Finance and Economics Discussion Series

Federal Reserve Board, Washington, D.C.
ISSN 1936-2854 (Print)
ISSN 2767-3898 (Online)

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2023-003

Please cite this paper as:
Curti, Filippo, and Marco Migueis (2023). "The Information Value of Past Losses in Operational Risk," Finance and Economics Discussion Series 2023-003. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2023.003.

The Information Value of Past Losses in Operational Risk ⋆

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August 11, 2022

Abstract

Operational risk is a substantial source of risk for US banks. Improving the performance of operational risk models allows banks' management to make more informed risk decisions by better matching economic capital and risk appetite, and allows regulators to enhance their understanding of banks' operational risk. We show that past operational losses are informative of future losses, even after controlling for a wide range of financial characteristics. We propose that the information provided by past losses results from them capturing hard to quantify factors such as the quality of operational risk controls, the risk culture, and the risk appetite of the bank.

Keywords: Banking; Operational Risk; Risk Management

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

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1. Introduction

Operational risk is a major source of risk for financial institutions and has grown in recent years. Several institutions have been severely damaged or bankrupted due to operational loss events. Barings Bank, a 350-year old institution, failed because Nick Leeson's rogue transactions caused a $1.3 billion loss (Jeremy (1995)). Jérôme Kerviel's rogue trades cost Société Générale over $7 billion after he evaded numerous layers of computer controls and audits (Clark and Jolly (2016)). In the US, large financial institutions experienced tens of billions of dollars of losses due to the improper origination, securitization, and foreclosure practices in the lead up to the 07/08 financial crisis.[1] More recently, Wells Fargo experienced multiple costly operational failures whose full impact has yet to be determined (Wattles et al. (2018)). The relevance of operational risk is recognized by US regulators, as demonstrated by 29% of the advanced approaches capital requirements of the ten large, internationally active US bank holding companies (BHCs) with approved capital models resulting from operational risk as of the end of 2019 – more than market risk, which corresponds to 5% of advanced approaches capital requirements, and equivalent to 47% of credit risk advanced approaches capital requirements (Afonso et al. (2019)).[2] Furthermore, projected operational losses under the severely adverse scenario reached $144 billion for BHCs participating in the 2020 Dodd-Frank Act Stress Test (DFAST), corresponding to 33% of the projected pre-provision net revenue (PPNR) losses of DFAST BHCs.[3]

[1]See for example https://www.justice.gov/opa/pr/justice-department-federal-and-state-partners-secure-record-13-billion-global-settlement and https://www.justice.gov/opa/pr/bank-america-pay-1665-billion-historic-justice-department-settlement-financial-fraud-leading.

[2]The advanced approaches are model-based capital requirements to which only large, internationally active banks are subject in the US. All US banks are also subject to standardized risk-based capital requirements, which do not currently include operational risk.

[3]Multiple academic studies have also demonstrated the large magnitude of operational risk. For example, de Fontnouvelle et al. (2006) showed that operational risk capital would likely exceed market risk capital and could reach several billion dollars in internationally active banks. Cummins et al. (2006) and Gillet et al. (2010) find strong market reactions to operational loss events. And

Given the magnitude of operational risk, achieving a better understanding of its drivers and enhancing its modeling is of utmost importance for practitioners and regulators. This paper contributes to this understanding by researching whether past losses are predictive of future exposure.

We investigate whether the inclusion of past operational losses improves the performance of operational risk models, and generally find that it does even when accounting for a wide range of quantifiable controls. We do not claim that past losses cause future losses, but rather that they predict future losses because they capture hard-to-quantify drivers of exposure. In particular, we believe past losses proxy for banks' operational risk control quality, risk culture, and risk appetite. Banks with worse risk controls and less risk averse cultures are likely to experience larger and more numerous operational losses. As internal controls and risk culture are unlukely to change overnight (Lazear (1995), Kreps (1996)), an association between controls and culture and operational losses explains why past operational losses are predictive of future operational losses.

We analyze different operational loss event types separately and find that past losses are predictive of future losses for all events types. In addition, we investigate how far back past losses help predict future losses and find that past losses are informative up to three years prior. Also, we show that past losses suffered by peers are informative, even after controlling for an individual bank's past losses. This finding suggests that past losses are not only useful proxies for bank-specific risk drivers, but also for systemic risk drivers. We perform quantile regressions to assess whether past losses are also predictive of tail exposure, and find that they are. Lastly, we find that historical loss frequency is generally more predictive of future exposure

Allen and Bali (2007) investigate the cyclicality in operational risk and estimate that approximately 18% of banks returns compensate for operational risk, and the figure increases to 39% for depository institutions.

than historical loss severity, likely because loss frequency is a more stable metric of exposure than loss severity.

We consider multiple robustness checks. First, we add firm and time fixed effects to our regressions and find that past losses remain predictive of future losses. This result implies that the exposure factors which past losses proxy for are not immutable within firms, nor fully driven by aggregate time series trends. Second, we compare the performance of models including past losses with models including other metrics of operational risk management, specifically the risk management index from Ellul and Yerramilli (2013) and the number of Federal Reserve operational risk exam findings, and find that past losses outperform these other metrics in predicting operational risk exposure. We also replicate our main regressions assigning losses to their date of accounting (the date in which losses resulted in an impact in financial statements), instead of the date of occurrence (the date when a bank judges the loss event to have occurred) used in other regressions, and find that the results do not materially change.

Our study contributes to the literature exploring the drivers and predictors of operational risk (Chernobai et al. (2012), Cope et al. (2012), Cope and Carrivick (2013), Wang and Hsu (2013), Abdymomunov and Mihov (2019), Abdymomunov et al. (2020), and Curti et al. (2020)). Previous studies have argued that operational risk is linked to poor control practices, and have shown that operational risk correlates with corporate governance and executive compensation (Chernobai et al. (2012)), with board diversity (Wang and Hsu (2013)), and with regulatory assessments of banks' risk management practices (Abdymomunov and Mihov (2019)). To this point, no study has examined whether past operational losses are informative of future operational losses. The persistence of operational loss experience that we find supports the view that operational risk is driven by hard-to-measure factors such as internal controls risk culture, and risk appetite. Thus, despite our different focus, the findings of our paper are consistent with this previous literature. In addition, our study contributes to the broader literature assessing the performance of risk models in banking. This literature includes studies on credit risk, such as Rajan et al. (2015) and Shumway (2001), and on market risk, such as Berkowitz (2002); however, similar studies are lacking for operational risk. Our results show that past losses significantly improve models ability to predict future losses.

How to best model operational risk is of particular policy interest at moment because the Basel Committee has introduced a new standardized framework for calculating operational risk capital (Basel Committee on Banking Supervision (2017)), which allows for two variants of the calculation, one including losses and the other not. The Basel agreement set an expectation that the operational risk standardized approach be implemented by January 2023, and thus, and regulators around the world will have to decide in the forthcoming months which version of the calculation to adopt. Certain jurisdictions have signaled their intention to not use historical losses in the calculation of operational risk capital (e.g., the European Union, Canada), while others have not yet made their intentions clear (e.g., the US). Operational risk is also a critical component of banks losses in stress testing exercises, such as DFAST. And the Federal Reserve uses historical operational losses in the calculation of stress operational losses in its supervisory model. Our results inform policy considerations around operational risk measurement by suggesting that incorporating historical losses in the operational risk capital requirements is likely to result in a more risk sensitive approach, and that incorporating historical losses in stress test models is likely to result in more accurate measurement of exposure.

Operational failures can significantly affect banks' balance sheets and hamper their ability to carry out day-to-day activities. At the same time, as the size and structural complexity of financial firms have increased, so has the challenge of understanding and mitigating operational risk. Our study can help banks' risk managers build more accurate operational risk models. Better estimates of exposure would allow banks to better match their economic capital with their risk appetite and, thus, make better business decisions.

The remainder of this paper is organized as follows. Section 2 describes the data. Section 3 presents our regression results. Lastly, Section 4 concludes.

2. Data Sample and Variable Definitions

2.1. Operational Loss Data

This paper relies on operational loss event data, financial statements, and other supervisory information of 38 publicly traded BHCs that participate in the DFAST program. Operational loss event data follows the reporting requirements of the FR Y-14Q form and is provided by financial institutions with consolidated assets of $50 billion or more.[4] Loss information (including loss amounts and counts) is used from 2000Q1, or as far back as available, and up to 2017Q4.[5] The data is highly granular and provides information such as amounts, dates, classifications, and descriptions. Definitions of the variables used in the analysis are presented in Appendix A.

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),

[4]More information about FR Y-14Q reporting requirements, instructions and forms can be found at `http://www.federalreserve.gov/apps/reportforms/`.

[5]According to the FR Y-14Q reporting instructions, BHCs must report *"a complete history of operational losses starting from the point-in-time at which the institution began capturing operational loss event data in a systematic manner." The vast majority of BHCs in our sample report losses for periods prior to the Dodd-Frank Act. BHCs were already collecting such loss data in a systematic manner under the Basel II supervisory framework and for internal use. These data are subject to specific data quality checks, including regular exams conducted by Federal Reserve internal audit functions.*

Damage to Physical Assets (DPA), Business Disruption and System Failures (BDSF), and Execution, Delivery and Process Management (EDPM). Appendix A provides definitions of each event type.

