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

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Abstract

While operational risk is often perceived as largely idiosyncratic and with limited systemic implications, this study documents a significant positive relation between operational risk and systemic risk contribution at large U.S. bank holding companies (BHCs). The relation is driven by high-severity operational risk events. It is more pronounced for systemically important BHCs, closer-to-distress BHCs, and during adverse macroeconomic conditions. We additionally document the specific business lines and types of operational risk that contribute to systemic risk. Overall, our findings provide evidence that operational risk can have consequences spreading beyond specific institutions and pose a threat to overall financial system stability.

Keywords: Banking; Systemic Risk; Operational Risk

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

1. Introduction

Systemic risk is an important and policy-relevant topic. Widespread failures and losses of financial institutions can impose a significant externality on the rest of the economy and household wealth. For example, Atkinson et al. (2013) estimates that 40% to 90% of annual U.S. GDP, or about \$6 trillion to \$14 trillion, was foregone due to the 2008 global financial crisis. Concurrently, U.S. households lost additional \$16 trillion or 24% of their net worth.[1]

In the banking sector, systemic risk is usually thought of as stemming from interlinkages and interdependencies across institutions, or herding in correlated risks. The impending failure of a "super" bank threatens to impose significant losses on other institutions. Interconnections among banking organizations increase losses, and failures that occur simultaneously because banks take correlated risks have magnified effects on the financial system. The possibility of contagious runs on institutions further compound systemic problems (e.g., Goldstein and Pauzner (2004); Acharya and Yorulmazer (2008); Acharya (2009); and Bebchuck and Goldstein (2011)). In contrast, this paper investigates a different and somewhat unlikely 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)). 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, respectively, in separate incidents of unauthorized trading (Clark and Jolly (2008), Silver-Greenberg (2012)). Large banks and hedge fund investors lost multiple billions to Bernard Madoff's Ponzi scheme (Efrati et al. (2008)). Most recently, Wells Fargo experienced a number of costly operational failures resulting in a \$1 billion fine from the Consumer Financial Protection Bureau (CFPB)

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

and the Office of the Comptroller of the Currency (OCC) for mortgage and insurance abuses (Wattles et al. (2018)). While these cases of operational risk events are dramatic and well-documented, it is unknown if they also have systemic risk consequences whereby they could trigger severe instability or the collapse of the financial industry. In fact, operational risk is oftentimes perceived as a largely idiosyncratic and company-specific risk (e.g., Lopez (2002), Chernobai et al. (2012)) with limited systemic implications.

This paper addresses the fundamental empirical question of whether losses from operational risk rise to the level of a significant threat to the financial system. To do so, we employ a number of recently developed measures of systemic risk such as ΔCoVaR (Adrian and Brunnermeier (2016)), SRISK (Acharya et al. (2012); Brownlees and Engle (2017)), and SES (Acharya et al. (2017)). In addition, we 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 data at the individual company level that is significantly richer and more comprehensive.

We find that – controlling for previously established determinants of systemic risk and other types of risks including credit, interest rate, leverage, and liquidity risks – operational risk at large U.S. BHCs is significantly positively related to systemic risk. This relation is robust to alternative estimation approaches including instrumental variable (IV) regressions, which mitigate concerns about the potentially endogenous relation between the two risks. A plausible 100% increase of quarterly operational losses at a BHC is associated with a 0.48 standard deviations increase in that BHC's contribution to systemic risk. When we drill down, we find that operational risk tail events dominate non-tail 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 only operational losses in particular event types and business lines significantly contribute to systemic risk.

To better understand the nature of the association between systemic and operational risks, and identify mechanisms through which operational losses have amplified systemic risk effects, we additionally explore potential interactions of operational risk with firm characteristics and the state of the macroeconomic environment. First, we show that operational risk has stronger effects on systemic risk when it affects systemically important institutions and institutions that are closer to distress. Second, we show that operational risk has more pronounced systemic risk effects in adverse macroeconomic conditions, when BHCs are in a weaker financial standing and cross-bank risk transmission is magnified.

Overall, our results suggest that operational risk contributes to systemic risk, whereby the effects could occur through at least two channels. The first channel is through the reduction of market value and the increase of leverage of the bank holding company affected by the operational risk event. The second channel is through spill-over effects, and specifically, the reduction in market value of related institutions. In this paper, we provide evidence that operational risk impacts systemic risk contributions through both of these channels.

