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ijmrset@gmail.com



www.ijmrset.com



An Empirical Study on Bank Risk Aggregation

Darshan Pannegar Ns, Darshan Mr, Prof Prithwiraj Das

MBA STUDENT – AIMS IBS BUSINESS SCHOOL, India

MBA STUDENT – AIMS IBS BUSINESS SCHOOL, India

AIMS IBS BUSINESS SCHOOL, India

ABSTRACT: Lack of appropriate risk data hinders risk aggregating. Financial statement risk mapping is an innovative approach to addressing data shortage and inconsistency. Current research has found. Traditional approaches to risk aggregation often exclude off-balance sheet items (OBS items), which might provide inconsistent results. To better aggregate financial statement risks, we map OBS items into risk categories. We conduct an empirical investigation to determine whether the impact of OBS activities and OBS risk categories on overall risk varies with bank size. In the years between 2007 and 2014, the 16 publicly traded Indian commercial banks issued a total of 487 quarterly financial statements. Our empirical research indicates that the impact of OBS operations on overall risk varies with bank size. Although both large and small banks face a positive correlation between OBS credit risk and total risk, there is a negative correlation between OBS operational risk and total risk. Overall OBS activities correlate favorably with a big bank's total risk but adversely with a small bank's total risk.

I. INTRODUCTION

Basel II was criticized for not taking OBS risks into consideration (Blundell-Wignall and Atkinson 2010). Since both on- and off-balance-sheet actions may be risky, OBS risk must be included into a bank's total risk exposure (BCBS 1986). The Basel Committee has already improved the regulatory capital structure to handle any risk (BCBS 2010). Therefore, there is an urgent need for a trustworthy risk aggregation model that takes both on- and off-balance-sheet hazards into consideration. We call the processes by which several risks are combined into one quantifiable whole "risk aggregation" (Li et al. 2015).

Simulation studies have been used to quantify credit risk, market risk, and liquidity risk (Acerbi and Scandolo 2008), but the reality is far more severe. External, verifiable data is utilized to augment internal loss data in operational risk. Data on operational risk hasn't convinced everyone (BCBS 2003; Chavez-Demoulin et al. 2006). Risk aggregate findings are less reliable and trustworthy due to data scarcity and heterogeneity. Using the publicly available financial accounts of commercial banks, recent studies have developed empirical indicators for risk. It has proven possible to summarize marginal risks by looking at financial statements.

On-balance-sheet assets are the foundation of Kretzschmar et al.'s analysis. Qualitative inferences would suffer in the absence of OBS derivatives. While Alessandri and Drehmann (2010) concentrated on balance sheet assets and liabilities, Drehmann et al. (2010) also include things off-balance-sheet (OBS). Including this detail increases confidence in the made-up financial institution. Profit and loss (P&L) items might be reclassified as high, medium, or low risks. Earnings volatility is the definition of risk, and hence P&L items that arise from it may be utilized as surrogates for hazards (Kuritzkes, Schuermann, 2007).

The technique presented here improves the risk aggregation paradigm based on financial statements by classifying OBS items. It's a better way to spread out danger. We model two hypothetical banks of different sizes to examine the impact of bank size on OBS expansion (DeYoung and Rice 2004). Credit, market, liquidity, and operational risks are aggregated across all 16 of India's listed commercial banks from 2007 to 2014. We show that OBS operations raise total risk and that the degree of the bank effect matters by comparing total risk with and without OBS activities. When people engage in OBS, the results of risk summaries will be inaccurate. To evaluate the degree of risk-taking among Indian commercial banks, we compare data from before and after the subprime crisis. What follows is the rest of the paper. In the following paragraphs, we will discuss the improved approach to risk aggregation based on financial



statements. The methods used to collect and organize data and the most important empirical findings are discussed in Section 3. Results, limitations, and directions for further study are summed up in Section 4.

II. LITERATURE REVIEW

Our purpose is to analyze commercial banks' exposure to market, liquidity, operational, and credit risk. A counterparty's failure is most institutions' biggest credit risk (Mustika et al. 2015). Market risk is the risk of financial loss owing to fluctuations in a bank's principal trading assets (BCBS 1996). A bank faces liquidity risk when it can't pay its debts on time or engage in new prospects without undue risk (BCBS 2008). Operational risk refers to the potential for loss due to insufficient or failing internal processes, personnel, and systems or external occurrences. (Li et al. 2014).

