Banking Sector Operational Losses and Macroeconomic Environment ☆

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Abstract

We investigate the relationship between operational losses at large U.S. banking organizations and the macroeconomic environment. We find evidence of a negative relationship between macroeconomic growth and operational losses in two Basel II loss event type categories: Clients, Products, and Business Practices and Execution, Delivery, and Product Management. Losses in these two categories comprise about 90 percent of the total industry losses in our sample. Our analysis suggests that the negative correlation of losses in these two categories with macroeconomic growth is concentrated in the tails of loss distributions.
(JEL classification: C22 C23 G21)

Keywords: Operational risk, Basel II, Stress testing

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1. Introduction

International banking regulatory standards defines operational risk as the risk of loss resulting from inadequate or failed internal processes, people, and systems or from external events (The Basel Committee on Banking Supervision (2006)). In recent years, media and other public sources reported numerous very large operational losses occurred in the banking industry. For example, the nation's five largest mortgage servicers, Bank of America Corporation, JPMorgan Chase & Co., Wells Fargo & Company, Citigroup Inc., and Ally Financial Inc. collectively agreed to a $25 billion settlement with U.S. Federal government to address past improper mortgage loan servicing and foreclosure fraud, UBS lost $2.3 billion to unauthorized trades, and Royal Bank of Scotland Group PLC (RBS) lost $275 million in settlement to resolve allegations of misleading investors in mortgage-backed securities.[1] Therefore, operational losses are an important source of risk for banks and understanding the key factors of operational risk as well as quantifying their impacts is an important task in risk measurement and management. One key risk factor of the financial stability of the banking sector is the macroeconomic environment. In recent years, in response to the regulatory requirements introduced after the recent financial crisis, banks increased effort to internally build empirical models to estimate the impact of stress macroeconomic environments on operational losses. At the same time, due to the lack of good quality data, the broad nature of operational losses, and difficulty in observing and measuring drivers of operational losses, quantification of this impact is a challenging risk quantification area.

Interactions between the real sector of the economy and the banking sector are well-understood through credit and market risks. However, the relationship between operational risk and the macroeconomic environment is still not a well-studied research area. As discussed in Chernobai et al. (2011), operational losses might be procyclical or countercyclical to the business cycle. On one hand, banks may reduce transaction volume in stressful economic periods, leading to fewer operational losses. For example,

[1] In the literature on operational risk, de Fontnouvelle et al. (2006) show that operational losses can exceed the market risk.

retail fraud-related losses may decrease during periods of economic contraction due to decline in transaction volume. On the other hand, however, one could argue that the economic stress reveals operational risk on surface. For example, large-scale improperly marketed products might be discovered when the economy experiences liquidity constraints. Thus, how operational risk and the macroeconomic environment are related is an empirical question which is not well-studied.

In this paper, we investigate the relationship between operational losses of the banking sector and macroeconomic environment. We base our study on supervisory operational loss data reported by large banking organizations to the Federal Reserve for stress testing purposes. Our selected sample of data comprises near to two hundred thousand observations. Most of previous studies use samples of data with around two thousand to seven thousand observations from two public datasets: Algo FIRST and SAS OpRisk Global Data. As discussed in de Fontnouvelle et al. (2006), public sources of data are based on publicly available information, are biased towards larger losses, and may not report all significant losses.

We model the relationship between operational losses and real GDP growth using panel regression analyses of individual banks' quarterly losses by each event type. It is known that operational losses have very heavy-tailed distributions. To analyze the roles of large tail losses and smaller losses in the relationship between operational losses and the macroeconomic environment, we separately study tail losses and small losses in the distributions of losses, in addition to total losses.

Using data from 2003 through 2012, we find evidence that banking industry operational losses are negatively correlated with macroeconomic growth in certain event types of losses. In particular, we find negative correlations between losses and real GDP growth in two Basel II loss event type categories: Clients, Products, and Business Practices and Execution, Delivery, and Product Management. In total, losses in these two categories comprise about 90 percent of all industry losses and also represent the bulk of losses for most individual banks in our data sample. Our analysis suggests that the correlation of losses in these two categories with macroeconomic growth is concentrated in the tails of loss distributions. We also find that the tail losses in the External Fraud event

type category are negatively correlated with real GDP growth, while the body losses in this category are positively correlated with real GDP growth. We explain this finding with a positive correlation of smaller fraud-related losses with the volume of banking transactions, while larger losses might be revealed during economic and financial stress periods. Smaller losses in Employment Practices and Work Safety category appear to be negatively correlated with economic growth, while we find no strong evidence of the relationship between tail losses in this category with macroeconomic conditions.

The literature on the relationship between operational risk and macroeconomic factors is in its infancy. Research in this area is also constrained by the availability of reliable data. Allen and Bali (2007) find evidence of cyclical components in their operational risk measurement. In contrast to most of the literature on operational risk which uses operational loss data, this study uses equity return data to proxy operational risk. Hess (2011) compares value-at-risk from a parametric distribution that fit into two sub-samples of loss data and finds evidence of the increase in the tail of loss severity distribution for trading and sales and retail brokerage business lines during the recent financial crisis. Chernobai et al. (2011) find evidence of the increase in loss frequency of some loss event types with economic downturn. Cope et al. (2012) find the relationships between the severity of operational losses and regulatory and legal indicators of different countries. Cope and Carrivick (2013) compare total losses, loss counts, and average losses in four sub-periods of data and find evidence of increases in the frequency and severity of operational losses during the recent financial crisis.

