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The implicit subsidy to the Indian banking system

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Abstract

The paper studies the effects of the implicit government guarantee on a sample of six major Indian banks and derives estimates of default risk implicitly 'insured' by the government. This is obtained by comparing two measures of default risk for a bank. The first measure is estimated from bank equity prices assuming equity holders are not benefitting from a government bail-out. The second derives from bank Credit Default Swap (CDS) spreads. CDS only pays out if a bank defaults on its debt. Default risk derived from CDS should capture the joint risk of the bank becoming distressed and the government not bailing out creditors. It is typically lower than the default risk derived from equity prices. The difference between the two measures is used to quantify the implicit subsidy to Indian banks. While these subsidies have declined from the levels seen during the global financial crisis and the shock from the Covid-19 pandemic, they remain non-trivial.

Key words: Implicit subsidies, contingent claims analysis, jump diffusion, credit default swap, bootstrapping.

JEL classification: G13, G21, G28, H20.

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1 Introduction

Even more than a decade and half after the global financial crisis (GFC), the issue of 'too important to fail' banks is still relevant. Regulatory authorities across jurisdictions have addressed the problem of systemically important banks (SIBs) with a two-pronged approach. First, the Basel III capital reforms devised by the Basel Committee on Banking Supervision (BCBS) recommend increasing both the quality and level of the regulatory capital base with a view to reducing the probability of default of SIBs. Second, SIBs have been made more resolvable by subjecting them to special resolution regimes. Resolution aims to ensure banks and other financial institutions can be allowed to fail in an orderly way. In the European Union, a new resolution regime has been implemented via the Banking Recovery and Resolution Directive (BRRD). This has introduced changes to the creditor waterfall which make it easier for losses to be imposed on banks' creditors as part of a resolution process. This is known as 'bail-in' to distinguish it from 'bail-out' using public funds. In line with international standards, banks must meet a minimum requirement for own funds and eligible liabilities (MREL) which is earmarked for loss absorption in the event of resolution. Liabilities eligible for MREL include regulatory capital, including equity and subordinated bonds, and a new class of senior "bail-in" bonds.[1] In the UK, the Bank of England is the resolution authority and sets the level of MREL.

In India, the Reserve Bank of India (RBI), India's central bank, is empowered to deal with the resolution of private sector banks by way of mergers, suspension of management and liquidation. However, government-owned banks or public sector banks (PSBs), which account for more than half of Indian bank assets cannot be resolved without government permission.[2] Laws governing resolution of financial institutions do not contain provisions for bail-in.[3]There could be an expectation of government support in case of solvency concerns. To the extent that this is anticipated by a bank's creditors, these institutions may benefit from lower funding costs, a form of implicit subsidy from the government. In India, and many other jurisdictions, these guarantees are not limited to SIBs. Smaller banks, with a high degree of government ownership or interconnectedness may also be too important to fail.

[1]Lindstrom and Osborne (2020) show that the risk sensitivity of senior bond spreads increased since the implementation of the BRRD in 2015, suggesting that the introduction of the new bail-in regime resulted in a sustained change in investors' perception of the likelihood of being bailed in.

[2]The IMF India Financial Sector Assessment Programme (FSAP) 2025 concluded that resolution powers and tools are limited mostly to compulsory mergers or liquidation, and entail higher contingent fiscal costs than well-designed resolution regimes [IMF and Bank (2025)].

[3]The Financial Resolution and Deposit Insurance (FRDI) Bill 2017 [Government (2018)], was an attempt to consolidate India's regulatory framework on bank resolution and was referred to parliament for consideration. Subsequently, the Government decided to withdraw the Bill due to apprehensions among the public about the 'bail-in' clause for resolution of bank failure which was perceived to be against the interest of the depositors [Pandey and Patnaik (2019)].

The RBI has historically used mergers as a resolution mechanism in the banking sector, with losses imposed only on shareholders. In March 2020, the RBI helped engineer a capital injection and restructuring of Yes Bank, India's fourth-largest private sector bank, to prevent a run on the bank and to preserve broader financial stability. On March 14, 2020, Yes Bank received a total capital injection of Indian rupees (INR) 100 billion (GBP 1.09 billion) in total from the State Bank of India and a group of private sector banks (HDFC, ICICI Bank, Axis Bank, Kotak Mahindra Bank, Federal Bank, Bandhan Bank, IDFC First Bank) [Gupta (2024)]. On November 17, 2020, RBI instructed Lakshmi Vilas Bank, a failing private-sector bank, to be merged with the Indian subsidiary of Singapore's DBS bank [Shikha and Kapsis (2024)].

Reliance on mergers as a resolution mechanism is not just used by the RBI and is resorted to by most regulatory authorities. Credit Suisse had a resolution strategy based on bail-in, and the Swiss Financial Market Supervisory Authority and the Swiss National Bank had plans to execute that strategy. In the end, the Swiss authorities chose not to go down the resolution route and instead orchestrated the state-brokered commercial merger of Credit Suisse by its domestic banking rival UBS [FINMA (2023), Pascal et al. (2023)]. This was announced on 19 March 2023. Nevertheless, the contractual writedown of all the outstanding Additional Tier 1 (AT1) capital instruments issued by Credit Suisse was a key element of the transaction. The writedown extinguished liabilities amounting to CHF 16 billion from the bank's balance sheet. In May 2023, JP Morgan Chase took over US bank First Republic in a deal brokered by regulators. JP Morgan paid $10.6bn (£8.5bn) to the Federal Insurance Deposit Corp (FIDC), after First Republic had been shut down [Gupta et al. (2025)]. First Republic had been under pressure since March 2023, when the collapse of two other US lenders, Silicon Valley Bank (SVB) and Signature Bank, sparked fears about the state of the banking system.

