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Systemic operational risk: spillover effects of large operational losses in the European banking industry

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Systemic Operational Risk:
Spillover Effects of Large Operational Losses in the European Banking Industry

Purpose: The aim of this paper is to study the information content of operational loss events occurring at European financial institutions with respect to the announcing bank's industry rivals from an equity investor's perspective.

Design/methodology/approach: We conduct an event study to identify spillover effects of operational loss events using the Carhart (1997) four-factor model as a benchmark model. In addition, we conduct multiple regression analyses to investigate the extent to which firm-specific factors or the market environment affect abnormal returns.

Findings: We observe significant negative abnormal returns following operational loss announcements exceeding € 50 million for both the announcing firms and their competitors. In addition, we find that stock market reactions occur only within a very small event window around the announcement date, indicating a high degree of market efficiency. Finally, abnormal returns tend to be insignificant for smaller loss amounts.

Originality/value: While operational risk is often believed to be strictly firm-specific, our results show that large operational risk events are not purely idiosyncratic; rather, they are systemic in the sense that they have contagious effects on non-event banks. Thus, we shed new light on how operational risk affects equity investors' investment behaviour in an opaque and highly interconnected banking market.

1 Introduction

Along with credit risk and market risk, operational risk – defined by the Basel Committee on Banking Supervision as "*the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events*" (BCBS, 2006, p. 144) – has been considered a crucial risk category by bank risk managers as well as by financial market supervisors since at least the adoption of the Basel II Accord in the EU in 2006, and it has received considerable and increasing attention in academic research since the early 2000s. The aim of this paper is to study stock market investors' reactions to the announcement of operational loss events occurring at European financial institutions. In an informationally efficient capital market, such negative surprises with respect to a firm's financial health should be reflected almost instantaneously in the latter's stock price. However, in a highly interconnected financial market, it is less clear whether and how the firm's competitors are affected by the event. There may be a strong connection between an affected financial institution and its competitors, such as would be the case if, for example, negative and material information issued by a financial institution were to alter market participants' perception of the firm's rivals. The following example illustrates the underlying problem. Following a lengthy investigation by U.S. and European authorities, several financial institutions were fined for being involved in setting a key benchmark rate. In Europe, the Financial Services Authority (FSA) imposed a £ 59.5 million penalty on Barclays Bank for manipulating the London Interbank Offered Rate ("LIBOR") and the Euro Interbank Offered Rate ("EURIBOR") in June 2012.[1] Barclays Bank was the first bank to be fined by the FSA, but since then, other investigations into similar allegations have led to fines being imposed on several other financial institutions, including UBS (£ 160 million)[2] in late 2012, the Royal Bank of Scotland (£ 87.5 million)[3] and Rabobank (£ 105 million)[4] in 2013, Lloyds Bank (£ 105 million)[5] in 2014, as well as Deutsche Bank (£ 226 million)[6]

[1] http://www.fsa.gov.uk/static/pubs/final/barclays-jun12.pdf (accessed December 14, 2015).
[2] http://www.fsa.gov.uk/static/pubs/final/ubs.pdf (accessed December 14, 2015).
[3] http://www.fsa.gov.uk/static/pubs/final/rbs.pdf (accessed December 14, 2015).
[4] http://www.fca.org.uk/static/documents/final-notices/rabobank.pdf (accessed December 14, 2015).
[5] http://www.fca.org.uk/static/documents/final-notices/lloyds-bank-of-scotland.pdf (accessed December 14, 2015).

one year later.[7] These examples raise at least two questions: Do stock market investors anticipate negative (i.e., contagious) effects on other financial institutions, for instance increases in counterparty risk? Or do they, rather, take operating losses occurring at one financial institution as an indication of competitive advantages for other market participants, leading to positive stock market reactions that benefit the competitors?

We follow an event study approach to answer these questions and to investigate both the direction and the strength of potential spillover effects of operational risk events in the European banking industry. We observe significant negative abnormal returns following operational loss announcements exceeding € 50 million for both the announcing firms and their competitors. In addition, we find that stock market reactions occur only within a very small event window around the announcement date, indicating a high degree of market efficiency. Moreover, abnormal returns tend to be insignificant for smaller loss amounts and do not seem to be sensitive to firm-specific or macroeconomic factors other than to the correlation between the stock prices of the announcing firm and those of the industry rivals. Finally, in line with Moosa and Li (2013)[8] and contrary to studies by Fiordelisi et al. (2013), Gillet et al. (2010), and Sturm (2013), we do not find evidence in favour of reputational damage due to operational loss announcements for our sample of European banks. All in all, we contribute to the literature on operational risk by showing that large operational loss events are not purely idiosyncratic but systemic in the sense that they have contagious effects on non-event banks. Thus, we shed new light on how operational risk affects equity investors' investment behaviour in an opaque and highly interconnected banking market.

The remainder of the paper is structured as follows. In Section 2, we provide a brief overview of relevant literature and develop the hypotheses to be tested. Section 3 outlines the data and the methodology used. Section 4 discusses our empirical results. Section 5 concludes.

[6] http://www.fca.org.uk/your-fca/documents/final-notices/2015/deutsche-bank-ag (accessed December 14, 2015).
[7] Ashton and Christophers (2015) and McConnell (2013, 2014) provide comprehensive descriptions of the LIBOR scandal as well as respective regulatory actions that were triggered by these events.
[8] Analysing market reactions to 163 operational loss events at British firms Moosa and Li (2013) show that declines in market value do not exceed reported loss amounts and hence imply no evidence in favour of reputational damages due to the announcement of operational loss events.

2 Hypotheses

Negative spillover effects of corporate events such as bank failure have been studied extensively for the U.S. financial industry (e.g., Aharony and Swary, 1983, Akhigbe and Madura, 2001, Jorion and Zhang, 2007, Lamy and Thompson, 1986, and Pettway, 1980), across different countries (e.g., Ferreira and Gama, 2007, Gande and Parsley, 2005, and Iyer and Peydró, 2011), and for other industries (e.g., Cohen and Frazzini, 2008).[9] In addition, Lang and Stulz (1992) contribute to the spillover literature by showing that a bankruptcy announcement can also positively affect industry rivals, indicating a competitive, rather than contagious, effect. In this case, the bankruptcy announcement increases the probability that rivals will benefit from growing demand and a reallocation of market shares.

Compared to events like corporate bankruptcies (Jorion and Zhang, 2007),[10] large operational losses are typically harder to predict and thus not fully anticipated by stock market investors (Chernobai et al., 2011). As a consequence, the announcement of operational losses provides an interesting starting point for studies on banking market microstructure and on investor behaviour in opaque but highly interconnected markets (e.g., Biell and Muller, 2013, Cannas et al., 2009, Cummins et al., 2006, Fiordelisi et al., 2013, 2014, Gillet et al., 2010, Moosa and Silvapulle, 2012, Perry et al., 2005, and Sturm, 2013).

