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Operational Loss Recoveries and the Macroeconomic Environment: Evidence from the U.S. Banking Sector*

W. Scott Frame†, Nika Lazaryan‡, Ping McLemore§ and Atanas Mihov±

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Abstract

Using supervisory data from large U.S. bank holding companies (BHCs), we document that operational loss recovery rates decrease in macroeconomic downturns. This procyclical relationship varies by business lines and loss event types and is robust to alternative data aggregations, macroeconomic measurement horizons, and estimation methodologies. Further analysis shows that resource constraints faced by BHC risk management functions are a plausible explanation for these patterns. Our findings offer new evidence on how economic shocks transmit to banking industry losses with implications for risk management and supervision.

Keywords: Operational risk, operational losses, loss recoveries, macroeconomic environment, banking sector

JEL Classifications: G21, G28, G29

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† W. Scott Frame, Federal Reserve Bank of Dallas, scott.frame@dal.frb.org.

‡ Nika Lazaryan, Federal Reserve Bank of Richmond, nika.lazaryan@rich.frb.org.

§ Ping McLemore, Federal Reserve Bank of Richmond, ping.mclemore@dal.frb.org.

± Atanas Mihov, University of Kansas, amihov@ku.edu.

I. Introduction

Operational risk at large banking organizations has garnered increased attention from risk managers and regulators in the wake of the global financial crisis and subsequent headline-grabbing losses.[1] In one example, the failure of the auction rate securities (ARS) market in 2008 led to massive operational losses for many banks that marketed and sold these securities.[2] In a different example, the investment arms of several large foreign banking organizations lost hundreds of millions of dollars to Bernard Madoff's Ponzi scheme discovered in 2008.[3]

Systematic regulatory data collection has revealed that operational risk is more prevalent and economically important than previously understood. Curti et al. (2021) document that operational losses exceeded 25% of net income for the largest U.S bank holding companies (BHCs) between 2001 and 2016; and Afonso et al. (2019) find that operational risk accounted for 30% of average regulatory capital for these same institutions as of 2016:Q4. Research has also found that, like credit losses, gross operational losses are countercyclical (Abdymomunov et al., 2020). The heavy-tailed nature of operational loss distributions poses unique challenges to BHC capital management and solvency, and may even raise financial stability concerns (e.g., Berger et al., 2022).

This paper provides novel evidence about operational loss recoveries using comprehensive supervisory data reported by large U.S. bank holding companies (BHCs) to the Federal Reserve.[4] While the data is limited to the 35 largest BHCs, these institutions account for more than 81% of

[1] Basel Committee on Banking Supervision (2006) defines operational risk as losses resulting from inadequate or failed internal processes, people, and systems or from external events.

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

[3] See *Wall Street Journal*: "Top Broker Accused of $50 Billion Fraud" (A. Efrati, T. Lauricella, D. Searcey, December 12, 2008).

[4] A recovery is defined as an independent occurrence in which funds or economic benefits are recouped related to the original operational loss event, excluding provisions, provision write-backs, and funds received from insurance providers (Federal Reserve, 2020). See Section II.B. for detailed discussion on operational loss recoveries.

banking industry assets as of 2019:Q4. Prior studies note that public sources of data built from press accounts miss many operational loss events (e.g., De Fontnouvelle et al., 2006; Abdymomunov et al., 2020) and operational loss recoveries are not reported.

We begin by providing descriptive evidence on operational loss recoveries overall, as well as across business lines and event types. We then examine temporal variation in these recoveries and their linkage to the contemporaneous macroeconomic environment. Like the underlying [gross] operational losses, an understanding of the cross-sectional and time-series properties of operational loss recovery rates is important for risk management and supervision of financial institutions. For example, if operational loss recoveries are procyclical (countercyclical), then recoveries will increase (decrease) the financial impact during economic downturns.

Our core findings can be summarized as follows. First, we document that on average about 7.6% of operational losses are recovered. Second, using a summary macroeconomic measure (the first principal component of six key macroeconomic indicators spanning labor markets, financial markets, and property markets), we document a procyclical relationship between operational loss recovery rates and the strength of the macroeconomy. Third, the recovery rates of tail operational losses (relative to BHCs' total assets) are similarly negatively correlated with macroeconomic performance, although the relationship is economically and statistically weaker. Fourth, operational loss recovery rates for seven out of the nine reported business lines and six out of the seven reported event types decrease in adverse macroeconomic environments.

We advance a channel to explain the procyclical relationship between operational loss recovery rates and the macroeconomy: BHC risk management functions are time and resource constrained during adverse economic conditions, especially in light of more frequent tail losses during these periods (Abdymomunov et al., 2020). Consistent with this hypothesis, we first show that a higher number of severe tail operational loss events discovered at BHCs is associated with lower loss recovery rates. We further document a higher incidence of discovered tail operational loss events at BHCs in adverse macroeconomic environments. This result is also interesting from a financial stability perspective because it suggests that BHCs with higher gross operational losses during a downturn recover less, which amplifies the ultimate losses. Last, we find that operational loss events occurring in adverse macroeconomic environments are more likely to be discovered sooner, but BHCs take significantly more time to account for them. This delay in accounting for discovered losses provides further evidence that the increased resource constraint during adverse economic conditions is a mechanism underlying the procyclical recovery-macroeconomy relationship.

Our study primarily contributes to the literature on operational risk at financial institutions. Curti et al. (2021) show that larger BHCs have higher operational losses per dollar of total assets and Frame, et al. (2021) find that faster growing BHCs are operationally riskier. Chernobai et al. (2021) document that operational risk at BHCs increases with business complexity. Chernobai et al. (2011), Wang and Hsu (2013) and Abdymomunov and Mihov (2019) link corporate governance and risk management quality to operational risk outcomes. Curti et al. (2022) show that BHCs with socially responsible workforce policies experience lower operational losses per dollar of total assets and a lower incidence of tail risk events. Cope and Carrivick (2013) and Abdymomunov et al. (2020) link operational risk to the state of the macroeconomy but do not analyze operational loss recoveries. Our study is, to our knowledge, the first to provide systematic descriptive evidence on operational loss recoveries in the banking industry.[5] We also provide direct evidence of a link between loss recoveries and macroeconomic conditions.

[5] Two exceptions here are Curti and Mihov (2018) and Curti and Mihov (2021), who study U.S. BHC loss recoveries from one specific operational loss type, fraud. In contrast, we study recoveries across all operational loss types. Further, we focus on the relation of operational loss recoveries with the macroeconomic environment, which these two papers do not examine.

Our paper also draws a parallel to the credit risk literature, which has examined recovery rates in the context of credit losses (e.g., Altman and Kishore, 1996; Khieu et al., 2012; Jankowitsch et al., 2014; Carey and Gordy, 2021). Some of these studies focus explicitly on the sources of systematic variation in recoveries owing to the importance of the topic for risk management and financial institution supervision (e.g., Frye, 2000; Altman et al., 2005; Acharya et al., 2007; James and Kizilaslan, 2014; Mora, 2015). Our paper complements this literature by showing that the recovery rates for a second major risk stripe at financial institutions, operational risk, also covary with the state of the macroeconomic environment. This implicitly suggests a positive correlation in recovery rates across risk categories (i.e., recovery rates are lower for both credit and operational losses during economic downturns) that exacerbates financial institutions' sensitivity to macroeconomic shocks.

The fact that operational loss recovery rates significantly depend on the business cycle also has important implications for financial institution risk management and supervision. The aim of risk management is to reduce the risk of large losses and the financial institution's vulnerability to such losses. Key measures of operational risk can appear misleadingly low when only idiosyncratic factors are considered. The Global Financial Crisis revealed shortcomings in financial institutions' ability to assess ex ante risks, including operational risk. To help protect the economy from future financial instability, one key change supervisors have introduced is stress testing large BHCs whereby the likelihood of a large loss is explicitly conditioned on adverse macroeconomic outcomes.[6] Therefore, supervisors' confidence about how well an intermediary passes the stress test depends on how robustly modeled the link is between adverse economic outcomes and operational losses (as well as losses arising from credit and market risk).

[6] For more information on stress tests and capital planning, please see: https://www.federalreserve.gov/supervisionreg/stress-tests-capital-planning.htm.

Our study provides a framework for conducting macro-based stress testing of operational loss recovery risk. We document the average level of recovery rates and estimate their sensitivity to the macroeconomic environment (both in the aggregate and more granularly across business lines and event types). In addition, we document other important aspects of recoveries including how long it takes BHCs to discover and recover operational losses and how such lags are also related to the business cycle. This is important because recovery lags may be crucial for the ultimate value of recoveries to financial institutions (e.g., long recovery lags may reduce the recovery benefits to capital-constrained or distressed institutions).