Our study contributes to this literature in several dimensions. First, we model a loss amount as a function of macroeconomic variables. While, the above listed papers find the relationship between operational losses and the macroeconomic environment, most of them do not explicitly quantify the links between loss amounts and macroeconomic factors. Chernobai et al. (2011) quantify the relationship between loss frequency and macroeconomic variables; however, they do not model loss severity. Our model predicts a total loss value, which is the main interest of risk management, given macroeconomic conditions. Second, we quantify the role of the tail and the body of the loss distribution in the relationship of losses with macroeconomic conditions. It allows us to

understand the distributional sources of the relationship between operational losses and macroeconomic variables. Third, we study the relationship between operational losses and macroeconomic growth using supervisory data which are substantially richer than public datasets used in the previous literature.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 describes our statistical methodology for loss aggregation. Section 4 reports results and robustness checks. Section 5 concludes.

2. Data

We use supervisory operational loss data reported by U.S. bank holding companies (BHCs) according to schedule E of the FR Y-14Q reporting form.[2] The Federal Reserve System collects the FR Y-14Q detailed data, including operational loss data, for capital assessments and stress testing of BHCs with total consolidated assets of $50 billion or more. Board of Governors of the Federal Reserve System (2014) reports that the 2014 capital and stress testing assessment covered 30 BHCs. The schedule for reporting operational loss data requires BHCs to report historical individual losses in USD. Each loss has a loss date and classified by Basel II operational loss event type categories and business lines.

Operational risk quantification is a relatively new risk quantification area and many banks started rigourous loss collection relatively recently. The objective of this paper is to study the relationship between operational losses and macroeconomic environment. Therefore, the reliability of time series of data is an important criterion for our sample selection. For our sample of data we select 23 BHCs out of 30, excluding BHCs with short data collection period or inconsistent data collection across quarters in the sample period. For our study, we use sample of loss data for the period from 2003 though 2012, excluding all data prior to 2003. Our data analysis suggests that most of BHCs in our unbalanced sample of loss data have relatively consistent data reporting for this period. While it is desirable to have a longer sample period, the extension of the sample to the

[2]The FR Y-14Q reporting form and the instruction is publicly available online at http://www.federalreserve.gov/apps/reportforms/.

period prior to 2003 would considerably reduce the number of BHCs in the early part of the unbalanced panel data. It might cause estimation results to be driven by a few banks with available data in the early part of the sample rather than by the banking industry as a whole.

Banks determine their own thresholds for collecting individual losses. To avoid the impact of variation in data collection thresholds on our results, we truncate data to a uniform dollar amount and adjust for inflation. To preserve confidentiality of the data, we transform losses from USD terms into some unit using an arbitrary multiplier. After data truncation, the sample of loss data comprises more than 197,000 individual loss events. Our sample size is substantially larger than the number of observations in vendor datasets reported by Algo FIRST, SAS OpRisk Global Data, and the Operational Riskdata eXchange (ORX) association, which are commonly used in the literature. For example, Chernobai et al. (2011) use the sample of data with 2,426 loss event reported by the Algo FIRST dataset. Hess (2011) uses data reported by SAS OpRisk Global Data with around 7,300 loss events from the banking industry. Cope et al. (2012) use the ORX Global Loss Data Database and after uniform truncation their study contains around 57,000 loss observations from the banking industry around 130 countries.

Following Chernobai et al. (2011), we analyze operational loss data by Basel II operational loss event type categories. Although two-dimensional analysis of data by business lines and event types is desirable, we do not conduct such analysis for two reasons. First, banks classify data by their own business lines for internal risk management and modeling purposes. In practice, internal business line classifications vary among banks and are quite different from the standard Basel II business line classification. Classification of data by Basel business line categories is usually a challenging exercise for banks and may not be uniform across banks in data. Meanwhile, classification of losses by event types is reasonably intuitive process. Second, high granularity of data classification creates risk of a considerably smaller number of observations of some individual banks in each quarter, especially in the tail which is one of the key area of interest in this study. In Table 1, we provide descriptions of event types defined by The Basel Committee on Banking Supervision (2006). The rest of the paper uses the abbreviations of event types

from this table.

Table 1: Basel II event type categories

Event-Type Category	Abbreviation	Definition
Internal fraud	IF	Losses due to acts of a type intended to defraud, misappropriate property or circumvent regulations, the law or company policy, which involves at least one internal party
External fraud	EF	Losses due to acts of a type intended to defraud, misappropriate property or circumvent the law, by a third party
Employment Practices and Workplace Safety	EPWS	Losses arising from acts inconsistent with employment, health or safety laws or agreements, from payment of personal injury claims, or from diversity / discrimination events
Clients, Products and Business Practices	CPBP	Losses arising from an unintentional or negligent failure to meet a professional obligation to specific clients (including fiduciary and suitability requirements), or from the nature or design of a product.
Damage to Physical Assets	DPA	Losses arising from loss or damage to physical assets from natural disaster or other events.
Business disruption and system failures	BDFS	Losses arising from disruption of business or system failures
Execution, Delivery and Process Management	EDPM	Losses from failed transaction processing or process management, from relations with trade counterparties and vendors

Source: The Basel Committee on Banking Supervision (2006).