Our study contributes to two research streams. It is the first to emphasize the systemic implications of operational risk, and thus extends the literature on operational risk at financial institutions. By linking operational losses to systemic risk, our study also contributes to the broader debate on the nature of systemic risk and its determinants. Our findings also have potential policy implications. The Basel Accord capital rules, and specifically the Standardized Measurement Approach (SMA) in Basel III, treat all bank business lines equally. This study can help to better inform the weights placed on each of these categories in the calculation of operational risk-based capital since different business lines contribute differently to systemic risk. Consistent with the SMA, our findings also suggest that a convex weighting of large operational risk events in the estimation of capital requirements for BHCs are appropriate. Specifically, firms exposed to the large operational risks should be subject to 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 and develops our hypotheses. 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

Relative to the coverage of other types of bank risks – such as credit risk, leverage risk, interest rate risk, and liquidity risk – operational risk has received much less attention in the academic literature. 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 operational risk impact on market values of U.S. banks. Dahen and Dionne (2010) and Abdymomunov and Curti (2015) 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 (2017) specifically 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. (2017) study the association between BHC operational losses and the U.S. macroeconomy. Finally, Gillet et al. (2010) investigate the relation between operational risk and reputation in the banking system.

To this point, 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 doing so, we provide an in-depth account of the specific mechanisms through which operational risk can affect systemic risk, and document important specific firm-level and macroeconomic 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. Berger et al. (2017) and Sedunov (2018) 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. (2017) 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 seemingly idiosyncratic and organization-specific risk exposures such as operational losses can have implications for financial system stability and can contribute to systemic risk. We document the specific types of operational losses and the responsible business lines that drive this relation. We also identify important amplifying channels for the systemic effects of operational risk, which can 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 crisis posed by Carey et al. (2012).

3. Hypothesis Development

This section outlines the channels through which operational risk of large BHCs may affect systemic risk. There are two main non-mutually exclusive and potentially concurrent groups of channels or mechanisms. The first group of channels work by directly reducing the market value of the BHC experiencing the operational losses, which increases that BHC's market leverage. The second set of channels operate through financial network spill-overs, in which the market value of other financial institutions that are related to the BHC affected by operational risk are impacted. The potential effects associated with the two groups of channels, further discussed in Sections 3.1 and 3.2, lead to our main hypothesis tested in this study:

Hypothesis 1A: *Operational risk increases U.S. bank holding company systemic risk contributions, ceteris paribus.*

Hypothesis 1B: *Operational risk does not affect U.S. bank holding company systemic risk contributions, ceteris paribus.*

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 counter-parties 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.

The second channel through which BHC market value may be decreased 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 has been caught engaging in 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.

The third channel linking operational risk with a lower market value of equity is through 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. Spill-over Channels

In addition, there are at least three channels through which operational risk of a BHC may spill over and affect the market values of financial institutions that are related to that BHC. First, investors may fear that similar operational difficulties are present but still 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 counter-parties 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.

On the other hand, it is also possible that some BHCs may gain from the operational loss 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. This last channel is directionally different from all previously discussed ones: it counteracts and may potentially offset other direct and spill-over channels, and thus neutralize adverse operational risk consequences on systemic risk.

4. Data Sample and Variable Definitions

4.1. Operational Risk

4.1.1. Loss Data

This study uses supervisory data of operational risk 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 with consolidated assets of $50 billion or more, that participated in the 2017 Dodd-Frank Act Stress Test (DFAST) program.[2] The data provide information points such as loss amounts, loss dates, loss classifications, and loss descriptions.

[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.

Consistent with Basel II definitions, losses are categorized into seven event types. The 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 A 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 most significant event type is CPBP, which accounts for 78.3% of losses or $216.3 billion. The second most significant event type by share of total losses is EDPM; it accounts 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 can also be 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 B 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 most significant business line generating operational losses is RB, which accounts for 47.2% of losses or $130.6 billion. The second most significant business line is CO, which accounts for 18.3% of losses or $50.6 billion. CF and TS also contribute significantly to total losses, and account for 11.0% and 13.0%, 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 (2017)) 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].[3] Our data is substantially richer than operational loss data sets offered by private vendors. 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.[4] To examine the relationship between operational risk and systemic risk, our

[3]The original operational loss data contains losses from 38 institutions. Due to the availability of data requisite for the calculations of systemic risk measures described in Section 4.2, the number of institutions in our sample drops 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. The 26 institutions in our sample account for 73.7% of the total consolidated assets of all U.S. bank holding companies and U.S intermediate holding companies with assets of $1 billion or more as of 2016:Q4.

[4]From a reporting consistency perspective, we note that the accounting date is the most consistently used date across banks. This reflects the fact that banking organizations follow the same accounting standards in determining the financial impact of operational loss events on the institutions' financial statements. In contrast, occurrence and discovery dates are less uniformly reported across institutions due to variations in

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

In this section we describe the various measures of operational risk that we relate to BHC systemic risk contribution. 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. (2017) and take a natural logarithm transformation of quarterly loss to account for its heavy-tailed distribution. Heavy tailed distributions of loss severities are also well-established for individual operational risk events (e.g., Chernobai and Rachev (2006), Jobst (2007)). Figure 3 provides confirmatory evidence and shows that 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 "non-tail" events in a quarter. A loss is defined 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 the quantiles are considered non-tail events. Second, following the same definition of tail and non-tail events, we sum all the losses defined as tail events in a quarter to obtain the aggregate amount of tail dollar losses for each BHC. Using the same procedure, we evaluate the aggregate amount of non-tail losses

the institutions' internal data management systems as well as uncertainties about when loss events actually occurred or were discovered (Abdymomunov and Mihov (2017)). Data checks, data exams and horizontal reviews across banks led by the Federal Reserve System have mitigated known differences.

for each BHC and, as per our main measure, we take the natural logarithm transformation to account for the heavy tailed nature of operational losses.

