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ABSTRACT

This study explores the concentration-stability nexus in the context of a spurt of restructuring mergers that have taken place in the Indian banking sector in the recent past. Using the contingent claims approach (Merton, 1974), we measure the vulnerability of the financial system over time as well as constituent banks' contributions to systemic risk both before and after the mergers and during different stress periods in financial markets. Through our empirical analysis, we establish that merged entities have contributed more to financial instability. However, the destabilizing effect is primarily due to banks' standalone risk profiles and ownership characteristics rather than size-based concentration. The results have significant policy implications both in terms of identifying and monitoring systemically important banks and for regulatory oversight on bank consolidations.

Key Words: Financial Crisis, Systemic risk, Financial Stability, Mergers, Marginal Risk Contribution, Contingent Claims Analysis

JEL Classification: G01, G21, G28, F32, G34, C13

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1. Introduction

Estimating systemic risk of the financial sector of any economy became a matter of key concern for regulators the world over after the global financial crisis of 2007-2008. The crisis underscored the fact that micro-prudential regulations of the risk profile and capital adequacy of individual banks and financial institutions may not suffice in ensuring the safety and stability of the financial system as a whole. Thus, even though a bank, on a stand-alone basis, may appear to be "safe", it may also be too big and have strong common linkages to the financial system and interconnectedness with other institutions. This may increase its risk contribution to financial instability, which is likely to be exacerbated during periods of severe macroeconomic shock. Macro-prudential supervision of financial markets thus faced twin challenges. The first was to derive indicators of systemic risk, which not only captured its extent and probability but also did so in a forward-looking manner in order to provide sufficient early warning signals. The second was to identify systemically important financial institutions, through an assessment of their effect on market stability. This influence could be via their size effect or through their idiosyncratic solvency risk, which, if "significant" enough, could pose a greater threat to financial stability during crisis periods.

Furthermore, it was observed during the 2008 financial crisis, that governments in various countries of Europe and the US used mergers and acquisitions as a preferred, privately arranged, bail-out mechanism for the too-big-to-fail distressed banks. While such bank consolidations did prevent additional burden on fiscal funds, they were open to the criticism that, in turn, they created mega banks and a more concentrated bank market, which had the potential to change the dynamics of future systemic vulnerabilities.

The above concerns opened up afresh the debate surrounding the connection between bank consolidations and financial stability. Those who championed the concentration-stability relationship founded their arguments upon the benefits to financial markets due to the increased economic efficiency of larger and fewer banks in terms of enhanced franchise value and lower risk-taking. The proponents of the concentration-fragility relationship put forward alternative theories based on strength of market power, moral hazard due to state guarantees and capital infusion that supported the mergers, and the risk of contagion created through a more networked system of fewer and larger banks post-consolidation. These conflicting hypotheses have been examined primarily with data from developed economies as seen in the existing literature and have not been explored sufficiently in the financial markets of emerging economies like India.

The Indian banking sector has seen its fair share of 30 mergers and acquisitions in the three decades following the year 1991, when the first set of banking reforms was undertaken. Some of these were strategic; with acquiring banks seeking to leverage synergies and grow inorganically. Others were government-assisted or privately arranged takeovers of weak or non-viable banks by their stronger counterparts. All of these mergers were approved by the Reserve Bank of India (RBI) – the regulator and supervisor of Indian banks. However, their systemic risk implications remained unaddressed both in academic literature and from a policy perspective and warrant additional research.

The recent spurt of public sector bank (PSB) amalgamations that have taken place under the government's latest reform initiatives from 2016 onwards provides us with a unique natural experiment to analyse the concentration-fragility nexus in India's banking sector. To do so, we use Merton's (1973,1974) contingent claims analysis (CCA) to develop a market-based measure of systemic risk – which we call the risk-neutral systemic distress probability. We use this metric to identify two distinct historical periods of banking crisis in India since 2012. The first crisis spanned three years from March 2012 to March 2015, and was caused by worsening asset quality and burgeoning losses, especially among public sector banks, which led to the subsequent PSB mergers. The second crisis was exogenous and triggered by the Covid-19 pandemic between March 2020 and March 2021, when both global and domestic financial markets at large were stressed. In this context, it is relevant to mention that the RBI measures and monitors the stress in the banking sector using various indicators, which are published in its half-yearly Financial Stability Reports. A key metric used by RBI is the Banking Stability Index (BSI), which is an average of five component indices which represent soundness, asset quality, profitability, liquidity and efficiency, measured by a number of financial ratios of banks (RBI FSR, June 2020). This index provides an aggregated picture of systemic risk in banking but uses ex-poste data and also does not attribute it to constituents.

In order to assess the stability effect of mergers, we specify two bank-level risk metrics - standalone risk-neutral probability of default (PD) and marginal contribution to systemic risk – both derived based on the CCA framework. The former captures idiosyncratic insolvency risk of a bank and the latter measures the extent to which an individual bank reduces or worsens systemic distress. Our empirical analysis uses quarterly panel data from March 2012 to June 2022 for a mix of merged banks and other large, unconsolidated public and private banks as a control group. We find that merged banks have an adverse effect on financial stability. However, the channel of transmission is primarily through banks' idiosyncratic insolvency risk captured by their standalone PD, lower Tier 1 capital adequacy, higher credit to deposit ratio and non-performing loans ratio. Bank size per se, does not have a significant impact. Furthermore, ownership characteristics also matter in determining systemic risk contribution as public sector banks in general and those with higher government shareholding contribute more towards destabilising the system during a crisis.

Our research makes some important contributions to the existing studies of systemic risk and financial stability. This is, to the best of our knowledge, the first study of systemic risk in India, using the contingent claims analysis, which is a theoretically sound, and empirically well-tested framework for measuring systemic risk (Bisias et. al., 2012). The CCA based financial market risk analytics are estimated using both market returns and balance sheet characteristics, and as such address both forward-looking expectations of the performance of the individual banks and the banking sector in aggregate as well as the institutional and system-wide leverage that can create potential stress. Second, we add to the substantial body of literature on the merger-concentration-stability relationship with unique insights derived from consolidations in the Indian banking sector.

The rest of the paper is organized as follows. In section 2, we present a comprehensive review of the studies that have evaluated the concentration-fragility relationship using systemic risk metrics and its attribution to consolidations in the banking sector. In Section 3 we describe our analytical framework and elucidate the measurement of the system-level and bank-level insolvency risk and the marginal contribution to systemic risk. Section 4 provides a brief background on the database and methodology followed in our study. Section 5 preludes our empirical analysis by representing some stylized facts relating to mergers and systemic risk in the Indian banking sector. Section 6 summarizes our empirical findings, including the robustness of the models used. Finally, Section 7 concludes with important policy implications.

2. Literature Review

The early theoretical and empirical literature surrounding the debate on whether a more concentrated banking system is beneficial or detrimental has been extensively surveyed by Canoy et al. (2001), Carletti et al. (2002), Carletti and Hartmann (2003) and Berger et. al (2004) and revolves around the effects of concentration on financial safety via bank competition, risk taking and franchise value. One view is that concentration and bank consolidation reduce competition such that banks can exploit their market power in pricing loans and deposits and thereby enhance charter value. Furthermore, under imperfect competition, banks take fewer risks on their asset side and create better diversified portfolios. This argument was first proposed by Keeley (1990) who provided empirical evidence from US markets in support of the negative trade-off between intensity of competition and bank safety. Subsequently, it was theoretically ascertained by Cordella and Yeyati (2002) and Repullo (2004) and empirically demonstrated by Salas and Saurina (2003) for a European country. Furthermore, Marquez (2002) showed that with more competing banks, screening ability reduces and increases the risk of adverse selection of borrowers. Jiminez et al. (2013) found evidence of a negative relationship between loan market power measured by the Lerner index and bank risk in terms of non-performing loans. From a cross-country analysis for the period 1980-1997, Beck et al. (2006) proved that there was a lower likelihood of occurrence of financial crises for national banking systems which were more concentrated, though on the contrary, they also indicated that competitive banking systems (through lower entry barriers and national institutions which foster competition) were more resilient. Furthermore, studies also suggested that the contagion effect on the system can be reduced or avoided by the larger, oligopolistic banks during crises through better co-ordination (Saez and Shi, 2004) and provision of timely liquidity (Allen and Gale, 2000, 2004). Thus, with constituents having higher profitability, safer portfolios and better risk-based capital ratios, a less competitive and more concentrated bank market is also less fragile and less prone to systemic risk.