Among the pioneering studies with a focus on operational risk of banks and insurance companies, Cummins et al. (2006) base their analysis on 403 loss data from Algorithmics, Inc., a database that contains operational loss events, and found a strong statistically significant negative impact on stock price reactions to operational loss announcements for US banks and insurers. Moreover, their results show that the market value loss significantly exceeds the operational loss amount reported in the news, indicating a negative impact on company reputation. Perry et al. (2005) find, based on 115 operational loss events occurring at financial firms worldwide, an immediate impact on market value and that the market value declines twice as much if the loss is caused by internal events like fraud. They conclude that internal fraud has a negative impact on reputation.

[9] See Kaufman (1994) for a review of earlier studies on bank contagion.

[10] Jorion and Zhang (2007) show that corporate bankruptcies tend to be anticipated by stock market investors, leading to weaker spillover effects than observed, for instance, in case of a sudden shock to a firm's CDS spread.

Interestingly, though, the intersection of these two areas – spillover effects of corporate events and operational losses – is covered by only very few academic studies. For instance, in a conceptual paper, Moosa (2007) discusses whether operational risk is really idiosyncratic or whether there should be contagious effects of operational risk events. Similarly, McConnell and Blacker (2011) discuss systematic properties of operational risk in the context of the recent global financial crisis.

Among the very few empirical papers on the impact of operational losses on non-announcing firms is a study by Cummins et al. (2012). They analyse the market value impact of 573 operational loss events on non-announcing U.S. firms (both financial and insurance companies) between 1978 and 2010, as recorded in the Algo First database. They show that operational loss events have a negative influence on returns of non-announcing financial institutions and insurers within as well as across the financial industry. Moreover, they show that spillover effects seem to depend on firm characteristics, rather than being purely contagious.

Based on the assumption that financial markets exhibit a high degree of informational efficiency, we expect banks' market values to react negatively shortly after the announcement of an operational loss event. Hence, our first hypothesis is as follows:

Hypothesis 1: *Operational loss events have a negative impact on the stock prices of announcing financial institutions.*

Prior event studies on the stock market impact of operational risk events indicate that the decline in the announcing financial institution's market value may be even larger than the loss itself (e.g., Cummins et al., 2006, Fiordelisi et al., 2014, Gillet et al., 2010, and Sturm, 2013). However, evidence regarding this effect is typically mixed (e.g., Sturm, 2013). Assuming that operational losses convey negative information to the stock market in excess of the loss itself, we propose the following second hypothesis:

Hypothesis 2: *Declines in the market values of financial institutions announcing operational losses are larger than the loss itself.*

Large operational loss events may induce either negative or positive stock market reactions. On the one hand, Aharony and Swary (1983) argue that losses due to fraud are uncorrelated among banks and that operational loss events in general should be idiosyncratic. As a consequence, spillover effects on other banks should not occur. On the other hand, a financial institution's announcement of a large operational loss may raise concerns on the part of other banks' shareholders with respect to the stability of their particular investment target or of the banking industry as a whole, which may lead to a negative spillover effect. Thus, it is conceivable that operational loss announcements signal an increased likelihood of future operational losses at other financial institutions. Since the quality of a firm's risk management system is typically hard to assess for outside investors, an unexpected operational loss announcement at one bank may induce market participants to update their beliefs about the quality of risk management at other banks, potentially leading to an industry-wide decline in stock prices. However, operational risk events may also induce positive spillover effects, leading investors to withdraw from the announcing firm and instead to invest in stocks of competing financial institutions. As these contagion and competition effects may appear simultaneously, we are interested in the net effect and propose the following third hypothesis:

Hypothesis 3: *Large operational losses have an effect on the market value of the announcing bank's industry rivals.*

Finally, following previous literature on spillover effects caused by bank failures (Akhigbe and Madura, 2001, Lang and Stulz, 1992) or by operational risk announcements in the financial industry (Cummins et al., 2012), we analyse whether such spillover effects are purely contagious or rather information-based, depending on firm-specific, event-specific, or macroeconomic factors. A discussion of relevant factors and of our expectations regarding their respective signs is included in Subsection 3.3. Our fourth and final hypothesis is as follows:

Hypothesis 4: *Spillover effects of operational losses vary conditional on firm-specific, event-specific, and macroeconomic factors.*

3 Data and Methodology

3.1 Sample Selection

Our sample contains 72 operational loss events recorded in the ÖffSchOR database[11] with expected losses exceeding € 50 million that occurred between January 2000 and December 2013 and relate to publicly traded banks from a country on the FTSE[12] list of countries in developed Europe.[13] Unlike Cummins et al. (2012), we do not differentiate between investment banks and commercial banks, as most European banks are universal banks that employ both business models.

We define the dates at which the operational losses were first announced as event dates, and we use Nexis to verify whether the announcement dates contained in ÖffSchOR database are correct. Nexis contains business information as well as general news provided by newspapers, professional and trade magazines, company profiles, and industry reports from a variety of sources (http://www.lexisnexis.com/en-us/products/nexis.page). Whenever we find an earlier press release in Nexis, we adjust the announcement date accordingly. If the announcement date is not a trading date, we define the next trading day as the announcement date. The mean value of the maximum expected loss in our sample is € 586 million. Since some events relate to more than one firm or occurred at the same date, the total number of distinct event dates for which we analyse spillover effects is 62.

3.2 Measuring Abnormal Returns

We conduct an event study[14] to identify spillover effects of operational loss events. In a first step, we measure abnormal stock returns for banks that announce an operational loss during the event window t = -10 to t = +10, with day zero being the respective announcement day. While this part of the analysis has been conducted before on a similar dataset by Sturm (2013), it serves as a test of whether the event dates are specified correctly and whether the events are informative. In a second step, we address our main

[11] ÖffSchOR is managed by the Association of German Public Sector Banks (Bundesverband öffentlicher Banken). For further details, see http://www.voeb-service.de/ (accessed on 29 August 2016).

[12] These countries are Austria, Belgium, Luxembourg, Denmark., Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.

[13] A list with all events, their estimated loss amount, and the event date are available on request.

