Business Environmental Determinants of Operational Risk in German Speaking Countries

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Abstract

Based on a broad dataset containing about 800 operational risk events in financial institutions in German-speaking countries since the 1980s, we study whether changes in certain firm-specific and business environmental factors reflect or even anticipate the occurrence of operational risk events. Consistent with prior studies, we find a positive and significant relationship between firm size and operational losses. In addition, we identify positively significant relationship between regulatory capital and GDP growth on one side and operational risk events on the other side. Furthermore, we observe inter alia a positively significant coefficient for core capital and return on equity by cooperative banks. Concerning macroenvironmental factors we observe negative and strong significant coefficient for unemployment rate in the same subsample, suggesting that during increasing unemployment the operational risk exposure goes down. We find a weak and positive association between operational loss events and interest rate growth across commercial banks. In terms of different event type categories, we observe a strong and positive coefficient for the variable excessive growth by the event type “External Fraud”. This indicates that financial institutions with aggressive growth strategy suffer from higher external risk exposure. Moreover, we find a weakly significant and negative relationship between cash holding and operational loss exposure across the same subset. Finally, with respect to other firm-specific and macroenvironmental factors we find no significant relationship to operational losses, a finding that runs contrary to prior empirical evidence for other countries.

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1. Introduction

Several prominent loss events from the recent past show that even banks operating a supposedly sophisticated risk management system are not safe from falling victim to operational risk.[1] As operational risk can materialise in various forms like fraud, accounting errors, IT failure, modelling errors, or natural disasters, and as it may coincide with other types of business risk, identifying and properly managing operational risk is a challenging task.

In this context, our research focuses on the interaction of observable firm-specific and business environment factors on the one hand and operational risk events in financial institutions on the other hand in four German-speaking countries, namely Germany, Austria, Switzerland, and Liechtenstein. Existing empirical studies provide evidence that both firm-specific and macroenvironmental factors can have a significant impact on a firm's operational risk exposure (Chernobai et al. 2011; Cope et al. 2012; Wang and Hsu 2013). Moreover, prior research found cyclical components in operational risk measures (Allen and Bali 2007), as well as a positive correlation between operational losses and financial crises (Hess 2011). In addition, operational losses are shown to have an immediate impact on stock market performance of financial institutions (Biell and Mueller 2013; Cummins et al. 2006; Gillet et al 2010; Sturm 2013).

We perform multivariate regression analyses to study whether changes in certain firm-specific and business environmental factors reflect or even anticipate the occurrence of operational risk events. In selecting explanatory variables we mainly draw on the above mentioned literature. This allows us to compare our results with prior results relating to other countries, and enables us to corroborate claims put forward by Cope et al. with respect to the effects of the geographic region on operational risk exposure.

The analysis is based on operational loss data provided by the Association of German Public Sector Banks (Bundesverband öffentlicher Banken). The final sample consists of 607 loss events that occurred in 316 financial institutions between 1991 and 2013. Our results show a positive and significant relationship between firm size and operational losses, which is consistent with prior studies, indicating that larger firms exhibit a greater exposure to operational risk, probably due to higher transaction volumes and increased complexity of operations. In addition, we identify positively significant relationship between regulatory capital and GDP growth on one side and operational risk events on the other side. Furthermore, we observe inter alia a positively significant coefficient for core capital and return on equity by cooperative banks. Concerning macroenvironmental factors we observe negative and strong significant coefficient for unemployment rate in the same subsample, suggesting that during increasing unemployment the operational risk exposure goes down. We find a

[1] For instance, in 2011 major operational loss events occurred at Bank of America ($8.5 billion), Lloyds Banking Group ($5.28 billion), UBS ($2.3 billion), and Royal Bank of Scotland Group ($1.719 billion). Cf. Pajaczkowski, B., 2011 in Review – Risks Old and New, Algo FIRST Newsletter, January 2012.

weak and positive association between operational loss events and interest rate growth across commercial banks. In terms of different event type categories, we observe a strong and positive coefficient for the variable excessive growth by the event type “External Fraud”. This indicates that financial institutions with aggressive growth strategy suffer from higher external risk exposure. Moreover, we find a weakly significant and negative relationship between cash holding and operational loss exposure across the same subset. Finally, with respect to other firm-specific and macroenvironmental factors we find no significant relationship to operational losses, a finding that runs contrary to prior empirical evidence for other countries. As we control for time and firm fixed effects in our analyses, this suggests that these factors’ explanatory power identified by prior research may be unique to the respective country or geographical region studied, and thus does not allow for a generalization.

2. Literature review and hypothesis development

Very little research has been done on determination of operational losses on firm-specific and business environment perspectives, which could be attributed on lack of operational loss data. However there are several studies that can be divided into two classes. The first class of papers considers reputational losses due to the announcement of operational losses. The second class of articles deals with determinants of operational losses.

Among the first series of papers, Cummins et al. (2006) based on OpVar database, conduct an event study analysing the market value impact of operational loss events in the US banking and insurance industries. They find a strongly significant and negative stock price reaction to announcements of operational loss events indicating a negative impact on firm´s reputation. Perry and de Fontnouvelle (2005) find that firm´s market value declines by more than the announced loss amount stemming on data sets from Algo OpData and OpVantage First databases. Moreover, they show that the market reaction to losses caused by internal fraud is more severe than to external fraud losses, arguing that investors may view operational losses occurred due to internal fraud as an indicator that further losses are more likely to occur in the future. Cannas et al. (2009) study the market reaction to operational loss announcements by US and European financial institutions using OpVar database. More specifically, they focus on announcements of operational losses due to internal fraud indicating an immediate and negative reaction on stock prices. Based on 152 losses occurred in US and European companies from OpVantage First database Gillet et al. (2010) analyse the market reaction after the announcement of operational losses. Furthermore, they measure the impact of operational loss announcement dividing to three different event dates: first press cutting date, recognition date by the company and settlement date. They observe a negative and significant reaction around both the press and the recognition date. Moreover, they find that the investors overreact when they do not know the loss amount and that the losses are significantly worse, if the loss is occurred due to fraud. Fiordelisi et al. (2013) report, based on the sample of 215 operational losses experienced by 163 European Banks from Algo OpData, that reduction of stock prices due to operational loss events announcement is larger for profitable and poorly capitalized banks than that for non-profitable and well-capitalized banks. Sturm (2013) studies the reputational losses due to the discovery of operational losses based

on 136 loss events in European financial institutions stemming from ÖffSchOR Database. He reports a significant negative stock market reaction after the first press announcement. Furthermore, he shows that reputational losses are influenced more due to firm characteristics than by the loss event type. Especially, the results report, that financial institutions with a high rate of liabilities to total assets suffer more severe damages to reputation from operational loss events than financial firms with more equity.
Biell and Mueller (2013) analyze the timing of stock market respond to announcement of 279 operational loss events from Algo OpData database. They find that firm market price reaction to operational losses involving internal fraud occur earlier and are far more rapid in comparison to other events. Furthermore they show, that investor's respond is faster to operational loss disclosure by "pure banks" than by investment banks or other industry sectors. Moreover, the results report, that the respond to loss announcement in bull market is longer but earlier than in bear market.

The second class of articles by Chernobai et al. (2011), Moosa (2011), Cope et al. (2012) and Wang and Hsu (2013) provide evidence that both firm-specific and macroenvironmental factors can have a significant impact on a firm's operational risk exposure and lie as a cornerstone of our study.

Chernobai et al. (2011) based on 925 operational loss events among 176 US financial institutions from Algo First Database provide a comprehensive analysis of the firm-specific and macroeconomic variables that determine the operational risk events occurrence. They report that most operational losses can be attributed to internal control weaknesses. They found that younger, more complex and financial weaker firms with a high number of antitakeover provisions and with CEOs with a larger amount of options and bonus based compensation experience more operational losses. Moreover, they show a positive relation between operational risk and credit risk.

