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Empirically Assessing and Modeling Spillover Effects from Operational Risk Events in the Insurance Industry

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EMPIRICALLY ASSESSING AND MODELING SPILLOVER EFFECTS FROM OPERATIONAL RISK EVENTS IN THE INSURANCE INDUSTRY

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ABSTRACT

The aim of this paper is 1) to empirically investigate the impact and influencing factors of spillover effects to US and European insurers caused by operational losses in the US and European banking and insurance industry and 2) to propose and calibrate a model for such spillover effects based on the empirical findings, which to the best of our knowledge has not been done previously. Toward this end, we conduct an event study and find significant spillover effects due to operational losses, whereby a higher number of firms faces contagion effects than competitive effects. A regression analysis further reveals that spillover effects are rather information-based than pure, as event and firm characteristics have a significant impact, specifically external fraud, the return on equity of the announcing firm and the similarity between the announcing and the non-announcing firm in terms of size. Based on the empirical findings, we fit a distribution and model spillover effects and underlying operational losses to assess respective risk measures. The results show that spillover risk can be considerable for non-announcing firms as well as from a portfolio view, which has important risk management implications.

Keywords: Spillover effects; operational risk; contagion; event study

JEL Classification: G14; G22; G32

1. INTRODUCTION

Operational losses can result in substantial reputational losses for announcing firms in the financial services industry, as stock price reactions can by far exceed the size of the primary operational loss (see, e.g., Cummins et al., 2006; Cannas et al., 2009; Gillet et al., 2010; Fiordelisi et al., 2013; 2014; Sturm, 2013). However, reputation risks do not only occur due to own actions or inactions, respectively, but also due to associations with third parties such as industry competitors (see, e.g., Csiszar and Heidrich, 2006). Thus, operational losses or adverse events in general do not only affect the announcing firm, but may also have externalities, i.e. spillover effects to non-directly involved non-announcing firms. First empirical investigations of spillover effects from operational risk events by Cummins et al. (2012) and Kaspereit et al. (2017) observe signif-

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icant spillover effects. The consideration of spillover effects is thus not only of high relevance for individual firms, which may suffer financial losses, but also for investors with portfolios consisting of stocks of financial firms as well as insurance companies providing protection against operational losses and such spillover effects (as is the case for the reputation insurance policy by Munich Re, see Gatzert et al., 2016), for instance. Thus, this paper aims to 1) further investigate the impact and determinants of spillover effects from operational risk events for insurers in the US and Europe, i.e., factors that cause (perceived) interconnectedness and links between firms, and 2) to provide a model of spillover effects that is calibrated based on the empirical results, which to the best of our knowledge has not been done previously.

Empirical research concerning spillover effects has been conducted for a variety of distinct events in the banking industry (for reviews see, e.g., Kaufman, 1994; Flannery, 1998), the insurance industry and other industries, with a more detailed overview of respective studies presented in Section 2. From a broader perspective of operational losses in general instead of specific events, Cummins et al. (2012) investigate spillover effects for US banks and insurers and Kaspereit et al. (2017) for European banks, which is thus the closest work to this paper. Most empirical studies also analyze factors that may influence the links between firms in a network and thus the impact of resulting spillover effects, such as firm characteristics of the announcing and the non-announcing firm, the proximity of the firms (e.g., in terms of size or geographical distance) or the event causing spillover effects. Roehm and Tybout (2006) further study when scandals spill over in an experimental setting and Yu and Lester (2008) as well as Yu et al. (2008) theoretically investigate this topic, for instance.

We contribute to the literature by extending previous research in several ways. While Cummins et al. (2012) investigate spillover effects of operational loss events on US insurers *inter alia*, to the best of our knowledge such an analysis has not been conducted including European insurers to date. We further study an extended set of factors influencing spillover effects, especially with respect to the question what constitutes firm networks or similarity in the financial services industry. Most importantly, while Cannas et al. (2009) model reputation risk after internal fraud events for announcing firms, ours is the first paper to (mathematically) model spillover effects of different operational loss types to non-announcing firms using the results of the preceding empirical analyses and to calculate respective risk measures, which has not been done previously.

In particular, we focus on 162 large operational loss events of US and European banks and insurers from 2008 to 2017 taken from the ÖffSchOR database and investigate resulting spillover effects of each event on up to 217 publicly listed US and European insurers. Following the event study literature, spillover effects are calculated as cumulative abnormal returns (CARs) using the five-factor model proposed by Fama and French (2015). Besides investigating the size and significance of the respective spillover effects, we further study the impact of event characteristics, of characteristics of the announcing and the non-announcing firm and of similarities between the announcing and the non-announcing firms by means of regression analyses. Next, we propose a model for spillover effects, which takes respective influencing factors into account and is calibrated based on the empirical analyses, whereby the underlying operational losses are modeled using the scaling approach by Dahen and Dionne (2010). Finally, numerical analyses based on a Monte Carlo simulation are conducted to assess risk measures for spillover effects such as the value at risk (VaR).

The results show significant spillover effects to non-announcing insurers. The findings further support the hypotheses that event characteristics, firm characteristics and similarity between firms influence spillover effects. Specifically, external fraud events, the return on equity (RoE) of the announcing firm and similarity in terms of size exhibit significant effects. In addition, we find that a Laplace distribution describes CARs due to spillover effects best among the considered distributions. Finally, the simulation of spillover effects shows that spillover effects can be highly relevant and thus pose a substantial risk for the respective firms, especially for a high number of relevant announcing firms, and for investors with a portfolio of financial firms. This is also of great importance for insurance companies offering insurance contracts against reputational losses (including spillover effects), which may have to cover the losses of several financial companies insured, thus exhibiting considerable potential for concentration risks.

The paper is structured as follows. Section 2 gives background information on spillover effects, reviews previous literature and develops general hypotheses. Section 3 presents the methodology for empirically assessing spillover effects and their influencing factors. Section 4 provides an approach for modeling spillover effects based on empirical results. Section 5 presents the underlying data and empirical results. In Section 6, the mathematical model for spillover effects is calibrated and numerical results of the simulation are displayed, and Section 7 concludes.

2. Literature Review and General Hypotheses

Spillover effects are the sum of two offsetting effects: “contagion effects” and “competitive effects” (see Lang and Stulz, 1992). Contagion effect means that a non-announcing firm suffers a financial loss like the announcing firm. Stakeholders may conclude that similar adverse events will also affect other firms in the future (see Cummins et al., 2012; Kaspereit et al., 2017). This could lead to an anticipation of higher regulatory costs or, more generally, reduce estimations of expected future cash flows and influence the cost of capital (see Cummins et al., 2012). Apart from intra-industry effects, i.e., from an announcing insurer to a non-announcing insurer, also inter-industry spillover effects from banks to insurers can occur due to a deteriorated reputation of the entire financial services industry, particularly against the background of increasing integration of the financial services market. Insurers thereby compete with banks concerning personal and commercial financial products, as they offer similar products or products with the same goal (see Cummins et al., 2012). For this reason, however, also intra- and inter-industry competitive effects may occur, meaning that non-announcing firms gain from an adverse event of an announcing firm. One main reason for this is that customers might switch from an announcing firm, which is weakened due to an adverse event, to other non-announcing firms (see Cummins et al., 2012; Kaspereit et al., 2017).