Table 2, Panel A presents descriptive statistics. On average, BHCs lose \$230 million per quarter to operational risk. Furthermore, the standard deviation of the quarterly loss is high relative to the mean, indicating substantial time-series and cross-sectional variation of operational losses. The 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 primary dependent variable, *Systemic Risk (PC)*, is the first principal component of three systemic risk contribution measures: SES, $SRISK$, and $\Delta CoVaR$. The first principal component is evaluated using a correlation matrix, instead of a variance-covariance matrix, to account for the different scale of the individual systemic risk measures. Table 1, Panel C presents the definition of the systemic risk contribution measures, discussed in detail next. 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 (2012), 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 (2012), 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 our 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: Marginal Expected Shortfall (MES) and Leverage (LVG). 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:

$$MES_{i,t} = -\frac{1}{\#days} \sum_{\tau=1}^{\tau^*} R_{i,\tau} \tag{7}$$

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.

LVG is estimated using the traditional approximation using book liabilities and market equity:

$$LVG_{i,t} = \frac{(Book\ Assets_{i,t} - Book\ Equity_{i,t}) + Market\ Equity_{i,t}}{Market\ Equity_{i,t}} \tag{8}$$

Acharya et al. (2017) use MES and LVG 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 MES and LVG from prior to the crisis. From the regression output, they estimate the following equation:

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

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

4.3. Control Variables

In addition to operational risk metrics, all our multivariate regression analyses also include a number of BHC-level control variables. They can be classified in two broad groups: characteristics that are relevant for systemic risk contribution of BHCs and proxies for BHC exposures to significant risks other than operational risk.

With regards to the first group of variables, we include five controls. To account for the business volume of a bank, we include bank size (*Ln(Size)*). To account for firm value, growth opportunities and profitability, we include the market-to-book ratio (*M-to-B*) and return on assets (*RoA*).[5] 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*).[6]

In all our analyses, we also control for BHCs' exposure to other important risks that these institutions face. Specifically, we focus on controlling for the following four risks: financial, credit, liquidity and interest rate risks. To control for financial risk we include BHC leverage (*Leverage*). To control for credit risk, we include the ratio of non-performing loans over total loans (*NPL-to-TL*). To control for liquidity risk, we include a BHC's liquidity coverage ratio (*LCR*). To control for interest rate risk, we include a measure of the mismatch between short-term repricable assets and short-term repricable liabilities (*Maturity Gap*).

4.4. Pairwise Correlations

As a first step to uncovering the relation between systemic risk and operational risk, we start with some visual evidence. Figure 4 plots cross-sectional averages of BHC systemic risk contribution and operational dollar losses through time. One can note a general alignment in the spikes of *Systemic Risk (PC)* and *OpLoss* with the most severe operational losses surfacing in periods of financial stress, when systemic risk is also elevated (e.g., the global financial crisis).[7]

[Insert Figure 4 about here]

As a second step, we employ simple correlation analysis. Table 3, Panel A reports pairwise

[5]To avoid possible mechanical effects, *M-to-B* and *RoA* are estimated 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.

[6]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.

[7]Appendix A examines the potential lagged effects of operational risk on systemic risk. We find evidence that operational risk not only affects systemic risk contemporaneously, but also has lasting lagged effects.

correlation coefficients between *Systemic Risk (PC)*, *SRISK*, ΔCoVaR, *SES*, *MES*, *LVG* and *Ln(OpLoss)*. Several observations can be made.

[Insert Table 3 about here]

First, the correlation between the *Systemic Risk (PC)* and the individual systemic risk contribution measures that comprise the variable is high – in excess of 75% in all cases. Second, the correlation between *Systemic Risk (PC)* and *Ln(OpLoss)* is 32%, indicating that BHCs which contribute more to systemic risk suffer higher operational losses. Third, the correlation between the individual systemic risk contribution measures and *Ln(OpLoss)* is positive in all cases, indicating that the relation is consistent across different measures of systemic risk. All correlation coefficients are significant at the 1% level.

Table 3, Panel B provides additional information on the correlation between *Systemic Risk (PC)* and different metrics of operational risk. *Systemic Risk (PC)* is significantly positively correlated with all measures of operational risk.