[14] The standard event study methodology is comprehensively explained by Kothari and Warner (2007) and MacKinlay (1997).

research questions and determine abnormal returns on competitor portfolios. Specifically, we estimate the parameters of the benchmark model during the pre-event period ranging from t = -220 to t = -20 by regressing daily returns of value-weighted competitor bank portfolio returns on factor returns of the benchmark model. As a benchmark model, we apply the Fama and French (1992, 1993, 1996) model, including the extension proposed by Carhart (1997). Thus, explanatory factors include overall market return MKT_{it}, the factor SMB_{it} that captures return differences between small and large stocks, the factor HML_{it} that captures return differences between stocks with high and low book-to-market equity, and the factor MOM_{it} that captures differences in returns between past winner and past loser stocks. The factors used in this study are determined for the cluster of countries from developed Europe as defined by FTSE. We follow the approach outlined in Fama and French (1993), and Carhart (1997) but estimate MKT_t, SMB_t, HML_t, and MOM_t on a daily basis. Both market and accounting data are obtained from Compustat Global. The momentum factor, MOM_{it}, captures return differences between two portfolios of firms with above- and below-median returns in the previous 250 trading days, respectively.

Portfolio returns R_{Pt} are determined using all listed companies with a SIC code between 6000 and 6999 that are incorporated in a FTSE Developed Europe country and are available in Compustat. We only exclude from the sample firms that announce an operational loss at the event date or on any other day during the event window. In this manner, we ensure that our results reflect the spillover effects of operational loss events only and are not diluted by market reactions to direct operational loss exposure. Building portfolios for each event is a conservative approach to controlling for cross-correlation of returns, an econometric issue that is present in studies on single events affecting multiple firms (Jaffe, 1974; Kolari and Pynnonen, 2010). Thus, the model to estimate abnormal returns, AR_{Pt}, subtracts the expected return (i.e., the term in parentheses) from the observed return, R_{Pt}, during the event period:

$$AR_{Pt} = R_{Pt} - (RF_t + \alpha_P + \beta_P (MKT_t - RF_t) + s_P SMB_t + h_P HML_t + m_P MOM_t) \tag{1}$$

where P denotes an index that is specific to the event and competitor portfolio and t denotes the trading day relative to the event day. RF_t is a proxy for the risk-free rate, for which we choose short-term interest rates for the Euro area from the website of the Organisation for Economic Co-operation and Development. Note that the coefficients α_P, β_P, s_P, h_P, and m_P in Equation (1) are drawn from an ordinary least squares regression based on data from the pre-event estimation period, which in our study spans from day t = -220 to t = -20 relative to the event date. The abnormal returns are then estimated during the event period ranging from t = -5 to t = +5.

After determining abnormal portfolio returns in accordance with Equation (1), these returns are aggregated across *N* events, as outlined in Equation (2). AAR_t is the average abnormal return at day t relative to the event date.

$$AAR_t = \frac{1}{N}\sum_{p=1}^{N} AR_{Pt} \tag{2}$$

Since capital market reactions may extend over several days, we aggregate average abnormal returns across time. Aggregating average abnormal returns from $t = \tau_1$ to $t = \tau_2$ yields the cumulative average abnormal return, $CAAR[\tau_1, \tau_2]$.

$$CAAR[\tau_1, \tau_2] = \sum_{t=\tau_1}^{\tau_2} AAR_t \tag{3}$$

To test the hypothesis that firm- and event-specific factors affect abnormal returns of competitor banks, we calculate cumulative abnormal returns, $CAR_i[\tau_1, \tau_2]$, by aggregating each firm's abnormal returns across time.

$$CAR_P[\tau_1, \tau_2] = \sum_{t=\tau_1}^{\tau_2} AR_{Pt} \tag{4}$$

We choose three established test procedures to assess statistical significance of abnormal returns in the presence of cross-correlation. Cross-correlation is an econometric issue that may be present in our study even after we build portfolios because event or estimation windows partly overlap in calendar time (Karafiath, 2008). The first test is the crude dependence adjustment test proposed by Brown and Warner (1980, pp. 223, 253), which accounts for cross-correlations between abnormal returns by calculating the standard error on the basis of pre-event period average abnormal returns. The second is the test of standardized residuals corrected for event-induced changes in volatility and cross-correlation developed by Kolari and Pynnonen (2010, p. 4003). The third test we apply is the non-parametric rank test corrected for event-induced changes in volatility of rankings as proposed by Corrado and Zivney (1992, p. 475). We perform rank tests for cumulative average abnormal returns in accordance with Cowan (1992, p. 346).

We deal with the issue of thin trading by applying the trade-to-trade approach as outlined in Maynes and Rumsey (1993, pp. 148–149). In addition, we include only those observations in the analysis for which Equation (1) can be estimated with at least 50 observations.

3.3 Cross-Sectional Variation in Abnormal Returns

To test the hypothesis that firm- and event-specific factors affect abnormal returns of competitor banks, we use the regression approach outlined in Equation (5). Event- and firm-specific cumulative abnormal returns are regressed on the most recent values of several factors identified in prior literature as potential determinants of operational losses (e.g., Chernobai et al., 2011) or of spillover effects induced by other types of events with negative information content (e.g., Jorion and Zhang, 2009).

The variable $lnMVE_i$ is the natural logarithm of the market value of equity of the announcement firm. Market value of equity is measured as the product of price per share (Compustat item PRCCD) and common shares outstanding (CSHOC). We expect that the larger the firm that announces the operational loss event, the larger the impact on competitor firms (e.g., Krause and Giansante, 2012). Larger firms have higher media coverage, and their operational losses therefore are more likely to attract investors' attention. $lnLOSS_i$ is the natural logarithm of the maximum expected loss in millions of euros. We hypothesize that the larger the maximum expected loss, the larger the impact on competitor firms because the loss itself is presumably considered a more serious event that may trigger stronger regulation or alter investors' probability assessment of future operational loss events. We include $CORR_{ij}$, the correlation between the daily stock market returns of the competitor and the announcing firm, in the estimation window (Jorion and Zhang, 2007, 2009, 2010). A higher correlation of stock market returns indicates a higher similarity of cash flows; therefore, we expect competitor firms to be more affected by spillover effects if the correlation between their stock market returns and the stock market return of the announcing firm is higher.

