Operational Risk is More Systemic than You Think: Evidence from U.S. Bank Holding Companies ☆

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January 10, 2020

Abstract

While operational risk is generally perceived as idiosyncratic with limited systemic implications, we document that operational risk significantly threatens financial stability. Using supervisory data on large U.S. bank holding companies (BHCs) over 2002:Q1-2016:Q4, we find operational losses increase systemic risk through both direct channels that impair market values of loss-experiencing BHCs and spillover channels to related institutions. Findings are driven by tail events, are more pronounced for systemically important and closer-to-distress BHCs, and vary by business lines, event types, and financial and economic environments. Results add to the operational risk and systemic risk literatures, and have key policy implications.

Keywords: Banking; Systemic Risk; Operational Risk

JEL Classification: G15, G18, G19, G21, G32

☆We thank Azamat Abdymomunov, Richard Brandt, Anna Chernobai, Luke Carrivick, Brian Clark, Jeff Gerlach, Rustom Irani, Yanbo Jin, Marco Migueis, Patricia Mosser, Greg Niehaus, Christophe Perignon, Samuel Rosen, Stacey Schreft, Sergey Tsyplakov, Greg Udell, and conference and seminar participants at the 2018 Operational Risk Research Conference, the 2018 American Bankers Association Risk Quantification Forum, the Cyber Risk to Financial Stability: State-of-the-Field Conference (Columbia University), the 8th Fixed Income and Financial Institutions Conference, the 2019 Financial Intermediation Research Society Conference, the 2019 ORX Conference at Northern Trust, the 2019 Financial Management Association Annual Meeting, the 2019 Philly Five Conference, and the Office of Financial Research for helpful comments and suggestions. We thank Jeffrey Cheng and Cooper Killen for research assistance. All errors are those of the authors alone. The views expressed in this paper do not necessarily reflect the position of the Federal Reserve Bank of Richmond or the Federal Reserve System.

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1. Introduction

Systemic risk is an important research- and policy-relevant topic. Widespread financial institution failures and losses can impose significant negative externalities on the economy and household wealth. Atkinson et al. (2013) estimate that between \$6 and \$14 trillion, or 40% to 90% of annual U.S. GDP, was foregone due to the Global Financial Crisis. U.S. households lost an additional \$16 trillion or 24% of their net worth.[1]

In the banking sector, systemic risk is traditionally thought of as stemming from interlinkages and interdependencies across large institutions or herding behavior that results in correlated risk taking. The impending failure of a systemically important institution threatens to impose significant losses on other institutions. Interconnections among banking organizations increase these losses, and failures that occur simultaneously because banks have correlated risks can magnify the effects on the financial system. The possibility of contagious runs on institutions further compound systemic risk problems (e.g., Goldstein and Pauzner (2004); Acharya and Yorulmazer (2008); Acharya (2009); and Bebchuck and Goldstein (2011)).

In contrast to this traditional view, our paper investigates a different and somewhat surprising source of systemic risk – operational losses of U.S. bank holding companies. Losses from operational risk are related to the malfunction or break down of technology or support systems, including cases of employee fraud or errors (e.g., Jarrow (2008)). Operational risk may be increasing in importance as more and more banks begin to partner with fintech firms and cyber threats continue to grow (e.g., Santucci (2018)).

Many high-profile losses in the financial industry have been traced to operational risk. For example, Société Générale and JPMorgan Chase lost over \$7 billion and \$5 billion,

[1]These estimates do not include the extra costs of government programs to treat the crisis, which may have been significant. Losses from the European Sovereign Debt Crisis were in trillions of euros from the state aid alone (Beesley (2012)).

respectively, in separate incidents of unauthorized trading (Clark and Jolly (2008), Silver-Greenberg (2012)). Large banks and hedge fund investors lost tens of billions of dollars to Bernard Madoff's Ponzi scheme (Efrati et al. (2008)). More recently, Wells Fargo experienced a number of costly operational failures resulting in a \$1 billion fine from the Consumer Financial Protection Bureau (CFPB) and the Office of the Comptroller of the Currency (OCC) for mortgage and insurance abuses (Wattles et al. (2018)). Along with affecting large banks, operational risks affect community banks as well. Federal Reserve Bank of St. Louis President James Bullard noted that "operational risk will someday equal or exceed credit risk for many community banks" (Bullard (2018)).

Despite the growing importance of operational risk (e.g., Abdymomunov et al. (2019)), it is unknown if it has systemic risk consequences. Operational risk is usually perceived as idiosyncratic (e.g., Lopez (2002), Chernobai et al. (2012)) with limited systemic implications. To date, there have been no investigations of this issue to our knowledge. This is an important omission in the literature.

This paper addresses the fundamental question of whether operational losses threaten the financial system. We employ as our dependent variables a number of recently developed measures of BHC contributions to systemic risk: SRISK (Acharya et al. (2012); Brownlees and Engle (2017)), ΔCoVaR (Adrian and Brunnermeier (2016)), and SES (Acharya et al. (2017)). To capture the commonality among these measures, we primarily focus on their first principal component, *Systemic Risk (PC)*, but we also show that our results are robust to using the three individual measures. While a prior study, Cummins et al. (2006), documents a negative effect of publicly known operational losses reported by the media on banks' market value of equity, we emphasize that market value of equity is not a direct measure of systemic risk. Systemic risk measures the health of the financial system as well as that of the individual bank.

We also use detailed supervisory data on operational losses reported by large U.S. bank holding companies to the Federal Reserve System for stress testing purposes as mandated by the Dodd-Frank Wall Street Reform and Consumer Protection Act. De Fontnouvelle et al. (2006) emphasize that public sources of data often omit significant operational loss events. In contrast to the publicly available data commonly used in the operational risk literature, we utilize supervisory data at the individual company level that is significantly richer and more comprehensive.

We find that operational risk at large U.S. BHCs is statistically and economically significantly positively related to systemic risk. This relation holds controlling for previously established determinants of systemic risk and other types of risks, including credit, interest rate, leverage, and liquidity risks. Our finding is robust to alternative estimation approaches, including instrumental variable regressions, which mitigate potential endogeneity concerns. When we drill down, we find that operational risk tail events dominate nontail events in systemic importance. An event in the top 1% tail of the operational loss distribution is related to an increase in a BHC's contribution to systemic risk by approximately two standard deviations. In further analysis, we document that operational losses in only some particular event types and business lines significantly contribute to systemic risk.

To better understand the association between operational losses and systemic risk, and to identify mechanisms behind this association, we additionally explore interactions of operational risk losses with firm characteristics and the financial and economic environment. We find that operational losses have stronger effects on systemic risk when they affect systemically important institutions and institutions that are closer to distress. We also find that operational losses have more pronounced impacts on systemic risk contributions during financial crises and adverse economic conditions, although the main results are still present during normal times. We also find that operational losses contribute to systemic risk through both direct channels that impair the BHCs experiencing the losses and spillover channels to other financial institutions.

Our study contributes to the research literatures on both operational and systemic risks. Our findings have policy implications as well. The Basel Accord capital rules related to operational risk, specifically the Standardized Measurement Approach (SMA) of Basel III, treat operational risks from all bank business lines equally. This study can help to better inform these weights given our findings that only some business lines significantly contribute to systemic risk. Our findings also suggest that a convex weighting of large operational risk events in the determination of capital requirements for BHCs may be appropriate. Specifically, our findings suggest that firms exposed to very large operational risks should be subject to much stricter capital requirements since they contribute disproportionately more to systemic risk.

The remainder of the paper is organized as follows. Section 2 details our contributions to the literature. Section 3 outlines the channels through which operational risk may affect systemic risk. Section 4 describes the data, including operational risk measures and systemic risk contribution measures that we employ. Section 5 presents our regression results, and Section 6 presents robustness checks. Section 7 concludes.

2. Related Literature

Operational risk has received much less attention in the academic literature than other bank risks such as credit risk, leverage risk, interest rate risk, and liquidity risk (Ellul and Yerramilli (2013)). In part, this likely reflects the difficulty of obtaining reliable data on operational risk exposures, and in part, this may reflect a belief that such risks are not systemically important. Some of the existing papers aim to define and measure operational risk. Jarrow (2008) formally defines operational risk. Allen and Bali (2007) use equity returns to estimate operational risk. Cummins et al. (2006) document the impact of operational risk on market values of U.S. banks. Dahen and Dionne (2010) examine aspects of operational risk modeling.

Other studies focus on understanding the nature of operational risk. Chernobai et al.

(2012) and Cope et al. (2012) study the various determinants of operational risk and its loss severity. Wang and Hsu (2013) and Abdymomunov and Mihov (2019) focus on the effects of board composition and risk management quality on operational risk. Chernobai et al. (2018) show that bank expansions into non-banking activities result in more operational risk, and argue this is due to an increase in bank complexity. Curti and Mihov (2018) document that larger banking organizations have higher operational losses per dollar of total assets, a result largely driven by their failure to meet professional obligations to clients, or from the design of their products. Abdymomunov et al. (2019) study the association between BHC operational losses and the U.S. macroeconomy. Abdymomunov and Ergen (2017) apply a copula framework and find that occurrences of large losses are positively correlated across banks. They do not, however, directly test the systemic risk implications of operational risk events. Finally, Gillet et al. (2010) investigate the relation between operational risk and reputation in the banking system.

To date, no studies examine the systemic implications of operational risk. The purpose of this paper is to expand the operational risk literature by testing whether and under what circumstances operational losses become systemic concerns. In so doing, we provide an in-depth account of the specific mechanisms through which operational losses can affect systemic risk, and document important specific firm-level and financial and economic environment channels that amplify the operational risk effects on systemic risk.

We also contribute to a growing literature that examines the nature of systemic risk. Brunnermeier et al. (2012) and Engle et al. (2014) examine the bank-level and macroeconomic determinants of systemic risk, respectively. Sedunov (2018) and Berger et al. (2019) examine the impact of regulatory actions during the financial crisis on systemic risk in the U.S. Additionally, Karolyi et al. (2017) study the effect of cross-border bank flows on systemic risk in recipient countries around the world, while Frame et al. (2019) study the effect of foreign investment on systemic risk for U.S. banks. Brunnermeier et al. (2017) examine the relation between systemic risk and asset pricing bubbles. Finally, Giglio et al. (2016) study the relation between systemic risk and the macroeconomy.

Our findings suggest that operational losses can contribute to systemic risk. We document that tail events drive this relation, and we also identify the specific types of operational losses and the business lines that affect systemic risk. We offer channels for the systemic effects of operational risk and distinguish between sets of these channels. Our findings may help guide risk managers and policy makers on how to mitigate some of these effects. More generally, our paper also relates to the important questions about regulatory failures, capital requirements, risk management, and corporate governance in the financial crisis posed by Carey et al. (2012).

3. Channels

This section outlines two sets of channels through which operational risk of large BHCs may affect systemic risk. The first set work through directly reducing the market value of the BHC experiencing the operational losses, which in turn increases that BHC's market leverage. The second set operate through financial network spillovers, in which the market values of related financial institutions are impacted.

3.1. Direct Channels

There are at least three channels through which operational risk may reduce the market value of a BHC. The first is through direct monetary losses related to operational risk events. These include but are not limited to losses from improper supervision of traders and resulting unauthorized trading, legal costs related to lawsuits associated with the operational risk events, reimbursement to counterparties that were harmed by mistakes made by the BHC, damages from natural disasters, and government-imposed fines, activity restrictions, and additional capital requirements. These costs come directly out of the BHC's equity and reduce its market value, raising its market leverage.

The second channel through which BHC market value may decrease is through the loss of future business or productivity from reputational damage. Deposit, loan, financial guarantee, and derivative contract customers may be less willing to deal with an institution that has a history of costly operational mistakes or improper business practices. Some key personnel with important institutional knowledge may also leave or require higher compensation to stay with a BHC that has tarnished reputation. Any expected future loss of business or productivity is associated with lower expected future profits, which reduces market value and raises market leverage.