III. METHODOLOGY

3.1 Data description

To guarantee fiscal homogeneity, we gathered quarterly panel data from each of the 16 A-share listed Indian commercial banks from 2007 to 2014. Only publicly traded institutions' financial reports are accessible to the public and new accounting requirements were introduced in 2007. 2007-2009 quarterly data is missing as ABC and CEB became public in 2010. BOBJ's second quarter 2007 data is missing, along with data for BONJ, BONB, and CCB. With outliers eliminated, we have 487 relevant data points from which to estimate risk.

Our empirical research uses loan impairment loss, OBS items, and loan loss provision, even though these measures are only provided yearly and semiannually in financial statements. We must make assumptions to collect quarterly information on these accounts. OBS items are on par with semiannual items in the first quarter and annual items in the third. We first calculate R , the loan impairment loss-to-asset impairment loss ratio, using yearly and semiannual data. We'll call the average of this ratio across the whole sample period \bar{R} . Say each quarter R is precisely \bar{R} . For quarterly loan impairment loss, multiply quarterly asset impairment loss by \bar{R} . The quarterly loan loss provision is also given. The average loan loss provision for the study period is R_0 . Using average quarterly loan volume times R_0 produces quarterly loan loss provision. Statistically, the sample size is too small to make definite conclusions regarding the 16 Indian commercial banks mentioned from 2007 to 2014. Maximum 32 bank financials. We create hypothetical financial institutions using Alessandri and Drehmann (2015) to address this information gap and give empirical insights into the overall risk faced by Indian commercial banks (2017). (2010). In this investigation, we create two hypothetical banks, one huge and one small, and compare their median asset size. Four of India's top banks are owned by the government. ABC's financial statements are less transparent than competitors' due to delayed time to market. In this scenario, the enormous bank's assets are equivalent to the median of three state-owned banks. The hypothetical tiny bank's assets equal the mean of the three least small banks. The major bank had risk-weighted assets of 43,462 billion INR at year's end 2014 while the little bank had 2,262 billion INR. These two fake financial companies communicate 487 pieces of information, more than a genuine one. Our made-up hypothetical institutions have comparable asset sizes to real banks; thus, they resemble the Indian financial sector. In conclusion, when data is scarce, empirical study may be done using hypothetical banks that are representative of the industry as a whole.

Empirical result & Discussion

To compute the marginal risk distribution, you must first subtract the actual risk return from the expected risk return (4). The dispersion from the risk return, which is a consequence of the macroeconomic context as well as the actions of the banking sector, has an effect on the marginal risk distribution. The predicted risk return of each individual bank is used to establish the horizontal axis coordinates of the marginal risk distribution. Table 1 lays out the divergence measurements for risk-adjusted returns for your perusal. When it comes to return on risk exposure, market risk has the biggest variation (7.80 percent) and fattest tails (kurtosis = 60.67). The volatility of the liquidity risk is thus 0.51 percent, while the kurtosis of the liquidity risk is 17.59 percent. Credit risk (-1.08) and operational risk (3.47) both have narrower tails, with 0.50 and 0.31 percent volatilities, respectively, based on their respective kurtosis statistics. Credit risk is the only one of the four that has a normal distribution; the others are all tilted to the right. Market risk is 5.71, liquidity risk is 3.14, and operational risk is 1.26, skewed somewhat to the right. Table 2 displays the risk-return profiles of two fictitious institutions. In terms of returns, we anticipate 0.44 percent for credit risk, -9.62 percent for market risk, -0.56 percent for liquidity risk, and -0.64 percent for operational risk. The projected return for market risk at the small bank is greater than at the large bank (-8.27 percent), but it is lower for credit risk (0.40 percent), liquidity risk (-0.66 percent), and operational risk (-0.76 percent). The marginal risk distribution is defined by the expected risk



return as well as the deviation from the risk return; as a result, we are able to compute the marginal risk distributions of the two made-up banks. Table 3 displays the following marginal risk distributions for your perusal: There are considerable disparities in the marginal risk distributions of large and small financial institutions. The bank is likely to experience average credit risks of 1.20 percent, market risks of 0.77 percent, liquidity risks of 0.20 percent, and operational risks of 0.21 percent, respectively. This is a certainty of 99.9 percent. The average credit risk is 1.15 percent, while market risk is 0.59 percent, liquidity risk is 0.09 percent, and operational risk is -0.31 percent. According to the median figures, the major bank has the most credit risk, which comes in at 1.20 percent, and the lowest operational risk, which comes in at -0.21 percent, between liquidity risk at 0.16 percent and market risk at 1.00 percent (-0.88 percent). The credit risk at the little bank is 1.16 percent, whereas the market risk is just 0.47 percent. Liquidity risk was 5% and operational risk was -0.32% at the median. The value at risk (VaR) estimations for varying degrees of assurance on different risks are shown in Table 3's last four columns. According to the findings of the empirical research, the market risk associated with the big bank is higher than that of the small bank, although the credit risk, liquidity risk, and operational risk are lower.