The concentration-stability view point, as discussed above, has been challenged by various studies. Mishkin (1999) was one of the earliest to suggest that bank consolidation increases systemic risk since larger institutions engage in potentially riskier activities because of the moral hazard associated with implicit protection of too-big-to-fail entities. De Nicoló (2000), in a cross-country study for the 1988-1998 period corroborated the premise that for larger-sized banks, charter value decreases and insolvency risk increases as higher risk-taking by banks offsets the size-related diversification benefits and economies of scale. Furthermore, De Nicoló et al. (2003) highlighted global trends in bank consolidation and indicated that the risk profiles of the larger financial conglomerates were higher and did not bode well for the resilience of the banking system. Subsequently, it was shown theoretically by Boyd and De Nicoló (2005) that when large banks charge higher loan rates due to market power, their loan customers are induced to get into risky business, which transmits to higher credit risk for the bank. Schaeck et al. (2009) applied a direct measure of competitive conduct in banking sectors across 38 countries during 1980-2003 to provide evidence that systemic crisis prospects were lower and time to crisis was longer in more competitive banking systems. Finally, taking cognizance of firm interdependencies in signaling systemic risk potential, and measuring them through correlations of stock returns, De Nicolo and Kwast (2002) found a positive consolidation elasticity of correlations within a sample of large and complex banking organizations in the US over 1988-99.

The complex, multi-faceted and possibly ambiguous relationship between concentration and stability was highlighted by Allen and Gale (2004) whose applications of different economic models to this problem yielded conflicting results. In a theoretical framework, Martinez-Miera and Repullo (2010) first presented the possibility of a non-linear ("U"-shaped) relationship where systemic risk is high in monopolistic markets due to domination of risk-taking effects; it reduces as competition initially increases; and peaks again in highly diffused markets due to the adverse effects of margins getting squeezed. This premise was empirically supported by Jimenez et al. (2013) with standard measures of concentration applied to data from the Spanish banking system.

The occurrence of the global financial crisis (2007-2008) alerted academicians and policy-makers to the fact that systemic risk (or instability) in the financial markets had to be defined and evaluated differently from just the simple aggregate of the standalone insolvency risk of banks. This triggered the design of a host of systemic risk indicators to estimate the probability and cost of financial crises. It also initiated the need to measure systemic importance of individual institutions in terms of their negative marginal externalities on the system created due to their exposure and contribution to sectoral vulnerabilities. The measures which gained popularity included the Joint Probability of Default (JPoD) by Segoviano and Goodhardt (2009), the Marginal Expected Shortfall (MES) and Systemic Expected Shortfall (SES) by Acharya et al. (2017); the Conditional Value at Risk (CoVaR) by Adrian & Brunnermeier (2016), the SRISK and NSRISK by Brownlees and Engle (2017) and the Distress Insurance Premium (DIP) by Huang, et al. (2009, 2012). The Contingent Claims Analysis (CCA) methodology of Merton (1974) was also adopted to measure distance-to-default and quantify systemic risk and individual contributions of financial institutions from market-implied losses (Lehar, 2005, Gray et al., 2008 and Gray and Jobst, 2010). These measures were used widely to study systemic risk in country-specific and cross-country financial markets.

New research post the global financial crisis, revisited the concentration-stability nexus particularly from the perspective of bank mergers and acquisitions, many of which were initiated by policy-makers as a means to prevent bank failures and costly bail-out packages. Vallascas and Hagendorff (2011), analysed European bank consolidations using Merton's distance-to-default model to show that mergers motivated by regulatory incentives increased the default risk of acquiring banks, especially if they were relatively safe before the consolidation. Based on MES applied to a dataset of international, domestic and cross-border mergers, Weiß et. al (2014) evidenced that systemic risk increases following mergers for all constituent entities and thereby refuted the concentration-stability hypothesis. They suggested that the moral hazard problem of government ownership and deposit guarantees, along with the implicit protection associated with the too-big-to-fail status of merged entities led to the destabilizing effect of bank consolidation and not the acquirer size. Maslak and Senel (2019) proved the opposite using multiple systemic risk metrics applied to bank mergers in the United States, during the global financial crisis. They found that market-adjusted systemic risk decreased for the acquirers during the crisis and the effect was not significantly different for government-assisted mergers vis-à-vis private ones. Their results pertaining to the influence of large banks on financial stability were conflicting for different metrics – MES and NSRISK indicated that aggregate exposure to systemic risk increased due to increase in large banks' risk whereas ΔCoVAR suggested that large banks played a significant role in reducing aggregate contributions to systemic risk. Van Dellen et. al. (2018) demonstrated that bank mergers and acquisitions were risk-neutral, using a longer time period and larger sample. However, they cautioned that there could be substantial scope for increase in the likelihood of acquirers' contribution to systemic risk if potential risk reduction benefits did not materialize. IJtsma et. al. (2017)'s study for European banks also concluded that both enforced and market-driven mergers hardly affect stability of the individual banks or the financial system at the country level. Thus, the discussion on the effects of consolidation on the financial system remained moot.

For the Indian banking sector, the RBI used the JPoD metric to show that systemic risk had shot up during the period of the global financial crisis of 2007-2008 but fell to very low levels in 2011 (RBI, FSR, 2011). Acharya et al (2012) applied MES to compare the risk contributions of state-owned banks and private banks and demonstrated that vulnerable private banks performed poorly during the crisis but not so public sector banks because of the implicit government guarantee and forbearances. Verma et. al. (2019) applied the Tail-Event driven NETwork (TENET) risk model to reveal the presence of interconnectedness among banks during crises and also to identify systemically important banks (SIBs) through marginal effects. Critical issues pertaining to shareholders and managers arising from bank consolidations in India up to 2007 were highlighted by Jayadev and Sensarma (2007). Their event study suggested that where mergers took place through regulatory intervention, shareholders of neither the bidder nor target bank benefitted. However, they presented arguments in support of larger banks. Basis the amalgamation of the State Bank of India with its subsidiaries in 2017, Krishnamurthy (2017) discoursed upon the key challenges in the exercise and the need for policy makers too plan carefully the subsequent rounds of crisis affected bank mergers. Das and Kumbhakar (2022) analyzed the post-crisis bank consolidations in India to show that cost efficiencies did not improve subsequently and had the potential to weaken the banking system. Gupta and Kashiramka (2021) identified the SIBs in India by measuring the SRISK based expected capital shortfall in a systemic event. They indicated that public sector banks contributed more to systemic risk than private banks. From the India- related research, it is clear that the influence of mergers and banking concentration on the financial system and its constituents has not been comprehensively addressed. This is an important gap that our study tries to fill.