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. In equation form, we have:

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

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 bank in a given quarter. $Ctrls$ represents a vector of control variables previously 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 – *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, which suggests 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 0.14 standard deviations increase in *Systemic Risk (PC)* ($= (0.067 * 0.294)/0.141$). Alternatively, 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 Columns (4) and (5), we also separately examine the two components of SES – LVG and MES – in order to distinguish between the 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) vis-á-vis spill-overs to the market values of related institutions (the "MES" channel). $Ln(OpLoss)$ is significantly positively related to both LVG and MES. We interpret this as evidence supporting both groups of channels.[8]

5.2. Operational Risk Event Types and Business Lines

Operational risk is an amalgamation of various types of subcomponent risks (Chernobai et al. (2012)). In the previous section, we documented a significant relation between BHC systemic risk contribution and operational losses after aggregating losses across event types and business lines. Such aggregation ignores the potential heterogeneity of operational risk in the different categories and essentially embodies the assumption that operational risk from all event types and business lines have similar systemic risk implications.

In this section, 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. 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, empirical (event type and business line) drivers of the previously documented association between systemic risk contribution and operational losses. 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 at conventional levels in three cases – for Internal Fraud in Column (1); for Clients, Products and Business Practices in Column (4); and for

[8] Section 3.2 discussed three potential channels for the spill-over of operational risk to the market values of related institutions. Two of those channels suggested a negative spill-over (i.e. related institutions' market values would decrease) and one channel suggested a positive spill-over (i.e. related institutions' market values would increase). Our results thus suggest that the "negative spill-over" channels dominate as operational losses and MES are positively related.

Execution, Delivery, and Process Management in Column (7). Column (8) further shows that operational losses from the three event types remain significantly positively correlated with systemic risk when included in the same regression specification. As presented in Table 1, Panel A, 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 at conventional levels in two specifications – for Retail Banking in Column (3); and for Corporate Other 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 B, 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." Figure 2 shows that RB and CO are the two operational risk business lines that account for the largest portion of losses in our sample – 47% and 18%, respectively, of total operational losses.

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 Operational Risk

In the previous sections, we documented a positive association between BHC systemic risk contribution and operational losses. In this section, we examine whether such results are particularly driven by tail operational risk. The distinction between the average levels of operational risk at an organization and tail risk is important. Higher but stable operational losses have adverse implications for banking organizations' profitability and performance. However, such losses are easy to anticipate and reserve for, and therefore should not be a first-order concern in terms of an organization's soundness and stability. In contrast, tail risk is difficult to anticipate and reserve for, oftentimes resulting in a serious unexpected shock to a financial institution, and is more relevant for banking organizations' risk of failure, and thus contribution to systemic risk. Overall, tail events should be more likely to destabilize a financial intermediary, and subsequently the financial system through cascading effects, than non-tail events.

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

[Insert Table 6 about here]

Table 6, Panel A presents results for the frequency-based tail and non-tail 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 non-tail events. Lastly, Columns (3), (6) and (9) show that the results change only marginally when the frequency of tail and non-tail losses are pulled together in the same specification. The economic significance of experiencing a tail operational risk event is relatively large. For example, based on the regression specification in Column (3), 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 1.894 (=0.267/0.141) standard deviations.

Table 6, Panel B presents results for dollar-based tail and non-tail 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 (7) 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. Lastly, Columns (3), (6) and (9) show that the results are very similar when the amounts of tail and non-tail losses are pulled together 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 system that their failure could cause traumatic damage, both to financial markets and the larger economy. These institutions are often referred to as "Global Systemically Important Banks" or GSIBs. A number of institutions in our sample are designated as GSIBs. In view 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. Naturally, one would expect that operational risks at systemically important banks should have a more pronounced effect and contribute more to systemic risk.

To investigate this amplifying channel, we use a GSIB score methodology developed by the Basel Committee on Banking Supervision, and subsequently adopted in the U.S., for designating global banks as systemically important.[9] The GSIB score aggregates 12 indicators across several conceptual categories: the size of the financial institutions, their interconnectedness, lack of readily available substitutes for the services they provide, their complexity, and their global (cross-jurisdictional) activities. Firms having a score above a specified threshold are designated as GSIBs. These include the following 8 institutions (all of which are in our sample): JPMorgan Chase, Citigroup, Bank of America, Goldman Sachs, Morgan Stanley, Wells Fargo, Bank of New York Mellon, and State Street (Federal Reserve System (2015)).

In our analysis, we use both a binary indicator identifying the GSIBs in our sample (*GSIB Indicator*) as well as a continuous score measuring the systemic importance of BHCs (*GSIB Score*). *GSIB Score* is as of 2016:Q4, the last quarter in our sample, and is constructed based on information contained in Form FR Y-15 following the methodology described in Federal Reserve System (2015).[10] We then estimate models similar to Eq. (10), but include interaction terms between *Ln(OpLoss)* and the measures of BHC systemic importance, *GSIB*

[9] The Federal Reserve System implemented a GSIB 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 GSIB score.

[10] Data collected by Form FR Y-15 are only available post 2013:Q4. For simplicity, we use GSIB measurements as of the last period in our sample, 2016:Q4. Our results are robust to using earlier periods.