Moosa (2011) analyses the relationship between unemployment rate and 3239 operational loss events referring to US firms using Fitch Risk Database. Results show a significantly positive association between unemployment rate and operational loss severity, though an insignificant relation to operational loss frequency.

Cope et al. (2012) analyses various regulatory, legal, geographical and economic factors that influence operational loss severity across 130 countries. Using 57,000 losses among four risk event types from Operational Riskdata eXchange database they find a significant relationship firstly between losses due to internal fraud on the one side and constraints on executive power and the prevalence of insider trading on the other side, secondly between losses referring to event type "Clients, Products and Business Practices" on the one hand and securities and shareholder protection laws, restrictions on banking activity, supervisory power, and the prevalence of insider trading on the other hand, thirdly between the losses due to external fraud on one side and geographic region, governance index and GDP on the other side. With respect to losses corresponding to event type "Employment Practices and Workplace Safety" they report a significant relationship with geographic region and GDP.

Many of the firm-specific and macroenvironmental factors, that were proved to be statistically significant in above mentioned studies, are used in our research. Regarding to firm-specific variables, we use total asset to control for firm size. We expect to observe a positive relationship between the firm size and operational loss exposure as the larger firms are engaged in more complex and wide types of business activities. We include cash to total asset ratio and expect a negative association with operational loss exposure, because financial institutions withhold more cash at the cost of lower opportunities to invest or to grant credit. This argument contradicts with the argument by Chernobai et al. (2011), that firms with financial constraints hold cash to reduce the possibility of future cash shortage. We use core and regulatory capital as a proxy for “stable banks”. As the calculation of risk weighted assets needed for estimating Tier1 and Tier3 has changed during last decades, we use total asset in lieu to risk weighted assets defined by Basel Committee on Banking Supervision. For these variables we expect a positive relationship with operational loss exposure as the financial institutions with higher core and regulatory capital are supposed to be more stable. One can argue that financial institutions with higher core or regulatory capital tend to decrease financial distress. We choose return on equity as a common measure to profitability and expect to see a positive association with operational risk. This argument is consistent with the argument put forward by Chernobai et al. (2011), that profitable firms can afford themselves to spend more for better internal control. To analyse the correlation between operational and credit risk we define a dummy variable, called $Ex\_GR_{D,}$ which indicates rapid and aggressive growth strategy of financial institution. We follow the arguments by the Office of the Comptroller of the Currency (OCC) (2001) that this strategy increased the risk exposure because of the capacity of internal control and management is exceeded. Hence we expect a positive correlation between excessive growth variable and operational risk exposure. The last firm-specific variable we use in our research is the age of financial institution. For this variable we expect to see a negative association with operational risk as the older institutions are supposed to have advanced risk management processes and internal control practices.

Regarding macroenvironmental factors we use GDP growth rate, IFO Business Climate Index growth rate, MSCI_EU growth rate[2], Unemployment growth rate, Interest Rate growth rate to study the relationship with operational risk. Chernobai et al. (2011) and Moosa (2011) argue that operational losses can increase or decrease in booming economy as well as in busting economy. They suggest following examples to support their arguments: on the one side (a) institutions have less resources to invest in improvement of internal control during busting economy; (b) internal and external fraud increase when the economy is in recession; on the other side (a) credit card fraud is common (widespread) in booming economy; (b) financial institutions are taking more risk in a strong economy.

3. Data and methodology

3.1. Description of data

Our empirical analysis is based on multiple databases. We analyse operational loss data from the ÖffSchOR database provided by the Association of German Public Sector Banks (Bundesverband öffentlicher Banken, VÖB). The vendor collects information on operational loss events in financial institutions from public sources such as newspapers and or company websites, with reported losses usually exceeding 100,000 Euro. The database contains detailed descriptions of approximately 800 operational risk events dating back to the 1980s, including loss occurrence date, loss amount (in corresponding currency)[3], the event trigger, firm name, geographical location, and a reference to the

[2] In our study we also use DAX and CDAX instead of MSCI_EU and receive similar results which we not present in this paper.

[3] All variables in foreign currencies are converted into euro based on the current exchange rate.

source of the information. Loss events are classified into seven event type categories and in eight business lines according to the Basel II framework.

In addition, we use firm-specific financial statement data from either the Hoppenstedt database (a proprietary commercial database), the Bundesanzeiger (a federal gazette) or annual reports obtained directly from the financial institutions. The macroeconomic variables are obtained from OECD iLibrary, German Bundesbank, MSCI Inc. and IFO Institute. Descriptions of variables used in the study are provided in Table 1.

Table 1

Description of Variables

Variable	Description	Source
OL	Operational loss, which is natural logarithm of the value of the event	ÖffSchOR
F_SIZE	Firm size is the natural logarithm of the total assets of a financial institution	Hoppenstedt/ Bundesanzeiger
CASH_TA	Ratio of cash to total assets	Hoppenstedt/ Bundesanzeiger
TIER1R	Tier 1 ratio is a proxy for Basel Tier 1 core capital ratio (core capital to total risk-weighted assets) estimated using core capital to total assets	Hoppenstedt/ Bundesanzeiger
TIER3R	Tier 3 ratio is a proxy for required total regulatory capital ratio (total regulatory capital to total risk-weighted assets) estimated using required total regulatory capital to total assets	Hoppenstedt/ Bundesanzeiger
ROE	Return on equity is measured as a ratio of net income to the book value of equity	Hoppenstedt/ Bundesanzeiger
Ex_GR_D	DUM EXCESS GR is a dummy variable equal to 1 if a financial institute experiences positive growth of liabilities (Δliabilities) and assets (ΔTA) in the previous year and the growth of liabilities exceeds the growth of assets.(Consistent with Chernobei et al. 2011)	Hoppenstedt/ Bundesanzeiger
F_AGE	Firm age is equal to number of months a firm is operating. Firm age is equal 0, if a merger has taken place.	Hoppenstedt/ Bundesanzeiger
GDPgrowth	Gross Domestic Product growth rate is calculated with respect to the same quarter of the previous year for each country.	OECD
UNEMPgrowth	Unemployment growth rate is calculated with respect to the same month of the previous year for each country	OECD
IRgrowth	Interest Rate growth rate is calculated with respect to the same month of the previous year	German Bundesbank
MSCI_EU	MSCI_EU growth rate is calculated with respect to the same month of the previous year	MSCI Inc
IFO_Index	IFO Business Climate Index growth rate is calculated with respect to the same month of the previous year	IFO Institut

We restrict our attention on operational losses occurred between 1991 and 2012 in German-speaking countries namely Germany, Austria, Switzerland, and Liechtenstein, because on the one hand the majority of operational risk events in ÖffSchOR database (almost 90%) occurred in this countries, on the other hand it provides some homogeneity in our sample. Further we exclude non-financial institutions from our sample and restrict our attention to firms with complete information. After combining all the datasets discussed above our sample consists of 449 loss events from 203 financial institutions over the last 20 years.

3.2. Descriptive statistics

The descriptive statistics of all financial institutions operational loss events and of the variables mentioned earlier are reported in Table 2. There are 607 loss events among 316 financial institutions with the mean operational loss of 20 million Euro. For comparison, Gilet et al. (2010) report the mean loss amount of 277 million USD for the 49 largest losses in 47 European companies, while Sturm (2013) documents an average operational loss of 140 million Euro for 136 loss events for European financial institutions. These differences could be due to different time periods used in their studies as well as their focus on publicly listed companies. The maximum loss amount in our data 1,600 million Euro is caused (belongs) by Deutsche Bank whereas the minimum loss amount is 52,000 Euro reported from savings bank Hagen. The mean and the median of operational losses are almost 21 million and 368 thousand, respectively. This indicates that severity distribution of operational losses is skewed to the right, which is consistent with the reported data used by Cummins et al. (2006), Chernobei et al. (2011) and Sturm (2013). Furthermore, Table 2 shows that on average financial institutions in our sample report 4,0% and 6,0% core and regulatory capital ratio, respectively. The average of total assets and cash holdings are 294,076 million Euro and 3,451 million Euro, respectively. The financial institutions in our analyses are on average 72 years old.

