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A few rotten apples: non-performing loans, external frauds, and operational losses in a leading Indian bank

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ABSTRACT

Using novel, proprietary data on operational losses from a large government-owned bank in India, we provide evidence that only 3% operational risk events (particularly external frauds) account for more than 80% of aggregate operational losses. Operational losses are power-law distributed and exhibit steep increases in their tail operational value-at-risk. We also show that extreme operational losses in a given year are driven mostly by the previous year's NPL (non-performing loan) level, with a one standard deviation rise in NPLs associated with about a 1% rise in extreme operational losses.

Keywords: Operational risk; power law; non-performing loans.

1. Introduction

Operational risk relates to losses arising from insufficient or ineffective internal processes, personnel, systems, or external events and is more challenging to measure than market and credit risk (BCBS, 2011). As a result, recommendations from the Basel Committee include specific frameworks for the computation of capital requirements for operational risk losses (BCBS, 2004, 2017, 2023). The scope of operational risk is broad and includes risks related to fraud, litigation, physical damage, reputation, etc. Further, in contrast to credit or market risks, operational risks are non-financial and undiversifiable.

This study is motivated by i) the potential of operational risk events to pose a significant threat to the financial stability of banks, ii) the need for a better understanding of the distribution of operational losses, and iii) the presence of significant proportions of non-performing loans (NPLs) in Indian government-owned banks (GOBs) and their impact on operational losses. Our motivation is firmly rooted in prior academic investigations, which show that operational risk events account for a large proportion of dollar losses in banks (Abdymomunov et al., 2020), attract strong market reactions, negative press, reputational damage, and significant declines in market value (Barakat et al., 2019; Cummins et al., 2006), and can have a devastating impact on the financial stability of banks and the economy (Berger et al., 2022). Further, we test if aggregate operational losses are driven by only a small set of prominent events and whether past non-performing loans have a significant bearing on future values of extreme operational losses.

Using proprietary, granular operational loss panel data spanning 2007-2020, comprising 2,197 branch-year observations from a major GOB in India, we provide empirical evidence of power law distribution in operational losses—with a scaling parameter of 1.34—where a small number of external fraud events (~6%) drive most of the aggregate operational losses (~95%). This also gets reflected in the steep rise in the operational value-at-risk levels

(OpVaR), e.g., for percentiles 90, 95, 99, and 99.5, the OpVaR values are (in Indian Rupees (INR) millions) 18.8, 156, 1,545 and 2,744 respectively. These findings are consistent with prior evidence that operational loss distributions are heavy-tailed (Chernobai & Rachev, 2006; Frame et al., 2023; Jobst, 2007).

Additionally, using panel quantile regressions, we document that an increase in NPLs in the current year has a significantly positive association with next year's extreme operational loss levels. This result is primarily driven by weak credit management in Indian GOBs. In advanced countries, banks recover losses by liquidating collateral. In India, however, law enforcement and collateral titles are weak, which implies that counterparty defaults often assume the form of an operational risk event.[1] Poor credit management often leads to GOBs classifying credit default events as external frauds and recognizing haircuts as operational losses. For illustration, a common difficulty afflicting Indian GOBs is their inability to recover NPLs by liquidating the collateral since funds were siphoned and the collateral sold off by the borrower without the bank's knowledge. Consequently, this credit default event gets recognized as external fraud, and the loss gets categorized as an operational loss. This is one important reason why we document strong associations between NPLs and future operational losses.

Another contributing factor linking NPLs, and operational risk is as follows. After the global financial crisis, central banks lowered interest rates and purchased financial securities to boost the economy (Fawley & Neely, 2013), which lowered lending standards and raised risk-taking incentives due to high competition among banks (Cubillas & González, 2014; Dell'Ariccia & Marquez, 2006). Lower lending standards lead to higher NPLs. To improve the recovery, banks with higher levels of NPLs often take even higher risks and extend more loans,

[1] Diversion of bank loans for other purposes by borrowers is commonly acknowledged by the Reserve Bank of India as a major cause for NPLs.

which exacerbates the NPLs (Zhang et al. 2016) and increases systematic risk (Beltrame et al. 2018). Such systematic factors may also significantly influence large operational losses (Allen & Bali, 2007; Cope et al., 2012). Thus, high levels of NPLs may signal potential operational losses in subsequent years.