The purpose of this study is to derive a market-based estimate of the size of the implicit subsidy to the Indian banking system represented by a sample of six major banks. There are a number of different approaches that can be used to estimate these implicit subsidies, as discussed in Section 2. In this paper, the implicit subsidy is estimated using contingent claims analysis (CCA) which is based on the principle that holders of a bank's debt can produce a 'contingent claim' on the government that could bail out the bank were it to fail. The CCA framework is implemented by comparing two measures of default risk for each bank.

The first is obtained using a structural credit risk model, introduced in Black and Scholes (1973) and Merton (1974), which defines the probability of default based on the risk-adjusted balance sheet of banks whose assets may be above or below promised payments on its debt obligations. Under this approach, equity holders have a call option on the bank's total value after outstanding liabilities have been paid off. Thus, debt holders effectively write a European put option to equity holders and receive the option premium as compensation for holding risky debt. This measure relies on equity prices and, assuming equity holders are not benefitting from a government bail-out, put option values obtained from this approach would be free from any implicit government guarantee.

In the second measure, the put option values of each bank are computed directly from their Credit Default Swap (CDS) spreads. CDS is an over-the-counter contract settled in the credit derivative market that can be used to insure against credit risk of a bond issuer. A CDS pays out if the bank defaults on its debt. Therefore, the put option values obtained from CDS spreads should capture the joint risk of the bank becoming distressed and the government not bailing out debt holders. It should, therefore, be lower than the put option estimated from equity prices. The difference between the two put option values provides a measure of the nominal value of the implicit subsidy received by an individual bank. The ratio of the two put option values can be used to derive the proportion of default risk of a bank that is believed to be 'insured' by the government.

Using this method, implicit subsidies are estimated for the 6 largest Indian banks by market capitalisation [Axis Bank, HDFC Bank, ICICI Bank, Kotak Mahindra Bank, Bank of Baroda (BOB) and the State Bank of India (SBI)], as on 31 December 2024, over the 20-year period 2005.1-2024.12. These 6 banks are taken to be a representation of the whole Indian banking system. Of these, BOB and SBI are PSBs. In June 2024, the Government held a majority stake of 64% in BOB [BOB (2024)] and 57% in SBI [SBI (2024)]. HDFC Bank, ICICI Bank and SBI are classified as Domestic Systemically Important Banks (D-SIBs) by the RBI [RBI (2023)]. Each D-SIB is awarded a Systemic Importance Score, on the basis of which additional Common Equity Tier 1 (CET1) requirements are imposed.

Our results show that implicit subsidies to the Indian banking sector have decreased, from the levels seen during the GFC, and the shock from the Covid-19 pandemic, but remain non-trivial. PSBs backed by the government may be viewed as safer as they can be more readily recapitalised to shore up their capital base. Creditors would then ask for a lower risk premium, taking into account expected future transfers from the government, implying a higher level of implicit subsidy to PSBs. This is not to suggest that debt holders of even 100% state-owned banks would have all their liabilities insured by the government at all times. The guarantees are implicit because the government does not have any explicit, ex ante commitment to intervene. Our results show that implicit subsidies tend to peak in the midst of a crisis. During tranquil periods the implicit subsidy to PSBs has tended to higher than that of private sector banks. However, during periods of financial crisis the implicit subsidy to the Indian private sector banks surpassed that of PSBs. This could be attributed to their greater sensitivity to shocks in financial markets witnessed during crisis periods.

The RBI has adopted the Basel III capital adequacy framework which applies to public as well as private sector banks. Increases in the equity capital base required under Basel III have resulted in the Indian banking system raising its average Tier 1 capital ratios from 10% of Risk Weighted Assets (RWA) in 2008 to 15.5% of RWA in 2024. The default protection provided by higher equity levels can substitute for the protection provided by implicit subsidies by increasing investor confidence and lowering borrowing costs. While higher equity levels in Indian banks, may have decreased the implicit government guarantees, they have not eliminated them.

This paper contributes to the literature on implicit subsidies, and the pricing of bank debt, by implementing a novel technique to quantify the subsidy based on information from banks' equity prices and CDS spreads. Analysis of implicit government subsidies for banks has been largely confined to developed markets in the UK, US and Euro area where banking systems are driven by private sector banks. To the best of my knowledge this study is the first attempt to estimate implicit subsidies for banks in an emerging market, such as India, where PSBs still maintain a dominant presence. Although banks account for about two-thirds of the Indian financial system assets, the empirical literature on the Indian banking system is sparse. This paper is an attempt to fill a gap in the literature by focussing on an issue, that remains significant, but has not been addressed.

The rest of the paper is organised as follows. Section 2 provides a brief literature review and outlines results from previous studies. Section 3 describes the CCA modeling framework and its application to estimate put option values or expected losses from bank equity prices. Section 4 estimates put option values from bank CDS spreads. Section 5 computes the implicit subsidy as the difference between the put option values derived from bank equity prices and the put option values derived from bank CDS spreads. Section 6 concludes.