Indicator and *GSIB Score*. Due to the inclusion of BHC fixed effects, we are unable to identify the coefficients on the time-invariant *GSIB Indicator* and *GSIB Score*. Table 7 presents the results.

[Insert Table 7 about here]

Both Columns (1) and (2) show more pronounced systemic effects of operational risk when operational losses impact systemically important BHCs. The coefficients on *GSIB Indicator* Ln(OpLoss)* and *GSIB Score*Ln(OpLoss)* are both positive and significant at least at the 5% level. 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 banks. 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 evaluated over the prior 12 quarters. For presentation purposes, we linearly transform the variable 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, *Inv Z-Score* and *PD* are lagged 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]

Column (1) suggests that *Inv Z-Score* is not significantly related to systemic risk contribution. Column (3), on the other hand, confirms 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. 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. Macroeconomic Environment

Financial firms' contributions to systemic risk in adverse macroeconomic conditions are potentially magnified by their interconnections and correlated risk taking. Further, operational losses are more likely to surface during periods of economic stress (Abdymomunov et al. (2017)). In this section, we examine whether macroeconomic 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 is equals to 1 for quarters during the period [2007:Q3-2009:Q4], and 0 otherwise. Additionally, we adopt the macroeconomic measure used in Abdymomunov et al. (2017), *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. For presentational purposes, we linearly transform the index so that higher values denote worse macroeconomic conditions.

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 the macroeconomic variables. Table 9 presents the results.

[Insert Table 9 about here]

Columns (1) and (3) suggest that BHC systemic risk contribution is higher during adverse macroeconomic 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 especially when the macroeconomic environment deteriorates. 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 macroeconomic adversity and systemic vulnerability.

6. Robustness Checks: Instrumental Variable Regressions

Two identification concerns may confound the interpretation of our results. First, it could be that there is reverse causation, so that 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. To address this issue, we estimate instrumental variable regressions. We use firm-specific variables as instruments that predicate BHC operational risk exposures, but should have limited effect on the systemic risk contribution of a bank conditional on controls. These include BHC cost efficiency and outstanding operational risk supervisory examination findings. Second, it is possible that our analyses are not capturing the relation between systemic risk contribution and operational risk but rather a relation between systemic risk contribution and an uncontrolled for BHC-specific risk factor that is correlated with operational losses. To address this issue, we again estimate IV 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 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 stripe such as operational risk become systemic in nature? The evidence in this study suggests that it can. We find a significant positive relation between operational losses at large BHCs in the United States and the systemic risk contributions of these BHCs. The relation is driven by high-severity operational risk tail events, and is more pronounced for systemically important BHCs, for BHCs that are closer to distress and during adverse macroeconomic environment. 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.

This study answers an important open question in the literature. While prior research on operational risk and systemic risk has mostly focused on describing and understanding their general nature and determinants, the possible relation between the two types of risk has not been explored. We fill this void by investigating the systemic implications of operational losses. Our research also has clear policy implications. The Standardized Measurement Approach 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 should be relatively smaller. Our findings also suggest a convex weighting of large past operational losses be applied in the estimation of capital requirements for banks, since high-severity tail operational risks contribute proportionally more to systemic risk. These policy issues may take on more importance in the future as the application of the Standardized Measurement Approach in the U.S. is further clarified and finalized.

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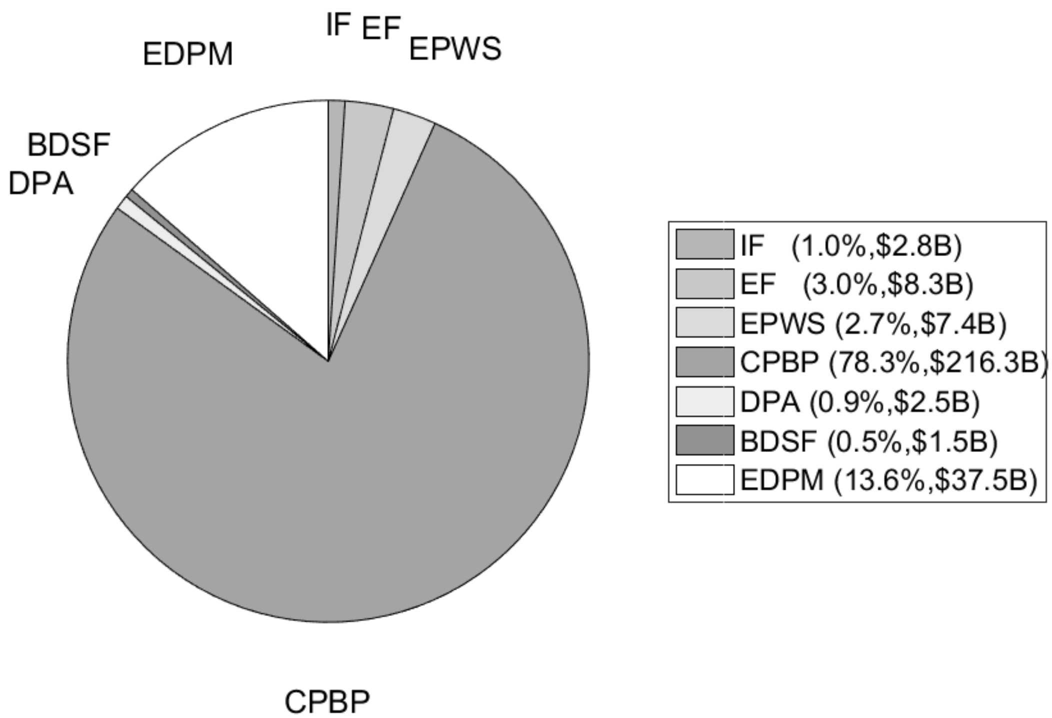