Various empirical research studies spillover effects after distinct events by means of an event study. For the banking industry, Aharony and Swary (1983; 1996) and Akhigbe and Madura (2001) investigate the impact of bank failures on rivals, and Goldsmith-Pinkham and Yorulmazer (2010) focus on the bank run and bailout of Northern Rock. Spillover effects of other events studied in the banking industry include loan-loss reserve announcements (see Docking et al., 1997), dividend cuts (see Bessler and Nohel, 2000; Slovin et al., 1999), disclosure of supervisory or regulatory enforcement actions (see Slovin et al., 1999; Jordan et al., 2000), negative earnings surprises (see Prokopczuk, 2010) and stock issues (see Slovin et al., 1992). Brewer and Jackson (2002) and Kabir and Hassan (2005) investigate spillover effects for insurers besides banks in the context of financial distress announcements and the long-term capital management crisis, respectively. Several other studies focus specifically on spillover effects in the insurance industry. The impact of failures of distinct life insurers is investigated by Fenn and Cole (1994), Avila and Eastman (1995), Haley and Sigler (1996), Szewczyk et al. (1997) and Cowan and Power (2001). Egginton et al. (2010) examine spillover effects of the American International Group (AIG) bailout and Jonsson et al. (2009) study two scandals at Skandia. Furthermore, Fields et al. (1998) investigate the influence of financial distress at Lloyd’s of London for property-liability insurers and Angbazo and Narayanan (1996) the impact of Hurricane Andrew, whereby also property-liability insurers with no direct claim exposure are affected. Cheng et al. (2010) focus on spillover effects for insurance brokers and insurers from a civil suit against Marsh in the context of contingent commissions. Park and Xie (2014) examine the impact of reinsurer downgrades on property-liability insurers and also find spillover effects when no reinsurance arrangement between the parties exists. Polonchek and Miller (1999) study the effect of equity issuance of insurers on rivals.

Besides research focusing on the financial services industry, empirical studies on spillover effects for different industries exist. Lang and Stulz (1992) study intra-sector effects of bankruptcy announcements for various industries. In the context of product safety and quality, Bosch et al. (1998) examine externalities of airplane crashes, Freedman et al. (2012) of toy recalls and Jarrell and Peltzman (1985) of drugs and automobile recalls. Hill and Schneeweis (1983) further study the impact of the Three Mile Island nuclear accident for utility firms. Goins and Gruca focus on the impact of layoff announcements as an example of managerial action for non-announcing firms in the oil and gas industry. Intra-industry effects of adverse accounting irregularities for various industries are investigated by Xu et al. (2006) and Gleason et al. (2008).

Empirical research for a broad set of operational loss events is conducted by Kaspereit et al. (2017) and Cummins et al. (2012). Kaspereit et al. (2017) examine spillover effects for European banks caused by operational loss events of publicly traded European banks by means of an event study of stock returns. For this purpose, 72 events with a loss amount of at least EUR 50 million from 2000-2013 are selected from the ÖffSchOR database. Using a four-factor model to calculate CARs, Kaspereit et al. (2017) find significantly negative effects for both announcing and non-announcing firms, which are not significant for smaller loss amounts. Regression analyses show that spillover effects do not depend on firm-specific or on other tested influencing factors apart from the correlation of stock prices as a general indicator of firm similarity. Cummins et al. (2012) study spillover effects of operational risk events for US banks and insurers, traded on NYSE, AMEX or Nasdaq, by calculating CARs with a market-based model. 415 bank and 158 insurance events with a loss amount of at least USD 50 million from Algo OpData from 1978-2010 are investigated. Significantly negative intra- and inter-sector spillover effects are observed, which are similar but smaller in magnitude when using a threshold of USD 10 million for considered events as a robustness check. Conducting regression analyses, Cummins et al. (2012) find significant influences of the natural logarithm of the loss amount of the operational risk event, of Tobin's Q of the non-announcing firm and, for some sub-panels, also of the equity-to-assets ratio of the non-announcing firm. Significant coefficients are also observed for the considered operational loss event type dummies, suggesting different spillover effects for different event types.

Consistent with the majority of prior empirical work, which finds significant spillover effects following various events, our first general Null hypothesis is as follows:

H_1: Operational loss events do not cause spillover effects to non-announcing firms.

Rejecting this hypothesis implies that operational loss events cause spillover effects to non-announcing firms.

One can further differentiate between pure and information-based spillover effects, whereby pure effects refer to irrational re-pricing versus rational re-pricing due to certain characteristics for information-based effects (see Aharony and Swary, 1983). Thus, various research exists on possible factors influencing spillover effects, specifically the proximity or links between firms, firm characteristics in general or circumstances of the underlying event at the announcing firm. In this context, the vast majority of empirical studies conducting cross-sectional analyses of spillover effects finds evidence that spillover effects are rather information-based than pure (see, e.g., Aharony and Swary, 1983; 1996; Bessler and Nohel, 2000; Jordan et al., 2010; Cowan and Power, 2001; Brewer and Jackson, 2002; Cheng et al., 2010; Goldsmith-Pinkham and Yorulmazer, 2010; Cummins et al., 2012), which is also concluded in the literature review by Flannery (1998).

Further general Null hypotheses to be tested are therefore:

H_2: Spillover effects do not depend on event characteristics.
H_3: Spillover effects do not depend on characteristics of the announcing and the non-announcing firm.
H_4: Spillover effects do not depend on similarities between the announcing and the non-announcing firm.

Specific variables, which might influence the size and direction of spillover effects, are explained and defined in what follows. In case no significant influencing factors are detected, spillover effects appear to be purely contagious.

Among the event characteristics, we investigate the impact of *Loss amount*, i.e., the natural logarithm of the size of the underlying operational loss of the announcing firm. Events with a higher loss amount are perceived as more serious in general and ought to cause stronger spillover effects for this reason (see Kaspereit et al., 2017). In addition, as extreme loss events occur less frequently, they are more likely to convey new information (see Cummins et al., 2012). Since empirical research concerning operational losses finds that certain event types, such as external fraud (see, e.g., Fiordelisi et al., 2014) and internal fraud (see, e.g., Gillet et al., 2010; Fiordelisi et al., 2014), have a special role, we further examine the impact of three dummy variables consistent with other empirical studies (see, e.g., Sturm, 2013), *Internal fraud, External fraud* and *CPBP* (clients, products & business practices), in comparison to the reference category of all other operational loss event types.[1]

For the characteristics of the announcing firm *A*, we include $Size_A$ as the natural logarithm of the book value of total assets. Due to higher media and thus investor attention for larger firms (see Akhigbe and Madura, 2001; Kaspereit et al., 2017), we expect to find stronger spillover effects when the announcing firm is large because of greater information transfers (see Goins and Gruca, 2008). Furthermore, we investigate the influence of the profitability of the announcing firm in terms of the return on equity, RoE_A, i.e., net income divided by book equity. Since operational

[1] Operational loss events can be categorized in the following types: 1) internal fraud, 2) external fraud, 3) employment practices and workplace safety (EPWS), 4) clients, products & business practices (CPBP), 5) damage to physical assets (DPA), 6) business disruption and system failures (BDSF), 7) execution, delivery & process management (EDPM) (see Basel Committee on Banking Supervision, 2004, p. 224 f.).

loss events for highly profitable firms are less expected, they may cause higher damage (see Fiordelisi et al., 2013). This could lead to higher competitive effects, but operational loss events at highly profitable firms might also deteriorate the reputation of the entire financial services sector, resulting in contagion effects.

Similarly, with respect to characteristics of the non-announcing firm *NA*, we include $Size_{NA}$ as the natural logarithm of the book value of total assets. Since larger firms have better controls in general (see Kaspereit et al., 2017) and the likelihood of experiencing similar loss events may thus be judged as small, larger firms might see competitive effects after loss announcements of rivals. However, as larger firms are also more complex (see Kaspereit et al., 2017), they are also more vulnerable to operational losses. We also examine the effect of RoE_{NA}, the return on equity of the non-announcing firm. Profitability may serve as an indicator of high status, which in turn grants the benefit of the doubt (see Yu et al., 2008) and may insulate the non-announcing firm (see Jonsson et al., 2009). Moreover, profitable firms have more resources for controls, rendering own adverse events in the future less likely (see Kaspereit et al., 2017), which also supports competitive spillover effects. In addition, we investigate $Leverage_{NA}$ as a proxy for insolvency risk (see, e.g., Cummins et al., 2012), the ratio of the book value of equity to the book value of total assets of the non-announcing firm. Since financial distress is less likely with more equity, such non-announcing firms might experience competitive effects (see Lange and Stulz, 1992; Aharony and Swary, 1996; Akhigbe and Madura, 2001; Cummins et al., 2012). However, richer firms (higher equity-to-assets ratio) are also more likely to be targeted by lawsuits according to the "deep-pocket" theory, rendering losses more probable (see Cummins et al., 2012). Last, we include a dummy variable US_{NA}, which takes the value of 1 for US non-announcing firms and 0 otherwise, i.e., for European firms, to capture potential regional differences, as Fiordelisi et al. (2014) find higher reputation losses in Europe than in North America.