In unreported results, we observe that, unlike advanced economies, external frauds in Indian banks contribute to over 90% of aggregate operational losses in terms of value and account for approximately 70% of operational risk events in terms of frequency.[2] Despite this unique setting, research on operational risk remains limited, primarily due to restricted access to the data on operational risk events. We emphasize that the granularity of our dataset is unique, especially in its quarterly frequency and branch-level details of the extent and typology of operational losses. This is in contrast to the US and European studies in which such data are sourced from regulators overseeing stress-testing operations, which often omit significant operational loss events (De Fontnouvelle et al., 2006). In other words, our unique dataset, the distinctive context of the Indian banking system, with the dominance of GOBs and the notable presence of NPLs and operational losses stemming from external frauds, presents a compelling setting for research.

Our results have important policy implications. If operational losses are indeed fat-tailed, the quick resolution of the top worst offenders—comprising a vast majority of aggregate losses—can lead to high recoveries and lower provisioning than that mandated by regulators. Yet another application of our findings is forecasting next year's extreme operational losses based on the current year's NPL levels since we show that high level of NPLs in the current year signal significant extreme operational losses in the next year.

[2] Following the guidelines provided in Basel Accords II, operation risk events are categorized into seven types: a) business disruption & system failure; b) clients product & business practices; c) damage to physical assets; d) execution delivery & process management; e) external fraud; f) employment practices & workplace safety; and g) internal fraud.

Section 2 provides a discussion of related literature. This is followed by a description of the method, data, and empirical model in Section 3. Section 4 discusses the results, and the paper concludes with a summary and discussion in Section 5.

2. Literature Review

Prior studies show operational risk events are more likely to occur in younger, more complex, financially distressed, and poorly governed firms (Abdymomunov et al., 2020; Chernobai et al., 2011, 2021). Additionally, systematic and macroeconomic factors also contribute to operational risk in financial institutions (Allen & Bali, 2007; Cope et al., 2012). Abdymomunov & Mihov (2019) find that companies following better risk management practices before the financial crisis experienced lower operational losses during the financial crisis and in the post-crisis period.

Announcement of operational loss events can significantly damage the reputation of the financial institution, primarily due to the litigious tone in the media (Barakat et al., 2019; Galletta et al., 2023). When operational loss events are made public, banks experience significantly negative abnormal returns, leading to a considerable loss in their market values (Cummins et al., 2006; Gillet et al., 2010; Shafer & Yildirim, 2013), which tend to exceed the disclosed operational losses indicating sizeable reputational damages. The adverse market reaction tends to be stronger for operational losses due to internal and external frauds (Fiordelisi et al., 2014; Gillet et al., 2010). Furthermore, following the announcement, banks often experience aggressive downward revisions of earnings forecasts by banking analysts (Gya et al., 2021).

3. Methodology

3.1. Data

We obtain proprietary information on operational losses from a leading Indian GOB. Our sample consists of 3,341 operational risk events of the bank during 2007-2020. Further, we collect proprietary quarterly data on NPLs and advances from the bank. After removing the missing data, we obtained a panel data sample of 2,197 branch-year observations. BCBS (2017) stipulates that at least ten years of annual data are mandatory for applying a standardized approach to compute operational risk. In comparison, our dataset's thirteen-year duration with quarterly frequency and detailed information about the type and scale of operational loss events is richer and granular.

3.2. Empirical Model

Following the methodology of Clauset et al. (2009), we test whether the operational losses of the bank follow a power law distribution. Further, we employ panel quantile regressions to examine the effect of prior years' NPL quantiles on large operational losses in the current year. Our unit of analysis is branch-year. We control for total loan advances by the bank in the previous year and test the following model:

$$\begin{aligned} Ln\,(Operational\ Loss)_{\mathrm{it}} &\\ &= \beta_0 + \beta_1\, Ln\,(NPL)_{\mathrm{t-1}} + \beta_2\, Ln(Advances)_{\mathrm{t-1}} + \text{Branch Fixed Effects} \\ &+ \text{Year Fixed Effects} + \varepsilon_{\mathrm{it}} \ldots\ldots\ldots\ldots\ldots (1) \end{aligned}$$

We control for total advances extended by the bank in year t-1, $Ln\ (Advances)_{t-1}$, and following Kumar (2020), use branch and year fixed effects to account for unique branch (year) characteristics that remain invariant with time (branch). Using branch fixed effects subsumes many relevant omitted variables that depend on branch-specific factors in explaining large operational losses (Beck et al., 2018; Kumar, 2020). We cluster standard errors at the branch level to correct for heteroscedasticity and autocorrelation. Table 2 presents the descriptive statistics for these variables.