Our findings also conceptualize that BHCs have a recourse to recoup operational losses once such losses have occurred. The recovery rates may depend on the strength of BHC risk management functions. Losses during downturns may ultimately be determined not only by BHCs' ex ante risk exposures but also by BHCs' actions to recoup losses. Consequently, downsizing bank risk management functions during downturns may be counterproductive as an approach to counter decreased profitability due to higher losses during such periods. BHC recovery plans and frameworks may also be taken into consideration by supervisors when estimating conditional losses in stress testing exercises.

The rest of the paper is organized as follows. Section II describes the data sources, variable construction, and summary statistics to contextualize historical operational losses and recoveries at BHCs. Sections III and IV lay out our empirical results and robustness checks, respectively, which link operational loss recoveries to the macroeconomic environment. Section V explores a particular economic channel that may give rise to this observed correlation. Section VI concludes.

II. Data Sample and Variable Definitions

II.A. Operational loss sample

This study uses supervisory operational loss data reported to the Federal Reserve by large U.S. bank holding companies for stress testing purposes, as required by the Dodd-Frank Act. The data follows FR Y-14Q reporting requirements (current as of April 2020) and is provided by 35 financial institutions with consolidated assets of $100 billion or more that participated in the 2020 Dodd-Frank Act Stress Test (DFAST) program. Although our operational loss data are from a relatively small number of BHCs, these institutions account for the majority of U.S. banking industry assets (81% as of 2019:Q4). The data is granular and provides information about individual losses, including loss and recovery amounts, loss classifications, and in some cases, loss descriptions.

Operational losses are classified in the supervisory data by business line of origination: 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). Operational losses are also categorized into event types consistent with Basel II definitions: 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 presents definitions of each business line (Panel A) and loss event type (Panel B).

[Insert Table 1 about here]

The large banking organizations in our sample have different thresholds for collecting individual operational losses. To mitigate the impact of heterogeneity in these collection thresholds, we discard operational losses below $10,000, which is the highest submission threshold across reporting institutions. The final sample contains 709,546 individual loss events from a total of 35 large BHCs over the period [2005:Q1-2019:Q4]. We note that this supervisory data is substantially richer than other sources of data based on publicly available information about operational losses (e.g., De Fontnouvelle et al., 2006; Abdymomunov et al., 2020).

Table 2 presents a matrix of operational loss amounts and the share of these losses by business line and event type. The table shows that Retail Banking (RB) is the business line generating the most operational losses in dollar terms over the sample period ($194 billion or 55.9% of total losses). Corporate Level (CO) and Trading and Sales (TS) are also economically significant, accounting for 17.5% and 12.7% of total losses, respectively. The event type with the largest proportion of total operational losses over the sample period is Clients, Products, and Business Practices (CPBP) ($268 billion or 77.1% of losses). The second largest event type by share of total losses is Execution, Delivery, and Process Management (EDPM) ($47 billion or 13.7% of losses).

[Insert Table 2 about here]

Occurrence, discovery, and accounting dates are reported for each operational loss event. The data reporting instructions define these dates as follows: (i) occurrence date -- the date when the operational loss event occurred or began; (ii) discovery date -- the date when the operational loss event was first discovered by the institution; and (iii) accounting date -- the date when the financial impact of the operational loss event was recorded on the institution's financial statements. To examine the relation between operational loss recoveries and macroeconomic conditions, we use the operational loss discovery quarters for linking recovery rates to macroeconomic measures. The choice of the discovery date is motivated by the reasoning that risk managers make recovery decisions (i.e., whether they would pursue a recovery from an operational loss event and what resources they would allocate to that process) at the time the operational loss is discovered, and these decisions are directly and indirectly affected by the macroeconomic conditions at the time. Section IV shows our results are also robust to an alternative scheme of matching operational loss recoveries to the macroeconomic environment, which averages macroeconomic measures between loss discovery and accounting dates.

There are usually time lags between the quarter in which an operational loss event occurs and when the loss is discovered, and time lags between when the loss is discovered and when the loss is accounted for. Table 3 presents the average number of quarters between occurrence and discovery (Panel A), and between discovery and accounting (Panel B) of operational loss events by business line and operational loss type.

[Insert Table 3 about here]

The "average" operational loss event takes a BHC 1.0 quarters to discover and another 1.6 quarters to account for following discovery. However, there is notable heterogeneity across events from the different business lines. Retail Brokerage (RK) events take the longest to discover (2.4 quarters on average), while loss events in Trading and Sales (TS) and Retail Banking (RB) take the shortest time to discover (less than one quarter). Once discovered, losses from Corporate Level (CO) take the longest to account for (3.4 quarters on average), while losses from Payment and Settlement (PS) take the shortest (one quarter on average).

One can also observe significant variation in occurrence to discovery and discovery to accounting time lags across loss event type categories. Operational loss events within Clients, Products, and Business Practices (CPBP) take the longest to discover (2.5 quarters on average), while External Fraud (EF) and Damage to Physical Assets (DPA) take the shortest (less than one quarter on average). Once discovered, losses from Clients, Products, and Business Practices (CPBP) take the longest to account for (4.4 quarters on average), while losses from External Fraud (EF) and Business Disruption and System Failures (BDSF) take the shortest (0.7 quarters on average).

II.B. Operational losses and operational loss recoveries

After operational losses occur and are discovered, a BHC may subsequently recover some proportion of these gross losses. Formally, a recovery is defined as an independent occurrence in which funds or economic benefits are recouped related to the original operational loss event, excluding provisions, provision write-backs, and funds received from insurance providers (Federal Reserve, 2020). Recovery amounts are scaled by gross loss amount to calculate operational loss recovery rates.

Table 4 presents a matrix of the average operational loss recovery rates (without parentheses) by business line and event type over the sample period. The average recovery rate is 7.6%, with substantial variation across BHC business lines and loss event types. The Payment and Settlement (PS) and Commercial Banking (CB) business lines have the highest recovery rates (13.0% and 11.9%, respectively). By contrast, losses from Corporate Finance (CF), Trading and Sales (TS), and Retail Brokerage (RK) generally have the lowest recovery rates (all under 2%). Turning to event types, External Fraud (EF) events have the highest average recovery rate (11.6%), while Employment Practices and Workplace Safety (EPWS) events have the lowest recovery rates (1.1%).

[Insert Table 4 about here]

Table 4 also presents (in parentheses) the proportion of the total number of events with non-zero (positive) recovery by business line and event type. Across the full sample, 12.2% of operational loss events have associated recoveries. The Commercial Banking (CB) business line and the External Fraud (EF) event type have the highest proportion of loss events with non-zero recoveries (19.5% and 18.1%, respectively). The Trading and Sales (TS) business line and the Clients, Products and Business Practices (CPBP) event type have the lowest proportion of non-zero recovery events (2.8% and 3.4%, respectively).

II.C. Macroeconomic indicators

Abdymomunov et al. (2020) document a relationship between operational losses and the macroeconomy and emphasize that multiple macroeconomic factors may impact operational losses. We extend this idea to operational loss recoveries and calculate a single summary measure of macroeconomic conditions using six aggregates covering real economic activity and asset markets, which are plausibly related to operational loss recoveries. All six of these variables can be constructed from variables covered in the Federal Reserve System's scenario design framework for stress testing (Federal Reserve, 2014, 2021b), and therefore can be readily applied in macroeconomic stress testing of operational risk.

The first is the quarterly seasonally adjusted monthly unemployment rate (*UR*) for the civilian, non-institutional population aged 16 years and older.[7] We use *UR* as a broad measure of U.S. economic activity and labor markets.[8] The second and third variables represent residential and commercial real estate property conditions. Specifically, *Ln(HPI)* is the log-transformed U.S. house price index.[9] *Ln(CREPI)* is the log-transformed U.S. commercial real estate price index.[10] *VIX* is defined as the U.S. Market Volatility Index, converted to a quarterly frequency by using the maximum close-of-day value in each quarter.[11] It measures U.S. financial market volatility and proxies for financial market conditions. *BBB-T10Yr Spread* is the spread between the quarterly average yield for 10-year BBB-rated corporate bonds and the 10-year Treasury yield.[12] BBB-*T10Yr Spread* provides a measure of credit market conditions. Finally, we include the spread between the quarterly average yields for 10-year and

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[7] Source: Bureau of Labor Statistics, series LNS14000000.
[8] Our results are robust to using alternative broad measures of economic activity such as U.S. gross domestic product (GDP) growth.
[9] Source: Z.1 Release, Federal Reserve Board, series FL075035243.Q.
[10] Source: Z.1 Release, Federal Reserve Board, series FL075035503.Q.
[11] Source: Chicago Board Options Exchange.
[12] Sources: Corporate 10 Year Yield-to-Maturity Index, ICE Data Indices, LLC, C4A4 series and constructed by Federal Reserve staff based on the Svensson smoothed term structure model, respectively.