Finally, we study a set of variables concerning the similarity between the announcing and the non-announcing firm. In general, similar firms ought to experience higher market reactions (see Kaspereit et al., 2017). If one organization faces a crisis, stakeholders might conclude that similar events are likely to happen at similar organizations as well (see Yu et al., 2008), thus moving to the alternatives farthest away (see, e.g., Jonsson et al., 2009). Extending the analysis of Kaspereit et al. (2017), who investigate the correlation of stock market returns as a general measure of firm similarity in the context of spillover effects from operational losses, we study in more detail which factors lead to similarity by including four different variables in this regard. First, we measure similarity in terms of size consistent with Jonsson et al. (2009), for instance, and examine *Ratio Size* as one over the absolute difference between the natural logarithm of the book value of total assets of the announcing and the non-announcing firm, whereby higher values thus represent higher similarity in terms of size. Since non-announcing firms more similar to the announcing firm are also punished more for the reasons above, we expect to find contagion effects in case of high size similarity (see, e.g., Aharony and Swary, 1983; 1996). Furthermore, we investigate the effect of *Ratio Leverage*, the equity-to-assets ratio of the non-announcing firm divided by the equity-to-assets ratio of the announcing firm. Since less risky firms are likely to be preferred after an adverse event, competitive effects ought to occur for non-announcing firms with a higher equity-to-assets ratio than the announcing firm. Moreover, we include the dummy variable *Same Industry*, which takes the value of 1 in case the announcing firm belongs to the insurance industry like the non-announcing firm and 0 otherwise, i.e., for announcing banks, to investigate if differences concerning intra- and inter-industry effects are present. While the financial services industry is increasingly integrated, as laid out in the beginning of this section, still more similarity and thus rivalry within one sector can be expected (see Goins and Gruca, 2008), meaning stronger intra-industry effects (also see Brewer and Jackson, 2002). Last, we study the impact of regional proximity by including the dummy variable *Same Region*, which takes the value of 1 if both the announcing and the non-announcing firm are from the US or Europe and 0 otherwise. Since similar economic conditions are present in the same region and the public is more aware of local information, spillover effects might be stronger when regional proximity exists (see, e.g., Aharony and Swary, 1996; Jordan et al., 2000; Brewer and Jackson, 2002; Goins and Gruca, 2008).

3. METHODOLOGY

To empirically assess spillover effects resulting from operational loss events of an announcing firm *A* to a non-announcing firm *NA*, we conduct an event study. As we focus on the insurance industry, we use the five-factor model by Fama and French (2015) as a benchmark model, which allows taking into account common return variations among the sample firms in regard to industry characteristics. The model is described by

$$R_{NA,j,t} - r_{f,t} = \alpha_{NA,j} + \beta_{1_{NA,j}}\left(R_{m,t} - r_{f,t}\right) + \beta_{2_{NA,j}} SMB_t + \beta_{3_{NA,j}} HML_t + \beta_{4_{NA,j}} RMW_t + \beta_{5_{NA,j}} CMA_t + \varepsilon_{NA,j,t}. \quad (1)$$

$R_{NA,j,t}$ is the return of a non-announcing firm *NA* for event *j* on day *t*, calculated from the total return index, which considers dividends and splits. The excess return on the market ($R_{m,t}$ - $r_{f,t}$) is the first factor of the Fama and French (2015) five-factor model with $r_{f,t}$ being the risk-free return, the other factors being SMB_t (small minus big size), HML_t (high minus low book-to-market value ratio), RMW_t (robust minus weak profitability) and CMA_t (conservative minus aggressive investment). The intercept $\alpha_{NA,j}$ and the factors loadings $\beta_{1,\ldots,5\ NA,j}$ are estimated by an ordinary least squares (OLS) regression with error term $\varepsilon_{NA,t}$ for a standard estimation window of 250 trading days, ending one trading day before the first day of the longest event window around the first press date of the loss event (day 0). In case the first press date was no trading day, the next trading day was taken as day 0.

Abnormal returns $AR_{NA,j,t}$ are calculated by subtracting the estimated returns from the observed returns, i.e.,

$$AR_{NA,j,t} = R_{NA,j,t} - \left(\alpha_{NA,j} + \beta_{1NA,j}\left(R_{m,t} - r_{f,t}\right) + \beta_{2NA,j}SMB_t + \beta_{3NA,j}HML_t + \beta_{4NA,j}RMW_t + \beta_{5NA,j}CMA_t + r_{f,t}\right). \quad (2)$$

CARs for an event window from day τ_1 to day τ_2 are then obtained by summing up the respective abnormal returns, i.e.,

$$CAR_{NA,j}(\tau_1;\tau_2) = \sum_{t=\tau_1}^{\tau_2} AR_{NA,j,t}. \quad (3)$$

To test the significance of the CARs and thus H_1, we employ a parametric and a non-parametric test statistic robust to event clustering. Specifically, we use the test statistics proposed by Boehmer et al. (1991) and the generalized sign test by Cowan (1992), in line with Cummins et al. (2012).

To examine the influence of the L = 14 variables on spillover effects as laid out in Section 2 and to thereby test $H_{2\text{-}4}$, we conduct an OLS regression with the CARs as the dependent variable, which is given by

$$\begin{aligned} CAR_{NA,j}(\tau_1;\tau_2) = \alpha &+ \beta_1 Loss\,amount_j + \beta_2 Internal\ fraud_j + \beta_3 External\ fraud_j + \beta_4 CPBP_j + \\ &\beta_5 Size_A + \beta_6 RoE_A + \beta_7 Size_{NA} + \beta_8 RoE_{NA} + \beta_9 Leverage_{NA} + \beta_{10} US_{NA} + \\ &\beta_{11} Ratio\,Size + \beta_{12} Ratio\,Leverage + \beta_{13} Same\,Industry + \beta_{14} Same\,Region + \varepsilon_{NA,j} \\ = \alpha &+ \sum_{l=1}^{L} \beta_l \cdot x_l. \end{aligned} \quad (4)$$

Standard errors are thereby clustered by event, following Jorion and Zhang (2009) and Kaspereit et al. (2017).

4. Modeling Spillover Effects and Underlying Operational Losses

Based on the empirical analysis of spillover effects and influencing factors in networks, we further provide a model of spillover effects resulting from underlying operational losses.

4.1 Modeling underlying operational loss events

Toward this end, we first follow Eckert and Gatzert (2017) and assume that the total operational loss S_A for an announcing firm A in a certain period (e.g., one year) is given by

$$S_A = \sum_{i=1}^{I} S_{A,i} = \sum_{i=1}^{I} \sum_{k=1}^{N_{A,i}} X_{A,i,k}, \quad (5)$$

[2]

where $S_{A,i}$ denotes the operational loss of an announcing firm due to one of the seven Basel II event types i=1,... I (= 7), $N_{A,i}$ represents the number of losses caused by an operational loss of event type i in the considered period and $X_{A,i,k}$ is the severity of the k^{th} operational loss of event type i. For simplification purposes we assume independence between the single losses $X_{A,i,k}$, between the severity $X_{A,i,k}$ and the frequency $N_{A,i}$ of losses, as well as between the respective frequencies $N_{A,i}$. We further assume that $N_{A,i}$ follows a Poisson process with parameter $\lambda_{A,i}$ and that $X_{A,i,k}$ follows a truncated lognormal distribution with truncation point T (due to small losses typically not being recorded in databases) and parameters $\mu_{A,i}$ and $\sigma_{A,i}$. All model assumptions can be changed and extended if necessary, e.g. by taking into account dependencies between the relevant risk processes. In addition, since spillover effects typically occur for larger operational losses, one potential extension is to apply Extreme Value Theory to approximate losses that exceed a certain threshold by modeling heavy upper tails of operational losses above a certain threshold using, e.g. a Generalized Pareto Distribution for the tail (see, e.g., Gourier et al., 2009; Hess, 2011; Gatzert and Kolb, 2014).