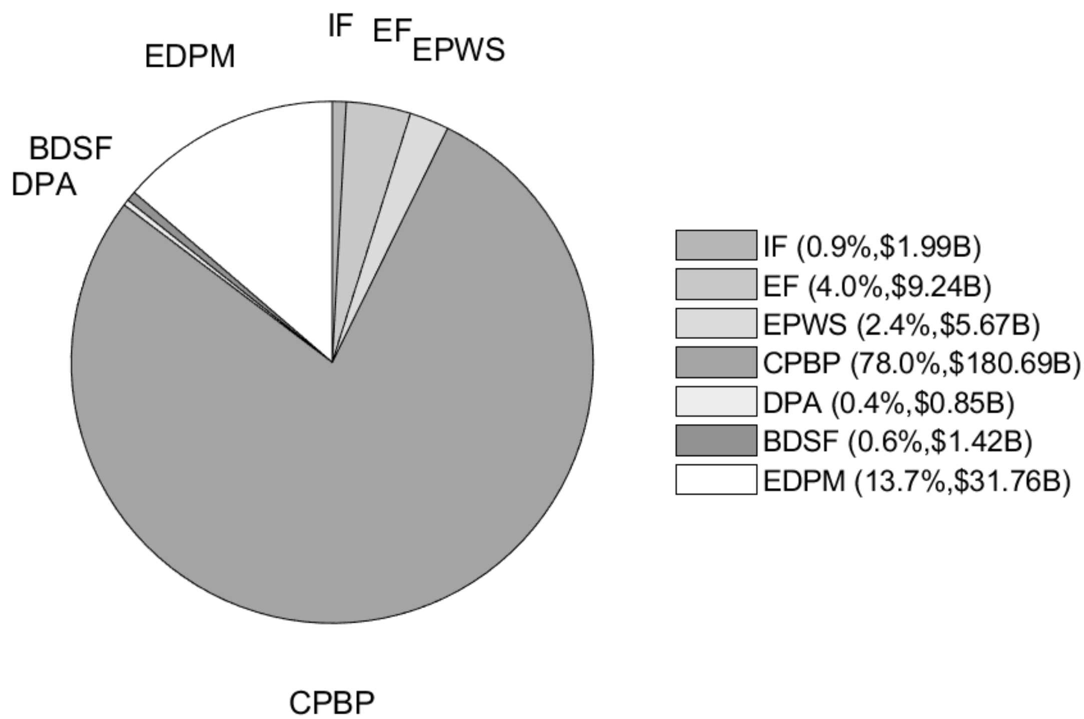

Figure 1: **Operational Losses by Event Type**
This figure presents the allocation of operational loss amounts (percentage of total losses and U.S. dollar loss amounts in billions) by event type. The sample includes 300,549 operational loss events incurred by 38 large U.S. bank holding companies over the period [2000:Q1-2017: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).

Figure 1 presents the U.S. dollar loss amounts by event type category, as well as the share of total losses corresponding to each event type. In aggregate, DFAST-participating BHCs have suffered more than $230 billion in operational losses since 2000Q1. The most significant event type is CPBP, which accounts for $180 billion, or 78%, of losses. EDPM is the second category by contribution representing $31 billion or 13% of losses. The remaining five event types comprise around \$20 billion or less than 10% of losses.

The reporting threshold for individual operational losses varies across BHCs; thus, to ensure consistency across BHCs, we discard losses below \$20,000, the highest reporting threshold for institutions participating in the DFAST program. The final sample in our data consists of 300,549 individual loss events from 38 bank holding companies over the 2000Q1 - 2017Q4 period. Our data source is substantially richer than publicly available data used in other academic studies.[6] Financial statement data are obtained from FR Y-9C reports when available and supplemented with data from Bloomberg otherwise.[7]

2.2. Operational Loss Metrics

The dependent variable in the regressions of this paper is the natural logarithm of the total amount of operational losses suffered by a BHC in a quarter. We focus on total losses – instead of, for example, loss frequency as in Chernobai et al. (2012) — because total losses are the metric of exposure that is most relevant to risk managers and regulators. To mitigate the volatility of loss totals, reduce the influence of outlier observations and not given undue weight to the observations of the largest firms in regressions, we have chosen to take natural logs (and do the same for explanatory variables that incorporate quantities). The use of logs also facilitates the inclusion of certain control variables that are not proportional to firm scale (e.g., tier 1 capital ratio, ROE) in regressions. Total operational losses for quarter t are the sum of the

[6] For example, Chernobai et al. (2012) uses 2,426 operational loss events from Algo FIRST.

[7] Some firms in our sample, such as Goldman Sachs and Morgan Stanley, did not become BHCs until late in our sample period and so were not required to fill the FR Y-9C report for the earlier portion of our sample. Also, some non-bank holding companies (e.g., Countrywide Financial) merged with or were acquired by BHCs in our sample. For consistency between the loss datasets and the financial statement variables used for these companies, Y-9C data was augmented by Bloomberg data where appropriate.

loss amounts of all events with a loss amount of at least $20k and an occurrence date in quarter t.

We consider three metrics of past loss experience to predict future losses: the natural logarithm of average quarterly total operational losses, the natural logarithm of average quarterly operational loss frequency, and the natural logarithm of average operational loss severity. These three averages are calculated over one calendar year (e.g., the average quarterly total operational losses for 2018Q2 corresponds to average of the total operational losses in 2017Q3, 2017Q4, 2018Q1, and 2018Q2). Frequency and severity represent two dimensions of a bank's operational risk exposure. Frequency reflects how often operational loss events occur in a bank, while severity reflects how damaging these events are on average. Total operational losses combine these two dimensions into a single measurement of exposure. Average frequency is typically more stable than average severity and average total operational losses because the latter two can experience large swings due to extreme loss events. Descriptive statistics of the operational loss metrics are presented in Table 1 Panel A.

Table 1: **Descriptive Statistics**
This table presents descriptive statistics. The sample includes 1,266 quarterly observations of 38 large bank holding companies over the period [2000:Q1-2017:Q4] for which requisite data are available. Panel A reports descriptive statistics on operational risk metrics. Panel B reports descriptive statistics on other variables used in our analyses.

Panel A: Operational Risk Measures

	Mean	Std	P25	P50	P75
OpLoss_{t+1}	182.956	1,288.472	3.627	11.885	61.974
$\text{Ln}(\text{OpLoss}_{t+1})$	2.947	1.804	1.501	2.524	4.104
$\overline{OpLoss}$	187.596	745.063	5.209	15.782	82.765
$\text{Ln}(\overline{OpLoss})$	3.263	1.799	1.826	2.820	4.428
$\overline{Frequency}$	240.547	398.536	31.000	67.875	228.000
$\text{Ln}(\overline{Frequency})$	4.533	1.327	3.466	4.232	5.434
$\overline{Severity}$	0.490	1.107	0.124	0.203	0.453
$\text{Ln}(\overline{Severity})$	0.311	0.339	0.117	0.185	0.374
$\overline{OpLossInd}$	304.940	300.462	83.911	205.400	428.166
$\text{Ln}(\overline{OpLossInd})$	5.276	0.971	4.430	5.325	6.060
$\overline{FrequencyInd}$	459.855	83.472	385.320	474.340	519.059
$\text{Ln}(\overline{FrequencyInd})$	6.113	0.191	5.954	6.162	6.252
$\overline{SeverityInd}$	597,326	520,255	217,709	423,060	839,678
$\text{Ln}(\overline{SeverityInd})$	12.978	0.802	12.291	12.955	13.641

Panel B: Control Variables

	Mean	Std	P25	P50	P75
Size	496,969	689,981	114,976	171,164	386,296
Ln(Size)	12.398	1.119	11.652	12.050	12.864
II-to-NII	1.806	3.356	1.007	1.770	2.657
RoE	10.267	38.456	5.785	11.046	15.719
T1 Capital	11.902	3.699	10.631	12.014	13.620
Equity Vol	37.288	26.966	21.068	27.933	38.728
CCAR Age	7.656	8.959	0.000	4.000	14.000
ME Index	109.460	11.693	101.270	105.064	112.970
Risk Management	1.006	0.259	0.761	1.065	1.213
OpRisk MR(I)A	4.577	8.982	0.000	1.000	5.000
Ln(OpRisk MR(I)A)	1.058	1.059	0.000	0.693	1.792

2.3. Control Variables

The regressions in this paper include a variety of firm-specific control factors that previous research has found relevant in explaining operational risk exposure. The first and most important control is firm size, as measured by the natural logarithm of total assets. Previous research has shown that asset size is positively associated with operational losses (Abdymomunov and Curti (2020), and Curti et al. (2020)).[8] The net interest income to noninterest income ratio has been used in the banking literature as a proxy for diversification, and previous studies have shown that this ratio affects profitability and risk (Baele et al. (2007) and Elsas et al. (2010)). The design of the Basel Committee new standardized approach also indicates that firms with a larger focus on non-traditional banking activities (and thus more noninterest income) likely experience more operational risk. For these reasons, we have included the net interest income to noninterest income ratio in our regressions. We borrow three additional controls from Chernobai et al. (2012): return on equity (ROE), tier 1 capital ratio, and equity return volatility.[9] Chernobai et al. (2012) find that operational loss frequency is negatively associated with the tier 1 capital ratio, positively associated with equity return volatility, and positively associated with ROE (albeit in this last case, the effect is not statistically significant). We also control for how long the firm has been subject to CCAR, as the tighter supervision associated with CCAR may have contributed to improve firms' risk management practices, and thus affected firms' losses. Finally, we control for the macroeconomic environment by using an index proposed by Abdymomunov et al. (2020). Descriptive statistics of the control variables are provided in Table 1 Panel B.