Table 2

Descriptive statistics

				------------------------------- Quantiles ------------------------------- ---				
Variable	n	Mean	S.D.	Min	.25	Mdn	.75	Max
firm-specific Variables								
OL	607	20890906	1.0e+08	52000.00	1.5e+05	368794.81	2.5e+06	1.6e+09
TA	494	294076219392	4.9e+11	1.8e+07	2.1e+09	24229603328	3.9e+11	2.2e+12
Cash	485	3451798016	7.6e+09	158.00	3.3e+07	298000000	4.9e+09	9.3e+10
TIER1R	461	0.04	0.02	0.01	0.03	0.04	0.05	0.28
TIER3R	460	0.06	0.03	0.02	0.04	0.05	0.07	0.33
ROE	492	0.03	0.21	-2.34	0.02	0.05	0.08	1.68
Ex_GR_D	607	0.24	0.43	0.00	0.00	0.00	0.00	1.00
FirmAge	508	853.92	742.10	0.00	126.00	606.00	1620.00	2604.00
business environmental factors								
GDP_{gr}	607	0.01	0.03	-0.07	0.00	0.02	0.03	0.05
$UNEMP_{gr}$	607	-0.02	0.12	-0.34	-0.10	-0.02	0.04	0.60
IR_{gr}	607	-0.04	0.56	-0.92	-0.35	0.01	0.16	2.27
IFO_{gr}	606	0.01	0.11	-0.22	-0.05	-0.00	0.09	0.23

$MSCI\_EU_{gr}$	607	0.03	0.23	-0.44	-0.12	0.09	0.17	0.48

To minimize heterogeneity, the sample is divided into public-sector banks, cooperative banks and commercial banks. Almost half of our sample about 50,0% consists of commercial banks (see Table 3). Both the mean and median of operational losses are the highest for commercial banks. Cooperative banks show on average the highest returns on equity of about 0.06% in comparison to public-sector banks and commercial banks with 0.03% and 0.01%, respectively. Moreover, significant differences were observed in means of all variables but ROE and firm age across the subgroups, as shown in Table 4. Regarding the latter variable, cooperative banks turn out to be significantly younger than the other two types of financial institutions, but there is no significant difference in age between commercial and public-sector banks. To account for differences in bank characteristics, we control for bank specific effects in our model. Moreover we divide operational risk events into seven event types according to the Basel II framework. Table 3 displays the number of observations for each financial institution/event type combination. The events tend to cluster in three of the seven event types, namely in Employment Practices and Workplace Safety, Internal Fraud and External Fraud. These event types represent 91,8% of the entire sample, which is consistent with patterns observed by Chernobei et al. (2011), Sturm (2013), Cummins et al. (2006) and de Fontnouvelle et al. (2006). However, the distribution of operational losses by event types differs slightly from the one observed by Cope et al. (2012) regarding event type EPWS (almost 22% from Total) and differs noticeably from the distribution reported by Moosa (2011). We exclude event type DPA from our model as we think the losses arising from nature disaster could not be explained by the firm specific and macro-economic variables we consider. Further, we drop the event type BDSF for which we have no observation and combine observations from event types EPWS and EDPW in a single category called "Others".[4] Table 5 shows descriptive statistics of variables around the four resulting event types. Both the mean and the median of operational losses corresponding to event type "Others" exceed those relating to event types IF, EF and CPBP. However, the mean comparison test for this subgroup shows contradictory results. For instance, the mean of operational losses and cash for event type 1 (IF) differs significantly (p-value<0.05) and (p-value<0.1), respectively, from those for event type 2 (EF), but insignificantly (p-value>0.1) from those for event type 4 (CPBP). Appendix A contains further details on the significant values of mean comparison test among above mentioned four event types. The means of most of the variables in subgroup EF differ from those of the rest of the event types. Taking this into the consideration, we create a new category, labelled "lack of internal control" (LoIC) which consist all this 3 event types: IF, CPBP and Others, shown in Table 6. This method is similar to Chernobei et al. (2011).

Table 3

Frequency of operational losses across financial institutions and event types. Abbreviations: IF – Internal Fraud; EF –External Fraud; EPWS – Employment Practices and Workplace Safety; CPBP – Clients, Products and

[4] For comparison, Wang and Hsu (2013) focus on three groups of event types namely CPBP, IF+EF, and "Others" (including all other event types, except DPA).

Business Practices; DPA - Damage to Physical Assets; BDSF - Business disruption and system failures; EDPW - Execution, Delivery & Process Management.

FI\ET	IF	EF	EPWS	CPBP	DPA	BDSF	EDPW	All	Total across FI
PUBbanks	52	76	3	32	10	0	0	173	28,45%
COOPbanks	33	65	0	18	15	0	0	131	21,55%
COMMERCIALbanks	80	94	5	107	4	0	13	304	50,00%
Total	165	235	8	158	29	0	13	608	100,00%
Total across ET	27,14%	38,65%	1,32%	25,99%	4,77%	0,00%	2,14%	100%	

Table 4

Descriptive statistics around financial institutions

				------------------------------ Quantiles ----------------------------- ----				
Variable	n	Mean	S.D.	Min	.25	Mdn	.75	Max
Public-sector Bnaks								
OL	173	12446552**	5.9e+07	52000.00	1.5e+05	3.1e+05	1.9e+06	6.0e+08
TA	154	60706902016***	1.2e+11	3.4e+08	2.1e+09	5.0e+09	3.2e+10	4.4e+11
Cash	154	583111104***	1.5e+09	6.4e+06	3.7e+07	1.1e+08	3.8e+08	9.2e+09
TIER1R	148	0.04***	0.02	0.01	0.03	0.04	0.05	0.10
TIER3R	144	0.06***	0.02	0.03	0.05	0.06	0.07	0.10
ROE	154	0.03	0.11	-0.74	0.02	0.03	0.05	0.80
FirmAge	158	860.20	848.80	0.00	120.00	396.00	1848.00	2604.00
Cooperative banks								
OL	131	1198814.5***	3.9e+06	73000.00	1.2e+05	2.0e+05	6.2e+05	3.0e+07
TA	89	2447792896***	5.9e+09	3.3e+07	3.7e+08	8.4e+08	1.7e+09	3.3e+10
Cash	87	30115568***	4.9e+07	4.3e+05	1.0e+07	1.8e+07	3.0e+07	2.8e+08
TIER1R	82	0.06***	0.01	0.03	0.05	0.06	0.06	0.10
TIER3R	85	0.07***	0.02	0.03	0.06	0.07	0.08	0.13
ROE	87	0.06	0.09	-0.32	0.03	0.05	0.07	0.68
FirmAge	92	619.10***	630.79	0.00	96.00	240.00	1296.00	1776.00
Commercial banks								
OL	303	34226012***	1.4e+08	60000.00	1.9e+05	6.0e+05	6.0e+06	1.6e+09
TA	251	540665085952***	5.8e+11	1.8e+07	3.8e+10	3.7e+11	8.4e+11	2.2e+12
Cash	244	6482388480***	9.7e+09	158.00	7.2e+08	4.5e+09	7.9e+09	9.3e+10
TIER1R	231	0.03***	0.02	0.01	0.02	0.03	0.04	0.28
TIER3R	231	0.05***	0.03	0.02	0.03	0.04	0.06	0.33
ROE	251	0.01	0.27	-2.34	0.00	0.05	0.12	1.68
FirmAge	258	933.81	692.27	0.00	156.00	1164.00	1620.00	1872.00