2 Related literature

As described in Noss and Sowerbutts (2012), the approaches used to estimate the implicit subsidies can be broadly classified into two types. The first are the 'funding cost advantage' models that value the subsidy as the aggregate reduction in the cost of bank funding due to an implicit government guarantee. In this approach, the cost the bank faces in issuing its debt is compared with a higher counterfactual cost that it would face in the absense of implicit government support. Funding cost advantage models can be differentiated by two approaches to estimate this counterfactual. The first is the size-based approach that assumes that only large banks or SIBs would be supported by governments in the event of their failure, and consequently enjoy a reduced cost of funding compared with smaller banks within the banking system. The funding cost advantage enjoyed by the larger banks are determined by simply comparing their bond yield spreads over a market benchmark (for example, EURIBOR in the euro area or MIBOR in India) with those of smaller banks. It is assumed that, in the counterfactual case where government support is withdrawn, large banks would face the same cost of funding as smaller banks. However, this measure based on simple bond spread differentials can be misleading as it ignores economies of scale and scope. If larger banks generate higher returns with lower risks they would evidently benefit from lower funding costs as compared to smaller banks. The second is the ratings-based approach based on the fact that credit-rating agencies often issue two ratings for a bank: a 'stand-alone rating' and a 'support rating'. Both reflect an external assessment of the probability of a bank defaulting on its debt, but only the latter includes the possibility of a bank receiving government support. This approach compares the bank's actual cost of funding (reflecting its 'support rating') with an estimate of the higher cost of funding a bank would face in the absence of the implicit guarantee. What drives this approach is that markets use ratings for pricing debt instruments and these ratings affect bond spreads. A drawback of this approach is that credit rating agencies often have divergent views. Under both the size-based and ratings approach, the difference between the actual and counterfactual cost of funding is assumed to reflect the size of the government guarantee.

Another approach is the contingent claims analysis (CCA) methodology that value the subsidy as the expected payment from the government to the banking system necessary to prevent default. It involves the application of option pricing models to estimate the fair value of credit risk insurance and the modeling framework is described in Sections 3 and 4.

Noss and Sowerbutts (2012) use both a funding cost advantage model (ratings based) and CCA approach to estimate the implicit subsidy for four large UK banks in 2010. They arrive at a broad range of estimates across the different approaches. The funding advantage approach estimates the implicit subsidy in 2010 to be around GBP 40 billion. The options price contingent claims methods produce estimates of around GBP 120 billion.

Ueda and Di Mauro (2013) estimate the implicit subsidy for 900 banks across a variety of countries for 2007 and 2009 using expectations of government support embedded in credit ratings provided by Fitch. Fitch produces both 'stand-alone' and 'support' ratings. They found that the implicit subsidy value was already sizable as of end-2007 and increased substantially by the end-2009, after key governments confirmed bailout expectations. Their results indicate a support rating that is 3-4 notches above the stand-alone rating for SIBs.

Kelly et al. (2016) represents a somewhat different approach as they compare actual option prices of individual institutions and financial sector indices. They conclude that financial sector equity holders enjoy a sizeable government subsidy. Note that this subsidy comes in addition to the implicit subsidies due to debt. Kelly et al. (2016) are amongst a few who point that the standard approach of using equity price leads to a "contamination", as expectations of public sector assistance are already embedded in these prices, thus biasing downwards estimates of implicit subsidies.

Gudmundsson (2016) implements the CCA approach with a jump diffusion option pricing model to estimate the implicit subsidy in a sample of 11 GSIB banks with a capital requirement surcharge of 1.5 percent or higher. The results suggest that the subsidy declined following the GFC in 2008-2009 as banks' asset volatilities declined and equity levels improved. The weighted-average subsidy for the 11 G-SIBs peaked during the crisis and declined to half that level in the post-crisis era.

Liu et al. (2016) investigated the impact of deposit insurance schemes on banks' credit risk and found that banks in countries with explicit deposit insurance systems have higher CDS spreads, supporting what they call the "moral hazard view". They provide some evidence that the moral hazard effect due to the presence of explicit deposit insurance increases the probability of default more for banks with lower asset quality and lower liquidity, relative to financially sound ones.

Acharya et al. (2016) examine if expectations of implicit government support are embedded in the credit spreads of unsecured bonds issued by large U.S. financial institutions. They find that in the pre-Dodd Frank time period bond spreads were less sensitive to risk for large financial firms compared to smaller financial institutions, consistent with investors expecting large financial firms to benefit from implicit government guarantees. In the post-Dodd Frank period after 2012, there were no differences in the spread-risk sensitivity of large financial firms compared to small financial firms. These results are consistent with a strengthening of market discipline in the aftermath of the policy reforms implemented following the GFC.

Cummings and Guo (2020) examine whether SIBs realise an implicit subsidy when raising wholesale debt funding and evaluates the effectiveness of the Basel III capital reforms in reducing the subsidy. Using primary bond market data for Australian banks, their estimations suggest that, before the reforms, SIBs were raising wholesale debt funding at costs that did not reflect the risk inherent in their operations compared to other banks. But after the reforms Basel III were implemented, the subsidy was reduced by approximately one-half.

3 Data

The models are calibrated using market information and balance sheet data of the 6 largest Indian banks by market capitalisation: Axis bank (henceforth Axis), HDFC bank (henceforth HDFC), ICICI bank (henceforth ICICI), Kotak Mahindra Bank (henceforth Kotak), Bank of Baroda (henceforth BOB) and State Bank of India (SBI). I obtain daily market equity data and semi-annual balance sheet data on total liabilities, Tier 1 capital and Risk Weighted Assets from the London Stock Exchange Group (LSEG) Workplace. The combined panel dataset comprises observations for each bank j over a six-month period. As a measure of the benchmark risk-free rate of interest, I selected the spot yield on 5-year UK government bonds. Daily 5-year spot yields are sourced from the estimated yield curves for the UK published by the Bank of England. The credit rating of UK government bonds is high enough for their yields to qualify for an approximation of the risk-free rate of interest.[4]

4 Estimating expected losses from bank equity prices

In order to estimate the put option values of individual banks we develop a framework to implement Merton's jump-diffusion model [Merton (1976)], which augments Merton's structural credit risk model [Merton (1974)] with a jump process. Jump diffusions can incorporate rare, large fluctuations in asset prices as witnessed during crises. The empirical distribution of asset returns differs in many ways from the diffusion process assumed in the Black and Scholes (1973) and Merton (1974) models. The assumption that asset price returns follow a normal distribution could underestimate the value of government implicit subsidies as it would ignore the non-normal behaviour of asset prices, observed particularly in banks. This measure relies on equity prices and, assuming equity holders are not benefiting from a government bail-out, put option values obtained from this approach should be free of any implicit government guarantee. The model parameters are used to back out the asset values of the six banks. Expected losses of individual banks are modelled as a put option which can be observed as a credit spread over the risk-free rate of interest.