3-month Treasuries, *T10Yr-T3M Spread*, to incorporate the market's expectations about future economic conditions.[13]

We summarize the information contained in *UR*, *Ln(HPI)*, *Ln(CREPI)*, *VIX*, *BBB-T10Yr Spread* and *T10Yr-T3M Spread* into a single measure of macroeconomic activity using principal component analysis (PCA). Following prior studies (e.g., Stock and Watson, 1999; Ludvigson and Ng, 2007; Koopman et al., 2011), we use PCA as a dimension-reduction methodology to relate observed variables to a small set of orthogonalized factors/components. In our analysis, we focus solely on the first principal component as our measure of the macroeconomic environment (*ME*) as it adequately summarizes variation in the underlying data by explaining 66% of the variables' variances over the sample period. *ME* has a mean of 0 and a standard deviation of 1.99 over our sample period, with higher values denoting more adverse macroeconomic conditions.

[Insert Figure 1 about here]

Figure 1 presents the average quarterly operational loss recovery rate and the composite measure of the macroeconomic environment (along with the unemployment rate for context) over the sample period [2005:Q1-2019:Q4]. There is a notable pattern for average operational loss recovery rates over the business cycle. Recovery rates drop in adverse macroeconomic conditions and pick up in benign conditions.

III. Regression Results

III.A. Operational loss recoveries and macroeconomic environment

We next investigate the empirical relation between operational loss recoveries and macroeconomic conditions by estimating ordinary least squares (OLS) regressions of the form:

[13] Source: H.15 Release, Federal Reserve Board, series RIFSGFSM03_N.B.

$$RR_{j,i,m,n,t} = a_i + a_m + a_n + \beta ME_t + \varepsilon_{j,i,m,n,t} \tag{1}$$

where *j, i, m, n,* and *t* index loss events, BHCs, business lines, event types, and quarters, respectively. Section IV.C shows that our results are robust to alternative econometric approaches such as quasi-maximum likelihood estimation (QMLE). *RR* represents the recovery rate of operational risk event *j* that is discovered at BHC *i* in quarter *t*. *ME* measures the state of the macroeconomy in quarter *t* and (as previously defined) is the first principal component of *UR*, *Ln(HPI)*, *Ln(CREPI)*, *VIX*, *BBB-T10Yr Spread*, and *T10Yr-T3M Spread*. We report specifications with both *ME* and the individual macroeconomic variables separately.

Our specifications omit BHC- or loss-event-level controls. To the extent that BHC- and loss-event-level variables are either uncorrelated with the macroeconomic environment or are endogenous to and driven by it, our specifications should properly estimate the relation between loss recoveries and the macroeconomic environment. However, we do saturate the model with various fixed effects for BHCs (a_i), business lines (a_m) and loss types (a_n), which should largely eliminate sample composition concerns. Regression standard errors are clustered at the BHC-quarter level.[14] Table 5 presents the results.

[Insert Table 5 about here]

The results in Column (1) indicate that the average operational loss recovery rate is lower in adverse macroeconomic conditions, as the coefficient estimate of *ME* is negative and statistically significant at the 1% level. A one-standard-deviation increase in *ME*, which represents a deterioration in macroeconomic conditions, is associated with a 1.21 (-0.609×1.99) percentage point decrease in the average operational loss recovery rate. Given an unconditional recovery rate of 7.6 percentage points,

[14] In robustness tests, we use alternative regression specifications where we model the time series of the average quarterly operational loss recovery rates (i.e., equal- or loss-weighted recovery rates from operational loss events aggregated into a single recovery time series). Such an approach ensures that time periods with higher frequencies of operational losses receive the same relative weight as time periods with lower frequencies of operational loss events. Our results are robust to such an alternative regression approach. See Section IV for more details.

this effect is material. For more context, we note that the average operational loss during our sample period is \$489,270 in 2019-constant dollar terms and that a BHC experiences 458 operational losses per quarter on average. A one-standard-deviation deterioration in the macroeconomic environment thus suggests that the average BHC in our sample will lose \$2.7 (\$489,270×458×1.21%) million more per quarter to operational risk due to lower recoveries in operational loss events. Columns (2) through (7) demonstrate that the coefficient signs of the individual variables comprising our composite macroeconomic indicator *ME* are generally consistent with the interpretation that adverse macroeconomic conditions are associated with lower operational loss recovery rates. The coefficients are statistically significant at the 5% level or better in all specifications.

III.B. Decomposition by BHC business lines and operational loss types

Operational risk is an amalgamation of various types of subcomponent risks (Chernobai et al., 2011). Further, operational loss events occur in the context of different BHC business lines. As discussed in Section II.A, the operational loss events in our data are classified into nine BHC business lines and seven operational loss types. The significant relation between the average operational loss recovery rate and macroeconomic conditions established in Table 5 ignores the possibility that the relationship may vary by business line and event type.

In this section, we re-estimate the relation between operational loss recovery rates and the state of the macroeconomic environment for individual business lines and event types separately. *Ex ante*, we do not have a clear expectation regarding the recovery rate sensitivity of individual subcategories with respect to macroeconomic conditions. We thus examine the specific business line and event type drivers of the previously documented association between the average operational loss recovery rate and macroeconomic conditions. Table 6 presents the results.

[Insert Table 6 about here]

Table 6, Panel A presents results for operational losses categorized by business line. The coefficient of *ME* is negative across eight out of nine specifications, and statistically significant for seven of those: Trading and Sales (TS), Retail Banking (RB), Commercial Banking (CB), Payment and Settlement (PS), Agency Service (AS), Asset Management (AM), and Retail Brokerage (RK). These business lines account for most operational losses in our sample (a combined 78% of dollar losses and 94% of the total number of loss events). The magnitude of the coefficient on *ME* for Payment and Settlement (PS) is the largest among the specifications, which implies that recovery rates of losses in this business line are most sensitive to the macroeconomic environment. The coefficient of *ME* is insignificant for Corporate Finance (CF) and Corporate Level Non-Business Line Specific (CO).

Table 6, Panel B presents the results for operational loss recovery rates categorized by event type. The coefficient of *ME* is negative and statistically significant (at least at the 5% level) in six cases: Internal Fraud (IF), External Fraud (EF), Employment Practices and Workplace Safety (EPWS), Clients, Products and Business Practices (CPBP), Business Disruption and System Failures (BDSF), and Execution, Delivery and Process Management (EDPM). In terms of sensitivity to the macroeconomic environment, the magnitude of the *ME* coefficient for External Fraud (EF) is the largest in absolute value. Overall, our results indicate that operational loss recoveries in most BHC business lines and loss event types are negatively related to macroeconomic conditions.

The most notable exception to this generally negative relationship is for losses arising from Damage to Physical Assets (DPA). The coefficient of *ME* in this instance is significantly positive, but we interpret this result with caution as it is likely spurious. Chernobai et al. (2011) among others note the "unpredictable nature" of DPA losses, which are rooted in events such as natural disasters or terrorism. DPA loss recoveries are thus unlikely to be reliably determined by factors such as the macroeconomic environment.

III.C. Recoveries of tail operational losses

A well-known property of operational risk is the heavy tails of the empirical loss distributions (e.g., Chernobai and Rachev, 2006; Jobst, 2007; Abdymomunov et al., 2020). Our prior analysis examined the association between the operational loss recovery rates and the state of the macroeconomic environment by modeling the recovery rates across operational losses of all sizes. Here the focus is on the recovery rates of tail operational loss events. Tail operational losses pose significant challenges for BHC operations, capital management, and solvency, making them particularly important from risk management and supervisory perspectives.

We use three different definitions of tail operational losses. We begin with the 709,546 individual loss events in our sample and scale individual loss amounts by the BHCs' total assets in the current quarter. We calculate the 90^{th}, 95^{th} and 99^{th} percentiles of the resulting empirical distribution and categorize all loss events with severities above the respective percentiles as "tail losses." Table 7 presents results from regressing individual tail loss recovery rates on our macroeconomic index, *ME*, using specifications analogous to Equation 1.

[Insert Table 7 about here]

Adverse macroeconomic conditions (higher values for *ME*) are generally associated with lower average recovery rates of tail operational loss events. Across the three specifications, a one standard deviation increase in *ME* is related to a 0.2-0.9 percentage points decrease in the recovery rate of tail events. The coefficient estimates of *ME* are statistically significant at conventional levels in two out of three specifications (90^{th} and 95^{th} percentile tail definitions). These results overall suggest that the state of the macroeconomy is relevant not only for the average operational loss recoveries, but also those for severe operational risk events. We come back to these results in Section V, which conceptualizes some potential economic channels behind our findings.

