# U.S. Banking Sector Operational Losses and the Macroeconomic Environment

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**Abstract**

Using supervisory data from large U.S. bank holding companies (BHCs), we find that BHCs incur more operational losses in adverse macroeconomic conditions driven significantly by the higher frequency and severity of tail events. Among different operational risk types, we find that losses from BHCs' failure to meet obligations to clients or from the design of their products are particularly counter-cyclical. We also show that larger and more leveraged BHCs have a higher macroeconomic sensitivity of operational risk. Overall, our findings provide new evidence regarding U.S. banking organizations' exposure to macroeconomic shocks with implications for risk management practices and supervisory policy.

*Keywords:* Operational Risk; Operational Losses; Macroeconomic Environment; Banking Sector; Stress Testing

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# 1 Introduction

The 2007-2009 global financial crisis was at the epicenter of a number of operational risk events that rocked the U.S. banking industry. In one example, foreclosure abuses, particularly during the crisis period (e.g., the use of "robo-signed" affidavits in foreclosure proceedings; deceptive practices in the offering of loan modifications; failures to offer non-foreclosure alternatives before foreclosing on borrowers with federally insured mortgages; and filing improper documentation in federal bankruptcy court), resulted in multi-billion dollar settlements to resolve violations of state and federal law.[1] In a different example, the market failure of auction rate securities (ARS) in 2008, precipitated by a significant deterioration in credit market conditions, similarly led to massive operational losses for many banks that had marketed and distributed these securities.[2]

The staggering losses of the financial crisis contributed to the prominence of operational risk as an important financial risk stripe, and banks now hold substantial capital to protect against operational losses. Based on publicly available information of 10 large bank holding companies, capital held against operational risk amounts to 28% of total regulatory capital on average. Such an amount is substantial when compared to capital held against other widely recognized types of risk such as market and credit risk (6% and 66% of total regulatory capital, respectively).[3] Given the magnitude of operational losses and that many of the most severe losses had their origins in the crisis or surfaced as the economy and financial markets deteriorated, the relation between operational risk and the macroeconomic environment has

[1]See *New York Times*: "States Negotiate $26 Billion Agreement for Homeowners" (N. Schwartz, S. Dewan, February 8, 2012).

[2]See *U.S. Securities and Exchange Commission*: "SEC Finalizes ARS Settlements With Citigroup And UBS, Providing Nearly $30 Billion in Liquidity to Investors" (December 11, 2008); "SEC Finalizes ARS Settlement to Provide $7 Billion in Liquidity to Wachovia Investors" (February 5, 2009); "SEC Finalizes ARS Settlements With Bank of America, RBC, and Deutsche Bank" (June 3, 2009 ).

[3]These estimates are based on the Federal Financial Institutions Examination Council (FFIEC) 101 Reporting Form as of 2017:Q4 for the following 10 bank holding companies: BNY Mellon, Citigroup, Goldman Sachs, JPMorgan Chase, Morgan Stanley, Northern Trust, State Street, UBS, US Bancorp, and Wells Fargo.

become a central question with potentially first-order implications for financial stability, credit intermediation, risk management and supervisory policy. Investigating this relation is the focus of our study. The existence of a relation between operational risk and the macroeconomic environment would have two broad implications. First, BHCs should be able to reduce the occurrence of operational losses by strengthening risk management practices at particular points in the business cycle. Second, prudential regulations should reflect the sensitivity of operational risk to macroeconomic conditions in requiring financial firms to control risks and hold adequate capital.

International banking standards define operational risk as the risk of loss resulting from inadequate or failed internal processes, people, and systems or from external events (Basel Committee on Banking Supervision (2006)). Different perspectives on the potential association between operational losses and the macroeconomic environment have emerged in the academic literature (Chernobai et al. (2012)). Operational losses can be procyclical in nature, whereby banks incur smaller operational losses when transaction volumes subside and risk appetite decreases in stressful economic times. Alternatively, as suggested by the examples above, operational losses can be countercyclical in nature, whereby operational losses occur and surface during periods of economic stress. Economic shocks and financial market dislocations might put stress on companies' business practices and lead to risk management lapses that result in hefty operational losses (e.g., litigation costs and regulatory fines). In addition, adverse macroeconomic conditions might also reveal already existing risky practices (e.g., product misrepresentation) and other underlying operational risks (e.g., financial fraud) that similarly trigger severe financial losses. The relation between operational losses and the macroeconomy, whether losses increase or decrease in macroeconomic downturns, is ultimately an empirical question. However, the lack of high-quality operational risk data has thus far hindered properly and accurately investigating this topic.

In the current study, we use supervisory operational loss data reported by large U.S.

bank holding companies to the Federal Reserve System (FRS) for stress testing purposes as mandated by the Dodd-Frank Wall Street Reform and Consumer Protection Act. As De Fontnouvelle et al. (2006) caution, public sources of operational loss data may not report all significant cases. In contrast to vendor datasets commonly used in the operational risk literature, our data at the individual firm level is substantially richer. Using this data from 2000:Q1 to 2013:Q4, we document a robust association between operational losses in the U.S. banking sector and the U.S. macroeconomic environment.

Our main findings can be summarized as follows. Using a summary measure — the first principal component of five key macroeconomic indicators spanning real economic activity as well as financial and property markets — we document a significant association between operational losses and the strength of the macroeconomy. In particular, higher operational losses occur at bank holding companies in an adverse macroeconomic environment. A one standard deviation decrease in our macroeconomic measure (representing a deterioration of the macroeconomy) is associated with a 16.5% increase in quarterly BHC operational losses on average.[4] In 2018-constant dollar terms, this translates into a $36.2 million incremental loss, compared to an average bank-quarter operational loss of $220.1 million. In addition, from a financial stability perspective, we crucially show that larger and more leveraged institutions have a higher macroeconomic sensitivity of operational risk.

There are a number of operational loss types, each of which may have a different relation to the macroeconomic environment. In further analysis, we separately investigate the specific types of losses that drive the previously discussed relationship. The Basel Committee on Banking Supervision (2006) defines seven categories of operational losses: Internal Fraud (IF), External Fraud (EF), Employment Practices and Workplace Safety (EPWS), Clients, Products and Business Practices (CPBP), Damage to Physical Assets (DPA), Business Dis-

[4]As a reference point, our macroeconomic measure decreased by more than 3 standard deviations from the beginning of the global financial crisis in 2007:Q4 to the peak of the crisis in 2008:Q4.

ruption and System Failures (BDSF), and Execution, Delivery and Process Management (EDPM). Our analysis indicates that five event types (IF, EF, CPBP, BDSF and EDPM) out of the seven are significantly related to our macroeconomic measure. The largest event type accounting for the majority of dollar losses in our sample, CPBP, is particularly strongly correlated with the macroeconomic environment.

Due to the heavy-tailed nature of individual operational loss distributions, a large portion of the total operational dollar losses at financial institutions is usually accounted for by a few, high-severity loss events (e.g., Dahen and Dionne (2010) and Abdymomunov and Curti (2015)). To understand the role of individual high-severity losses in our results, we conduct two additional sets of analyses. First, we study whether macroeconomic conditions are related to the incidence of tail operational risk at financial institutions. Tail operational risk has direct implications for BHCs' risk profiles as it poses difficulties for capital planning and management, and can be an important contributing factor towards bank distress. Here, we find consistent evidence that adverse macroeconomic conditions are associated with higher incidence of tail operational risk at bank holding companies.

Second, we analyze the association between the severity of individual loss events and the macroeconomic environment. We show that while operational loss severity decreases at the lower quantiles of the loss distribution, loss severity increases at the higher quantiles of the distribution in an adverse environment. These results have two implications. First, they suggest that an increase in the severity of large individual losses during macroeconomic stress, in addition to the higher frequency of tail events, is a contributing factor to the overall association between operational risk and macroeconomic conditions. Second, the directionally opposite impact of the macroeconomic environment on large and small losses indicates that the dispersion of operational losses increases during adverse conditions and, further, suggests that the loss severity distribution of operational risk events is dependent on the state of the macroeconomy. This finding thus challenges assumptions in traditional operational risk capital modeling techniques (e.g., the Loss Distribution Approach), which oftentimes assume constant, time-independent loss severity distributions.[5]

Overall, the results in this study indicate a significant negative association between operational losses at financial institutions and the strength of the macroeconomic environment. We argue that banking organizations are more likely to make costly operational mistakes or lapse into risky practices when the economy and financial markets are under stress. We take care to differentiate our interpretation from one whereby a macroeconomic decline and financial stress "cause" operational losses. We admit that causality is difficult to argue since there could be important feedback mechanisms, where massive (operational) losses in the financial industry could fuel further economic distress and decline (e.g., Allen et al. (2012)).

This study is among the first to emphasize the significant association between operational losses in the banking industry and macroeconomic conditions, and thus extends the literature on operational risk at financial institutions. It also contributes to the literature on bank risk and the literature on the financial effects of macroeconomic conditions. Our findings highlight that adverse swings in macroeconomic factors set off large, potentially catastrophic losses at banking organizations. An implication of our results is that common triggers of seemingly idiosyncratic exposures could be of systemic importance. In the case of operational risk, much of which is organization-specific, a common trigger such as a macroeconomic shock could induce correlated spikes in default probabilities across financial institutions with far-reaching consequences for financial system risk and stability, credit intermediation, and even the real economy (e.g., Jermann and Quadrini (2012), Allen et al. (2012)).

Our findings could inform risk management practices. Specifically, banking organizations might benefit from tightening internal processes and controls during macroeconomic

[5] The Loss Distribution Approach is the most common methodology used by large financial institutions around the world to quantify required capital for operational risk under the Advanced Measurement Approaches, one of the three methods allowed by Basel II regulation (Basel Committee on Banking Supervision (2006)). For a detailed modelling discussion of the Loss Distribution Approach, see Klugman et al. (1998) and Embrechts et al. (2004).

downturns to reduce the occurrence of operational losses. Moreover, our findings have potential policy implications and contribute to the regulatory debates on stress testing. With particular regard to operational risk, banking practitioners have often struggled to uncover a meaningful relation between operational risk and the state of the macroeconomy, and have challenged its existence.[6] In addition to providing direct evidence of that relation, our findings highlight particular channels through which it occurs (e.g., operational risk types, frequency of losses, incidence of tail events, loss severity distribution). Moreover, we show that larger and more leveraged BHCs have a more pronounced sensitivity of operational risk to macroeconomic conditions. From a prudential regulation perspective, this suggests that operational risk can be particularly destabilizing during periods of economic stress at less capitalized and larger, more systemically important banking organizations. Overall, our study implicitly provides evidence supporting quantitative stress testing frameworks in operational risk that can be used to determine the ability of banking organizations to endure adverse financial conditions and evaluate loss outcomes under various economic scenarios.

The rest of the paper is organized as follows. Section 2 discusses prior research. Section 3 describes our data sources, construction of variables and summary statistics. Sections 4 and 5 lay out our empirical results and present robustness checks. Section 6 concludes.