To obtain the respective distribution parameters for the operational losses, we adopt the scaling approach by Dahen and Dionne (2010), which allows a differentiation of operational loss events depending on (firm) characteristics, and additionally integrate the adjustment used in Eckert and Gatzert (2017) to differentiate between event types. The parameter $\lambda_{A,i}$ of the Poisson distribution is then given by

$$\lambda_{A,i} = \frac{1}{10} e^{\left(\beta 0_A + \beta 1_A \ln(Assets)_A + \beta 2_A Capitalization_A + \beta 3_A Mean\ Salary_A + \beta 4_A Real\ GDP\ Growth_A\right)} \cdot \frac{number\ of\ operational\ losses\ of\ type\ i\ in\ the\ database}{total\ number\ of\ operational\ losses\ in\ the\ database}. \quad (6)$$

Concerning the severity of operational losses, we use “Model 1” proposed by Dahen and Dionne (2010), again following Eckert and Gatzert (2017), as we do not differentiate by line of business, since the announcing firms in our analysis can be insurers or banks. Thus, an observation of an operational loss event i $\hat{X}_{DB,i}$ from the database can be approximately scaled to a specific firm A ($\hat{X}_{A,i}$) with

$$\hat{X}_{A,i} = \hat{X}_{DB,i} \cdot \frac{\exp\left(\alpha_A \cdot \ln\left(Assets_A\right)\right)}{\exp\left(\alpha_A \cdot \ln\left(Assets_{DB}\right)\right)} = \hat{X}_{DB,i} \cdot \left(\frac{Assets_A}{Assets_{DB}}\right)^{\alpha A}, \quad (7)$$

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2 This model is one way to quantify operational losses, and depending on the respective firm, other approaches might be more suitable. See, e.g., Chaudhury (2010) for an overview of operational risk models.

with α_A being a parameter estimated by Dahen and Dionne (2010), average assets from the database $Assets_{DB}$ and the assets of the respective announcing firm $Assets_A$. Thus, the scaled mean and standard deviation of operational losses (that are assumed to follow a truncated lognormal distribution) for some illustrative announcing firm A is calculated by inserting the average assets from the database $Assets_{DB}$ and the respective mean and standard deviation of the loss amount for event type i $\hat{X}_{DB,i}$ in Equation (7). The parameters $\mu_{A,i}$ and $\sigma_{A,i}$ of the assumed truncated lognormal distribution can then be obtained from these moments (see Eckert and Gatzert, 2017).

4.2 Modeling spillover effects

To model spillover effects mathematically, we proceed in the same way as the event study methodology and consider spillover effects as the market value loss using cumulative abnormal returns for a given event window around the operational loss event date, which is also done in Eckert and Gatzert (2017) for modeling reputational losses. Given that the k^{th} operational loss of type i of the announcing firm A $X_{A,i,k}$ exceeds a threshold H above which spillover effects occur, we define the spillover effect $Sp_{NA,A,i,k}$ to a non-announcing firm NA as the change in its market capitalization $M_{NA,i,k}$ by multiplying the market capitalization with the CAR of the non-announcing firm, i.e.,

$$Sp_{NA,A,i,k} = M_{NA,i,k} \cdot CAR_{NA,i,k}\left(\tau_1,\tau_2\right)\cdot 1_{\{X_{A,i,k}\geq H\}}. \tag{8}$$

Thus, the total spillover effect $Sp_{NA,A}$ to the non-announcing firm due to operational losses of the announcing firm is given by

$$Sp_{NA,A} = \sum_{i=1}^{I}\sum_{k=1}^{N_{A,i}} Sp_{NA,A,i,k} = \sum_{i=1}^{I}\sum_{k=1}^{N_{A,i}} M_{NA,i,k} \cdot CAR_{NA,i,k}\left(\tau_1,\tau_2\right)\cdot 1_{\{X_{A,i,k}\geq H\}}. \tag{9}$$

Since the CARs can take negative or positive values, the net effect of contagion and competitive effects is thus considered. While the frequency of spillover effects for the non-announcing firm is generally assumed to be equal to the frequency of operational losses of the announcing firm, the spillover effect is set to zero in case the operational loss amount is not high enough.

To model the severity of CARs in Equation (9), we fit a distribution function by means of maximum likelihood estimation for the CARs calculated using the event study approach explained in Section 3. In particular, based on the data we later examine four possible continuous distributions for the spillover effects, which are defined for positive and negative values to allow for both contagion and competitive effects: logistic, normal, Gumbel and Laplace distribution.

To take into account the empirical findings concerning influencing factors of spillover effects, the regression analysis of Equation (4) is re-estimated using the L^* significant explanatory variables x to calculate the average CAR as

$$\overline{CAR_{NA,A,i,k}\left(\tau_1,\tau_2\right)} = \alpha + \sum_{l=1}^{L^*} \beta_l \cdot x_l \,, \tag{10}$$

which can then be applied to adjust the first parameter of a fitted distribution.

5. EMPIRICAL RESULTS

5.1 Sample and data sources

Operational loss events as one important underlying cause of spillover effects are taken from the ÖffSchOR database, provided by VÖB-Service GmbH, which was also used by Kaspereit et al. (2017) for spillover effects to European banks and Sturm (2013) for studying reputational effects of announcing firms, for instance. In ÖffSchOR, operational loss events of financial services firms with a loss amount of at least EUR 100,000 have been collected since 2008. Besides descriptions of the event and the loss amount, ÖffSchOR provides information such as the event type of the operational loss according to Basel II, the announcing firm and the press date. We select events from ÖffSchOR with a publicly listed bank or insurer from the US or Europe as the announcing firm with data available from Datastream and take into account events from the year of the beginning of the data collection in 2008 until the end of 2017, i.e., a ten-year event period. This leads to 391 loss events in total. However, as described before, we only use events with a loss amount that exceeds a certain threshold, as large losses attract more attention and therefore ought to be more likely to cause considerable (reputational) spillover effects. We set this threshold to EUR 50 million since we find the highest proportion of significant CARs here, which is also consistent with Kaspereit et al. (2017) and generally with Cummins et al. (2012) (who use a threshold of USD 50 million) and will be subject to robustness checks. This results in 162 operational loss events.[3] Summary statistics for the operational loss data are provided in Table 1.

Table 1: Summary statistics of operational loss data

	Mean	Median	Std.	Min	Max	Number
External fraud	876.33	286.00	1,404.22	60.00	3,700.00	6
Internal fraud	890.07	220.00	1,709.96	70.32	6,320.00	13
CPBP	1,005.56	312.40	1,844.32	51.58	12,554.67	133
Other	496.76	434.28	461.11	50.34	1,498.00	10
Total	960.10	310.70	1,759.35	50.34	12,554.67	162

Notes: The figures are based on operational loss events from 2008 until 2017 with a loss amount of at least EUR 50 million and are displayed in EUR million, where applicable.

[3] For a threshold of EUR 10 million, we obtain 244 operational loss events.