4. Results and analysis

4.1. Power-law distribution in operational losses

Table 1 shows the largest operational losses as a proportion of total operational losses. The top 10 (0.3%) events account for 37.15% of operation losses; the top 20 (0.6%) and 50 (1.5%) account for 47.65% and 65.27% of total operational losses, respectively. The top 3% operational risk events (top 100 in terms of rupee value) contribute to more than 80% of the aggregate operational losses. Approximately 6% of operational risk cases are responsible for nearly 95% of the operational losses, indicating the presence of a power law.[3]

A formal test of the power law, using maximum likelihood estimate, bootstrapping with 500 simulations provides a threshold value (Xmin) of 99,900 and alpha (scaling parameter) of 1.341. Figures 1 and 2 present the cumulative sum of the threshold value and scaling parameter using 500 simulations. There are 2,142 operational loss events (~62%) with a value higher than INR 99,900. We get a p-value of 0.45 using 100 simulations. Thus, we fail to reject the null hypothesis that data are generated from a power law distribution at the 5% and 1% significance levels (Clauset et al., 2009). Additionally, in unreported results, log-log plots yield a slope of -0.43 and an R^2 of 0.96, providing further evidence supporting the power law (Gabaix 2016).

4.2. Role of non-performing loans

The Indian banking system is troubled with NPLs, which significantly threaten the banking sector's stability and economy. To tackle this concern, the Reserve Bank of India (RBI) and the policymakers have implemented various measures, such as the establishment of debt recovery tribunals (DRTs) in 1993; the introduction of SARFAESI (Securitisation and Reconstruction of Financial Assets and Enforcement of Security Interest) Act, 2002 and IBC (Insolvency and Bankruptcy Code), 2016. The high level of NPLs in the Indian banking system is often attributed to the government ownership of banks, weak risk management systems, and

[3] The power law is a relationship of type $Y = \alpha X^{\beta}$ where α is a constant and β is the exponent of power law (Gabaix, 2016). Informally it is also referred to as the 80-20 rule, where 80% of the variation is attributable to only 20% of the events.

corporate governance concerns. GOBs comprise over 70% of the Indian banking system and account for most NPLs.

Prior research shows that banks often report high levels of NPLs prior to their failure (Barr et al., 1994). Banks with high levels of NPLs tend to exhibit lower efficiency due to increased operating costs (Phung et al., 2022). Additionally, Zhang et al. (2016) find that banks with higher levels of NPLs tend to take more risks and lend more in order to improve recovery, which further deteriorates the quality of loans extended by the bank. This behavior is a consequence of moral hazard problems (where the manager invests in pet projects, inadequately monitors, or extends risky loans), which leads to high levels of NPLs (Zhang et al., 2016). Moral hazard problems, such as poor managerial oversight of internal processes, people, and inadequate checks and balances of borrowed funds, can lead to operational losses, most of which are caused by external frauds. Additionally, high levels of NPLs in a banking system contribute to systematic risk (Beltrame et al., 2018). Prior research provides evidence that macroeconomic and systematic factors may significantly influence the large operational losses in banks (Allen & Bali, 2007; Cope et al., 2012). Thus, high levels of NPLs may signal potential operational losses in subsequent years. We empirically test the relationship between NPLs and operational losses using panel quantile regression.

Table 3 reports the results from the panel quantile regression analyses examining the association between prior year's NPLs and tail quantiles of operational losses. The results are presented for the 90th, 95th, and 99th operational loss percentile in panels A, B, and C, respectively. In Panel A, we find that the coefficient on NPL_{t-1} is positive and statistically significant (coefficient = 0.89, t-statistic = 2.66). The regression estimates suggest that a one standard deviation increase in NPLs leads to a 1% rise in operational losses of the bank in the next financial year. Further, we show that the coefficient on previous year's advances is statistically insignificant, suggesting that total advances on their own may not result in operational losses unless the bank has high NPLs. Our results remain consistent with quantile regressions at the 95th and 99th percentile in Panel B and C, respectively (see Table 4).