The third channel linking operational risk losses with a lower market value of equity is the public sell-off or short sales that drive the value of the BHC's value below its fundamental value based on the BHC's expected future earnings. This could occur because of uncertainty about the size and scope of the operational losses, disutility of owning stock in companies with bad publicity, or panic-driven sell-off in reaction to unfavorable news.

3.2. Spillover Channels

There are at least three channels through which the operational loss of a BHC may spill over to the market values of related financial institutions and raise their market leverage, creating cascading effects that can reach back to the bank that suffered the original loss. First, investors may fear that similar operational difficulties are present, but yet undiscovered, in comparable financial institutions. These other institutions may follow similar industry practices, herd in similar business products, use similar operating systems and business platforms, or operate in similar regulatory and competitive environments.

Second, operational losses at an individual BHC may expose other financial institutions to risks and losses. Some BHCs may be subject to credit risks from being counterparties to inter-institutional loans, deposits, and derivative contracts. Similarly, other institutions that regularly participate with the troubled BHC in the syndicated loan market or payments system may suffer business losses that reduce their market values, raising their market leverage.

Third, it is also possible that some BHCs may gain from the operational losses at another BHC. Competitors in the product market may be able to increase market share and profitability when customers shun the BHC suffering operational risk. Similarly, financial institutions that compete in the same labor market may also be able to hire talented displaced workers from an affected BHC that they would not otherwise be able to attract.

Notably, unlike the first five channels, this last channel runs in the opposite direction, and may potentially offset some of the other direct and spillover channels. However, it is improbable that it would be sufficiently strong to more than reverse the other channels and result in reduced systemic risk from operational losses. Another bank's gain would seem very unlikely to be greater than the losses suffered by the original bank.

4. Data Sample and Variable Definitions

4.1. Operational Risk

4.1.1. Loss Data

As noted previously, we use supervisory data on operational losses submitted by large financial institutions pursuant to the Dodd-Frank Wall Street Reform and Consumer Protection Act. The Federal Reserve System collects such data for stress testing purposes under the Comprehensive Capital Analysis and Review (CCAR) program. The operational risk data follow the reporting requirements of the FR Y-14Q form (current as of April 2017) and are provided by financial institutions that participated in the 2017 Dodd-Frank Act Stress Test (DFAST) program with consolidated assets of $50 billion or more.[2] While the original data contains losses from 38 institutions, the availability of data requisite for the calcula-

[2]More information about FR Y-14Q reporting requirements, instructions and forms can be found at: http://www.federalreserve.gov/apps/reportforms/. Subsequent to the Economic Growth, Regulatory Relief, and Consumer Protection Act of 2018, financial institutions with under $100 billion in total assets are no longer required to file the FR Y-14Q reports, effective May 2018.

tions of systemic risk measures described in Section 4.2 reduces the number of institutions in our sample from 38 to 26. Although our operational loss data comes from a small number of institutions, these institutions account for the majority of U.S. banking industry assets (73.7% as of 2016:Q4). The data provide information such as loss amounts, loss dates, loss classifications, and loss descriptions.

Consistent with Basel II definitions, we categorize operational losses into seven event types. These event types are: 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). Table 1, Panel B presents definitions of each loss type.

[Insert Table 1 about here]

Figure 1 presents the share of total losses and U.S. dollar loss amounts by event type category. The event type with the largest proportion of total losses is CPBP, which accounts for 78.3% of losses or $216.3 billion. This suggests that the majority of BHC losses due to operational risk are the result of poor services to customers or flawed products. A review of the data further indicates that CPBP contains many of the largest and most severe losses incurred by BHCs over our sample period. The second largest event type by share of total losses is EDPM, accounting for 13.6% of losses or $37.5 billion. The remaining five event types combined comprise 8.1% of total losses, or $22.5 billion.

[Insert Figure 1 about here]

Operational losses are also classified by business line of origination (Federal Reserve System (2017)). There are nine categories: Corporate Finance (CF), Trading and Sales (TS), Retail Banking (RB), Commercial Banking (CB), Payment and Settlement (PS), Agency

Services (AS), Asset Management (AM), Retail Brokerage (RK), and Corporate Level Non-Business Line Specific (CO). Table 1, Panel C presents definitions of each business line. Figure 2 presents the share of total losses and U.S. dollar loss amounts by business line category.

[Insert Figure 2 about here]

The figure shows that the business line generating the largest operational losses is RB, which accounts for 47.2% of total losses or $130.6 billion. In other words, losses from retail banking account for almost half of total operational losses. The business line with the second-most losses is CO, which accounts for 18.3% of total losses or $50.6 billion. CF and TS are also nontrivial, as they account for 11.0% and 13.0% of total losses, respectively. The remaining five business lines combined comprise 10.4% of total losses, or $28.8 billion.

The reporting threshold for individual operational losses varies across financial institutions. To mitigate the impact of this heterogeneity in loss reporting thresholds, we follow prior research (e.g., Abdymomunov and Mihov (2019)) and discard losses below $20,000 dollars, which is the highest reporting threshold for institutions participating in the DFAST program. The final sample consists of 290,872 individual loss events from 26 large financial institutions over the period [2002:Q1 - 2016:Q4]. Our data is substantially richer than operational loss data sets offered by private vendors that rely on publicly available information. For example, Hess (2011) uses loss data from SAS OpRisk Global Data, which consists of around 7,300 loss events. Chernobai et al. (2012) analyze loss data from Algo FIRST, which consist of 2,426 events. As discussed in De Fontnouvelle et al. (2006), operational risk data sets based on publicly available information are likely to omit substantial losses otherwise contained in the supervisory data used in this study.

Each loss instance reports occurrence, discovery, and accounting dates. The data reporting instructions define these dates as follows: occurrence date — the date when the operational loss event occurred or began; discovery date — the date when the operational loss event was first discovered by the institution; and accounting date — the date when the financial impact of the operational loss event was recorded on the institution's financial statements. From a reporting consistency perspective, 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. In contrast, occurrence and discovery dates are less uniformly reported across institutions due to variations in the institutions' internal data management systems as well as uncertainties about when loss events actually occurred or were discovered (Abdymomunov and Mihov (2019)). To examine the relationship between operational risk and systemic risk, our analysis aggregates loss data at the bank-quarter level, where we use the quarter of operational loss financial statement impact (accounting date) for aggregation purposes. We build an unbalanced panel of 1,070 BHC-quarter observations in accordance with individual bank data availability.

4.1.2. Operational Risk Measures

Our main measure of operational risk is the total dollar value of operational losses incurred by a BHC during a given quarter. We follow Abdymomunov et al. (2019) and calculate a natural logarithm transformation of quarterly loss to account for its heavy-tailed distribution. The literature also shows that heavy-tailed distributions of loss severities for individual operational risk events are common (e.g., Chernobai and Rachev (2006), Jobst (2007)). Indeed, Figure 3 suggests that within our data, a few large losses, or tail events, account for the majority of dollars lost to operational risk.

[Insert Figure 3 about here]

To specifically focus on the relation between operational risk tail events and systemic risk contribution, we construct two sets of variables. First, we calculate the number of "tail" and "nontail" events in a quarter. We define a loss as a tail event if the ratio of the loss amount to BHC assets is higher than the 99.0^{th}, 99.5^{th} or 99.9^{th} quantiles of the unconditional distribution of the ratio in our sample. Losses below these quantiles are considered nontail events. Second, we sum all the losses defined as tail events in a quarter to obtain the aggregate amount of tail dollar losses for each BHC and then take the natural log, and similarly for nontail events.

Table 2, Panel A presents descriptive statistics. On average, U.S. BHCs lose $230 million per quarter to operational risk. Furthermore, the standard deviation of the quarterly loss is high relative to the mean, which indicates substantial time-series and cross-sectional variation of operational losses. The quarterly average dollar sum of tail events (using the 99.0^{th} quantile definition of tail risk) is $194 million, which represents 85% of the average quarterly loss.

[Insert Table 2 about here]

4.2. Systemic Risk Measures

Our main dependent variable, *Systemic Risk (PC)*, is the first principal component of three systemic risk contribution measures: $SRISK$, $\Delta CoVaR$, and SES, which we discuss in detail in the next three sections. We evaluate the first principal component of these measures using a correlation matrix instead of a variance-covariance matrix to account for the different scale of the individual systemic risk measures. Table 2, Panel B presents summary statistics.

4.2.1. Expected Capital Shortfall - SRISK

Acharya et al. (2012) provide a measure, further refined by Brownlees and Engle (2017), for determining bank i's contribution to systemic risk at time t, called $SRISK_{i,t}$. It is the expected capital shortfall of bank i conditional on a crisis at time t. Specifically, $SRISK_{i,t}$ measures how much capital bank i would need in a crisis at time t to maintain a given capital-to-assets ratio. $SRISK_{i,t}$ is empirically measured using market data on equities and balance sheet data on liabilities:

$$
\begin{aligned}
SRISK_{i,t} &= E_{t-1}(Capital\ Shortfall_i | Crisis) \\
&= E_{t-1}(k(Debt_i + Equity_i) - Equity_i | Crisis) \\
&= kDebt_{i,t-1} - (1-k)(1 - LRMES_{i,t})Equity_{i,t}
\end{aligned}
\tag{1}
$$

where k is a prudential level of book equity relative to assets; $LRMES_{i,t}$ is the long-run marginal expected shortfall (MES) at time t for bank i, defined as the decline in equity values conditional on a financial crisis. Following Brownlees and Engle (2017), we set k equal to 8%. $SRISK_{i,t}$ is constructed from size, leverage, and exposure to market risk. Exposure to market risk is based on comovements of firm equity value with broad equity market measures. This is roughly analogous to a "downside beta" of the firm, and is correlated with the firm's CAPM beta.

4.2.2. $\Delta CoVaR$

$\Delta CoVaR$ represents the change in the value at risk (VaR) of the entire financial system that occurs when a given institution goes into distress. This measure can be thought of as an estimate of one institution's contribution to aggregate systemic risk. We estimate $\Delta CoVaR$ directly following the quantile regression methodology of Adrian and Brunnermeier (2016). First, we define financial system returns as X_{system} and individual institution returns as X_i using equity returns. We then estimate VaR and $CoVaR$ as a function of a vector of state variables, M. We define q as the q^{th} quantile of the return distribution. For our estimates, we set q as the 5^{th} quantile of the return distribution.

In the first step, we run the following regressions, using weekly data:

$$X_{i,t} = \alpha_i^q + \gamma_i^q M_{t-1} + \epsilon_{i,t}^q \tag{2}$$

$$X_{system|i,t} = \alpha_{system|i}^q + \gamma_{system|i}^q M_{t-1} + \beta_{system|i}^q X_{i,t} \epsilon_{sytem|i,t}^q \tag{3}$$

We then use the predicted values from the first step to calculate:

$$VaR^q_{i,t} = \hat{\alpha}^q_i + \hat{\gamma}^q_i M_{t-1} \tag{4}$$

$$CoVaR^q_{i,t} = \hat{\alpha}^q_{system|i} + \hat{\gamma}^q_{system|i} M_{t-1} + \hat{\beta}^q_{system|i} VaR^q_{i,t} \tag{5}$$

Finally, for each institution, we calculate $\Delta CoVaR_{i,q,t}$:

$$\begin{aligned} \Delta CoVaR^q_{i,t} &= CoVaR^q_{i,t} - CoVaR^{50}_{i,t} \\ &= \hat{\beta}^q_{system|i}(VaR^q_{i,t} - VaR^{50}_{i,t}) \end{aligned} \tag{6}$$

The vector of state variables in the Adrian and Brunnermeier (2016) approach to estimating $CoVaR$ includes six variables: the change in the three-month Treasury yield, the change in the slope of the yield curve (ten-year Treasury rate minus three-month Treasury rate), TED Spread (three-month LIBOR minus three-month Treasury rate), the change in the credit spread (Moody's Baa-rated bond yield minus ten-year Treasury rate), the weekly U.S. market returns, and the U.S. market equity volatility (calculated using CRSP market returns).