3. Measuring Bank-level Insolvency Risk and Systemic Risk: Analytical Framework

The methodology followed in our estimation of systemic risk is based on the contingent claims analysis (CCA) framework developed by Merton (1974), which estimates a firm's standalone risk of default as per the option pricing model formulated by Black and Scholes (1973). This method, without loss of generalization, can be applied to measure the insolvency risk of individual banks and elegantly extended to estimate the systemic risk of the financial sector. The application of CCA to risk measurement of financial entities and systems has many advantages. First, the data is publicly available for all banks which have issued common equity in the market. Second, equity data incorporates forward-looking expectations of the market in a way that only balance sheet indicators of bank risk cannot. Third, the data is available at high frequency and allows faster updates of the risk measures. Finally, at a system-level, the measure incorporates implicit diversification or concentration effects of constituent banks and allows us to derive marginal effects.

3.1 Bank-level Insolvency Risk

We first describe the CCA methodology as applied to a simplified balance sheet of a firm (a bank in our case). The capital structure of a firm is assumed to comprise junior equity and risky debt which matures at time T and has a face value at maturity given by *D* (the book value of outside liabilities of the firm). Thus, at any point in time *t*, the firm's market value of assets (A_t) is the sum of the market value of equity E_t and the market value of risky debt D_t, that is:

$$A_t = E_t + D_t \qquad \text{..........(1)}$$

A_t is stochastic and can potentially decline below *D* (often referred to as the distress barrier or default threshold) at time *T*, whereby the scheduled debt will not be repaid, effectively leading to default by the firm, that is insolvency of the bank.

Equity holders of the firm have a junior, contingent claim on the residual value of the firm's assets after all the debt obligations (*D*) are paid in entirety in the non-default states. Equity investors thus hold a call option on the market value of assets A_t as the underlying, *D* as the strike price, and *T-t* as the maturity of the option. At time T, they thus receive the maximum of either asset value less the debt payment or nothing, in which case the firm defaults, as shown in equation 2.

$$E_T = Max(A_T - D, 0) \qquad \text{..........(2)}$$

If the market value of assets falls, the value of the call option, measured by the market value of equity E_t, decreases and the firm's risk of default on the debt obligations increases. E_t can be estimated (using Black-Scholes option pricing under the risk-neutral probability measure) as

$$E_t = A_t N(d_1) - De^{-r(T-t)} N(d_2) \qquad \text{..........(3)}$$

where, *r* is the risk-free interest rate.

The risk-neutral threshold asset returns d_1 and d_2 are given by:

$$d_1 = \frac{\ln(A_t / D) + (r + \sigma_A^2 / 2)(T-t)}{\sigma_A \sqrt{T-t}} \qquad \text{..........(3a)}$$

$$d_2 = d_1 - \sigma_A \sqrt{T-t} = DD_t$$

……….(3b)

Where, σ_A represents the volatility of the market value of assets and the function *N(.)* is the cumulative standard normal distribution function.

The threshold asset return d_2 can be interpreted as the risk-neutral distance-to-default (DD_t) of the firm at time t. $N(d_2)$ is the risk-neutral probability that the call option will be exercised, that is market value of assets will exceed the default point. Thus, $1-N(d_2) = N(-d_2)$ represents the risk-neutral probability (PD_t) that the market value of assets will fall below the default point and the firm will default. In the context of an individual bank, higher the value of PD_t, higher the standalone insolvency risk.

Figure 1 provides a diagrammatic conceptualization of the distance to default and default probability.

[Figure 1]

From equations 3, it is clear that to estimate the risk-neutral probability of default; we need firm level information on the market value of assets (A_t) and the volatility of asset returns (σ_A). The default threshold (D) can be estimated by the book value of total outside liabilities for the firm and can be obtained from balance sheet information. The horizon of the debt obligation if assumed to be 1 year (that is, $T-t = 1$) leads to a one-year probability of default measure. The market value of equity (E_t) can be measured by the market capitalization of the individual bank.

To solve for the two unknowns (A_t and σ_A), along with equation 3, we use equation 4 below, which captures the leveraged stochastic nature of market value of equity (E_t).

$$E_t \sigma_E = A_t \sigma_A N(d_1) \qquad \text{……….(4)}$$

where, σ_E represents the standard deviation of logarithmic equity returns observable in the market.

Applying the Newton-Raphson method, the values of A_t and σ_A are iteratively derived by solving equation 5.

$$\min_{A_t \sigma_A} \left[A_t N(d_1) - De^{-r(T-t)} N(d_2) - E_t\right]^2 + [A_t \sigma_A N(d_1) - E_t \sigma_E]^2 \qquad \text{……….(5)}$$

3.2 Systemic Risk

The methodology described in section 3.1 can be extended to analysis of systemic risk-neutral default probability, by defining the system as a portfolio of all banks. Thus, the market capitalization of the defined financial system is the sum total of the market capitalization of the banks that comprise the system. The system level equity volatility is estimated by the standard deviation of bank index returns where the bank index is constructed as the weighted average equity prices of the constituent banks.

The default threshold for the system is the sum total of the book value of outside liabilities of all banks within the defined system. This definition of the systemic default threshold may lead to double counting of interbank liabilities of the banks within the system (Drehmann & Tarashev, 2011). In the absence of bilateral bank lending and borrowing information, we are unable to adjust for the same in estimating total debt. However, since the proportion of interbank borrowings is only a very small proportion of total liabilities of each bank, its impact on systemic risk can be assumed to be negligible.

For i = 1 to n constituent banks in the system with individual default threshold given by D^i_t and market capitalization given by E^i_t, the systemic default threshold D^{Sys}_t and the systemic market capitalization E^{Sys}_t, is defined as

$$D_t^{Sys} = \sum_i D_t^i \qquad \text{..........(6)}$$

$$E_t^{Sys} = \sum_i E_t^i \qquad \text{..........(7)}$$

I represents the system index of equity prices. I is given by

$$I_t^{Sys} = \frac{\sum_i w_t^i P_t^i}{\sum_i w_t^i} \qquad \text{..........(8)}$$

where, P^i_t and w^i_t are the equity price and number of shares outstanding at time t, respectively of the i-th constituent bank in the system.

The index logarithmic returns are estimated as:

$$R_t^{Sys} = \ln\left(\frac{I_t^{Sys}}{I_{t-1}^{Sys}}\right) \qquad \text{..........(9)}$$

Using the index returns series estimated by equation 9, we can calculate the volatility of index returns σ_E^{Sys} which represents the systemic volatility in equity returns. Thereafter, the contingent claims analysis described above leads to estimates of implied market value of systemic assets (A_t^{Sys}) and volatility in systemic asset values (σ_A^{Sys}). We can then estimate the systemic risk-neutral default probability as follows.

$$PD_t^{Sys} = N(-DD_t^{Sys}) \qquad \text{..........(10)}$$

In the context of a group of banks representing the financial system, it PD_t^{Sys} be interpreted as a time-varying measure of systemic risk, such that, the higher its value, the greater the instability of the financial system.

An important feature of this measure of systemic risk is that as long as banks' asset returns are imperfectly correlated, the system-level risk-neutral PD will always be lower than the weighted average PD of the constituent banks. The systemic PD will therefore implicitly incorporate the diversification effect across banks which, depending upon the level of correlation, can increase or reduce financial stability of the system.

3.3 Bank-Level Marginal Contribution to Systemic Risk

Given our definition of systemic risk in section 3.2, we can now measure the extent to which constituent banks participate in the same as a simple, top-down measure of marginal risk contribution. The top-down approach measures system risk first and then attributes it to individual financial institutions. Using this approach, the marginal contribution of banks to systemic PD is backed out by examining the difference between the systemic PD with and without the individual bank. This identifies ex-post, the extent to which individual banks increase or reduce financial instability. In this context, it is important to distinguish our measure of systemic risk contribution from other measures like MES and SRISK, which are defined as a bank's exposure to systemic risk and capture a bank's distress potential conditional on financial market stress. Our measure on the other hand is aligned to the participation approach specification of banks' systemic importance as described in Drehmann & Tarashev (2011).