Figure 1: **Operational Losses by Event Type**
This figure presents the allocation of operational loss amounts (percentage of total losses and U.S. dollar loss amounts in billions) by event type. The sample includes 290,872 operational loss events incurred by 26 large U.S. bank holding companies over 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 A.

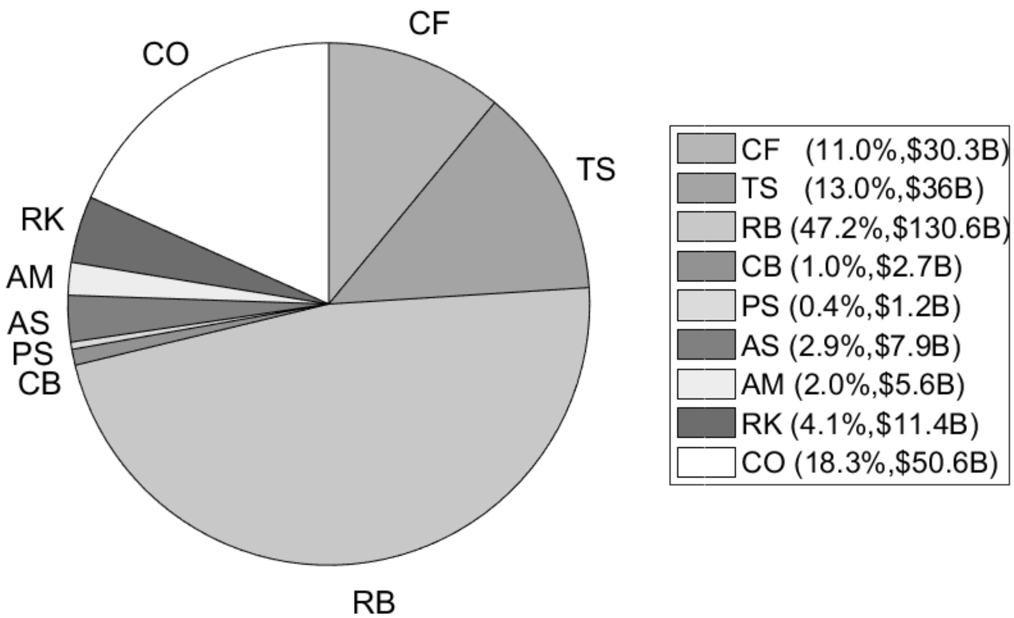

Figure 2: **Operational Losses by Business Line**
This figure presents the allocation of operational loss amounts (percentage of total losses and U.S. dollar loss amounts in billions) by business line. The sample includes 290,872 operational loss events incurred by 26 large U.S. bank holding companies 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 B.