For the event study, we follow Cummins et al. (2012) and consider the event window (-15;15) as the longest event window, which allows sufficient time for market reactions after the event and also accounts for potential information leakage prior to the first press date, and further use various subsets as event windows.[4] Spillover effects of the selected 162 events in terms of CARs are investigated for all publicly listed US and European insurers with market and balance sheet data available from Datastream, which is used as the source for firm data. Data is obtained in EUR, consistent with the currency of the loss amount in ÖffSchOR. Hence, the impact of each event is examined for up to 217 non-announcing insurers. Eliminating observations with missing variables in the regression analysis, we end up with n = 26,912 observations for the base case of the regression analysis. Summary statistics of the announcing and non-announcing sample firms are displayed in Table 2.

Table 2: Summary statistics of sample firms in the data set corresponding to Table 1

		Announcing firms	Non-announcing firms
Number		31	217
	Thereof US banks	8	-
	Thereof European banks	21	-
	Thereof US insurers	0	111
	Thereof European insurers	2	106
Total assets (book value)	Mean	925,348.64	50,806.86
	Median	845,788.25	3,669.24
	First Quartil	326,108.30	380.87
	Third Quartil	1,495,664.73	27,270.27
	Standard deviation	661,136.67	127,621.64
Equity-to-assets ratio (leverage)	Mean	0.07	0.20
	Median	0.06	0.20
	First Quartil	0.05	0.10
	Third Quartil	0.09	0.31
	Standard deviation	0.04	1.05
RoE	Mean	0.05	0.09
	Median	0.06	0.09
	First Quartil	0.05	0.03
	Third Quartil	0.09	0.14
	Standard deviation	0.25	1.32

Notes: Figures refer to the period from 2008 to 2017 and are displayed in EUR million, where applicable.

5.2 Empirical results regarding spillover effects to the insurance industry

Table 3 presents the mean and median values of CARs of non-announcing European and US insurers after announcements of operational loss events for different event windows, as well as two significance tests. The significance tests reveal that significant spillover effects occur for almost all considered event windows, generally rejecting Null hypothesis H_1. For the event windows (-5;5), (-15;15), (0;5) and (0;15), the mean CARs are significantly different from zero at least at a 10% level based on both the applied parametric and non-parametric significance test,

[4] We thank Kenneth French for providing the factors for their five-factor market model for US and European firms online at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

and the mean CARs for the event windows (-1;1), (-10;10) and (0;1) are significant according to the non-parametric test by Cowan (1992).

Table 3: Analysis of spillover CARs

	Mean	Median	BMP	COW
CAR(-1;1)	0.245%	0.000%	1.197	6.104***
CAR(-5;5)	0.455%	-0.012%	1.868*	4.948***
CAR(-10;10)	0.274%	-0.170%	0.165	1.889**
CAR(-15;15)	0.311%	-0.080%	2.457**	4.102***
CAR(0;1)	0.051%	-0.022%	-0.965	3.070***
CAR(0;5)	0.115%	-0.152%	-1.782*	-1.923**
CAR(0;10)	0.223%	-0.126%	0.879	1.232
CAR(0;15)	0.227%	-0.146%	2.164**	1.716**

Notes: BMP is the parametric test-statistic for the mean CAR proposed by Boehmer et al. (1991). COW is the non-parametric test-statistic for the mean CAR of Cowan's (1992) generalized sign test. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Concerning the sign of the CARs and thus the emergence of contagion or competitive effects, we observe that while the mean CAR is positive for all examined event windows and ranges from 0.051% to 0.455%, the median CAR is negative for all event windows with a range from -0.170% to 0.000%. This suggests that firms experience more often contagion effects, but some relatively strong competitive effects occur as well. The absolute magnitude is thereby similar to the results reported by Cummins et al. (2012) for operational loss events of US banks and insurers.

Since the significance tests of the CARs reveal the highest significance level for the event window (-15;15) and this event window also shows the highest proportion of single significance CARs based on an ordinary t-test as suggested by MacKinlay (1997), we use the event window (-15;15) as the base case for the following analyses, consistent with Cummins et al. (2012), and further conduct robustness checks by using different event windows.

To examine which factors influence the emergence of spillover effects and to investigate whether spillover effects are information-based rather than pure, we conduct regression analyses. Table 4 shows the influence of the variables with respect to event characteristics, characteristics of the announcing and the non-announcing firm, and the similarity between firms as laid out in Section 2 on the CARs in the event window (-15;15) as the dependent variable.[5] While the adjusted R^2 is rather low, it is still higher than the one reported by Kaspereit et al. (2017) and Cummins et al. (2012) in a similar context, and the F-statistic is highly significant.

[5] As a multicollinearity check, variance inflation factors were examined. The highest one, being 4.69 for $Leverage_{NA}$, is below the generally cited critical value of 10 (see Marquardt, 1970).

Table 4: Results of the OLS regression with respect to factors that influence spillover effects (Equation (4))

	Regression coefficient	P-value
Loss amount	-0.0006	0.815
Internal fraud	0.0320	0.320
External fraud	0.1401***	0.000
CPBP	0.0062	0.745
$Size_A$	0.0050	0.261
RoE_A	-0.1733***	0.001
$Size_{NA}$	-0.0002	0.865
RoE_{NA}	0.0003	0.716
$Leverage_{NA}$	0.0007	0.841
US_{NA}	0.0089	0.125
Ratio Size	-0.0005**	0.039
Ratio Leverage	0.002	0.454
Same Industry	-0.0249	0.272
Same Region	-0.0049	0.396
Intercept	-0.0616	0.432
n=26,912		
Adj. R^2=0.0179		
P-value F=0.0000		

Notes: The dependent variable is *CAR*(-15;15). Robust standard errors clustered by event are applied. *** and ** denote statistical significance at the 1% and 5% level, respectively.

The regression analysis shows three significant effects. External fraud events have a significantly positive effect compared to other operational loss event types, while the RoE of the announcing firm and a larger similarity between the announcing and the non-announcing firm in terms of size significantly negatively affect the spillover CARs. This means that when a firm faces an external fraud event, non-announcing firms experience rather competitive than contagion effects. Furthermore, in the case of an adverse event at a firm with a high RoE, non-announcing firms *ceteris paribus* also suffer, probably because operational loss events at highly profitable firms deteriorate the reputation of the entire financial services sector. In addition, a relatively high similarity of size of the announcing and the non-announcing firm has a negative impact on CARs, suggesting that firms with similar characteristics (in terms of size) are regarded as more susceptible to similar operational losses.

Thus, the findings reject all three respective Null hypotheses, i.e., characteristics of the operational loss event (H_2), firm characteristics (H_3) and similarities between the announcing and non-announcing firm (H_4) significantly influence spillover effects, which in general seem to be rather information-based than pure, consistent with the results of Cummins et al. (2012).[6]

As a robustness check, we use the CARs for other event windows as the dependent variable in the regression analysis. For the event window (-10;10), for instance, which is also used by Cummins et al. (2012) besides the event window (-15;15), we find the same three significant effects. The RoE of the announcing firm has a significant effect in the regression analyses for all eight considered event windows, the similarity concerning size in six cases and the external fraud dummy variable in five cases. For robustness purposes, we further apply the regression analysis for a lower operational loss amount threshold of EUR 10 million (n=40,892), which also yields the same results, i.e., a significantly positive coefficient of *External fraud* and significantly negative coefficients for RoE_A and *Ratio Size*.

6. Mathematical Model Application with Numerical Simulation Analysis of Spillover Effects

6.1 Input parameters for the underlying operational loss of an illustrative announcing firm

For the purpose of the numerical simulation analysis, we investigate spillover effects of losses originating from one illustrative announcing firm with (firm) characteristics as assumed by Dahen and Dionne (2010) over the period of one year, namely a bank with assets USD 100,000 million (EUR 83,333 million), capitalization (ratio of capital divided by total assets) 0.1, mean salary USD 50 thousand, and real GDP growth 3.7, which are used for scaling in Equations (6) and (7). The further needed parameters for Equation (6) and (7) are displayed in Table 5, based on which the parameters $\mu_{A,i}$ and $\sigma_{A,i}$ of the assumed truncated lognormal distribution can be obtained as shown in Eckert and Gatzert (2017). A summary of the resulting parameters for modeling the frequency and severity of operational losses is provided in Table 6. Realizations of operational losses are obtained by means of a Monte Carlo simulation with 10 million iterations using fixed random numbers to ensure comparability of the results.