Table 2 reports the mean and median of each descriptive statistic of bank loss distributions by seven standard Basel event type categories. The means and standard deviations of losses vary considerably across banks, suggesting substantial differences in scales and variations of losses among banks. CPBP event type losses have very heavy-tailed distributions for most banks and it is the event type category with the largest share of losses in the entire industry. CPBP event type comprises 72% of the total industry losses in our sample. The large losses in this category are mainly litigation losses. EDPM is the second largest event type comprising 18% of the total losses in our sample. Most of the losses in this category are related to improper transaction processing. Thus, modeling operational losses in these two categories should be the key focus of our study.

Table 2: Descriptive statistics of operational loss data

	IF	EF	EPWS	CPBP	DPA	BDSF	EDPM
Number of observations							
median	63	551	265	231	58	69	868
mean							
Average loss							
median	15,762	7,333	12,434	132,439	20,022	17,809	17,717
mean							
Standard deviation							
median	46,051	45,638	42,222	902,167	65,514	70,172	162,096
mean							
90th percentile							
median	26,013	10,083	17,079	61,835	21,362	35,225	18,483
mean							
95th percentile							
median	67,745	18,155	29,367	187,896	39,239	65,294	35,260
mean							
99th percentile							
median	194,422	54,991	159,801	1,423,039	325,246	249,159	172,930
mean							
Share of losses above 95th pct.							
median	54.3%	47.3%	52.7%	80.6%	61.6%	48.6%	60.3%
mean							
Share in bank's total loss							
median	1.6%	10.5%	4.8%	52.5%	0.7%	0.8%	26.3%
mean							
Share in total industry loss	1.4%	3.8%	3.5%	71.6%	0.7%	1.4%	17.7%

The table reports the descriptive statistics of operational loss data of 23 bank holding companies for the period 2003-2012. To preserve confidentiality of the data, losses are transformed from USD to some unit using an arbitrary multiplier. The table reports the median and mean of the distribution of each statistic among banks in the sample.

3. Statistical methodology

3.1. Motivation

First, we motivate why one should expect a relationship of operational losses in certain event type categories with the macroeconomic environment. Second, we report preliminary analysis of the relationship of operational losses with the macroeconomic environment and motivate our statistical methodology of standardization.

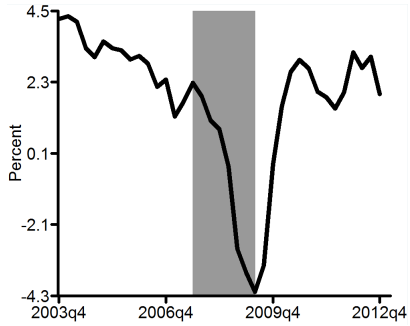
Losses in some categories are not expected to be correlated with macroeconomic factors. Description of DPA and BDSF event types, provided in Table 1, and our analysis of data suggest that losses in these categories are mainly random in nature.

Therefore, we do not model losses in these two event types. These two event types comprise only 2.1 percent of the total industry losses during our sample period.

Fraud-related losses in IF and EF categories may be related with the business cycle. For example, while rogue trading, which is classified as internal fraud, might occur regardless of economic conditions, the risk of large losses from rogue trading increases when the economy is in a contraction phase, causing the increase in uncertainties in fundamental values of assets and volatilities of financial markets. Retail external fraud may grow with the increase in transaction volume as a result of an economic expansion. Meanwhile, sizable financial fraudulent schemes might surface during periods of economic downturn when financial liquidity constraints are more likely to build. CPBP losses from improperly marketed products could be related to macroeconomic stress. For example, poor mortgage underwriting standards with improper mortgage documentation and credit scores were revealed during the recent financial crisis. During the recent financial crisis such poor quality mortgage loans packaged in mortgage-backed securities caused extremely large litigation losses in the banking industry. EDPM losses also might be correlated with macroeconomic conditions. Incorrectly processed transactions, for example, should lead to larger losses during economic contractions when financial markets are volatile.

Operational losses tend to have long lags from the period of loss event to when the loss is discovered and accounted for. These lags are random and may vary considerably. For example, legal cases might take considerable period of time from the time of a loss event to time of the legal case initiation and to time of the loss settlement. Depending on the legal case, this time-lag might substantially variate. Therefore, it is unrealistic to expect quarterly macroeconomic changes to impact operational losses of all banks with a specific time lag. To account for uncertainty in lags, we use a four-quarter moving average of losses. The one-year period is also consistent with the one-year horizon in the capital estimation for operational risk. Our measure of macroeconomic changes is real GDP growth measured as the year-over-year change in logarithm of real GDP and expressed in percent terms (Figure 1). The real GDP data are obtained from St. Louis FRED database. The regression of the one-period lag of real GDP growth on logarithm

Figure 1: Annual GDP growth



The figure displays quarterly data of the year-over-year change in logarithm of real GDP and expressed in percent terms. The shaded area is the period from the beginning of financial crisis in 2007:Q3 through the end of the recession in 2009:Q2.

of the four-quarter moving sum of losses should yield an estimate of the impact of macroeconomic change on losses within one year. Our objective is to capture the impact of large changes in the economy on operational losses and the real GDP growth rate is a collective macroeconomic variable that represents the business cycle. While many other macroeconomic and financial variables, in addition to real GDP growth, can potentially be related to operational losses, we control only for real GDP growth to avoid any multicollinearity issues which is strongly present in persistent series.