5. Summary and Conclusion

We study the operational losses of a large government-owned bank in India and provide evidence that operational losses are power-law distributed. About 6% of top operational loss events contribute ~95% of aggregate losses. Using panel quantile regression, we further document that previous year NPLs are strongly associated with the bank's top 1%, 5%, and 10% operational losses in the current year, suggesting that large levels of current NPL signal high subsequent operational losses. Hence, enhancing the credit monitoring of a few large borrowers could lead to substantial recoveries and lower provisioning for banks; and NPL levels could help predict future operational losses. Therefore, strengthening credit risk management systems and enforcement of collateral titles would not only alleviate NPL's concerns but also mitigate operational risk losses.

Table 1. Operational Losses in a Major Government-Owned Bank in India.

	Total	Top10	Top20	Top50	Top100
Operational Losses (in millions of INR)	152,950.10	56,813.94	72,888.32	99,825.96	124,259.80
Proportion of Losses	100%	37.15%	47.65%	65.27%	81.24%
Number of Events	3,341	10	20	50	100
Proportion of Events	100%	0.30%	0.60%	1.50%	2.99%

Note: This table provides the details of the largest operational losses (in terms of rupee value) and the corresponding proportion of operational risk events. INR = Indian rupees.

Table 2. Descriptive Statistics.

(N = 2,197)

Statistic	Mean	St. Dev.	Q1	Q2	Q3	P90	P95	P99
Ln (Operational Loss)	13.08	2.93	10.84	13.11	14.63	16.75	18.87	21.16
Ln (NPLs)	25.45	1.12	24.22	26.00	26.54	26.61	26.64	26.64
Ln (Advances)	28.24	0.33	27.96	28.45	28.50	28.51	28.54	28.54

Note: This table presents the descriptive statistics of variables. St. Dev. = Standard Deviation, Q1 = 25^{th} Percentile; Q2 = Median; Q3 = 75^{th} Percentile; P90 = 90^{th} Percentile; P95 = 95^{th} Percentile; P99 = 99^{th} Percentile. *Ln (Operational Loss)* = natural logarithm of operational losses; *Ln (NPLs)* = Natural logarithm of total non-performing loans of the bank; *Ln (Advances)* = Natural logarithm of total loans extended by the bank; N = Number of branch-year observations.

Table 3. Operational Losses and Non-Performing Loans (NPLs).

DV: ***Ln (Operational Loss)***

Panel A: 90th Percentile

Variable	**Coefficient**	**Std. Error**	**t-statistic**
Intercept	-9.38	18.58	-0.51
Ln (NPLs)t-1	0.89	0.34	2.61***
Ln (Advances)t-1	0.15	0.92	0.16
Branch Fixed Effects	Yes		
Year Fixed Effects	Yes		
Observations	2,197		

Panel B: 95th Percentile

Variable	**Coefficient**	**Std. Error**	**t-statistic**
Intercept	-39.80	20.54	-1.94*
Ln (NPLs)t-1	0.80	0.32	2.47**
Ln (Advances)t-1	1.35	1.00	1.35
Branch Fixed Effects	Yes		
Year Fixed Effects	Yes		
Observations	2,197		

Panel C: 99th Percentile

Variable	**Coefficient**	**Std. Error**	**t-statistic**
Intercept	-11.27	20.89	-0.54
Ln (NPLs)t-1	1.04	0.35	2.96***
Ln (Advances)t-1	0.19	1.02	0.19
Branch Fixed Effects	Yes		
Year Fixed Effects	Yes		
Observations	2,197		

Note: This table presents the quantile regression analyses of operational losses on non-performing loans at the 90th, 95th, and 99th percentile in Panel A, B, and C. Standard errors are clustered at the branch level. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10%, 5%, and 1% levels (two-tailed). DV = dependent variable; *Ln (Operational Loss)* = natural logarithm of operational losses; *Ln (NPLs)* = Natural logarithm of total non-performing loans of the bank; *Ln (Advances)* = Natural logarithm of total loans extended by the bank.

Table 4. Economic Significance.

Statistic	**90th Percentile**	**95th Percentile**	**99th Percentile**
Ln (NPLs)$_{t-1}$	1.00%	0.89%	1.17%

Note: This table presents the economic impact of one standard deviation change in lagged NPLs on current (log) operational losses at the 90th, 95th, and 99th percentile. *Ln (NPLs)* = Natural logarithm of total non-performing loans of the bank.