4.2.3. Systemic Expected Shortfall - SES

Systemic Expected Shortfall (SES) measures an institution's "propensity to be undercapitalized when the system as a whole is undercapitalized" (Acharya et al. (2017)). A financial institution's SES is a linear combination of two key components: Leverage (LVG) and Marginal Expected Shortfall (MES). LVG is estimated using the traditional approximation using book liabilities and market equity:

$$LVG_{i,t} = \frac{(Book\ Assets_{i,t} - Book\ Equity_{i,t}) + Market\ Equity_{i,t}}{Market\ Equity_{i,t}} \tag{7}$$

MES estimates how individual institutions' stock returns react to those of the entire market (including non-financial companies) when aggregate returns are low. MES is calculated using the 5% of the worst days of market returns over the previous quarter of return data:

$$MES_{i,t} = -\frac{1}{\#days} \sum_{\tau=1}^{\tau^*} R_{i,\tau} \tag{8}$$

where $R_{i,\tau}$ represents the daily returns of the institution, and $\tau = 1$ to τ^* represent days in which the market is in the tail of its return distribution.

Acharya et al. (2017) use LVG and MES in a cross-sectional regression to estimate SES. They regress the percentage stock returns of large U.S. institutions during the global financial crisis (which the authors call "realized SES") on LVG and MES from prior to the crisis. From the regression output, they estimate the following equation:

$$SES_{i,t} = 0.02 - 0.04LVG_{i,t-1} - 0.15MES_{i,t-1} \tag{9}$$

which we use to calculate fitted values of SES for all bank-quarters in our sample. For presentation purposes, we multiply SES by -1, so that higher values indicate higher contribution to systemic risk.

4.3. Control Variables

In addition to operational and systemic risk metrics, all of our multivariate regression analyses include a number of BHC-level control variables. We classify these variables in two broad groups: characteristics that are relevant for the systemic risk contribution of BHCs and proxies for BHC exposures to other types of risk.

We include five controls to account for a BHC's systemic risk contribution. We include bank size (*Ln(Size)*) based on the total assets of the BHC. To account for firm value, growth opportunities and profitability, we include the market-to-book ratio (*M-to-B*) and return on assets (*RoA*).[3] To account for exposure to non-traditional business activities, we include the non-interest to interest income ratio (*NII-to-II*). Lastly, to account for a BHC's ability to manage risks, we use a rating that evaluates the quality of BHC risk management functions (*Risk Mgmt*).[4]

In all our analyses, we control for a BHCs' exposure to other important risks. Specifically, we focus on leverage, credit, liquidity, and interest rate risks. To control for leverage risk, we include BHC leverage (*Leverage*). We control for credit risk by including the ratio of non-performing loans to total loans (*NPL-to-TL*). To account for liquidity risk, we include a BHC's liquidity coverage ratio (*LCR*). Finally, to measure interest rate risk, we include the mismatch between short-term repriceable assets and short-term repriceable liabilities (*Maturity Gap*).

4.4. Correlations

We start with a simple correlation analysis. Table 3, Panel A reports correlation coefficients between *Systemic Risk (PC)*, *SRISK*, ΔCoVaR, *SES*, *LVG*, *MES* and *Ln(OpLoss)*. We make several observations.

[Insert Table 3 about here]

First, the correlations between the *Systemic Risk (PC)* and the individual systemic risk contribution measures that comprise it are high – in excess of 75% in all cases. Second, the correlation between *Systemic Risk (PC)* and *Ln(OpLoss)* is 32%, indicating that BHCs that suffer higher operational losses contribute more to systemic risk. Third, the correlations between *Ln(OpLoss)* and the individual systemic risk contribution measures are positive in

[3] To avoid possible mechanical effects, we estimate *M-to-B* and *RoA* at the end of the prior quarter. In unreported estimations, we confirm the robustness of our results to alternative lagging schemes for the independent variables, including lagging all independent variables by one quarter.

[4] This rating has been developed and maintained by the Federal Reserve System, and is part of the RFI/C(D) and BOPEC rating systems. For more information on the rating systems see the following supervisory letters: SL 9591, SL 9569, SR 9517, SR 9522, and SR 0418.

all cases, indicating that the relation is consistent across different measures of systemic risk. All correlations are statistically significant at the 1% level.

Table 3, Panel B provides additional information on the correlations between the different metrics of operational risk and *Systemic Risk (PC)*. Again, the correlations are all statistically significant at the 1% level.[5]

5. Regression Results

5.1. Operational Losses

To more rigorously examine whether operational risk is related to systemic risk, we next employ multivariate regressions that better enable us to control for confounding effects. We estimate the following main regression:

$$Systemic\ Risk_{i,t} = \beta_i + \beta_t + \beta_1 Ln(OpLoss)_{i,t} + \beta_k Ctrls_{i,t} + \epsilon_{i,t} \tag{10}$$

where i indexes BHCs, and t indexes quarters. *Systemic Risk* is one of four systemic risk metrics: *Systemic Risk (PC)*, $SRISK$, $\Delta CoVaR$, and SES. $Ln(OpLoss)$ represents log-transformed operational losses incurred by a BHC in a given quarter. *Ctrls* represents a vector of control variables described in Section 4.3. β_i represents BHC fixed effects, which absorb potentially different levels of systemic risk contribution and operational losses at BHCs. β_t represents time (year and seasonal) fixed effects, which broadly capture period-specific and seasonal shocks common across companies. We cluster standard errors at the BHC and quarter levels to account for within-bank and within-quarter correlation of the error terms. Table 4, Panel A presents the results for our main measure of systemic risk –

[5] Due to space limitations in the table, we do not report correlations with tail and nontail operational risk measures using the 99.5$^{\text{th}}$ quantile definition. We note, however, that the correlation coefficients are directionally and statistically consistent with those of the tail and nontail measures using the 99.0$^{\text{th}}$ and 99.9$^{\text{th}}$ quantile definitions.

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Systemic Risk (PC).

[Insert Table 4 about here]

Column (1) starts with a pooled regression specification with no fixed effects. The coefficient on $Ln(OpLoss)$ is positive and statistically significant at the 1% level, suggesting that institutions with higher operational losses contribute more to systemic risk. Columns (2)-(4) further suggest that the positive association in Column (1) is robust to the introduction of both BHC and time fixed effects. Based on the specification in Column (4) with both BHC and time fixed effects, a one standard deviation increase in $Ln(OpLoss)$ is associated with a 0.14 standard deviation increase in *Systemic Risk (PC)* $(= (0.067 * 0.294)/0.141)$. Given the heavy-tailed nature of operational risk, a plausible 100% increase of quarterly operational losses is associated with a 0.067 increase in *Systemic Risk (PC)* or 0.48 standard deviations $(= 0.067/0.141)$.

Table 4, Panel B, Columns (1)-(3) show the relation between operational risk and systemic risk is robust across all three measures from which *Systemic Risk (PC)* is derived – $SRISK$, $\Delta CoVaR$, and SES. The coefficient of $Ln(OpLoss)$ is positive and significant at least at the 5% level in all cases. In Columns (4) and (5), we also separately examine the two components of SES, LVG and MES, in order to distinguish between the sets of channels through which operational risk affects systemic risk: the reduction in an affected BHC's market value and the increase in its market leverage (the "LVG" channel) versus spillovers to the market values of related institutions (the "MES" channel), that increase other institutions' leverage. $Ln(OpLoss)$ is significantly positively related to both LVG and MES. We interpret this as evidence supporting both groups of channels.

5.2. *Operational Risk Event Types and Business Lines*

As noted above, operational risk is an amalgamation of various types of subcomponent risks (Chernobai et al. (2012)). The significant relation between operational losses and

BHC systemic risk contributions established thus far ignores the potential heterogeneity of operational risk in the different categories and essentially embodies the assumption that operational risks from all event types and business lines have similar systemic risk implications.

Here, we re-estimate the relation between systemic risk contribution and operational losses at the individual event type and business line category levels. Specifically, we re-estimate Eq. (10) for each event type and business line separately as well as jointly. Ex ante, we do not have a clear expectation of which particular subcategories of operational losses should be more correlated with BHC systemic risk contribution. We thus examine the specific event type and business line drivers of the previously documented association between operational losses and systemic risk contributions. Table 5 presents the results.

[Insert Table 5 about here]

Table 5, Panel A presents the results for operational losses categorized by event type. The coefficient of $Ln(OpLoss)$ is significant in three cases – for Internal Fraud (IF) in Column (1); for Clients, Products and Business Practices (CPBP) in Column (4); and for Execution, Delivery, and Process Management (EDPM) in Column (7). Column (8) further shows that operational losses from these three event types remain significantly positively related to systemic risk when included jointly in the same regression specification. As presented in Table 1, Panel B, IF captures losses from "[a]cts of a type intended to defraud, misappropriate property or circumvent regulations, which involves at least one internal party"; CPBP – from "[a]n unintentional or negligent failure to meet a professional obligation to specific clients, or from the nature or design of a product"; and EDPM – from "[f]ailed transaction processing or process management, from relations with trade counterparties and vendors." Importantly, Figure 1 shows that CPBP and EDPM are the two operational risk event types accounting for the largest portions of losses, representing respectively 78% and 14% of total losses in our sample.

Table 5, Panel B presents results for operational losses categorized by business line. The coefficient of $Ln(OpLoss)$ is significant in two specifications – for Retail Banking (RB) in Column (3); and for Corporate Other (CO) in Column (9). Column (10) confirms operational losses from the two business line categories both remain significantly positively correlated with systemic risk when estimated in the same regression specification. According to Table 1, Panel C, RB captures losses related to "[r]etail and private lending and deposits, banking services, trust and estates, investment advice, merchant/commercial/corporate cards, private labels and retail", while CO captures "[l]osses originating from a corporate/ firm-wide function that cannot be linked to a specific business line." As noted above, RB and CO are the two business lines that account for the largest portions of operational losses in our sample – 47% and 18%, respectively.

The above findings suggest that the link between systemic and operational risk is largely driven by the event types and business lines that contain most operational dollar losses in our sample. Given that operational risk is heavy-tailed and few catastrophic losses account for the majority of dollar losses, our findings here might indicate that the relation between systemic risk contribution and operational losses is driven primarily by the event types and business lines with most severe operational loss events. We explicitly focus on high-severity operational losses and examine their effects on systemic risk in more detail next.

5.3. Tail versus Nontail Operational Risk

We next examine whether observed effects of operational losses on systemic risk contributions are particularly driven by tail versus nontail operational losses. This distinction is important. High but stable operational losses have adverse implications for banking organizations' profitability and performance. However, such losses are easy to anticipate, and therefore should not be a first-order concern in terms of an organization's stability and systemic risk contibutions. In contrast, tail risk is difficult to anticipate, often results in a serious unexpected shock to a financial institution. Overall, tail events should be more likely to destabilize a financial intermediary, and subsequently the financial system through cascading effects, than nontail events.

As discussed in Section 4.1.2, to focus on the relation between tail and nontail operational risk events and systemic risk contribution, we construct two sets of variables. First, we calculate the number of tail and nontail events incurred by a BHC in a given quarter, where we use three different distribution thresholds to identify tail and nontail events – above and below the 99^{th}, 99.5^{th}, and 99.9^{th} percentile. Second, following the definition of tail and nontail events in each case, we sum all the losses defined as tail and nontail events in a quarter to obtain aggregate amounts of tail and nontail losses for each BHC. Table 6 presents regression results of systemic risk contribution on our different tail and nontail operational loss measures.