As demonstrated above, the distribution of operational losses are heavy-tailed. Linear regressions cannot fit such data. To mitigate the impact of extreme losses on linear regressions, we winsorize individual losses at the 99th percentile within each bank's sample prior to constructing a time series of loss data. As Table 2 shows, the 99th percentiles of the loss distributions are already heavy-tailed and, therefore, winsorizing preserves heavy-tail characteristics of the loss distributions.

For each event type, we run panel regressions of log-transformed dollar losses on macroeconomic growth in our preliminary analysis. Following Shih et al. (2000) and Dohen and Dionne (2010), who find that losses are correlated with the firm's size, our regressions control for the total asset size of individual banks. We run panel regressions with fixed effects to control for unobservable bank characteristics that impact operational losses in addition to the bank size. Equation 3.1 describes this regression.

$$ln(l_{i,t}) = \alpha_i + ln(Size_{i,t})\beta + g_{t-1}\gamma + \varepsilon_{i,t}, \tag{3.1}$$

where $l_{i,t}$ is the sum of losses in bank i for quarters $t-3$ through t, α_i is the fixed effect of bank i, $Size_{i,t}$ is the total asset size of bank i in quarter t, and g_{t-1} is the year-over-year change in logarithm of real GDP between quarters $t-1$ and $t-5$ expressed in percent terms.

Panel A of Table 3 reports estimation results from the described panel regressions. Our estimation results suggest that, except for CPBP, losses are negatively correlated to macroeconomic growth. Although the sign of the coefficient for real GDP growth is negative for CPBP losses, it is statistically insignificant. Since CPBP is the largest category of losses in the banking sector, a deeper analysis is necessary to determine whether operational losses are countercyclical to macroeconomic growth.

We find that losses of CPBP and EDPM event types are positively correlated with banks' total assets. The coefficients for the total asset variable are statistically significant with p-values less than 0.001. This result is consistent with findings in the literature that the firm size is a significant factor of operational losses. The coefficients for the total assets for other event types are statistically insignificant. Smaller banks in our sample might have large portfolios of retail-fraudulent losses relative to banks with larger total assets. Therefore, the total assets of a bank may not be a good measure of the size of fraud-related operations. For example, banks concentrated in credit card activities have smaller total assets, but larger volumes of credit card transactions. Thus, transaction volume would be a more appropriate measure of the size for credit card operational risk.

As we show in Section 2, losses have very heavy-tailed distributions, so the relationships of operational losses in the tail of the loss distribution with macroeconomic growth might be different from losses in the body of the distribution. To analyze the role of very large losses and smaller body losses in the results in Panel A in Table 3, we run two additional panel regressions separating losses above and below the 95th percentile. Panels B and C of Table 3 report estimation results from these regressions. The body losses of only IF and EDPM event types have statistically significant negative correlations with real GDP growth. The tail losses of only EF and EPWS event types appear

Table 3: Estimation results: panel regressions of bank's losses on real GDP growth

	Total	IF	EF	EPWS	CPBP	EDPM
A. Dependent variable: log of bank's loss						
Real GDP growth	-0.074	-0.060	-0.108	-0.021	-0.100	-0.029
	(0.000)	(0.023)	(0.000)	(0.078)	(0.000)	(0.005)
Total Asset	0.703	-0.527	-0.447	-0.302	0.756	0.382
	(0.000)	(0.012)	(0.042)	(0.010)	(0.000)	(0.000)
Adj. R^2	0.788	0.574	0.711	0.765	0.598	0.879
B. Dependent variable: log of bank's body losses						
Real GDP growth	-0.062	-0.051	0.021	0.014	-0.088	-0.025
	(0.000)	(0.032)	(0.447)	(0.192)	(0.000)	(0.002)
Total Asset	0.490	-0.492	-0.255	-0.187	0.429	0.291
	(0.000)	(0.004)	(0.199)	(0.076)	(0.001)	(0.000)
Adj. R^2	0.838	0.592	0.729	0.797	0.724	0.879
C. Dependent variable: log of bank's tail losses						
Real GDP growth	-0.128	-0.136	-0.383	-0.327	-0.240	-0.066
	(0.000)	(0.112)	(0.000)	(0.000)	(0.003)	(0.229)
Total Assets	1.804	0.033	-1.026	0.055	3.332	1.339
	(0.000)	(0.969)	(0.030)	(0.932)	(0.000)	(0.004)
Adj. R^2	0.474	0.431	0.624	0.377	0.370	0.458
Number of observations	755	500	687	693	747	677

Panel A of the table reports results of the panel regressions using all losses of each bank. Panel B (Panel C) reports results of regressions using losses below (above) the 95th percentile of each bank's loss distribution. Parentheses report p-values of estimates. The model utilizes bank fixed effects and robust variance. Individual losses are winsorized at the 99th percentile. Real GDP growth is defined as the year-over-year change in logarithm of real GDP expressed in percent terms.

to be negatively correlated with macroeconomic growth.