As variables that are specific to the competitor firm, we include several variables that have been identified by Chernobai et al. (2011) as relevant in a model that explains the incidence of operational loss events. We include $lnMVE_j$, as previously defined for the announcement firm, to control for firm size affecting spillovers. Following Chernobai et al. (2011), we argue that larger firms have better controls but also have to process higher volumes of trades and manage more complex transactions. Therefore, our expectations regarding the effect of the size of the competitor firm on spillovers are ambiguous. We include MTB_j, which is market-to-book ratio defined as the market value of equity over the book value of common equity (CEQ), as a proxy for default risk and financial distress (Fama and French, 1992). We hypothesise that the more severe the financial distress, the larger the expected spillover effect of operational loss events because the competitor firm has fewer financial resources to settle the issue and implement better internal controls. We include $TIER1R_j$, which is the ratio of common equity to total assets (AT), as a further measure of risk. Chernobai et al. (2011) argue that this ratio is an adequate proxy for Tier 1 capital, which cannot be measured because of a lack of data on risk-weighted assets. $TIER1R_j$ is essentially the inverse of the leverage ratio. We expect that spillover effects are less pronounced if $TIER1R_j$ is higher, as financial institutions with higher core capital are supposed to be more resistant to negative shocks (Berger et al., 2008; Kwan and Eisenbeis, 1997). We include ROE_j, which is the return of equity of the competitor firm, measured by the ratio of income before extraordinary items (IB) to common equity. Profitability may be positively related to spillover effects because banks that are more profitable can devote more resources to internal control. On the other hand, profitability can be positively related to moral hazard because employees may engage in fraudulent activities to meet higher internal profitability targets (Chernobai et al., 2011). Hence, our expectations regarding the effect of the competitor firm's profitability on spillover effects are ambiguous. We include $RETSD_j$, which is the standard deviation of the competitor firm's daily stock market returns during the estimation period, as a further proxy for risk. The data items from Compustat to calculate daily returns are share price, PRCCD, and an adjustment factor, TRFD. As in the case of the market-to-book ratio, we expect that risk is negatively related to spillover effects. We include $DUM\_EXC\_GR_j$, which is a dummy variable that indicates whether a firm has experienced excessive growth in the recent year. Excessive growth is defined as growth in total liabilities (LT) being larger than growth in total assets, with both growth in liabilities and total assets having to be positive. This dummy variable is expected to be negatively related to spillover effects since excessive growth is often accompanied by risk management and internal control deficiencies (Chernobai et al., 2011; Foos et al., 2010). As the final competitor firm-specific variable, we include AGE_j, which is the number of years since a firm went public. Younger firms may have higher operational risk because their internal control systems are less developed (Chernobai et al., 2011). Therefore, we expect a positive relationship between age and cumulative abnormal returns.

As a macroeconomic control variable (without any a priori expectations regarding its effect on spillovers from operational losses), we include annual growth in gross domestic product,[15] GDP_GR_t, measured as the percentage change in the EU's quarterly gross domestic product relative to the same quarter of the previous year. GDP data for the European Union is obtained from the website of the Federal Reserve Bank of St. Louis.[16] We further control for short-term stock market trends by including the overall return on the FTSE Developed Europe portfolio over the 30 trading days prior to the event, $MKT1M_t$.

Moreover, as prior studies find that the market reaction to operational loss announcements may be conditional on the type of loss event (see, for instance, Biell and Muller, 2013; Fiordelisi et al., 2014; Gillet et al., 2010; Perry et al., 2005), we include dummy variables $CATEGORY_i$ as a control for different event categories.[17]

$$\begin{aligned} CAR_{ij}[\tau_1, \tau_2] = {} & \beta_o + \beta_1 lnMVE_i + \beta_2 lnLOSS_i + \beta_3 CORR_{ij} + \beta_4 lnMVE_j + \beta_5 MTB_j \\ & + \beta_6 TIER1R_j + \beta_7 ROE_j + \beta_8 RETSD_j + \beta_9 DUM\_EXC\_GR_j \\ & + \beta_{10} AGE_j + \beta_{11} GDP\_GR_t + \beta_{12} MKT1M_t + \Sigma\beta_{cat} CATEGORY_i + \varepsilon_{ij} \end{aligned} \quad (5)$$

In an alternative specification expressed by Equation (6), we include event dummies, instead of event-specific factors. While this approach controls for all observable and non-observable event-specific factors, it is unable to measure the effect of these factors on spillovers.

15 For instance, favorable economic conditions can decrease the riskiness of banks, as the intention of credit holders to fulfill their obligations will be higher. On the other hand, during an economic downturn, both firms and households may fail to keep up with their payment obligations due to decrease in disposable income.

16 https://research.stlouisfed.org/fred2/tags/series?t=eu%3Bgdp%3Bquarterly.

17 The Basel Committee on Banking Supervision classifies operational losses into the following seven event types: "internal fraud", "external fraud", "clients, products and business practices", "employment practices and workplace safety", "business disruption and system failures", "execution, delivery, and process management;" and "damage to physical assets" (BCBS, 2006). In line with Wang and Hsu, (2013), we control for the event types "external fraud" and "clients, products, and business practices" explicitly, and we allocate all other event types to a single category ("other").

$$CAR_{ij}[\tau_1, \tau_2] = \beta_o + \beta_1 CORR_{ij} + \beta_2 lnMVE_j + \beta_3 MTB_j + \beta_4 TIER1R_j + \beta_5 ROE_j + \beta_6 RETSD_j + \beta_7 DUM\_EXC\_GR_j + \beta_8 AGE_j + \Sigma\beta_{event} EVENT_i + \varepsilon_{ij} \quad (6)$$

While in Equations (5) and (6), estimates of coefficients are consistent, standard errors should account for the fact that many of these *CAR*s are measured over the same period for each bankruptcy event. As a result, we report t-statistics based on clustered standard errors, which are adjusted for event clustering (Jorion and Zhang, 2009, p. 2070).

4 Results

4.1 Effects of Operational Loss Events on Announcing Firms

Table 1 shows (cumulative) average abnormal returns for banks that announced an operational loss larger than € 50 million. The day zero average abnormal return is statistically significant at conventional levels and amounts to -1.28%. For the period τ_1 = - -5 to τ_2 = +5, the cumulative average abnormal return is -3.11%. Overall, we take the results as a strong confirmation of Hypothesis 1. If the ratio of the nominal loss to a firm's market capitalization is added to the stock return on day zero, statistically significant abnormal returns are hardly observable. Only for the period τ_1 = -5 to τ_2 = +5 do we observe a negative cumulative average abnormal return of -1.73%, which is statistically significant at the 10% level only if the crude dependence adjustment test is used as a reference. We conclude that while large operational losses have information content, reputational damage is limited in comparison to the damage caused by the direct loss of funds in the course of the operational loss event. This result does not lend support to Hypothesis 2, and it is in line with prior findings reported in Moosa and Li (2013). However, it runs contrary to some of the findings reported in Fiordelisi et al. (2013), Gillet et al. (2010), and Sturm (2013), which we mainly attribute to differences in benchmark models (market model vs. Fama-French-Carhart), operational loss thresholds (€ 0.1 million vs. € 50 million), and significance tests (parametric vs. non-parametric) employed.