4.1 Payoffs to equity and debt holders

Banks have assets (A) that change in value over time, and a fixed amount of debt (D) that is due at some point of time in the future (T). Assets of a bank are uncertain and change due to factors such as profit flows and risk exposures. Default risk over a given horizon is driven by uncertain changes in future asset values relative to promised payments on debt. The value of the bank is split into two - that which goes to the equity holders and that which goes to the debt holders or creditors. If, at the time (T) when the debt falls due, the assets have more than enough value to repay the liabilities (D), the excess value ($A - D$) goes to the equity holders. In the absence of any insurance, the payout to the creditors is what they are owed (D). If the assets are not enough to repay the liabilities, then the bank defaults, and the creditors receive what is left of the assets. So the market value of the debt, denoted

[4] At the time of writing, UK Government bond (gilts) credit ratings are AA by Fitch Ratings and Standard & Poor's (S&P) Global; Aa3 by Moody's. All three ratings are accompanied by a stable outlook, indicating no immediate plans for a downgrade. India's government bond (IGB) credit ratings are BBB- with a positive outlook by S&P Global; BBB- with a positive outlook by Fitch Ratings and ; Baa3 with a stable outlook by Moody's.

as (B), is equivalent in value to risk-free debt minus a guarantee against default. As demonstrated in Merton (1977), this guarantee can be calculated as the value of a put option on the assets (A) with an exercise price equal to (D).

$$B = D - \max[D - A, 0]. \tag{1}$$

If we introduce a guarantee, we can view the realised cost to the guarantor, C, as the payout in case of default and zero otherwise.

$$C = \max[D - A, 0]. \tag{2}$$

Having identified the nature of the payoffs to debt and equity holders, the next step is to examine how the value of the bank's assets evolve through time relative to a default barrier. Stochastic assets evolve relative to a distress barrier and determine the value of liabilities with implicit options. The probability that the assets will be below the distress barrier is the probability of default.

4.2 Asset evolution according to a jump diffusion process

In the basic structural credit risk model, attributed to Merton (1974), the market value of a firm's assets A evolve according to a Geometric Brownian Motion (GBM) depicted in equation (3)

$$\frac{dA}{A} = \mu dt + \sigma dW_t \tag{3}$$

where μ is the expected growth rate of the firm's asset value, σ is the asset volatility. W_t stands for a standard Brownian motion.

In this study, we apply the Merton (1976) jump diffusion model which was put in place to relax the prior assumption that trading was continuous. The model has time invariant coefficients, constant volatility and log-normally distributed jump sizes. Jumps allow higher moment features such as skewness and leptokurtic behaviour in the distribution of asset price returns. Changes in asset values consist of a continuous diffusion component which is modelled as a GBM, and a discontinuous jump component, modelled as a Poisson process. The evolution of the asset value A_t is given by the stochastic differential equation,

$$\frac{dA_t}{A_t} = \mu dt + \sigma dW_t + d(\sum_{q=0}^{N_t}(J_q - 1)) \tag{4}$$

where the last term models the jumps. The jumps capture the price impact of extreme events, which arrive only at discrete points in time and these arrivals are described by a Poisson process N_t, characterised by its arrival rate λ. A jump is modelled by a random variable J, which transforms the asset value A_t to JA_t. The difference $(J-1)$ is the relative change in price when a Poisson jump occurs. The jump size J_q is a sequence of independent identically distributed nonnegative random variables. In the absence of outside news, the asset price simply follows a GBM. In the model all sources of randomness, N_t, W_t and $J's$, are assumed to be independent. Solving the stochastic differential equation (4) gives the dynamics of the asset price:

$$A_t = A_0 \exp\{(\mu - \frac{1}{2}\sigma^2)t + \sigma W_t\} \prod_{q=0}^{N_t} J_q \tag{5}$$

where A_0 is the asset price at time zero. If we denote $Y_q = \log J_q$, we have

$$X_t = \log \frac{A_t}{A_o} = (\mu - \frac{1}{2}\sigma^2)t + \sigma W_t + \sum_{j=0}^{N_t} Y_q, \tag{6}$$

The jump size is drawn randomly from a distribution with probability density function $J(Q)$ which is independent of both the GBM and the Poisson process. The jump size J is a log-normally distributed random variable:

$$\ln J \sim N(\mu_q, \sigma_q^2). \tag{7}$$

The expected value of the jump size can be written as:

$$E[J-1] = \exp(\mu_q + \frac{\sigma^{2_q}}{2}) - 1. \tag{8}$$

Augmenting the diffusion process with jumps adds three extra parameters $(\lambda, \mu_q, \sigma_q)$ to the BSM framework which contains two parameters (μ, σ). Using the approach of Ball and Torous (1983) and discretising over $[t, t+\Delta]$, the solution takes the form

$$\Delta X_t = (\mu - \frac{1}{2}\sigma^2)\Delta + \sigma \Delta W_t + \sum_{j=0}^{\Delta N_t} Y_q, \tag{9}$$

where $\Delta W_t = W_{t+\Delta} - W_t \sim N(0, \Delta)$, where $\Delta N_t = N_{t+\Delta} - N_t$ is the number of jumps occuring in the interval $[t, t+\Delta]$.