[Insert Table 6 about here]

Table 6, Panel A presents results for the frequency-based tail and nontail measures. Columns (1), (4), and (7) show that the frequency of tail events is positively related to systemic risk contribution. The coefficients are significant at least at the 5% level. Columns (2), (5) and (8) suggest that systemic risk contribution is not impacted by the frequency of nontail events. Lastly, Columns (3), (6) and (9) show that the results are unchanged when the frequency of tail and nontail losses are pooled in the same specification.

Table 6, Panel B presents results for dollar-based tail and nontail measures. Columns (1), (4), and (7) show that the dollar amount of tail events is positively related to systemic risk contribution. The coefficients are statistically significant at the 1% level. Columns (2) and (5) suggest that systemic risk contribution is not impacted by the loss amounts of events below the tail threshold. Column (8) shows that the total loss amount of events below the 99.9^{th} quantile is positively and significantly related to systemic risk contribution, which is particularly driven by the very high quantile used to define tail risk. In combination with the insignificant results for nontail operational risk in Columns (2) and (5), the significant results in Column (8) further suggest the existence of material losses between the 99.5^{th} and 99.9^{th} quantiles of the loss distributions that are of systemic importance. Lastly, Columns (3), (6) and (9) show that the results are unchanged when the amounts of tail and nontail losses are in the same specification. Overall, the results in Table 6 suggest that operational risk contributes to BHC systemic risk primarily through tail operational losses.

5.4. Systemically Important BHCs

Certain banking organizations are so central to the U.S. and global financial systems that their failure could cause devastating damage, both to financial markets and the larger economy. These institutions are often referred to as "Global Systemically Important Banks" or G-SIBs. A number of institutions in our sample are designated as G-SIBs. In light of our findings that operational losses at large U.S. BHCs increase systemic risk, this motivates us to examine if "systemic importance" serves as an amplifying channel for the association between operational and systemic risks. It may be expected that operational losses at systemically important banks should have more pronounced effects and contribute more to systemic risk.

To investigate this amplifying channel, we use a G-SIB score methodology developed by the Basel Committee on Banking Supervision, and subsequently adopted in the U.S., for designating global banks as systemically important.[6] As discussed in Federal Reserve System (2015), the G-SIB score aggregates 12 indicators across several conceptual categories: the size of the financial institutions, their interconnectedness, the lack of readily available substitutes for the services they provide, their complexity, and their global (cross-jurisdictional)

[6]The Federal Reserve System implemented a G-SIB capital surcharge subsequent to a recommendation from the Basel Committee on Banking Supervision (Federal Reserve System (2015)). As part of this U.S. regulation, Form FR Y-15 collects from BHCs of $50 billion or more the information needed to construct the G-SIB score.

activities. Firms having a score above a specified threshold are designated as G-SIBs. As of 2016:Q4, there are 8 U.S. G-SIBS: JPMorgan Chase, Citigroup, Bank of America, Goldman Sachs, Morgan Stanley, Wells Fargo, Bank of New York Mellon, and State Street, all of which are in our sample.

In our analysis, we use both a binary indicator identifying which BHCs are considered systemically important according to the Federal Reserve (*G-SIB Indicator*) as well as a continuous score measuring the systemic importance of BHCs (*G-SIB Score*). Because measurements are only available for the last several quarters in our sample, we use variables constructed as of 2016:Q4, the last quarter in our sample. We then estimate models similar to Eq. (10), but include interaction terms between *Ln(OpLoss)* and the measures of BHC systemic importance, *G-SIB Indicator* and *G-SIB Score*. Due to the inclusion of BHC fixed effects, we are unable to identify the coefficients on the time-invariant *G-SIB Indicator* and *G-SIB Score*. Table 7 presents these results.

[Insert Table 7 about here]

Both Columns (1) and (2) suggest that the systemic effects of operational risk occur through operational losses incurred by systemically important BHCs. The coefficients on *G-SIB Indicator*Ln(OpLoss)* and *G-SIB Score*Ln(OpLoss)* are both positive and significant at least at the 5% level. In contrast, the coefficient of *Ln(OpLoss)* is indistinguishable from 0 in both specifications. The results thus suggest that the systemic consequences of operational risk flow through destabilization of banking organizations central to the U.S. financial system stability.

5.5. BHC Distance to Default

Higher operational losses are associated with higher systemic risk contribution at BHCs. Further, financial firms' contribution to systemic risk increases with their probability of default (Huang et al. (2012)). Because the impending failure of large institutions threatens to impose significant losses on other institutions in the financial system, destabilizing operational losses could have more pronounced systemic risk effects when institutions are close to distress. We focus on this issue in the current section. Specifically, we investigate whether BHC distance to default serves as an amplifying channel for the relation between operational losses and systemic risk contribution.

We construct two measures of distance to default – *Inv Z-Score* and *PD*. *Inv Z-Score* is defined as the sum of a BHC's mean return on assets and mean capitalization ratio divided by the standard deviation of return on assets, where the averages and the standard deviations are calculated over the prior 12 quarters. For presentation purposes, we multiply the variable by -1 so that higher values reflect higher likelihood of distress. *PD* is the probability of default of a BHC based on the Black-Scholes-Merton option-pricing model following Hillegeist et al. (2004). To mitigate concerns that operational risk is driving the distress measures, we lag *Inv Z-Score* and *PD* by one period. We then estimate models similar to Eq. (10), but include interaction terms between *Ln(OpLoss)* and *Inv Z-Score* (or *PD*). Table 8 presents the results.

[Insert Table 8 about here]

The results in Column (1) suggests that *Inv Z-Score* is not significantly related to systemic risk contribution. The findings in Column (3), however, confirm the findings in Huang et al. (2012) that systemic risk contribution is positively related to BHC probability of default. Columns (2) and (4) show that the relation between systemic risk contribution and operational risk is more pronounced for BHCs that are closer to distress. The coefficients on *Inv Z-Score**Ln(OpLoss)* and *PD*Ln(OpLoss)* are both positive and significant at least at the 5% level. Overall, the results in Table 8 suggest that an additional channel of the operational risk effects on systemic risk is through further destabilization of financially weak institutions.

5.6. Financial and Economic Environment

BHCs' contributions to systemic risk in adverse financial conditions are potentially magnified by their interconnections and correlated risk taking. Additionally, operational losses are more likely to surface during financial and economic downturns (Abdymomunov et al. (2019)). In this section, we examine whether financial and economic stress serves as an amplifying channel for the relation between operational losses and systemic risk contribution, which we previously documented.

To investigate this issue empirically, we follow Berger and Bouwman (2013) and define a financial crisis indicator variable, *Financial Crisis*, which equals 1 for quarters during the period [2007:Q3-2009:Q4], and 0 otherwise. Additionally, we adopt the financial and economic conditions measure used in Abdymomunov et al. (2019), *ME Index*. *ME Index* is defined as the first principal component of the year-over-year U.S. real GDP growth rate, the year-over-year growth rate in the U.S. CoreLogic House Price Index, the year-over-year growth rate in the U.S. Commercial Real Estate Price Index, the CBOE U.S. Market Volatility Index, and the spread between the U.S. 10-year BBB-rated corporate bond yield and the 10-year U.S. Treasury bond yield. Higher values denote worse financial and economic environment.

We estimate models similar to Eq. (10), where we additionally include interaction terms between *Ln(OpLoss)* and *Financial Crisis* (or *ME Index*). We do not include time fixed effects to accommodate the purely time-series nature of *Financial Crisis* and *ME Index*. Table 9 presents the results.

[Insert Table 9 about here]

Columns (1) and (3) suggest that BHC systemic risk contribution is higher during adverse financial and economic conditions. Column (2) shows that the effects of operational losses on systemic risk contribution are especially pronounced during the 2008 financial crisis.

The coefficient on *Financial Crisis*Ln(OpLoss)* is positive and significant at the 1% level. Column (4) further confirms that operational losses contribute to systemic risk particularly during economic downturns. The coefficient on *ME Index*Ln(OpLoss)* is also positive and significant at the 1% level. Overall, these results highlight that the destabilizing effects of operational risk on the financial system are more pronounced at times of financial and economic stress.

6. Robustness Checks: Instrumental Variable Regressions

Two identification concerns may confound the interpretation of our results. First, there may be reverse causation, in which there are feedback loops from systemic risk contribution to operational risk. For example, system-wide shocks may generate operational losses across a number of institutions as employees and managers may be distracted or desperate during systemic events. To address this issue, we estimate instrumental variable regressions. We focus on using BHC-specific variables as instruments that affect BHC operational risk exposures, but should have limited effect on the systemic risk contributions of a BHC conditional on model controls. These include BHC cost efficiency and outstanding operational risk supervisory examination findings.

Cost efficiency refers to the abilities of bank managers to monitor and control their expenses (Berger and Mester (1997)). Outstanding supervisory examination findings refer to Matters Requiring Immediate Attention (MRIAs) and Matters Requiring Attention (MRAs). MRIAs arising from an examination, inspection, or any other supervisory activity that are of significant importance and urgency. The Federal Reserve requires that banking organizations address these immediately. Similarly, MRAs constitute matters that are important and that the Federal Reserve is expecting a banking organization to address over a reasonable period of time, but not necessarily "immediately."[7] We use only MRIAs and MRAs that are

[7] More information regarding MRIAs and MRAs can be found at: https://www.federalreserve.gov/

specifically related to operational risk issues.

Second, there may be omitted variables related to both operational risk and systemic risk, thus raising the possibility that our analyses are not capturing the relation between systemic risk contribution and operational risk. To address this issue, we again estimate instrumental variable regressions using industry operational losses (but excluding the institution of interest) as an instrument. While overall industry operational losses should be relevant to the operational losses experienced by specific institutions (e.g., through common cross-BHC operational risk exposures due to, for example, offering similar products and services and engaging in similar business practices), operational losses at the industry level should not reflect bank-specific characteristics. Table 10 presents the instrumental variable regression results.

[Insert Table 10 about here]

Table 10, Panel A presents first-stage results. Column (1) shows that the cost efficiency of an institution is inversely related to operational losses (i.e. a more cost efficient institution suffers less operational losses). Columns (2) and (3) show that the number of outstanding operational risk supervisory findings is positively related to operational losses. Finally, Column (4) shows that operational losses are positively correlated across institutions. In all cases, the instruments are statistically significant at conventional levels and the adjusted R^2 of the regressions are reasonably high. Further, the F-statistics exceed 20, well above the threshold of 10 prescribed by Stock et al. (2002). Such evidence suggests we do not suffer from weak instrumental variable issues.

Table 10, Panel B presents second-stage results. Across all specifications, the estimated coefficient of $Ln(OpLoss)$ retains its positive sign and is statistically significant at least at

`supervisionreg/srletters/sr1313a1.pdf`. Data on MRIAs and MRAs are collected and maintained by the Federal Reserve System.

the 10% level. Overall, our IV analysis mitigates concerns regarding reverse causality and omitted BHC-level variable problems that could be biasing the estimated relation between operational losses and systemic risk contribution.

7. Conclusion

Can a largely idiosyncratic risk become systemic in nature? The evidence in this study suggests that it can. We find a statistically and economically significant positive relation between operational losses at large bank holding companies (BHCs) in the U.S. and the systemic risk contributions of these BHCs. The relation is driven by high-severity operational risk tail events of certain types and business lines, and is more pronounced for systemically important BHCs, for BHCs that are closer to distress, and during adverse financial and economic environments. Our findings are especially important in light of recent dramatic and well-known operational risk events in the global financial system, and the high economic and social costs of systemic crises.

The literatures on operational risk and systemic risk have mostly focused on describing and understanding the general nature of these two types of risk. However, the possible relation between operational risk and financial system distress has not been addressed. We add to these literatures by exploring the systemic implications of operational risk.