Thus, the marginal risk contribution (MRC) of *i-th* bank to the system at time *t* is given by

$$MC1_t\big|i = PD_t^{Sys-i} - PD_t^{Sys} = N(-DD_t^{Sys-i}) - N(-DD_t^{Sys}) \qquad \text{……….(11)}$$

If the measure is positive for the *i-th*, bank, it implies that the system without the *i-th* bank is riskier in terms of a higher systemic *PD* and thus, the *i-th* bank creates diversification benefits which reduce systemic risk and acts as a stabilizing influence on the financial system. If the MRC is negative, it implies that the *i-th* bank increases systemic risk and its presence makes the financial sector more vulnerable to stress conditions. Figure 2 demonstrates the marginal risk contribution concept graphically.

[Figure 2]

4. Database and Methodology

In order to implement the systemic risk and marginal risk contribution measures for the Indian banking sector, we have defined the financial system in terms of a sample of large domestic commercial banks. This sample includes 24 banks from the pre-merger period, representing 77.74% of total banking sector assets as of financial year ending 31-March-2017. The number of banks in the sample is reduced to 13 in the post-merger period representing 79.24% of banking sector assets as of financial year ending 31-Mar-2021. The sample is a mix of all banks that were involved in the merger process from 2016 to 2020 and also the control group of large private banks and unconsolidated large PSBs. However, small private sector banks, non-merging small PSBs and foreign banks have been excluded since their impact on systemic risk would be minimalistic.

Monthly closing stock price and market capitalization data of each bank is taken from March 2011 to July 2022 from the National Stock Exchange (NSE) database. Monthly rolling, annualized volatility of equity returns is estimated for the period March 2012 to July 2022, using the preceding 12 month's stock returns. The risk-free rate r is chosen as the 10-year yields on government securities. The default point for each bank is estimated as the sum of total deposits and borrowings; which along with data for other financial variables, is taken from the quarterly financial statements of each bank and RBI database.

For our empirical analysis we have used the variables depicted in Table 1.

[Table 1]

This section discusses the bank-level model that is used in our empirical analysis to estimate the impact of banking sector mergers and resultant concentration on systemic risk, as measured by the marginal risk contribution (MRC). As per the definition of MRC in section 3, positive values of MRC indicate an alleviation effect of the bank on the system, whereas negative values correspond to destabilizing effects of the bank on the financial system. Thus, a positive coefficient for an explanatory variable in our model implies that higher values of the variable make MRC less negative or more positive and thereby reduce the vulnerability of the system due to the presence of the bank.

We explain the variations in MRC estimates using system GMM (Arellano & Bover, 1995; Blundell & Bond, 1998) and bias-corrected fixed effects (Everaert & Pozzi, 2007) models. The general fixed-effects model takes the following form

$$MRC_{it} = \alpha_0 + \beta' X_{it} + a_i + \varepsilon_{it} \qquad \text{……….(12)}$$

where ε_{it} denotes the error term and a_i is the unobserved heterogeneity that does not change with time. MRC represents the marginal risk contribution. X denotes the bank control variables. Subscripts i and t refer to the i-th bank at the t-th period. It is worth noting that the inclusion of standalone PD (as shown in section 3) as one of the explanatory variables in the regression model may lead to the problem of endogeneity. PD encapsulates the insolvency risk of the bank, which varies over time because of the bank's endogenously changing risk profile of assets and liabilities.

Endogeneity bias can be addressed by carrying out a few dynamic panel estimations. Two main categories of techniques exist - GMM estimators and bias-corrected least square dummy variable (LSDV) estimators. The GMM estimator has a significant advantage in that it eliminates the potential endogeneity problem (refer to Arellano & Bover, 1995; Blundell & Bond, 1998). The dynamic panel data model is expressed as follows.

$$MRC_{it} = \alpha_0 + \alpha_1 MRC_{it-1} + \beta' X_{it} + a_i + u_{it} \qquad \text{……….(13)}$$

where u_{it} denotes a random term and MRC_{it-1} is the MRC estimate of bank *i* at period *t–1*.

Another way to address the endogeneity issue is to use the bias-corrected LSDV model. However, Monte Carlo simulations show that the GMM estimator has a high standard error than the LSDV model (Roodman, 2009). Everaert and Pozzi (2007) use the bootstrap correction, which maintains high efficiency compared to GMM and rectifies the bias in the LSDV estimates; this is also known as a bias-corrected fixed-effects model (BCFE) model in the literature and we employ this, following the specification of Everaert and Pozzi (2007) and Zaman et al. (2022):

$$MRC_{it} = \alpha_0 + \alpha_1 MRC_{it-1} + \beta' X_{it} + a_i + \epsilon_{it} \qquad \text{……….(15)}$$

Where ϵ_{it} denotes a random term and a_i is the unobserved heterogeneity and MRC_{it-1} is the MRC estimate of bank i at period t–1. The assumptions underlying this model are

1. $\mathrm{E}(\epsilon_{it}\epsilon_{ls}) = 0\ (for\ i\ \neq l\ or\ t \neq s\ or\ both)$
2. $\mathrm{E}(a_i a_l) = 0\ (for\ i\ \neq l\ )$
3. $\mathrm{E}(a_i \epsilon_{lt}) = 0\ (for\ \forall\ i, l, t)$
4. $\mathrm{E}(X_{it}\epsilon_{ls}) = 0\ (for\ \forall\ i, l, t, s)$
5. $\mathrm{E}(X_{it} a_l) = unknown\ (for\ \forall\ i, l, t)$
6. $\mathrm{E}(MRC_{i1}\epsilon_{ls}) = 0\ (for\ \forall\ i, l, t)$
7. $\mathrm{E}(MRC_{i1} a_l) = unknown\ (for\ \forall\ i, l)$

Bias-corrected (BC) estimator has been further improved with finite-sample properties (Breitung, Kripfganz, and Hayakawa, 2021) and we have used the BCFE and biased corrected random effect (BCRE) model. As the analytical form of the bias is known, by adjusting the respective moment conditions the BC estimator for both FE and RE can correct it directly at the source. It can also address the problem of higher-order autoregressive models. As the BC estimator is a method of moments estimator and follows a known asymptotic distribution, standard errors can be readily computed. We report the robust standard errors which are adjusted to cross-sectional dependence.

We also perform two-step system GMM models that fulfils all three additional conditions: the presence of significant AR (1) correlation, absence of significant AR (2) correlation, and valid over-identifying conditions.

Next, we discuss the variables that are specific to the banks and concentration risk. The Herfindahl-Hirschman Index or market share of top "n" banks has been often used as a measure of bank concentration. However, this measure is more meaningful in the context of cross-country analyses over longer periods of time. Since our study focuses on the national banking sector, we use the more direct measure of TA to indicate size-based concentration which allows us to differentiate across banks the effects of increasing size both due to business growth and due to mergers. CAR_t1 represents the bank's soundness in terms of availability of good quality capital to absorb losses; GNPA measures the bank's ex-poste credit risk; CD ratio captures the bank's liquidity risk; and OPEXTA depicts the cost efficiency of the bank. Other than these variables, government ownership has been captured both by the binary variable Ownership and GOIS which measures the percentage shareholding of the government in the bank's equity.