Table 5

Descriptive statistics around four event types

				------------------------------ Quantiles ---------------------------------				
Variable	n	Mean	S.D.	Min	.25	Mdn	.75	Max
IF (ET1)								
OL	165	22768652	1.0e+08	70000.00	4.0e+05	1.3e+06	6.3e+06	1.2e+09
TA	120	2.8e+11	4.8e+11	1.8e+07	2.7e+09	2.4e+10	3.9e+11	2.2e+12
Cash	117	3.6e+09	7.6e+09	158.00	3.7e+07	3.8e+08	3.2e+09	4.1e+10
TIER1R	111	0.04	0.03	0.01	0.02	0.04	0.05	0.28
TIER3R	111	0.06	0.04	0.02	0.04	0.05	0.07	0.33
ROE	121	-0.00	0.29	-2.34	0.02	0.04	0.08	0.36
FirmAge	128	838.27	777.61	0.00	108.00	396.00	1596.00	2232.00
EF (ET2)								
OL	235	7309648	4.9e+07	52000.00	1.2e+05	2.0e+05	7.0e+05	6.1e+08
TA	198	2.4e+11	4.9e+11	1.1e+08	1.5e+09	7.4e+09	2.1e+11	2.2e+12
Cash	195	2.4e+09	4.4e+09	1.2e+06	2.6e+07	1.1e+08	3.2e+09	1.9e+10
TIER1R	188	0.05	0.02	0.01	0.03	0.04	0.06	0.18
TIER3R	188	0.06	0.02	0.02	0.04	0.06	0.07	0.19
ROE	196	0.03	0.12	-0.74	0.02	0.05	0.06	0.68
FirmAge	200	813.89	749.18	0.00	120.00	402.00	1650.00	2604.00
CPBP (ET4)								
OL	157	35857176	1.5e+08	60000.00	1.5e+05	4.1e+05	7.6e+06	1.6e+09
TA	128	3.9e+11	4.7e+11	5.7e+07	1.3e+10	2.2e+11	6.3e+11	2.2e+12
Cash	125	5.2e+09	1.1e+10	1.0e+06	1.9e+08	2.9e+09	6.6e+09	9.3e+10
TIER1R	115	0.03	0.01	0.01	0.02	0.03	0.04	0.08
TIER3R	116	0.05	0.02	0.02	0.03	0.04	0.06	0.10
ROE	127	0.05	0.24	-1.40	0.02	0.05	0.12	1.68
FirmAge	132	959.36	704.64	24.00	156.00	1032.00	1620.00	2232.00
Others (ET3+ET7)								
OL	21	74764056	1.4e+08	70000.00	3.2e+05	1.1e+06	9.9e+07	5.2e+08
TA	20	4.5e+11	5.9e+11	4.8e+08	3.5e+10	2.0e+11	4.6e+11	2.2e+12
Cash	20	4.9e+09	8.3e+09	9.4e+06	2.5e+08	1.1e+09	5.8e+09	3.3e+10
TIER1R	20	0.04	0.02	0.01	0.02	0.03	0.04	0.10
TIER3R	18	0.05	0.02	0.02	0.03	0.04	0.06	0.10
ROE	20	-0.08	0.24	-0.73	-0.18	0.02	0.08	0.17
FirmAge	20	832.80	768.85	36.00	138.00	708.00	1506.00	2208.00

Table 6

Descriptive statistics around all event types, EF and LoIC

				------------------------------ Quantiles --------------------------------				
Variable	n	Mean	S.D.	Min	.25	Mdn	.75	Max

EF (ET2)								
OL	235	7309648***	4.9e+07	52000.00	1.2e+05	200000	7.0e+05	6.1e+08
TA	198	239653863424**	4.9e+11	1.1e+08	1.5e+09	7375033856	2.1e+11	2.2e+12
CashBar	195	2394791424***	4.4e+09	1.2e+06	2.6e+07	108223288	3.2e+09	1.9e+10
TIER1R	188	0.05***	0.02	0.01	0.03	0.04	0.06	0.18
TIER3R	188	0.06***	0.02	0.02	0.04	0.06	0.07	0.19
ROE	196	0.03	0.12	-0.74	0.02	0.05	0.06	0.68
FirmAge	200	813.89	749.18	0.00	120.00	402.00	1650.00	2604.00
lack of internal control (ET1+ET3+ET4+ET7)								
OL	343	31943000***	1.3e+08	60000.00	2.3e+05	900000	7.4e+06	1.6e+09
TA	268	347478949888**	4.9e+11	1.8e+07	4.1e+09	120683339776	4.5e+11	2.2e+12
CashBar	262	4447059456***	9.4e+09	158.00	6.8e+07	936223488	6.6e+09	9.3e+10
TIER1R	246	0.04***	0.02	0.01	0.02	0.03	0.05	0.28
TIER3R	245	0.05***	0.03	0.02	0.03	0.05	0.06	0.33
ROE	268	0.02	0.27	-2.34	0.02	0.05	0.09	1.68
FirmAge	280	894.96	743.21	0.00	126.00	894.00	1620.00	2232.00

Table 7 tabulates the annual frequency of operational losses in our sample from 1991 to 2013 for each country. The vast majority of the events (about 75%) occurred in Germany and especially in the last decade. The financial institutions in Austria, Switzerland, and Liechtenstein experienced few operational losses until the early 2000s. It is evident from this table that the frequency of operational events reached a peak around 2010 and then declined.

Table 7

Frequency of operational losses by year and country

year\country	AUT	GER	SUI/LIE	Total	Percent	cummulated losses
1991	1	0	0	1	0,16%	0,16%
1992	1	6	0	7	1,15%	1,32%
1993	0	3	0	3	0,49%	1,81%
1994	2	10	0	12	1,98%	3,79%
1995	0	2	2	4	0,66%	4,45%
1996	2	6	2	10	1,65%	6,10%
1997	0	9	1	10	1,65%	7,74%
1998	9	2	2	13	2,14%	9,88%
1999	3	6	0	9	1,48%	11,37%
2000	0	10	3	13	2,14%	13,51%
2001	0	11	5	16	2,64%	16,14%
2002	1	10	1	12	1,98%	18,12%
2003	1	27	1	29	4,78%	22,90%
2004	7	24	6	37	6,10%	29,00%
2005	7	36	7	50	8,24%	37,23%
2006	6	17	0	23	3,79%	41,02%
2007	9	43	6	58	9,56%	50,58%
2008	6	66	7	79	13,01%	63,59%
2009	13	59	7	79	13,01%	76,61%

2010	11	61	9	81	13,34%	89,95%
2011	3	22	3	28	4,61%	94,56%
2012	10	17	1	28	4,61%	99,18%
2013	1	4	0	5	0,82%	100,00%
Total	93	451	63	607	100,00%	100,00%

3.3. Methodology

We study the relationship between operational loss events on the one side and firm-specific and macroeconomic covariates on the other side through OLS regression analyses of pooled cross-sectional and time-series data. In addition, we include country and year dummies to account for aggregate changes across countries and over time. The advantage of pooled cross-sectional time-series data over cross-sectional or time-series data only is the larger amount of data used in estimation model. The resulting regression model is as follows:[5]

$$\begin{aligned} OL = {} & \beta 0 + \beta 1 F_{SIZE} + \beta 3 CASH_{TA} + \beta 4 TIER1R + \beta 5 TIER3R + \beta 6 ROE + \beta 7 DUM_{Excess_{GR}} \\ & + \beta 8 F_{AGE} + \beta 9 GDPgrowth + \beta 10\, UNEMPgrowth + \beta 11\, IRgrowth \\ & + \beta 12 IFOgrowth + \beta 13 MSCI_{EUgrowth} + \sum Year + \sum Ctry + \varepsilon \end{aligned} \tag{1}$$

Furthermore, we reproduce our basic model for certain subsets of interest. First, we study the relationship of operational losses and the above variables for commercial, public-sector and cooperative banks separately. Second, we focus on the analysis of specific operational event types, namely LoIC and EF.

