fraud events, the literature is ambiguous. In particular, the variation of the reputational loss caused by external fraud events depending on the time window in Figure 1 results from the calibration based on results in Fiordelisi et al. (2014), who find that the mean CAR due to external fraud events is larger in the time window (-20,20) than in (-10,10), which is due to higher negative abnormal returns in the time period (-20,-11), i.e. considerably before the loss announcement. This is in contrast to Biell and Muller (2013), who observe that market reactions due to external fraud events usually do not occur so early (but with focus on European firms only). Thus, further research regarding the choice of the event window is highly relevant, also in regard to asymmetric event windows focusing on a few days before the event and more days after the event. However, irrespective of the event window, our results show that the mean reputational loss is considerably higher than the actual mean operational loss.

Figure 1: Mean annual operational loss and mean reputational loss in $ million in the base case depending on the chosen *event window* for different event types (input data regarding reputational losses based on Fiordelisi et al., 2014 and calibrated to the base case)



Therefore, these first results already strongly emphasize the high relevance of reputational losses and ultimately the severe consequences of operational risks, which due to reputational losses (in the sense of market value effects reflecting financial losses) can considerably (and by a multiple) exceed the operational loss for the reasons laid out above.

In addition to the considerable increase in the total mean loss (from $3.23 million to $23.68 million), the relative distribution of the event types *before* and *after* accounting for reputational losses changes considerably. In particular and as expected from previous work, reputational losses are especially relevant for internal fraud and external fraud. Before accounting for reputational losses, for example, internal fraud has a share of 7.6% of the total mean loss, and after accounting for reputational losses the share increases to 28.0% (see Table 4). Similarly, the share of external fraud increases from 19.2% to 32.6% and thus even exceeds clients, products & business practices (32.3%), which by far represented the largest share of operational losses before accounting for reputation risk (67.2%). Therefore, taking into account reputational losses considerably affects the distribution of losses among event types resulting from operational risks. These results also imply that risk management should place special emphasis on these event types and implement effective risk measures to reduce the likelihood and impact of these operational risk event types (see also analyses based on approach 3).

Studying risk measures: Standard deviation and value-at-risk

Similar findings were obtained when considering the standard deviation of losses (i.e. a considerable increase can be observed using closed-form expressions) as shown in Table 5, where diversification effects can be observed in case of the total loss[20] (consisting of operational and reputational losses, right column) as well as in case of studying the standard deviation of the sum of losses for different event types (last row). The diversification effect is particularly pronounced across event types (overall reaching 49.0%).

Table 5: Standard deviation of the annual operational and reputational losses depending on the *event type* (values in million \$) based on Tables 1 and 2 (see Equations (12) and (17) in the Appendix)

Operational risk event type	*Operational loss*	*Reputational loss*	*Total loss*	*Diversification effect between rep. and op. loss*
Internal fraud	3.56	43.05	44.82	3.8%
External fraud	7.45	40.15	44.14	7.3%
Employment practices & workplace safety	1.79	12.35	13.34	5.7%
Clients, products & business practices	21.26	22.73	37.12	15.6%
Execution delivery & process management	2.29	4.98	6.63	8.8%
Sum	36.35	123.27	146.06	8.5%
Standard deviation of the sum of event types (independence between event types)	22.99	64.49	74.55	14.8%
Diversification effect across event types	36.7%	47.7%	49.0%	

To obtain further insight, we additionally consider the value at risk, which is widely used in the banking and insurance supervision (also for operational risk) (see Gatzert and Schmeiser, 2008). In Table 6, we compare different confidence levels of 97.5%, 99.5% and 99.9% using Monte Carlo simulation with 10 million paths. Since the considered operational loss events (exceeding \$1 million) are very seldom in case of the two event types "employment practices & workplace safety" and "execution delivery & process management" (see low intensity in Table 2, No. 3 and 5), the value at risk for the considered confidence level of 97.5% is not positive as the intensity is below 1%, which also holds for several other cases in Table 6. Table 6 further shows that the low intensity can imply an increase in the value at risk when considering the value at risk of the sum of losses across different event types due to higher overall losses, thus indicating a risk concentration rather than diversification benefits.[21] In addition, the higher the confidence level, the higher the diversification benefit, which also results from more available data. These observations emphasize the problem of quantifying operational risk and of deriving solvency capital requirements based on a risk measure in case of low probability and high impact risks. This is even more pronounced in case of reputational

[20] Note that the standard deviation of the total loss can be calculated analogously to Equations (13) and (17) in the Appendix because only operational losses exceeding \$1 million are considered, i.e. the indicator function in Equation (4) is always equal to 1, thus implying independence between the severity of operational and reputational losses.

[21] A comparison of capital requirements under different regulatory regimes based on different risk measures can be found in Gatzert and Schmeiser (2008), who also study the tail value at risk as a coherent risk measure.

losses, which only depend on the frequency distribution of operational losses (with low intensity) with a deterministic loss size (mean CAR) instead of a stochastic loss as is done in the next subsection.

As in case of the mean loss, the value at risk of the total loss is much higher when taking into account reputational losses for all event types, especially for internal and external fraud, which arises as the total loss distribution is shifted by adding the deterministic reputational loss value in Equation (4) to the operational losses.