5. Mergers and Systemic Risk in the Indian Banking Sector: Stylized Facts

The period from the year 2017 to 2020 saw a number of mergers in the Indian commercial banking sector. The mergers were primarily among public sector banks, bringing their numbers down from 27 to 12 within a short period of three years. The consolidation process started with State Bank of India, the largest PSB, absorbing its five associate banks, two of which were publicly listed, and a small unlisted bank. This was followed by Bank of Baroda acquiring two smaller PSBs. In the final stage, ten banks were amalgamated into four large banks Table 2 specifies the details of the mergers.

[Table 2]

The mergers were orchestrated entirely by the Indian government as part of its reform agenda for strengthening and repositioning public sector banks after the sector went through a period of rapidly worsening credit quality and eroding capital (NPA crisis). Thus, while all the banks were solvent at the time of their respective mergers, many of their balance sheets were highly stressed. Typically, the acquiring Banks were larger and healthier, with lower non-performing assets (NPAs) and higher capital adequacy ratios (CAR). Most of the target banks were smaller and weaker and a few were under business constraints imposed by the Reserve Bank of India under the Prompt Corrective Action (PCA) framework, due to their worsening risk profile. Table 3 summarises the financial positions of the acquiring and target banks in the pre and post-merger periods. The merged entities were obviously bigger and increased the banking sector concentration as depicted by the jump in their share in total banking sector assets post-merger. The increasing concentration in the Indian banking sector was also evident from the nearly doubled value of Hirschman-Herfindahl Index based on the asset share of commercial banks and a sharp increase in the share of the top 10 banks in total assets from 2013 to 2022, as seen in Table 3a.

[Table 3]

[Table 3a]

Furthermore, as budgeted by the government, around Rs. 3.11 trillion capital was infused in public sector banks between 2017 and 2021, so as to strengthen their balance sheets and create market confidence in the consolidation process. As shown in Table 4, around 60.5% of this capital was allocated to the PSBs which were amalgamated.

[Table 4]

The PSB mergers were achieved within a fairly short window of time sandwiched between two systemic crises – the endogenous non-performing assets (NPA) crisis between 2012 and 2015; and the Covid-19 pandemic-driven financial market stress between 2020 and 2021, which occurred even while the last of the mergers were being completed. Figure 3 highlights the two financial sector crisis events in terms of the systemic risk-neutral probability of default derived using the contingent claims analysis. The systemic shock of the pandemic to the banking sector was short-lived but much more intense, with elevated PDs as compared to the NPA crisis.

[Figure 3]

Both the government owned banks and private banks were adversely impacted in the two crisis periods. However, the nature and extent of systemic shock within the two banking groups were distinctly different. As shown in Figure 4, the systemic PD of PSBs showed greater variability and was higher than that of private banks during the NPA crisis. However, private sector banks were more stressed than the PSBs during the Covid period. Diversification benefits across private and public sector banks during both crises were evident as the overall systemic PDs were much lower than those of either of the standalone banking groups.

[Figure 4]

Figure 5 demonstrates the trends in standalone risk-neutral PDs of all the banks which were amalgamated. Insolvency risk had increased for all the banks during the NPA crisis, but the PSBs which were subject to regulatory restrictions under the PCA were the worst performers, clearly justifying the need for a resolution process for these banks. The standalone risk of all the banks spiked significantly around their respective merger period. The merged entities, despite their relatively stronger balance sheets, had elevated standalone insolvency risk during the Covid period.

[Figure 5]

As can be seen from table 5a, all the target banks had an adverse impact on financial stability, with negative marginal risk contributions on average under the NPA crisis. Also, the participation of the acquirer banks in systemic vulnerability was higher post their merger during the Pandemic as compared to the pre-merger financial shock. On the other hand, the private banks and unconsolidated PSBs collectively reduced systemic risk in both the crises (Table 5b). This indicates a possible consolidation-fragility hypothesis for the Indian banking sector.

[Table 5a]

[Table 5b]

6. Empirical Analysis

We summarize the findings of our econometric analyses in this section. Table 6 indicates the results of the one-stage system GMM, Table 7 reports the results of the two-stage system GMM and Table 8 represents the results of the biased corrected fixed effect model. All the standard errors represent robust standard errors. All results are validated for no autocorrelation and no heteroscedasticity.

[Table 6]

[Table 7]

[Table 8]

The results of our empirical model (Model 2, Table 6) show that the merged entities contribute adversely to systemic fragility in the Indian banking sector as shown by the negative coefficient for the variable Merged which is significant at 10 percent level. The contribution to systemic risk is dominated by the standalone insolvency risk of banks as depicted by the negative and highly significant (at 1% level) coefficient of PD in Models 1 (Table 6), Model 3 (Table 7), and Model 7 (Table 8). The variable TA on the other hand, which captures bank size, has a positive but non-significant impact on financial stability as seen in Model 1 (Table 1), and does not have a meaningful influence on marginal risk contribution in any of the other models. The combined results suggest that banks' contributions to systemic risk and therefore their systemic importance are primarily influenced by their standalone risk profile rather than due to increasing banking sector concentration created by larger or merged banks. In fact, larger banks per se, would enhance financial stability (due to the positive coefficient) if their standalone insolvency risk is low. The adverse effect of stressed mergers on systemic risk gets offset by a safer, albeit larger merged entity. Thus, broadly, the evidence favors consolidation-fragility but refutes the concentration-fragility relationship.

The signs of the coefficients of the other explanatory variables represented in the Table 6, 7 and 8 are as would be expected, whenever they are significant. The two-quarter lagged Tier 1 capital adequacy is significant at 5% level in Model 1 (Table 6) and one-quarter lagged Tier 1 CAR is significant in Model 9 (Table 8). Tier 1 capital adequacy is a measure of banks' soundness and ability to absorb unexpected large losses. Thus, banks which have maintained adequately high levels of good quality capital well in advance, have a greater stabilizing effect on the system during crisis since they are better able to withstand adverse financial shocks. On the other hand, instantaneous and one-quarter lagged Tier 1 CAR do not have a statistically significant impact (Model 1, Table 6) or have a statistically significant but negative impact (Model 3, Table 7) on systemic risk contribution of banks. This may be due to contemporaneous erosion of the created capital base arising from losses during the crisis creating an adverse effect on systemic stability.

The CD ratio has a negative coefficient and is highly significant (at 5% level in Model 1 and 1% level in all other Models). Higher value of the CD ratio typically occurs when credit is growing faster than deposits and is an indicator of greater liquidity stress of the bank, which can adversely impact financial stability. The GNPA ratio shows a statistically significant negative impact on the marginal risk contribution of banks in Models 4, 5, 6, 8, and 9. Clearly, larger loan losses can be expected to make the bank a greater threat to the system.

We also obtain an interesting result for the variables Ownership (Model 2, and 4) and GOIS (Model 1, and 8), whose statistically significant negative coefficients evidently suggest that public sector banks, and especially those with higher shareholding by the government transmitted greater shocks to the financial system as opposed to private sector banks. Government shareholding in PSBs typically increases due to recapitalization of those banks which may otherwise fail since they cannot raise capital from the market and such bail-outs do not bode well for financial stability. This result corroborates the moral hazard risk of government ownership in the context of systemic impact and provides a strong justification for the privatization policy that the Indian government is pursuing under its reforms agenda for the banking sector.

7. Conclusion

Which is better from a financial stability perspective – a fragmented banking system with greater competition among many small players or a concentrated one with large banks benefitting from economies of scale? Do banking sector consolidations make the financial system more vulnerable? What are the drivers of systemic risk contributions by banks? These are questions which have plagued academicians, policy makers and banking supervisors for many decades. The debate surrounding concentration-stability, and more specifically, consolidation-fragility, revived during the global financial crisis, when restructuring mergers were used as fiscal cost saving rescue measure for potential bank failures. Despite richer data sets, covering wider geographies and longer time frames, the empirical results have remained conflicting and inconclusive. These concerns are equally relevant for the Indian banking sector but have been scantily researched and superficially addressed. Our paper presents, for the first time, a comprehensive study of systemic risk and its dynamics in the backdrop of two financial crises and a spurt of government-led bank mergers that have occurred over the last decade in India.