Table 1 here

4.2 Spillover Effects of Operational Loss Events

The results of the analysis of competitor portfolios' abnormal returns around operational loss announcements of European banks are shown in Table 2. The day zero abnormal return is -0.32% and statistically significant across all test statistics. For the event window $\tau_1 = -1$ to $\tau_2 = +1$ and $\tau_1 = -1$ to $\tau_2 = +5$, cumulative average abnormal returns on the competitor portfolios are -0.72% and -1.02%, respectively. The results are statistically significant for all sub-periods. We take this as a strong indication in favour of Hypothesis 3, namely that, at least for short periods around the announcement date, a negative spillover effect of large operational loss events exists. The (untabulated) average number of firms in the portfolios is 154. In comparison, Cummins et al. (2012) report the day zero abnormal returns of -0.01% and -0.03% for commercial and investment banks in the U.S., respectively, implying that the contagion effect due to operational loss announcements is stronger across the European banking industry than in the U.S. banking sector.

Table 2 here

4.3 Results of the Cross-Sectional Analysis of Spillover Effects

Table 3 contains descriptive statistics for the variables in the cross-sectional analysis of cumulative average abnormal returns. We only use the day zero abnormal return and the cumulative abnormal return for the period $\tau_1 = -1$ to $\tau_2 = +1$ as dependent variables in the cross-sectional analysis. However, using cumulative abnormal returns over other periods instead does not qualitatively alter our results. We winsorize cumulative abnormal returns and all variables that may include extreme observations – i.e., MTB_j, $TIER1R_j$ and ROE_j, at the 99.5th and 0.05th percentile. As Table 3 indicates, this procedure is successful in eliminating extreme observations that may bias the regression results.

Table 3 here

The results of the regression analysis are displayed in Table 4. We acknowledge that the model fit is low (adjusted R-squared range between 0.0070 and 0.0043). None of the variables except $CORR_{ij}$ exhibit the expected sign and significance at conventional levels, which indicates rejection of Hypothesis 4. This result does not change even when we include several other variables that may serve as additional factors explaining spillover effects around large operational loss announcements (e.g., the growth in the budget of the

European and Securities Authority and its predecessor, the Committee of European Securities Regulators; the classification of a bank as globally systemically relevant by the Financial Stability Board; interest spreads between long- and short-term interbank lending rates; and the interest rate of high-yield European corporate bonds).[18] In sum, these results indicate that spillover effects mainly occur for financial institutions whose stock returns exhibit a strong correlation with announcing firms' stock returns and that they are not conditional on firm characteristics, on the nature of the loss event, or on the macroeconomic environment. As a consequence, stock market reactions to operational loss events do not appear to be information-based but purely contagious.

Table 4 here

4.4 Robustness

As a robustness check, we lower the threshold for operational loss events to € 10 million in terms of maximum expected loss, which provides us a sample of 130 events and 103 distinct event dates with an average maximum expected loss in the amount of € 33.5 million (not tabulated). As can be seen from Table 5 Panel A, statistical significance is lower if these smaller operational loss events are included in the analysis. Only for the crude dependence adjustment test, significant results can be observed in the periods τ_1 = -1 to τ_2 = +0, τ_1 = -1 to τ_2 = +5, and τ_1 = -1 to τ_2 = +3. We conclude that operational loss events require a certain magnitude (size) in order to cause statistically significant spillover effects.

Table 5 here

Due to the limited sample size of 72 operational loss events on 62 distinct event dates, we refrain from deleting observations with confounding events in the main analysis. The implicit assumption behind this is that confounding events are purely random and should be canceled out in the aggregate analysis. We now relax this assumption and omit competitors with a confounding event occurring during the event window from the portfolio of rival firms. For each competitor, key developments recorded in Capital IQ and earnings announcements recorded in I/B/E/S for the period τ_1 = -1 to τ_2 = +1 are

[18] Results of the analysis including these additional variables are available from the authors upon request. For a discussion of the respective variables, see De Bruyckere et al. (2013) and Lohse et al. (2014).

considered as confounding events. As Table 5 Panel B indicates, even if these confounding events are excluded, negative spillovers are still present.

5 Conclusion

In general, bank events are expected to have intra- and inter-industry spillover effects because of their business across sectors. Based on a sample of 72 large operational loss events at European banks, we analyse the market value effects of operational loss events on the announcing banks and their industry rivals. We find that, in line with earlier evidence for the U.S. capital market, in particular, operational losses are associated with negative abnormal stock returns for both the announcing firm and other firms in the financial industry. The latter findings suggest empirical evidence for a contagion effect across the European banking industry due to large operational loss announcements. However, for our European sample, we do not find evidence in favour of the existence of a strongly negative reputation effect of operational losses on the announcing firm. Moreover, unlike other studies for the U.S. market, we do not find our results on spillover effects to be sensitive to firm characteristics, to the event type, or to the macroeconomic environment. As a consequence, our findings, rather, lend support to the hypothesis that spillover effects tend to be not information-based but purely contagious.

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References

Aharony, J. and Swary, I. (1983), "Contagion effects of bank failures: Evidence from capital markets", *Journal of Business*, Vol. 56 No. 3, pp. 305–322.

Akhigbe, A. and Madura, J. (2001), "Why do contagion effects vary among bank failures?", *Journal of Banking & Finance*, Vol. 25 No. 4, pp. 657–680.

Ashton, P. and Christophers, B. (2015), "On arbitration, arbitrage and arbitrariness in financial markets and their governance: unpacking LIBOR and the LIBOR scandal", *Economy and Society*, Vol. 44 No. 2, pp. 188–217.

BCBS. (2006), "Basel II: International Convergence of Capital Measurement and Capital Standards: A Revised Framework - Comprehensive Version", available at: http://www.bis.org/publ/bcbs128.htm.

Berger, A.N., Deyoung, R., Flannery, M.J., Lee, D. and Öztekin, Ö. (2008), "How Do Large Banking Organizations Manage Their Capital Ratios?", *Journal of Financial Services Research*, Vol. 34 No. 2–3, pp. 123–149.

Biell, L. and Muller, A. (2013), "Sudden crash or long torture: The timing of market reactions to operational loss events", *Journal of Banking & Finance*, Vol. 37 No. 7, pp. 2628–2638.

Brown, S.J. and Warner, J.B. (1980), "Measuring security price performance", *Journal of Financial Economics*, Vol. 8 No. 3, pp. 205–258.

Cannas, G., Masala, G. and Micocci, M. (2009), "Quantifying reputational effects for publicly traded financial institutions", *Journal of Financial Transformation. - Capco Institute*, Vol. 27, pp. 76–81.

Carhart, M.M. (1997), "On persistence in mutual fund performance", *Journal of Finance*, Vol. 52 No. 1, pp. 57–82.

Chernobai, A., Jorion, P. and Yu, F. (2011), “The Determinants of Operational Risk in U.S. Financial Institutions”, *Journal of Financial & Quantitative Analysis*, Vol. 46 No. 6, pp. 1683–1725.