Table 6: Value at risk (VaR) of the annual operational and reputational losses in the base case depending on the *event type* (values in million \$) for different confidence levels based on Tables 1, 2 and 3

	VaR Operational loss			*VaR Reputational loss*			*VaR Total loss*		
Event type	97.5%	99.5%	99.9%	97.5%	99.5%	99.9%	97.5%	99.5%	99.9%
Internal fraud	-	13.1	41.5	-	290.0	290.0	-	303.4	338.0
External fraud	3.4	31.4	90.8	226.7	226.7	226.7	230.1	259.6	350.1
Employment practices&workplace safety	-	3.1	18.6	-	145.5	145.5	-	148.6	164.4
Clients, products & business practices	19.8	95.6	256.8	94.3	94.3	188.6.3	114.5	206.7	363.3
Execution delivery & process management	-	6.1	29.4	-	58.7	58.7	-	64.7	88.4
Sum	23.2	149.3	437.1	321.0	815.2	909.5	344.6	983.0	1304.2
Value at risk of the sum of event types (independence between event types)	32.3	111.7	274.5	226.7	290.0	466.6	291.8	373.8	556.2
Diversification effect across event types	-39.3%	25.2%	37.2%	29.4%	64.4%	48.7%	15.3%	62.0%	57.4%

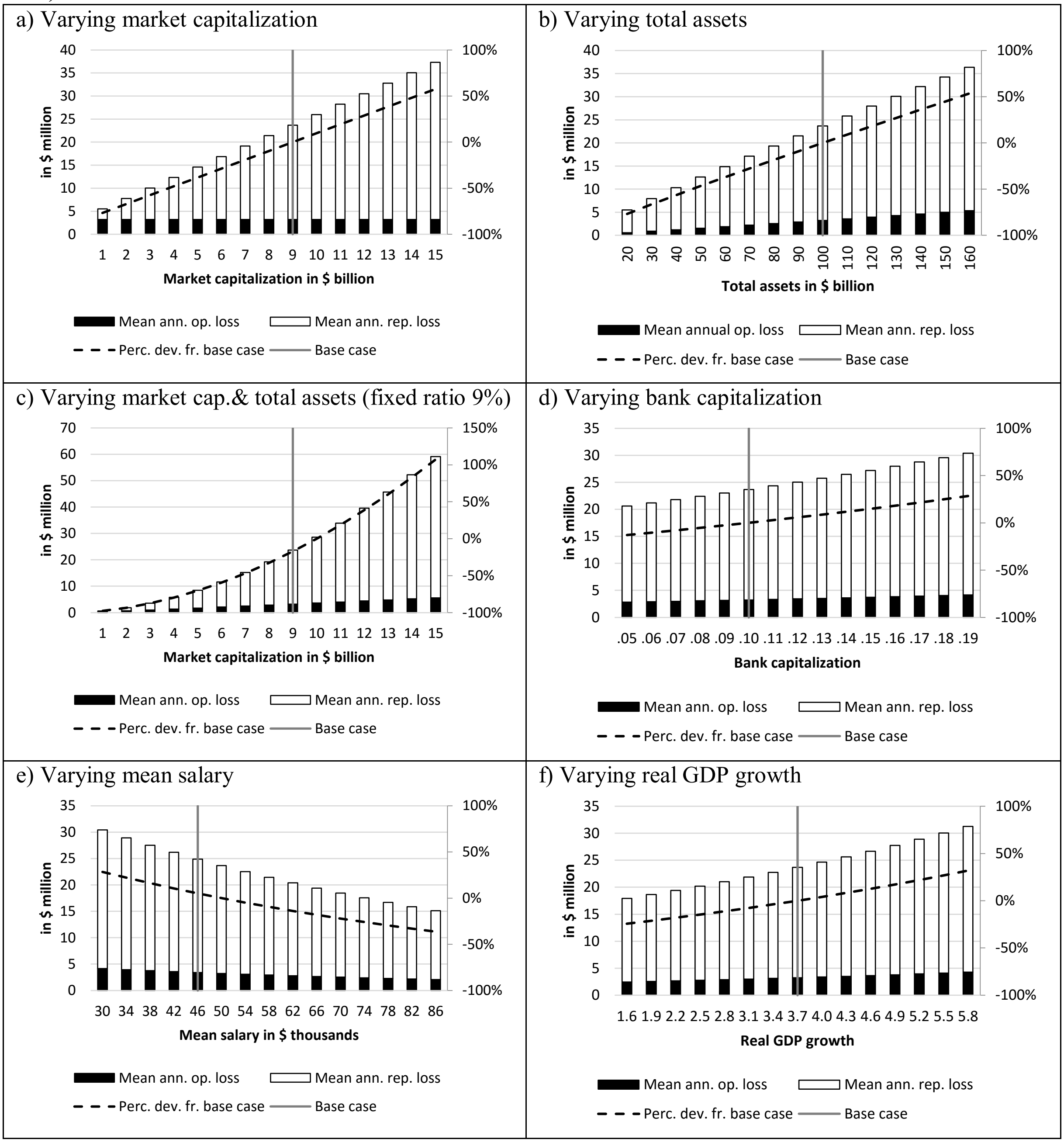
Sensitivity analyses: The impact of firm characteristics and input parameters on operational and reputational losses

Since the use of the scaling model (see Appendix for details) allows investigating the effect of certain firm characteristics on the size of the mean annual operational and reputational loss (see Equations (7) and (10) in the Appendix), Figure 2 presents sensitivity analyses regarding the input parameters from Table 1 to study their impact on the absolute value of operational losses (black bar) and reputational losses (white bar) as well as on the relation between the two. The dashed line refers to the y-axis on the right side and shows the respective percentage deviation of the total mean loss given the new parameters as compared to the base case, which is marked by the grey vertical line.