# 2 Related Literature

Our paper is specifically related to the literature on operational risk at financial institutions. Using equity returns to estimate operational risk, Allen and Bali (2007) find some evidence of its cyclicality. The authors further suggest that approximately 18% of financial institutions'

[6] Recognizing such difficulties, Federal Reserve System (2014a) states "BHCs have found it challenging to identify meaningful relationships between operational losses and macroeconomic factors. Limited datasets and potential problems classifying and reporting events contribute to the difficulties. Specifically, the limited length of operational loss datasets makes finding robust correlations to macroeconomic and financial variables difficult for many firms."

returns compensate for operational risk, with this number growing to 39% for depositary institutions. Cope et al. (2012) link operational loss severity to various regulatory, legal, geographical, and economic development indicators in an international context. Wang and Hsu (2013) investigate the relation between board composition and operational risk at financial institutions. Chernobai et al. (2012) and Abdymomunov and Mihov (2017) show that operational losses can be linked to a failure of internal controls and processes, and focus on the importance of corporate governance and risk management practices in mitigating operational risk. Chernobai et al. (2012) also provides some evidence on the relation between operational loss frequency and the macroeconomic environment but does not analyze aggregate dollar loss amounts or loss severity. Hess (2011) and Cope and Carrivick (2013) examine the effects of the recent crisis on operational risk losses in the financial services industry, but do not quantify the relation between operational risk and the macroeconomic environment. In contrast to the existing literature, our study provides direct evidence of a link between operational losses of bank holding companies and macroeconomic conditions.

We show that higher operational losses occur in a deteriorating macroeconomy driven by a higher frequency of operational losses and particularly by a higher incidence of tail operational risk events. We identify the types of losses and the types of banks that drive this relation. Importantly, we also document a contrasting relation between individual loss severity and the macroeconomy at the lower and upper ends of the loss severity distribution.

More broadly, our paper also contributes to the large and growing literature on bank performance and risk (e.g., Keeley (1990), Demsetz and Strahan (1997), Hellmann et al. (2000), Demirguc-Kunt and Detragiache (2002), Laeven and Levine (2009), Ellul and Yerramilli (2013)). In addition, our study is also related to the literature on the effects of macroeconomic conditions on economic and financial outcomes (e.g., Schwert (1989), Arnold et al. (2013), Hackbarth et al. (2006), Bansal et al. (2014), Flannery and Protopapadakis (2002), Erel et al. (2012), Bhamra et al. (2010), Lettau et al. (2008), Buch et al. (2014)).

# 3 Operational Loss Sample and Variable Definitions

## 3.1 Operational Risk Data

This study uses supervisory data of operational losses submitted by large financial institutions to the Federal Reserve System for stress testing purposes pursuant to the Dodd-Frank Wall Street Reform and Consumer Protection Act. The data follows FR Y-14Q reporting requirements and is provided by U.S. bank holding companies and intermediate holding companies (IHCs) with total consolidated assets of $50 billion or more.[7] The data is highly granular, providing information points such as loss amounts, loss dates, loss classifications, and loss descriptions. Consistent with Basel II definitions, losses are categorized into seven event types: Internal Fraud, External Fraud, Employment Practices and Workplace Safety, Clients, Products and Business Practices, Damage to Physical Assets, Business Disruption and System Failures, and Execution, Delivery and Process Management. Table 1 presents definitions of each loss type.

[Insert Table 1 about here]

Banks have different thresholds for collecting information on individual operational losses. To mitigate the impact of firm heterogeneity in data collection thresholds on our results, we follow prior research (e.g., Abdymomunov and Mihov (2017)) and discard operational losses below $20,000 dollars, which is the highest reporting threshold for participating institutions. The final sample contains 298,170 individual loss events from 38 large financial institutions

[7]Pursuant to the Federal Reserve's Dodd-Frank enhanced prudential standards ("EPS") final rule, foreign banking organizations with $50 billion or more in U.S. non-branch/agency assets are required to place their U.S. subsidiaries underneath top-tier U.S. intermediate holding companies. In our study, we refer to both BHCs and IHCs as bank holding companies. More information about FR Y-14Q reporting requirements, instructions and forms can be found at: http://www.federalreserve.gov/apps/reportforms/.

over the period [2000:Q1-2013:Q4].[8] Our data is substantially richer than datasets offered by private vendors. For instance, Chernobai et al. (2012) use a sample with 2,426 loss events from Algo FIRST and Hess (2011) uses around 7,300 loss events from SAS OpRisk Global Data. As discussed in De Fontnouvelle et al. (2006), public operational loss datasets are likely to omit material loss events otherwise contained in the supervisory data that we use.

## 3.2 Operational Risk Characteristics

Table 2 presents descriptive statistics. Panel A summarizes information at the individual loss event level. Our sample comprises a total of 298,170 loss events across all banks and event types. The average loss amount is around \$1.11 million, with the $5^{\text{th}}$ and $95^{\text{th}}$ percentiles around \$0.02 and \$0.56 million. Such statistics, combined with a large standard deviation of \$78.31 million, suggest that the operational loss distribution is extremely heavy tailed.

[Insert Table 2 about here]

Figure 1 shows the distribution of losses across the seven event types. The majority of the dollar losses are concentrated in CPBP, EDPM and EF. These three event types account for roughly 94.9% of all operational losses. CPBP alone accounts for 79.5%. With only 15.1% of the total loss count, CPBP is a high-severity and moderate-frequency loss category. EDPM is the second largest loss event type, accounting for 12.1% of total dollar losses, and EF is the third largest, comprising 3.3% of total dollar losses. In contrast to CPBP, EF is a relatively low-severity and high-frequency category. IF, DPA and BDSF account for the lowest proportion of dollar losses at 1.1%, 1.0% and 0.6%, respectively.

[8] Although our operational loss data comes from a small number of institutions, these institutions account for the majority of U.S. bank industry assets. The 38 institutions in our sample account for 85.2% of the total consolidated assets of all U.S. bank holding companies and U.S intermediate holding companies with assets of \$1 billion or more as of 2017:Q4.

[Insert Figure 1 about here]

To focus on the association between banks' operational losses and the macroeconomic environment, we aggregate individual losses at the BHC-quarter level in much of our analysis. The aggregated BHC-quarter panel is unbalanced (reflecting availability of individual bank data) and comprises 1,509 bank-quarter observations. Table 2, Panel B reports descriptive statistics. The average quarterly operational loss at BHCs is close to $220 million, with a standard deviation of $1,408 million, reaffirming the heavy tailed nature of operational risk even at an aggregated level and also suggesting substantial differences across BHCs.

## 3.3 Operational Risk Dates

The operational loss data used in our study reports three dates: occurrence date, discovery date, and accounting date. *Occurrence date* records the date that the operational loss event occurred or began. *Discovery date* records the date that the operational loss event was first discovered by the institution. *Accounting date* records the date that the financial impact of the operational loss event was recorded on the institution's financial statements. It also corresponds to the date legal reserves are established by banks, and in the case of large legal losses, precedes a settlement date which may take place with considerable time lags.[9,10]

Table 3 summarizes the time lags between the occurrence, discovery and accounting of

[9] Related to the establishment of loss reserves, the Financial Accounting Standards Board (FASB) requires a charge to income for an estimated loss from a loss contingency if: (a) information available prior to issuance of the financial statements indicates that it is probable that an asset had been impaired or a liability had been incurred at the date of the financial statements, and (b) the amount of loss can be reasonably estimated. For more information, see: `http://www.fasb.org/pdf/fas5.pdf`.

[10] From a reporting consistency perspective, we note that the accounting date is the most consistently used date across banks. This reflects the fact that banking organizations follow the same accounting standards in determining the financial impact of operational loss events on the institutions' financial statements. Occurrence and discovery dates are potentially less uniformly reported across institutions due to variations in the institutions' internal data management systems and in some cases uncertainties about when loss events actually occurred or were discovered. Data checks, data exams and horizontal reviews across banks led by the Federal Reserve System have mitigated known differences.

operational losses. On average, it takes 264 days between the occurrence of an operational risk event and the financial impact of the event. While the majority of individual events financially impact banks within 100 days of their occurrence, some events take substantially longer. Time lags are materially different across operational loss event types. For example, the median time lag is only 2 days for BDSF. Business disruptions and system failures are usually quickly discovered and accounted. In contrast, the median time lag for CPBP is 86 days. Operational risk events related to issues with product design, business practices and clients take longer to detect, resolve and account.

[Insert Table 3 about here]

Table 3 further suggests that all event types have some operational losses with long time lags. The 95$^{\text{th}}$ percentiles of the lag distributions range from 600 to 2,300 days across the different event types. The descriptions of losses with extremely long time lags suggest that oftentimes such losses accrued over many years until they are finally discovered and accounted. In one case, a bank charged incorrect service fees due to a coding error. In another case, a bank incorrectly filed fiduciary client's tax returns. In both instances, the operational mistakes remained undiscovered and continued to generate "future liabilities" over long periods of time as practices appeared to be "business as usual" until reconciliation activities due to changes in businesses or accounting systems revealed those events.

While we observe a wide distribution of loss amounts among cases with extremely long time lags, large tail losses are rarely among them. For example, the 5% of events with the longest time lags in CPBP (the event type which accounts for 79.5% of total dollar loss and has the most heavy-tailed severity distribution) account only for 6% of CPBP dollar losses. Moreover, a review of the most severe events that occurred during 2007-2009 financial crisis reveals that a significant proportion of them financially impacted BHCs within relatively short periods after occurrence.

The time lag between the occurrence, discovery and accounting of operational risk events raises the important question of which of the three dates should be used to link operational losses to macroeconomic conditions. Does the macroeconomic environment affect the extent of damage at the point when an event initially occurs, at the point when it gets discovered by an institution, or at the point when the loss financially impacted the institution? Different perspectives exist and arguments can be made for each choice of date. We take unauthorized trading as an example. On one hand, the state of the macroeconomic environment may be a key factor for a rogue trader's decision to engage in fraud (i.e. occurrence date is relevant). On the other hand, once the rogue employee engages in unauthorized trading, macroeconomic environment may be again a key factor when the fraud materializes into a loss, gets discovered and financially impacts the institution (i.e. discovery and accounting dates are relevant).

In our analysis, we focus on the occurrence date for aggregation purposes. The choice is guided by our research question, and the implications for risk management practices and supervisory policy. Specifically, the occurrence date is well-suited to analyze the part of the business cycle when banks are most likely make costly operational mistakes and get exposed to operational risk. The occurrence date reflects the point at which banks (i.e. their employees) make actual operational decisions, and is a relevant date from a prudential supervisory policy and risk management perspectives. Using this date should also be informative regarding when financial institutions can strengthen risk management practices to prevent operational loss events from occurring with respect to the business cycle and can also inform risk evaluation from a supervisory perspective.

In Section 4.6, we also analyze "accounting dates," as those are better aligned with the time of operational loss financial impact on banks. We emphasize that results based on accounting dates are relevant for supervisory policy and particularly for the estimation of regulatory capital related to operational risk (e.g., minimum capital requirements and stress-testing). While we do not report results using discovery dates, we confirm the robustness of our results to using those instead of occurrence and accounting dates.