Our research also has potential policy implications. The Standardized Measurement Approach (SMA) in Basel III requires banks to calculate operational risk capital based on pre-defined income activities. Our results can help to better inform the weights placed on each of the income activities for the calculation of operational risk-based capital. Specifically, our results suggest that relatively larger weights be applied to the income components generated by business lines such as retail banking. Conversely, our results suggest that operational losses from activities like commercial banking, agency services and retail brokerage do not pose as much of a systemic threat and thus their weights may be relatively smaller.

Our findings also support the convex weighting of large past operational losses in the SMA, since high-severity tail operational risk events contribute proportionally more to systemic risk compared to nontail events.

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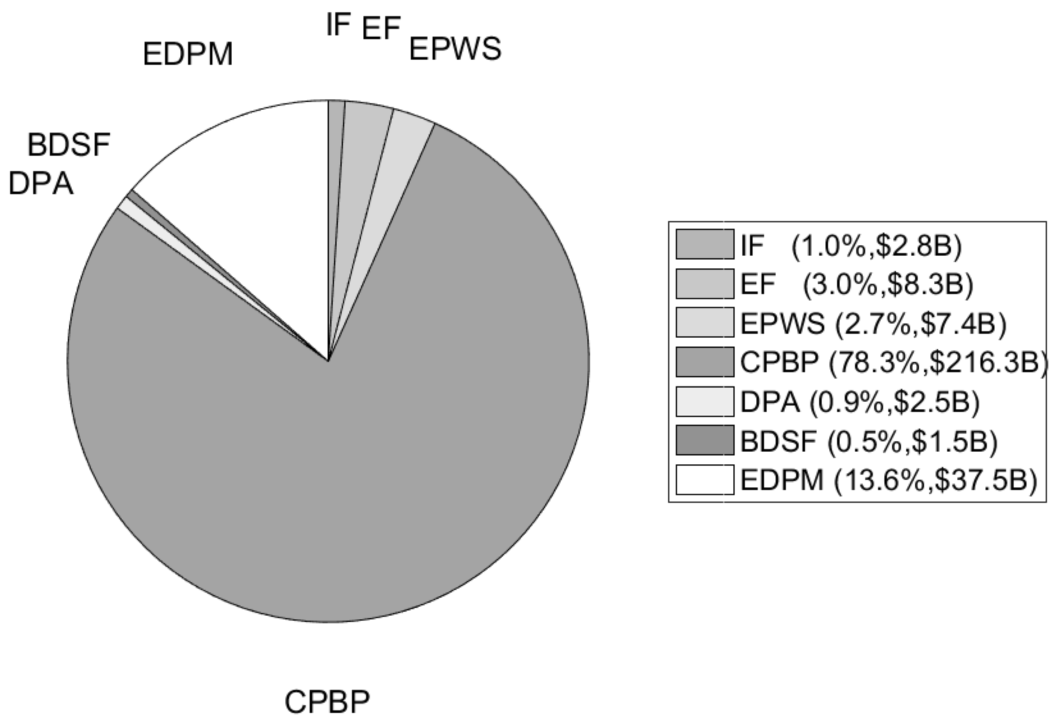

Figure 1: **Operational Losses by Event Type**
This figure presents the allocation of operational loss amounts (percentage of total losses and U.S. dollar loss amounts in billions) by event type. The sample includes 290,872 operational loss events incurred by 26 large U.S. bank holding companies over the period [2002:Q1-2016:Q4]. The nomenclature for event types is 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). Event type definitions are provided in Table 1, Panel B.

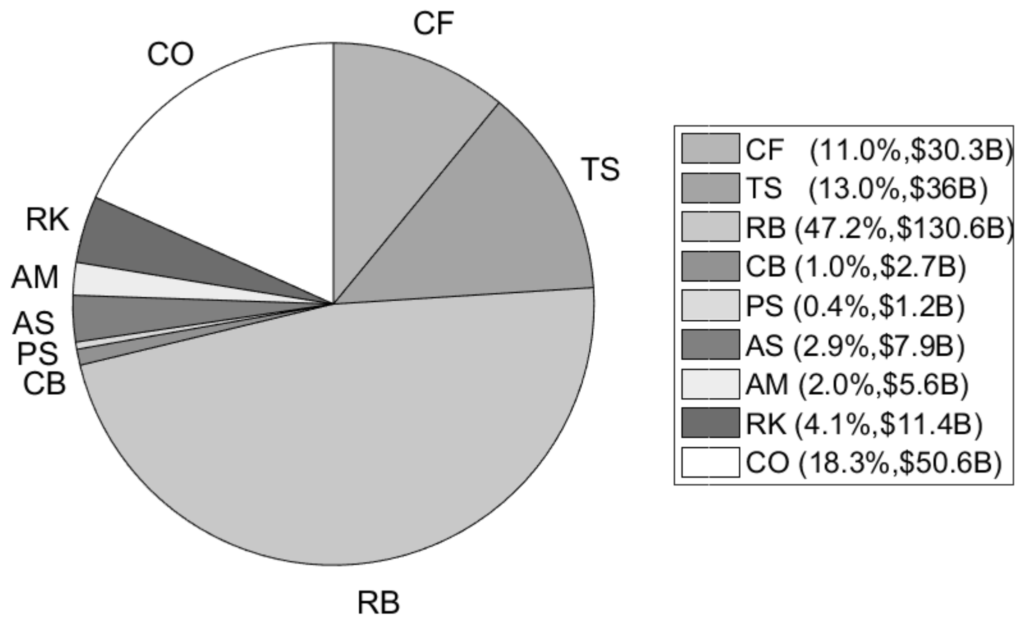

Figure 2: **Operational Losses by Business Line**
This figure presents the allocation of operational loss amounts (percentage of total losses and U.S. dollar loss amounts in billions) by business line. The sample includes 290,872 operational loss events incurred by 26 large U.S. bank holding companies over the period [2002:Q1-2016:Q4]. The nomenclature for business lines is as follows: Corporate Finance (CF), Trading and Sales (TS), Retail Banking (RB), Commercial Banking (CB), Payment and Settlement (PS), Agency Services (AS), Asset Management (AM), Retail Brokerage (RK), Corporate Level (CO). Business line definitions are provided in Table 1, Panel C.

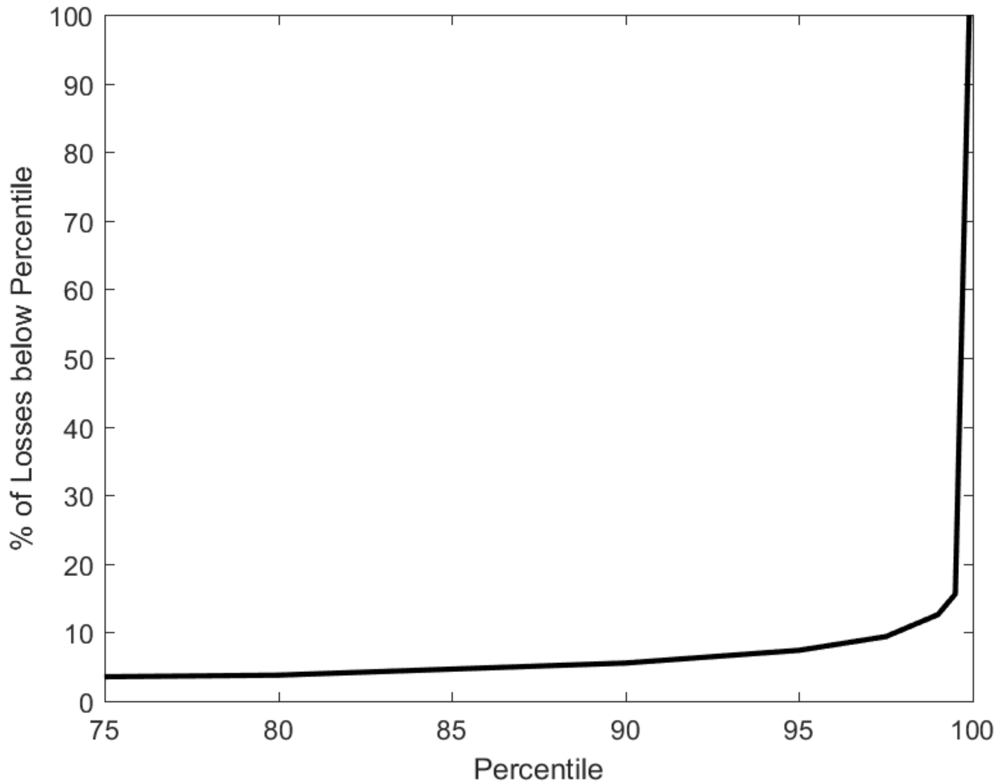

Figure 3: **The Heavy Tails of Operational Losses**
This figure presents the percentage of total operational losses with severities below a given percentile of the unconditional distribution of loss severities. The sample includes 290,872 operational loss events incurred by 26 large bank holding companies operating in U.S. over the period [2002:Q1-2016:Q4].

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Table 1: **Definitions**

This table presents variable definitions in Panel A, operational loss event type definitions according to Basel Committee on Banking Supervision (2006) in Panel B, and operational loss business line definitions according to Federal Reserve System (2017) in Panel C.

Panel A: Variables	
Dependent Variables: *Systemic Risk Measures*	
SRISK	The expected capital shortfall of a BHC conditional on a crisis (Acharya et al. (2012), Brownlees and Engle (2017)). We derive a quarterly level measure by averaging daily values within a quarter.
ΔCoVaR	The change in the value at risk of the financial system conditional on a BHC being in distress relative to the BHC's median state (Adrian and Brunnermeier (2016)).
SES	The systemic expected shortfall of a BHC, which measures the BHC's propensity to be undercapitalized when the system as a whole is undercapitalized (Acharya et al. (2017)).
LVG	The market leverage of a BHC (Acharya et al. (2017)).
MES	The marginal expected shortfall of a BHC, which measures the BHC's average return on days when the market as a whole is in the tail of its return distribution (Acharya et al. (2017)).
Systemic Risk (PC)	The first principal component of SES, SRISK, and ΔCoVar (higher values denote higher systemic risk).
Key Independent Variables: *Operational Risk Measures*	
OpLoss	The financial impact sum of operational loss events incurred by a BHC over a calendar quarter in billions of U.S. Dollars.
Ln(OpLoss)	A natural log transformation of *OpLoss*, defined as *Ln(1+OpLoss)*.
N Tail Evt	The number of loss events incurred by a BHC over a calendar quarter that have a ratio of loss amount to BHC assets higher than the 99.0^{th}, 99.5^{th} or 99.9^{th} quantile of the unconditional distribution of the ratio.
N NonTail Evt	The number of loss events incurred by a BHC over a calendar quarter that have a ratio of loss amount to BHC assets lower than the 99.0^{th}, 99.5^{th} or 99.9^{th} quantile of the unconditional distribution of the ratio.
Tail OpLoss	The financial impact sum (in billions of U.S. Dollars) of loss events incurred by a BHC over a calendar quarter that have a ratio of loss amount to BHC assets higher than the 99.0^{th}, 99.5^{th} or 99.9^{th} quantile of the unconditional distribution of the ratio.
Ln(Tail OpLoss)	A natural log transformation of *Tail OpLoss*, defined as *Ln(1+Tail OpLoss)*.