[8]Following Chernobai et al. (2012), multiple studies have used market value of equity to control for size in operational risk studies. We have chosen not to do so because meaningful market value of equity figures are not available for multiple firms in our sample, as they are US holding companies of foreign firms (e.g., Deutsche Bank, Barclays), and thus using market value of equity as a control would meaningfully restrict our sample. Also, we believe the scale of operations of a bank is better represented by its total assets than by its market value of equity. Nevertheless, we have estimated the regressions of this paper using market value of equity instead of total assets on the more restricted sample for which market value of equity is available, and estimates of the effect for our variables of interest remain similar. Results are available upon request.

[9]ROE is the net income divided by equity capital. Tier 1 capital ratio is tier 1 capital divided by risk-weighted assets. Equity return volatility is the annual daily volatility of returns over the previous calendar year.

2.4. Pairwise Correlation

Table 2 presents the pairwise correlation between the variables included in this study. In the forthcoming regressions, we explain total operational losses in a given quarter by using lagged values of explanatory variables, and thus we include total operational losses one period ahead of the explanatory variables considered in Table 2. Log total operational losses are highly correlated with lagged log average total operational losses as well as with lagged log average operational loss frequency (78.9% and 77.3%, respectively — see Panel A). The correlation with lagged log average loss severity is weaker (27.3%), but still statistically significant.

Log total operational losses are highly correlated with lagged log total assets (75%). Correlations with other control variables are weaker, and some of them are not statistically significant. Of the remaining control variables, the ones whose correlation with log total operational losses has highest magnitude are the net-interest income to noninterest income ratio (-18.5%) and the tier 1 capital ratio (-16.9%).

Table 2: **Pairwise Correlations**

This table presents pairwise correlations. The sample includes 1,266 quarterly observations of 38 large bank holding companies over the period [2000:Q1-2017:Q4] for which requisite data are available. Panel A reports pairwise correlations between different operational loss metrics. Panel B reports pairwise correlations between realized total operational loss in quarter $t+1$ and control variables used in our analyses.

Panel A: Operational Risk Measures

	Ln(OpLoss$_{t+1}$)	Ln($\overline{OpLoss}$)	Ln($\overline{Frequency}$)	Ln($\overline{Severity}$)	Ln($\overline{OpLossInd}$)	Ln($\overline{FrequencyInd}$)	Ln($\overline{SeverityInd}$)
Ln(OpLoss$_{t+1}$)	1.000						
Ln($\overline{OpLoss}$)	0.839	1.000					
	(0.000)						
Ln($\overline{Frequency}$)	0.840	0.878	1.000				
	(0.000)	(0.000)					
Ln($\overline{Severity}$)	0.421	0.675	0.282	1.000			
	(0.000)	(0.000)	(0.000)				
Ln($\overline{OpLossInd}$)	0.326	0.331	0.170	0.348	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)			
Ln($\overline{FrequencyInd}$)	0.270	0.279	0.099	0.341	0.908	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Ln($\overline{SeverityInd}$)	0.331	0.334	0.183	0.340	0.995	0.861	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Panel B: Control Variables

	Ln(OpLoss$_{t+1}$)	Ln(Size)	II-to-NII	RoE	T1 Capital	Equity Vol	Risk Mgmt	CCAR Age	ME Index	Risk Management	Ln(OpRisk MR(I)A)
Ln(OpLoss$_{t+1}$)	1.000										
Ln(Size)	0.770	1.000									
	(0.000)										
II-to-NII	-0.176	-0.170	1.000								
	(0.000)	(0.000)									
RoE	0.013	-0.020	0.060	1.000							
	(0.653)	(0.467)	(0.032)								
T1 Capital	-0.177	-0.037	-0.015	-0.076	1.000						
	(0.000)	(0.185)	(0.600)	(0.007)							
Equity Vol	0.139	-0.005	-0.032	-0.061	-0.078	1.000					
	(0.000)	(0.861)	(0.261)	(0.030)	(0.006)						
Risk Mgmt	0.049	0.217	-0.054	-0.070	0.282	0.051	1.000				
	(0.086)	(0.000)	(0.058)	(0.014)	(0.000)	(0.071)					
CCAR Age	-0.101	0.216	-0.041	0.051	0.282	-0.376	0.233	1.000			
	(0.000)	(0.000)	(0.148)	(0.071)	(0.000)	(0.000)	(0.000)				
ME Index	0.179	0.009	-0.081	-0.058	-0.191	0.801	-0.099	-0.411	1.000		
	(0.000)	(0.760)	(0.004)	(0.038)	(0.000)	(0.000)	(0.000)	(0.000)			
Risk Management	0.089	0.191	0.088	0.141	-0.078	-0.053	-0.183	0.191	-0.010	1.000	
	(0.041)	(0.000)	(0.044)	(0.001)	(0.074)	(0.223)	(0.000)	(0.000)	(0.819)		
Ln(OpRisk MR(I)A)	0.326	0.342	-0.035	0.058	0.254	-0.140	-0.026	-0.084	-0.160	0.231	1.000
	(0.000)	(0.000)	(0.257)	(0.061)	(0.000)	(0.000)	(0.399)	(0.006)	(0.000)	(0.000)	

3. Empirical Analysis

3.1. Hypothesis

The main hypothesis we test with this study is whether past operational loss levels are predictive of future operational loss levels. We include in our analysis a wide range of controls, drawn from the literature on the determinants of operational risk. Nevertheless, we expect past losses to be predictive of future losses because operational losses generally result from failures of firm's control processes and correlate with the firm's culture, and both internal controls and risk culture change slowly and are not directly measured by our other regression controls. In testing this hypothesis, we use the following regression equation:

$$Ln(OpLoss_{i,t+1}) = \beta_1 + \beta_2 Ln(\overline{OpLossMetrics_{i,t}}) + \sum_{j=1}^{k} \beta_j x_{j,i,t} + \epsilon_{i,t} \tag{1}$$

Where $OpLoss_{t+1}$ are total operational losses in quarter t+1, $\overline{OpLossMetrics_{i,t}}$ are metrics of operational loss experience reflecting averages between quarter t-3 and quarter t, $x_{j,i,t}$ is a control variable (control variables include log of total assets, net-interest income to noninterest income ratio, ROE, tier 1 capital ratio, equity return volatility, number of years the firm has been in CCAR, and the macroeconomic environment index) as measured in quarter t, and $\epsilon_{i,t}$ is the error term.

3.2. Main Regression

Table 3 presents our main regression results. We include a regression just with the control variables plus two additional regressions: one that includes lagged average total operational losses as an explanatory variable; and another that separately includes lagged average loss frequency and lagged average loss severity as explanatory variables.

Table 3: **Operational Loss Metrics and Current Losses**

This table reports coefficients from panel regressions of realized total operational losses at quarter $t+1$ on operational loss metrics and control variables measured in quarter t. The estimation sample comprises an unbalanced panel of 1,266 quarterly observations of 38 large bank holding companies over the period [2000:Q1-2017:Q4] for which requisite data are available. $Ln(OpLoss_{t+1})$ is the natural log transformation of the total operational losses (in millions) incurred by a BHC over a given calendar quarter. In Column (1), we only include control variables. In Column (2) we include $Ln(\overline{OpLoss})$, the natural log transformation of BHC quarterly average total operational loss measured over the prior four quarters, in addition to control variables. In Column (3) we include $Ln(\overline{Frequency})$ and $Ln(\overline{Severity})$, the natural log transformation of BHC quarterly average loss frequency and quarterly average loss severity, respectively, over the prior four quarters. Standard errors are clustered by BHC and quarter. P-values are presented in parentheses.

	Ln(OpLoss$_{t+1}$)		
	(1)	(2)	(3)
Ln($\overline{OpLoss}$)		0.510***	
		(0.000)	
Ln($\overline{Frequency}$)			0.852***
			(0.000)
Ln($\overline{Severity}$)			0.389***
			(0.002)
Ln(Size)	1.306***	0.601***	0.382***
	(0.000)	(0.000)	(0.000)
II-to-NII	−0.025**	−0.014**	−0.023***
	(0.050)	(0.020)	(0.000)
RoE	0.002	0.001	0.000
	(0.298)	(0.279)	(0.320)
T1 Capital	−0.032**	−0.022***	−0.034**
	(0.012)	(0.009)	(0.025)
Equity Vol	0.000	−0.001	0.000
	(0.908)	(0.791)	(0.833)
CCAR Age	−0.047***	−0.024***	−0.035***
	(0.000)	(0.002)	(0.000)
ME Index	0.009	0.002	0.001
	(0.156)	(0.694)	(0.867)
N	1,266	1,266	1,266
Adj R^2	0.677	0.738	0.778
BIC	3,704.456	3,447.104	3,244.402
Δ BIC	0	-257.352	-460.054

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

We find that average total operational losses are predictive of future total operational losses. A 1% increase in average total operational losses is associated with a 0.51% increase in expected total operational losses in the ensuing quarter. This coefficient is statistically significant, and the Bayesian information criterion (BIC) shows that the regression model including lagged average total operational losses performs meaningfully better (lower BIC) than the baseline regression with the control variables alone.[10]

The regression in column (3) includes, separately, lagged average loss frequency and lagged average loss severity. Both dimensions of operational risk exposure prove predictive of operational loss totals. Nevertheless, the estimated coefficient of lagged average frequency is much larger than the estimated coefficient of lagged average severity. A 1% increase in average loss frequency is associated with a 0.85% increase in expected total operational losses in the ensuing quarter; while a 1% increase in average loss severity is associated with a 0.39% increase in expected total operational losses in the ensuing quarter. This regression performs much better than regression (2) according to the BIC, which indicates that taking into account separately frequency and severity of losses is likely to be add information relative to relying solely in past loss totals.