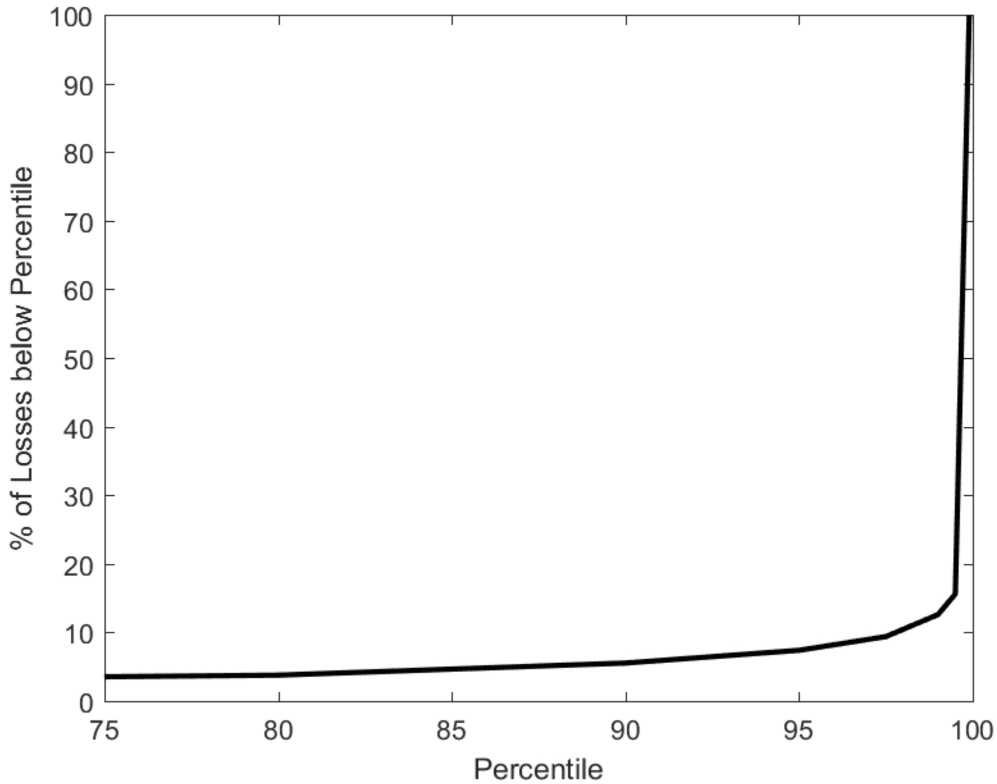

Figure 3: **The Heavy Tails of Operational Losses**
This figure presents the percentage of total operational losses with severities below a given percentile of the unconditional distribution of loss severities. The sample includes 290,872 operational loss events incurred by 26 large bank holding companies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

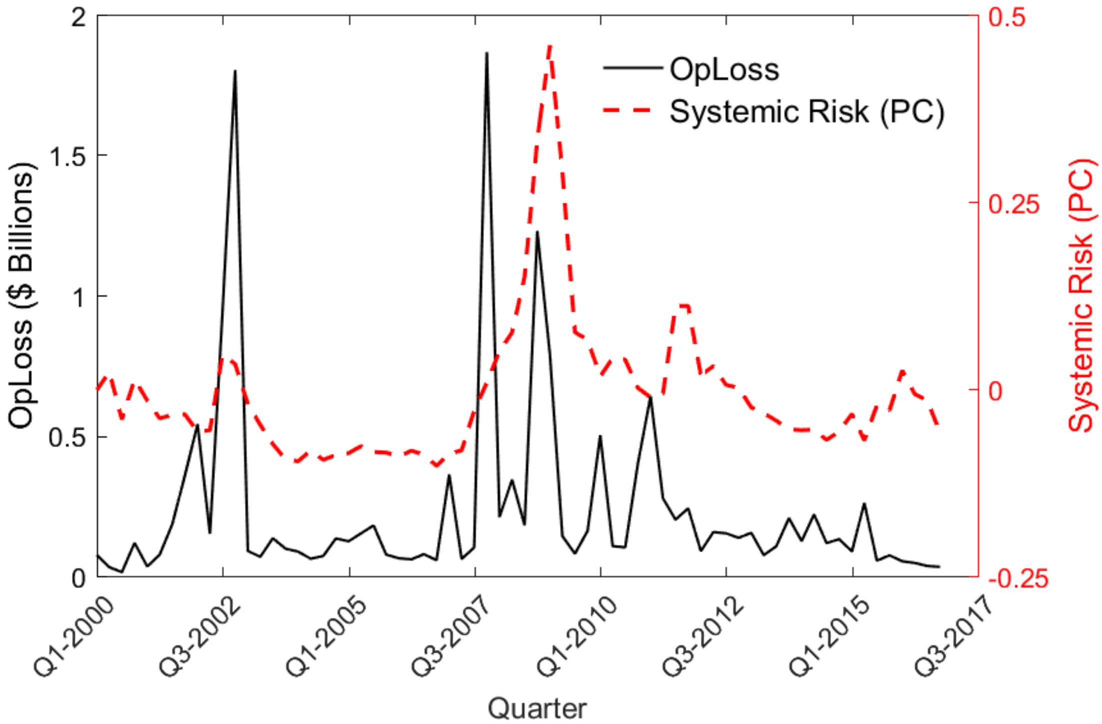

Figure 4: **Operational Losses and Systemic Risk through Time**
This figure presents average operational losses, *OpLoss*, and systemic risk, *Systemic Risk (PC)*, through time. The sample includes 1,070 quarterly observations of 26 large bank holding companies over the period [2002:Q1-2016:Q4] for which requisite data are available. Variable definitions are provided in Table 1, Panel C.

Table 1: **Definitions**

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

Panel A: 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 B: 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.

Panel C: Variables

Dependent Variables: *Systemic Risk Measures*	
SES	The systemic expected shortfall of a BHC, measuring the BHC's propensity to be undercapitalized when the system as a whole is undercapitalized (Acharya et al. (2017)).
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)).
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)*.
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^{th}, 99.5^{th} or 99.9^{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)*.

Table Continued...