We construct market-based, forward-looking measures of systemic probability of default (PD), bank-level PD and bank-wise contribution to systemic PD, based on the contingent claims approach of Merton (1974). The sensitivity of our systemic risk metric to both the long-drawn NPA crisis (2012- 2016) and the relatively short-lived but intense Covid pandemic driven crisis in India highlights its use as an effective macroprudential tool in identifying and monitoring the timing, duration and severity of bouts of financial instability.

We find that consolidation of stressed banks does increase the systemic risk contributions of acquiring entities. However, concentration in the banking sector, created either through inorganic mergers or inherent growth, is not the driving factor. The destabilizing effect of banks is more significantly a function of moral hazard of government ownership and of the standalone risk profile of the banks in terms of credit, market and liquidity risk. Furthermore, adequate and early build-up of loss buffers of good quality capital act as an alleviating factor but not if it is recapitalization of weak banks by the government. Thus, defining a systemically important bank primarily by size may not suffice and micro prudential norms must continue to focus on risk controls at a bank-level, irrespective of size. In fact, large, well-capitalized banks may actually mitigate systemic risk during crises if their idiosyncratic risk of failure is low. Regulatory oversight of bank amalgamations should therefore focus on minimizing merger-related worsening of insolvency risk through better diversification, risk management and strong capital adequacy, to ensure that there are no adverse consequences on financial stability.

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Table 1
Variable Definitions and Data Sources

Variable	*Definition*	*Source*
Dependent Variable MRC	Individual Bank's Marginal Risk Contribution to Systemic Risk as derived in Section 3	Authors' Calculation
Explanatory Variables		
Merged	Bank-wise binary variable, which takes value 1 if bank has been amalgamated and 0 otherwise	Public Information
PD	Bank-wise risk neutral probability of default as defined in Section 3	Author's Calculation
TA	Natural logarithm of total assets of the bank, measures bank size	Banks' quarterly financial statements
Control Variables		
MRCL1	One quarter lagged value of MRC	Authors' Calculation
Ownership	Binary variable, which takes value 1 for public sector banks and 0 for private banks	Banks' quarterly financial statements and annual reports
CAR_t1; CAR_t1L1; CAR_t1L2	Tier 1 Capital Adequacy Ratio = $\frac{Tier\ 1\ Regulatory\ Capital}{Risk\ Weighted\ Assets}$ CAR_t1L1; CAR_t1L2 representing 1 quarter and 2 quarter lagged values of Tier 1 Capital Adequacy Ratio respectively	
CD	Credit to deposit ratio	
GOIS	Share of government holding in the bank's equity	
GNPA	Gross non-performing loans as a ratio of total loans	
OPEXTA	Operating expenses as a ratio of total assets	

Table 2
Mergers of Indian Public Sector Banks

Merger Date	*Acquiring Bank*	*Target Banks*	*Share Conversion Ratio*
Feb-17	State Bank of India (SBI)	State Bank of Bikaner and Jaipur (SBBJ)	0.28
		State Bank of Mysore (SBM)	0.22
		State Bank of Travancore (SBT)	0.22
		State Bank of Hyderabad (SBH)	Unlisted Target
		State Bank of Patiala (SBP)	Unlisted Target
		Bharatiya Mahila Bank (BMB)	Unlisted Target
Mar-19	Bank of Baroda (BOB)	Dena Bank	0.11
		Vijaya Bank	0.402
Mar-20	Punjab National Bank (PNB)	Oriental Bank of Commerce (OBC)	0.23
		United Bank of India (UBI)	0.0242
Mar-20	Indian Bank	Allahabad Bank	0.115
Mar-20	Canara Bank	Syndicate Bank	0.158
Mar-20	Union Bank	Andhra Bank	0.325
		Corporation Bank	0.33

Source: Authors' Computation

Table 3

Pre and Post Merger Financial Performance of Public Sector Banks

Bank	*Asset Share*	*GNPA Ratio*	*Tier I CAR*	*Acquiring Bank*	*Asset Share*	*GNPA Ratio*	*Tier I CAR*
	31-Mar-17				**31-Mar-18**		
SBBJ	0.82%	15.52	7.13	**SBI**	**22.65%**	**10.91**	**10.36**
SBH	1.15%	20.77	9.22				
SBM	0.63%	25.68	8.09				
SBP	0.87%	23.15	7.78				
SBT	0.89%	16.79	9.94				
BMB	0.01%	9.54	138.89				
SBI	**19.09%**	**6.90**	**10.35**				
	31-Mar-19				**31-Mar-20**		
Dena Bank*	0.66%	21.07	..	**BOB**	**6.43%**	**9.40**	**10.71**
Vijaya Bank	1.16%	6.58	8.14				
BOB	**4.70%**	**9.61**	**11.55**				
	31-Mar-20				**31-Mar-21**		
Syndicate Bank	1.81%	12.04	8.41	**Canara Bank**	**5.89%**	**8.93**	**10.08**
Canara Bank	**4.02%**	**8.04**	**10.12**				
	31-Mar-20				**31-Mar-21**		
Allahabad Bank*	1.43%	17.10	8.01	**Indian Bank**	**3.19%**	**9.85**	**11.93**
Indian Bank	**1.72%**	**6.87**	**12.08**				
	31-Mar-20				**31-Mar-21**		
OBC*	1.49%	12.67	8.91	**PNB**	**6.43%**	**14.12**	**11.49**
UBI*	0.85%	13.40	3.56				
PNB	**4.61%**	**14.21**	**11.91**				
	31-Mar-20				**31-Mar-21**		
Corporation Bank*	1.27%	13.80	9.04	**Union Bank**	**5.47%**	**13.74**	**10.35**
Andhra Bank	1.35%	16.07	8.16				
Union Bank	**3.06%**	**14.15**	**10.75**				

Note: * Banks under PCA framework of RBI

Source: RBI Database: Authors' Computation

Table 3a
Trend in Banking Sector Concentration in India

	HHI Based on Asset Share	*Share of top 10 banks in Total Banking Sector Assets*
2013	5.82%	37.35%
2014	5.90%	38.00%
2015	6.12%	38.47%
2016	6.37%	39.29%
2017	6.77%	40.61%
2018	8.54%	45.12%
2019	8.48%	45.01%
2020	8.89%	48.04%
2021	10.11%	50.71%
2022	10.14%	51.04%

Source: Annual Reports and RBI Database: Authors' Computation

Table 4
Merging Banks' Share of Government Capital Infusion from FY 2016 to FY 2021

Merging Banks Groups	*Share*
SBI and Associate	6.4%
BOB+ Vijaya Bank + Dena Bank	8.1%
PNB + OBC + UBI	17.8%
Indian Bank + Allahabad Bank	6.4%
Canara Bank + Syndicate Bank	6.9%
Union Bank + Andhra Bank + Corporation Bank	14.8%
Total	100%

Source: Banks' Annual Reports: Authors' Computation

Table 5a

Marginal Risk Contribution of Acquiring PSBs

	NPA Crisis (2012-2015)			Pandemic Crisis (2020-2021)
SBI	-0.001%	SBBJ	0.000%	-0.029%
		SBT	0.000%	
		SBM	0.001%	
BOB	-0.001%	Dena	-0.001%	-0.011%
		Vijaya	0.000%	
Canara	-0.008%	Syndicate	-0.004%	-0.012%
PNB	-0.006%	OBC	-0.004%	0.043%
		United Bank	-0.002%	
Union Bank	-0.006%	Andhra	-0.002%	-0.048%
		Corporation	0.000%	
Indian	-0.002%	Allahabad	-0.003%	-0.016%
Average	**-0.004%**		**-0.001%**	**-0.012%**