## 3.4 Macroeconomic Indicators

The nature of operational risk events and their underlying causes suggest that operational risk can be related to a number of macroeconomic drivers. We construct a single measure of macroeconomic environment using five macroeconomic indicators (*GDP Growth*, *HPI Growth*, *CREPI Growth*, *VIX* and *BBB-T10Yr Sprd*) that represent key macroeconomic areas (e.g., real economic activity, and financial and property markets) and are also plausibly linked to operational risk realizations. Below we define each of these variables and then explain the method of constructing a single measure.

*GDP Growth* is the year-over-year growth rate in U.S. real gross domestic product (GDP). We use *GDP Growth* as a broad measure of U.S. economic activity, which reflects the entire state of the real economy.[11] *HPI Growth* is defined as the year-over-year growth rate of the CoreLogic U.S. House Price Index. Similarly, *CREPI Growth* is the year-over-year growth rate in the U.S. Commercial Real Estate Price Index. *HPI Growth* and *CREPI Growth* are measures of property market conditions; declining real estate prices are an important source of stress to BHCs' balance sheets, which could trigger operational losses (e.g., litigation losses related to improperly marketed products such as mortgages). While both *HPI Growth* and *CREPI Growth* measure the state of property markets, housing and commercial real estate comprise disparate property market sectors to which banks may have different exposures.

*VIX* is defined as the Chicago Board Options Exchange's (CBOE) Market Volatility Index, converted to a quarterly frequency by using the maximum close-of-day value in a

[11] Our results are robust to using alternative broad measures of economic activity and labor markets such as the U.S. unemployment rate.

given quarter. It measures U.S. financial market volatility and proxies for financial market conditions. A particularly useful aspect of *VIX* is that it captures trading and financial market stress, such as market panics, during which financial asset prices move rapidly in unexpected directions. *BBB-T10Yr Sprd* is the spread between the U.S. BBB corporate yield (quarterly average of the yield on 10-year BBB-rated corporate bonds) and the 10-year Treasury yield (quarterly average of the yield on 10-year U.S. Treasury bonds). *BBB-T10Yr Sprd* captures financial stress in credit markets such as the deterioration in the quality of borrowers' balance sheets or capital positions of financial intermediaries, complementing the information in *VIX*.[12]

To condense the information contained in *GDP Growth*, *HPI Growth*, *CREPI Growth*, *VIX* and *BBB-T10Yr Sprd* into a single measure of macroeconomic activity, we apply the method of principal component analysis (PCA). Following prior studies (e.g., Stock and Watson (1999), Ludvigson and Ng (2007), Koopman et al. (2011)), we use PCA as a dimension-reduction methodology to relate observed variables to a small set of orthogonalized factors/components. In our analysis, we focus solely on the first principal component as our measure of the macroeconomic environment, *ME*, as it adequately summarizes variation in the underlying data by explaining a high proportion of the variables' variances — 69%.[13] Lower values of *ME* denote adverse macroeconomic conditions. Table 2, Panel A (Panel B) reports that *ME* has a mean of -0.189 (-0.232) and standard deviation of 2.011 (2.006).

## 3.5 Pairwise Correlations and Plots

We start with visual evidence to contextualize the association between operational losses and macroeconomic conditions. Figure 2, Panel A plots quarterly operational dollar losses

[12] All five of these quantities can be constructed from variables covered by the Federal Reserve System in their scenario design framework for stress testing (Federal Reserve System (2014b)) and therefore can be readily applied in macroeconomic stress testing of operational risk.

[13] In unreported tests, we find that other principal components beyond the first are not significantly related to BHC operational losses.

averaged across BHCs and $ME$ through time.

[Insert Figure 2 about here]

The figure shows that operational losses tend to occur when the macroeconomy is on a deteriorating path, with some severe losses appearing during the economic slowdown of the early 2000s and the 2007-2009 global financial crisis. Notably, a relation between operational risk and macroeconomic conditions is not evident in benign times. We emphasize the better visual alignment between macroeconomic downturns and the financial impact (accounting) of operational losses, rather than the occurrence. This is consistent with arguments in Section 4.6 that some existing but latent risky practices and undiscovered operational errors tend to surface and result in severe financial losses when business activity slows down or when financial markets are under stress.

Moreover, we find similar evidence when we examine the most severe losses from individual operational risk events in Figure 2, Panel B. This suggests that an important channel for the potential relation between operational risk and macroeconomic environment might be through individual losses with high severity. We also highlight the volatile nature of operational risk. While some periods are marked by relatively low averages, several quarters show explosive losses, driven by the occurrence or accounting of relatively infrequent but very severe losses.

We next conduct a simple correlation analysis to quantify the unconditional pairwise relation between operational losses and the macroeconomic variables. Table 4 presents the results.

[Insert Table 4 about here]

*Ln(Loss)* and *ME* are negatively correlated, suggesting an increase in the occurrence of operational dollar losses at BHCs in an adverse macroeconomic environment. The correlation coefficient is 0.04, statistically different from 0 at the 10% level. In addition, *Ln(Loss)* is also significantly correlated with two of the five individual macro-financial variables underlying *ME*: *HPI Growth* and *VIX*. In contrast, it is not significantly related to *GDP Growth*, *CREPI Growth* and *BBB-T10Yr Sprd* at conventional statistical levels. Clearly, these results reflect confounding and uncontrolled BHC effects, which we address with our regression specifications in the next section. Finally, we observe a high correlation among the macro-financial variables, with absolute values of coefficients always in excess of 0.50.

# 4 Empirical Results

## 4.1 Operational Losses

In our next set of results, we explore the relation between macroeconomic conditions and operational losses in a regression setting. We follow previous operational risk studies (e.g., Cope et al. (2012), Dahen and Dionne (2010), Na et al. (2006)) and use ordinary least squares (OLS) regressions. We include BHC fixed effects to ensure that the relation between operational losses and the macroeconomic environment are estimated "within BHC." Our specifications do not include time-varying BHC-level controls. To the effect that time-varying BHC-level variables are either uncorrelated with the macro environment or are endogenous to and driven by the macro-financial environment, our specifications should properly estimate the relation between losses and *ME*.[14] Formally, we use the following specification:

$$OpLoss_{i,t} = \beta_i + \beta_1 ME_t + \epsilon_{i,t}, \tag{1}$$

[14] In unreported tests, we confirm the robustness of our results to including time-varying controls (e.g., bank size, revenue structure, leverage) in addition to BHC fixed effects.

where $i$ indexes BHCs and $t$ indexes time periods (quarters). $OpLoss_{i,t}$ represents one of three loss measures of BHC $i$ during quarter $t$: a natural log transformation of operational dollar losses, denoted by *Ln(Loss)*; a natural log transformation of operational loss frequency, denoted by *Ln(Freq)*; and a natural log transformation of average operational loss severity, denoted by *Ln(Sev)*, where loss severity is calculated as the ratio of a dollar loss to loss frequency in a given quarter. *ME* measures the state of the macroeconomy and is defined as the first principal component of *GDP Growth*, *CREPI Growth*, *HPI Growth*, *VIX* and *BBB-T10Yr Sprd*. $\beta_i$ are BHC fixed effects. We cluster standard errors at the BHC and quarter levels to account for within-BHC and within-quarter correlation of the regression error terms. Table 5 presents the results.

[Insert Table 5 about here]

The results in Column (1) suggest that higher operational losses occur at U.S. BHCs in adverse macroeconomic conditions. The coefficient estimate of *ME* is negative and statistically significant at the 1% level. A one standard deviation decrease in *ME* is associated with a 16.5% increase in BHC operational losses. In 2018-constant dollar terms, this translates into a $36.2 million increase in quarterly dollar losses at the BHC level, relative to an average BHC quarterly loss of $220.1 million. In Columns (2) and (3), we report results using loss frequency and average loss severity as the dependent variables, respectively. Loss frequency, *Ln(Freq)*, is significantly negatively correlated with *ME*.[15] While average loss severity, *Ln(Sev)*, is also negatively correlated with *ME*, the relation is statistically insignificant at conventional levels. Even though the incidence of severe losses significantly increases during downturns (see Section 4.3), the overall increase in the frequency of operational loss

[15]In unreported tests, we confirm the robustness of our results to using alternative regression functional forms for count data (e.g., Negative Binomial).

events moderates the severity of such events. We revisit and further examine the relation between individual loss severity and macroeconomic environment along different quantiles in the loss severity distribution in Section 4.4.

## 4.2 Operational Losses by Event Type

Operational risk is an amalgamation of various types of subcomponent risks (Chernobai et al. (2012)). As previously discussed, the Basel II Accord defines seven major loss categories: IF, EF, EPWS, CPBP, DPA, BDSF, and EDPM. While the previous section documented a robust relation between aggregate operational losses at the BHC level and macroeconomic conditions, we have not yet explored the analogous relation within individual operational risk types. This omission masks potentially heterogeneous effects, whereby only some of the operational loss types may drive the association with the macroeconomy.

Based on event type category definitions and economic intuition, we *a priori* expect that losses in six out of the seven event types (IF, EF, EPWS, CPBP, BDSF and EDPM) could all be plausibly associated with macroeconomic conditions. The only loss type we expect to be uncorrelated is DPA, which is mainly related to natural disasters. To empirically test whether losses in the different loss categories are related to macroeconomic conditions, we re-estimate Eq. (1) for each event type separately. Table 6 presents the results.

[Insert Table 6 about here]

The results show that five out of the seven loss categories are significantly related to macroeconomic conditions: IF, EF, CPBP, BDSF and EDPM. Columns (1), (2), (4), (6) and (7) indicate that coefficient estimates of *ME* are statistically significant at least at the 5% level. Losses from BHCs' failure to meet obligations to clients, the design of products or business practices (CPBP) have a particularly strong association with the macroeconomic environment. The magnitude of the coefficient on *ME* in Column (4) is the largest among the seven specifications.

To contextualize these findings and provide some anecdotal evidence, we review the descriptions of some of the largest operational losses that occurred during the 2007-2009 financial crisis for each of the five event types. We find that rogue trading is a significant root cause for large IF losses, whereby the immense financial market volatility of the period likely contributed to the materialization of unauthorized trades into substantial monetary losses. For EF, we observe large losses from mortgage fraud related to BHCs' credit exposures (e.g., falsified financial reports and loan guarantees in credit extension). For CPBP, losses related to litigation and corrective regulatory actions for product misrepresentation to customers and the failure to meet professional obligations to clients account for many of the higher losses. For example, as discussed in the introduction, foreclosure abuses amid the bursting of the housing bubble led to massive fines and penalties for the violations of state and federal law. Improperly functioning financial markets during the crisis (e.g., the market failure of auction rate securities) were similarly a source of considerable losses. For BDSF and EDPM, we observe cases of significant losses related to system failures in trading platforms and improper trading executions, in which information technology malfunctions and employee mistakes were compounded by rapid, unexpected movements in financial asset prices.