Thus, the above results do not provide conclusive evidence for the relationship of operational losses with the macroeconomic environment. Given statistical properties of operational losses and substantial variations of losses across banks, the linear regression might not accurately capture the loss dynamics, especially for tail losses. For example, CPBP losses have a very heavy-tailed loss distribution which, even when aggregated with smaller body losses, might dominate dynamics of all CPBP losses. Also, the above naïve panel regressions might be misspecified due to omitted factors. While fixed effects should capture some characteristics of banks, they may not capture important time varying factors which are difficult to measure. Therefore, in the next section, we propose

standardizing losses of different banks to make data series more suitable for the linear regression. The standardization also makes the loss dynamics comparable across different banks and allows us to analyze the relationship between aggregated standardized losses and macroeconomic growth.

3.2. Standardization methodology

In this subsection, we describe the methodology of loss standardization to make loss dynamics comparable across banks. After standardization, we aggregate standardized losses of all banks into a single time series. This aggregated time series reflects the overall dynamics of operational losses in the banking industry. Standardization also prevents aggregated loss dynamics from being dominated by the loss dynamics of individual banks. We study aggregated losses for two reasons. First, our objective is to understand the relationship of banking industry operational losses with the macroeconomic environment. Aggregation reduces the impacts of idiosyncratic losses from individual banks on our results for the entire banking industry. Second, loss aggregation also allows us to better illustrate our results while keeping confidentiality of firms in the supervisory data.

The aggregation of losses of different banks is not trivial. Simple addition of losses would create strong bias toward banks with large amounts of losses due to their loss scales. Such simple addition would not properly represent the loss dynamics of the entire banking industry. For our study, we scale losses before aggregating them in order to mitigate the risk emerging from disproportionate losses of different banks. Several studies propose various scaling methods (e.g., Na et al. (2006), Cope and Labbi (2008), and Dohen and Dionne (2010)), however, scaling of operational losses remains a challenging task for practitioners. Given the wide range of loss types and the nature of operational risk, it is difficult to find factors that could be used for scaling losses. In our analysis, we standardize losses of each bank by demeaning and dividing by the sample standard deviation. This statistical method avoids dependence on scaling factors and accounts for key statistical differences in loss data of various banks, while preserving the dynamics of losses of each bank. After this transformation, time series of individual banks' loss data are comparable across banks and their aggregation accurately represents the entire banking industry.

We perform standardization and aggregation of losses by each event type separately. The input data for our standardization method are the winsorized losses described in Subsection 3.1. We use winsorized data rather than the raw data because losses are very heavy-tailed. Adjustments for the two first moments through standardization are not sufficient transformation for a linear regression and winsorizing the data helps to mitigate this shortcoming. The standardization and aggregation of losses for each event type has four steps. First, we demean individual event losses and divide by the standard deviation of losses of each bank. Second, we aggregate individual standardized event losses to the quarterly time series for each bank. This step results in a panel of time series of standardized losses by banks. Third, we construct time series of four-quarter moving sum of losses for each bank. Last, we aggregate individual four-quarter moving sum losses of individual banks into a single time series by taking averages of each bank losses in each quarter. This step produces the moving sum time series of annual standardized losses aggregated at the industry level.[3]

4. Results

4.1. Estimation results

The first column of Figure 2 displays the time series of aggregated standardized losses for five event types. One visually observes that aggregated losses increased during the recent financial crisis period. To formally test this relationship, we run a time series regression of aggregated standardized losses on real GDP growth. The regression is described by the below equation:

$$s_t = \alpha + g_{t-1}\gamma + \varepsilon_t, \tag{4.1}$$

where s_t is aggregated standardized four-quarter losses for quarters $t-3$ through t, α is the intercept term, and g_{t-1} is the year-over-year change in logarithm of real GDP between quarters $t-1$ and $t-5$ expressed in percent terms.

[3]An alternative way of standardizing losses is to standardize logarithm of losses rather than losses. Na et al. (2006) motivates scaling losses in log terms. In our analysis, we aggregate losses and directly adding logarithm of losses would imply multiplication rather than addition of losses. In addition, if a bank reports zero losses in some quarters the log transformation does not work for our purposes.

Panel A of Table 4 reports estimation results for each event type. In contrast to the results from the panel regressions of loss amounts, the regression of aggregated standardized losses produces a statistically significant negative correlation between real GDP growth and losses for all event types, except EF. This result supports that the standardization of heavy-tailed distributions helps to depict the relationship between losses and macroeconomic variables. Later in this subsection, we revisit our estimation result that suggests a positive correlation of aggregated standardized EF losses with real GDP growth.