4. Results

4.1. Empirical results at aggregate level

We apply our first model to study the relationship between operational loss events on the one side and firm-specific and macroeconomic covariates on the other side after considering correlations between explanatory variables. Table 8 shows the correlation coefficients for all the variables used in our basic model. There is a high correlation between TIER1R and TIER3R, which is reasonable since the calculation of total regulatory capital (Tier 3) includes core capital (Tier 1). Moreover, we observe a high correlation between the explanatory variables GDP on the one side and IR_{gr} as well as $UNEMP_{gr}$ on the other side. There is also a high correlation among $MSCI\_EU_{gr}$ and IFO_{gr}. To avoid multicollinearity, we modify regression model (1) by dropping the variables TIER1R, IFO_{gr}, $UNEMP_{g}$ and IR_{gr} (model 2), and TIER3R, $MSCI\_EU_{gr}$ and GDP (model 3). The results are shown Table 9.[6]

[5] Variables used in Eq. (1) are defined in Table 1.
[6] The calculated variance inflation factor (VIF) suggests a higher degree of multicollinearity for the variables TIER1R (6.96) and TIER3R (6.85) (see Appendix A2).

Table 8

Correlation of Variables

	OL	F_SIZE	Cash_TA	TIER1R	TIER3R	ROE	Ex_GR$_D$	F_AGE	GDP$_{gr}$	MSCI_EU$_{gr}$	IFO$_{gr}$	UNEMP$_{gr}$	IR$_{gr}$
OL	1.0000												
F_SIZE	0.2350*	1.0000											
Cash_TA	0.0466	-0.2436*	1.0000										
TIER1R	-0.1432*	-0.6277*	0.1576*	1.0000									
TIER3R	-0.0941*	-0.6067*	0.1252*	0.9172*	1.0000								
ROE	-0.0287	-0.0296	-0.0072	0.0316	0.0408	1.0000							
Ex_GR$_D$	0.0119	-0.0568	-0.0344	-0.0175	-0.0082	0.1024*	1.0000						
F_AGE	0.0027	0.1755*	0.0615	-0.1654*	-0.1529*	0.0084	0.0654	1.0000					
GDP$_{gr}$	0.1246*	0.0167	0.0473	-0.0103	0.0490	0.0282	0.0549	-0.0031	1.0000				
MSCI_EU$_{gr}$	0.0337	0.0505	0.1038*	-0.0504	-0.0139	0.1781*	-0.0359	0.0136	0.3301*	1.0000			
IFO$_{gr}$	-0.0563	0.0292	0.0674	-0.0035	0.0101	0.1007*	-0.0713	0.0290	0.3794*	0.7706*	1.0000		
UNEMP$_{gr}$	0.0670	0.0258	-0.0467	-0.0650	-0.0652	0.0012	-0.0751	-0.0288	-0.5179*	0.0632	-0.0171	1.0000	
IR$_{gr}$	0.0472	-0.0044	0.0357	0.0605	0.1070*	0.0402	0.0727	-0.0157	0.6723*	0.0707	0.1249*	-0.4984*	1.0000

* Significant at 5%. This Table indicates Pearson´s correlation coefficient matrix.

The regression findings are reported in Table 9. Our empirical results support our hypothesis that larger firms exhibit higher operational risk exposure than smaller firms. Furthermore, we find that TIER3R is significantly positive, implying that as regulatory capital increases, firms encounter higher operational losses. However, there seems to be no significant relationship between cash holding, return on equity and firm age on one hand and operational losses on the other hand. With respect to macroeconomical variables, we find a positive and significant coefficient only for GDP (in both cases). Regarding time and country dummies, we run a Wald test of hypothesis that the coefficients of these dummies are jointly 0, which is strongly rejected for all three subsets.

Table 9

Empirical results at aggregate level (Model 1).

OL	1	2	3
firm-specific Variables			
F_SIZE	0.163***	0.162***	0.158***
	(4.031)	**(4.182)**	**(3.744)**
Cash_TA	-2.531	-0.959	5.969
	(-0.530)	(-0.216)	(0.864)
TIER1R	-18.19*		6.597
	(-1.699)		(1.451)
TIER3R	21.94**	6.925**	
	(2.472)	**(2.101)**	
ROE	0.249	0.0982	0.226
	(0.510)	(0.210)	(0.446)
DUM_Excess_GR	0.315	0.238	0.207
	(1.460)	(1.120)	(0.954)
F_AGE	-0.0547	-0.0588	-0.0599
	(-0.786)	(-0.850)	(-0.860)

business environmental factors			
GDPgrowth	20.28***	10.48**	
	(2.929)	**(2.174)**	
IFOgrowth	-5.800*		-0.882
	(-1.919)		(-0.675)
MSCI_EUgrowth	2.212	0.205	
	(1.524)	(0.328)	
UNEMPgrowth	1.624		1.308
	(0.906)		(0.704)
IRgrowth	0.0722		0.431
	(0.247)		(1.645)
Constant	10.69***	12.39***	12.87***
	(4.951)	**(8.447)**	**(8.899)**
Year effect	yes	yes	yes
Country effect	yes	yes	yes
Observations	441	446	449
R-squared	0.271	0.254	0.252

***, **, and * indicate the two-tailed p-value<0.01, p<0.05, and p<0.1, respectively.

4.2. Empirical results given different types of financial institutions

Financial institutions in our sample differ with respect to their levels of complexity as well as to the range of banking services they offer. Moreover, comparing the means and medians of the variables corresponding to the three types of financial institutions, we find significant differences among the subgroups. For these reason we run specific regressions for each type of financial institution and present the results separately for the public-sector, cooperative and commercial banks sub-samples in Table 10. The results show that coefficients for firm size for the first two subgroups have the expected signs and are statistically significant. The results consistent with the arguments brought forward by Acharya et al. (2012) that smaller firms tend to be riskier than larger firms. For the public-sector bank sample we find almost the same behaviour as for the whole sample. In this subgroup, the only difference lies in the relationship between regulatory capital and operational losses, which is statistically insignificant. The Wald test of the hypothesis that the coefficients of country dummies are jointly 0 is not rejected for the public-sector banks subset.

For the cooperative banks subgroup, we find evidence regarding the positive and weakly significant association of core capital with operational risk exposure. This finding is different from our results using global sample analyses. Nevertheless, this evidence is consistent with the findings of Chernobei et al. (2011) regarding the association of this variable with operational risk events. However, they report a negative relationship for US financial institutions. Second, inconsistent with Chernobei et al. (2011) we find a negative and insignificant relationship between the variables cash to total assets and operational losses. However, this evidence shows that cooperative banks with higher cash holding suffer less from operational losses. We attribute this result in part to the reduction of credit volumes we observed which may cause a decrease in operational risk exposure. This result is also consistent with the findings reported by Acharya et al. (2012) showing a negative relationship between cash to total assets and credit spreads. Third, we find a significant and decreasing relationship between the unemployment rate and operational losses only for this subgroup. Regarding the sign, this finding is inconsistent with the findings by Moosa (2011) that operational loss severity, but not frequency, is positively related to unemployment. Fourth, we observe a strong positive relationship between operational loss exposure and return on equity which also applies only to cooperative banks. Finally, with respect to the commercial banks subgroup, we obtain insignificant results across both regression models (see columns 5 and 6).