IV. Additional Analyses

This section presents robustness checks. In Section IV.A, we consider alternative approaches of data aggregation in modeling recovery rates. In Section IV.B, we consider alternative horizons of macroeconomic conditions. In Section IV.C, we use alternative econometric methodologies to model recovery rates.

IV.A. Data granularity

Our main regression specifications are at the loss event level – i.e., there is an observation for each operational loss experienced by a given BHC in our sample. An alternative approach is to model the time series of average quarterly operational loss recovery rates for each BHC. We borrow this idea of recovery rate aggregation from existing literature that links credit spreads to business cycle fluctuations (e.g., Gilchrist and Zakrajsek, 2012; Saunders et al., 2021). The advantage of this alternative approach is that it ensures that each quarter with its unique macroeconomic environment is given equal weight in the regression estimations. Put differently, it avoids overweighting time periods with higher frequencies of operational losses. Formally, we use the following specification:

$$RR_t = a + \beta ME_t + \varepsilon_t \tag{2}$$

where t indexes calendar quarters. RR represents the average quarterly operational loss recovery rate calculated across all operational loss events discovered in quarter t. We aggregate operational loss recoveries in two different ways. First, we calculate an equal-weighted average recovery rate across all operational loss events that are discovered in a quarter. Second, we also calculate a loss-amount-weighted average recovery rate. ME again measures the macroeconomic environment in quarter t. We report specifications with both ME and the individual macroeconomic variables separately. We use Newey-West standard errors robust to heteroskedasticity and a 4-lag order of autocorrelation. Table

8, Panels A (equal-weighted average recovery rate) and B (loss-amount-weighted average recovery rate) present the results.

[Insert Table 8 about here]

The regression results in both panels suggest that our main results are robust to the alternative modeling technique of using a single recovery time series of average recovery rates. Specifically, the effects of the macroeconomic measure continue to persist, indicating lower average recovery rates during periods of adverse macroeconomic environment. If anything, the magnitude of the *ME* coefficient in our primary specification (Equation 1) is more conservative – less than half in magnitude – than the *ME* coefficient produced by the "aggregate" specifications in this section.

IV.B. Macroeconomic measurement horizon

In our analyses above, we used the discovery quarter of the operational loss events as the relevant quarter for the macroeconomic environment. We believe this assumption is reasonable because: (1) most operational loss events are accounted for relative quickly (within two quarters); and (2) BHC managers make decisions to pursue recovery and allocate resources to the recovery process at the time of operational loss discovery. Here, we instead link the recovery rate of an operational loss event to the macroeconomic environment by averaging the macroeconomic environment from the quarter of the loss discovery to the quarter of the loss accounting.

Table 8, Panel C shows that the coefficient estimates from these specifications are economically and statistically close to those produced by our baseline approach in Table 5. Our findings are thus not sensitive to this alternative way of matching operational loss recoveries to the state of the macroeconomic environment.

IV.C. Quasi-maximum likelihood estimation methodology

The operational loss recovery rates are bounded between 0 and 1, with a large concentration of observations at the boundary of 0, and to a lesser extent, at the boundary of 1. An OLS estimation of Equation 1 may have similar limitations to using a linear probability specification to model binary data (Wooldridge, 2002). That is, the impact of any explanatory variable may not be constant throughout its range of values and the predicted value is not guaranteed to be bounded between 0 and 1. OLS would also ignore important nonlinearities that might exist with our recovery data.

We next test the robustness of our baseline results in Table 5 using a quasi-maximum likelihood estimation (QMLE) methodology that has been applied in modelling the recovery rates of credit losses (Dermine and Neto de Carvalho, 2006; Khieu et al., 2012). Specifically, the econometric method applies a transformation G(.) on the data, which maps the [0–1] recovery rates onto the whole real line [−ω, + ω] (McCullagh and Nelder, 1989). While several functional forms for G(.) are available, we follow Papke and Wooldridge (1996), Dermine and Neto de Carvalho (2006), and Khieu et al. (2012) and employ the logistic function. (The results are qualitatively similar if we use other link functions such as the cumulative normal distribution function.) We then use QMLE to estimate Equation 1, in which the non-linear estimation procedure maximizes the Bernoulli log-likelihood function. QMLE produces consistent and asymptotically normally distributed estimates as noted by Gourieroux et al. (1984). Table 8, Panel D presents the results from our estimations.

The coefficient estimates of the macroeconomic variables in all specifications are directionally the same as those in Table 5, and statistically significant at the 1% levels. We again find that operational loss recovery rates are lower in adverse macroeconomic conditions.

V. Potential Economic Channels

This section attempts to provide some economic intuition for the procyclicality of operational loss recovery rates. We propose that the documented relationship reflects resource constraints faced by BHC risk management functions that are exacerbated during economic downturns. A particular reason is that BHC risk management functions are beleaguered by various risk realizations in downturns (e.g., Brunnermeier, 2009; Ivashina and Scharfstein, 2010). This includes operational risk, which is acutely countercyclical – i.e., BHCs suffer significantly more gross operational losses during downturns (Abdymomunov et al., 2020). Ultimately, risk management resource constraints (e.g., due to elevated losses and consequent declines in institutions' profitability or workforce size) hinder BHCs' abilities to pursue operational loss recoveries of an increasing number of operational loss events during downturns, resulting in lower average recovery rates.

V.A. Three tests

To examine this proposed channel, we first test whether operational loss recovery rates are negatively related to the number of severe operational risk (tail) events discovered by BHCs in a quarter. Tail loss events should consume more loss recovery resources as BHCs have more incentives to pursue them. We use the following regression specifications to do so:

$$RR_{j,i,m,n,t} = a_i + a_m + a_n + \beta_1 Ln(Loss)_j + \beta_2 Ln(N\ Tail)_{i,t} + \varepsilon_{j,i,m,n,t} \tag{3}$$

where *j, i, m, n,* and *t* index events, BHCs, business lines, event types, and quarters, respectively. *RR* represents the operational loss recovery rate of operational risk event *j* that is discovered at BHC *i* in quarter *t*. *Ln(Loss)* measures the log-transformed loss amount of event *j*. *Ln(N Tail)* measures the log-transformed number of tail operational loss events discovered at BHC *i* in quarter *t*, where we separately use the three different measures of tail losses from Section V.C. All regressions include

BHC, business line, and event type fixed effects. Standard errors are clustered at the BHC-quarter level. Table 9 presents the results.

[Insert Table 9 about here]

Column (1) shows a positive relation between operational loss recovery rates and operational loss amounts. BHCs tend to recover more from events with larger gross loss amounts, consistent with the idea that institutions expend more effort in pursuing recoveries of larger operational losses. Columns (2)-(4), on the other hand, show that operational loss recovery rates are smaller in quarters when BHCs discover more tail operational loss events. This is consistent with the idea that, in quarters when BHCs are dealing with more tail events, more resources are consumed, and operational loss recovery rates are lower on average. Columns (5)-(7) further suggest that when we consider loss amounts and frequency measures of tail losses together, the statistical and economic significance of the coefficients remains qualitatively unchanged.

The conjecture that recoveries of larger operational losses require more resources is also indirectly supported by our findings in Section III.C which showed that the negative relationship between operational risk recovery rates and our macroeconomic measure *ME* is somewhat weaker for the most severe tail operational risk events. For example, while the coefficient of *ME* is negative, it is statistically insignificant when estimated on the set of the most severe tail events (99^{th} percentile tail definition). A reason this might occur is that BHCs prioritize the recovery of their largest operational losses, which renders tail loss recovery rates less sensitive to macroeconomic conditions.

Next, we investigate whether adverse macroeconomic conditions are associated with a higher incidence of tail operational risk events. Our specifications are at the BHC-quarter level as follows:

$$Ln(N\ Tail)_{i,t} = a_i + \beta ME_t + \varepsilon_{i,t} \quad (4)$$

where *i* and *t* index BHCs and quarters, respectively. *Ln(N Tail)* measures the log-transformed number of tail operational loss events discovered by BHC *i* in quarter *t*. *ME* measures the state of the macroeconomy in quarter t and is defined as before. a_i are BHC fixed effects. Standard errors are clustered at the quarter level. Table 10 presents the results. Columns (1)-(3) present specifications estimated via OLS. We find consistent evidence across all three specifications. Adverse macroeconomic conditions are associated with a higher incidence of tail operational loss events. Columns (4)-(6) present estimations via a Negative Binomial regression to ensure the robustness of these results to the use of a count-based model.