Figure 2a shows that increasing the market capitalization c.p. leads to higher reputational losses, consistent with the model assumptions, while operational losses remain unaffected. In addition, c.p. increasing the total assets of the considered firm (Figure 2b) implies higher operational losses as well as higher reputational losses, which is consistent with findings in Dahen and Dionne (2010) as well as Fiordelisi et al. (2013). However, also consistent with findings in Fiordelisi et al. (2013), the results show that reputational losses are relatively more severe for larger firms and that the gap between the operational and reputational losses considerably increases for firms with higher asset values.

In the base case (Table 1), the considered firm exhibits a market capitalization of \$9 billion and total assets of \$100 billion, implying a ratio of 9%. Therefore, in Figure 2c, the total assets are adjusted accordingly as the market capitalization is increased to ensure the preset ratio of 9%. As before, we observe that reputational losses are relatively more severe for larger firms despite the same ratio of market capitalization to total assets, indicating that larger firms may exhibit a considerably larger exposure to reputational losses, which is also consistent with the literature (see, e.g., Fiordelisi et al., 2013). Figures 2d and 2f show that the mean annual operational and reputational losses increase with an increasing bank capitalization and real GDP growth, respectively, while Figure 2e shows that losses decrease with an increasing mean salary. However, once again the effects are more pronounced for the reputational loss than for the operational loss. Our findings with respect to operational losses are thereby consistent with results in Dahen and Dionne (2010), who study the frequency and severity of operational losses. Moreover, a higher frequency of operational losses increases the likelihood of more reputational losses and therefore of a higher mean annual reputational loss, which supports our results regarding the reputational losses.

Figure 2: Effects of varying certain firm characteristics on the mean annual operational and reputational losses (in $ million, left y-axis) and percentage deviation from base case (right y-axis)



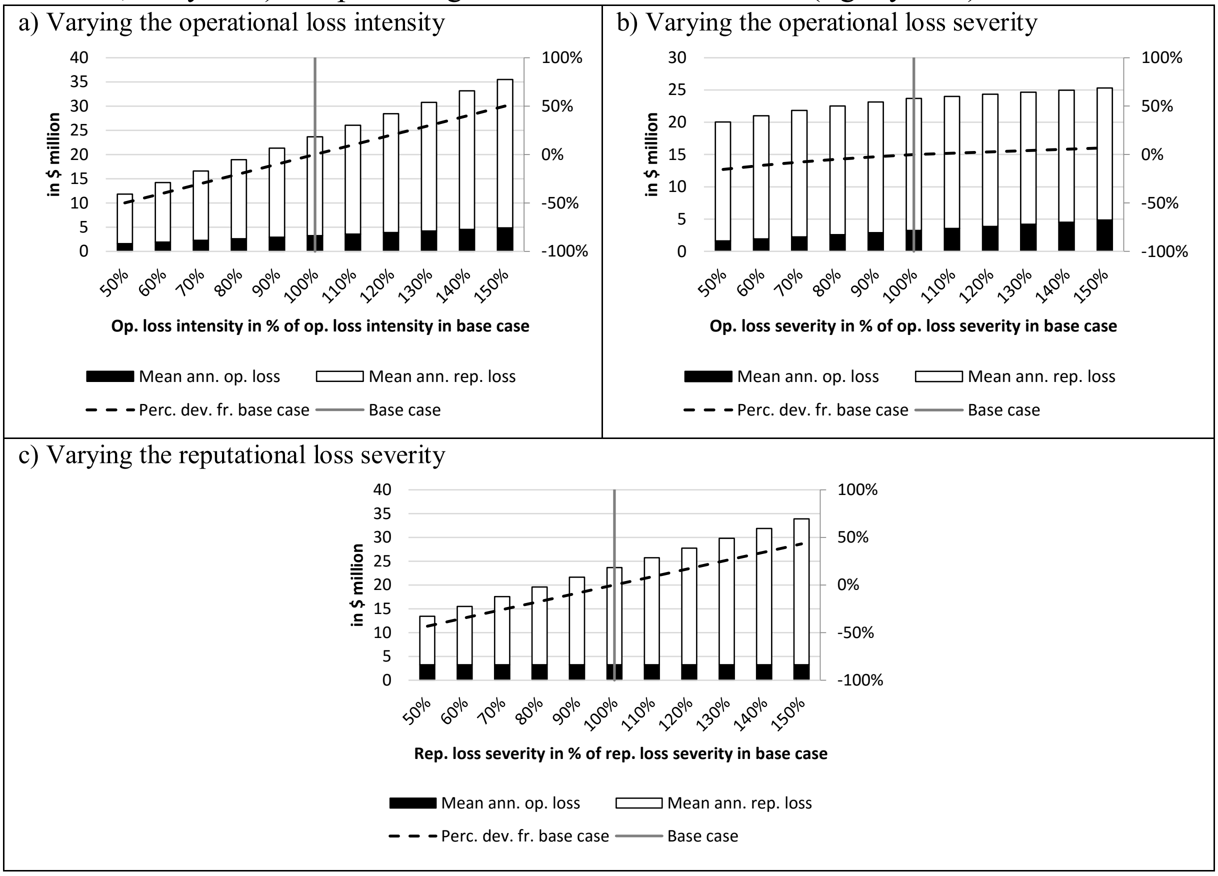
Furthermore, we use the model to conduct comprehensive sensitivity analyses as displayed in Figure 3. This is particularly relevant against the background of the general difficulty with data availability that may imply a potential risk of misestimating input parameters regarding operational and reputational risks (intensity and severity) as discussed at the end of Section 3.