Table 10

Empirical results for different type of financial institutions (Model 2)

OL	Public-sector Banks		Cooperative banks		Commercial banks	
	1	2	1	2	1	2
firm-specific Variables						
F_SIZE	0.385***	0.299**	0.210***	0.243**	-0.00423	0.0922
	(3.532)	(2.460)	(3.023)	(2.483)	(-0.0386)	(0.847)
Cash_TA	0.253	3.459	-20.91	-22.12	-19.05	12.16
	(0.0381)	(0.480)	(-1.460)	(-1.389)	(-1.275)	(1.018)
TIER1R		-11.57		16.38*		9.495
		(-0.709)		(1.771)		(1.639)
TIER3R	18.27		5.764		2.092	
	(1.462)		(1.180)		(0.407)	
ROE	-0.139	-1.636	2.287***	2.186**	0.0867	0.385
	(-0.0729)	(-0.612)	(2.798)	(2.283)	(0.170)	(0.712)
Ex_GR_D	0.0539	-0.0541	0.242	0.191	0.487	0.514
	(0.131)	(-0.128)	(0.907)	(0.642)	(1.374)	(1.376)
F_AGE	-0.140	-0.126	0.0675	0.0639	0.211	0.168
	(-1.153)	(-1.052)	(0.779)	(0.764)	(1.479)	(1.157)
business environmental factors						
GDP_{gr}	23.60**		6.757		4.079	
	(2.240)		(1.380)		(0.552)	
IFO_{gr}		1.220		-1.909		-2.686
		(0.634)		(-1.317)		(-1.268)
$MSCI\_EU_{gr}$	0.645		-0.460		-0.451	
	(0.612)		(-0.699)		(-0.469)	
$UNEMP_{gr}$		1.095		-6.056**		2.511
		(0.161)		(-2.277)		(1.256)
IR_{gr}		0.715		-0.540		0.611*
		(1.295)		(-1.385)		(1.657)
Constant	7.603*	13.70***	10.81***	6.018***	14.35***	9.938***
	(1.736)	(3.743)	(6.323)	(2.733)	(4.926)	(3.893)
Year effect	yes	yes	yes	yes	yes	yes
Country effect	No	No	yes	yes	yes	yes
Observations	140	144	81	79	225	226

R-squared	0.360	0.354	0.566	0.605	0.304	0.317

The values of t-statistics are reported in parentheses. ***, **, and * indicate the two-tailed p-value<0.01, p<0.05, and p<0.1, respectively.

4.3. Empirical results given different event type

As discussed earlier, some operational risk event types may exhibit a stronger relationship with firm-specific and business environment factors than others. However, mean comparison test confirm that the apparent differences between the explanatory variables around the event type category “External Fraud” and that of category “LoIC” are statistically significant at the 1% level. Thus, we perform additional analyses on the relationship among operational loss events for event types “External Fraud” and “Lack of Internal Control” and our explanatory variables (see Table 11). External Fraud losses indicate a strong positive association with firm size and Excess-GR dummy as well as a significantly negative association with the cash ratio. In addition we find a weak relationship between regulatory capital and External Fraud. Moreover, when we include a variable interest rate in our regression model (see second column of Table 11), we find a significantly increasing association with External Fraud. Among other business environmental factors, we find that both GDP and Unemployment rate show a positive, and both IFO and MSCI_EU a negative, relationship with External Fraud, though these macroeconomical variables are statistically insignificant for event type “External Fraud” in both subgroups. For this subgroup the Wald test failed to reject the hypothesis that all country dummy coefficients are jointly 0.

Regarding event type category “Lack of Internal Control” firm size is the only variable showing a significant association with operational risk exposure.

Table 11

Empirical results for different event type (Model 3)

OL	External Fraud	External Fraud	Lack of Internal Control	Lack of Internal Control
	1	2	1	2
firm-specific Variables				
F_SIZE	0.135**	0.162***	0.166**	0.136**
	(2.379)	(2.677)	(2.569)	(2.031)
Cash_TA	-14.57*	10.92	-4.855	-6.174
	(-1.928)	(1.070)	(-0.848)	(-1.032)
TIER1R		6.242		3.076
		(0.576)		(0.536)
TIER3R	11.98*		4.827	
	(1.757)		(1.163)	
ROE	1.522	1.269	0.486	0.663
	(1.545)	(1.281)	(0.813)	(1.076)
Ex_GR_D	0.802***	0.868***	-0.0208	-0.114
	(2.862)	(2.964)	(-0.0578)	(-0.315)

F_AGE	-0.0596	-0.0847	-0.0975	-0.0789
	(-0.655)	(-0.964)	(-0.903)	(-0.737)
business environmental factors				
GDP_{gr}	8.259		12.61	
	(1.327)		(1.248)	
IFO_{gr}		-2.103		0.978
		(-1.146)		(0.408)
$MSCI\_EU_{gr}$	-0.588		0.544	
	(-0.685)		(0.520)	
$UNEMP_{gr}$		2.171		1.810
		(0.459)		(0.939)
IR_{gr}		0.936**		0.385
		(2.160)		(0.854)
Constant	9.277***	7.254***	13.99***	14.62***
	(5.680)	(2.630)	(5.336)	(7.617)
Year effect	yes	yes	yes	yes
Country effect	No	No	yes	yes
Observations	182	183	237	239
R-squared	0.294	0.341	0.263	0.257

***, **, and * indicate the two-tailed p-value<0.01, p<0.05, and p<0.1, respectively.

5. Robustness test

The results presented in Table 9 were derived using our basic regression model. In this model we applied inter alia country dummies to control for aggregate changes across countries. To test for robustness, we check whether the results are stable if our model is estimated using only specific subset of the global data. Therefore, we run our regression model using data for each country separately. This will ensure that the prevalence of data from certain countries does not bias our findings. The results are shown in Table 12. We find that the results for Germany are generally consistent with the results for the entire sample. Nevertheless, we find significantly negative association between operational risk events and cash ratio for German financial institutions. The variable GDP which is positive and significant in aggregate level could not be confirmed for two specific subsets. Moreover we observe a strong negative correlation between UNEMPgr and operational risk. Inconsistencies we observe in datasets only containing data from Austria, Switzerland, or Liechtenstein, which are statistically insignificant in many cases, may be caused by the severe reduction of the number of observations (see Cope et al. (2013)).

Furthermore, we restrict our attention on three operational risk event types, namely IF, CPBP and “others”, and check whether the results are still consistent when we use these three event types separately instead of at an aggregated level (LoIC). We estimate the model based on data from each event type separately. Table 13 reports the respective results. The findings show that firm size remains significant for event type categories CPBP and LoIC. Moreover, we observe weak significant and positive association between Ex_GR_D and GDP on the one hand and operational losses of event type category CPBP on the other hand. Regarding Ex_GR_D, this observation seems consistent with expectations, since financial institutions with an aggressive growth strategy (liability growth exceeds assets growth), should be more prone to losses related to event type CPBP, which includes inter alia activities such as guideline violations, aggressive sales, market manipulation, insider trading, product defects, or model errors.[7]