The estimated asset values for each bank are transformed into log returns, $\Delta\left[ln\left(A_t\right)\right] = ln(A_{t+1}) - ln(A_t)$. For estimation purposes, we need the probability density function of X_t as in (6). Since the calibration is done in discrete time we work with ΔX_t as defined in (9) so that the density function now has a finite number of terms. The approximation assumes that $\lambda\triangle$ converges to zero; this type of discrete time specification is referred to as a Bernoulli diffusion model. When the time difference Δt is small, by the properties of the Poisson process N_t, we know that $P(\Delta N_t = 0) = 1 - \lambda\Delta t$, $P(\Delta N_t = 1) = \lambda\Delta t$ and $P(\Delta N_t > 1) = 0$. Therefore, the density in log returns, $f_{\Delta X_t}$ can be thought of as a Bernoulli random variable that has a mixture distribution for a small $\triangle t$. During Δt, the density in log returns is a weighted average of the diffusion density $(f_{\Delta Diff})$ and jump density $(f_{\triangle Jump})$ given by:

$$f_{\Delta X_t} = (1 - \lambda\Delta t) f_{\Delta Diff} + \lambda\Delta t (f_{\Delta Diff} * f_{\triangle Jump}). \tag{10}$$

In equation (10) the diffusion part of the process is:

$$f_{\Delta Diff} \sim N((\mu - \frac{\sigma^2}{2})\Delta t, \sigma^2 \Delta t), \tag{11}$$

and the jump part is:

$$(f_{\triangle Diff} * f_{\triangle Jump}) \sim N([(\mu - \frac{\sigma^2}{2})\Delta t + \mu_q], \sigma^2 \Delta t + \sigma_q^2) \tag{12}$$

Denoting the distribution of daily log returns in a bank's asset values as $\triangle X = \Delta \ln V_t$, the log-likelihood function over the set of parameter values $\theta = \{\mu, \sigma, \lambda, \mu_q, \sigma_q\}$, can be written as:

$$\log L(\theta \mid \Delta x_1, ...\Delta x_T) = \sum_{t=1}^{T} \log f_{\Delta x}(\Delta x_t \mid \theta) \tag{13}$$

4.3 Estimating the parameters of the jump diffusion process

The normal practice for estimating the parameters would be to maximise the log-likelihood function over a set of given parameter values $\{\mu, \sigma, \lambda, \mu_q, \sigma_q\}$. However, in this case, the standard maximum likelihood (ML) procedure is not valid as the log return in the Bernoulli diffusion model is a mixture of two normal distributions with different means and variances as given by equations (11) and (12). The likelihood function is not well-behaved, which indicates the occurrence of discontinuous jumps. Moreover, since the intensity parameter, λ, is unknown *ex ante*, it is not possible to identify from which of the two normal distributions each observation originates. This, coupled with the fact that the two normal distributions are different, the ML estimator does not exist.[5] Maximising the log-likelihood function, according to equation (13) fails to determine robust parameter estimates since the likelihood equation has a flat surface. A solution to the problem would be to devise a method that would not require all the five parameters to be optimised simultaneously.

A two-stage estimation process is used to calibrate the model parameters. The most intuitive way to calibrate the model would be to use a bank's asset values. But these are not directly observable. However, for publicly traded banks, the equity price is closely observed in the market. By assuming that the bank's market value exhibits characteristics similar to those of the observable equity price, we can estimate the jump parameters $\{\lambda, \mu_q, \sigma_q\}$ directly from the market capitalisation data. The remaining diffusion parameters $\{\mu, \sigma\}$ are then estimated using ML. This two-stage estimation process is described in the following two sections.

4.4 Detecting jumps as change points

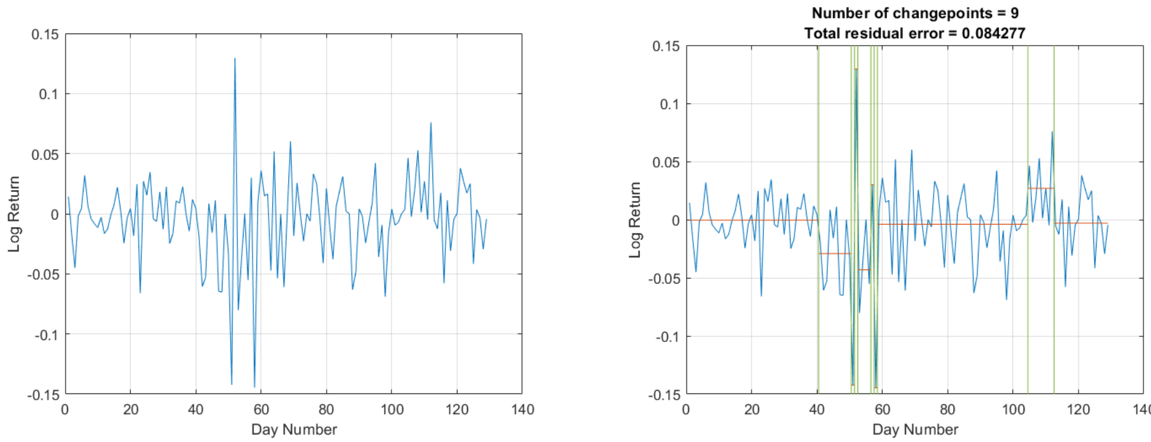
The jump parameters $\{\lambda, \mu_q, \sigma_q\}$ are estimated using the observable market capitalisation, of each sample bank, over an estimation window of six months from 2005 to 2024. We expect structural breaks in the time series of log returns of the market capitalisation when the mean of the series undergoes significant changes. For the estimation, there is a need to identify the precise time when the mean changes abruptly. These are called "change points". A change point reflects a discontinuity or jump in the time series of log returns. If the intensity parameter λ is small, then in a period of 1 day, the log returns will either jump once or not at all. As an illustration, the left-hand side panel Figure 1 shows the daily log returns in the market capitalisation of a SBI in 2020 (January to June).