Table Continued...	
NonTail OpLoss	The financial impact sum (in billions of U.S. Dollars) of loss events incurred by a BHC over a calendar quarter that have a ratio of loss amount to BHC assets lower than the 99.0$^{\text{th}}$, 99.5$^{\text{th}}$ or 99.9$^{\text{th}}$ quantile of the unconditional distribution of the ratio.
Ln(NonTail OpLoss)	A natural log transformation of *NonTail OpLoss*, defined as *Ln(1+NonTail OpLoss)*.
Independent Variables: *BHC Characteristics and Other Variables*	
Size	BHC total assets (in billions of U.S. dollars).
Ln(Size)	A natural log transformation of *Size*, defined as *Ln(Size)*.
M-to-B	The ratio of BHC market value of equity to book value of equity.
NII-to-II	The ratio of BHC non-interest income to interest income.
RoA	BHC return on total assets.
Risk Mgmt	BHC risk management indicator variable equal to 1 if the risk management rating assigned by the Federal Reserve System to a given BHC is greater than 3 (the rating scale is [1, 5], with higher values denoting weaker risk management practices).
Leverage	BHC total assets divided by book value of equity.
NPL-to-TL	The ratio of BHC non-performing loans (90 days past due or more, and nonaccrual) to total loans.
LCR	BHC liquidity coverage ratio, defined as the ratio of high-quality liquid assets to total net cash outflows over a 30-day stress period.
Maturity Gap	BHC maturity gap, defined as the difference between all assets that either reprice or mature within a year and all the liabilities that reprice or mature within a year.
G-SIB Indicator	An indicator variable equal to 1 if a BHC is deemed systemically important by the Federal Reserve, 0 otherwise (Federal Reserve System (2015)). As of 2016:Q4, the following BHCs in our sample are considered G-SIBs: JPMorgan Chase, Citigroup, Bank of America, Goldman Sachs, Morgan Stanley, Wells Fargo, Bank of New York Mellon, and State Street.
G-SIB Score	A continuous measure of bank systemic importance based on size, interconnectedness, cross-jurisdictional activity, substitutability, and complexity (Federal Reserve System (2015)). The score is calculated as of 2016:Q4.
Inv Z-Score	BHC risk measure, defined as the sum of a BHC's mean return on assets and mean capitalization ratio divided by the standard deviation of return on assets, where the averages and the standard deviations are evaluated over the prior 12 quarters. The variable is multiplied by -1 so that higher values denote higher probability of distress.

Table Continued...	
PD	The probability of default of a BHC based on the Black-Scholes-Merton option-pricing model (Hillegeist et al. (2004)).
Financial Crisis	An indicator variable equal to 1 if the quarter is within the subprime lending crisis during [2007:Q3-2009:Q4] as defined in Berger and Bouwman (2013), 0 otherwise.
ME	U.S. financial and economic environment measure, 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. Higher values denote worse conditions.
Independent Variables: *Operational Risk Instruments*	
Cost Efficiency	The cost efficiency of a BHC, measured with the Fourier-flexible form in the spirit of Berger and Mester (1997)
OpRisk MR(I)A	The number of outstanding operational risk supervisory examination findings at a BHC as of a given quarter. Examination findings include Matters Requiring Immediate Attention and Matters Requiring Attention.
Ln(OpRisk MR(I)A)	A natural log transformation of *OpRisk MR(I)A*, defined as *Ln(1+OpRisk MR(I)A)*
Mgmt MR(I)A	The number of outstanding operational risk supervisory examination findings, specifically regarding management practices, at a BHC as of a given quarter. Examination findings include Matters Requiring Immediate Attention, and Matters Requiring Attention.
Ln(Mgmt MR(I)A)	A natural log transformation of *Mgmt MR(I)A*, defined as *Ln(1+Mgmt MR(I)A)*
IndOpLoss	The asset weighted average of operational dollar losses for all the institutions in our sample, with the exclusion of the one of interest, over a calendar quarter, in billions of U.S. Dollars.
Ln(IndOpLoss)	A natural log transformation of *IndOpLoss*, defined as *Ln(1+IndOpLoss)*.

Panel B: Event Types

Event Type Category	Short	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.

Panel C: Business Lines

Business Line Category	Short	Activity Groups
Corporate Finance	CF	Mergers and acquisitions, underwriting, privatizations, securitization, research, debt (government, high yield), equity, syndications, IPO, secondary private placements.
Trading and Sales	TS	Fixed income, equity, foreign exchanges, commodities, credit, funding, own position securities, lending and repos, brokerage, debt, prime brokerage.
Retail Banking	RB	Retail and private lending and deposits, banking services, trust and estates, investment advice, Merchant/commercial/corporate cards, private labels and retail.
Commercial Banking	CB	Project finance, real estate, export finance, trade finance, factoring, leasing, lending, guarantees, bills of exchange.
Payment and Settlement	PS	Payments and collections, funds transfer, clearing and settlement.
Agency Services	AS	Escrow, depository receipts, securities lending (customers) corporate actions, issuer and paying agents.
Asset Management	AM	Pooled, segregated, retail, institutional, closed, open, private equity.
Retail Brokerage	RK	Execution and full service.
Corporate Level (Non-Business Line Specific)	CO	Losses originating from a corporate/firm-wide function that cannot be linked to a specific business line.

Table 2: **Descriptive Statistics**

This table presents descriptive statistics. The sample includes 1,070 quarterly observations of 26 large bank holding companies over the period [2002:Q1-2016:Q4] for which requisite data are available. Panel A reports descriptive statistics on operational risk measures. Panel B reports descriptive statistics on systemic risk measures. Panel C reports descriptive statistics on other variables used in our analyses. Variables definitions are reported in Table 1, Panel A.

Panel A: Operational Risk Measures

	N	Mean	Std	P25	P50	P75
OpLoss	1,070	0.230	1.322	0.005	0.016	0.109
Ln(OpLoss)	1,070	0.118	0.294	0.005	0.016	0.103
N Tail Evt 99.0	1,070	1.963	2.183	1.000	2.000	3.000
N NonTail Evt 99.0	1,070	239.625	366.824	29.000	72.000	232.000
N Tail Evt 99.5	1,070	0.968	1.331	0.000	1.000	1.000
N NonTail Evt 99.5	1,070	240.620	367.042	30.000	73.000	234.000
N Tail Evt 99.9	1,070	0.207	0.531	0.000	0.000	0.000
N NonTail Evt 99.9	1,070	241.381	367.240	31.000	73.500	235.000
Tail OpLoss 99.0	1,070	0.194	1.301	0.000	0.007	0.049
Ln(Tail OpLoss 99.0)	1,070	0.092	0.284	0.000	0.007	0.047
NonTail OpLoss 99.0	1,070	0.035	0.064	0.003	0.007	0.031
Ln(NonTail OpLoss 99.0)	1,070	0.033	0.056	0.003	0.007	0.031
Tail OpLoss 99.5	1,070	0.186	1.296	0.000	0.003	0.038
Ln(Tail OpLoss 99.5)	1,070	0.086	0.282	0.000	0.003	0.037
NonTail OpLoss 99.5	1,070	0.043	0.082	0.003	0.009	0.040
Ln(NonTail OpLoss 99.5)	1,070	0.040	0.068	0.003	0.009	0.040
Tail OpLoss 99.9	1,070	0.161	1.279	0.000	0.000	0.000
Ln(Tail OpLoss 99.9)	1,070	0.067	0.274	0.000	0.000	0.000
NonTail OpLoss 99.9	1,070	0.068	0.145	0.004	0.013	0.065
Ln(NonTail OpLoss 99.9)	1,070	0.060	0.104	0.004	0.013	0.063

Panel B: Systemic Risk Measures

	N	Mean	Std	P25	P50	P75
SRISK	1,070	0.006	0.029	-0.004	-0.000	0.006
ΔCoVaR	1,070	0.010	0.007	0.006	0.008	0.011
SES	1,070	0.389	0.298	0.243	0.325	0.447
LVG	1,070	10.107	7.402	6.477	8.518	11.558
MES	1,070	0.033	0.020	0.020	0.027	0.038
Systemic Risk (PC)	1,070	0.003	0.141	-0.076	-0.034	0.037

Panel C: BHC Controls and Other Variables						
	N	Mean	Std	P25	P50	P75
Size	1,070	485.875	663.287	80.460	157.039	657.087
Ln(Size)	1,070	5.379	1.230	4.388	5.056	6.488
M-to-B	1,070	1.437	0.873	0.828	1.162	1.864
NII-to-II	1,070	0.972	0.980	0.419	0.607	0.979
RoA	1,070	1.289	1.234	0.905	1.345	1.830
Risk Mgmt	1,070	0.013	0.114	0.000	0.000	0.000
Leverage	1,070	9.938	2.344	8.307	9.526	11.461
NPL-to-TL	1,070	0.022	0.018	0.009	0.016	0.030
LCR	1,070	0.818	1.041	0.173	0.336	1.151
Maturity Gap	1,070	0.288	0.133	0.194	0.301	0.376
G-SIB Indicator	1,070	0.385	0.487	0.000	0.000	1.000
G-SIB Score	1,070	0.042	0.054	0.003	0.013	0.073
Inv Z-Score	1,030	-61.541	64.564	-81.502	-38.785	-19.368
PD	1,065	0.005	0.025	0.000	0.000	0.000
Financial Crisis	1,070	0.178	0.382	0.000	0.000	0.000
ME Index	1,070	9.303	12.070	1.130	5.795	12.799
Cost Efficiency	1,065	0.605	0.236	0.436	0.635	0.763
OpRisk MR(I)A	1,070	4.181	10.307	0.000	0.000	3.500
Ln(OpRisk MR(I)A)	1,070	0.807	1.110	0.000	0.000	1.498
Mgmt MR(I)A	1,070	2.658	6.582	0.000	0.000	2.000
Ln(Mgmt MR(I)A)	1,070	0.647	0.957	0.000	0.000	1.099
IndOpLoss	1,070	0.733	1.287	0.181	0.262	0.590
Ln(IndOpLoss)	1,070	0.323	0.263	0.159	0.218	0.387

Table 3: **Variable Correlations**

This table presents variable correlations. The sample includes 1,070 quarterly observations of 26 large bank holding companies over the period [2002:Q1-2016:Q4] for which requisite data are available. Panel A reports correlations between different systemic risk measures and our main measure of operational risk. Panel B reports correlations between our main measure of systemic risk and different operational risk measures. Variable definitions are reported in Table 1, Panel A.

Panel A: Systemic Risk Measures

	Systemic Risk (PC)	SRISK	ΔCoVaR	SES	LVG	MES	Ln(OpLoss)
Systemic Risk (PC)	1.000						
SRISK	0.788	1.000					
	(0.000)						
ΔCoVaR	0.777	0.375	1.000				
	(0.000)	(0.000)					
SES	0.871	0.554	0.539	1.000			
	(0.000)	(0.000)	(0.000)				
LVG	0.868	0.553	0.529	1.000	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)			
MES	0.680	0.352	0.791	0.514	0.507	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Ln(OpLoss)	0.315	0.425	0.139	0.212	0.212	0.082	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	

Panel B: Operational Risk Measures

	Systemic Risk (PC)	Ln(OpLoss)	N Tail Evt 99.0	N NonTail Evt 99.0	N Tail Evt 99.9	N NonTail Evt 99.9	Ln(Tail OpLoss 99.0)	Ln(NonTail OpLoss 99.0)	Ln(Tail OpLoss 99.9)	Ln(NonTail OpLoss 99.9)
Systemic Risk (PC)	1.000									
Ln(OpLoss)	0.315	1.000								
	(0.000)									
N Tail Evt 99.0	0.192	0.350	1.000							
	(0.000)	(0.000)								
N NonTail Evt 99.0	0.189	0.535	0.272	1.000						
	(0.000)	(0.000)	(0.000)							
N Tail Evt 99.9	0.151	0.569	0.508	0.204	1.000					
	(0.000)	(0.000)	(0.000)	(0.000)						
N NonTail Evt 99.9	0.190	0.536	0.279	1.000	0.206	1.000				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
Ln(Tail OpLoss 99.0)	0.297	0.957	0.361	0.443	0.609	0.444	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
Ln(NonTail OpLoss 99.0)	0.283	0.590	0.358	0.933	0.243	0.934	0.505	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
Ln(Tail OpLoss 99.9)	0.254	0.926	0.284	0.344	0.610	0.345	0.983	0.395	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Ln(NonTail OpLoss 99.9)	0.331	0.618	0.490	0.828	0.288	0.830	0.554	0.923	0.408	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Table 4: **Systemic Risk and Operational Losses**

This table reports coefficients from panel regressions of systemic risk on operational losses and control variables. The estimation sample comprises an unbalanced panel of 1,070 quarterly observations of 26 large bank holding companies over the period [2002:Q1-2016:Q4] for which requisite data are available. *Systemic Risk (PC)* measures BHC systemic risk and is defined as the first principal component of *SRISK*, $\Delta CoVar$, and *SES*. *Ln(OpLoss)* is a natural log transformation of operational dollar losses incurred by a BHC over a given calendar quarter. Panel A reports regressions using *Systemic Risk (PC)* as the dependent variable. In Column (1), we do not include fixed effects. In Column (2), we include BHC fixed effects. In Column (3), we include time (year and seasonal) fixed effects. In Column (4), we include BHC and time (year and seasonal) fixed effects. Panel B reports regressions using *SRISK*, $\Delta CoVar$, *SES*, *LVG* or *MES*, respectively, as dependent variables. All specifications in Panel B include BHC and time (year and seasonal) fixed effects. Standard errors are clustered at the BHC and quarter levels in both panels. Variables definitions are reported in Table 1, Panel A. T-statistics are presented in parentheses.