Source: NSE Equity Prices and RBI database: Authors' Computation

Table 5b

Marginal Risk Contribution of Private Banks and Unconsolidated PSBs

	NPA Crisis (2012-2015)	*Pandemic Crisis (2020-2021)*
Axis Bank	-0.017%	-0.032%
HDFC Bank	0.159%	0.239%
ICICI Bank	-0.015%	-0.006%
Kotak	0.029%	0.097%
Yes Bank	-0.007%	-0.209%
BOI	-0.008%	-0.013%
Central Bank	-0.002%	0.003%
Average	**0.020%**	**0.011%**

Source: RBI Database: Authors' Computation

Table 6

One Stage Arellano-Bover/Blundell-Bond Estimation

Model1		*Model2*	
MRC1.	0.66543***	MRCL1	0.7262***
CAR_t1	-0.0013	CD	-0.0008***
CAR_t1L1.	-0.0013	Ownership	-0.0202**
CAR_t2L2.	0.0033**	Merged	-0.0100**
PD	-0.0027***	OpexTA	0.0264
CD	-0.0004**	_cons	0.06885077***
TA	0.0027		
GOIS	-0.0002***		
_cons	0.0118		

Note: *** denotes 1% level of significance, ** denotes 5% level of significance, * denotes 10% level of significance.

Source: Authors' Estimation

Table 7

Two-Stage Arellano-Bover/Blundell-Bond Estimation

Model 3		*Model4*		*Model 5*	
MRCL1.	0.6986***	MRCL1.	0.7151***	MRCL1	0.7326***
CAR_t1	-0.0003**	CD	-0.0007***	CD	-0.0007***
PD	-0.0029***	Ownership	-0.1501*	Merged	-0.0044**
CD	-0.0004***	GOIS	-0.00003	GNPA	-0.0015***
OpexTA	0.0259*	GNPA	-0.0008***	_cons	0.0689***
GOIS	-0.0003	_cons	0.1583***		
GNPA	0.00005				
_cons	0.0423*				

Note: *** denotes 1% level of significance, ** denotes 5% level of significance, * denotes 10% level of significance.

Source: Authors' Estimation

Table 8

BCFE is Biased Corrected Fixed Effect Estimation

Model 6 (FE)		*Model 7 (FE)*		*Model 8 (RE)*		*Model 9 (RE)*	
MRCL1.	0.6843***	MRCL1	0.6674***	MRCL1.	0.7065***	MRCL1.	0.7094***
CD	-0.0004***	PD	-0.0018***	CAR_t1	0.00056***	CAR_t1	0.0002
OpexTA	-0.0180**	OpexTA	-0.0184*	CD	-0.0004***	CD	-0.0004**
GNPA	-0.0005*	GNPA	0.0003	Merged	-0.0035***	Ownership	-0.0065***
_cons	0.040***	_cons	0.01209**	GNPA	-0.0004*	GNPA	-0.0006**
				GOIS	-.00008**	GOIS	-0.00001
				_cons	.02887**	_cons	0.0328**

Note: *** denotes 1% level of significance, ** denotes 5% level of significance,
* denotes 10% level of significance.

Source: Authors' Estimation

Figure 1
Firm's Distance to Default and Default Probability,
(adapted from Bohn and Crosbie, 2004)