[6] We find the same three significant effects when excluding operational loss events announced by insurers, i.e., when only investigating bank events.

Table 5: Relevant input parameters from Dahen and Dionne (2010) to be inserted into Equations (6) and (7)

Regression coefficients		*Descriptive statistics operational loss events*			
			Number	Mean	Std.
Frequency		External fraud	74	16.640	31.253
β_0	-10.0998	Internal fraud	52	9.413	17.855
β_1	0.8858	CPBP	137	31.469	67.281
β_2	2.7740	DPA	2	44.793	61.912
β_3	-0.0125	EPWS	17	8.917	15.338
β_4	0.1323	EDPM	17	13.869	18.011
		BDSF	1	5.584	0
Severity		Total number of losses	300		
α_A	0.1809	Average assets		38,617	

Notes: In USD million, where applicable.

Table 6: Summary of resulting input parameters for modeling operational losses as the basis for spillover effects for an illustrative announcing bank (with assets USD 100,000 million, capitalization 0.1, mean salary USD 50 thousand, and real GDP growth 3.7)

Event type *i*	Frequency (Poisson)	Severity (truncated lognormal)	
	$\lambda_{A,\mathrm{i}}$	$\mu_{A,i}$	$\sigma_{A,i}$
External fraud	0.0314	2.168	1.245
Internal fraud	0.0220	1.497	1.272
CPBP	0.0581	2.733	1.318
DPA	0.0008	3.439	1.034
EPWS	0.0072	1.517	1.214
EDPM	0.0072	2.291	0.999
BDSF	0.0004	1.892	0.000

6.2 Estimating the mathematical spillover model

While the frequency of the spillover effects is driven by the underlying operational loss events, the severity of spillover effects must be separately estimated based on our data set. We thus fit four possible continuous distributions to the empirically observed spillover CARs (see Equation (9)), which are defined for positive and negative values to allow for both contagion and competitive effects (logistic, normal, Gumbel and Laplace distribution). Both the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) indicate that the Laplace distribution (double exponential distribution) based on a maximum likelihood estimation describes the data concerning the spillover CARs among the considered distributions best (AIC=-23,843.06, BIC=-23,826.48), followed by the logistic distribution, which was found to fit reputational losses of the announcing firm following operational loss events best by Cannas et al. (2009). This holds for all examined event windows and also for an operational loss amount threshold of EUR 10 million. For the event window (-15;15) the resulting estimated parameters of the Laplace distribution are μ=-0.000798 and b=0.122695.

To take into account the empirical results of the regression analysis concerning the influencing factors of the CARs in Table 4 when modeling spillover effects by means of a Monte Carlo simulation, the distribution is adjusted as described in Equation (10), depending on firm and event characteristics, i.e. *External fraud*, RoE_A, and *Ratio Size* are needed as the three significant variables that drive spillover effects.[7]

To derive the first parameter of the Laplace distribution, we need further assumptions regarding the announcing and the non-announcing firm. In particular, we study spillover effects from the announcing firm as described in Section 6.1 to one illustrative non-announcing firm. As input parameters (firm characteristics) of the non-announcing firm, we use the average values of the sample of non-announcing insurers considered in the event study for the year 2017, i.e. a market capitalization of EUR 7,730 million and a book value of total assets of EUR 60,186 million. Since no value for the RoE of the announcing firm is provided by Dahen and Dionne (2010), we assume a value of 0.0745 based on data of the announcing firms in our event study for 2017. Overall, this results in the first parameter of the Laplace distribution of μ=0.1168 for external fraud events and μ=-0.0148 for the other event types.

Spillover effects occur each time the underlying operational loss of the announcing firm exceeds the threshold of EUR 50 million, whereby operational losses of the different event types are generated using a Monte Carlo simulation with respective input parameters provided in Table 6.

6.3 Results of the simulation analysis

Table 7 presents the resulting spillover effects for the illustrative non-announcing insurer caused by different types of operational losses of one announcing firm in EUR million and in percent of market capitalization over one year. We can observe that the annual loss due to spillover effects from one announcing firm to the considered insurer amounts to EUR 0.83 million on average, reflecting a -0.01% mean loss in market capitalization, indicating that the contagion effect dominates the competitive effect in general. The VaR for a confidence level of 0.5% suggests that a one-in-200-years loss due to spillover effects from one announcing firm is about EUR 260.54 million, corresponding to 3.37% of the market capitalization. The tail value at risk (TVaR), i.e., the mean of losses exceeding the VaR, for the worst 0.5% of the cases results in EUR 1,209.95 million or 15.65% of market capitalization.[8]

[7] Re-estimating Equation (4) with the significant variables only, results in similar (significant) coefficients as displayed in Table 4, namely 0.1316 for *External fraud*, -0.1700 for RoE_A and -0.0007 for *Ratio Size*.

[8] For a comparison, the simulation was also conducted with the unadjusted estimated parameters of the fitted Laplace distribution, i.e., without considering influencing factors on spillover effects. The general result that the contagion effect dominates the competitive effect remains the same, while the extent of contagion effects is smaller. For instance, the VaR amounts to EUR -180.76 million (2.34% of market capitalization) and the TVaR to EUR -1,127.19 million (14.58% of market capitalization) in this case.

Table 7: Results of the simulation analysis of spillover effects from one announcing firm to an illustrative non-announcing insurer

	Mean	Std.	VaR 0.5%	TVaR 0.5%
In EUR million	-0.83	149.12	-260.54	-1,209.95
In % of market capitalization	-0.01%	1.93%	-3.37%	-15.65%

We further investigate the impact of different assumptions other than the average values for the firm characteristics. We first vary the size of the non-announcing firm, thus affecting size similarity, and consider a small non-announcing insurer (10% quantile of the sample of non-announcing insurers in 2017, assets EUR 121 million), a larger but still below average insurer in terms of size (25% quantile, assets EUR 679 million), an above average insurer in terms of size (75% quantile, assets EUR 47,492 million) and a large insurer (90% quantile, assets EUR 184,345 million). As the assumed size of the non-announcing firm was relatively similar to the size of the announcing firm before, all four alternative cases lead to fewer similarity (smaller or larger). Therefore, the resulting annual loss due to spillover effects is lower. For instance, the mean annual loss varies between EUR 0.64 million and EUR 0.74 million, the VaR between EUR -244.72 million (-3.17% of market capitalization) and EUR -253.54 million (-3.28% of market capitalization) and the TVaR between EUR -1,194.05 million (-15.45% of market capitalization) and EUR -1,202.90 million (-15.56% of market capitalization).

Next, we vary the RoE of the announcing firm by assuming an announcing firm with low profitability (10% quantile of the sample of announcing firms in 2017, RoE 0.0160), an announcing firm with higher but still below average profitability (25% quantile, RoE 0.0528), an announcing firm with above average profitability (75% quantile, RoE 0.0867) and an announcing firm with high profitability (90% quantile, RoE 0.1223). Since the results for the standard deviation are rather similar, we focus the discussion on the remaining statistics. With an increasing RoE, the mean annual spillover effect decreases from EUR 0.10 million to EUR -1.59 million. For the case with particularly low profitability, we thus even find that the competitive effect dominates the contagion effect on average, leading to a small gain, whereby in case of high profitability, the mean annual loss almost doubled compared to the base case. The VaR ranges from EUR -183.32 million (-2.37% of market capitalization) to EUR -323.55 million (-4.19% of market capitalization). The TVaR amounts to between EUR -1,132.59 million (-14.65% of market capitalization) to EUR -1,273.18 million (-16.47% of market capitalization).