[Insert Table 10 about here]

A successful recovery of certain losses, such as those that occur due to human or systems related errors, among others, may depend on how quickly BHCs discover and account for them. Finally, we examine how operational loss time lags relate to macroeconomic conditions. To explore this relationship, we use the specifications from Equation 1, replacing recovery rates with our time lag variables:

$$Time\ Lag_{j,i,m,n,t} = a_i + a_m + a_n + \beta ME_t + \varepsilon_{j,i,m,n,t} \quad (5)$$

Time Lag is either *Ln(OccuToDisc)* or *Ln(DiscToAcct)*. *Ln(OccuToDisc)* is the natural log transformation of 1 plus the number of quarters between loss occurrence and discovery dates, and *Ln(DiscToAcct)* is the natural log transformation of 1 plus the number of quarters between discovery and accounting dates. *ME* is again the composite measure of the state of the macroeconomy. *ME* is measured as of the occurrence quarter when *Ln(OccuToDisc)* is the dependent variable and as of the discovery quarter when *Ln(DiscToAcct)* is the dependent variable. We continue to cluster standard errors at the BHC-quarter level. Table 11 presents the results.

[Insert Table 11 about here]

Panels A and B illustrate a predominantly negative association between *Ln(OccuToDisc)* and *ME* indicating that operational losses tend to be discovered sooner if they occur in adverse macroeconomic conditions. Consistent with Abdymomunov et al. (2020), the results suggest that operational losses tend to "surface" during stressful conditions, while it takes BHCs longer on average to discover the occurrence of an operational loss in times of robust economic activity. Based on the specification reported in Panel A, Column (1), a one-standard-deviation increase in *ME* (i.e., deterioration in macroeconomic conditions) is associated with a 0.20 (-0.10×1.99) quarter decrease in the average time it takes a BHC to discover an operational loss event. Given an unconditional length of 1 quarter for loss discovery, this effect is material – a 20% decrease in the average time from occurrence to discovery. Across the different business lines in Panel A and event types in Panel B, the discovery lag for Corporate Level (CO) in Panel A and Clients, Products and Business Practices (CPBP) in Panel B have the highest sensitivity to macroeconomic conditions – more than 4 and 3 times larger in magnitude than the overall sensitivity across all events reported in Panel A, Column (1). In cases when coefficient estimates are statistically insignificant at conventional levels, they must be interpreted with caution.

Panels C and D report regressions of the lag between discovery and accounting dates on *ME* across different business lines and event types, respectively. Here we see a predominantly positive association between *Ln(DiscToAcct)* and our macroeconomic indicator. BHCs take generally longer to recognize operational losses on their books when losses are discovered in an adverse macroeconomic environment. Based on the specification reported in Panel C, Column (1), a one-standard-deviation increase in *ME* (i.e., deterioration in macroeconomic conditions) is associated with a 0.36 (0.18×1.99) quarter increase in the average time it takes a BHC to account for an operational loss event once discovered. Given an unconditional length of 1.6 quarters for loss accounting, this effect is material – a 23% increase in the average time from discovery to accounting. Across the different business lines in Panel C and event types in Panel D, the accounting lag for Corporate Finance (CF) in Panel C and Clients, Products and Business Practices (CPBP) in Panel D have the highest sensitivity to macroeconomic conditions. As we have noted before, coefficient estimates that are statistically insignificant should be interpreted with caution.

V.B. Discussions

While we believe that the resource constraint channel is the primary driver of our finding that BHCs experience lower operational loss recovery rates in adverse macroeconomic environment, there may also be secondary channels. In the interests of brevity and maintaining focus on our main findings, we leave any substantial efforts to test and differentiate among these additional plausible channels to future research. We also admit that testing some of these additional channels directly is challenging. We provide a short discussion of such additional channels next.

The recoveries associated with certain operational loss types, such as fraud or intentional damage to assets, may require assistance from external parties, such as law enforcement or the judicial system. Such external parties may have limited capacity to assist banking organizations during economic downturns due to an increased demand for their own services as criminal activity is higher during downturns (e.g., Raphael and Winter-Ebmer, 2001). Consequently, the recovery rates of operational losses that require the involvement of law enforcement agencies and legal system authorities may decline in downturns due to these external parties' capacity constraints.

Recoveries of operational losses may also depend on BHCs' business counterparties (e.g., clients, vendors, or guarantors) and their ability to pay. For example, the recoveries from losses due to human or system errors, such as duplicate transactions or incorrect settlement amounts, would entail retrieving funds from recipient entities. To the extent that the financial condition of BHCs' counterparties deteriorates during downturns, any monetary recoveries from such entities may be more difficult and lower operational loss recovery rates.

In addition, recoveries of losses from human or system error may also decrease during downturns because BHCs are tardy in acting, while loss recoveries may depend on BHCs' swift recovery measures. This tardiness may be rooted in increased constraints on the workforce or simply because BHCs wait until market volatility and financial turmoil subside. Regardless of the reason, tardiness in actions to recover from operational losses may negatively impact recovery prospects.

VI. Conclusion

This study presents descriptive evidence on operational loss recoveries at financial institutions and investigates their relation to macroeconomic conditions. We use rich supervisory data on operational loss recoveries from the 35 largest BHCs in the U.S. over the period [2005:Q1-2019:Q4] to conduct our tests. We show that recovery rates tend to be lower in adverse conditions, including when we only focus on high-severity operational loss events. We document the specific BHC business lines and event types behind this relation. Finally, we show evidence that operational risk time lags (the time between operational risk occurrence and discovery, and the time between operational loss discovery and accounting) are also related to macroeconomic conditions.

We conclude that there exists a robust association between operational loss recovery rates and the macroeconomic environment. Our research makes a novel contribution to the growing operational risk literature and has relevance for BHC risk managers and supervisors. Specifically, our analysis provides evidence of systematic variation in operational loss recovery rates, which supports a quantitative approach to operational risk management with regards to macroeconomic risks. Of course, the evidence in this paper provides generalized relationships in the data sample, which may not be applicable to specific BHCs or institutions outside the scope of the data. Aware of such limitations, we believe nonetheless that our results are relevant to and aligned in principle with the Dodd-Frank Act supervisory stress-testing framework.

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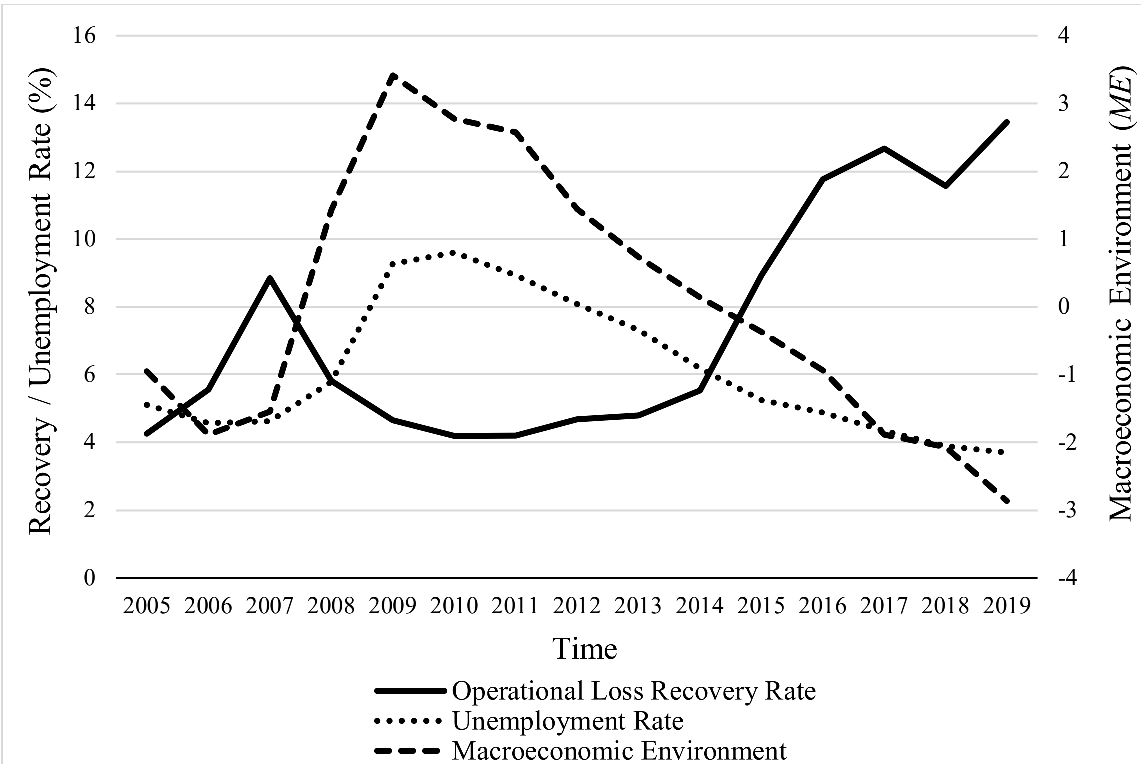

Figure 1. Operational Loss Recovery Rates and the Macroeconomic Environment
This figure presents quarterly average operational loss recovery rates and a composite measure of the macroeconomic environment (*ME*). *ME* is the first principal component of six U.S. macroeconomic indicators: unemployment rate (*UR*), the log-transformed U.S. house price index (*Ln(HPI)*), the log-transformed U.S. commercial real estate price index (*Ln(CREPI)*), the Chicago Board Options Exchanges' Market Volatility Index (*VIX*), the spread between the U.S. BBB corporate yield and the 10-year Treasury yield (*BBB-T10Yr Spread*), and the spread between 10-year Treasury yield and 3-month Treasury yield (*T10Yr-T3M Spread*). The operational loss recovery rates are based on 709,546 operational loss events from 35 large U.S. bank holding companies over the period [2005:Q1-2019:Q4].