Figure 3a shows the impact of the estimated operational loss intensity on the mean annual operational and reputational loss. The x-axis shows the operational loss intensity in percent of the operational loss intensity in the base case (see Table 2) and the left y-axis the resulting mean annual operational (black bar) and reputational loss (white bar) in $ million. As in Figure 2, the dashed line represents the percentage deviation (right y-axis) of the mean total loss given the adjusted parameters from the base case (grey vertical line). As can be seen from the results, a higher operational loss intensity (than estimated, i.e. above 100% of the base case value) leads to a higher mean annual operational loss size, but the mean annual reputational loss size increases even more, which can be explained by the higher number of operational losses that potentially cause reputational losses. Thus, underestimating the actual operational loss intensity does not only imply an underestimation of operational losses (which is expected), but it can imply a considerable underestimation of reputational losses that result from the underlying operational risk event.

Furthermore, c.p. varying the operational loss severity in Figure 3b between 50% and 150% of the severity in the base case, besides impacting the mean annual operational loss size, also at least slightly affects the mean annual reputation loss size by way of the probability that only large operational losses lead to reputational losses. In general, assuming considerably lower or higher operational losses on average, one can see that the mean annual reputational loss always clearly exceeds the mean annual operational loss. This is also emphasized in Figure 3c, where we varied the reputational loss severity. Assuming reputational losses with a severity of 50% of the severity in the base case, the mean annual reputational loss size is still clearly higher than the mean annual operational loss size.

Overall, the sensitivity analyses and the percentage deviations when comparing the losses calculated using the base case calibration and the adjusted input parameters show that a misestimation of input parameters (e.g. due to difficult data availability) can considerably impact the results, even though the general tendency remains unchanged. However, the findings also emphasize the importance of reputational losses even more, since in all variations, reputational losses clearly exceed the underlying operational losses.

Figure 3: Effects of varying intensity and severity of operational and reputational losses (in $ million, left y-axis) and percentage deviation from base case (right y-axis)



4.3 Assessing operational losses incorporating reputational losses using distributional assumptions for reputational losses – Approach 2

To obtain further insight, in the second approach we assume that the reputational loss (i.e. the CAR) caused by an operational loss of event type i follows a logistic distribution with parameters α_i and β_i, where α_i represents the mean and β_i the standard deviation. To our knowledge, only Cannas et al. (2009) empirically estimate these parameters for reputational losses, stating that a logistic distribution provides a good fit for reputational losses from internal fraud events. To obtain a first impression of the impact of stochastic reputational losses and to keep the numerical analyses as consistent as possible, we use the empirically estimated mean reputational loss from Fiordelisi et al. (2014) that depends on the event type as exhibited in Table 2 (right column) to calibrate α_i, while for β_i we use the estimate from Cannas et al. (2009) for internal fraud events for all event types (due to a lack of alternative data), i.e., while α_i depends on the event type, $\beta_i = 0.0375$ is constant for all i and then varied to examine the impact on the results.

Studying the standard deviation and value at risk

Since the mean reputational loss is set to be the same as in the previous section, the mean operational and reputational losses are the same as in Table 4. Therefore, we directly focus on the standard deviation of the reputational losses as exhibited in Table 7, where we use Equation (17) in the Appendix to derive the reputational loss and analogously derive the total loss. The results show that as expected, the standard deviation of reputational losses is much higher when assuming a logistic distribution for the CAR (driven by β). For example, the standard deviation of the sum of reputational losses from different event types amounts to \$226.57 million as compared to \$64.49 million in case of the first deterministic approach where the volatility only arises from the stochastic frequency of operational losses (Table 5).

Table 7: Standard deviation of the annual operational and reputational losses depending on the *event type* (values in \$ million) based on Tables 1, 2 and 3 (Approach 2) (see Equations (12) and (17) in the Appendix)

Operational risk event type	*Operational loss*	*Reputational loss*	*Total loss*	*Diversification effect between rep. and op. loss*
Internal fraud	3.56	100.56	101.33	2.7%
External fraud	7.45	115.61	117.06	4.9%
Employment practices & workplace safety	1.79	53.41	53.65	2.8%
Clients, products & business practices	21.26	149.26	152.11	10.8%
Execution delivery & process management	2.29	52.20	52.39	3.9%
Sum	36.35	471.04	476.54	6.1%
Standard deviation of the sum of event types (independence between event types)	22.99	226.57	229.63	8.0%
Diversification effect across event types	36.7%	51.9%	51.8%	

At the same time, diversification effects between operational and reputational losses are considerably lower as compared to the first approach (Table 5, right column), but diversification benefits are higher across different event types (e.g., in case of reputational losses 51.9% instead of 47.7% in Table 5, bottom row). Further analyses regarding β confirmed that, as expected, the standard deviation of the sum over different event types considerably increases with increasing β.