Table 12

Results for different countries

OL	Austria		Germany		Switzerland/Liechtenstein	
	1	2	1	2	1	2
firm-specific Variables						
F_SIZE	0.304	0.382	0.120***	0.0999**	1.616	3.502**
	(1.143)	(1.318)	(2.812)	(2.216)	(1.756)	(2.538)
Cash_TA	15.66	2.246	-25.66***	-26.37***	49.41	22.56
	(0.685)	(0.111)	(-2.958)	(-2.878)	(0.257)	(0.867)
TIER1R		-1.097		4.886		171.1
		(-0.0443)		(1.198)		(1.824)
TIER3R	-8.394		7.463**		37.92	
	(-0.332)		(2.225)		(1.215)	
ROE	0.499	1.092	0.0682	0.0102	7.708	3.813
	(0.302)	(0.568)	(0.126)	(0.0180)	(1.037)	(0.497)
Ex_GR_D	0.0107	0.506	0.105	0.0208	3.813	6.835*
	(0.0100)	(0.476)	(0.479)	(0.0918)	(1.495)	(2.155)
F_AGE	0.0749	0.210	-0.109	-0.115	1.235	2.481*
	(0.161)	(0.483)	(-1.553)	(-1.627)	(1.355)	(2.211)
business environmental factors						
GDP_{gr}	90.54**		5.438		64.35	
	(2.194)		(1.178)		(1.024)	
IFO_{gr}		-7.999		-1.562		29.87
		(-1.461)		(-1.278)		(1.447)
$MSCI\_EU_{gr}$	-4.485		0.0210		1.327	
	(-1.547)		(0.0339)		(0.172)	
$UNEMP_{gr}$		-21.74**		-3.638		24.34
		(-2.508)		(-1.013)		(1.647)
IR_{gr}		-0.200		-0.0640		7.672
		(-0.161)		(-0.205)		(1.727)
Constant	1.249	3.932	12.81***	11.52***	-35.21	-92.22*
	(0.129)	(0.440)	(6.224)	(6.929)	(-1.329)	(-2.104)
Year effect	yes	yes	yes	yes	yes	yes
Country effect	No	No	No	No	No	No
Observations	47	46	371	375	28	28

[7] We also control for nonlinear effects in our firm-specific variables (results not reported), and find that our main results continue to hold.

R-squared	0.577	0.578	0.211	0.217	0.481	0.641

***, **, and * indicate the two-tailed p-value<0.01, p<0.05, and p<0.1, respectively.

Table 13

Results for each event types individually and jointly

OL	Internal Fraud		Clients, Products and		Others		Lack of Internal Control		External Fraud	
	1	2	1	2	1	2	1	2	1	2
firm-specific Variables										
F_SIZE	0.0236	0.0945	0.382***	0.380**	0.882	8.431	0.166**	0.136**	0.162***	0.135**
	(0.240)	(1.053)	(2.641)	(2.619)	(0.368)	(1.432)	(2.569)	(2.031)	(2.677)	(2.379)
Cash_TA	-5.047	1.101	-21.86	-20.55	-8.650	-865.7	-4.855	-6.174	10.92	-14.57*
	(-0.584)	(0.129)	(-1.615)	(-1.626)	(-0.0290)	(-3.276)	(-0.848)	(-1.032)	(1.070)	(-1.928)
TIER1R	-0.288		9.325		152.9			3.076	6.242	
	(-0.0377)		(0.384)		(0.616)			(0.536)	(0.576)	
TIER3R		5.855		0.762		114.4	4.827			11.98*
		(1.471)		(0.0356)		(0.815)	(1.163)			(1.757)
ROE	-0.173	-0.187	0.610	0.656	4.158	-112.9	0.486	0.663	1.269	1.522
	(-0.399)	(-0.407)	(0.348)	(0.439)	(0.221)	(-1.838)	(0.813)	(1.076)	(1.281)	(1.545)
Ex_GR_D	-0.342	-0.197	1.118*	1.182**	-3.664	18.61	-0.0208	-0.114	0.868***	0.802***
	(-0.695)	(-0.438)	(1.726)	(2.097)	(-1.394)	(1.454)	(-0.0578)	(-0.315)	(2.964)	(2.862)
F_AGE	-0.156	-0.200	0.0186	0.00441	-1.122	-2.463	-0.0975	-0.0789	-0.0847	-0.0596
	(-1.122)	(-1.482)	(0.102)	(0.0247)	(-1.108)	(-3.027)	(-0.903)	(-0.737)	(-0.964)	(-0.655)
business environmental factors										
GDP_{gr}		1.022		41.72*		-259.0	12.61			8.259
		(0.0777)		(1.891)		(-3.898)	(1.248)			(1.327)
IFO_{gr}	4.029		-1.137		-76.81			0.978	-2.103	
	(1.559)		(-0.225)		(-2.119)			(0.408)	(-1.146)	
$MSCI\_EU_{gr}$		1.868		-0.746		78.96	0.544			-0.588
		(1.522)		(-0.355)		(1.378)	(0.520)			(-0.685)
$UNEMP_{gr}$	-2.260		3.007		43.77			1.810	2.171	
	(-0.401)		(1.062)		(0.238)			(0.939)	(0.459)	
IR_{gr}	0.0873		1.136		-15.38			0.385	0.936**	
	(0.132)		(1.471)		(-0.237)			(0.854)	(2.160)	
Constant	13.22***	11.86***	7.376	6.950	19.08	-174.8	13.99***	14.62***	7.254***	9.277***
	(4.031)	(5.163)	(1.392)	(1.392)	(0.286)	(-1.148)	(5.336)	(7.617)	(2.630)	(5.680)
Year effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	106	106	113	113	20	18	237	239	183	182
R-squared	0.332	0.347	0.446	0.459	0.918	0.993	0.263	0.257	0.341	0.294

***, **, and * indicate the two-tailed p-value<0.01, p<0.05, and p<0.1, respectively.

6. Conclusion

Consistent with prior studies, we find a positive and significant relationship between firm size and operational losses. In addition, we identify positively significant relationship between regulatory capital and GDP growth on one side and operational risk events on the other side. In a second stage we investigate whether there is a different relationship between our explanatory variables and operational risk exposure across various subsamples. We observe inter alia a positively significant coefficient for core capital and return on equity by cooperative banks. Concerning macroenvironmental factors we observe negative and strong significant coefficient for unemployment rate in the same subsample, suggesting that during increasing unemployment the operational risk exposure goes down. Furthermore we find a weakly and positive association between operational loss events and interest rate growth across commercial banks. After dividing our sample in two event types' categories namely "External Fraud" and "Luck of internal Control", we observe a strong and positive coefficient for the Ex_GR_D by the first subset. This indicates that financial institutions with aggressive growth strategy suffer from higher external risk exposure. Moreover, we find a weakly significant and negative relationship between cash holding and operational loss exposure. Finally, with respect to other firm-specific and macroenvironmental factors we find no significant relationship to operational losses, a finding that runs contrary to prior empirical evidence for other countries. Our results hold both at the aggregate level and for different event types as well as for different financial institutions.