Thus, while the relative impact of spillover risks in terms of market capitalization seems to be relatively small when considering the mean of -0.01% of market capitalization of the base case, the consequences for relevant risk measures that are also used for risk-based regulation are considerable. In addition, one has to keep in mind that the results in Table 7 only refer to spillover effects from operational loss events of *one* announcing firm to the considered non-announcing firm. In general, a higher number of potential announcing firms has to be considered and the results can be extended to take this situation into account. For instance, when assuming independence between operational losses in different firms and assuming 100 potential announcing financial services firms (with similar characteristics) instead of only one, this would lead to a mean annual loss due to spillover effects in one non-announcing firm of EUR 83 million (1.07% of market capitalization) instead of EUR 0.83 million. Therefore, the results indicate that spillover effects may indeed represent a considerable risk for firms, which would be even more relevant when considering portfolios of firms that are subject to spillover risk.

7. SUMMARY

This paper empirically investigated spillover effects from operational risk events in banks and insurers as well as relevant influencing factors for insurers and proposed a new mathematical modeling approach for spillover risk that was calibrated based on the empirical data, which was used for a numerical simulation analysis. The empirical analysis was based on an event study for various event windows regarding the impact of 162 large operational losses of US and European banks and insurers from 2008 to 2017 on up to 217 publicly listed US and European insurers per event. Next, we investigated potential influencing factors (event and firm characteristics) concerning the size and direction of spillover effects using regression analyses, thereby also examining what constitutes networks or similarities in the financial services industry. In addition, robustness checks regarding the chosen event window and the operational loss amount threshold above which spillover effects occur were conducted. Based on the data, a distribution for spillover effects was chosen and fitted, which allows positive and negative values to consider contagion and competitive effects. The severity and frequency of the underlying operational loss event types of the announcing firm was modeled using a classical loss distribution approach along with a scaling approach to account for firm and other conditions. Finally, a Monte Carlo simulation was applied to examine descriptive statistics and risk measures of spillover effects from one announcing firm to an illustrative non-announcing firm with average firm characteristics of the insurers in the sample.

The results show significant CARs for almost all considered event windows, supporting the general hypothesis that spillover effects to non-announcing firms occur after the announcement of (large) operational losses. In particular, more firms in the sample appear to experience contagion effects when considering the negative median CAR, but some relatively strong competitive effects as indicated by a positive mean CAR occur as well. The regression analysis concerning influencing factors on spillover effects reveals significant effects of event characteristics, firm characteristics and the similarity between the announcing and the non-announcing firm, also supporting these three general hypotheses. This implies that spillover effects are rather information-based than pure. In particular, external fraud events *ceteris paribus* have a significantly positive impact on the CAR of non-announcing firms. In addition, the RoE of the announcing firm exhibits a significantly negative effect, indicating that operational loss events at profitable firms can deteriorate the reputation of the entire financial services industry, leading to contagion effects. A higher similarity between firms in terms of size has a significantly negative impact on CARs of the non-announcing firm following operational losses as well, as stakeholders consider it likely that similar events also happen at these firms and may thus move to different organizations. The results remain similar when using different event windows and a lower threshold for the size of operational losses.

When fitting the proposed model, we find that spillover CARs are best described by a Laplace distribution among the considered continuous distributions, which holds for all examined event windows and different operational loss size thresholds. Simulating spillover effects dependent on event and firm characteristics based on the previous findings for an average non-announcing insurer, we find that the contagion effect seems to dominate the competitive effect on average, with considerable consequences for the respective risk measures value at risk and tail value at risk, with the latter amounting to about 16% of the non-announcing firm's market capitalization.

Overall, our results emphasize that spillover effects can represent a considerable risk for individual firms, especially for several relevant announcing firms and further depending on the respective network structure (i.e., the influencing factors of spillover effects). Spillover effects should thus be taken into account in risk management considerations and respective measures, such as crisis communication strategies, should be adopted to reduce their impact. The proposed model application can thereby help to quantitatively assess spillover risks and to conduct scenario analysis from a single firm perspective and from a portfolio perspective, which is relevant for investors holding a portfolio of financial firms or insurance companies providing insurance coverage against such spillover effects.

REFERENCES

Aharony, J., Swary, I. (1983): Contagion Effects of Bank Failures: Evidence from Capital Markets. *Journal of Business*, 56(3): 305-322.

Aharony, J., Swary, I. (1996): Additional Evidence on the Information-Based Contagion Effects of Bank Failures. *Journal of Banking & Finance*, 20(1): 57-69.

Akhigbe, A., Madura, J. (2001): Why do Contagion Effects Vary among Bank Failures?. *Journal of Banking & Finance*, 25(4): 657-680.

Angbazo, L. A., Narayanan R. (1996): Catastrophic Shocks in the Property-Liability Insurance Industry: Evidence on Regulatory and Contagion Effects. *Journal of Risk and Insurance*, 63(4): 619-637.

Avila, S., Eastman, K. (1995): The Market Effects of Life Insurer Insolvencies and the Implications for Regulators. *Journal of Insurance Regulation*, 13(3): 302-328.

Basel Committee on Banking Supervision (2004): International Convergence of Capital Measurement and Capital Standards: A Revised Framework. http://www.bis.org/publ/bcbs107.pdf, accessed: 07/25/2018.

Bessler, W., Nohel, T. (2000): Asymmetric Information, Dividend Reductions, and Contagion Effects in Bank Stock Returns. *Journal of Banking & Finance*, 24(11): 1831-1848.

Boehmer, E., Musumeci, J., Poulsen, A. B. (1991): Event-Study Methodology under Conditions of Event-Induced Variance. *Journal of Financial Economics*, 30(2): 253-272.

Bosch, J. C., Eckard, E. W., Singal, V. (1998): The Competitive Impact of Air Crashes: Stock Market Evidence. *Journal of Law and Economics*, 41(2): 503-519.

Brewer, E., Jackson, W. E. (2002): Inter-Industry Contagion and the Competitive Effects of Financial Distress Announcements: Evidence from Commercial Banks and Life Insurance Companies. Working Paper, Federal Reserve Bank of Chicago, Chicago.

Cannas, G., Masala, G., Micocci, M. (2009): Quantifying Reputational Effects for Publicly Traded Financial Institutions. *Journal of Financial Transformation*, 27: 76-81.

Chaudhury, M. (2010): A Review of the Key Issues in Operational Risk Capital Modeling. *Journal of Operational Risk*, 5(3): 37-66.

Cheng, J., Elyasiani, E., Lin. T.-T. (2010): Market Reaction to Regulatory Action in the Insurance Industry: The Case of Contingent Commission. *Journal of Risk and Insurance*, 77(2): 347-368.

Cowan, A. R. (1992): Nonparametric Event Study Tests. *Review of Quantitative Finance and Accounting*, 2: 343-358.

Cowan, A. R., Power, M. L. (2001): Interfirm Stock Price Effects of Asset-Quality Problems at First Executive Corporation. *Journal of Risk and Insurance*, 68(1): 151-173.

Csiszar, E., Heidrich, G. W. (2006): The Question of Reputational Risk: Perspectives from an Industry. *The Geneva Papers on Risk and Insurance*, 31: 382-394.

Cummins, J. D., Lewis, C. M., Wei, R. (2006): The Market Value Impact of Operational Loss Events for US Banks and Insurers. *Journal of Banking & Finance*, 30(10): 2605-2634.

Cummins, J. D., Wei, R., Xie, X. (2012): Financial Sector Integration and Information Spillovers: Effects of Operational Risk Events on U.S. Banks and Insurers. Working Paper, Temple University, Philadelphia.

Dahen, H., Dionne, G. (2010): Scaling Models for the Severity and Frequency of External Operational Loss Data. *Journal of Banking & Finance*, 34(7): 1484-1496.

Docking, D. S., Hirschey, M., Jones, E. (1997): Information and Contagion Effects of Bank Loan-Loss Reserve Announcements. *Journal of Financial Economics*, 43(2): 219-239.