Cohen, L. and Frazzini, A. (2008), “Economic Links and Predictable Returns”, *The Journal of Finance*, Vol. 63 No. 4, pp. 1977–2011.

Corrado, C.J. and Zivney, T.L. (1992), “The specification and power of the sign test in event study hypothesis tests using daily stock returns”, *Journal of Financial and Quantitative Analysis*, Vol. 27 No. 3, pp. 465–478.

Cowan, A.R. (1992), “Nonparametric event study tests”, *Review of Quantitative Finance and Accounting*, Vol. 2 No. 4, pp. 343–358.

Cummins, J.D., Lewis, C.M. and Wei, R. (2006), “The market value impact of operational loss events for US banks and insurers”, *Journal of Banking & Finance*, Vol. 30 No. 10, pp. 2605–2634.

Cummins, J.D., Wei, R. and Xie, X. (2012), “Financial sector integration and information spillovers: Effects of operational risk events on U.S. banks and insurers”, *Working Paper, Temple University*.

De Bruyckere, V., Gerhardt, M., Schepens, G. and Vander Vennet, R. (2013), “Bank/sovereign risk spillovers in the European debt crisis”, *Journal of Banking & Finance*, Vol. 37 No. 12, pp. 4793–4809.

Fama, E.F. and French, K.R. (1992), “The cross-section of expected stock returns”, *Journal of Finance*, Vol. 47 No. 2, pp. 427–465.

Fama, E.F. and French, K.R. (1993), “Common risk factors in the returns on stocks and bonds”, *Journal of Financial Economics*, Vol. 33 No. 1, pp. 3–56.

Fama, E.F. and French, K.R. (1996), “Multifactor explanations of asset pricing anomalies”, *Journal of Finance*, Vol. 51 No. 1, pp. 55–84.

Ferreira, M.A. and Gama, P.M. (2007), "Does sovereign debt ratings news spill over to international stock markets?", *Journal of Banking & Finance*, Vol. 31 No. 10, pp. 3162–3182.

Fiordelisi, F., Soana, M.-G. and Schwizer, P. (2013), "The determinants of reputational risk in the banking sector", *Journal of Banking & Finance*, Vol. 37 No. 5, pp. 1359–1371.

Fiordelisi, F., Soana, M.-G. and Schwizer, P. (2014), "Reputational losses and operational risk in banking", *The European Journal of Finance*, Vol. 20 No. 2, pp. 105–124.

Foos, D., Norden, L. and Weber, M. (2010), "Loan growth and riskiness of banks", *Journal of Banking & Finance*, Vol. 34 No. 12, pp. 2929–2940.

Gande, A. and Parsley, D.C. (2005), "News spillovers in the sovereign debt market", *Journal of Financial Economics*, Vol. 75 No. 3, pp. 691–734.

Gillet, R., Hübner, G. and Plunus, S. (2010), "Operational risk and reputation in the financial industry", *Journal of Banking & Finance*, Vol. 34 No. 1, pp. 224–235.

Iyer, R. and Peydró, J.-L. (2011), "Interbank Contagion at Work: Evidence from a Natural Experiment", *Review of Financial Studies*, Vol. 24 No. 4, pp. 1337–1377.

Jaffe, J.F. (1974), "Special information and insider trading", *Journal of Business*, Vol. 47 No. 3, pp. 410–428.

Jorion, P. and Zhang, G. (2007), "Good and bad credit contagion: Evidence from credit default swaps", *Journal of Financial Economics*, Vol. 84 No. 3, pp. 860–883.

Jorion, P. and Zhang, G. (2009), "Credit contagion from counterparty risk", *Journal of Finance*, Vol. 64 No. 5, pp. 2053–2087.

Jorion, P. and Zhang, G. (2010), "Information transfer effects of bond rating downgrades", *Financial Review*, Vol. 45 No. 3, pp. 683–706.

Karafiath, I. (2008), "Incomplete temporal overlap and cross-sectional independence in event studies", *Applied Financial Economics Letters*, Vol. 4 No. 2, pp. 81–86.

Kaufman, G.G. (1994), "Bank contagion: A review of the theory and evidence", *Journal of Financial Services Research*, Vol. 8 No. 2, pp. 123–150.

Kolari, J.W. and Pynnonen, S. (2010), "Event study testing with cross-sectional correlation of abnormal returns", *Review of Financial Studies*, Vol. 23 No. 11, pp. 3996–4025.

Kothari, S.P. and Warner, J.B. (2007), "Chapter 1 - Econometrics of Event Studies", in Eckbo, B.E. (Ed.), *Handbook of Empirical Corporate Finance*, Elsevier, San Diego, pp. 3–36.

Krause, A. and Giansante, S. (2012), "Interbank lending and the spread of bank failures: A network model of systemic risk", *Journal of Economic Behavior & Organization*, Vol. 83 No. 3, pp. 583–608.

Kwan, S. and Eisenbeis, R.A. (1997), "Bank Risk, Capitalization, and Operating Efficiency", *Journal of Financial Services Research*, Vol. 12 No. 2–3, pp. 117–131.

Lamy, R.E. and Thompson, G.R. (1986), "Penn Square, Problem Loans, and Insolvency Risk", *Journal of Financial Research*, Vol. 9 No. 2, pp. 103–111.

Lang, L.H.P. and Stulz, R.M. (1992), "Contagion and competitive intra-industry effects of bankruptcy announcements", *Journal of Financial Economics*, Vol. 32 No. 1, pp. 45–60.

Lohse, T., Pascalau, R. and Thomann, C. (2014), "Public enforcement of securities market rules: Resource-based evidence from the Securities and Exchange Commission", *Journal of Economic Behavior & Organization*, Vol. 106, pp. 197–212.

MacKinlay, A.C. (1997), “Event Studies in Economics and Finance”, *Journal of Economic Literature*, Vol. 35 No. 1, pp. 13–39.

Maynes, E. and Rumsey, J. (1993), “Conducting event studies with thinly traded stocks”, *Journal of Banking & Finance*, Vol. 17 No. 1, pp. 145–157.

McConnell, P. (2013), “Systemic operational risk : the LIBOR manipulation scandal”, *The Journal of Operational Risk*, Vol. 8 No. 3, pp. 59–99.

McConnell, P. (2014), “LIBOR manipulation: operational risks resulting from brokers’ misbehavior”, *The Journal of Operational Risk*, Vol. 9 No. 1, pp. 77–102.

McConnell, P. and Blacker, K. (2011), “The role of systemic people risk in the global financial crisis”, *Journal of Operational Risk*, Vol. 6 No. 3, pp. 65–123.

Moosa, I. (2007), “Misconceptions about operational risk”, *Journal of Operational Risk*, Vol. 1 No. 4, pp. 97–104.