The effects of the control variables that are statistically significant have the expected sign. Asset size is positively associated with losses, while the net-interest to noninterest income ratio (larger likely means less complex), the tier 1 capital ratio (larger means less risky), and the number of years of participation in CCAR (larger likely means less risk) are negatively associated with losses. ROE, equity return volatility, and the macroeconomic environment index are not statistically significant predictors of total operational losses in our regressions. Notably, the effect of asset size meaningfully decreases when past loss metrics are included in the regressions.

[10]Kass and Raftery (1995) showed that a model should be strongly preferred to another when its BIC is are more than six units larger.

This indicates that while size is a good proxy for operational risk exposure, the inclusion of metrics of loss experience adds relevant information relative to models that consider size alone. [11]

These regression results are consistent with operational loss exposure being persistent and partly driven by factors that cannot be easily accounted for through through financial statement metrics. These factors are likely to include operational risk control quality, risk culture, and risk appetite. Such factors influence operational loss history and are slow moving. Therefore, they likely explain why operational loss history predicts future operational losses, even after controlling for various balance sheet and business model factors. These results support the inclusion of historical operational losses in the modeling of future operational risk exposure. In addition, the results support the separate consideration of frequency and severity in operational risk models.

3.3. Regressions by Event Type

Table 4 shows regressions by operational loss event type (i.e., both the dependent variable and the lagged loss metric are calculated using only losses from a certain event type). There are seven event types under the Basel categorization: internal fraud (IF); external fraud (EF); employment practices and workplace safety (EPWS); clients, products, and business practice (CPBP); damage to physical assets (DPA); business disruption and systems failures (BDSF); and execution, delivery, and process management (EDPM) (Basel Committee on Banking Supervision (2006)). All these regressions include the same set of controls as the regressions in the previous

[11] We also considered alternative specifications where both the dependent loss total variable and the explanatory lagged losses variables were scaled by total assets, and the results regarding the significance of historical losses remain. See Appendix B.

subsection.[12]

Lagged average total operational losses (Panel A) are predictive of future total operational losses across all event types, except for damage to physical assets. Meanwhile, the regressions where lagged average loss frequency and lagged average loss severity are accounted for separately (Panel B) show that lagged average loss frequency is always positively associated with future total losses and statistically significant. The effect of average loss severity is positive and statistically significant for CPBP and EDPM — the event types with the highest dollar losses — but is negative and statistically significant for BDSF. The negative association between past BDSF loss severity and future BDSF losses may reflect firms investing in their operational resilience after large disrupations and, therefore, minimizing future losses. In the other event types, lagged average loss severity is not a statistically significant predictor of future total operational losses. For all event types, except EPWS, the regression that separately accounts for frequency and severity performs better according to the BIC than the regression that includes lagged average total operational losses alone.

[12]Note that banks sometimes have zero operational loss events in a quarter. In those cases, the log of operational loss frequency plus one and the log of operational loss severity plus one equal zero.

Table 4: **Event Types**

This table reports coefficients from panel regressions of realized total operational losses at quarter $t+1$ on operational loss metrics and control variables measured in quarter t by event type. The estimation sample comprises an unbalanced panel of 1,266 quarterly observations of 38 large bank holding companies over the period [2000:Q1-2017:Q4] for which requisite data are available. $Ln(OpLoss_{t+1})$ is the natural log transformation of the total operational losses (in millions) of a specific event type incurred by a BHC over a given calendar quarter. $Ln(\overline{OpLoss})$ is the natural log transformation of BHC quarterly average total operational loss of a specific event type measured over the prior four quarters. $Ln(\overline{Frequency})$ and $Ln(\overline{Severity})$ are the natural log transformation of BHC quarterly average loss frequency and quarterly average loss severity of a specific event type, respectively, over the prior four quarters. Event types are as follows: Internal Fraud (IF), External Fraud (EF), Employment Practices and Workplace Safety (EPWS), Clients, Products and Business Practices (CPBP), Damage to Physical Assets (DPA), Business Disruption and System Failures (BDSF), and Execution, Delivery and Process Management (EDPM). Panel A reports results using $Ln(\overline{OpLoss})$ as an explanatory variable. Panel B reports resulting using $Ln(\overline{Frequency})$ and $Ln(\overline{Severity})$ as explanatory variables. Control variables (*Ln(Size)*, *II-to-NII*, *RoE*, *T1 Capital*, *Equity Vol*, *CCAR Age*, *ME Index*) are included in all regressions of this table, but their coefficient estimates are omitted for brevity. Standard errors are clustered by BHC and quarter. P-values are presented in parentheses.

Panel A: Average Total Operational Losses as Explanatory Variable

	$\text{Ln}(\text{OpLoss}_{t+1})$						
	(1) IF	(2) EF	(3) EPWS	(4) CPBP	(5) DPA	(6) BDSF	(7) EPDM
$\text{Ln}(\overline{OpLoss})$	0.341***	0.794***	0.681***	0.325***	0.101	0.244***	0.657***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.177)	(0.006)	(0.000)
BHC Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,266	1,266	1,266	1,266	1,266	1,266	1,266
Adj R^2	0.428	0.761	0.774	0.635	0.148	0.444	0.754
BIC	1,877.808	2,223.694	1,823.787	4,120.929	1,626.008	1,770.557	2,860.405
Δ BIC	-139.9486	-1166.4607	-494.2363	-102.0532	-4.1706	-57.4873	-559.6169

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

Panel B: Average Loss Frequencies and Average Loss Severities as Explanatory Variables

	Ln(OpLoss$_{t+1}$)						
	(1) IF	(2) EF	(3) EPWS	(4) CPBP	(5) DPA	(6) BDSF	(7) EPDM
Ln($\overline{Frequency}$)	0.365***	0.533***	0.416***	0.534***	0.179***	0.376***	0.740***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln($\overline{Severity}$)	0.008	0.138	0.088	0.245***	−0.015	−0.138***	0.671**
	(0.890)	(0.284)	(0.464)	(0.001)	(0.667)	(0.000)	(0.017)
BHC Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,266	1,266	1,266	1,266	1,266	1,266	1,266
Adj R^2	0.458	0.802	0.763	0.646	0.202	0.505	0.772
BIC	1,814.533	1,995.262	1,890.379	4,086.652	1,548.508	1,629.954	2,772.317
Δ BIC	-203.224	-1394.8931	-427.6448	-136.3302	-81.6704	-198.0902	-647.7053

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

Increases in lagged average total losses predict the largest increases in EF, EPWS, and EDPM losses (a 1% increase in lagged average event type total losses is associated with a 0.79%, a 0.68%, and a 0.66% increase in the ensuing quarter event type total losses, respectively). While increases in lagged average event type loss frequency predict the largest increases in EDPM, CPBP, and EF (a 1% increase in lagged average event type loss frequency is associated with a 0.74%, 0.53%, and 0.53% increase in the ensuing quarter event type total losses, respectively). EDPM losses also have the strongest association with lagged average loss severity (a 1% increase in lagged average event type loss severity is associated with a 0.67% increase in the ensuing quarter event type total losses).

The weak relationship between DPA losses and metrics of its lagged loss experience (lagged average total losses are not significant, and in the frequency & severity regression the BIC improvement obtained from introducing the historical loss metrics is the smallest among the event types) is unsurprising because they are driven more by external events (e.g., weather events) than by internal controls, risk culture, and risk appetite. So, this weaker relationship is consistent with the mechanism we hypothesize explains why past operational losses are predictive of future operational losses.

These event type regressions strongly support the robustness of our top-of-the-house results, as they show that the relevance of past operational losses in predicting future operational losses is not a feature of one kind of operational loss event, but rather a general property of operational risk exposure across its various dimensions.

3.4. Lag Structure

To further understand the dependency of operational losses across time, we performed additional regressions where we discretely added up to four years of average loss metrics. Table 5 presents the regression results. Panel A focuses on using lagged average total losses, while the regressions in Panel B use lagged average loss frequency and lagged average loss severity separately. In the regression in the first column, only the average for the year previous to the quarter to be explained is used; while in the second column, the average for the year previous to that is added; and so on. To allow for fair comparisons across these regressions, we only included the observations that could be included in all regressions (i.e., the first observation in these regressions refers to the start of the fifth year for which there is data for a bank because four lag years are needed, rather than just one lag year as is the case in the other regressions in this paper). This approach implies that the number of observations is lower (1036) than in the other regressions in this paper (1266), and that the regression results from column 1 in Panel A and B are slightly different from those in Table 3.