Table 1. Business Line and Event Type Definitions
This table presents BHC business line definitions in Panel A and operational loss event type definitions in Panel B.

Panel A: 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 B: Event Types		
Event type category	Short	Description
Internal Fraud	IF	Acts of a type intended to defraud, misappropriate property, or circumvent regulations, which involves at least one internal party
External Fraud	EF	Acts of a type intended to defraud, misappropriate property, or circumvent the law, by a third party
Employment Practices and Workplace Safety	EPWS	Acts inconsistent with employment, health or safety laws or agreements, from payment of personal injury claims, or from diversity / discrimination events
Clients, Products and Business Practices	CPBP	An unintentional or negligent failure to meet a professional obligation to specific clients, or from the nature or design of a product
Damage to Physical Assets	DPA	Damage to physical assets from natural disasters or other events
Business Disruption and System Failures	BDSF	Disruption of business or system failures
Execution, Delivery and Process Management	EDPM	Failed transaction processing or process management, from relations with trade counterparties and vendors

Table 2. BHC Operational Loss Amounts by Business Line and Loss Event Type

This table reports average operational loss amounts ($ Billions) across bank holding company (BHC) business lines and loss event types. Business lines (reported vertically) are: 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 Non-Business Line Specific (CO). Event types (reported horizontally) 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). The last row of each panel reports the total dollar amount for each event type. The last column reports the total dollar amount for each business line. Percentage values of totals are in parentheses. The sample includes 709,546 operational loss events from 35 large U.S. BHCs over the period [2005:Q1-2019:Q4].

	IF	EF	EPWS	CPBP	DPA	BDSF	EDPM	Total
CF	0.14	0.04	0.66	13.20	0.06	0.02	1.55	15.67
	(0.04%)	(0.01%)	(0.19%)	(3.80%)	(0.02%)	(0.01%)	(0.45%)	(4.51%)
TS	0.82	0.80	0.57	31.34	0.08	2.33	8.16	44.11
	(0.24%)	(0.23%)	(0.16%)	(9.03%)	(0.02%)	(0.67%)	(2.35%)	(12.71%)
RB	1.16	13.24	3.23	152.97	0.33	0.64	22.60	194.18
	(0.33%)	(3.81%)	(0.93%)	(44.06%)	(0.10%)	(0.18%)	(6.51%)	(55.93%)
CB	0.06	0.81	0.14	2.54	0.01	0.04	1.59	5.19
	(0.02%)	(0.23%)	(0.04%)	(0.73%)	(0.00%)	(0.01%)	(0.46%)	(1.50%)
PS	0.09	0.14	0.03	0.92	0.00	0.14	0.49	1.81
	(0.03%)	(0.04%)	(0.01%)	(0.26%)	(0.00%)	(0.04%)	(0.14%)	(0.52%)
AS	0.02	0.08	0.10	4.00	0.01	0.13	3.61	7.95
	(0.01%)	(0.02%)	(0.03%)	(1.15%)	(0.00%)	(0.04%)	(1.04%)	(2.29%)
AM	0.02	0.11	0.22	4.48	0.00	0.02	1.72	6.57
	(0.01%)	(0.03%)	(0.06%)	(1.29%)	(0.00%)	(0.01%)	(0.50%)	(1.89%)
RK	0.43	0.28	1.94	6.77	0.01	0.12	1.48	11.03
	(0.12%)	(0.08%)	(0.56%)	(1.95%)	(0.00%)	(0.04%)	(0.43%)	(3.18%)
CO	0.11	0.19	1.73	51.41	0.63	0.30	6.27	60.65
	(0.03%)	(0.05%)	(0.50%)	(14.81%)	(0.18%)	(0.09%)	(1.80%)	(17.47%)
Total	2.86	15.69	8.63	267.62	1.15	3.75	47.46	347.16
	(0.82%)	(4.52%)	(2.49%)	(77.09%)	(0.33%)	(1.08%)	(13.67%)	(100.00%)

Table 3. Operational Loss Time Lags by Business Line and Event Type

Panel A reports the number of quarters between operational loss occurrence date and loss discovery date across bank holding company (BHC) business lines and operational loss event types. Panel B reports the number of quarters between operational loss discovery date and recovery accounting date across BHC business lines and loss event types. Business lines (reported vertically) are: 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 Non-Business Line Specific (CO). Event types (reported horizontally) 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). The last row of each panel reports the average time lags for each event type. The last column reports the average time lags for each business line. The sample includes 709,546 operational loss events from 35 large U.S. BHCs over the period [2005:Q1-2019:Q4].

	IF	EF	EPWS	CPBP	DPA	BDSF	EDPM	Total
Panel A: Occurrence to Discovery								
CF	4.2	0.3	0.8	2.3	0.4	0.2	2.1	1.1
TS	1.7	0.4	2.1	4.0	0.1	0.2	0.6	0.8
RB	1.0	0.4	1.2	1.8	0.2	1.2	2.0	0.9
CB	2.4	0.3	0.8	2.0	0.3	0.9	2.1	1.0
PS	2.0	0.2	2.3	2.1	0.0	0.7	1.7	1.3
AS	3.7	0.6	2.0	3.3	0.1	0.8	1.7	1.7
AM	1.0	0.3	0.5	2.3	0.8	0.9	1.3	1.3
RK	3.4	0.6	1.7	4.6	0.8	1.2	0.9	2.4
CO	1.5	0.5	0.7	3.4	0.4	0.9	3.2	2.0
Total	1.3	0.4	1.1	2.5	0.3	0.7	1.8	1.0
Panel B: Discovery to Accounting								
CF	4.1	1.0	2.5	6.8	1.1	0.9	2.3	2.8
TS	3.4	1.3	4.4	7.2	0.9	0.2	0.4	1.1
RB	1.1	0.7	4.4	4.4	2.5	1.4	2.4	1.5
CB	1.7	0.8	3.5	3.6	2.7	1.1	1.5	1.4
PS	4.0	0.5	4.7	1.7	2.8	0.8	0.8	1.0
AS	0.7	0.8	2.4	2.7	0.9	1.2	1.4	1.5
AM	4.9	1.5	3.6	4.4	1.5	0.6	0.8	1.4
RK	3.1	1.1	4.3	3.8	3.7	0.9	0.7	2.5
CO	1.9	0.7	5.5	4.5	2.5	1.0	2.5	3.4
Total	1.4	0.7	4.3	4.4	2.3	0.7	1.9	1.6

Table 4. Recovery Rate and Recovery Frequency

This table reports average percentage recovery rates and recovery frequency (in parentheses) across bank holding company (BHC) business lines and loss event types. Recovery rate is defined as operational loss recovery amount divided by gross loss amount. Recovery frequency is defined as the proportion of total events with positive recovery and is reported in parentheses. Business lines (reported vertically) are: 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 Non-Business Line Specific (CO). Event types (reported horizontally) 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). The last row reports operational loss recovery rates and recovery frequencies for each event type. The last column reports operational loss recovery rates and recovery frequencies for each business line. The sample includes 709,546 operational loss events from 35 large U.S. BHCs over the period [2005:Q1-2019:Q4].