Panel A: Systemic Risk - Principal Component

	Systemic Risk (PC)			
	(1)	(2)	(3)	(4)
Ln(OpLoss)	0.085***	0.078***	0.073***	0.067***
	(5.010)	(4.862)	(4.937)	(4.293)
Ln(Size)	−0.000	0.033	0.012*	0.027
	(−0.004)	(1.065)	(1.870)	(0.766)
M-to-B	−0.058***	−0.069**	−0.057***	−0.066**
	(−2.765)	(−2.256)	(−3.317)	(−2.113)
NII-to-II	−0.007	−0.040**	−0.009	−0.029**
	(−0.670)	(−2.054)	(−0.967)	(−2.062)
RoA	−0.030*	−0.039**	−0.016*	−0.019
	(−1.774)	(−1.971)	(−1.710)	(−1.551)
Risk Mgmt	0.114	0.144	0.157	0.170
	(0.777)	(1.256)	(1.153)	(1.359)
Leverage	0.016***	0.005	0.013***	0.003
	(3.807)	(0.853)	(4.620)	(0.561)
NPL-to-TL	1.034	0.776	−0.156	0.529
	(1.391)	(0.949)	(−0.161)	(0.544)
LCR	0.005	−0.008	0.008	0.002
	(0.434)	(−0.880)	(1.305)	(0.264)
Maturity Gap	−0.071	−0.283***	0.018	−0.135
	(−1.449)	(−2.708)	(0.552)	(−1.130)
BHC FE	No	Yes	No	Yes
Time FE	No	No	Yes	Yes
N	1,070	1,070	1,070	1,070
Adj R^2	0.404	0.481	0.562	0.599

*, **, and *** denote significance at the 10%, 5%, and 1% level

Panel B: Systemic Risk - Individual Measures

	(1) SRISK	(2) ΔCoVaR	(3) SES	(4) LVG	(5) MES
Ln(OpLoss)	0.020***	0.002***	0.054**	1.348**	0.001***
	(4.468)	(2.812)	(2.551)	(2.545)	(2.774)
Ln(Size)	−0.004	0.002**	0.111**	2.774**	0.002
	(−0.307)	(1.993)	(2.103)	(2.104)	(1.070)
M-to-B	−0.014	−0.001	−0.141***	−3.514***	−0.005*
	(−1.429)	(−0.734)	(−2.859)	(−2.855)	(−1.786)
NII-to-II	−0.009	−0.001**	−0.013	−0.325	−0.003***
	(−1.426)	(−2.169)	(−0.754)	(−0.735)	(−2.748)
RoA	−0.001	−0.001*	−0.061**	−1.525**	−0.003***
	(−0.370)	(−1.735)	(−2.042)	(−2.028)	(−3.562)
Risk Mgmt	0.029	0.001	0.511	12.742	0.008*
	(1.163)	(0.702)	(1.637)	(1.631)	(1.834)
Leverage	0.001	−0.000	0.009	0.215	−0.001*
	(0.852)	(−1.083)	(1.587)	(1.607)	(−1.649)
NPL-to-TL	0.350	−0.007	−0.453	−11.657	0.091*
	(1.135)	(−0.218)	(−0.316)	(−0.326)	(1.937)
LCR	0.000	0.000	−0.007	−0.184	0.000
	(0.173)	(1.528)	(−0.409)	(−0.412)	(0.400)
Maturity Gap	−0.032	0.002	−0.436**	−10.963**	0.016*
	(−1.094)	(0.396)	(−2.019)	(−2.034)	(1.865)
BHC FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
N	1,070	1,070	1,070	1,070	1,070
Adj R^2	0.561	0.585	0.475	0.470	0.855

*, **, and *** denote significance at the 10%, 5%, and 1% level

Table 5: **Event Types and Business Lines**

This table reports coefficients from panel regressions of systemic risk on operational losses and control variables by event type and business line. The estimation sample comprises an unbalanced panel of 1,070 quarterly observations of 26 large bank holding companies over the period [2002:Q1-2016:Q4] for which requisite data are available. *Systemic Risk (PC)* measures BHC systemic risk and is defined as the first principal component of *SRISK*, $\Delta CoVar$, and *SES*. *Ln(OpLoss)* is a natural log transformation of operational dollar losses from a given *event type* or *business line* incurred by a BHC over a given calendar quarter. 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). Business lines are as follows: Corporate Finance (CF), Trading and Sales (TS), Retail Banking (RB), Commercial Banking (CB), Payment and Settlement (PS), Agency Services (AS), Asset Management (AM), Retail Brokerage (RK), Corporate Level (CO). Panel A reports results for different operational loss event types. Panel B reports results for different operational loss business lines. All specifications include BHC and time (year and seasonal) fixed effects. Control variables (*Ln(Size)*, *M-to-B*, *NII-to-II*, *RoA*, *Risk Mgmt*, *Leverage*, *NPL-to-TL*, *LCR*, *Maturity Gap*) are included, but their coefficient estimates are omitted for brevity. Standard errors are clustered at the BHC and quarter levels. Variables definitions are reported in Table 1, Panel A. Event type definitions are reported in Table 1, Panel B. Business line definitions are reported in Table 1, Panel C. T-statistics are presented in parentheses.

Panel A: Event Types

	Systemic Risk (PC)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(OpLoss IF)	0.683***							0.582***
	(5.198)							(14.841)
Ln(OpLoss EF)		−0.178						−0.203
		(−1.027)						(−0.730)
Ln(OpLoss EPWS)			0.121					0.084
			(0.663)					(0.403)
Ln(OpLoss CPBP)				0.063***				0.057***
				(4.173)				(4.259)
Ln(OpLoss DPA)					−0.356			−0.308
					(−0.397)			(−0.391)
Ln(OpLoss BDSF)						0.781		0.480
						(1.479)		(0.975)
Ln(OpLoss EDPM)							0.106*	0.098***
							(1.865)	(2.964)
BHC Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,070	1,070	1,070	1,070	1,070	1,070	1,070	1,070
Adj R^2	0.589	0.586	0.586	0.598	0.586	0.586	0.588	0.602

*, **, and *** denote significance at the 10%, 5%, and 1% level

Panel B: Business Lines

	Systemic Risk (PC)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ln(OpLoss CF)	0.003									0.007
	(0.188)									(0.319)
Ln(OpLoss TS)		0.054								0.039
		(1.460)								(1.385)
Ln(OpLoss RB)			0.087***							0.081***
			(4.582)							(3.105)
Ln(OpLoss CB)				−0.019						0.007
				(−0.099)						(0.036)
Ln(OpLoss PS)					−0.106					−0.059
					(−0.670)					(−0.418)
Ln(OpLoss AS)						−0.046				−0.040
						(−0.872)				(−0.661)
Ln(OpLoss AM)							0.052			0.051
							(0.568)			(0.474)
Ln(OpLoss RK)								−0.035		−0.063
								(−0.447)		(−0.963)
Ln(OpLoss CO)									0.100*	0.086*
									(1.779)	(1.779)
BHC Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,070	1,070	1,070	1,070	1,070	1,070	1,070	1,070	1,070	1,070
Adj R^2	0.585	0.587	0.599	0.585	0.585	0.586	0.586	0.585	0.594	0.603

*, **, and *** denote significance at the 10%, 5%, and 1% level

Table 6: **Tail versus Nontail Operational Risk**

This table reports coefficients from panel regressions of systemic risk on tail metrics of operational risk and control variables. The estimation sample comprises an unbalanced panel of 1,070 quarterly observations of 26 large bank holding companies over the period [2002:Q1-2016:Q4] for which requisite data are available. *Systemic Risk (PC)* measures BHC systemic risk and is defined as the first principal component of *SRISK*, $\Delta CoVar$, and *SES*. *N Tail Evt* is a frequency-based measure of tail operational risk defined as the number of loss events incurred by a BHC over a calendar quarter that have a ratio of loss amount to BHC assets higher than the 99.0^{th}, 99.5^{th} or 99.9^{th} quantile of the unconditional distribution of the ratio. *N NonTail Evt* is the number of loss events incurred by a BHC over a calendar quarter that have a ratio of loss amount to BHC assets lower than the 99.0^{th}, 99.5^{th} or 99.9^{th} quantile of the unconditional distribution of the ratio. *Ln(Tail OpLoss)* is a dollar-based measure of tail operational risk defined as the natural log transformation of the financial impact sum of loss events incurred by a BHC over a calendar quarter that have a ratio of loss amount to BHC assets higher than the 99.0^{th}, 99.5^{th} or 99.9^{th} quantile of the unconditional distribution of the ratio. *Ln(NonTail OpLoss)* is a natural log transformation of the financial impact sum of loss events incurred by a BHC over a calendar quarter that have a ratio of loss amount to BHC assets lower than the 99.0^{th}, 99.5^{th} or 99.9^{th} quantile of the unconditional distribution of the ratio. Panel A reports specifications using the frequency-based tail operational risk measures. Panel B reports specifications using the dollar-based tail operational risk measures. All specifications include BHC and time (year and seasonal) fixed effects. Control variables (*Ln(Size)*, *M-to-B*, *NII-to-II*, *RoA*, *Risk Mgmt*, *Leverage*, *NPL-to-TL*, *LCR*, *Maturity Gap*) are included, but their coefficient estimates are omitted for brevity. Standard errors are clustered at the BHC and quarter levels. Variables definitions are reported in Table 1, Panel A. T-statistics are presented in parentheses.