Column (3) indicates that while losses in EPWS are negatively related to *ME*, the relation is marginally insignificant at conventional levels (p-value of 0.12). While the association is not statistically significant and should be interpreted with caution, we find some anecdotal evidence that elevated losses during the crisis are from lawsuits related to wrongful termination and unpaid compensation (e.g., class action lawsuits by laid-off mortgage origination staff). Finally, consistent with our intuition, Column (5) shows that losses in DPA are not related to *ME* (p-value of 0.93).

Overall, such results indicate that losses in most operational risk event types are related to macroeconomic conditions. The five event types that are related account more than 95% of total operational losses in our data. The lack of a significant association for loss event types without any connection to the macroeconomy (i.e. DPA) also implicitly serves as a falsification test, suggesting the overall relation between operational losses and macroeconomic conditions are not likely to be driven by latent factors unrelated to the macro environment.

### 4.3 Incidence of Tail Operational Risk Events

Our analysis in the prior sections examined the association between operational risk and macroeconomic conditions by modeling the conditional average operational loss. In contrast, this section focuses on the frequency of tail loss events. The distinction between experiencing a higher level of operational risk vis-à-vis tail operational loss events is important. The situation where a bank incurs higher operational losses in adverse macroeconomic environment has implications for bank performance. However, if the higher level of operational losses is relatively easy to anticipate and reserve for, such a situation is not necessarily a first-order concern in terms of the institution's unexpected risk exposure and financial stability. In contrast, a higher incidence of tail operational loss events is more problematic as tail risk poses difficulties for loss reserving practices and capital management, and has more relevance for a bank's risk profile and risk of failure.

Tail risk is particularly relevant in the context of operational risk. In fact, a well-known property of operational losses is the extremely heavy tails of their distributions.[16] The heavy tails of operational risk are confirmed in our data: the summary statistics in Table 2, Panel A suggest that dollar losses are concentrated in a relatively few high-severity loss events. This is also evident in Figure 3 when we plot the proportion of cumulative dollar losses below a specific loss percentile against different percentile selections.

[16] See Chernobai and Rachev (2006), Jobst (2008) and Abdymomunov and Curti (2015) for discussions of operational loss distribution properties and their implications for risk modeling.

[Insert Figure 3 about here]

To empirically examine whether the state of the macroeconomy is related to the incidence of tail events, we use three measures of tail risk frequency (*Ln(NTail90)*, *Ln(NTail95)*, and *Ln(NTail99)*) constructed as follows. We start with the 298,170 individual loss events in our sample. We calculate the $90^{\text{th}}$, $95^{\text{th}}$ and $99^{\text{th}}$ percentiles of the BHC-specific empirical loss distributions. We categorize all loss events within a BHC that have severities above the respective percentiles ($90^{\text{th}}$, $95^{\text{th}}$ or $99^{\text{th}}$) as "tail losses." We then count the number of tail events that occur at a given BHC during a given quarter and apply a natural log transformation on these frequencies.[17] Table 7 presents regression results of the three tail loss measures on our macroeconomic index, *ME*, using specifications similar to Eq. (1).

[Insert Table 7 about here]

Adverse macroeconomic conditions are associated with a higher incidence of tail operational losses. Across the three specifications, a one standard deviation increase in *ME* is related to a 4.6-10.2% increase in the number of tail events. The coefficient estimates of *ME* are statistically significant at the 5% level or better. These results thus suggest that the state of the macroeconomy is relevant not only for average operational losses at financial institutions, but also for the occurrence of improbable, severe tail operational risk events.

## 4.4 Individual Loss Severities

The analysis so far suggests that U.S. bank holding companies experience larger quarterly operational losses and more frequent tail operational risk events in periods with adverse

[17] To deal with zero counts, we add 1 to all observations before we apply the natural log transformation. In unreported tests, we confirm the robustness of our results to using count data (Negative Binomial) regression models without transforming the tail event counts.

macroeconomic environment. We now take a step back and analyze individual loss events. Specifically, we analyze the relation between individual loss severity and macroeconomic conditions at different quantiles of the loss distribution. This analysis should provide insights on the potential dependency of operational loss severity on the business cycle, and further characterize BHCs' loss severity distributions in relation to macroeconomic conditions. For our purposes, we employ quantile regressions:

$$Z\ Ln(Loss)_{i,t,j} = \beta_0 + \beta_1 ME_t + \epsilon_{i,t,j}, \tag{2}$$

where $i$ indexes banks, $t$ indexes time periods (quarters), and $j$ indexes individual loss events.[18] $Z\ Ln(Loss)$ is the natural log transformation of operational loss $j$ incurred by BHC $i$ in quarter $t$, which has been standardized within BHC $i$:

$$Z\ Ln(Loss)_{i,t,j} = \frac{Ln(Loss)_{i,t,j} - \mu_i}{\sigma_i}. \tag{3}$$

$Ln(Loss)_{i,t,j}$ is the natural log transformation of operational loss $j$ incurred by BHC $i$ in quarter $t$, $\mu_i$ is the mean of *Ln(Loss)* and $\sigma_i$ is the standard deviation of *Ln(Loss)* calculated within BHC $i$.[19] This transformation of individual loss severities eliminates time-invariant components within BHCs, and also takes into account the variability of losses within BHCs. By using within-BHC variation of loss severities for regression coefficient identification, we mitigate concerns related to confounding differences in individual loss severities across BHCs (e.g., due to BHC size). *ME* measures the macroeconomic environment and is defined as the first principal component of *GDP Growth*, *HPI Growth*, *CREPI Growth*, *VIX* and *BBB-*

[18] While a linear OLS regression can model the conditional mean of the response variable given values of predictor variables, a quantile regression can model conditional quantiles of the response variable. Specifically, the quantile regression has the flexibility of estimating the relation between individual loss severity and the macroeconomic environment at various quantiles of the loss distribution, not just a single high quantile in which OLS would implicitly result in.

[19] Our results are robust to applying other transformations on individual loss severities (e.g., using the within-BHC ranks of individual losses or, alternatively, using operational losses scaled by BHC total assets.)

*T10Yr Sprd*. We present estimates at the 1st, 10th, 25th, 50th, 75th, 90th, and 99th percentiles of the operational loss distribution. Table 8, Panel A presents the results.

[Insert Table 8 about here]

Operational loss severities decrease in downturns at the lower percentiles of the loss distribution, while they simultaneously increase at the higher percentiles of the loss distribution. Further, the coefficient magnitudes are larger at the high quantiles of the loss distribution. As Figure 3 demonstrates, tail losses account for the majority of dollar losses (e.g., the 1% of largest losses accounts for 87.26% of the total dollar losses). These results thus suggest that an increase in the severity of large losses is a contributing factor, in addition to the higher frequency of tail events, to the overall association between operational risk and macroeconomic conditions. A potential explanation for the decrease in the severity of smaller losses during economic downturns could be lower values of certain banking transactions in adverse conditions (e.g., smaller loans, deposits, funds transfers, corporate and retail card payments), which might consequently translate into lower operational losses associated with these transactions (e.g., internal and external fraud).[20] In Table 8, Panel B we find similar results, when we standardize losses more granularly (i.e. within every BHC-event type as opposed to every BHC in Panel A).

The results in Table 8 also importantly suggests that the loss severity distribution of operational risk events is dependent on the state of the macroeconomy. Specifically, the dispersion of operational losses (i.e. the extent to which the operational loss distribution is "stretched") increases in an adverse macroeconomic environment. This finding challenges assumptions in traditional operational risk capital modeling techniques (e.g., the Loss Distribution Ap-

[20] We note that losses below the 25th percentile of the loss severity distribution account for only 0.61% of total dollar losses.

proach), which oftentimes assume constant, time-independent loss severity distributions. From a risk management perspective, and particularly in the evaluation of loss outcomes under various macroeconomic scenarios (as in stress testing), it might be appropriate to model and estimate loss distributions conditional on the macroeconomic scenarios, rather than simply moving along to higher quantiles of a "through-the-cycle" loss distribution.

## 4.5 Macro Sensitivity of Operational Risk and BHC Attributes

Our results linking operational risk at banking organizations and macroeconomic conditions have so far represented average relations across the institutions in our sample. However, there could be important differences in the macroeconomic sensitivity of operational risk across BHCs, which could be of interest to both supervisors and risk managers. In this section, we examine the cross-sectional variation of operational risk sensitivity to macroeconomic conditions in relation to three fundamental BHC attributes: size, profitability, and leverage.

More specifically, we estimate Eq. (1) separately for each BHC and then analyze how the regression coefficient $\beta_1$ (*ME Beta*) varies across BHC attributes. We measure size by BHC consolidated total assets, profitability by return on equity, and leverage by the ratio of BHC liabilities to consolidated total assets. To conduct our tests, we average BHC attributes within every BHC over time and run cross-sectional regressions of *ME Beta* on the time-averaged values of each attribute across BHCs.[21] For robustness, we also provide results where we take BHC attributes as of the last quarter in the sample (rather than averaging through time). Table 9 presents the results.

[Insert Table 9 about here]

[21]The lack of financial information for some foreign-headquartered holding companies with large operations in the U.S. reduces the number of organizations in the cross-section from 38 to 33.

Larger and more leveraged BHCs have a significantly higher sensitivity of operational risk to the macroeconomic environment (i.e. tend to incur more operational losses in adverse macroeconomic conditions). These results are interesting and important from a financial stability perspective as more operational risk at the largest and most leveraged banking organizations in adverse macroeconomic conditions could contribute to systemic risk and destabilize an already fragile financial system. In contrast, profitability is not significantly related to the macroeconomic sensitivity of operational risk at BHCs.

### 4.6 Financial Impact of Operational Risk

Our previous analyses suggest a robust relation between operational risk occurrence and the macroeconomy. We now focus on the accounting of operational risk (i.e. when risk surfaces and financially impacts banking organizations). As discussed in Section 3.3, the distinction between "occurrence" and "accounting" is important as there are sometimes significant time lags between when an event occurs and when it financially impacts an institution.

In view of these time lags, a question arises whether the financial impact (not only the occurrence) of operational losses is related to macroeconomic conditions. To answer this question, we re-estimate Eq. (1) using accounting dates instead of occurrence dates to link operational losses to macroeconomic conditions. Table 10, Panel A presents the results.

Column (1) suggests that operational risk not only occurs but also tends to surface and realize into losses in macroeconomic downturns. Columns (2) and (3) further indicate that the association between the financial impact of operational losses and macroeconomic conditions is through both average frequency and average severity of loss events.

[Insert Table 10 about here]

Table 10, Panel B presents results by loss event types. Losses from IF, EF, CPBP, BDSF and EDPM have a significant financial impact on banking organizations during economic downturns, which is consistent with Table 6 documenting a significant relation between macroeconomic conditions and the occurrence of operational risk in the same five event types. These results importantly suggest that both the occurrence and financial impact of losses in these event types are related to the macroeconomic cycle. A partial explanation is that, for many material events (especially those occurring in adverse conditions), the occurrence and financial impact of losses happen in relatively similar macroeconomic conditions. Moreover, the time lags between occurrence and accounting are reasonably short for the "average" loss event. In a significant number of cases, however, large losses surface and financially impact BHCs during downturns even though they occur in preceding periods (before the downturns when discovered).