As before, we further derive the value at risk for different confidence levels using Monte Carlo simulation with 10 million runs (Table 8). The value at risk for reputational losses (and therefore the total losses) is considerably higher than in Table 6, where the severity of reputational losses was deterministically given by the mean CAR. In addition, while the general results remain the same as in Table 6, the problems regarding the quantification of the value at risk of operational and reputational losses are even intensified in this setting due to the possibility of positive reputation effects arising from the assumption of a logistic distribution (see also the discussion in Section 3.2).

Table 8: Value at risk of the annual operational and reputational losses in the base case depending on the *event type* (values in $ million) for different confidence levels based on Tables 1, 2 and 3 (Approach 2)

	VaR Operational loss			*VaR Reputational loss*			*VaR Total loss*		
Event type	97.5%	99.5%	99.9%	97.5%	99.5%	99.9%	97.5%	99.5%	99.9%
Internal fraud	-	13.1	41.5	-	700.4	1325.3	-	712.5	1336.6
External fraud	3.4	31.4	90.8	-	788.9	1390.5	-	809.9	1413.2
Employment practices & workplace safety	-	3.1	18.6	-	-	760.0	-	-	771.5
Clients, products & business practices	19.8	95.6	256.8	175.4	896.5	1475.3	212.5	943.0	1531.4
Execution delivery & process management	-	6.1	29.4	-	-	672.0	-	-	689.0
Sum	23.2	149.3	437.1	175.4	2389.8	5623.1	212.5	2465.4	5741.7
Value at risk of the sum of event types (independence)	32.3	111.7	274.5	632.5	1279.0	1883.1	660.7	1311.7	1919.5
Diversification effect across event types	-39.3%	25.2%	37.2%	-260.6%	46.4%	66.5%	-210.9%	46.8%	66.6%

4.4 Assessing operational losses incorporating reputational losses using a probability for the occurrence of reputational losses – Approach 3

Finally, following the third approach presented in Section 3 we further investigate the effect of different probabilities for the occurrence of reputational losses, which can also be used for further sensitivity analyses. As in the previous section we assume that reputational losses are logistically distributed with the parameters given in Section 4.3. With the notation from Section 3.2 and following Fiordelisi et al. (2013), we assume that the critical level for reputational damage refers to the CAR in the lowest third of the respective logistic distribution, i.e., $x = q_{i,1/3}$ with $q_{i,1/3}$ being the 1/3-quantile of the CAR distribution. Additionally, as described in Section 3, the probability $p_{i,x}^{l}$ needs to be determined, which could be based on various characteristics of the firm or the event type, for instance. As there is no available data to calibrate the probability, we vary this probability and compare different cases, using $p_{i,x}^{l}$ = 25%, 33%, 50%, where $p_{i,x}^{l}$ = 33% corresponds to the situation in the second approach (since $x = q_{1/3}$). Different probabilities can be seen as different abilities of the firm to handle crisis communication, as different strength of the brand or other abilities regarding reputation risk management.

Studying the mean loss

Since the operational loss is the same as in the previous analysis, we focus on the mean reputational loss depending on the respective case. As expected, the results in Table 9 show that it is important for firms to aim to reduce the probability of reputational losses (even if the size of reputational losses remains the same). For instance, a reduction of the probability of a reputational loss from 50% to 25% leads to reputational losses of only about one fourth (from \$40.60 million to \$10.30 million).

Our analysis also indicates that it is especially worthwhile to reduce the probability of reputational losses following operational losses of the event type “clients, products & business practices”, which shows the strongest sensitivity to the assumed probability. In particular, a reduction of the probability from 50% to 25% leads to a reduction of mean reputational losses from \$14.74 million to \$0.77 million.

Table 9: Mean annual reputational losses depending on the *event type* (values in \$ million) based on Tables 1 and 2 (Approach 3) and depending on the *probability* that an operational loss causes reputational losses

Operational risk event type	$p_{i,x}^{l}$ = 25%	$p_{i,x}^{l}$ = 33% (see Table 4)	$p_{i,x}^{l}$ = 50%
Internal fraud	4.61	6.39	9.90
External fraud	4.62	7.11	12.17
Employment practices & workplace safety	0.46	1.05	2.20
Clients, products & business practices	0.77	5.48	14.74
Execution delivery & process management	-0.16	0.42	1.59
Sum	10.30	20.45	40.60

Further analyses showed that an increase in the probability for reputational losses implies slightly higher standard deviations and that the value at risk increases as well.

5. Summary and Implications

In this paper, we provide a model setting for operational risks which takes into account reputational losses resulting from operational risk events. According to Tonello (2007) and Regan (2008), reputational risk should be considered in enterprise risk management in an integrated way, i.e., when modeling the underlying risks (here: operational risk), its effects on reputation and potential financial consequences should be taken into account. Besides an assessment of reputational risk (here: caused by operational risk), our suggested model framework extends insight from pure empirical event studies, since it allows a more holistic interpretation of previous empirical results on operational and reputational losses and it offers first insight regarding the "true" impact of operational risks for financial firms. Furthermore, it allows conducting integrated scenario and sensitivity analyses for operational and reputational risks, which is also of high relevance under Basel III and Solvency II and of particular importance against the background of difficult data availability, where sensitivity analyses are vital.