	IF	EF	EPWS	CPBP	DPA	BDSF	EDPM	Total
CF	4.9	13.6	0.9	0.8	0.6	8.3	4.4	1.7
	(20.0)	(20.4)	(6.5)	(3.9)	(1.2)	(8.3)	(6.7)	(6.3)
TS	2.7	1.5	1.2	2.6	1.3	1.3	1.7	1.7
	(4.8)	(3.9)	(2.2)	(6.9)	(2.8)	(1.8)	(2.5)	(2.8)
RB	7.1	11.8	1.2	0.9	7.6	5.1	3.6	8.6
	(14.4)	(18.3)	(4.1)	(2.1)	(13.0)	(9.1)	(5.7)	(13.6)
CB	8.7	11.6	0.7	2.9	5.2	10.9	18.3	11.9
	(20.8)	(23.1)	(3.1)	(5.4)	(7.1)	(18.5)	(20.5)	(19.5)
PS	20.5	4.5	0.5	27.4	1.0	13.9	15.0	13.0
	(32.4)	(8.5)	(1.4)	(29.3)	(16.7)	(18.6)	(17.0)	(15.7)
AS	14.7	9.1	0.4	7.6	1.4	2.9	2.9	3.3
	(36.7)	(15.5)	(0.8)	(10.1)	(1.9)	(4.3)	(4.6)	(5.2)
AM	8.7	10.3	0.4	5.6	0.0	4.1	4.1	4.2
	(21.1)	(16.3)	(0.7)	(9.7)	(0.0)	(4.1)	(5.5)	(6.0)
RK	2.1	3.6	1.1	1.4	9.2	1.6	2.1	1.9
	(7.0)	(9.8)	(6.4)	(4.7)	(14.3)	(5.2)	(3.5)	(5.1)
CO	9.5	3.8	1.1	1.8	7.5	5.5	3.6	3.0
	(18.5)	(6.6)	(8.1)	(4.3)	(10.4)	(8.8)	(5.4)	(6.6)
Total	6.8	11.6	1.1	1.5	6.5	3.5	3.7	7.6
	(14.1)	(18.1)	(5.4)	(3.4)	(10.4)	(5.6)	(5.6)	(12.2)

Table 5. Operational Loss Recovery Rates and the Macroeconomic Environment

This table reports estimates from operational loss event-level regressions of the recovery rate on measures of the macroeconomic environment. *ME* is the first principal component of six U.S. macroeconomic indicators: unemployment rate (*UR*), the log-transformed U.S. house price index (*Ln(HPI)*), the log-transformed U.S. commercial real estate price index (*Ln(CREPI)*), the Chicago Board Options Exchanges' Market Volatility Index (*VIX*), the spread between the U.S. BBB corporate yield and the 10-year Treasury yield (*BBB-T10Yr Spread*), and the spread between 10-year Treasury yield and 3-month Treasury yield (*T10Yr-T3M Spread*). All models include bank holding companies (BHC), business line, and event type fixed effects. Standard errors are clustered at the BHC-quarter level and reported in parentheses. The sample includes 709,546 operational loss events from 35 large U.S. BHCs over the period [2005:Q1-2019:Q4]. ***, **, and * indicate $p<0.01$, $p<0.05$, and $p<0.1$, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ME	-0.609***						
	(0.071)						
Unemployment		-0.624***					
		(0.064)					
Ln(HPI)			8.766***				
			(0.844)				
Ln(CRE)				7.046***			
				(0.740)			
VIX					-0.028**		
					(0.011)		
BBB-T10Yr Sprd.						-0.450***	
						(0.126)	
T10Yr- T3M Sprd.							-0.901***
							(0.138)
Observations	709,546	709,546	709,546	709,546	709,546	709,546	709,546
Adjusted R^2	0.248	0.249	0.249	0.249	0.246	0.247	0.248

Table 6. Operational Loss Recovery Rates and the Macroeconomic Environment by Business Line and Event Type

This table reports estimates from operational loss event-level regressions of the recovery rate on the macroeconomic environment by business line (Panel A) and event type (Panel B). *ME* is the first principal component of six U.S. macroeconomic indicators: unemployment rate (*UR*), the log-transformed U.S. house price index (*Ln(HPI)*), the log-transformed U.S. commercial real estate price index (*Ln(CREPI)*), the Chicago Board Options Exchanges' Market Volatility Index (*VIX*), the spread between the U.S. BBB corporate yield and the 10-year Treasury yield (*BBB-T10Yr Spread*), and the spread between 10-year Treasury yield and 3-month Treasury yield (*T10Yr-T3M Spread*). Business lines are: 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 Non-Business Line Specific (CO). 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). Models in Panel A include bank holding companies (BHC) and event type fixed effects. Models in Panel B include BHC and business line fixed effects. Standard errors are clustered at the BHC-quarter level and reported in parentheses. The sample includes 709,546 operational loss events from 35 large U.S. BHCs over the period [2005:Q1-2019:Q4]. ***, **, and * indicate $p<0.01$, $p<0.05$, and $p<0.1$, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Business Line									
	CF	TS	RB	CB	PS	AS	AM	RK	CO
ME	-0.163	-0.246***	-0.610***	-1.757***	-2.189***	-0.395***	-0.878***	-0.196***	0.105
	(0.102)	(0.062)	(0.078)	(0.238)	(0.386)	(0.127)	(0.240)	(0.061)	(0.072)
Obs.	7,911	28,802	558,112	14,945	5,553	21,030	6,609	33,633	32,940
Adj R^2	0.058	0.018	0.271	0.153	0.202	0.032	0.053	0.057	0.066
Panel B: Event Type									
	IF	EF	EPWS	CPBP	DPA	BDSF	EDPM		
ME	-0.316**	-0.738***	-0.092***	-0.360***	0.793***	-0.420***	-0.431***		
	(0.142)	(0.104)	(0.034)	(0.065)	(0.218)	(0.134)	(0.084)		
Obs.	6,471	377,881	40,615	70,369	6,122	5,409	202,676		
Adj R^2	0.101	0.308	0.058	0.081	0.199	0.070	0.085		

Table 7. Tail Operational Loss Recovery Rates and the Macroeconomic Environment

This table reports estimates from operational loss event-level regressions of recovery rates on macroeconomic environment using only operational loss tail events at the 90th, 95th, and 99th percentiles. *ME* is the first principal component of six U.S. macroeconomic indicators: unemployment rate (*UR*), the log-transformed U.S. house price index (*Ln(HPI)*), the log-transformed U.S. commercial real estate price index (*Ln(CREPI)*), the Chicago Board Options Exchanges' Market Volatility Index (*VIX*), the spread between the U.S. BBB corporate yield and the 10-year Treasury yield (*BBB-T10Yr Spread*), and the spread between 10-year Treasury yield and 3-month Treasury yield (*T10Yr-T3M Spread*). All models include bank holding companies (BHC), business line, and event type fixed effects. Standard errors are clustered at the BHC-quarter level and reported in parentheses. The sample includes tail loss events from 35 large U.S. BHCs over the period [2005:Q1-2019:Q4]. ***, **, and * indicate $p<0.01$, $p<0.05$, and $p<0.1$, respectively

	(1)	(2)	(3)
	90th Percentile	95th Percentile	99th Percentile
ME	-0.450***	-0.369***	-0.105
	(0.088)	(0.084)	(0.139)
Observations	71,664	36,186	7,804
Adjusted R^2	0.066	0.060	0.078

Table 8. Robustness

This table reports robustness test results. Panel A reports time-series regressions of the quarterly equal-weighted average recovery rate on macroeconomic environment. Panel B reports time-series regressions of the quarterly loss-amount-weighted average recovery rate on *ME*. Panel C reports event-level regressions of recovery rate on *ME*, where *ME* is measured from the quarter of the loss discovery date to the quarter of the loss accounting date. Panel D reports event-level regressions of recovery rate on *ME*, where *ME* is measured as of the loss discovery date quarter. *ME* is the first principal component of six U.S. macroeconomic indicators: unemployment rate (*UR*), the log-transformed U.S. house price index (*Ln(HPI)*), the log-transformed U.S. commercial real estate price index (*Ln(CREPI)*), the Chicago Board Options Exchanges' Market Volatility Index (*VIX*), the spread between the U.S. BBB corporate yield and the 10-year Treasury yield (*BBB-T10Yr Spread*), and the spread between 10-year Treasury yield and 3-month Treasury yield (*T10Yr-T3M Spread*). In Panels A and B, we run ordinary least squares (OLS) regressions with Newey-West standard errors robust to heteroskedasticity and 4-lag order of autocorrelation. The sample includes 60 quarterly observations over the period [2005:Q1-2019:Q4]. In Panels C and D, we run OLS and the Quasi-MLE method for fractional response variables proposed by Papke and Wooldridge (1996), respectively. All models include bank holding companies (BHC), business line, and event type fixed effects. Standard errors are clustered at the BHC-quarter level and reported in parentheses. The sample includes 709,546 operational loss events from 35 large U.S. BHCs over the period [2005:Q1-2019:Q4]. ***, **, and * indicate $p<0.01$, $p<0.05$, and $p<0.1$, respectively.