VaR for market risk is more negatively skewed for the large bank than the smaller bank, indicating a bigger market risk for the former. The bigger financial institution has lower VaRs in both liquidity and operations. There is more of a credit risk with the large bank than with the smaller one. This alleviates concerns about the bank's creditworthiness, liquidity, and operations. Value at Risk (VaR) in the market at the 0.1 percentile is less for a large bank than a small bank (-23.92 percent). VaRs for liquidity risk and operational risk are negative for both the big and the small bank, while the former's are lower (-1.47 and -0.96 percent, respectively) (liquidity risk: -1.58 percent; operational risk: -1.06 percent). Valuation at risk (VaR) for credit risk is 0.31 percentage points higher for the larger bank (0.26 percent). When comparing large and small banks, market risk is greater for the former while credit, liquidity, and operational risks are lower for the latter.

VaR measurements are aggregated to estimate the overall risk. VaR measures the fraction of overall risk exposure that is attributable to the potential loss of capital. The large bank's marginal credit risk weight at year's end 2014 was 45.44, market risk weight 7.96, liquidity risk weight 46.56, and operational risk weight 46.56. Credit risk, market risk, liquidity risk, and operational risk for the bank are respectively 45.24 percent, 0.49 percent, 7.69 percent, and 46.58 percent. In order to get a feel for the level of risk involved, the total loss was computed. The term "total risk" will be used throughout the rest of the report to indicate Add-VaR and a 100% loss. Despite having a loss horizon of just a year, the information in our quarterly financial statements allows us to get valuable insight into overall risk (Danielsson and Zigrand 2006).

IV. ANALYSIS OF RESULT

Here, we conduct an empirical study to determine whether and how OBS operations influence the risk profile of Indian commercial banks. Unlike the current method, which only aggregates on-balance sheet hazards, our enhanced approach can detect both on-balance and off-balance sheet concerns. In order to get insight into how OBS operations as a whole affect the bank's entire risk profile, we first examine the anticipated outcomes of risk aggregation using the two frameworks. However, research on the impact of OBS on the risk profile of Indian commercial banks was elusive. No strong conclusions can be formed yet about whether OBS activities affect bank risks. OBS were formerly thought to reduce risk (Hassan et al. 1994). Despite evidence to the contrary (Papanikolaou and Wolff 2014), some believe OBS-focused banks are riskier. We compare 2014 total risk with and without OBS items to show experimentally that OBS risk affects Indian commercial banks' overall risk, with the impact varied by bank size. Incorporating OBS items into risk aggregation reduces the total risk for large banks from 587.12 billion INR to 576.68 billion INR with 99.9 percent confidence, while increasing the total risk for small banks from 27.14 billion INR to 27.71 billion INR. When it comes to overall risk, OBS activities tend to be detrimental for large banks but beneficial for smaller institutions. Large banks' risks would be overestimated and those of small banks would be underestimated if risk aggregation failed to account for OBS elements. The effect of OBS operations on a bank's overall risk may be modified through careful management of OBS risk. Items from OBS have both protecting and harmful properties.

The net effect of OBS items on bank risks is determined by the effectiveness of OBS risk management (Khasawneh et al. 2012). Due to its inexperience and lack of resources, the tiny bank takes up riskier OBS operations than its larger counterpart (Mercieca et al. 2007). Therefore, OBS items raise the overall risk for a small bank while lowering it for a big bank. In instance, the conventional deposits and loans sector is dominated by state-owned banks. Size does matter



when it comes to a bank's profitability, as shown by Zhao and Jian (2013). Because of the larger stakes involved in the OBS operations, the tiny bank takes more risks in an effort to increase its bottom line. The riskiness of a small bank rises, for instance, when OBS derivatives are used for speculating rather than as hedging instruments. The little bank's success is further hampered by its employees' lack of market and OBS transaction expertise. Therefore, OBS components are correlated adversely with overall risk at Indian big banks but favorably at Indian small banks. Figure 2 shows that there is no clear difference in overall risk with and without OBS elements, which reduces the urgency of including them in the risk aggregation framework. We then explain why the dissimilar risk aggregation caused by OBS parts is not immediately apparent. A statistic that may be used to show how the overall risk has changed because of OBS efforts is the rate of change, which is the ratio of total danger with OBS activities to total danger without OBS initiatives.