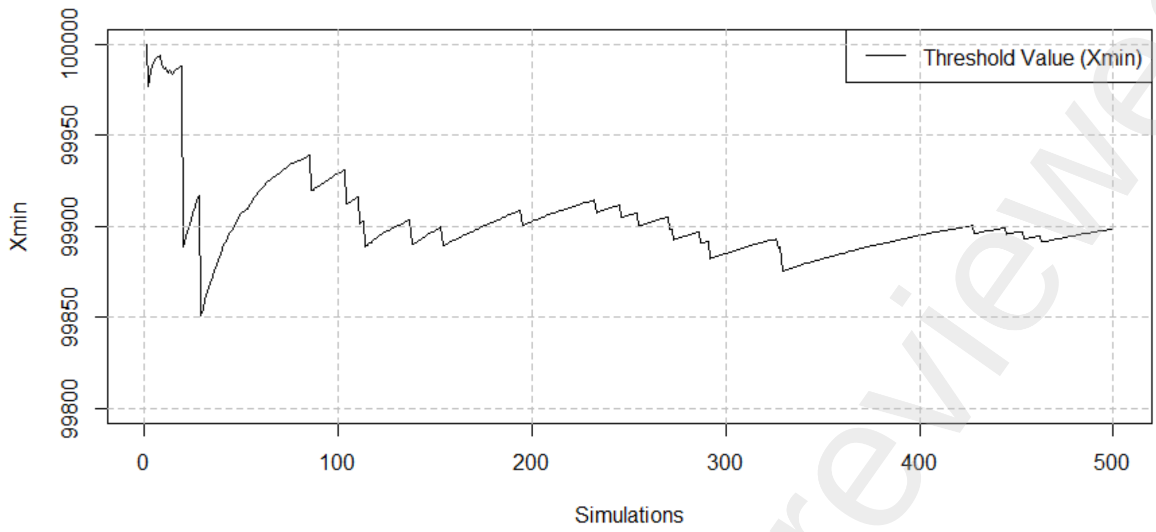

Figure 1. The cumulative sum of the threshold value (Xmin) using 500 simulations.

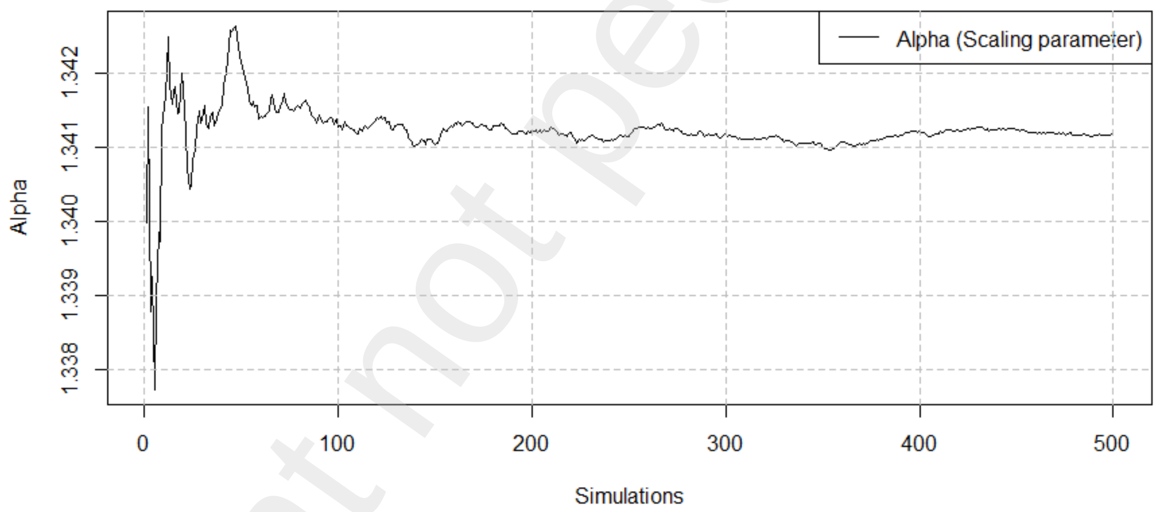

Figure 2: Cumulative sum of alpha (scaling parameter) using 500 simulations.

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