Panel A: Operational Risk Tail Loss Frequencies

	Systemic Risk (PC)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
N Tail Evt 99.0	0.251**		0.267**						
	(2.002)		(2.214)						
N NonTail Evt 99.0		−0.009	−0.009						
		(−1.588)	(−1.623)						
N Tail Evt 99.5				0.569***		0.567***			
				(2.676)		(2.955)			
N NonTail Evt 99.5					−0.009	−0.009			
					(−1.584)	(−1.634)			
N Tail Evt 99.9							1.954**		2.039**
							(2.297)		(2.321)
N NonTail Evt 99.9								−0.009	−0.009
								(−1.579)	(−1.618)
BHC Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,070	1,070	1,070	1,070	1,070	1,070	1,070	1,070	1,070
Adj R^2	0.587	0.590	0.591	0.588	0.590	0.592	0.590	0.590	0.594

*, **, and *** denote significance at the 10%, 5%, and 1% level

Panel B: Operational Risk Tail Loss Amounts

	Systemic Risk (PC)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ln(Tail OpLoss 99.0)	0.066***		0.065***						
	(4.481)		(4.290)						
Ln(NonTail OpLoss 99.0)		0.209	0.072						
		(1.107)	(0.429)						
Ln(Tail OpLoss 99.5)				0.064***		0.062***			
				(4.569)		(4.476)			
Ln(NonTail OpLoss 99.5)					0.219	0.128			
					(1.533)	(1.140)			
Ln(Tail OpLoss 99.9)							0.059***		0.054***
							(4.639)		(5.081)
Ln(NonTail OpLoss 99.9)								0.203***	0.163***
								(4.850)	(4.508)
BHC Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,070	1,070	1,070	1,070	1,070	1,070	1,070	1,070	1,070
Adj R^2	0.599	0.586	0.599	0.599	0.587	0.599	0.597	0.591	0.601

*, **, and *** denote significance at the 10%, 5%, and 1% level

Table 7: **Interactions with BHC Systemic Importance**

This table reports coefficients from panel regressions of systemic risk on operational losses, bank systemic importance measures, and control variables. The estimation sample comprises an unbalanced panel of 1,070 quarterly observations of 26 large bank holding companies over the period [2002:Q1-2016:Q4] for which requisite data are available. *Systemic Risk (PC)* measures BHC systemic risk and is defined as the first principal component of *SRISK*, $\Delta CoVar$, and *SES*. *Ln(OpLoss)* is a natural log transformation of operational dollar losses incurred by a BHC over a given calendar quarter. *G-SIB Indicator* is an indicator variable equal to 1 if a BHC is deemed systemically important by the Federal Reserve, 0 otherwise. *G-SIB Score* is a continuous measure of bank systemic importance. Both measures are calculated as of 2016:Q4 and capture the size of the financial institutions, their interconnectedness, lack of readily available substitutes for the services they provide, their complexity, and their global activities. All specifications include BHC and time (year and seasonal) fixed effects. Control variables (*Ln(Size)*, *M-to-B*, *NII-to-II*, *RoA*, *Risk Mgmt*, *Leverage*, *NPL-to-TL*, *LCR*, *Maturity Gap*) are included, but their coefficient estimates are omitted for brevity. Standard errors are clustered at the BHC and quarter levels. Variables definitions are reported in Table 1, Panel A. T-statistics are presented in parentheses.

	Systemic Risk (PC)	
	(1)	(2)
Ln(OpLoss)	−0.080	−0.007
	(−1.386)	(−0.196)
G-SIB Indicator * Ln(OpLoss)	0.150***	
	(2.705)	
G-SIB Score * Ln(OpLoss)		0.573***
		(2.699)
BHC Controls	Yes	Yes
BHC FE	Yes	Yes
Time FE	Yes	Yes
N	1,070	1,070
Adj R^2	0.600	0.600

*, **, and *** denote significance at the 10%, 5%, and 1% level

Table 8: **Interactions with BHC Distance to Default**

This table reports coefficients from panel regressions of systemic risk on operational losses, distance to default measures, and control variables. The estimation sample comprises an unbalanced panel of 1,070 quarterly observations of 26 large bank holding companies over the period [2002:Q1-2016:Q4] for which requisite data are available. *Systemic Risk (PC)* measures BHC systemic risk and is defined as the first principal component of *SRISK*, $\Delta CoVar$, and *SES*. *Ln(OpLoss)* is a natural log transformation of operational dollar losses incurred by a BHC over a given calendar quarter. *Inv Z-Score* measures BHC risk and is defined as the sum of a BHC's mean return on assets and mean capitalization ratio divided by the standard deviation of return on assets, where the averages and the standard deviations are evaluated over the prior 12 quarters. The variable is multiplied by -1 so that higher values denote higher probability of distress. *PD* measures a BHC's probability of default based on the Black-Scholes-Merton option-pricing model. All specifications include BHC and time (year and seasonal) fixed effects. Control variables (*Ln(Size)*, *M-to-B*, *NII-to-II*, *RoA*, *Risk Mgmt*, *Leverage*, *NPL-to-TL*, *LCR*, *Maturity Gap*) are included, but their coefficient estimates are omitted for brevity. Standard errors are clustered at the BHC and quarter levels. Variables definitions are reported in Table 1, Panel A. T-statistics are presented in parentheses.

	Systemic Risk (PC)			
	(1)	(2)	(3)	(4)
Ln(OpLoss)	0.065***	0.115***	0.069***	0.036***
	(4.061)	(4.231)	(4.022)	(3.120)
Inv Z-Score	0.000	−0.000		
	(0.571)	(−0.121)		
Inv Z-Score * Ln(OpLoss)		0.002**		
		(2.109)		
PD			1.892***	1.594***
			(2.994)	(2.890)
PD * Ln(OpLoss)				2.627***
				(2.890)
BHC Controls	Yes	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	1,030	1,030	1,065	1,065
Adj R^2	0.602	0.610	0.650	0.679

*, **, and *** denote significance at the 10%, 5%, and 1% level

Table 9: **Interactions with Financial and Economic Environment**

This table reports coefficients from panel regressions of systemic risk on operational losses, the financial and economic environment, and control variables. The estimation sample comprises an unbalanced panel of 1,070 quarterly observations of 26 large bank holding companies over the period [2002:Q1-2016:Q4] for which requisite data are available. *Systemic Risk (PC)* measures BHC systemic risk and is defined as the first principal component of *SRISK*, $\Delta CoVar$, and *SES*. *Ln(OpLoss)* is a natural log transformation of operational dollar losses incurred by a BHC over a given calendar quarter. *Financial Crisis* is an indicator variable equal to 1 if a given quarter is within the subprime lending crisis period during [2007:Q3-2009:Q4], 0 otherwise. *ME Index* is a continuous measure of the U.S. financial and economic environment. Higher values denote worse conditions. All specifications include BHC fixed effects. Control variables (*Ln(Size)*, *M-to-B*, *NII-to-II*, *RoA*, *Risk Mgmt*, *Leverage*, *NPL-to-TL*, *LCR*, *Maturity Gap*) are included, but their coefficient estimates are omitted for brevity. Standard errors are clustered at the BHC and quarter levels. Variables definitions are reported in Table 1, Panel A. T-statistics are presented in parentheses.

	Systemic Risk (PC)			
	(1)	(2)	(3)	(4)
Ln(OpLoss)	0.070***	0.031**	0.062***	−0.026
	(4.780)	(2.553)	(7.617)	(−1.159)
Financial Crisis	0.134***	0.123***		
	(3.398)	(3.387)		
Financial Crisis * Ln(OpLoss)		0.084***		
		(3.330)		
ME Index			0.006***	0.006***
			(6.196)	(5.510)
ME Index * Ln(OpLoss)				0.004***
				(3.223)
BHC Controls	Yes	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes	Yes
N	1,070	1,070	1,070	1,070
Adj R^2	0.569	0.576	0.645	0.668

*, **, and *** denote significance at the 10%, 5%, and 1% level

Table 10: **Instrumental Variables**

This table reports coefficients from instrumental variable regressions of systemic risk on operational losses, and control variables. The estimation sample comprises an unbalanced panel of 1,070 quarterly observations of 26 large bank holding companies over the period [2002:Q1-2016:Q4] for which requisite data are available. *Systemic Risk (PC)* measures BHC systemic risk and is defined as the first principal component of *SRISK*, $\Delta CoVar$, and *SES*. *Ln(OpLoss)* is a natural log transformation of operational dollar losses incurred by a BHC over a given calendar quarter. *Cost Efficiency* measures a BHC's cost efficiency. *Ln(OpRisk MR(I)A)* is a natural log transformation of the number of outstanding operational risk supervisory examination matters at a BHC as of a given quarter. *Ln(Mgmt MR(I)A)* is a natural log transformation of the number of outstanding operational risk supervisory examination matters, specifically regarding management practices, at a BHC as of a given quarter. *Ln(IndOpLoss)* is a natural log transformation of the asset-weighted average of operational dollar losses for all the institutions in our sample, with the exclusion of the one of interest, over a calendar quarter. Panel A reports the first stage regressions of operational losses on instrumental variables and control variables. Panel B reports the second stage regressions of systemic risk on instrumented operational losses. In both panels, Columns (1)-(3) include time (year and seasonal) fixed effects, but not BHC fixed effects. In both panels, Column (4) includes BHC fixed effects, but not time fixed effects. Standard errors are clustered at the BHC and quarter levels in all specifications. Variables definitions are reported in Table 1, Panel A. T-statistics are presented in parentheses.

Panel A: First Stage

	Ln(OpLoss)			
	(1)	(2)	(3)	(4)
Cost Efficiency	-0.084^{**}			
	(-2.223)			
Ln(OpRisk MR(I)A)		0.034^{***}		
		(2.946)		
Ln(Mgmt MR(I)A)			0.025^{*}	
			(1.932)	
Ln(IndOpLoss)				0.095^{***}
				(3.013)
Ln(Size)	0.126^{***}	0.121^{***}	0.125^{***}	0.109^{***}
	(13.556)	(12.636)	(13.280)	(3.101)
M-to-B	-0.019	-0.008	-0.008	0.025
	(-0.819)	(-0.347)	(-0.363)	(0.971)
NII-to-II	-0.046^{***}	-0.062^{***}	-0.057^{***}	-0.046^{**}
	(-3.554)	(-4.795)	(-4.458)	(-1.982)
RoA	-0.023^{**}	-0.023^{**}	-0.022^{**}	-0.015
	(-2.314)	(-2.336)	(-2.184)	(-1.416)
Risk Mgmt	-0.234^{***}	-0.221^{***}	-0.221^{***}	-0.295^{***}
	(-3.197)	(-3.051)	(-3.041)	(-3.842)
Leverage	0.012^{**}	0.012^{**}	0.012^{**}	0.010
	(2.326)	(2.350)	(2.329)	(1.465)
NPL-to-TL	0.847	0.999	0.947	1.469^{**}
	(1.122)	(1.335)	(1.260)	(2.098)
LCR	0.018	0.025^{**}	0.025^{**}	-0.018
	(1.356)	(2.147)	(2.116)	(-1.175)
Maturity Gap	0.130^{*}	0.089	0.090	-0.073
	(1.704)	(1.187)	(1.198)	(-0.626)
Time FE	Yes	Yes	Yes	No
BHC FE	No	No	No	Yes
N	1,065	1,070	1,070	1,070
Adj R^2	0.345	0.347	0.344	0.359
F-Statistic	21.743	22.005	21.719	21.752

*, **, and *** denote significance at the 10%, 5%, and 1% level

Panel B: Second Stage

	Systemic Risk (PC)			
	(1)	(2)	(3)	(4)
Ln(OpLoss)	0.289*	0.670***	0.868***	1.560*
	(1.666)	(5.162)	(4.382)	(1.888)
Ln(Size)	−0.016	−0.066***	−0.092***	−0.125
	(−0.740)	(−3.826)	(−3.526)	(−1.325)
M-to-B	−0.054***	−0.047***	−0.044***	−0.105**
	(−3.395)	(−5.222)	(−4.685)	(−2.293)
NII-to-II	0.001	0.020**	0.030***	0.040
	(0.072)	(2.546)	(2.762)	(0.894)
RoA	−0.011*	−0.003	0.002	−0.015
	(−1.649)	(−0.548)	(0.314)	(−0.713)
Risk Mgmt	0.204	0.285***	0.327***	0.579
	(1.110)	(7.280)	(6.469)	(1.493)
Leverage	0.010**	0.006**	0.003	−0.011
	(2.242)	(2.305)	(1.086)	(−0.713)
NPL-to-TL	−0.381	−0.614**	−0.766**	−1.749
	(−0.346)	(−2.038)	(−2.369)	(−1.173)
LCR	0.004	−0.007	−0.012*	0.025
	(0.543)	(−1.234)	(−1.760)	(1.102)
Maturity Gap	−0.003	−0.043	−0.063*	−0.093
	(−0.073)	(−1.352)	(−1.788)	(−0.524)
Time FE	Yes	Yes	Yes	No
BHC FE	No	No	No	Yes
N	1,065	1,070	1,070	1,070
Adj R^2	0.549	0.557	0.554	0.527

*, **, and *** denote significance at the 10%, 5%, and 1% level