The latter point is also reflected in some of the differences we observe regarding the association between operational risk and macroeconomic conditions at occurrence and accounting of losses for certain event types. For example, the relation between the financial impact of EF and the macroeconomic environment is somewhat stronger than the relation between the occurrence of EF and macroeconomic conditions. Anecdotal evidence suggests that some of the largest EF events spanned multiple years and began at various points of the business cycle (e.g., Bernard Madoff's Ponzi scheme) before they were discovered (and accounted) during the 2007-2009 financial crisis amid liquidity constraints, investor withdrawals, the housing market collapse, and the general financial turmoil. Similarly, the relation between the financial impact of CPBP and the macroeconomic environment is stronger than the relation between the occurrence of CPBP and macroeconomic conditions. Anecdotal evidence suggests that certain business practices and products (e.g., the underwriting and packaging of residential mortgages into mortgage-backed securities) had started occurring prior to the crisis, but had their financial impacts during the crisis when BHCs established legal reserves for litigation.

Overall, the results in this section suggest that operational losses not only occur but also financially impact banking organizations during economic downturns. These results are informative for regulators and supervisors, and particularly so with regards to the estimation of regulatory capital related to operational risk (e.g., minimum capital requirements). In a stress-testing context, they support quantitative frameworks in operational risk that can be used to determine the ability of banking organizations to endure adverse macroeconomic conditions, evaluate loss outcomes under various scenarios, and set capital levels accordingly.

# 5 Robustness Checks and Additional Analyses

This section discusses robustness checks and additional analyses that we have performed. First, we examine the association between BHC operational losses and specific measures of macroeconomic activity. Second, we examine the existence of potential lagged effects of the macroeconomic environment on operational losses. Third, we check whether our results are robust to the exclusion of data from the period post the global financial crisis.

## 5.1 Macroeconomic Indicators

Our primary measure of macroeconomic conditions, *ME*, summarizes information from five key macroeconomic and financial indicators that are plausibly related to operational risk realizations. We have used the first principal component of: the year-over-year U.S. real GDP growth rate (*GDP Growth*); the year-over-year growth rate in the U.S. CoreLogic House Price Index (*HPI Growth*); the year-over-year growth rate in the U.S. Commercial Real Estate Price Index (*CREPI Growth*); the CBOE U.S. Market Volatility Index (*VIX*); and the spread between the U.S. 10-year BBB-rated corporate bond yield and the 10-year U.S. Treasury bond yield (*BBB-T10Yr Sprd*). In summary, our measure of macroeconomic conditions is both economically and statistically significantly related to BHC operational risk. In this section, we re-estimate Eq. (1) using each of the variables used to construct *ME*, and document the drivers of the relation between operational losses and *ME*.

Table 11, Panel A presents the results. Columns (1)–(5) show that all five macroeconomic variables underlying *ME* are related to BHC operational losses at least at the 10% significance level. The coefficient signs of the macroeconomic variables are consistent with the interpretation that a weak macroeconomic environment is associated with elevated operational losses at financial institutions.

[Insert Table 11 about here]

## 5.2 Lagged Effects of Macroeconomic Environment

Our measure of macroeconomic conditions is relatively persistent through time. For example, the pairwise correlations between *ME* and its first lag is as high as 92%. An important question arises whether macroeconomic conditions can have a lagged effect on operational losses. To answer this question, we test whether the first few (up to three) lags of *ME* have explanatory power over operational losses. Table 11, Panel B presents the results.

Columns (1)-(3) show that *ME*'s first, second and third lags are consistently significantly negatively correlated with *Ln(Loss)* at least at the 10% level. Columns (4)-(7) show specifications including *ME* along with its lags. *ME* is negative and significant. In contrast, none of the three lags are significant at conventional levels in the presence of *ME*. We thus conclude that the lagged macroeconomic variables, *L1 ME-L3 ME*, have limited explanatory power over operational losses beyond *ME*.

### 5.3 Exclusion of Post-Crisis Losses

With operational risk, there are often delays between the time a risk is taken and when it materializes. Thus, there could be potential concerns over downward bias in event counts during the last several quarters of our sample period when macroeconomic conditions were generally improving. To mitigate such concerns, even though our data of operational risk events ends in 2017:Q4, we truncate our sample earlier at 2013:Q4, as not all risks taken by 2017:Q4 would have materialized by 2017:Q4. However, there might still be concerns that the later quarters of our sample do not reflect the full extent of BHCs' operational risk exposures. To further address such concerns, in this section of our study, we test the robustness of our results by excluding data from the post-global financial crisis period of the sample. Specifically, starting in 2013:Q4, we re-estimate Eq. (1) excluding one year worth of data at a time until the peak of the crisis in 2008:Q4.

Table 11, Panel C presents the results. Notably, Columns (1)–(5) indicate that our results are robust to the exclusion of the most recent data from our analysis, mitigating concerns that our results are driven by a downward bias in event reporting during the last several quarters of our sample period.[22]

## 6 Conclusion

This study investigates the relation between macroeconomic conditions and operational risk at financial institutions. A regulatory framework, the Dodd-Frank Wall Street Reform and Consumer Protection Act, provides us with a rich operational loss dataset for our tests. Using a sample of 298,170 individual operational loss occurrences from the 38 largest BHCs in the U.S. over the period [2000:Q1-2013:Q4], we present robust evidence that links the

[22]In unreported tests, where we use interactions of post-crisis time indicators and our macroeconomic index, we find confirmatory evidence of no significant differences in the relation between operational risk occurrence and macroeconomic conditions during the post-crisis period (relative to prior periods).

strength of the macroeconomic environment to firm operational loss experiences.

We show that BHCs incur more operational losses in adverse conditions driven by a higher frequency and severity of tail events. We document the specific operational risk types behind this relation. Further, we show that larger and more leveraged banking organizations have a higher macroeconomic sensitivity of operational risk. We also provide evidence that the loss severity distribution of operational risk events is related to the state of macroeconomy. Finally, we show that operational risk not only tends to occur but also financially impacts institutions more in adverse macroeconomic periods.

We conclude that a robust association between operational losses and the macroeconomic environment indeed exists. Our study makes a significant contribution on the link between financial institutions' risk and the state of the macroeconomy beyond what has been documented in the finance literature so far. Our research is directly relevant to risk managers at financial institutions, and has policy and supervisory implications. Specifically, our analysis implicitly supports a quantitative approach to operational risk management whereby financial institutions can link operational losses to the macroeconomic environment through statistical methods. Of course, the evidence in this paper generalizes relations to the entire set of banks we analyze and might not be applicable to some of the individual constituents in our sample or institutions outside the scope of our data. Cognizant of such limitations, we argue the results presented are generally aligned with the Dodd-Frank Act supervisory stress-testing framework.

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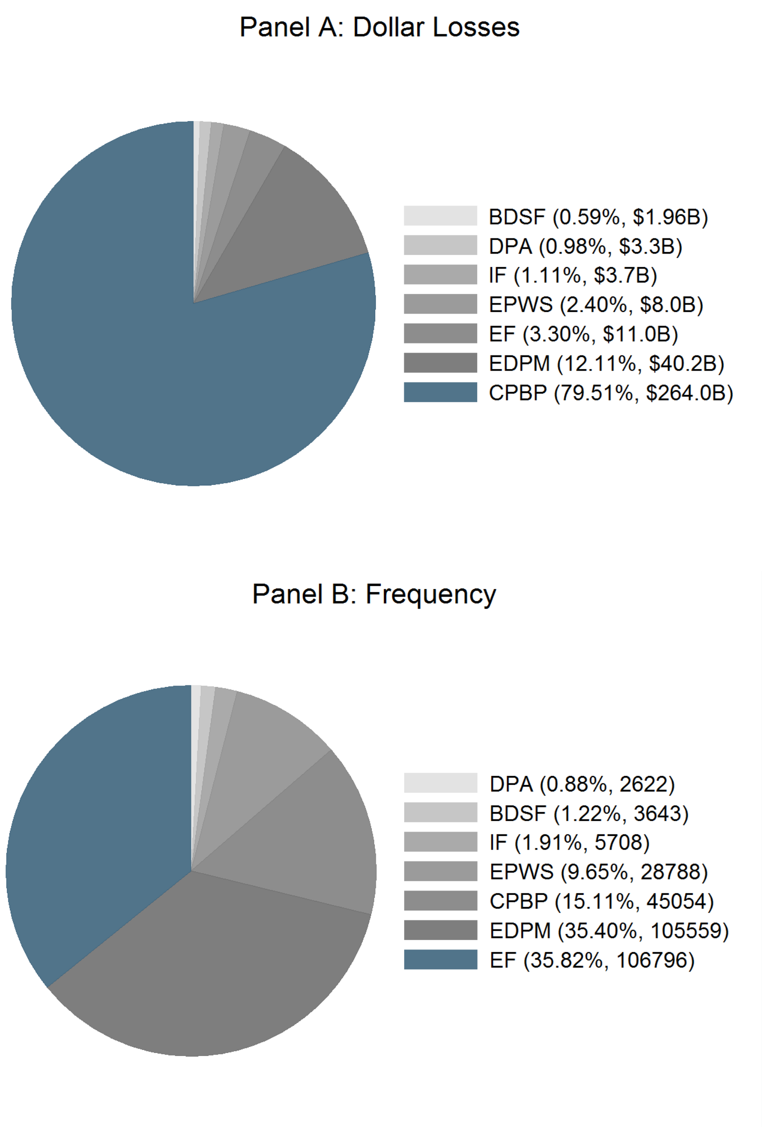


Figure 1: **Operational Losses by Event Type**
The sample includes 298,170 operational losses in 7 event types incurred by 38 large U.S. bank holding companies over the period [2000:Q1-2013:Q4]. The seven event types are as follows: Internal Fraud (IF), External Fraud (EF), Employment Practices and Workplace Safety (EPWS), Clients, Products and Business Practices (CPBP), Damage to Physical Assets (DPA), Business Disruption and System Failures (BDSF), and Execution, Delivery and Process Management (EDPM). Panel A presents the allocation of dollar losses (the percentage of total losses and U.S. dollar loss amounts) among the 7 operational risk event types. Panel B presents the allocation of loss frequencies (the percentage of the total number of losses and loss frequencies) among the 7 operational risk event types.