Variable	n	Mean	S.D.	Min	.25	Mdn	.75	Max
				------------------------------ Quantiles			--------------------------------	
All Financial institutions								
OL	610	20796410	1.0e+08	52000.00	1.5e+05	365897	2.5e+06	1.6e+09
TA	497	292306649088	4.9e+11	1.8e+07	2.0e+09	20749799424	3.9e+11	2.2e+12
Cash	488	3430788352	7.6e+09	158.00	3.3e+07	285700000	4.9e+09	9.3e+10
TIER1R	464	0.04	0.02	0.01	0.03	0.04	0.05	0.28
TIER3R	463	0.06	0.03	0.02	0.04	0.05	0.07	0.33
ROE	495	0.03	0.21	-2.34	0.02	0.05	0.08	1.68
FirmAge	511	853.28	739.97	0.00	132.00	696.00	1620.00	2604.00
Public-sector Banks								
OL	175	12331391	5.9e+07	52000.00	1.5e+05	340000	2.1e+06	6.0e+08
TA	156	59939946496	1.2e+11	3.4e+08	2.0e+09	4683150336	3.2e+10	4.4e+11
Cash	156	575692416	1.5e+09	4.5e+06	3.2e+07	107492768	3.7e+08	9.2e+09
TIER1R	150	0.04	0.02	0.01	0.03	0.04	0.05	0.10
TIER3R	146	0.06	0.02	0.03	0.05	0.06	0.07	0.10
ROE	156	0.03	0.11	-0.74	0.02	0.03	0.06	0.80
FirmAge	160	858.30	843.62	0.00	120.00	396.00	1842.00	2604.00
Cooperative banks								
OL	131	1198814	3.9e+06	73000.00	1.2e+05	200000	6.2e+05	3.0e+07
TA	89	2447792896	5.9e+09	3.3e+07	3.7e+08	840780992	1.7e+09	3.3e+10
Cash	87	30115568	4.9e+07	4.3e+05	1.0e+07	17572068	3.0e+07	2.8e+08
TIER1R	82	0.06	0.01	0.03	0.05	0.06	0.06	0.10
TIER3R	85	0.07	0.02	0.03	0.06	0.07	0.08	0.13
ROE	87	0.06	0.09	-0.32	0.03	0.05	0.07	0.68
FirmAge	92	619.10	630.79	0.00	96.00	240.00	1296.00	1776.00
Commercial banks								
OL	304	34114384	1.4e+08	60000.00	1.9e+05	592652.75	6.0e+06	1.6e+09
TA	252	538523500544	5.8e+11	1.8e+07	3.8e+10	3,58543E+11	8.4e+11	2.2e+12
Cash	245	6456312832	9.7e+09	158.00	7.2e+08	4534000128	7.9e+09	9.3e+10
TIER1R	232	0.03	0.02	0.01	0.02	0.03	0.04	0.28
TIER3R	232	0.05	0.03	0.02	0.03	0.04	0.06	0.33
ROE	252	0.01	0.27	-2.34	0.00	0.05	0.12	24838,00
FirmAge	259	933.36	690.97	0.00	156.00	1140.00	1620.00	1872.00

Appendix A.

A1. Mean comparison test among four event types

OLET1 vs OLET2 (p<0,05) sig	OLET1 vs OLET4 (p>0.10) no sig	OLET1 vs OLOthers (p<0,05) sig
TAET1 vs TAET2 (p>0.10) no sig	TAET1 vs TAET4 (p<0.10) sig	TAET1 vs TAOthers (p>0.1) no sig
CashET1 vs CashET2 (p<0.1) sig	CashET1 vs CashET4 (p>10) no sig	CashET1 vs CashOthers (p>0.10) no sig
TIER1RET1 vs TIER1RET2 (p<0.05) sig	TIER1RET1 vs TIER1RET4 (p<0.1) sig	TIER1RET1 vs TIER1ROthers (p>0.1) no sig
TIER3RET1 vs TIER3RET2 (p>0.1) no sig	TIER3RET1 vs TIER3RET4 (p<0.01) sig	TIER3RET1 vs TIER3ROthers (p>0.1) no sig
ROEET1 vs ROEET2 (p>0.10) no sig	ROEET1 vs ROEET4 (p>0.10) no sig	ROEET1 vs ROEOthers (p>0.10) no sig
F_AgeET1 vsF_AgeET2 (p>0.10) no sig	F_AgeET1 vsF_AgeET4 (p>0.10) no sig	F_AgeET1 vs F_AgeOthers (p>0.10) no sig
OLET2 vs OLET4 (p<0,01) sig	OLET2 vs OLOthers(p<0,01) sig	OLET1 vs OLET2 (p<0,05) sig
TAET1 vs TAET2 (p>10) no sig	TAET2 vs TAET4 (p<0,01) sig	TAET2 vs TAOthers (p<0.10) sig
CashET1 vs CashET2 (p<10) sig	CashET2 vs CashET4 (p<0.01) sig	CashET2 vs CashOthers (p<0.05) sig
TIER1RET1 vs TIER1RET2 (p<0.05) sig	TIER1RET2 vs TIER1RET4 (p<0.01) sig	TIER1RET2 vs TIER1ROthers (p<0.05) sig
TIER3RET1 vs TIER3RET2 (p>10) no sig	TIER3RET2 vs TIER3RET4 (p<0.01) sig	TIER3RET2vs TIER3ROthers (p<0.05) sig
ROEET1 vs ROEET2 (p>0.10) no sig	ROEET2 vs ROEET4 (p>0.10) no sig	ROEET2 vs ROEOthers (p<0.01) sig
F_AgeET1 vs F_AgeET2 (p>0.10) no sig	F_AgeET2 vs F_AgeET4 (p<0.10) sig	F_AgeET2 vs F_AgeOthers (p>0.10) no sig
OLET1 vs OLET4 (p>10) no sig	OLET2 vs OLET4 (p<0,01) sig	OLET4 vs OLOthers (p>10) no sig
TAET1 vs TAET4 (p<0.10) sig	TAET2 vs TAET4 (p<0,01) sig	TAET4 vs TAOthers (p>10) no sig
CashET1 vs CashET4 (p>10) no sig	CashET2 vs CashET4 (p<0.01) sig	CashET4 vs CashOthers (p>10) no sig
TIER1RET1 vs TIER1RET4 (p<0.1) sig	TIER1RET2 vs TIER1RET4 (p<0.01) sig	TIER1RET4 vs TIER1ROthers (p>0.1)no sig
TIER3RET1 vs TIER3RET4 (p<0.01) sig	TIER3RET2 vs TIER3RET4 (p<0.01) sig	TIER3RET4 vs TIER3ROthers (p>0.1) no sig
ROEET1 vs ROEET4 (p>0.10) no sig	ROEET2 vs ROEET4 (p>0.10) no sig	ROEET4 vs ROEOthers (p<0.05) sig
F_AgeET1 vsF_AgeET4 (p>0.10) no sig	F_AgeET2 vs F_AgeET4 (p<0.10) sig	F_AgeET4 vs F_AgeOters (p>0.10) no sig
OLET1 vs OLOthers (p<0,05) sig	OLET2 vs OLOthers(p<0,01) sig	OLET4 vs OLOthers (p>10) no sig
TAET1 vs TAOthers (p>10) no sig	TAET2 vs TAOthers (p<10) sig	TAET4 vs TAOthers (p>10) no sig
CashET1 vs CashOthers (p>10) no sig	CashET2 vs CashOthers (p<0.05) sig	CashET4 vs CashOthers (p>10) no sig
TIER1RET1 vs TIER1ROthers (p>0.1) no sig	TIER3RET2 vs TIER3ROthers (p<0.05) sig	TIER1RET4 vs TIER1ROthers (p>0.1)no sig
TIER3RET1 vs TIER3ROthers (p>0.1) no sig	TIER3RET2vs TIER3ROthers (p<0.05) sig	TIER3RET4 vs TIER3ROthers (p>0.1) no sig
ROEET1 vs ROEOthers (p>0.10) no sig	ROEET2 vs ROEOthers (p<0.01) sig	ROEET4 vs ROEOthers (p<0.05) sig
F_AgeET1 vs F_AgeOthers (p>0.10) no sig	F_AgeET2 vs F_AgeOthers (p>0.10) no sig	F_AgeET4 vs F_AgeOters (p>0.10) no sig

A2.Variance inflation factor (VIF) results

Variable	VIF	1/VIF
TIER1R	6.96	0.143597
TIER3R	6.85	0.145894
$MSCI\_EU_{gr}$	3.19	0.313839
IFO_{gr}	3.14	0.318768
GDP_{gr}	2.81	0.356133
IR_{gr}	2.10	0.475524
F_SIZE	1.86	0.536595
$UNEMP_{gr}$	1.76	0.567200
Cash_TA	1.13	0.882936
Ex_GR_{D}	1.09	0.915546
F_AGE	1.07	0.934696
ROE	1.06	0.940964
Mean VIF	2.75	

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