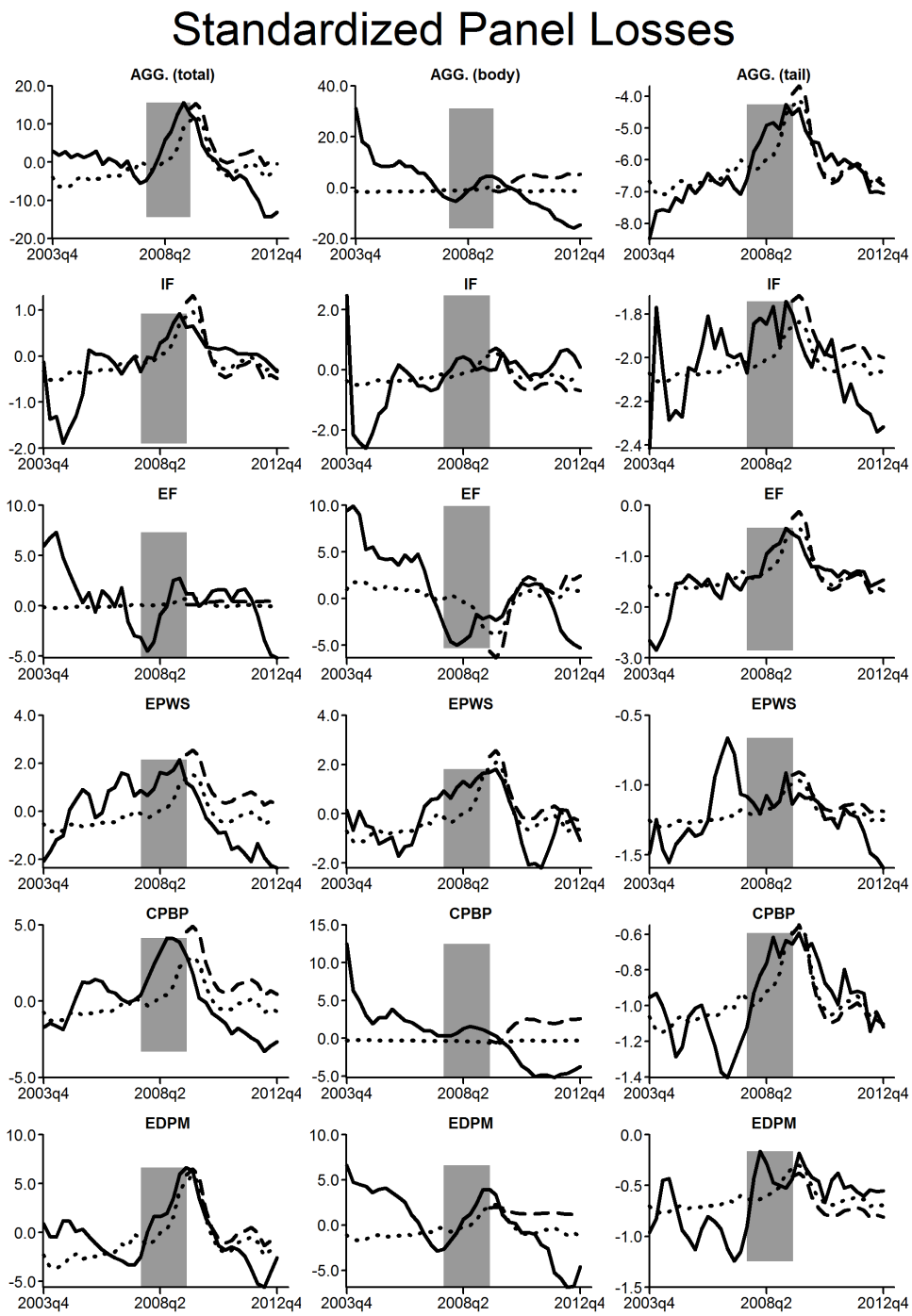
Table 4: Estimation results: regressions of aggregated standardized losses on real GDP growth

	Total	IF	EF	EPWS	CPBP	EDPM
A. Dependent variable: aggregated standardized loss						
Real GDP growth	-1.788	-0.200	0.124	-0.282	-0.486	-0.945
	(0.000)	(0.000)	(0.540)	(0.000)	(0.000)	(0.000)
Adj. R^2	0.292	0.442	(0.020)	0.181	0.237	0.457
B. Dependent variable: aggregated standardized body loss						
Real GDP growth	0.567	-0.155	0.973	-0.369	0.254	-0.136
	(0.370)	(0.027)	(0.000)	(0.000)	(0.232)	(0.560)
Adj. R^2	(0.013)	0.096	0.224	0.457	(0.007)	(0.021)
C. Dependent variable: aggregated standardized tail loss						
Real GDP growth	-0.383	-0.032	-0.182	-0.043	-0.069	-0.057
	(0.000)	(0.004)	(0.000)	(0.001)	(0.000)	(0.000)
Adj. R^2	0.656	0.123	0.555	0.156	0.433	0.162
Number of observations	37	37	37	37	37	37

Panel A of the table reports results of the time series regressions using all losses of each bank. Panel B (Panel C) reports results of regressions using losses below (above) the 95th percentile of each bank's loss distribution. Parentheses report p-values of estimates. The model utilizes bank fixed effects and robust variance. Individual losses are winsorized at the 99th percentile. Real GDP growth is defined as the year-over-year change in logarithm of real GDP expressed in percent terms.