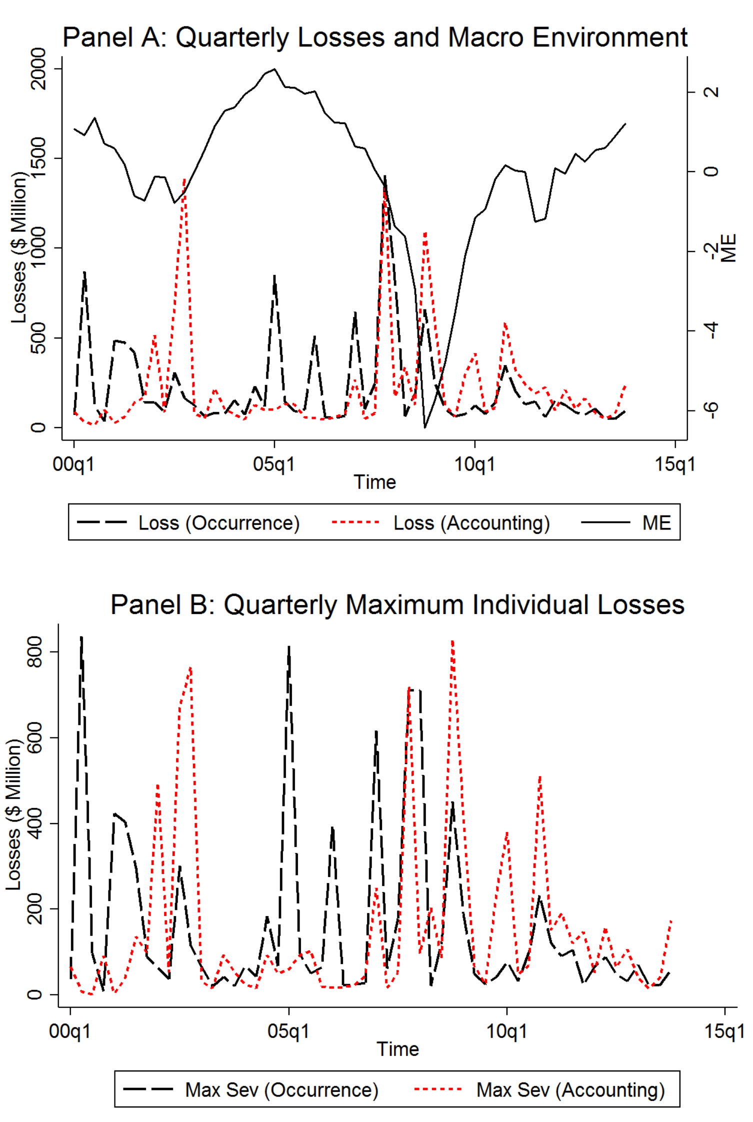


Figure 2: **Operational Losses and the Macroeconomic Environment through Time**
This figure presents plots of the operational losses for 38 large U.S. bank holding companies and the U.S. macroeconomic environment over the period [2000:Q1-2013:Q4]. Panel A plots quarterly losses and the macroeconomic environment. *Loss (Occurrence)* and *Loss (Accounting)* are the total operational losses (in millions of U.S. dollars) aggregated by occurrence and accounting dates, respectively, at the quarterly level for every BHC, then averaged across BHCs. *ME* is a measure of the U.S. macroeconomic environment (higher values denote better macroeconomic conditions). Panel B plots quarterly maximum individual losses. *Max Sev (Occurrence)* and *Max Sev (Accounting)* are the losses (in millions of U.S. dollars) for the most severe individual operational risk events for a given BHC in a given quarter, then averaged across BHCs.

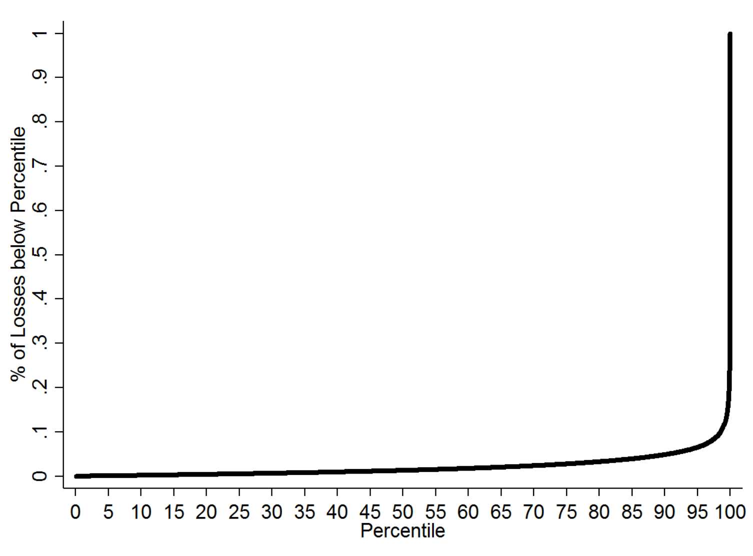


Figure 3: **Heavy-tailed Operational Loss Distribution**
This figure displays the percentage of the total loss amount below a given percentile of the operational loss distribution. The sample includes 298,170 operational loss events incurred by 38 large U.S. bank holding companies over the period [2000:Q1-2013:Q4].

Table 1: **Operational Loss Event Type Definitions**
This table presents operational loss event type definitions. Source: Basel Committee on Banking Supervision (2006).

| **Panel A: Event Type Category Definitions** | | |
|---|---|---|
| Event Type Category | Abbreviation | Description |
| Internal Fraud | IF | Acts of a type intended to defraud, misappropriate property or circumvent regulations, which involves at least one internal party. |
| External Fraud | EF | Acts of a type intended to defraud, misappropriate property or circumvent the law, by a third party. |
| Employment Practices and Workplace Safety | EPWS | 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 | An unintentional or negligent failure to meet a professional obligation to specific clients, or from the nature or design of a product. |
| Damage to Physical Assets | DPA | Damage to physical assets from natural disasters or other events. |
| Business Disruption and System Failures | BDSF | Disruption of business or system failures. |
| Execution, Delivery and Process Management | EDPM | Failed transaction processing or process management, from relations with trade counterparties and vendors. |

Table 2: **Descriptive statistics**

This table presents descriptive statistics. In Panel A, summary statistics are presented at the individual loss event level. The sample includes 298,170 operational losses incurred by 38 large U.S. bank holding companies over the period [2000:Q1-2013:Q4]. *Loss* is the gross amount lost in an operational loss event (in millions of U.S. dollars). *ME* is a measure of the U.S. macroeconomic environment (higher values denote better macroeconomic conditions). It is defined as the first principal component of *GDP Growth*, *HPI Growth*, *CREPI Growth*, *VIX*, and *BBB-T10Yr Sprd*. *GDP Growth* is the year-over-year U.S. real GDP growth rate. *HPI Growth* is the year-over-year growth rate in the U.S. CoreLogic House Price Index. *CREPI Growth* is the year-over-year growth rate in the U.S. Commercial Real Estate Price Index. VIX is the CBOE U.S. Market Volatility Index, converted to a quarterly frequency by using the maximum close-of-day value in any quarter. *BBB-T10Yr Sprd* is the spread between the U.S. 10-year BBB-rated corporate bond yield and the 10-year U.S. Treasury bond yield. In Panel B, summary statistics are presented at the BHC-quarter level. The sample includes 1,509 quarterly operational losses incurred by 38 large financial institutions over the period [2000:Q1-2013:Q4]. *Loss* is operational dollar losses incurred by a bank over a given calendar quarter (in millions of U.S. dollars). *Freq* is the frequency of operational losses incurred by a bank over a given quarter. *Sev* is the average operational loss severity experienced by a bank over a given quarter. *NTail90*, *NTail95*, and *NTail99* are frequencies of within-BHC tail operational losses at the $90^{\text{th}}$, $95^{\text{th}}$ and $99^{\text{th}}$ quantiles, respectively, that occur at a BHC over a given calendar quarter. *ME* is a measure of the U.S. macroeconomic environment (higher values denote better macroeconomic conditions). It is defined as the first principal component of *GDP Growth*, *HPI Growth*, *CREPI Growth*, *VIX*, and *BBB-T10Yr Sprd*. *GDP Growth* is the year-over-year U.S. real GDP growth rate. *HPI Growth* is the year-over-year growth rate in the U.S. CoreLogic House Price Index. *CREPI Growth* is the year-over-year growth rate in the U.S. Commercial Real Estate Price Index. VIX is the CBOE U.S. Market Volatility Index, converted to a quarterly frequency by using the maximum close-of-day value in any quarter. *BBB-T10Yr Sprd* is the spread between the U.S. 10-year BBB-rated corporate bond yield and the 10-year U.S. Treasury bond yield. *Total Assets* is BHC total consolidated assets. *ROE* is BHC return on equity, defined as the ratio of BHC income before discontinued operations and book value of equity. *Leverage* is the ratio of BHC liabilities to total assets.

**Panel A: Loss-event Level**

| | Mean | SD | P5 | P25 | P50 | P75 | P95 | N Obs |
|---|---|---|---|---|---|---|---|---|
| Loss | 1.114 | 78.308 | 0.021 | 0.028 | 0.044 | 0.099 | 0.563 | 298170 |
| ME | -0.189 | 2.011 | -4.772 | -1.145 | 0.088 | 1.215 | 2.125 | 298170 |
| GDP Growth | 0.017 | 0.019 | -0.032 | 0.013 | 0.019 | 0.028 | 0.037 | 298170 |
| HPI Growth | 0.016 | 0.098 | -0.159 | -0.043 | 0.012 | 0.096 | 0.162 | 298170 |
| CREPI Growth | 0.039 | 0.117 | -0.266 | 0.019 | 0.057 | 0.122 | 0.157 | 298170 |
| VIX | 28.575 | 13.415 | 14.600 | 19.600 | 23.800 | 32.200 | 48.000 | 298170 |
| BBB-T10Yr Sprd | 2.215 | 1.027 | 1.200 | 1.400 | 2.000 | 2.600 | 4.500 | 298170 |

**Panel B: BHC-quarter Level**

| | Mean | SD | P5 | P25 | P50 | P75 | P95 | N Obs |
|---|---|---|---|---|---|---|---|---|
| Loss | 220.072 | 1408.834 | 0.982 | 4.667 | 15.699 | 74.345 | 723.522 | 1509 |
| Freq | 197.594 | 372.772 | 6.000 | 24.000 | 53.000 | 164.000 | 1084.000 | 1509 |
| Sev | 1.423 | 11.311 | 0.069 | 0.129 | 0.233 | 0.636 | 3.720 | 1509 |
| NTail90 | 20.328 | 38.834 | 0.000 | 2.000 | 6.000 | 17.000 | 105.000 | 1509 |
| NTail95 | 10.151 | 19.321 | 0.000 | 1.000 | 3.000 | 8.000 | 52.000 | 1509 |
| NTail99 | 2.044 | 3.978 | 0.000 | 0.000 | 1.000 | 2.000 | 11.000 | 1509 |
| ME | -0.232 | 2.006 | -4.772 | -1.145 | 0.088 | 1.155 | 2.125 | 1509 |
| GDP Growth | 0.016 | 0.019 | -0.032 | 0.012 | 0.019 | 0.028 | 0.042 | 1509 |
| HPI Growth | 0.018 | 0.096 | -0.159 | -0.043 | 0.012 | 0.096 | 0.162 | 1509 |
| CREPI Growth | 0.033 | 0.121 | -0.266 | 0.018 | 0.057 | 0.122 | 0.157 | 1509 |
| VIX | 28.698 | 13.169 | 14.600 | 19.600 | 23.800 | 32.200 | 48.000 | 1509 |
| BBB-T10Yr Sprd | 2.238 | 1.017 | 1.300 | 1.400 | 2.100 | 2.600 | 4.500 | 1509 |
| Total Assets | 400.051 | 577.133 | 48.388 | 74.876 | 145.328 | 355.092 | 1938.470 | 1092 |
| ROE | 0.019 | 0.091 | -0.031 | 0.010 | 0.022 | 0.034 | 0.055 | 1089 |
| Leverage | 0.896 | 0.033 | 0.835 | 0.880 | 0.897 | 0.916 | 0.939 | 1092 |