Panel A: Time-Series Regression & Equal Weighted Recovery Rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ME	-1.258***						
	(0.275)						
Unemployment		-1.275***					
		(0.257)					
Ln(HPI)			17.695***				
			(3.421)				
Ln(CRE)				16.623***			
				(1.875)			
VIX					-0.056		
					(0.036)		
BBB-T10Yr Spread						-0.680	
						(0.439)	
T10Yr-T3M Spread							-1.782***
							(0.599)
Observations	60	60	60	60	60	60	60

Table 8. (Continue)

Panel B: Time-Series Regression & Loss-Amount-Weighted Weighted Recovery Rate							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ME	-2.312**						
	(0.898)						
Unemployment		-2.202**					
		(0.863)					
Ln(HPI)			34.618***				
			(12.250)				
Ln(CRE)				29.967***			
				(8.892)			
VIX					-0.096*		
					(0.057)		
BBB-T10Yr Spread						-1.406*	
						(0.739)	
T10Yr-T3M Spread							-3.280*
							(1.938)
Observations	60	60	60	60	60	60	60
Panel C: Event-Level Regression, ME Window [Loss Discovery Date, Loss Accounting Date]							
ME	-0.610***						
	(0.070)						
Unemployment		-0.628***					
		(0.064)					
Ln(HPI)			8.620***				
			(0.820)				
Ln(CRE)				7.053***			
				(0.734)			
VIX					-0.033***		
					(0.011)		
BBB-T10Yr Spread						-0.483***	
						(0.130)	
T10Yr-T3M Spread							-0.920***
							(0.136)
Observations	709,546	709,546	709,546	709,546	709,546	709,546	709,546
Adjusted R^2	0.248	0.249	0.249	0.249	0.247	0.247	0.248

Table 8. (Continue)

Panel D: Event-Level Quasi-MLE Regression							
ME	-0.118***						
	(0.014)						
Unemployment		-0.128***					
		(0.013)					
Ln(HPI)			1.629***				
			(0.175)				
Ln(CRE)				1.269***			
				(0.141)			
VIX					-0.006***		
					(0.002)		
BBB-T10Yr Spread						-0.100***	
						(0.034)	
T10Yr-T3M Spread							-0.170***
							(0.023)
Observations	709,546	709,546	709,546	709,546	709,546	709,546	709,546

Table 9. Recovery Rates, Loss Amounts, and the Number of Tail Loss Events

This table reports event-level regressions of recovery rate on loss amount and the number of tail loss events. *Ln(Loss)* is the log-transformed operational loss amount. *Ln(N Tail 90/95/99)* is the log-transformed number of assets-scaled tail operational losses at the 90th, 95th and 99th percentiles, respectively, that occur at a BHC over a given calendar quarter. All models include bank holding companies (BHC), business line, and event type fixed effects. Standard errors are clustered at the BHC-quarter level and reported in parentheses. The sample includes 709,546 operational loss events from 35 large U.S. BHCs over the period [2005:Q1-2019:Q4]. ***, **, and * indicate $p<0.01$, $p<0.05$, and $p<0.1$, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln(Loss)	0.684***				0.763***	0.769***	0.752***
	(0.047)				(0.051)	(0.052)	(0.052)
Ln(N Tail 90)		-1.290***			-1.430***		
		(0.270)			(0.270)		
Ln(N Tail 95)			-1.307***			-1.450***	
			(0.277)			(0.277)	
Ln(N Tail 99)				-1.209***			-1.308***
				(0.296)			(0.298)
Observations	709,546	709,546	709,546	709,546	709,546	709,546	709,546
Adjusted R^2	0.247	0.247	0.247	0.247	0.248	0.248	0.248

Table 10. Number of Tail Losses and the Macroeconomic Environment

This table reports regressions of the number of tail operational losses on macroeconomic environment. *N Tail 90/95/99* is the number of assets-scaled tail operational losses at the 90th, 95th and 99th percentiles, respectively, that occur at a bank holding company (BHC) over a given calendar quarter. *Ln(N Tail 90/95/99)* is the natural log transformation of *N Tail 90/95/99*. *ME* is the first principal component of six U.S. macroeconomic indicators: unemployment rate (*UR*), the log-transformed U.S. house price index (*Ln(HPI)*), the log-transformed U.S. commercial real estate price index (*Ln(CREPI)*), the Chicago Board Options Exchanges' Market Volatility Index (*VIX*), the spread between the U.S. BBB corporate yield and the 10-year Treasury yield (*BBB-T10Yr Spread*), and the spread between 10-year Treasury yield and 3-month Treasury yield (*T10Yr-T3M Spread*). We run ordinary least squares (OLS) regressions in Columns (1)-(3) and Negative Binomial regressions in Columns (4)-(6), respectively. All models include BHC fixed effects. Standard errors are clustered at the year-quarter level and reported in parentheses. The sample includes 1,550 quarterly observations from 35 large U.S. BHCs over the period [2005:Q1-2019:Q4]. ***, **, and * indicate p<0.01, p<0.05, and p<0.1, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(N Tail 90)	Ln(N Tail 95)	Ln(N Tail 99)	N Tail 90	N Tail 95	N Tail 99
ME	0.100***	0.115***	0.121***	0.088***	0.028***	0.040***
	(0.018)	(0.019)	(0.018)	(0.010)	(0.005)	(0.007)
Observations	1,550	1,550	1,550	1,550	1,550	1,550
Adjusted R^2	0.499	0.475	0.411			
Pseudo R^2				0.260	0.0347	0.0383

Table 11. Operational Loss Time Lags and the Macroeconomic Environment

This table reports event-level regressions of time lags on macroeconomic environment. In Panels A and B, the dependent variable is the log-transformed time lag (in quarters) between loss occurrence date and loss discovery date. In Panels C and D, the dependent variable is the log-transformed time lag between loss discovery date and recovery accounting date. *ME* is the first principal component of six U.S. macroeconomic indicators: unemployment rate (*UR*), the log-transformed U.S. house price index (*Ln(HPI)*), the log-transformed U.S. commercial real estate price index (*Ln(CREPI)*), the Chicago Board Options Exchanges' Market Volatility Index (*VIX*), the spread between the U.S. BBB corporate yield and the 10-year Treasury yield (*BBB-T10Yr Spread*), and the spread between 10-year Treasury yield and 3-month Treasury yield (*T10Yr-T3M Spread*). All models include bank holding companies (BHC), business line, and event type fixed effects. Standard errors are clustered at the BHC-quarter level and reported in parentheses. The sample includes 709,546 operational loss events from 35 large U.S. BHCs over the period [2005:Q1-2019:Q4]. ***, **, and * indicate $p<0.01$, $p<0.05$, and $p<0.1$, respectively.

Table 11 (Continue)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Occurrence to Discovery - All and by Business Lines										
	all	CF	TS	RB	CB	PS	AS	AM	RK	CO
ME	-0.099***	-0.166***	-0.025	-0.067***	-0.087***	-0.195***	-0.104**	-0.239***	-0.217***	-0.466***
	(0.020)	(0.025)	(0.028)	(0.020)	(0.025)	(0.041)	(0.047)	(0.078)	(0.063)	(0.087)
Obs.	709,546	7,911	28,802	558,112	14,945	5,553	21,030	6,609	33,633	32,940
Adj R^2	0.072	0.082	0.085	0.063	0.062	0.066	0.027	0.023	0.195	0.057
Panel B: Occurrence to Discovery - by Event Types										
	IF	EF	EPWS	CPBP	DPA	BDSF	EDPM			
ME	-0.040	-0.012*	-0.178***	-0.370***	0.016	-0.053*	-0.178***			
	(0.041)	(0.007)	(0.036)	(0.060)	(0.070)	(0.028)	(0.043)			
Obs.	6,471	377,881	40,615	70,369	6,122	5,409	202,676			
Adj R^2	0.140	0.034	0.073	0.132	0.034	0.059	0.035			
Panel C: Discovery to Accounting - All and by Business Lines										
	all	CF	TS	RB	CB	PS	AS	AM	RK	CO
ME	0.184***	1.019***	0.157***	0.185***	0.121***	0.107***	-0.008	0.121***	0.113***	0.212***
	(0.016)	(0.279)	(0.018)	(0.018)	(0.021)	(0.024)	(0.017)	(0.031)	(0.023)	(0.048)
Obs.	709,546	7,911	28,802	558,112	14,945	5,553	21,030	6,609	33,633	32,940
Adj R^2	0.167	0.117	0.256	0.178	0.113	0.147	0.037	0.139	0.226	0.164
Panel D: Discovery to Accounting - by Event Types										
	IF	EF	EPWS	CPBP	DPA	BDSF	EDPM			
ME	0.062**	0.046***	0.355***	0.364***	0.219***	-0.014	0.307***			
	(0.029)	(0.010)	(0.056)	(0.032)	(0.047)	(0.018)	(0.028)			
Obs.	6,471	377,881	40,615	70,369	6,122	5,409	202,676			
Adj R^2	0.080	0.048	0.184	0.182	0.222	0.109	0.095			