Moosa, I. and Li, L. (2013), “An operational risk profile: the experience of British firms”, *Applied Economics*, Vol. 45 No. 17, pp. 2491–2500.

Moosa, I. and Silvapulle, P. (2012), “An empirical analysis of the operational losses of Australian banks”, *Accounting & Finance*, Vol. 52 No. 1, pp. 165–185.

Perry, J., Fontnouvelle, D. and Patrick. (2005), *Measuring Reputational Risk: The Market Reaction to Operational Loss Announcements*, available at: http://papers.ssrn.com/abstract=861364.

Pettway, R.H. (1980), “Potential Insolvency, Market Efficiency, and Bank Regulation of Large Commercial Banks”, *Journal of Financial and Quantitative Analysis*, Vol. 15 No. 01, pp. 219–236.

Sturm, P. (2013), “Operational and reputational risk in the European banking industry: The market reaction to operational risk events”, *Journal of Economic Behavior & Organization*, Vol. 85, pp. 191–206.

Wang, T. and Hsu, C. (2013), “Board composition and operational risk events of financial institutions”, *Journal of Banking & Finance*, Vol. 37 No. 6, pp. 2040–2051.

Table 1. (Cumulative) average abnormal returns of firms announcing operational losses larger than € 50 million.

	Abnormal returns					Abnormal returns adjusted for nominal losses				
Day	**Events**	**(C)AAR**	**CRU**	**KOL**	**COR**	**Events**	**(C)AAR**	**CRU**	**KOL**	**COR**
-1	68	-0.31	-1.13	-0.96	-0.51	68	-0.31	-1.13	-0.96	-0.56
0	69	-1.28	-4.67***	-3.19***	-3.60***	69	0.40	1.46	1.18	0.89
+1	70	-0.23	-0.83	-0.81	-0.09	70	-0.23	-0.83	-0.81	-0.13
[0;+1]	70	-1.47	-3.79***	-2.26**	-2.66***	70	0.17	0.45	0.29	0.52
[-1;+0]	69	-1.58	-4.09***	-3.16***	-2.95***	69	0.10	0.25	0.29	0.27
[-1;+1]	70	-1.80	-3.79***	-2.57**	-2.46**	70	-0.15	-0.32	-0.32	0.14
[-1;+3]	69	-1.96	-3.19***	-2.47**	-1.73*	69	-0.34	-0.55	-0.14	0.29
[-1;+5]	61	-2.02	-2.79***	-2.18**	-1.88*	61	-0.64	-0.89	-0.45	-0.17
[-5;+5]	61	-3.11	-3.42***	-2.21**	-1.94*	61	-1.73	-1.90*	-1.31	-0.65

This table shows (cumulative) average abnormal returns ((C)AARs) in per cent around operational announcements of European banks. ((C)AARs) are adjusted for nominal losses in the right-hand section of the table by adding the ratio of the nominal operation loss over the market capitalization of the bank to its stock market return on day 0. Abnormal returns are calculated against a European version of the 4-factor model described in Carhart (1997) and Fama and French (1992, 1993, 1996). CRU is the crude dependence adjustment test proposed by Brown and Warner (1980, pp. 223, 253). KOL is the parametric (Kolari and Pynnonen, 2010, p. 4003) test statistic and COR the (Corrado and Zivney, 1992, p. 475) test statistic for the rank test. Asterisks indicate significance at the 10% [*], 5% [**] and 1% [***] levels.

Table 2. (Cumulative) average abnormal returns of competitor portfolios around operational losses larger than € 50 million.

Day	Events	(C)AAR	CRU	KOL	COR
-1	62	-0.25	-1.80*	-1.32	-1.61
0	62	-0.32	-2.32**	-2.39**	-2.61***
+1	62	-0.15	-1.05	-0.69	-0.47
[0;+1]	62	-0.47	-2.38**	-2.20**	-2.12**
[-1;0]	62	-0.57	-2.91***	-2.16**	-2.91***
[-1;+1]	62	-0.72	-2.98***	-2.37**	-2.64***
[-1;+3]	62	-0.77	-2.49**	-2.06**	-2.04**
[-1;+5]	62	-1.02	-2.76***	-2.27**	-1.99**
[-5;+5]	62	-1.13	-2.45**	-1.60	-2.08**

This table shows (cumulative) average abnormal returns ((C)AARs) in per cent of competitor portfolios around operational announcements of European banks. Determination of abnormal returns and test statistics is consistent with Table 1. Asterisks indicate significance at the 10% [*], 5% [**] and 1% [***] levels.

Table 3. Descriptive statistics of variables in the cross-sectional analysis.

	Mean	Sd	Min	P25	Med	P75	Max
***CAR*$_{ij}$[0;0]**	-0.16	2.23	-9.97	-0.97	0.00	0.63	9.06
***CAR*$_{ij}$[-1;+1]**	-0.30	3.95	-16.96	-1.86	-0.13	1.22	18.59
***lnMVE*$_i$**	24.33	0.90	18.96	24.12	24.39	24.63	26.22
***lnLOSS*$_i$**	19.39	1.02	17.73	18.56	19.36	20.08	23.22
***CORR*$_{ij}$**	0.30	0.23	-0.44	0.12	0.28	0.48	0.89
***lnMVE*$_j$**	20.66	1.96	14.56	19.26	20.61	21.93	25.89
***MTB*$_j$**	1.71	2.04	-0.25	0.58	1.18	2.07	16.05
***TIER1R*$_j$**	0.19	0.24	-0.02	0.05	0.08	0.19	0.97
***ROE*$_j$**	0.08	0.31	-2.16	0.04	0.09	0.15	2.07
***RETSD*$_j$**	0.03	0.01	0.00	0.02	0.02	0.03	0.09
***DUM_EXCESS_GR*$_j$**	0.16	0.37	0.00	0.00	0.00	0.00	1.00
***AGE*$_j$**	12.17	6.32	1.00	7.00	12.01	17.01	25.52
***GDP_GR*$_t$**	0.00	0.01	-0.03	0.00	0.00	0.01	0.02
***MKT1M*$_t$**	0.01	0.03	-0.11	-0.02	0.02	0.03	0.07
***CATEGORY*$_i$ (CPBP)**	0.74	0.44	0.00	0.00	1.00	1.00	1.00
***CATEGORY*$_i$ (External fraud)**	0.10	0.31	0.00	0.00	0.00	0.00	1.00
***CATEGORY*$_i$ (Internal fraud)**	0.07	0.25	0.00	0.00	0.00	0.00	1.00
***CATEGORY*$_i$ (Other)**	0.09	0.28	0.00	0.00	0.00	0.00	1.00