Table 3: **Time Lags between Occurrence, Discovery and Accounting of Loss Events**
This table presents descriptive statistics on the number of days between loss occurrence and discovery dates, loss discovery and accounting dates, and loss occurrence and accounting dates of loss events by event type, respectively. The estimation sample includes 298,170 individual loss events in 7 event types incurred by 38 large financial institutions over the period [2000:Q1-2013:Q4]. The abbreviations of the event types are as follows: Internal Fraud (IF), External Fraud (EF), Employment Practices and Workplace Safety (EPWS), Clients, Products and Business Practices (CPBP), Damage to Physical Assets (DPA), Business Disruption and System Failures (BDSF), and Execution, Delivery and Process Management (EDPM). *All* denotes all loss events.

| | Occurence to Discovery | | | | | Discovery to Accounting | | | | | Occurrence to Accounting | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | P5 | P50 | P95 | Mean | SD | P5 | P50 | P95 | Mean | SD | P5 | P50 | P95 |
| IF | 109 | 366 | 0 | 0 | 698 | 71 | 227 | 0 | 2 | 319 | 180 | 457 | 0 | 18 | 994 |
| EF | 49 | 197 | 0 | 0 | 244 | 62 | 163 | 0 | 8 | 216 | 111 | 282 | 0 | 39 | 469 |
| EPWS | 112 | 356 | 0 | 0 | 774 | 259 | 481 | 0 | 33 | 1279 | 371 | 615 | 0 | 63 | 1677 |
| CPBP | 260 | 624 | 0 | 0 | 1694 | 238 | 432 | 0 | 52 | 1106 | 498 | 802 | 0 | 86 | 2271 |
| DPA | 57 | 209 | 0 | 0 | 365 | 160 | 306 | 0 | 50 | 834 | 217 | 370 | 0 | 73 | 1047 |
| BDSF | 64 | 280 | 0 | 0 | 314 | 45 | 155 | 0 | 0 | 223 | 109 | 354 | 0 | 2 | 607 |
| EDPM | 172 | 523 | 0 | 0 | 1216 | 129 | 315 | 0 | 5 | 715 | 300 | 652 | 0 | 29 | 1764 |
| All | 132 | 437 | 0 | 0 | 881 | 132 | 320 | 0 | 12 | 728 | 264 | 581 | 0 | 39 | 1491 |

Table 4: **Correlations**

This table presents variable correlations. The sample includes 1,509 quarterly operational losses incurred by 38 large U.S. bank holding companies over the period [2000:Q1-2013:Q4]. *Ln(Loss)* is a natural log transformation of operational dollar losses incurred by a bank over a given calendar quarter. *ME* is a measure of the U.S. macroeconomic environment (higher values denote better macroeconomic conditions). It is defined as the first principal component of *GDP Growth*, *HPI Growth*, *CREPI Growth*, *VIX*, and *BBB-T10Yr Sprd*. *GDP Growth* is the year-over-year U.S. real GDP growth rate. *HPI Growth* is the year-over-year growth rate in the U.S. CoreLogic House Price Index. *CREPI Growth* is the year-over-year growth rate in the U.S. Commercial Real Estate Price Index. VIX is the CBOE U.S. Market Volatility Index, converted to quarterly frequency by using the maximum close-of-day value in any quarter. *BBB-T10Yr Sprd* is the spread between the U.S. 10-year BBB-rated corporate bond yield and the 10-year U.S. Treasury bond yield. p-values are presented in parentheses.

| Variables | Ln(Loss) | ME | GDP Growth | HPI Growth | CREPI Growth | VIX | BBB-T10Yr Sprd |
|---|---|---|---|---|---|---|---|
| Ln(Loss) | 1.000 | | | | | | |
| ME | -0.042 | 1.000 | | | | | |
| | (0.100) | | | | | | |
| GDP Growth | -0.023 | 0.898 | 1.000 | | | | |
| | (0.374) | (0.000) | | | | | |
| HPI Growth | -0.054 | 0.818 | 0.687 | 1.000 | | | |
| | (0.036) | (0.000) | (0.000) | | | | |
| CREPI Growth | -0.019 | 0.764 | 0.680 | 0.518 | 1.000 | | |
| | (0.451) | (0.000) | (0.000) | (0.000) | | | |
| VIX | 0.049 | -0.842 | -0.621 | -0.625 | -0.502 | 1.000 | |
| | (0.058) | (0.000) | (0.000) | (0.000) | (0.000) | | |
| BBB-T10Yr Sprd | 0.035 | -0.918 | -0.813 | -0.660 | -0.579 | 0.807 | 1.000 |
| | (0.170) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | |

Table 5: **Macroeconomic Environment and Operational Losses**

This table reports coefficients from panel regressions of operational loss measures on the macroeconomic environment. The estimation sample comprises an unbalanced panel of 1,509 quarterly losses incurred by 38 large U.S. bank holding companies over the period [2000:Q1-2013:Q4]. *Ln(Loss)* is a natural log transformation of operational dollar losses incurred by a bank over a given calendar quarter. *Ln(Freq)* is a natural log transformation of the frequency of operational losses incurred by a bank over a given calendar quarter. *Ln(Sev)* is a natural log transformation of the average operational loss severity experienced by a bank over a given calendar quarter. *ME* is a measure of the U.S. macroeconomic environment (higher values denote better macroeconomic conditions). All specifications include BHC fixed effects. The error terms are clustered at the quarter and BHC levels. p-values are presented in parentheses.

| | (1)<br>Ln(Loss) | (2)<br>Ln(Freq) | (3)<br>Ln(Sev) |
|---|---|---|---|
| ME | $-0.082^{***}$ | $-0.056^{***}$ | $-0.036$ |
| | (0.001) | (0.001) | (0.146) |
| BHC FE | *Yes* | *Yes* | *Yes* |
| N Obs | 1509 | 1509 | 1509 |
| Adj $R^2$ | 0.61 | 0.72 | 0.29 |

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table 6: **Macroeconomic Environment and Operational Risk Losses by Event Type**

This table reports coefficients from panel regressions of operational losses on the macroeconomic environment by loss event type. The estimation sample comprises an unbalanced panel of 1,509 quarterly losses in 7 loss types incurred by 38 large U.S. bank holding companies over the period [2000:Q1-2013:Q4]. The 7 event types are as follows: Internal Fraud (IF), External Fraud (EF), Employment Practices and Workplace Safety (EPWS), Clients, Products and Business Practices (CPBP), Damage to Physical Assets (DPA), Business Disruption and System Failures (BDSF), and Execution, Delivery and Process Management (EDPM). The dependent variable, *Ln(Loss)*, is a natural log transformation of operational dollar losses in a given event type incurred by a bank over a given calendar quarter. *ME* is a measure of the U.S. macroeconomic environment (higher values denote better macroeconomic conditions). All specifications include BHC fixed effects. The error terms are clustered at the quarter and BHC levels. p-values are presented in parentheses.

| | (1)<br>Ln(Loss)<br>IF | (2)<br>Ln(Loss)<br>EF | (3)<br>Ln(Loss)<br>EPWS | (4)<br>Ln(Loss)<br>CPBP | (5)<br>Ln(Loss)<br>DPA | (6)<br>Ln(Loss)<br>BDSF | (7)<br>Ln(Loss)<br>EDPM |
|---|---|---|---|---|---|---|---|
| ME | −0.020*** | −0.039** | −0.015 | −0.081** | 0.000 | −0.019** | −0.052*** |
| | (0.006) | (0.020) | (0.122) | (0.021) | (0.929) | (0.034) | (0.001) |
| BHC FE | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* |
| N Obs | 1509 | 1509 | 1509 | 1509 | 1509 | 1509 | 1509 |
| Adj $R^2$ | 0.43 | 0.65 | 0.74 | 0.53 | 0.20 | 0.44 | 0.66 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: **Macroeconomic Environment and Tail Operational Risk**

This table reports coefficients from panel regressions of tail operational risk measures on the macroeconomic environment. The estimation sample comprises an unbalanced panel of 1,509 quarterly losses incurred by 38 large U.S. bank holding companies over the period [2000:Q1-2013:Q4]. *Ln(NTail90)*, *Ln(NTail95)*, and *Ln(NTail99)* are natural log transformations of the frequency of within-BHC tail operational losses at the $90^{\text{th}}$, $95^{\text{th}}$ and $99^{\text{th}}$ quantiles, respectively, that occur at a BHC over a given calendar quarter. *ME* is a measure of the U.S. macroeconomic environment (higher values denote better macroeconomic conditions). All specifications include BHC fixed effects. The error terms are clustered at the quarter and BHC levels. p-values are presented in parentheses.

| | (1) Ln(NTail90) | (2) Ln(NTail95) | (3) Ln(NTail99) |
|---|---|---|---|
| ME | $-0.051^{***}$ | $-0.044^{***}$ | $-0.023^{**}$ |
| | (0.000) | (0.000) | (0.014) |
| BHC FE | *Yes* | *Yes* | *Yes* |
| N Obs | 1509 | 1509 | 1509 |
| Adj $R^2$ | 0.76 | 0.75 | 0.69 |

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table 8: **Macroeconomic Environment and Operational Loss Severity**

This table reports coefficients from quantile panel regressions of operational losses on the macroeconomic environment. The estimation sample includes 298,170 individual loss events incurred by 38 large financial institutions over the period [2000:Q1-2013:Q4]. *Z Ln(Loss)* is a natural log transformation of operational dollar losses (at the individual loss event level) incurred by a bank, standardized within BHCs in Panel A and standardized within BHC-event types in Panel B. *ME* is a measure of the U.S. macroeconomic environment (higher values denote better macroeconomic conditions). Estimates at the $1^{st}$, $10^{th}$, $25^{th}$, $50^{th}$, $75^{th}$, $90^{th}$, and $99^{th}$ percentiles are presented. p-values are presented in parentheses.