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.
GSIB 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 GSIBs: JPMorgan Chase, Citigroup, Bank of America, Goldman Sachs, Morgan Stanley, Wells Fargo, Bank of New York Mellon, and State Street.
GSIB 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 has been linearly transformed so that higher values denote higher probability of distress.
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.

Table Continued...	
ME	U.S. macroeconomic 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 macroeconomic 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).*

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 C.

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
GSIB Indicator	1,070	0.385	0.487	0.000	0.000	1.000
GSIB 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 pairwise 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 C.

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 C. 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. Event type definitions are reported in Table 1, Panel A. Business line definitions are reported in Table 1, Panel B. Variables 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 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 C. 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. *GSIB Indicator* is an indicator variable equal to 1 if a BHC is deemed systemically important by the Federal Reserve, 0 otherwise. *GSIB 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 C. T-statistics are presented in parentheses.

	Systemic Risk (PC)	
	(1)	(2)
Ln(OpLoss)	−0.080	−0.007
	(−1.386)	(−0.196)
GSIB Indicator * Ln(OpLoss)	0.150***	
	(2.705)	
GSIB 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 has been linearly transformed 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 C. 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 Macroeconomic Environment**

This table reports coefficients from panel regressions of systemic risk on operational losses, the macroeconomic 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* is a continuous measure of the U.S. macroeconomic environment. Higher values denote worse macroeconomic 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 C. 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 C. 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

Appendix A: Lagged Effects of Operational Risk on Systemic Risk

To examine the relation between operational and systemic risk, our analyses have linked the quarter when operational losses financially impact BHCs to the quarter when systemic risk of BHCs is measured. In this way, while we are better aligning the financial impact of operational risk with our market equity-based measures of systemic risk, the estimated effect of operational losses on systemic risk omits possible lagged effects of operational risk (e.g., due to the noise in or slow diffusion of information across market participants).

To more formally investigate the existence of lagged effects, we calculate three additional measures of lagged operational losses. Specifically, $Ln(OpLoss_{[t-1,t-4]})$, $Ln(OpLoss_{[t-5,t-8]})$ and $Ln(OpLoss_{[t-9,t-12]})$ measure log-transformed cumulative operational dollar losses that impact a BHC over calendar quarters $[t-1, t-4]$, $[t-5, t-8]$, and $[t-9, t-12]$, respectively, relative to the quarter (t) when *Systemic Risk (PC)* is measured. We then test whether these lagged measures of operational risk are significantly related to the systemic risk of BHCs in models similar to Eq. (10). Table A1 presents the results.

[Insert Table A1 about here]

For convenience, Column (1) replicates our main model specification from Table 4, Panel A, Column (4), regressing systemic risk on contemporaneously measured quarterly operational losses (*Ln(OpLoss)*). Columns (2)-(4) regress systemic risk on lagged operational losses. Notably, the coefficients on $Ln(OpLoss_{[t-1,t-4]})$ and $Ln(OpLoss_{[t-5,t-8]})$ in Columns (2) and (3) are significantly positively related to systemic risk at least at the 5% level. In contrast, while positive, the coefficient on $Ln(OpLoss_{[t-9,t-12]})$ in Column (4) is insignificant at conventional levels. Column (5) confirms these results when we include all four measures of operational losses in the same specification. The results here suggest that operational risk indeed has significant lagged effect on systemic risk.

Table A1: **Lagged Effects of Operational Risk on Systemic Risk**

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 the calendar quarter (t) when *Systemic Risk (PC)* is measured. $Ln(OpLoss_{[t-1,t-4]})$ is a natural log transformation of cumulative operational dollar losses incurred by a BHC over calendar quarters $[t-1, t-4]$ relative to the quarter (t) when *Systemic Risk (PC)* is measured. $Ln(OpLoss_{[t-5,t-8]})$ is a natural log transformation of cumulative operational dollar losses incurred by a BHC over calendar quarters $[t-5, t-8]$ relative to the quarter (t) when *Systemic Risk (PC)* is measured. $Ln(OpLoss_{[t-9,t-12]})$ is a natural log transformation of cumulative operational dollar losses incurred by a BHC over calendar quarters $[t-9, t-12]$ relative to the quarter (t) when *Systemic Risk (PC)* is measured. 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 C. T-statistics are presented in parentheses.

	Systemic Risk (PC)				
	(1)	(2)	(3)	(4)	(5)
Ln(OpLoss)	0.067***				0.059***
	(4.293)				(3.812)
Ln($OpLoss_{[t-1,t-4]}$)		0.074***			0.067**
		(3.774)			(2.380)
Ln($OpLoss_{[t-5,t-8]}$)			0.043**		0.047***
			(2.340)		(4.083)
Ln($OpLoss_{[t-9,t-12]}$)				0.004	0.008
				(0.126)	(0.397)
BHC Controls	Yes	Yes	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
N	1,070	1,022	956	876	876
Adj R^2	0.599	0.616	0.610	0.623	0.667

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