CAR$_{ij}$ is the cumulative abnormal return of competitor bank j when bank i announces the operational loss event. *lnMVE*$_i$ is the natural logarithm of the market value of equity of the announcement firm. *lnLOSS*$_i$ is the natural logarithm of the maximum expected loss in millions of euros. *CORR*$_{ij}$ is the correlation between the daily stock market returns of the competitor and the announcing firm in the estimation. *lnMVE*$_j$ is the natural logarithm of the market value of equity of the competitor firm. *MTB*$_j$ is the market-to-book ratio defined as the market value of equity over the book value of common equity. *TIER1R*$_j$ is the ratio of common equity to total assets. *ROE*$_j$ is the return on equity of the competitor firm, measured by the ratio of income before extraordinary items to common equity. *RETSD*$_j$ is the standard deviation of the competitor firm's daily stock market returns during the estimation period. *DUM_EXC_GR*$_j$ is a dummy variable that indicates whether firm has experienced excessive growth in the recent year. Excessive growth is defined as growth in total liabilities being larger than growth in total assets, with both growth in liabilities and total assets having to be positive. *AGE*$_j$ is the number of years that a firm has been public. *GDP_GR*$_t$ is the percentage change in quarterly gross domestic product relative to the same quarter of the previous year. *MKT1M*$_t$ is the cumulated return of the index return *MKT* over the 30 trading days prior to the event. *CATEGORY*$_i$(−) are dummy variables that indicate whether the operational loss event relates to one of the following categories: "clients, products and business practices", "external fraud", "internal fraud", or "other" ("business disruption and system failures" or "execution, delivery and process management").

Table 4. Results of the cross-sectional analysis.

	Exp.	$CAR_{ij}[0;0]$		$CAR_{ij}[-1;+1]$	
***lnMVE*i**	-	-0.0976		-0.1404	
		(-1.6072)		(-1.3601)	
***lnLOSS*i**	-	0.1125		0.2033*	
		(0.8024)		(1.8513)	
***CORR*ij**	-	-0.4495**	-0.5268**	-0.9889**	-0.9647**
		(-2.1163)	(-2.5542)	(-2.2350)	(-2.1593)
***lnMVE*j**	+	-0.0366	-0.0273	-0.0866	-0.0732
		(-1.1452)	(-0.8658)	(-1.6665)	(-1.3192)
***MTB*j**	+	0.0000	-0.0026	-0.0201	-0.0217
		(0.0008)	(-0.1825)	(-0.7188)	(-0.7836)
***TIER1R*j**	+	-0.2221	-0.2276	-0.2441	-0.2603
		(-1.4767)	(-1.5093)	(-0.9588)	(-1.0147)
***ROE*j**	+	0.0811	0.0858	0.1463	0.1798
		(0.6139)	(0.6793)	(0.4573)	(0.5692)
***RETSD*j**	-	-0.5853	0.7871	0.2402	-0.0249
		(-0.0982)	(0.1401)	(0.0226)	(-0.0024)
***DUM_EXCESS_GR*j**	-	-0.0714	-0.0519	-0.0407	-0.0541
		(-1.0239)	(-0.8335)	(-0.3397)	(-0.5128)
***AGE*j**	+	0.0035	0.0010	0.0138	0.0032
		(0.6662)	(0.1866)	(1.5315)	(0.3415)
***GDP_GR*t**	?	3.0457		18.5983	
		(0.4903)		(1.6351)	
***MKT1M*t**	?	-2.6481		-2.2216	
		(-1.1094)		(-0.5661)	
***CATEGORY* (CPBP)**	?	-0.0319		0.2252	
		(-0.2372)		(0.6488)	
***CATEGORY* (External fraud)**	?	-0.2544		0.0042	
		(-0.9953)		(0.0097)	
***CATEGORY* (Other)**	?	-0.6535**		-0.8366	
		(-2.0877)		(-1.4974)	
EVENT		NO	YES	NO	YES
Constant		2.0012	-1.0842	1.0231	0.2234
		(0.9779)	(-1.6433)	(0.3353)	(0.1916)
Observations		10,478	10,478	10,475	10,475
Adj. R^2		0.0070	0.0419	0.0114	0.0433
Firms		315	315	315	315
Events		61	61	61	61

This table shows the results for the regression models *5* and *6*. Variables are defined in Table 3. The cross-sectional analysis is based on 61 rather than 62 events as one event (Julius Baer) had to be excluded due to data limitations. Asterisks indicate significance at the 10% [*], 5% [**] and 1% [***] levels. Standard errors are clustered at the event level.

Table 5. Results of robustness tests.
A. (Cumulative) average abnormal returns of competitor portfolios around operational losses larger than € 10 million.

Day	Events	(C)AAR	CRU	KOL	COR
-1	103	-0.15	-1.40	-0.79	-1.08
0	103	-0.16	-1.49	-1.15	-1.36
1	103	-0.03	-0.31	0.09	0.36
[-5;+5]	103	-0.53	-1.49	-0.69	-0.54
[-1;+3]	103	-0.54	-2.26**	-1.25	-0.84
[-1;+5]	103	-0.59	-2.08**	-1.26	-0.62
[-1;0]	103	-0.31	-2.05**	-1.16	-1.68*

B. (Cumulative) average abnormal returns of competitor portfolios around operational losses larger than € 50 million when confounding events are eliminated.

Day	Events	(C)AAR	CRU	KOL	COR
-4	62	-0.23	-1.72*	-2.75***	-1.82*
-1	62	-0.23	-1.71*	-1.57	-0.99
0	62	-0.25	-1.83*	-1.76*	-1.71*
1	62	-0.03	-0.22	0.44	-0.08
[-1;+1]	62	-0.51	-2.17**	-1.72*	-1.51
[-5;+5]	62	-0.82	-1.83*	-1.67*	-1.29
[-1;+3]	62	-0.56	-1.86*	-1.53	-1.23
[-1;+5]	62	-0.64	-1.79*	-1.28	-1.42
[-1;0]	62	-0.48	-2.51**	-2.4**	-1.64

Panel A shows (cumulative) average abnormal returns ((C)AARs) in per cent of competitor portfolios around operational announcements of European banks. Panel B shows the percentage (cumulative) average abnormal returns ((C)AARs) of competitor portfolios around operational announcements of European banks when competitor firms with confounding events in the period $\tau 1$ = -1 to $\tau 2$ = +1 are eliminated. For each competitor, key developments recorded in Capital IQ and earnings announcements recorded in I/B/E/S are considered as confounding events. Abnormal returns are calculated against a European version of the 4-factor model described in Carhart (1997) and Fama and French (1992, 1993, 1996). Determination of test statistics is consistent with Table 1. Asterisks indicate significance at the 10% [*], 5% [**] and 1% [***] levels.