Detecting the change points is an optimisation problem whose solution can be found by implementing the dynamic programming algorithm described in Lavielle (2005) and Killick et al. (2012). The implementation of the algorithm is described in Appendix A and its output is shown in the right-hand side panel in Figure 1. Having identified the number of jumps within the time series of log returns in market capitalisation, we determine the jump rate λ, as the number of jumps divided by the total number of observations. In the case of SBI, shown in Figure 1, over the six-month observation period from January to June 2020, this was 0.08 (10 divided by 125). The corresponding mean jump size $\hat{\mu}_q$ is 0.0036, and the jump size volatility $\hat{\sigma}_q$ is 0.0879. This exercise is repeated across all six banks over the observation period from 2005 to 2024.

[5] For further clarification see Kiefer (1978), Honore (1998), and Hamilton (1994).

Figure 1: Daily Log Returns of Market Capitalisation of SBI with Identified Change Points, January-June 2020

Daily Log Returns of Market Capitalisation | Identified Change Points



Notes: It is assumed the log returns fluctuate around some underlying signal that could be associated with the factors driving the market capitalisation of the bank. The figure in the right-hand side panel shows that the mean of the series does not change during some time periods, which implies that the signal remains constant during any of these "distinct states". The horizontal lines capture these distinct states or regions whose starting and end date are identified by a distinct change point. During the course of these 130 trading days between Jan-June 2020, there are nine "change points" where the mean changes abruptly. The algorithm also returns the residual error of the signal against the modeled changes which, in this case, is 0.0843.

4.5 Calibrating the diffusion parameters

Having obtained estimates of the jump parameters $\{\lambda, \mu_q, \sigma_q\}$, we now estimate the remaining parameters μ and σ using conditional ML. We re-specify the negative of the log-likelihood for the mixed density function in equation (10) such that the parameter values, θ^*, can be written as:

$$\theta^* = \left\{\mu, \sigma, \hat{\lambda}, \hat{\mu}_q, \hat{\sigma}_q\right\}. \tag{14}$$

This indicates that the jump parameters are now held constant within the log-likelihood function for a bank's returns, and what varies is σ and μ. However, the value of the likelihood function is ultimately determined by a single unknown parameter, σ. As describe in the standard Merton (1974) model, the diffusion mean

$$\mu = \frac{(\log A_{t+\triangle} - \log A_t)}{T} + \frac{1}{2}\sigma^2 \tag{15}$$

is dependent on the diffusion volatility.

In order to calibrate the jump diffusion model, we choose exogenously an initial value of the unobserved volatility of asset value returns σ. A bank's actual asset value V is not observable. As mentioned above, if a bank's shares are publicly traded, we can observe its market value, which is reflected in the price of equity E. So the estimation process begins by fitting the jump diffusion model to the observed time series of bank equity prices (market capitalisation series) and then producing an initial estimate for the market value over the residual maturity $T - t$ so that

$$E_t = C_t = \sum_{k=0}^{\infty} \frac{e^{-\lambda T}(\lambda T)^k}{k!}[A_t e^{\mu T + k(\mu_q + \frac{\sigma_q^2}{2})} N(d_1) - De^{-rT}.N(d_2)], \tag{16}$$

where

$$d_1 = \frac{\ln \frac{A_t}{D} + (\mu + \frac{\sigma^2}{2})T + k(\mu_q + \sigma_q^2)}{\sqrt{\sigma^2 T + k\sigma_q^2}} \tag{17}$$

$$d_2 = d_1 - \sqrt{\sigma^2 T + k\sigma_q^2}. \tag{18}$$

Expected loss is modelled as a put option, P_t^E, where the present value of debt D represents the strike price

$$P_t^E = \sum_{k=0}^{\infty} \frac{e^{-\lambda T}(\lambda T)^k}{k!}[De^{-rT}.N(-d_2) - A_t e^{\mu T + k(\mu_q + \frac{\sigma_q{}^2}{2})} N(-d_1)]. \tag{19}$$

The market value of the bank (A) comprises the equity (E) and the market value of debt (B) at time t. It can be represented as:

$$A_t = E_t + B_t. \tag{20}$$

Put-call parity states that owning the asset A_t outright is equivalent to owning a portfolio comprising (i) a call option C_t at strike price D, (ii) a risk-free bond valued D at time T, and (iii) a short put option P_t^E with strike price D so that

$$A_t = C_t + De^{-rT} - P_t^E. \tag{21}$$

Rearranging we have:

$$C_t = A_t - (De^{-rT} - P_t^E). \tag{22}$$

In equation (22), $De^{-rT} - P_t^E$ is the market value of debt B_t. As an initial step, we solve for A_t using the jump diffusion parameters estimated from the observable changes in equity and equity volatility. After updating the parameter estimates based on this solution for A_t, we follow an iterative procedure until the estimates of A_t, $\mu, \sigma, \lambda, \mu_j$ and σ_j have converged.