Following the addition of OBS activities to the risk aggregation process, the rates of change for total risk exposure, Add-VaR, and total risk are graphically shown in Figure 3. Total risk change rate is clearly invisible. While overall risk decreases by 2.25 percentage points for the big bank, it rises by 2.59 percentage points for the small bank.

	Large hypothetical bank	Small hypothetical bank
Total risk (without OBS items)	587.12	27.14
Total risk (with OBS items)	576.68	27.71

Fig. 2 Analyzing the Full Risk without and with OBS

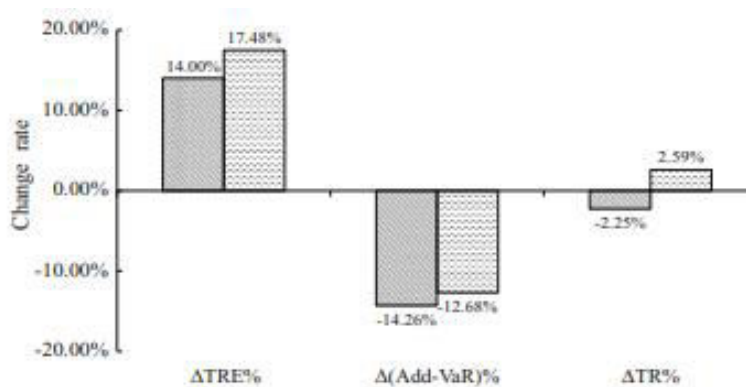


Fig. 3 The variation in risk aggregation due to the addition of OBS items

The scope of OBS activities at Indian banks is still somewhat small as compared to those at their Western counterparts. Based on the information at hand, we determine that the OBS items at the large bank constitute 15.41% of its total on-balance-sheet assets and those at the small bank constitute 19.21%. As a result, including OBS elements into the risk aggregating structure is both necessary and fair. Our method of aggregating risk is one of a kind because not only do we conduct an objective assessment of the overall influence that OBS operations have on the bank's total risk, but we also evaluate the impact that each OBS risk category has on the overall risk.



V. CONCLUSION

The method of risk aggregation that is based on financial information is expanded upon in this research by the addition of OBS activities. Because of this, we are able to simultaneously account for dangers that are on and off the balance sheet. In the component of the research that deals with empirical evidence, we make advantage of this revised approach by collecting information from each of India's 16 commercial banks that were listed between 2007 and 2014. This study evaluates the susceptibility of Indian financial institutions both before and after the subprime crisis using a split-sample approach. The findings of our analysis indicate that the activities of OBS have an impact on the level of risk that is borne by Indian commercial banks. For both big and small banks, there is a positive association between OBS credit risk and overall risk; however, there is an unfavorable correlation between OBS operational risk and total risk. The influence of each OBS risk class varies from bank to bank, which is one reason why the effect of OBS activities on total risk is proportional to the size of the bank. The activities of the OBS have a positive link with the risk that is posed by smaller banks, whereas their actions have a negative association with the risk that is posed by larger banks. If components of OBS were deleted from the risk aggregation process, the overall risk of the big bank would be exaggerated, while the risk of the small bank would be understated. According to the findings of the study on risk transformation, Indian commercial banks saw an increase in both their liquidity risk and market risk levels during the subprime mortgage crisis. This research suffers from a number of significant methodological flaws. To begin, it is not clear how big of an increase in risk there would be if OBS was included in the equation. If OBS factors are neglected throughout the process of risk aggregation, there is a good chance that the variance will increase. This is due to the growth of OBS activities as well as the need for consistent disclosure. The second problem is that there is no clear relationship between the various categories of risk and the outcomes that are shown in the financial statements. The credit risk and market risk that come along with interest income produced on a net basis both need to be considered. If there are any assets that do not have the potential for operational risk, then there is no risk at all. In subsequent research, the relationship may be refined based on more evidence that is gathered.

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