Our results based on input parameters from the empirical literature for the banking industry emphasize that reputational losses can by far exceed the original operational losses, which is consistent with previous event studies. In addition, taking into account reputational losses considerably affects the distribution of total losses among different operational risk event types. For instance, internal and external fraud events become the most relevant event types in terms of total losses among all seven event types, which only becomes transparent when considering the consequences of operational risks in an integrated way. These results also imply that risk management should place special emphasis on these event types and implement effective measures to reduce their likelihood and impact. An additional analysis including a potential reduction of the likelihood for reputational damage shows that in the present setting, the event type "clients, products & business practices" exhibits the strongest sensitivity and thus a great potential for the effectiveness of preventive measures.

We also find that diversification across different event types is highly relevant for operational risk, but also for reputation risk, and that this can considerably reduce the overall risk depending on the respective assumed dependencies. We also point out problems associated with quantifying risk using the value at risk for operational and reputational losses due to their low probability and high impact characteristics along with partly insufficient data, and that a qualitative assessment and management of these risks in addition to sensitivity analyses is vital.

The analysis follows the empirical literature by approximating reputational losses with market value losses. In this context, it is not entirely clear in which timeframe market value losses should be considered. Further research would be helpful to investigate the market value of an announcing firm over time and in the long-run. Our analysis would also benefit from more empirical insight regarding the different dimensions of reputational losses and by relating reputation risk events to revenue losses or consumer behavior, for instance.

The proposed approaches to incorporate reputation risk into an operational risk assessment represent first steps to obtain a more comprehensive understanding of the impact of operational risks by making use of the mean reputation loss (which is helpful for first insight due to the generally small database) or by assuming a distribution for reputational losses to illustrate the impact of randomness, which, however, requires further empirical analyses. Furthermore, a transfer of our results (based on empirical results from the banking industry) to the insurance industry would generally require new empirical analyses to calibrate the model based on insurance data. In this regard, sensitivity analyses showed that a misestimation of input parameters (e.g. due to difficult data availability) can considerably impact the results even though the general effects remain unchanged, and the findings also emphasized the importance of reputational losses, since in all cases reputational losses clearly exceeded the underlying operational losses.

Therefore, despite limitations, our findings strongly emphasize that neglecting potential reputational losses may lead to a severe underestimation of the actual impact of operational risk in general and of specific event types in particular (e.g., internal fraud and external fraud) and that an integrated operational and reputation risk management is vital for financial firms, which are particularly exposed to reputation risk. A risk assessment that does not take into account all possible consequences when applying scenario and sensitivity analyses can lead to a possible inadequate allocation of resources in enterprise risk management and to a potential underestimation of the relevance of preventive measures regarding operational risk.

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APPENDIX: THEORETICAL ANALYSES

A.1 Scaling the frequency and severity of operational losses

Frequency and severity of operational losses generally depend on firm characteristics (see, e.g., Dahen and Dionne, 2010). As we need to rely on external databases when calibrating the operational risk model, a scaling model is necessary to adjust the external data to the assumed characteristics of the considered firm *l*. In addition, the scaling model ensures an empirical analysis that is as consistent as possible and allows us to obtain deeper insight regarding the impact of firm characteristics on operational and reputational losses. In what follows, we apply the scaling model proposed in Dahen and Dionne (2010) for banks for the severity and frequency of external operational loss data.

In case a firm *m* that caused an operational loss can explicitly be identified in the external database, one can directly use the observed operational loss $\hat{X}^m_{i^m,j^m}$ (event type i^m and business line j^m) of firm *m* and scale the observed loss by means of the size (measured by total assets) of firms *m* and *l* and depending on the event type as well as the business line of the loss in order to obtain an estimate for the operational loss of firm *l*. Thus, let A^m and A^l be the total assets of firms *m* and *l*, respectively. Dahen and Dionne (2010, p. 1487) show that the operational loss of firm *l* (event type i^l and business line j^l) can be well described by

$$\hat{X}^l_{i^l,j^l} = \hat{X}^m_{i^m,j^m} \cdot \frac{\exp\left(\alpha \cdot \log A^l + \sum_{n=1}^{7} \beta_n \cdot 1_{\{i^l=n\}} + \sum_{p=1}^{8} \gamma_p \cdot 1_{\{j^l=p\}}\right)}{\exp\left(\alpha \cdot \log A^m + \sum_{n=1}^{7} \beta_n \cdot 1_{\{i^m=n\}} + \sum_{p=1}^{8} \gamma_p \cdot 1_{\{j^m=p\}}\right)},$$

where the respective input parameters for the seven event types (*n*) and the eight business lines (*p*) can be found in Dahen and Dionne (2010, p. 1490) ("model 3"). A simplified scaling approach also discussed in Dahen and Dionne (2010), but with considerable less explanatory power as pointed out by the authors, does not distinguish between business lines, assumes that $i^l = i^m = i$, and only scales the observed operational loss $\hat{X}^m_i$ by means of the size (measured by total assets) of firms *m* and *l*. The operational loss of firm *l* is then given by

$$\hat{X}^l_i = \hat{X}^m_i \cdot \frac{\exp\left(0.1809 \cdot \log A^l\right)}{\exp\left(0.1809 \cdot \log A^m\right)} = \hat{X}^m_i \cdot \left(\frac{A^l}{A^m}\right)^{0.1809}. \tag{6}$$

Since external databases generally do not provide information regarding which firm caused the operational loss, thus implying that A^m may not be known, we further adjust Equation (6) by using the average of the total assets of all firms in the considered external database, denoted by A^E. Thus, each observed operational loss in the external database $\hat{X}_i$ can then be approximately scaled to the size of firm l by

$$\hat{X}_i^l = \hat{X}_i \cdot \left(\frac{A^l}{A^E}\right)^{0.1809}. \tag{7}$$

The severity distribution for firm l $X_{i,k}^l$ can thus be estimated based on the scaled observations from the database $\hat{X}_i^l$ in Equation (7). In particular, the expected value and variance of the operational losses of firm l can be extracted from the database by scaling the values (expected value and variance) from the database using Equation (7).