Eckert, C., Gatzert, N. (2017): Modeling Operational Risk Incorporating Reputation Risk: An Integrated Analysis for Financial Firms. *Insurance: Mathematics and Economics*, 72: 122-137.

Egginton, J. F., Hilliard, J. I., Liebenberg, A. P., Liebenberg, I. A. (2010): What Effect Did AIG's Bailout, and the Preceding Events, Have on its Competitors?. *Risk Management and Insurance Review*, 13(2): 225-249.

Fama, E. F., French, Kenneth, R. (2015): A Five-Factor Asset Pricing Model. *Journal of Financial Economics*, 116(1): 1-22.

Fenn, G. W., Cole, R. A. (1994): Announcements of Asset-Quality Problems and Contagion Effects in the Life Insurance Industry. *Journal of Financial Economics*, 35(2): 181-198.

Fields, J. A., Klein, L. S., Myskowski, E. G. (1998): Lloyd's Financial Distress and Contagion within the US Property and Liability Insurance Industry. *Journal of Risk and Uncertainty*, 16(2): 173-185.

Fiordelisi, F., Soana, M.-G., Schwizer, P. (2013): The Determinants of Reputational Risk in the Banking Sector. *Journal of Banking & Finance*, 37(5): 1359-1371.

Fiordelisi F., Soana, M.-G., Schwizer, P. (2014): Reputational Losses and Operational Risk in Banking. *The European Journal of Finance*, 20(2): 105-124.

Flannery, M. J. (1998): Using Market Information in Prudential Bank Supervision: A Review of the U.S. Empirical Evidence. *Journal of Money, Credit and Banking*, 30(3): 273-305.

Freedman, S., Kearney, M., Lederman, M. (2012): Product Recalls, Imperfect Information, and Spillover Effects: Lessons from the Consumer Response to the 2007 Toy Recalls. *Review of Economics and Statistics*, 94(2): 499-516.

Gatzert, N., Kolb, A. (2014): Risk Measurement and Management of Operational Risk in Insurance Companies from an Enterprise Perspective. *Journal of Risk and Insurance*, 81(3): 683-708.

Gatzert, N., Schmit, J., Kolb, A. (2016): Assessing the Risks of Insuring Reputation Risk. *Journal of Risk and Insurance*, 83(3): 641-679.

Gillet, R., Hübner, G., Plunus, S. (2010): Operational Risk and Reputation in the Financial Industry. *Journal of Banking & Finance*, 34(1): 224-235.

Gleason, C. A., Jenkins, N. T., Johnson, W. B. (2008): The Contagion Effects of Accounting Restatements. *The Accounting Review*, 83(1): 83-110.

Goins, S., Gruca, T. S. (2008): Understanding Competitive and Contagion Effects of Layoff Announcements. *Corporate Reputation Review*, 11(1): 12-34.

Goldsmith-Pinkham, P., Yorulmazer, T. (2010): Liquidity, Bank Runs, and Bailouts: Spillover Effects During the Northern Rock Episode. *Journal of Financial Services Research*, 37(2-3): 83-98.

Gourier, E., Farkas, W., Abbate, D. (2009): Operational Risk Quantification using Extreme Value Theory and Copulas: From Theory to Practice. *Journal of Operational Risk*, 4(3): 1-24.

Haley, J. D., Sigler, K. J. (1996): Contagion Effects in the Life Insurance Industry Spring and Summer 1991. *Managerial Finance*, 22(3): 11-27.

Hess, C. (2011): The Impact of the Financial Crisis on Operational Risk in the Financial Services Industry: Empirical Evidence. *Journal of Operational Risk*, 6(1): 23-35.

Hill, J., Schneeweis, T. (1983): The Effect of Three Mile Island on Electric Utility Stock Prices: A Note. *Journal of Finance,* 38(4): 1285-1292.

Jarrell, G., Peltzman, S. (1985): The Impact of Product Recalls on the Wealth of Sellers. *Journal of Political Economy*, 93(3): 512-536.

Jonsson, S., Greve, H. R., Fujiwara-Greve, T. (2009): Undeserved Loss: The Spread of Legitimacy Loss to Innocent Organizations in Response to Reported Corporate Deviance. *Administrative Science Quarterly,* 54(2): 195-228.

Jordan, J. S., Peek, J., Rosengren, E. S. (2000): The Market Reaction to the Disclosure of Supervisory Actions: Implications for Bank Transparency. *Journal of Financial Intermediation*, 9(3): 298-319.

Jorion, P., Zhang, G. (2009): Credit Contagion from Counterparty Risk. *Journal of Finance*, 64(5): 2053-2087.

Kabir, M. H., Hassan, M. K. (2005): The Near-Collapse of LTCM, US Financial Stock Returns, and the Fed. *Journal of Banking & Finance*, 29(2): 441-460.

Kaspereit, T., Lopatta, K., Pakhchanyan, S., Prokop, J. (2017): Systemic Operational Risk: Spillover Effects of Large Operational Losses in the European Banking Industry. *Journal of Risk Finance*, 18(3): 252-267.

Kaufman, G. G. (1994): Bank Contagion: A Review of the Theory and Evidence. *Journal of Financial Services Research,* 8(2):123-150.

Lang, L. H. P., Stulz, R. M. (1992): Contagion and Competitive Intra-Industry Effects of Bankruptcy Announcements. *Journal of Financial Economics*, 32(1): 45-60.

MacKinlay, A. C. (1997): Event Studies in Economics and Finance. *Journal of Economic Literature*, 35(1): 13-39.

Marquardt, D. W. (1970): Generalized Inverses, Ridge Regression, Biased Linear Estimation, and Nonlinear Estimation. *Technometrics*, 12(3): 591-612.

Park, S. C., Xie, X. (2014): Reinsurance and Systemic Risk: The Impact of Reinsurer Downgrading on Property-Casualty Insurers. *Journal of Risk and Insurance*, 81(3): 587-621.

Polonchek, J., Miller, R. K. (1999): Contagion Effects in the Insurance Industry. *Journal of Risk and Insurance*, 66(3): 459-475.

Prokopczuk, M. (2010): Intra-Industry Contagion Effects of Earnings Surprises in the Banking Sector. *Applied Financial Economics,* 20(20): 1601-1613.

Roehm, M. L., Tybout, A. M. (2006): When Will a Brand Scandal Spill over, and How Should Competitors Respond?. *Journal of Marketing Research*, 43(3): 366–373.

Slovin, M. B., Sushka, M. E., Polonchek, J. A. (1992): Informational Externalities of Seasoned Equity Issues: Differences between Banks and Industrial Firms. *Journal of Financial Economics*, 32(1): 87-101.

Slovin, M. B., Sushka, M. E., Polonchek, J. A. (1999): An Analysis of Contagion and Competitive Effects at Commercial Banks. *Journal of Financial Economics*, 54(2): 197-225.

Sturm, P. (2013): Operational and Reputational Risk in the European Banking Industry: The Market Reaction to Operational Risk Events. *Journal of Economic Behavior & Organization*, 85: 191-206.

Szewczyk, S. H., Thomas, M. R., Tsetsekos, G. P. (1997): Contagion Effects in Stock Returns and Analysts' Forecasts: The Case of Mutual Benefit Life Insurance Corporation. *Quarterly Journal of Business and Economics*, 36(1): 3-15.

Xu, T., Najand, M., Ziegenfuss, D. (2006): Intra-Industry Effects of Earnings Restatements due to Accounting Irregularities. *Journal of Business Finance & Accounting*, 33(5): 696-714.

Yu, T., Lester, R. H. (2008): Moving Beyond Firm Boundaries: A Social Network Perspective on Reputation Spillover. *Corporate Reputation Review*, 11(1): 94-108.

Yu, T., Sengul, M., Lester, R. H. (2008): Misery Loves Company: The Spread of Negative Impacts Resulting from an Organizational Crisis. *Academy of Management Review*, 33(2): 452-472.