Similar to our previous analysis, to analyze the roles of the body and tail losses in the above results, we run time series regressions of the standardized aggregated body and tail losses. We standardize the body and tail losses separately using means and standard deviations of losses below and above the 95th percentile of losses for each bank and event type. The second and third columns of Figures 2 display the time series of

Figure 2: Aggregated standardized losses by event types



The figure displays standardized losses aggregated across banks by event types. Subsection 3.2 describes the standardization methodology. The shaded area is the period from the beginning of financial crisis in 2007:Q3 through the end of the recession in 2009:Q2.

Table 5: Sample correlations of the aggregated standardized losses

	IF	EF	EPWS	CPBP	EDPM
Total losses and body losses	0.814	0.819	0.230	-0.150	0.387
Total losses and tail losses	0.236	-0.272	0.696	0.717	0.707

The table reports sample correlations between the aggregated standardized total losses and the aggregated standardized body and tail losses by event types.

aggregated standardized body and tail losses, respectively. By comparing figures, one observes that the dynamics of CPBP and EDPM total losses are driven by the dynamics of the tail losses. Meanwhile, the dynamics of IF and EF losses are correlated with body loss dynamics. Table 5 reports sample correlations and formally confirms our visual observations.

Panels B and C of Table 4 report estimation results using the body and tail losses for each event type, respectively. The tail losses of CPBP and EDPM event types are negatively correlated with real GDP growth, while the body losses of these two event types do not produce statistically significant results. This outcome suggests that the negative correlations of the total aggregated CPBP and EDPM losses with real GDP growth are driven by the correlations of the tail losses with real GDP growth. IF losses appear to be negatively correlated in the body and in the tail. The correlation of EPWS body losses and real GDP growth is statistically significant, while the tail losses have a statistically insignificant correlation. Our analysis of the large loss descriptions also confirms that large EPWS loss events are usually random in nature and do not appear to be linked to macroeconomic conditions. The increase in EPWS body losses during economic decline could be related to improper employee firing in the process of streamlining employment costs.

An interesting result is that the EF tail losses are negatively correlated with real GDP growth, while the body losses have a positive correlation. We explain this result as follows. Relatively smaller EF losses may be related mainly to retail businesses. The volume of transactions of retail businesses are positively correlated with macroeconomic growth, and thus operational losses associated with these transactions might be pro-cyclical. Meanwhile, large EF losses might be discovered during economic downturns.

Financial fraudulent pyramids are one such example. This type of fraud is commonly discovered during the periods of liquidity constraints which might be related to macroeconomic conditions.

4.2. Robustness checks

In this subsection, we perform several robustness checks of our findings. First, we confirm that aggregated standardized series are not dominated by standardized losses of some banks due to considerably more heavy-tailed distributions of individual banks relative to other banks. To verify this hypothesis, we run panel regressions of standardized series of individual banks on real GDP growth. The panel regression treats all banks in the sample as equal panel units. Thus, the results are driven by all banks rather than individual banks. As Table 6 reports, the results for all event type losses, except IF, are robust to the regression method. These findings confirm that aggregated standardized loss time series reasonably represent dynamics of banking industry losses. We prefer the model based on the aggregated standardized losses to the panel regression of individual bank standardized losses because the aggregation reduces the impact of individual idiosyncratic losses.

Second, we check sensitivity of our results to the choice of the tail threshold. To allocate more observations to the tail, we reduce the tail threshold to the 90th percentile from the 95th percentile. Table 7 reports results of the time series regressions on aggregated standardized tail losses above the 90th percentile. The results for all event types, except IF, are robust to this change in the tail threshold. We do not increase the percentile to avoid a substantial decline in the number of observations in the tail, which could lead to inaccurate results.

Third, we check robustness of the results to the sample period choice. One may argue that it is too short to estimate accurately the model parameters. We expand the sample to the period from 2000 through 2012. As Table 8 reports, the results for all event types, except IF, are robust to the sample choice. The correlations for IF losses become statistically insignificant for total, body, and tail losses. We choose the shorter sample period for our main results because the period before 2003 includes relatively few banks. A longer sample might yield results that reflect the dynamics of few banks in

Table 6: Estimation results: panel regressions of standardized losses on real GDP growth

	Total	IF	EF	EPWS	CPBP	EDPM
A. Dependent variable: standardized bank's loss						
Real GDP growth	-1.976	-0.175	-0.117	-0.282	-0.495	-1.113
	(0.000)	(0.000)	(0.576)	(0.000)	(0.000)	(0.000)
Adj. R^2	0.060	0.039	(0.001)	0.016	0.024	0.060
B. Dependent variable: standardized bank's body loss						
Real GDP growth	-0.176	-0.123	0.678	-0.381	0.046	-0.463
	(0.690)	(0.002)	(0.034)	(0.000)	(0.797)	(0.009)
Adj. R^2	(0.001)	0.014	0.004	0.018	(0.001)	0.006
C. Dependent variable: standardized bank's tail loss						
Real GDP growth	-0.266	-0.032	-0.156	-0.039	-0.070	-0.055
	(0.000)	(0.406)	(0.000)	(0.026)	(0.002)	(0.074)
Adj. R^2	0.023	(0.001)	0.016	0.004	0.014	0.006
Number of observations	755	500	687	693	747	677

Panel A of the table reports results of the panel regressions using all losses of each bank. Panel B (Panel C) reports results of regressions using losses below (above) the 95th percentile of each bank's loss distribution. Parentheses report p-values of estimates. The model utilizes robust variance. Individual losses are winsorized at the 99th percentile. Real GDP growth is defined as the year-over-year change in logarithm of real GDP expressed in percent terms.

the earlier part of the sample rather than loss dynamics for the entire banking industry.