Furthermore, Dahen and Dionne (2010) also provide methods to scale the frequency of operational losses depending on the firm l's characteristics (total assets A^l, bank capitalization B^l,[22] mean salary MS^l,[23] and real GDP growth[24] GDP^l). As we assume that the number of operational losses follows a Poisson process with intensity λ^l, following Dahen und Dionne (2010), this can be expressed by

$$\lambda^l = g\left(A^l, B^l, MS^l, GDP^l\right). \tag{8}$$

As the scaling model does not distinguish between different event types, we extend Equation (8) by taking into account the portion p_i of the respective event type i in the database, i.e.,

$$p_i = \frac{number\ of\ operational\ losses\ of\ type\ i}{number\ of\ operational\ losses},$$

implying that the operational loss intensity of firm l is approximated by

$$\lambda_i^l = p_i \cdot g\left(A^l, B^l, MS^l, GDP^l\right). \tag{9}$$

In addition, since Dahen and Dionne (2010) consider a period of ten years, to obtain the intensity for operational losses in one year, the function g in Equation (9) is obtained by scaling the function in Dahen and Dionne (2010) with a factor of $1/10$, i.e.

[22] Capital divided by total assets (see Dahen and Dionne, 2010).

[23] Salaries and employee benefits divided by the number of full-time equivalent employees on the payroll (see Dahen and Dionne, 2010).

[24] Annual growth of Gross Domestic Product (GDP) depending on the country of firm l (see Dahen and Dionne, 2010).

$$g\left(A^l, B^l, MS^l, GDP^l\right) = \frac{1}{10} \cdot \exp\left(\alpha_1 + \alpha_2 \cdot \log A^l + \alpha_3 \cdot B^l + \alpha_4 \cdot MS^l + \alpha_5 \cdot GDP^l\right), \quad (10)$$

where the respective input parameters can be found in Dahen and Dionne (2010, p. 1493).

Note that these scaling assumptions are only made in order to conduct a more consistent empirical analysis and to obtain deeper insight regarding the impact of company characteristics on operational and reputational losses. One can also assume a distribution for operational losses along with estimated input parameters for the firm and then conduct the same analysis using the approaches proposed in this paper and without using these scaling approaches.

A.2 Operational losses

For the distributional assumptions laid out above (Poisson distribution), the mean operational loss of event type *i* depending on the firm's total assets is thus given by

$$\begin{aligned} E\left[S_i^l\right] &= E\left[\sum_{k=1}^{N_i^l} X_{i,k}^l\right] = E\left[N_i^l\right] \cdot E\left[X_{i,1}^l\right] = \lambda_i^l \cdot E\left[X_{i,1}^l\right] \\ &= p_i \cdot g\left(A^l, B^l, MS^l, GDP^l\right) \cdot \left(\frac{A^l}{A^E}\right)^{0.1809} E\left[X_{i,1}\right], \end{aligned} \quad (11)$$

where the second equation holds according to Wald (1944) and $X_{i,1}$ is one representative for the operational loss of event type i from the external database that is used for scaling firm l's operational losses (identically distributed for all k) (see Equation (7)). The variance of the operational losses is given by

$$\begin{aligned} Var\left[S_i^l\right] &= Var\left[\sum_{k=1}^{N_i^l} X_{i,k}^l\right] = E\left[N_i^l\right] \cdot Var\left[X_{i,1}^l\right] + Var\left[N_i^l\right] \cdot E\left[X_{i,1}^l\right]^2 \\ &= p_i \cdot g\left(A^l, B^l, MS^l, GDP^l\right) \cdot \left(Var\left[X_{i,1}^l\right] + E\left[X_{i,1}^l\right]^2\right) \\ &= p_i \cdot g\left(A^l, B^l, MS^l, GDP^l\right) \cdot \left(\frac{A^l}{A^E}\right)^{0.3618} \cdot \left(Var\left[X_{i,1}\right] + E\left[X_{i,1}\right]^2\right), \end{aligned} \quad (12)$$

where the second equation holds according to Blackwell-Girshick (see Klenke, 2013), because N_i^l and $X_{i,k}^l$ are independent (for all k) and $X_{i,k}^l$ are independent and identically distributed. The expected value and variance of the total operational losses are then given by

$$E\left[S^l\right] = E\left[\sum_{i=1}^{I} S_i^l\right] = \sum_{i=1}^{I} E\left[S_i^l\right] \text{ and} \tag{13}$$

$$Var\left[S^l\right] = Var\left[\sum_{i=1}^{I} S_i^l\right] = \sum_{i=1}^{I} Var\left[S_i^l\right] \tag{14}$$

given that the operational losses are independent for different event types i.