4.6 Estimated Put Option Values

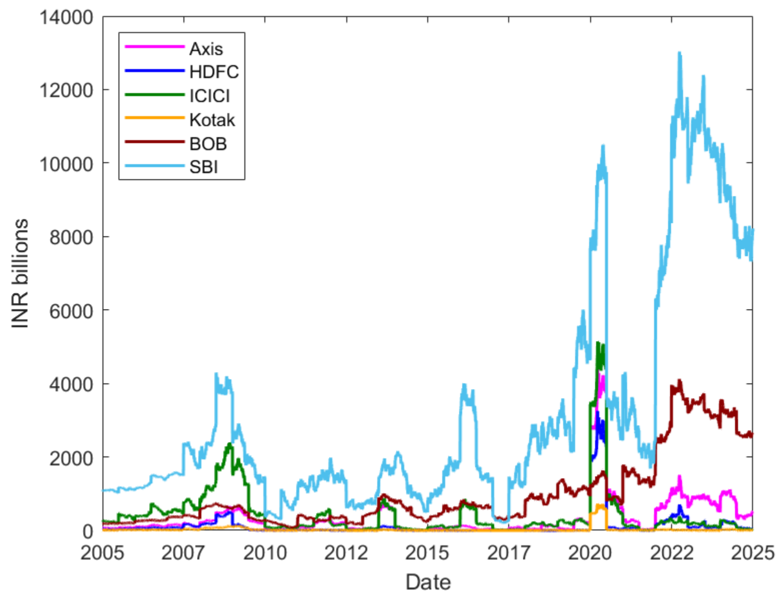
Based on the time series of the banks' observed equity prices, the risk-free rate and debt levels, the jump diffusion process given by equation (9) is used to back out a series of implied asset values, over a 20 year period, from 3 January 2005 to 30 December 2024 (with a total number of 5,194 observations), with six-month rolling windows.

The expected loss of a bank is the equivalent of the put option premium specified in equation (19). Figure 2 plots the expected losses (in INR billions) of the six sample banks from 2005 to 2024. The results show that expected losses of the two largest banks by market capitalisation at the time - SBI and ICICI - increased during height of the GFC in 2008. Expected losses across all banks are high, in part, due to the assumption of a time horizon of 5 years. This was necessary to enable a comparison with expected losses derived from CDS spreads which have a 5-year maturity. A time horizon of 1 year, typically used to measure default risk of financial institutions by global credit-rating agencies, would have resulted in expected losses of a much smaller magnitude. This is shown in Figure 3.

In 2015, the RBI initiated an asset quality review (AQR) of banks with a view to generating clean and fully provisioned bank balance sheets (Viswanathan (2016); Bhusan et al. (2024)). The

AQR revealed the high-incidence of non-performing assets (NPAs) in the Indian banking system. The proportion of these assets was much higher in PSBs. During the five years to 2015, Indian commerical banks had resorted to restructuring of loans in many cases to postpone recognition of non-performance. Following the AQR, banks initiated transparent recognition, reclassifying standard restructured advances as NPAs, and providing for expected losses on such advances. On April 1, 2018, Indian Accounting Standards (Ind- AS) converged with the International Financial Reporting Standard 9 (IFRS9) on expected losses [IMF and Bank (2018)]. Indian banks gross NPAs remained at a 12-year low of 2.6 percent in September 2024 [RBI (2024)].

Figure 2: Indian Banking Sector (6 Largest Listed Banks): Put Option Values based on bank equity prices with a time horizon of 5 years, 2005-2024 (In INR Billions)

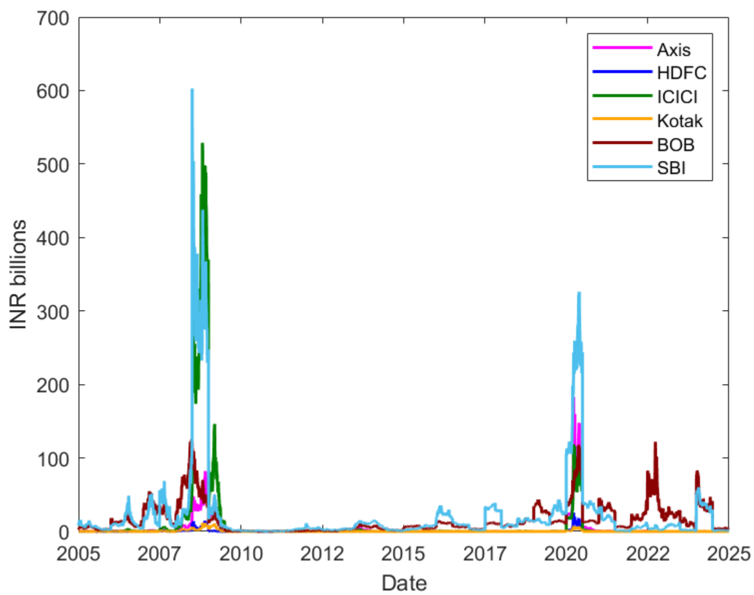


Notes: Over the period of observation from 2005 to 2024, expected losses of the six banks have remained positive, albeit with much smaller magnitudes, and with considerable variation across banks.
Source: Model Outputs

The Covid-19 pandemic led to acute stress in the global financial system. As the implications of the shock began to crystalise in mid-March 2020, financial markets faced unusually high selling pressure. The exogenous nature of the shock, set against the backdrop of a well-capitalised Indian banking system, led to a surge in expected losses driven by sharp falls in bank equity prices. Banks across global jurisdictions, witnessed a collapse in equity prices between March to September 2020. The Indian banking system was no exception. Expected losses of the SBI and BOB, remained elevated in 2022, but have since trended downwards. Expected losses of HDFC, ICICI and Kotak Mahindra stabilisied over 2022 and have remained low since then.