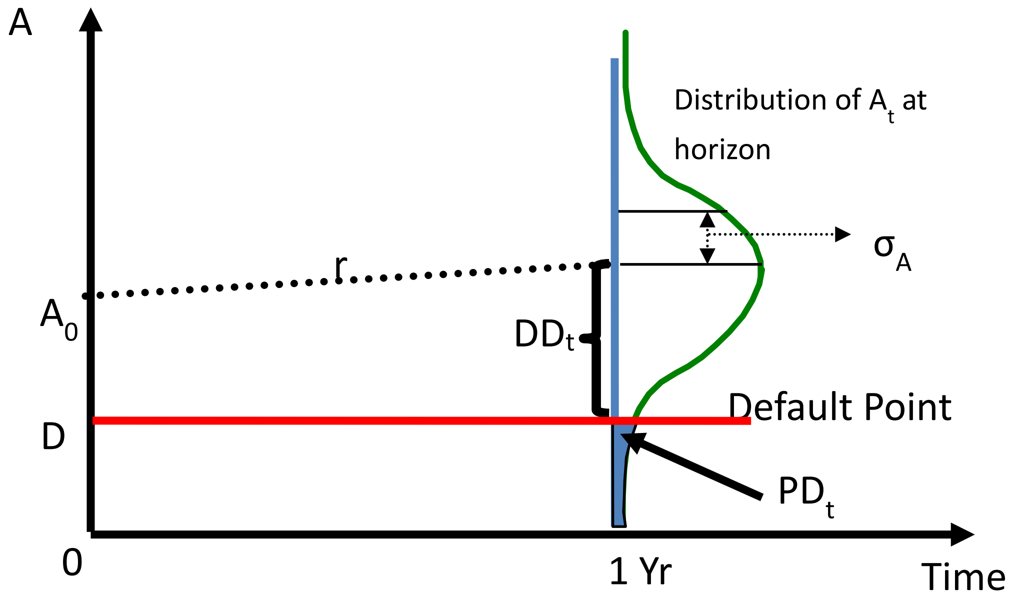


Figure 2
Marginal Risk Contribution of Bank i using the Top-Down Approach

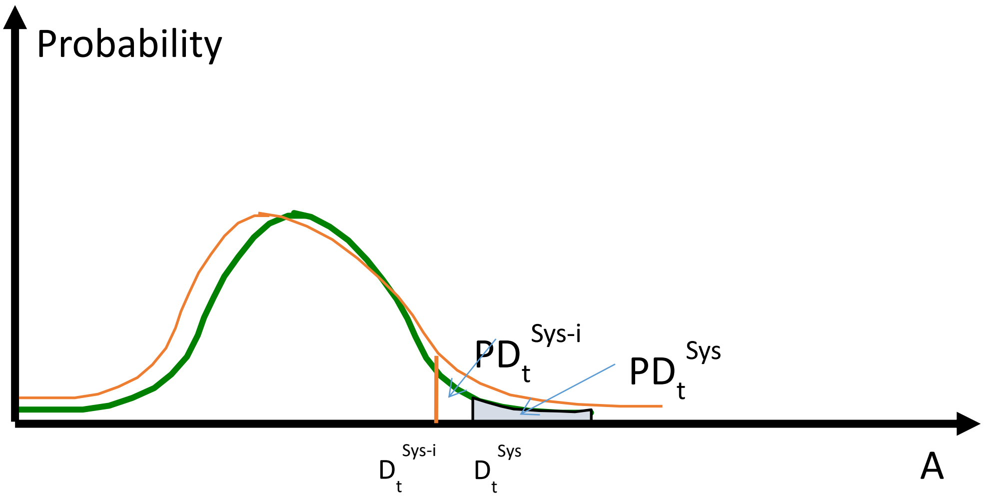
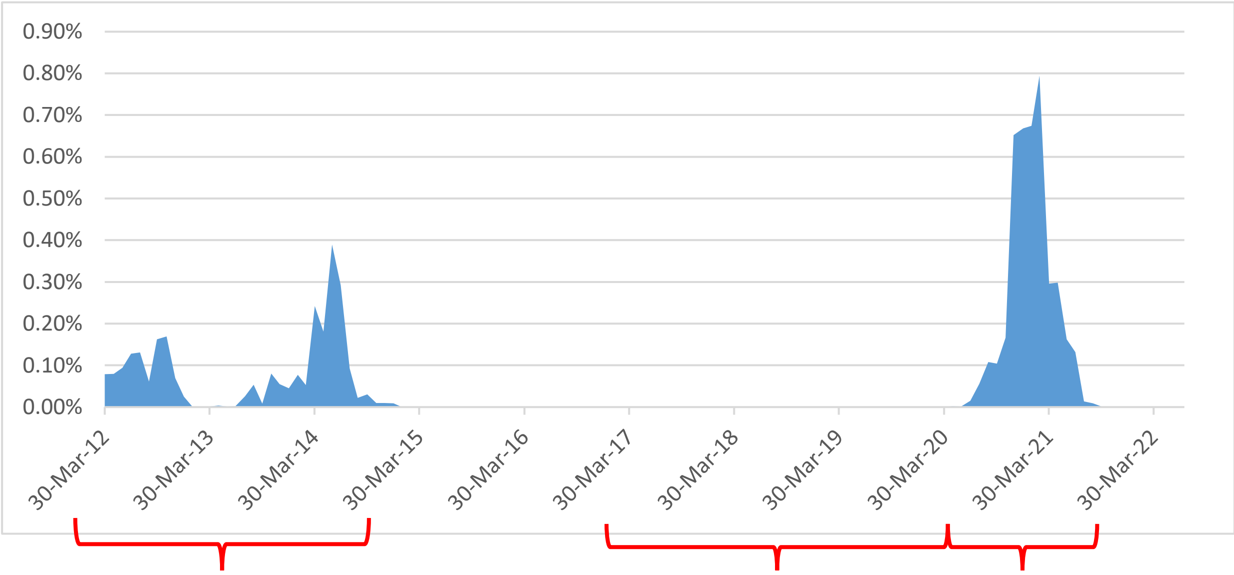


Figure 3

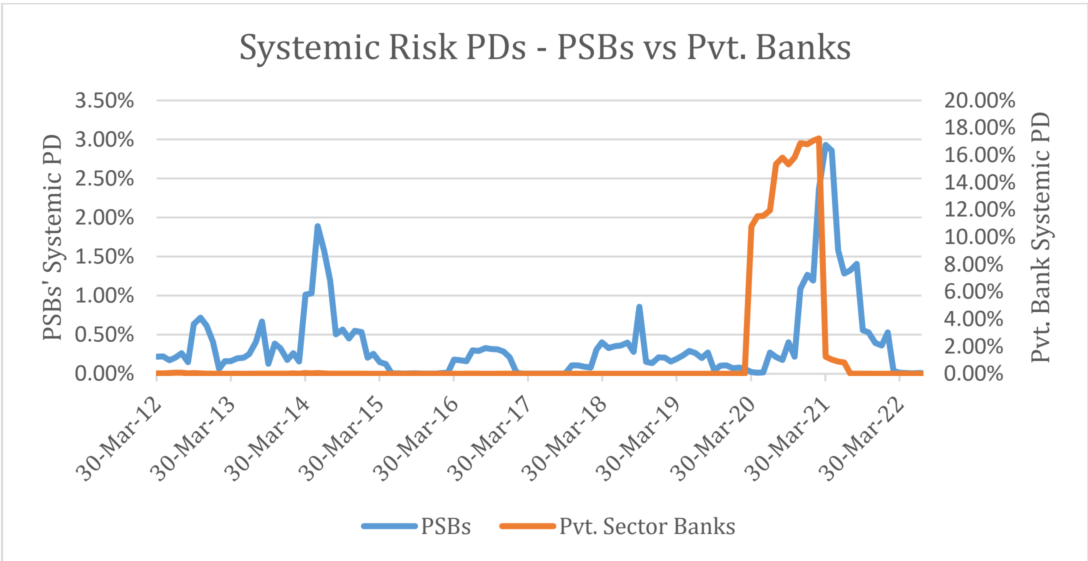
Systemic Risk Neutral Probability of Default in Aggregate Indian Banking Sector



Source: NSE Equity Data and RBI Database: Authors' Computation

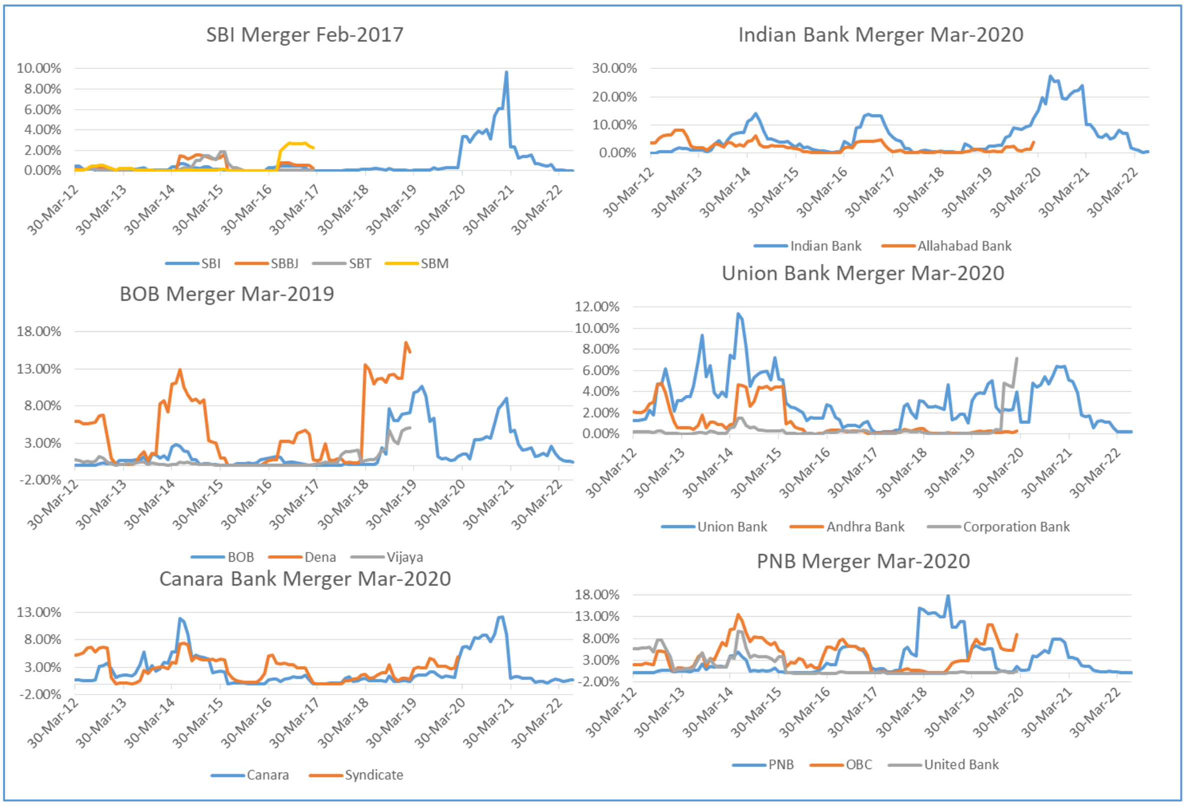
Figure 4

Systemic Risk of Public Sector Banks vs Private Banks



Source: NSE Equity Data and RBI Database: Authors' Computation

Figure 5
Pre and Post Merger Trends in Standalone PDs of Amalgamated Public Sector Banks



Source: NSE Equity Data and RBI Database: Authors' Computation