In summary, our robustness checks confirm the negative correlations between EF, CPBP, and EDPM tail losses and real GDP growth. The results for IF losses are not robust, so we do not claim that IF losses are correlated with macroeconomic conditions. Also, EPWS body losses appear to be negatively correlated with macroeconomic growth, but the correlation is insignificant in its tail.

4.3. Stress testing application

In this subsection, we discuss how our approach to modeling operational losses can be applied for stress testing purposes. A standard stress testing exercise is to estimate operational losses conditional on macroeconomic scenarios. Scenarios of real GDP growth and parameter estimates of our model can be used to predict time series of aggregated standardized losses. Next, the aggregated standardized loss forecasts need to be transformed to dollar loss forecasts. Assuming that the standardized loss dynamics are

Table 7: Estimation results: regressions of aggregated standardized losses on real GDP growth with the tail threshold at 90th percentile

	Total	IF	EF	EPWS	CPBP	EDPM
B. Dependent variable: aggregated standardized body loss						
Real GDP growth	1.843	-0.054	1.366	-0.199	0.683	0.047
	(0.026)	(0.265)	(0.000)	(0.000)	(0.044)	(0.827)
Adj. R^2	0.069	(0.010)	0.324	0.296	0.049	(0.028)
C. Dependent variable: aggregated standardized tail loss						
Real GDP growth	-0.442	-0.020	-0.117	-0.003	-0.130	-0.172
	(0.000)	(0.032)	(0.000)	(0.855)	(0.000)	(0.000)
Adj. R^2	0.543	0.075	0.368	(0.028)	0.476	0.513
Number of observations	37	37	37	37	37	37

Panel B (Panel C) reports results of regressions using losses below (above) the 90th percentile of each bank's loss distribution. Parentheses report p-values of estimates. The model utilizes robust variance. Individual losses are winsorized at the 99th percentile. Real GDP growth is defined as the year-over-year change in logarithm of real GDP expressed in percent terms.

common for all banks, the inverse of our standardization procedure leads to dollar losses. Specifically, dollar losses are obtained by multiplying predicted standardized losses by the sample standard deviation and adding the sample mean for each event type of an individual bank. The advantage of this approach is in using the estimated relationship between macroeconomic variables and industry aggregated loss dynamics. The data of an individual single bank may not be sufficient to depict the links of operational losses with macroeconomic factors that we find using the aggregated banking industry data.

5. Conclusion

We investigate the relationship between banking sector operational losses and macroeconomic growth. We study this relationship by Basel II event type categories. We find statistically significant correlations between macroeconomic growth and losses in CPBP and EDPM. Our analysis suggests that these correlations are concentrated in the tails of the loss distributions. We also find that EF tail losses are negatively correlated with macroeconomic growth, while EF body losses are positively correlated with macroeconomic growth. Finally, EPWS body losses appear to be negatively correlated with macroeconomic growth.

Table 8: Estimation results: panel regressions of standardized losses on real GDP growth with sample of data 2000:Q1-2012:Q4

	Total	IF	EF	EPWS	CPBP	EDPM
A. Dependent variable: standardized bank's loss						
Real GDP growth	-1.982	-0.178	-0.158	-0.254	-0.508	-1.107
	(0.000)	(0.000)	(0.470)	(0.000)	(0.000)	(0.000)
Adj. R^2	0.059	0.035	(0.001)	0.008	0.021	0.060
B. Dependent variable: standardized bank's body loss						
Real GDP growth	0.839	-0.084	1.032	-0.187	0.371	-0.263
	(0.105)	(0.021)	(0.003)	(0.005)	(0.103)	(0.119)
Adj. R^2	0.002	0.004	0.011	0.005	0.002	0.001
C. Dependent variable: standardized bank's tail loss						
Real GDP growth	-0.373	-0.029	-0.123	-0.005	-0.116	-0.160
	(0.000)	(0.122)	(0.000)	(0.789)	(0.000)	(0.001)
Adj. R^2	0.031	0.004	0.014	(0.001)	0.018	0.029
Number of observations	838	524	732	794	805	685

The sample of loss data is for the period from 2000:Q1 through 2012:Q4. Panel A of the table reports results of the panel regressions using all losses of each bank. Panel B (Panel C) reports results of regressions using losses below (above) the 95th percentile of each bank's loss distribution. Parentheses report p-values of estimates. The model utilizes robust variance. Individual losses are winsorized at the 99th percentile. Real GDP growth is defined as the year-over-year change in logarithm of real GDP expressed in percent terms.

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