Table 5: **Lagged Operational Loss Metrics and Current Losses**

This table reports coefficients from panel regressions of realized total operational losses at quarter $t+1$ on operational loss metrics and control variables measured in quarter t. The estimation sample comprises an unbalanced panel of 1,036 quarterly observations of 38 large bank holding companies over the period [2000:Q1-2017:Q4] for which requisite data are available. $Ln(OpLoss_{t+1})$ is the natural log transformation of the total operational losses (in millions) incurred by a BHC over a given calendar quarter. $Ln(\overline{OpLoss})$, $Ln(\overline{Frequency})$, and $Ln(\overline{Severity})$ are the natural log transformation of BHC quarterly average total operational loss, average loss frequency, and average loss severity measured over the prior four quarters. $Ln(\overline{OpLoss}_{t-4})$, $Ln(\overline{Frequency}_{t-4})$, and $Ln(\overline{Severity}_{t-4})$ are the natural log transformation of BHC quarterly average total operational loss, average loss frequency, and average loss severity measured over the quarters t-7 to t-4. $Ln(\overline{OpLoss}_{t-8})$, $Ln(\overline{Frequency}_{t-8})$, and $Ln(\overline{Severity}_{t-8})$ are the natural log transformation of BHC quarterly average total operational loss, average loss frequency, and average loss severity measured over the quarters t-11 to t-8. $Ln(\overline{OpLoss}_{t-12})$, $Ln(\overline{Frequency}_{t-12})$, and $Ln(\overline{Severity}_{t-12})$ are the natural log transformation of BHC quarterly average total operational loss, average loss frequency, and average loss severity measured over the quarters t-15 to t-12. Panel A reports regression results when lagged quarterly average total operational losses are used as explanatory variables. Panel B reports regression results when lagged quarterly average loss frequency and lagged quarterly average loss severity are used as explanatory variables. Control variables (*Ln(Size)*, *II-to-NII*, *RoE*, *T1 Capital*, *Equity Vol*, *CCAR Age*, *ME Index*) are included, but their coefficient estimates are omitted for brevity. Standard errors are clustered by BHC and quarter. P-values are presented in parentheses.

Panel A: Average Total Operational Losses as Explanatory Variables

	$\text{Ln}(\text{OpLoss}_{t+1})$			
	(1)	(2)	(3)	(4)
$\text{Ln}(\overline{OpLoss})$	0.503***	0.327***	0.279***	0.275***
	(0.000)	(0.000)	(0.000)	(0.000)
$\text{Ln}(\overline{OpLoss}_{t-4})$		0.329***	0.264***	0.262***
		(0.000)	(0.000)	(0.000)
$\text{Ln}(\overline{OpLoss}_{t-8})$			0.178***	0.173***
			(0.000)	(0.000)
$\text{Ln}(\overline{OpLoss}_{t-12})$				0.016
				(0.617)
BHC Controls	Yes	Yes	Yes	Yes
N	1,036	1,036	1,036	1,036
Adj R^2	0.741	0.760	0.766	0.766
BIC	2,799.761	2,725.988	2,708.425	2,715.157
Δ BIC	-203.7258	-277.4985	-295.0614	-288.3294

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

Panel B: Average Loss Frequencies and Average Loss Severities as Explanatory Variables				
	Ln(OpLoss$_{t+1}$)			
	(1)	(2)	(3)	(4)
Ln($\overline{Frequency}$)	0.842***	0.785***	0.795***	0.783***
	(0.000)	(0.000)	(0.000)	(0.000)
Ln($\overline{Frequency}_{t-4}$)		0.088	0.145	0.140
		(0.321)	(0.344)	(0.361)
Ln($\overline{Frequency}_{t-8}$)			−0.052	0.185
			(0.699)	(0.267)
Ln($\overline{Frequency}_{t-12}$)				−0.231**
				(0.021)
Ln($\overline{Severity}$)	0.288**	0.165*	0.106	0.064
	(0.015)	(0.052)	(0.160)	(0.526)
Ln($\overline{Severity}_{t-4}$)		0.467***	0.420***	0.413***
		(0.000)	(0.000)	(0.000)
Ln($\overline{Severity}_{t-8}$)			0.382***	0.375***
			(0.000)	(0.000)
Ln($\overline{Severity}_{t-12}$)				0.110
				(0.353)
BHC Controls	Yes	Yes	Yes	Yes
N	1,036	1,036	1,036	1,036
Adj R^2	0.787	0.792	0.794	0.795
BIC	2,601.683	2,593.127	2,592.031	2,600.051
Δ BIC	-399.8257	-410.3599	-411.4557	-403.4357

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

Panel B regressions generally show that the information provided by loss frequency is almost fully captured by frequency in the previous year (regression (4) shows the fourth lag of frequency negative and statistically significant, but regression (4) performs worse than regression (2) or (3) according to the BIC). Meanwhile, average loss severity in a two year and three year lag appears more predictive of losses than average loss severity in the previous year. This difference between frequency and severity likely results from frequency being a stable metric, not prone to upswings and downswings year-to-year, and thus once frequency increases, exposure can be expected to increase in the near future; while severity is volatile, and thus extrapolating into the future that exposure has increased after observing an increase in severity is only more certain after multiple years of high severity are observed.

Panel A regressions show that lagged average total losses are informative up to three years prior to the modeled quarter. The relevance of total losses up to three year lags is likely explained by the compound effect of frequency and severity, which, as discussed above, provide information about future exposure in the first lag (frequency) and in the second and third lag (severity).

3.5. Industry Experience

The hard-to-measure factors driving operational risk exposure (which we argue in this paper can be proxied by past losses) likely have commonalities across firms in the banking industry. For example, an increase in the rate of credit card fraud across the industry is likely to also provide information about the exposure of an individual firm that has not yet observed a large increase in fraud in its own credit cards. In this subsection, we formally test whether industry-wide historical operational loss experience helps explain the operational risk exposure of individual firms. To do so, we define three metrics of the industry-wide operational loss experience based on average total losses, average loss frequency, and average loss severity. Consistent with our firm-level historical metrics, we calculate industry averages over a four-quarter window. To separate the effect of a firm's own loss experience from the effect of the industry experience, we exclude a firm's losses from the calculations of the industry metric (thus, the industry loss metrics on a given quarter will vary slightly across the firms). Also, because the number and size of firms change through our sample, simple averages of industry loss metrics would move even if the average riskiness of firms, controlling for their size, is unchanged. To eliminate such confounding effects from our metrics of industry historical loss experience, we followed the following approach in calculating them:

1) To build the average industry-wide operational loss total and the average

industry-wide operational loss frequency for each observation, we took the following steps: i) we calculate the average total operational loss (average operational loss frequency) for all banks; ii) we sum these averages across all banks (except for the firm for which an observation refers to); 3) we sum total assets at time t for all banks (except for the firm for which the observation refers to); and 4) we divide the sum of average total losses (sum of average loss frequency) by the sum of total assets.

$$\overline{OpLossMetricsInd_{i,t}} = \frac{\sum_{m=1,m\neq i}^{N_t} \overline{OpLossMetrics_{m,t}}}{\sum_{m=1,m\neq i}^{N_t} Size_{m,t}} \tag{2}$$

Where $\overline{OpLossMetricsInd_{i,t}}$ is the average industry-wide operational loss (loss frequency) assigned to bank i in quarter t, N_t represents the number of banks in our sample in quarter t, $\overline{OpLossMetrics_{m,t}}$ is the average operational loss (loss frequency) of bank m measured in quarter t (calculated as described in Section 2.2), and $Size_{m,t}$ are the total assets of bank m in quarter t. This calculation provides the average total operational losses (average frequency of operational losses) per dollar of total assets in our industry sample.

2) To build the average industry-wide operational loss severity for each observation, we sum the severities of all losses for all banks in a given four quarter window and divide this sum by the total number of loss events (the losses experienced by the firm are excluded from the numerator and the denominator).

$$\overline{SeverityInd_{i,t}} = \frac{\sum_{x=1,x\not\subset i}^{S_t} Severity_x}{S_t - s_{i,t}} \tag{3}$$

Where $\overline{SeverityInd_{i,t}}$ is the average industry-wide operational loss severity assigned to bank i in quarter t, S_t represents the total number of operational loss events in quarters $t-3$ to t, $Severity_x$ is the dollar amount of loss event x, and $s_{i,t}$ represents the number of loss events of bank i in quarters $t-3$ to t. This simple average provides the average severity of a loss event in the industry, where all losses are equally weighted (and thus banks with more losses influence the average more).

Table 6 presents the regressions results where lagged average industry losses are included as explanatory variables together with firm lagged loss metrics (all control variables included in previous regressions are also included). The regression in column (1) pairs lagged average industry total losses with lagged average firm-level total losses, while the regression in column (2) separately accounts for lagged average industry loss frequency, lagged average industry loss severity, lagged average firm-level loss frequency, and lagged average firm-level loss severity.

Lagged average industry total losses are predictive of individual firms' exposure. A 1% increase in average industry total losses (excluding the firm) is associated with a 0.23% increase in expected total losses of a firm in the ensuing quarter. The inclusion of lagged average industry total losses in the regression only slightly attenuates the coefficient of lagged average firm-level total losses, from 0.510 (see Table 3 column 2) to 0.480.