A.3 Reputational losses

Using the first or second approach, based on Equation (4), the expected reputational loss R_i^l associated with an operational loss event type i can be similarly derived by

$$\begin{aligned} E\left[R_i^l\right] &= E\left[\sum_{k=1}^{N_i^l} Y_{i,k}^l\right] = E\left[\sum_{k=1}^{N_i^l} -M^l \cdot CAR_{i,k}^l\left(\tau_1,\tau_2\right)\cdot 1_{\left\{X_{i,k}^l \ge H_i^R\right\}}\right] \\ &= -M^l \cdot E\left[N_i^l\right]\cdot E\left[CAR_{i,1}^l\left(\tau_1,\tau_2\right)\cdot 1_{\left\{X_{i,1}^l \ge H_i^R\right\}}\right] \\ &= -M^l \cdot \lambda_i^l \cdot E\left[CAR_{i,1}^l\left(\tau_1,\tau_2\right)\right]\cdot P\left(X_{i,1}^l \ge H_i^R\right) \\ &= -M^l \cdot p_i \cdot g\left(A^l, B^l, MS^l, GDP^l\right)\cdot E\left[CAR_{i,1}^l\left(\tau_1,\tau_2\right)\right]\cdot P\left(X_{i,1} \ge H_i^R \cdot \left(\frac{A^E}{A^l}\right)^{0.1809}\right), \end{aligned}$$

(15)

where $E\left[CAR_{i,1}^l\left(\tau_1,\tau_2\right)\right] = \overline{CAR_i}\left(\tau_1,\tau_2\right)$ in case of the first and $E\left[CAR_{i,1}^l\left(\tau_1,\tau_2\right)\right] = \alpha_i$ in case of the second approach.

In Equation (15), the only unknown is the probability that the operational loss exceeds the threshold above which a reputational loss occurs. Given that the external database provides the respective information, one can estimate the probability from the number of observations. Alternatively, a certain distribution can be assumed for operational losses, which allows a specific derivation of the probability. In case of lognormally distributed loss severities, this probability is given by

$$P\left(X_{i,1}^l \ge \tilde{H}_i^R\right) = 1 - \frac{1}{\sqrt{2\pi}\sigma_i}\int_0^{\tilde{H}_i^R} \frac{1}{t}\exp\left(-\frac{\left(\ln t - \mu_i\right)^2}{2\sigma_i^2}\right)dt \tag{16}$$

with $\tilde{H}_i^R = H_i^R \cdot \left(\frac{A^E}{A^l}\right)^{0.1809}$, $\sigma_i^2 = \ln\left(\frac{Var\left[X_{i,1}\right]}{E\left[X_{i,1}\right]^2} + 1\right)$ and $\mu_i = \ln\left(E\left[X_{i,1}\right]\right) - \frac{\sigma_i^2}{2}$.

The variance is similarly given by

$$\begin{aligned}
Var\left[R_i^l\right] &= Var\left[\sum_{k=1}^{N_i^l} Y_{i,k}^l\right] = Var\left[\sum_{k=1}^{N_i^l} -M^l \cdot CAR_{i,k}^l\left(\tau_1,\tau_2\right) 1_{\left\{X_{i,k}^l \geq H_i^R\right\}}\right] \\
&= E\left[N_i^l\right] \cdot Var\left[-M^l \cdot CAR_{i,1}^l\left(\tau_1,\tau_2\right) \cdot 1_{\left\{X_{i,1}^l \geq H_i^R\right\}}\right] \\
&+ Var\left[N_i^l\right] \cdot E\left[-M^l \cdot CAR_{i,1}^l\left(\tau_1,\tau_2\right) \cdot 1_{\left\{X_{i,1}^l \geq H_i^R\right\}}\right]^2 \\
&= \lambda_i^l \cdot \left(M^l\right)^2 \cdot \left(Var\left(CAR_{i,1}^l\left(\tau_1,\tau_2\right) \cdot 1_{\left\{X_{i,1}^l \geq H_i^R\right\}}\right) + E\left[CAR_{i,1}^l\left(\tau_1,\tau_2\right) \cdot 1_{\left\{X_{i,1}^l \geq H_i^R\right\}}\right]^2\right) \\
&= \lambda_i^l \cdot \left(M^l\right)^2 \cdot E\left[\left(CAR_{i,1}^l\left(\tau_1,\tau_2\right) \cdot 1_{\left\{X_{i,1}^l \geq H_i^R\right\}}\right)^2\right] = \lambda_i^l \cdot \left(M^l\right)^2 \cdot E\left[\left(CAR_{i,1}^l\left(\tau_1,\tau_2\right)\right)^2 \cdot 1_{\left\{X_{i,1}^l \geq H_i^R\right\}}\right] \\
&= p_i \cdot g\left(A^l, B^l, MS^l, GDP^l\right) \cdot \left(M^l\right)^2 \cdot E\left[\left(CAR_{i,1}^l\left(\tau_1,\tau_2\right)\right)^2\right] \cdot P\left(X_{i,1} \geq H_i^R \cdot \left(\frac{A^E}{A^l}\right)^{0.1809}\right),
\end{aligned} \tag{17}$$

with $E\left[\left(CAR_{i,1}^l\left(\tau_1,\tau_2\right)\right)^2\right] = \left(\overline{CAR_i}\left(\tau_1,\tau_2\right)\right)^2$ in the first and $E\left[\left(CAR_{i,1}^l\left(\tau_1,\tau_2\right)\right)^2\right] = \frac{\beta_i^2\pi^2}{3} + \alpha_i^2$ in the second approach. The expected value and variance of the total reputational loss is derived as in Equations (13) and (14).