**Panel A: Losses Standardized Within BHCs**

| | (1)<br>Z Ln(Loss)<br>1st Pctl | (2)<br>Z Ln(Loss)<br>10th Pctl | (3)<br>Z Ln(Loss)<br>25th Pctl | (4)<br>Z Ln(Loss)<br>50th Pctl | (5)<br>Z Ln(Loss)<br>75th Pctl | (6)<br>Z Ln(Loss)<br>90th Pctl | (7)<br>Z Ln(Loss)<br>99th Pctl |
|---|---|---|---|---|---|---|---|
| ME | $0.005^{***}$ | $0.002^{***}$ | $-0.000$ | $-0.002^{**}$ | $-0.006^{***}$ | $-0.012^{***}$ | $-0.027^{***}$ |
| | (0.000) | (0.000) | (0.785) | (0.029) | (0.000) | (0.000) | (0.008) |
| N Obs | 298170 | 298170 | 298170 | 298170 | 298170 | 298170 | 298170 |

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Panel B: Losses Standardized Within BHC-Event Types**

| | (1)<br>Z Ln(Loss)<br>1st Pctl | (2)<br>Z Ln(Loss)<br>10th Pctl | (3)<br>Z Ln(Loss)<br>25th Pctl | (4)<br>Z Ln(Loss)<br>50th Pctl | (5)<br>Z Ln(Loss)<br>75th Pctl | (6)<br>Z Ln(Loss)<br>90th Pctl | (7)<br>Z Ln(Loss)<br>99th Pctl |
|---|---|---|---|---|---|---|---|
| ME | $0.008^{***}$ | $0.003^{***}$ | $0.002^{***}$ | $-0.001$ | $-0.003^{**}$ | $-0.011^{***}$ | $-0.025^{***}$ |
| | (0.000) | (0.000) | (0.000) | (0.412) | (0.025) | (0.000) | (0.007) |
| N Obs | 298170 | 298170 | 298170 | 298170 | 298170 | 298170 | 298170 |

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table 9: **Macroeconomic Sensitivity of Operational Risk and BHC Attributes**

This table reports coefficients from cross-sectional regressions of BHC operational risk sensitivity to macroeconomic conditions on BHC attributes. The estimation sample comprises 33 observations, one for every bank holding company in our data set with requisite operational risk and financial data. *ME Beta* is the regression coefficient $\beta_1$ from $Ln(Loss)_t = \beta_0 + \beta_1 ME_t + \epsilon_t$, which we estimate separately for every bank. *Ln(Loss)* is a natural log transformation of operational dollar losses incurred by a bank over a given calendar quarter. *ME* is a measure of the U.S. macroeconomic environment (higher values denote better macroeconomic conditions). *Ln(Total Assets)* is a natural log transformation of BHC total consolidated assets. *ROE* is BHC return on equity. *Leverage* is the ratio of BHC liabilities to total assets. In Columns (1)-(4), we average *Total Assets*, *ROE* and *Leverage* within BHCs over the sample period. In Columns (5)-(8), we take the values of *Total Assets*, *ROE* and *Leverage* as of the last quarter during the sample period. We use robust standard errors. p-values are presented in parentheses.

| | Average | | | | Last Quarter | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) ME Beta | (2) ME Beta | (3) ME Beta | (4) ME Beta | (5) ME Beta | (6) ME Beta | (7) ME Beta | (8) ME Beta |
| Ln(Total Assets) | $-0.061^{**}$ | | | $-0.031^{*}$ | $-0.063^{**}$ | | | $-0.035^{*}$ |
| | (0.022) | | | (0.078) | (0.022) | | | (0.050) |
| ROE | | $-0.738$ | | 1.116 | | 0.452 | | 1.303 |
| | | (0.597) | | (0.232) | | (0.743) | | (0.232) |
| Leverage | | | $-2.664^{**}$ | $-2.391^{**}$ | | | $-2.953^{**}$ | $-2.529^{**}$ |
| | | | (0.020) | (0.043) | | | (0.012) | (0.022) |
| N Obs | 33 | 33 | 33 | 33 | 33 | 33 | 33 | 33 |
| Adj $R^2$ | 0.16 | $-0.02$ | 0.29 | 0.29 | 0.18 | $-0.03$ | 0.33 | 0.36 |

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table 10: **Macroeconomic Environment and Financial Impact of Operational Losses**

This table reports coefficients from panel regressions of operational loss measures on the macroeconomic environment. The estimation sample comprises an unbalanced panel of 1,509 quarterly losses in 7 loss types incurred by 38 large U.S. bank holding companies over the period [2000:Q1-2013:Q4]. The 7 event types are as follows: Internal Fraud (IF), External Fraud (EF), Employment Practices and Workplace Safety (EPWS), Clients, Products and Business Practices (CPBP), Damage to Physical Assets (DPA), Business Disruption and System Failures (BDSF), and Execution, Delivery and Process Management (EDPM). Individual operational loss events are aggregated at the quarterly level, where the aggregation quarter is the one when the financial impact of the operational loss events was recorded on an institution's financial statements. *Ln(Loss)* is a natural log transformation of operational dollar losses incurred by a bank over a given calendar quarter. *Ln(Freq)* is a natural log transformation of the frequency of operational losses incurred by a bank over a given calendar quarter. *Ln(Sev)* is a natural log transformation of the average operational loss severity experienced by a bank over a given calendar quarter. *ME* is a measure of the U.S. macroeconomic environment (higher values denote better macroeconomic conditions). Panel A presents results for losses aggregated across event types. Panel B presents results for losses by event type. All specifications include BHC fixed effects. The error terms are clustered at the quarter and BHC levels. p-values are presented in parentheses.

**Panel A: Aggregated across Event Types**

| | (1) Ln(Loss) | (2) Ln(Freq) | (3) Ln(Sev) |
|---|---|---|---|
| ME | $-0.112^{***}$ | $-0.074^{***}$ | $-0.051^{*}$ |
| | (0.001) | (0.002) | (0.094) |
| BHC FE | $Yes$ | $Yes$ | $Yes$ |
| N Obs | 1509 | 1509 | 1509 |
| Adj $R^2$ | 0.57 | 0.65 | 0.28 |

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Panel B: By Event Type**

| | (1) Ln(Loss) IF | (2) Ln(Loss) EF | (3) Ln(Loss) EPWS | (4) Ln(Loss) CPBP | (5) Ln(Loss) DPA | (6) Ln(Loss) BDSF | (7) Ln(Loss) EDPM |
|---|---|---|---|---|---|---|---|
| ME | $-0.016^{*}$ | $-0.056^{***}$ | $-0.011$ | $-0.097^{***}$ | $-0.005$ | $-0.019^{**}$ | $-0.071^{***}$ |
| | (0.057) | (0.001) | (0.286) | (0.004) | (0.267) | (0.033) | (0.002) |
| BHC FE | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* |
| N Obs | 1509 | 1509 | 1509 | 1509 | 1509 | 1509 | 1509 |
| Adj $R^2$ | 0.42 | 0.63 | 0.70 | 0.52 | 0.18 | 0.44 | 0.63 |

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table 11: **Robustness Checks and Additional Analyses**

This table reports coefficients from panel regressions of operational losses on the macroeconomic environment. The estimation sample comprises an unbalanced panel of 1,509 quarterly losses incurred by 38 large U.S. bank holding companies over the period [2000:Q1-2013:Q4]. *Ln(Loss)* is a natural log transformation of operational risk dollar losses incurred by a bank over a given calendar quarter. *GDP Growth* is the year-over-year U.S. real GDP growth rate. *HPI Growth* is the year-over-year growth rate in the U.S. CoreLogic House Price Index. *CREPI Growth* is the year-over-year growth rate in the U.S. Commercial Real Estate Price Index. VIX is the CBOE U.S. Market Volatility Index, converted to quarterly frequency by using the maximum close-of-day value in any quarter. *BBB-T10Yr Sprd* is the spread between the U.S. 10-year BBB-rated corporate bond yield and the 10-year U.S. Treasury bond yield. *ME* is a measure of the U.S. macroeconomic environment (higher values denote better macroeconomic conditions). *L1 ME*, *L2 ME* and *L3 ME* are the first three lags of *ME*. Panel A presents regressions of operational losses on individual macroeconomic indicators. Panel B presents regressions of operational losses on the first three lags of *ME*. Panel C presents regressions excluding data from the post-global financial crisis. Specifically, in Column (1), the estimation uses data up to 2012:Q4. In Column (2), the estimation uses data up to 2011:Q4. In Column (3), the estimation uses data up to 2010:Q4. In Column (4), the estimation uses data up to 2009:Q4. In Column (5), the estimation uses data up to 2008Q4. All specifications include BHC fixed effects. The error terms are clustered at the quarter and BHC levels. p-values are presented in parentheses.

**Panel A: Macroeconomic Indicators**

| | (1) Ln(Loss) | (2) Ln(Loss) | (3) Ln(Loss) | (4) Ln(Loss) | (5) Ln(Loss) |
|---|---|---|---|---|---|
| GDP Growth | $-6.55^{**}$ | | | | |
| | (0.04) | | | | |
| HPI Growth | | $-2.47^{***}$ | | | |
| | | (0.00) | | | |
| CREPI Growth | | | $-0.74^{*}$ | | |
| | | | (0.08) | | |
| VIX | | | | $0.01^{***}$ | |
| | | | | (0.00) | |
| BBB-T10Yr Sprd | | | | | $0.13^{***}$ |
| | | | | | (0.00) |
| BHC FE | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* |
| N Obs | 1509 | 1509 | 1509 | 1509 | 1509 |
| Adj $R^2$ | 0.61 | 0.62 | 0.61 | 0.61 | 0.61 |

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Panel B: Lagged Effects of Macroeconomic Environment**

| | (1) Ln(Loss) | (2) Ln(Loss) | (3) Ln(Loss) | (4) Ln(Loss) | (5) Ln(Loss) | (6) Ln(Loss) | (7) Ln(Loss) |
|---|---|---|---|---|---|---|---|
| ME | | | | −0.130** | −0.102*** | −0.082*** | −0.138** |
| | | | | (0.021) | (0.003) | (0.008) | (0.013) |
| L1 ME | −0.061** | | | 0.047 | | | 0.029 |
| | (0.024) | | | (0.426) | | | (0.658) |
| L2 ME | | −0.049* | | | 0.023 | | 0.087 |
| | | (0.092) | | | (0.585) | | (0.228) |
| L3 ME | | | −0.046* | | | −0.001 | −0.072 |
| | | | (0.077) | | | (0.979) | (0.185) |
| BHC FE | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* |
| N Obs | 1509 | 1509 | 1509 | 1509 | 1509 | 1509 | 1509 |
| Adj $R^2$ | 0.61 | 0.61 | 0.61 | 0.61 | 0.61 | 0.61 | 0.61 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Panel C: Exclusion of Post-Crisis Losses**

| | (1) Ln(Loss) Up to 2012Q4 | (2) Ln(Loss) Up to 2011Q4 | (3) Ln(Loss) Up to 2010Q4 | (4) Ln(Loss) Up to 2009Q4 | (5) Ln(Loss) Up to 2008Q4 |
|---|---|---|---|---|---|
| ME | −0.082*** | −0.086*** | −0.088*** | −0.090*** | −0.102*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.002) |
| BHC FE | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* |
| N Obs | 1357 | 1205 | 1057 | 909 | 765 |
| Adj $R^2$ | 0.61 | 0.61 | 0.60 | 0.63 | 0.64 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$