Table 6: **Industry Operational Loss Metrics and Current Losses**
This table reports coefficients from quantile regressions of realized total operational losses at quarter $t+1$ on operational loss metrics and control variables measured in quarter t. The estimation sample comprises an unbalanced panel of 1,266 quarterly observations of 38 large bank holding companies over the period [2000:Q1-2017:Q4] for which requisite data are available. $Ln(OpLoss_{t+1})$ is the natural log transformation of the total operational losses (in millions) incurred by a BHC over a given calendar quarter. $Ln(\overline{OpLoss})$, $Ln(\overline{Frequency})$, and $Ln(\overline{Severity})$ are the natural log transformation of BHC quarterly average total operational loss, average loss frequency, and average loss severity measured over the prior four quarters. $Ln(\overline{OpLossInd})$ is the natural log transformation of industry quarterly average operational losses measured over the prior four quarters as per Equation 2. $Ln(\overline{FrequencyInd})$ is the natural log transformation of industry average loss frequency measured over the prior four quarters as per Equation 2. $Ln(\overline{SeverityInd})$ is the natural log transformation of industry average loss severity measured over the prior four quarters as per Equation 3. Control variables (*Ln(Size)*, *II-to-NII*, *RoE*, *T1 Capital*, *Equity Vol*, *CCAR Age*, *ME Index*) are included, but their coefficient estimates are omitted for brevity. Standard errors are clustered by BHC and quarter. P-values are presented in parentheses.

	$Ln(OpLoss_{t+1})$			
	(1)	(2)	(3)	(4)
$Ln(\overline{OpLossInd})$	0.400***	0.230***		
	(0.000)	(0.000)		
$Ln(\overline{OpLoss})$		0.480***		
		(0.000)		
$Ln(\overline{FrequencyInd})$			0.050	0.589**
			(0.926)	(0.049)
$Ln(\overline{Frequency})$				0.837***
				(0.000)
$Ln(\overline{SeverityInd})$			0.476***	0.025
			(0.001)	(0.781)
$Ln(\overline{Severity})$				0.374***
				(0.005)
BHC Controls	Yes	Yes	Yes	Yes
N	1,266	1,266	1,266	1,266
Adj R^2	0.690	0.742	0.690	0.779
BIC	3,657.678	3,433.605	3,663.431	3,247.969
Δ BIC	-46.7787	-270.8512	-41.0248	-456.4876

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

The regression where the effects of severity and frequency are taken separately (column 2) shows that average industry loss frequency is a statistically significant predictor of exposure, while average industry loss severity is not. A 1% increase in industry average loss frequency (excluding the firm) is associated with a 0.59%

increase in expected total losses of a firm in the ensuing quarter. The coefficients of lagged average firm-level loss frequency and lagged average firm-level loss severity are only slightly reduced relative to the regression that does not include industry losses (see Table 3 column 3). These results indicate that when losses become frequent in the industry, individual banks generally see their own loss totals increase. While industry average severity, which is meaningfully influenced by large losses, is not a statistically significant indicator of future exposure.

The results of this subsection suggest that operational risk presents commonalities across the industry, which are reflected in banks' loss experience. And thus, external loss data can contribute to the understanding of operational risk in individual firms. Still, these regressions also show that industry-wide factors do not explain away the association between a firms historical loss history and its operational risk exposure; therefore, this association is unlikely to be fully due to systemic factors such as higher regulatory scrutiny is some periods, and is likely in part due to factors idiosyncratic to a firm, such as its internal controls, risk culture, and risk appetite

3.6. Tail Exposure

Operational risk exposure is dominated by large, often idiosyncratic, events (Nešlehová et al. (2006) and Cope et al. (2009)). Thus, beyond understanding the drivers of expected operational losses, understanding and modeling the tail regions of the operational loss distribution is critical for effective risk management. In this subsection, we examine whether historical metrics of loss experience are predictive of tail losses using quantile regression. We present results for 95^{th} quantile regressions, which correspond to infrequent occurrences (i.e., one-in-twenty-years losses) while not quite to the extreme tail (e.g., the 99.9^{th} quantile used in the operational risk capital standards.[13] Our findings are generally robust to changes in the quantile used.[14] Table 7 presents the quantile regression results. All regressions include the same controls as the least squares regressions discussed in previous subsections.

The quantile regressions show broadly similar results to the least squares regressions. A 1% increase in lagged average total operational losses is associated with a 0.74% increase in the 95^{th} quantile of total operational losses in the ensuing quarter; while the regression that separately accounts for loss frequency and severity (column 3) shows that a 1% increase in lagged average loss frequency is associated with a 0.89% increase in the 95^{th} quantile of total operational losses in the ensuing quarter, and that a 1% increase in lagged average loss severity is associated with a 0.98% increase in the 95^{th} quantile of total operational losses in the ensuing quarter.

Loss metrics are often used by practitioners and regulators in capital and stress testing models that aim to project tail losses (Board of Governors of the Federal Reserve System (2020)). These quantile regressions corroborate the usefulness of using metrics based on past losses to model tail exposure.

[13] Detailed information on the US risk-based capital standards can be found at: https://www.govinfo.gov/content/pkg/FR-2007-12-07/pdf/07-5729.pdf

[14] Albeit coefficient standard errors do increase meaningfully as we move towards higher quantiles due to higher quantile estimates depending more heavily on a few tail observations.

Table 7: **Operational Loss Metrics and Tail Risk**

This table reports coefficients from 95^{th} quantile regressions of realized total operational losses at quarter $t+1$ on operational loss metrics and control variables measured in quarter t. The estimation sample comprises an unbalanced panel of 1,266 quarterly observations of 38 large bank holding companies over the period [2000:Q1-2017:Q4] for which requisite data are available. $Ln(OpLoss_{t+1})$ is the natural log transformation of the total operational losses (in millions) incurred by a BHC over a given calendar quarter. In Column (1), we only include control variables. In Column (2) we include $Ln(\overline{OpLoss})$, the natural log transformation of BHC quarterly average total operational losses measured over the prior four quarters, in addition to control variables. In Column (3) we include $Ln(\overline{Frequency})$ and $Ln(\overline{Severity})$, the natural log transformation of BHC quarterly average loss frequency and quarterly average loss severity, respectively, over the prior four quarters, in addition to control variables. Pseudo R^2 is presented to compare the performance of the regressions and is calculated following Koenker and Machado (1999). P-values are computed with bootstrap (100,000 samples) and presented in parentheses.

	Ln(OpLoss)		
	(1)	(2)	(3)
Ln($\overline{OpLoss}$)		0.740***	
		(0.000)	
Ln($\overline{Frequency}$)			0.886***
			(0.000)
Ln($\overline{Severity}$)			0.978*
			(0.054)
Ln(Size)	1.381***	0.525***	0.516***
	(0.000)	(0.000)	(0.002)
II-to-NII	−0.096***	−0.048	−0.057
	(0.002)	(0.388)	(0.146)
RoE	0.013**	−0.002	−0.002
	(0.020)	(0.766)	(0.330)
T1 Capital	−0.114*	−0.029	−0.064**
	(0.064)	(0.156)	(0.036)
Equity Vol	−0.001	−0.007	−0.002
	(0.704)	(0.428)	(0.814)
CCAR Age	−0.068***	−0.044***	−0.059***
	(0.000)	(0.000)	(0.000)
ME Index	0.013*	0.019	0.002
	(0.092)	(0.150)	(0.836)
N	1,266	1,266	1,266
Pseudo R^2	0.411	0.469	0.487

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

3.7. Time and Bank Fixed Effects

Table 8 Panel A shows the regressions results when quarter fixed effects are added to the regression. The statistical significance of lagged total operational losses, lagged operational loss frequency, and lagged operational loss severity in explaining total operational losses remains, while the magnitude of the coefficients is only slightly reduced. These regressions show that the results in this paper are robust to time effects as the predictive power of historical loss metrics is not an artifact of systemic effects relating to specific time periods.

In addition to quarter fixed effects, regressions in Table 8 Panel B include firm fixed effects as control variables. The inclusion of firm fixed effects reduces the explanatory power of historical loss metrics. Lagged average loss severity is no longer statistically significant and the coefficient of lagged average total losses decreases in magnitude meaningfully. The improvement of the BIC resulting from the inclusion of historical loss metrics is also much smaller than when firm effects are not included. The diminished explanatory power of historical loss metrics once fixed effects are included is not surprising because the internal control processes and cultural characteristics of firms originating operational risk exposure proxied by past losses are unlikely to change overnight, and thus are bound to be somewhat absorbed by firm fixed effects. Nevertheless, we note that, according to the BIC, the regression models that include historical operational losses are meaningfully superior to the one that does not. And the coefficient of lagged loss frequency does not lose much of its magnitude or its statistical significance, which suggests that the underlying risk factors that frequency proxies have meaningful variation through time and, thus, that loss frequency is a particularly relevant metric of future exposure.

Table 8: **Operational Loss Metrics and Current Losses with Time Fixed Effects**
This table reports coefficients from panel regressions of realized total operational losses at quarter $t+1$ on operational loss metrics and control variables measured in quarter t. The estimation sample comprises an unbalanced panel of 1,266 quarterly observations of 38 large bank holding companies over the period [2000:Q1-2017:Q4] for which requisite data are available. *Ln(OpLoss$_{t+1}$)* is the natural log transformation of the total operational losses (in millions) incurred by a BHC over a given calendar quarter. In Column (1), we only include control variables. In Column (2) we include *Ln($\overline{OpLoss}$)*, the natural log transformation of BHC quarterly average total operational losses measured over the prior four quarters. In Column (3) we include *Ln($\overline{Frequency}$)* and *Ln($\overline{Severity}$)*, the natural log transformation of BHC quarterly average loss frequency and quarterly average loss severity measured over the prior four quarters. Control variables (*Ln(Size)*, *II-to-NII*, *RoE*, *T1 Capital*, *Equity Vol*, *CCAR Age*, *ME Index*) are included in all specifications, but their coefficient estimates are omitted for brevity. All specifications include time (quarter) fixed effects. Standard errors are clustered by BHC and quarter. P-values are presented in parentheses.

Panel A: Time FE

	Ln(OpLoss$_{t+1}$)		
	(1)	(2)	(3)
Ln($\overline{OpLoss}$)		0.463***	
		(0.000)	
Ln($\overline{Frequency}$)			0.803***
			(0.000)
Ln($\overline{Severity}$)			0.385***
			(0.003)
BHC Controls	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
N	1,266	1,266	1,266
Adj R^2	0.708	0.754	0.788
BIC	3,932.454	3,721.854	3,538.713
Δ BIC	0	-210.6007	-393.7411

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

Panel B: Bank & Time FE			
	$\text{Ln}(\text{OpLoss}_{t+1})$		
	(1)	(2)	(3)
$\text{Ln}(\overline{OpLoss})$		0.180***	
		(0.001)	
$\text{Ln}(\overline{Frequency})$			0.782***
			(0.000)
$\text{Ln}(\overline{Severity})$			0.062
			(0.607)
BHC Controls	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
N	1,266	1,266	1,266
Adj R^2	0.780	0.785	0.797
BIC	3,796.313	3,776.976	3,708.847
Δ BIC	0	-19.3376	-87.4666

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

3.8. Comparison to Other Risk Management metrics

So far we have shown that past operational losses provide information regarding operational risk exposure, even when various financial metrics and fixed effects are controlled for. To further understand whether past operational losses are useful predictors of operational risk exposure, we compare models including historical loss metrics with models including alternative indicators of risk management quality.

Table 9 Panel A compares a regression model using historical operational loss metrics with a regression model using the risk management index (RMI) from Ellul and Yerramilli (2013). Data on RMI is only available up to 2013 and only for a subset of the firms that are included in the rest of the analysis.[15] Therefore, to better compare the performance of the RMI and the historical loss metrics, we restrict the sample to the period and the firms for which both are available. The bilateral correlation between the RMI and the log of future operational losses is only 5% (see

[15]We thank Andrew Ellul for sharing the RMI data with us.

Table 2 Panel B). In the regression analysis, once the controls used so far in this paper are accounted for, RMI is not a statistically significant predictor of operational losses and its inclusion in the regression does not meaningfully improve the performance of the model according to the BIC. Lagged operational loss severity performs worse as a predictor of operational risk in this subsample than in our full sample and loses statistical significance; meanwhile, the coefficient of operational loss frequency does not meaningfully change with the introduction of RMI as an additional control and retains statistical significance. These results indicate that historical loss frequency is likely a more reliable proxy for the idiosyncratic factors driving the operational risk of a firm than its RMI.

Table 9 Panel B introduces as an alternative explanatory variable the log of the number of the Federal Reserve operational risk supervisory findings that firms are subject to. Operational risk supervisory findings reflect issues where the Federal Reserve assesses the firms operational risk processes to not be adequate to meet regulatory requirements. To the degree that the issues identified by the Federal Reserve are material, a relation between supervisory findings and operational losses should be expected. The bilateral correlation between the log of the number of operational risk supervisory findings and the log of future operational losses is approximately 32%. Also, the regression results confirm this hypothesis. When included in a regression together with lagged operational loss severity and lagged operational loss frequency, the log of the number of operational risk findings is a statistically significant predictor of operational losses, and the model that includes the number of findings (column 4) outperforms the model that does not include the number of findings (column 3) according to the BIC. Meanwhile, the coefficients associated with lagged operational loss frequency and lagged operational loss severity do not change meaningfully, albeit lagged operational loss severity loses significance. These results indicate that while the supervisory findings are a relevant indicator of firm's operational risk, they do not substitute for the information provided by historical operational losses.

Table 9: **Operational Loss Metrics and Current Losses with Risk Management**
This table reports coefficients from panel regressions of realized total operational losses at quarter $t+1$ on operational loss metrics and control variables measured in quarter t. The estimation sample comprises an unbalanced panel of 1,266 quarterly observations of 38 large bank holding companies over the period [2000:Q1-2017:Q4] for which requisite data are available. *Ln(OpLoss*$_{t+1}$*)* is the natural log transformation of the total operational losses (in millions) incurred by a BHC over a given calendar quarter. In Column (1), we only include control variables. In Column (2), in addition to control variables, we include a metric capturing the quality of the bank holding companies risk management function. In Panel A, the risk management metric is *Risk Management* the risk management index developed by Ellul and Yerramilli (2013). In Panel B, the risk management metric is *Ln(OpRisk MR(I)A)* the natural log transformation of the number of MRIA and MRA outstanding at the beginning of the quarter of interest. In column (3) we include $Ln(\overline{Frequency})$ and $Ln(\overline{Severity})$, the natural log transformation of BHC quarterly average loss frequency and quarterly average loss severity measured over the prior four quarters in addition to control variables. In column (4) we include the risk management metric, $Ln(\overline{Frequency})$ and $Ln(\overline{Severity})$. Control variables (*Ln(Size)*, *II-to-NII*, *RoE*, *T1 Capital*, *Equity Vol*, *CCAR Age*, *ME Index*) are included in all specifications, but their coefficient estimates are omitted for brevity. All specifications in Panel A include time (quarter) fixed effects. All specifications in Panel B include BHC and time (quarter) fixed effects.Standard errors are clustered by BHC and quarter. P-values are presented in parentheses.

Panel A: Risk Management Index

	Ln(OpLoss$_{t+1}$)			
	(1)	(2)	(3)	(4)
Ln($\overline{Frequency}$)			0.953***	0.943***
			(0.000)	(0.000)
Ln($\overline{Severity}$)			0.105	0.095
			(0.411)	(0.429)
Risk Management		−0.534		−0.117
		(0.178)		(0.563)
BHC Controls	Yes	Yes	Yes	Yes
N	530	530	530	530
Adj R^2	0.712	0.716	0.785	0.785
BIC	1,627.363	1,625.897	1,483.200	1,489.002
Δ BIC	0	-1.466	-144.1628	-138.3608

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

Panel B: Operational Risk MR(I)A				
	Ln($OpLoss_{t+1}$)			
	(1)	(2)	(3)	(4)
Ln($\overline{Frequency}$)			0.867***	0.860***
			(0.000)	(0.000)
Ln($\overline{Severity}$)			0.368**	0.304*
			(0.016)	(0.063)
Ln(OpRisk MR(I)A)		0.126		0.107**
		(0.184)		(0.013)
BHC Controls	Yes	Yes	Yes	Yes
N	1,046	1,046	1,046	1,046
Adj R^2	0.701	0.705	0.796	0.798
BIC	2,974.962	2,968.342	2,589.092	2,582.218
Δ BIC	0	-6.6202	-385.8703	-392.7441

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

Overall, these results show that lagged operational losses are a strong predictor of operational risk exposure and outperform other risk management metrics identified in the literature.

3.9. Using Disaggregated Accounting Dates

The regressions in this paper (outside of this subsection) account for operational losses at their date of occurrence – the date in which a bank experiencing a loss event judges the loss event to have been triggered. This choice is justified by our focus in understanding whether past losses predict future losses, given the common factors that originate the past and future losses.

However, banks also record the accounting dates of their losses (i.e., the date or dates on which a loss event results in financial impacts for the bank). The accounting date is relevant because the accounting impacts of losses are a mechanism through which operational risk can directly lead to bankruptcy. Also, accounting dates are objective, while occurrence dates, albeit useful to understand risk, can suffer from measurement error because they often have to be estimated by banks. For these reasons, recent operational risk regulations, such as new standardized approach for operational risk (Basel Committee on Banking Supervision (2017)) require loss calculations to reflect accounting dates rather than occurrence dates.

To understand whether our results apply when accounting dates are used (both in constructing the dependent variable and in constructing the lagged loss metrics explanatory variables), we perform the regressions presented in Table 10.

The results hold. All lagged loss metrics remain statistically significant in the regressions that include them. The magnitude of the coefficient on lagged average loss frequency decreases only slightly. Meanwhile, the magnitude of the coefficient on historical loss severity more than doubles. This increase in the association between future exposure and lagged loss severity is likely due to the accounting measurement of severity being close to the realization of the future losses to be predicted, while in regressions that use occurrence dates some loss severity amounts have to be moved back in time several years despite the factors that influence them (such as the legal environment) potentially changing between when the loss event occurred and when the losses are accounted.

Table 10: **Operational Loss Metrics and Current Losses at the Time of Financial Impact**

This table reports coefficients from panel regressions of realized operational losses at quarter $t+1$ on operational loss metrics and control variables measured in quarter t. The estimation sample comprises an unbalanced panel of 1,266 quarterly observations of 38 large bank holding companies over the period [2000:Q1-2017:Q4] for which requisite data are available. $Ln(OpLoss_{t+1})$ is the natural log transformation of the total operational losses (in millions) incurred by a BHC over a given calendar quarter. In Column (1), we only include control variables. In Column (2) we include $Ln(\overline{OpLoss})$, the natural log transformation of BHC quarterly average total operational loss measured over the prior four quarters, in addition to control variables. In Column (3) we include $Ln(\overline{Frequency})$ and $Ln(\overline{Severity})$, the natural log transformation of BHC quarterly average loss frequency and quarterly average loss severity, respectively, over the prior four quarters. Standard errors are clustered by BHC and quarter. P-values are presented in parentheses. In this table, $Ln(OpLoss_{t+1})$, $Ln(\overline{OpLoss})$, $Ln(\overline{Frequency})$, and $Ln(\overline{Severity})$ are measured based on the date that losses result in a financial statement impact, rather than on their occurrence date (as is done in all other tables).

	Ln(OpLoss$_{t+1}$)		
	(1)	(2)	(3)
Ln($\overline{OpLoss}$)		0.529***	
		(0.000)	
Ln($\overline{Frequency}$)			0.797***
			(0.000)
Ln($\overline{Severity}$)			0.832***
			(0.000)
Ln(Size)	1.398***	0.672***	0.456***
	(0.000)	(0.000)	(0.000)
II-to-NII	−0.011	−0.007	−0.010
	(0.428)	(0.299)	(0.101)
RoE	0.002	0.001	0.000
	(0.248)	(0.276)	(0.858)
T1 Capital	0.029	0.002	0.007
	(0.126)	(0.762)	(0.629)
Equity Vol	0.005*	0.003	0.003
	(0.085)	(0.205)	(0.120)
CCAR Age	−0.013	−0.011**	−0.011**
	(0.136)	(0.030)	(0.040)
ME Index	−0.004	−0.004	−0.007
	(0.596)	(0.518)	(0.239)
N	1,266	1,266	1,266
Adj R^2	0.689	0.754	0.767
BIC	3,746.077	3,452.883	3,393.077
Δ BIC	0	-293.1934	-352.9993

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

4. Conclusion

The analysis presented in this paper provides substantial evidence that historical operational losses are predictive of operational risk exposure, even after multiple drivers of operational risk that have been identified in the literature (such as size) and alternative metrics of risk management quality are accounted for. The most likely explanation for this relationship of losses across time is that operational risk exposure is partly explained by factors such as internal controls, risk culture, and risk appetite, which are persistent through time (but not immutable). Historical losses proxy for these factors and, thus, provide information on exposure beyond other factors previously identified in the literature.

Among the metrics of historical loss experience, loss frequency proves the most reliable predictor of operational risk exposure. This is likely because the number of operational failures is more stable than the severity of failures and, thus, reflects more consistently the underlying drivers of exposure. A 1% increase in past average loss frequency is associated with a 0.85% increase in total operational losses. We also provide evidence that operational loss experience of other firms is useful in forecasting the loss experience of a firm, particularly the loss frequency rate in the industry. Such finding suggests that firms should expand and retain industry data sharing, as such data can help firms better understand their exposure. It also suggests that regulators should consider publishing aggregate information on operational loss trends.

The results of this paper support the use of historical losses in operational risk exposure models. Across the range of types of operational risk, from fraud to legal risk, operational loss history is predictive of future exposure. Past losses are not only useful to predict expected exposure, but also to predict tail exposure. Thus, industry practitioners and regulators should use historical loss experience to better understand banks' operational risk exposure. Such experience provides a guide for areas in which firms can improve their operational risk management and controls.

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Appendix A

Table A1: **Definitions**

This table presents variable definitions in Panel A and operational loss event type definitions according to Basel Committee on Banking Supervision (2006) in Panel B.

Panel A: Variables	
Operational Loss Metrics	
OpLoss	The sum of the losses resulting from operational loss events experienced by a BHC over a quarter (in millions of U.S. dollars).
Ln(OpLoss)	A natural log transformation of *OpLoss*, defined as *Ln(1+OpLoss)*.
$\overline{OpLoss}$	The quarterly average of *OpLoss* measured over the prior four quarters.
Ln($\overline{OpLoss}$)	A natural log transformation of $\overline{OpLoss}$, defined as $Ln(1+\overline{OpLoss})$.
$\overline{Frequency}$	The quarterly average number of loss events measured over the prior four quarters.
Ln($\overline{Frequency}$)	A natural log transformation of $\overline{Frequency}$, defined as $Ln(1+\overline{Frequency})$.
$\overline{Severity}$	The average severity of loss events measured over the prior four quarters.
Ln($\overline{Severity}$)	A natural log transformation of $\overline{Severity}$, defined as $Ln(1+\overline{Severity})$.
$\overline{OpLossInd}$	The size-weighted industry average of $\overline{OpLoss}$ calculated as per Equation 2.
Ln($\overline{OpLossInd}$)	A natural log transformation of $\overline{OpLossInd}$, defined as $Ln(\overline{OpLossInd})$.
$\overline{FrequencyInd}$	The size-weighted industry average of $\overline{Frequency}$ calculated as per Equation 2.
Ln($\overline{FrequencyInd}$)	A natural log transformation of $\overline{FrequencyInd}$, defined as $Ln(\overline{FrequencyInd})$.
$\overline{SeverityInd}$	Industry average loss event severity calculated as per Equation 3.
Ln($\overline{SeverityInd}$)	A natural log transformation of $\overline{SeverityInd}$, defined as $Ln(\overline{Severity})$.
Controls	
Size	BHC total assets (in millions of U.S. dollars).
Ln(Size)	A natural log transformation of *Size*, defined as *Ln(Size)*.
II-to-NII	The ratio of BHC net interest income to non-interest income.
RoE	BHC return on equity over a four quarter window.
T1 Capital	BHC Tier 1 Capital.
Equity Vol	Annualized BHC daily equity return volatility measured over the prior four quarters.
CCAR Age	The number of quarters since the BHC was first subject to the Comprehensive Capital Analysis and Review (CCAR). It takes the value of 0 for the quarters before the BHC become subject to CCAR.
ME	U.S. financial and economic environment measure, defined as the first principal component of *GDP Growth*, *HPI Growth*, *CREPI Growth*, *VIX*, and *BBB-T10Yr Sprd*. *GDP Growth* is the year-over-year U.S. real GDP growth rate. *HPI Growth* is the year-over-year growth rate in the U.S. CoreLogic House Price Index. *CREPI Growth* is the year-over-year growth rate in the U.S. Commercial Real Estate Price Index. *VIX* is the CBOE U.S. Market Volatility Index, converted to a quarterly frequency by using the maximum close-of-day value in any quarter. *BBB-T10Yr Sprd* is the spread between the U.S. 10-year BBB-rated corporate bond yield and the 10-year U.S. Treasury bond yield. Higher values denote worse conditions.
Risk Management	BHC risk management index (RMI) value developed by Ellul and Yerramilli (2013). A higher value corresponds to a higher quality of BHCs' risk management function.
OpRisk MR(I)A	The number of outstanding operational risk Matters Requiring Immediate Attention and Matters Requiring Attention findings at a BHC as of a given quarter.
Ln(OpRisk MR(I)A)	A natural log transformation of *OpRisk MR(I)A*, defined as *Ln(1+OpRisk MR(I)A)*.

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
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.

Appendix B

Table A2: **Operational Loss Metrics and Current Losses scaled by Size**
This table reports coefficients from panel regressions of realized operational losses at quarter $t+1$ scaled by Total Asset in quarter t on operational loss metrics scaled by Total Asset and control variables measured in quarter t. The estimation sample comprises an unbalanced panel of 1,266 quarterly observations of 38 large bank holding companies over the period [2000:Q1-2017:Q4] for which requisite data are available. $\frac{OpLoss_{t+1}}{Size}$ is the total operational losses incurred by a BHC over a given calendar quarter scaled by the BHC Total Assets at the end of the previous quarter t. In Column (1), we only include control variables. In Column (2) we include $\frac{\overline{OpLoss}}{Size}$, the BHC quarterly average total operational losses measured over the prior four quarters divided by BHC Total Assets, in addition to control variables. In Column (3) we include $\frac{\overline{Severity}}{Size}$ and $\frac{\overline{Frequency}}{Size}$, the BHC quarterly average loss frequency over the prior four quarters divided by BHC Total Assets and the quarterly average loss severity over the prior four quarters divided by BHC Total Assets,respectively. Standard errors are clustered by BHC and quarter. P-values are presented in parentheses.

		$\frac{OpLoss_{t+1}}{Size}$	
	(1)	(2)	(3)
$\frac{\overline{OpLoss}}{Size}$		0.242**	
		(0.042)	
$\frac{\overline{Severity}}{Size}$			29.110**
			(0.030)
$\frac{\overline{Frequency}}{Size}$			0.251***
			(0.000)
Ln(Size)	0.108***	0.080***	0.127***
	(0.000)	(0.009)	(0.000)
II-to-NII	−0.014**	−0.013***	−0.012**
	(0.015)	(0.010)	(0.024)
RoE	−0.000	−0.000	−0.001***
	(0.431)	(0.303)	(0.000)
T1 Capital	−0.024***	−0.022***	−0.019***
	(0.000)	(0.000)	(0.000)
Equity Vol	−0.002	−0.002	−0.002
	(0.154)	(0.195)	(0.140)
CCAR Age	−0.013***	−0.010***	−0.011***
	(0.000)	(0.005)	(0.000)
ME Index	0.003*	0.001	0.001
	(0.077)	(0.452)	(0.441)
N	1,266	1,266	1,266
Adj R^2	0.082	0.094	0.118
BIC	2,552.292	2,542.600	2,514.398
Δ BIC	0	-9.6917	-37.8937

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