Figure 3 shows the put option values of the 6 banks in which the time horizon for assessing default risk is taken to be 1 year. In structural credit risk models, default risk is inherently dependent on the time horizon. These models define default as a firm's asset value falling below a certain threshold level of debt, and the timing of this event depends on the chosen time frame. Under the Basel II capital adequacy framework, the RWA formula does not factor in a time horizon because this assumed to be fixed at 1-year (BCBS (2005)). If the bank applied for an Internal Rating Based (IRB) approach, it would be expected to provide its own estimates of expected losses over a 1-year horizon. For a 1-year horizon the default point, the asset value at which the firm will default, will lie somewhere between total liabilities and current, or short-term, liabilities. In a shift from the Basel framework, under IFRS9 the default probability under over the remaining life of a financial instrument has to be determined (see Bank and Eder (2022)). For the 5-year time horizon it was reasonable to set the default point for banks at the level of total liabilities. For a 1-year time horizon, the default point is set at 75 percent of total liabilities as proposed by Nazeran and Dwyer (2015).[6]

Figure 3: Indian Banking Sector (6 Largest Listed Banks): Put Option Values based on bank equity prices with a time horizon of 1 year, 2005-2024 (In INR Billions)



Notes: In 2024, expected losses of the Indian banking system have fallen to near pre-crisis levels.
Source: Model Outputs

At the height of the crisis in October 2008, the sharp decline in banks' asset values raised the expected losses in the Indian banking system to INR 900 bn (GBP 11 bn) which was half the total available amount of Tier 1 capital of INR 1800 bn (GBP 22 bn). Despite the stress caused by the Covid-19 pandemic, expected losses in the banking system have declined considerably. This has been facilated by government action to recapitalise and consolidate PSBs [IMF and Bank (2025)]. By the end of 2024, expected losses had fallen to INR 6 bn (GBP 73 million) against a Tier 1 capital base of INR 14.7 tn (GBP 137 bn). Empirical evidence suggests that the Indian banking system was insulated from the GFC owing to significant public ownership and conservative regulatory practices. The RBI report on Currency and Finance, for the year 2010 [RBI, ed (2010a)], broadly concluded that the

[6] This deviates from the practice of defining the default point as "current liability +1/2 long term liability," which originated in KMV research and has been cited in the academic literature [see Crosby and Bohn (2003)]. Estimating the default point as current liabilities plus one-half long-term liabilities would be problematic for banks, as financial firms typically do not report current liabilities as a separate item on their balance sheet.

GFC, which caused great turmoil in the developed economies, did not affect the profitability of Indian banking, in the same manner, due to the limited exposure of Indian banks to riskier assets and strong macroeconomic fundamentals. Eichengreen and Gupta (2013) observed that in the second half of 2008, there was a sharp increase in interbank borrowing rates. This was coupled with a flight of deposits from private sector banks to PSBs and to SBI in particular. However, this episode was shortlived. Gulati and Kumar (2016) used a measure of profit efficiency to conclude that the impact of the GFC on the Indian banking industry was modest. Rakshit and Bardhan (2022) also concluded that the effects of the GFC on bank profitability appeared insignificant. Our results, described in Section 5, will indicate that the impact of the GFC on the Indian banking system was contained, in part, due to the implicit subsidy provided by the Government.

5 Estimating expected losses from CDS spreads

In this section, I estimate expected losses of banks by calculating the value of the put option based on their CDS spreads. In a CDS contract, the protection buyer pays a premium (given by the CDS spread) and the protection seller agrees to compensate the buyer for any loss if the reference entities default. CDS spreads with banks as the underlying reference entities thus effectively capture the market's view of their credit risk and can be effective leading indicators of bank financial distress, particular during periods of financial crisis. CDS contracts are homogeneous and standardized with no requirement to select a benchmark risk-free interest rate to estimate default risk. Firm-level CDS present many advantages over bond markets in terms of price discovery, liquidity and standardization. Analysing a set of European and US banks, Avino et al. (2019) found that firm-level CDS spreads are strongly and significantly associated with future bank failure. Czech (2021) provides evidence of a positive liquidity spillover effect from CDS to bond markets, whereby bond trading volumes are larger for investors with CDS positions written on the debt issuer.

For a CDS contract, from a protection buyer's perspective, future cash flows include premium payments and the recovery of the credit loss in the event of default. As these payments are contingent on default, their present value depends on the default probability distribution. A key element in the valuation of credit derivatives such as CDS is the modelling of the time to default. The uncertainty underlying this event is captured in a default probability distribution, also known as the default term structure. The default term structure models the probability that a CDS issuer will default at any given time in the future.

The time to default of the credit derivative is denoted by T which can be viewed as a random variable. In this modelling framework, T is assumed to be the time-to-event (in this case default). Let $S(t)$ be the survival probability, the probability that the event has not occurred until time t. Let $F(t)$ be the failure probability, the probability that the event occurred by time t. $S(t)$ and $F(t)$ can be expressed as: $S(t) = P(T > t)$; $F(t) = P(T \leq t)$; $S(t) = 1 - F(t)$.

The default probability upto time t, is defined as the cumulative probability distribution function $F(t)$ of T, which can be expressed as:

$$F(t) = P[T \leq t] \tag{23}$$

The corresponding survival probability, that is the probability that no default occurs until time t, is given by:

$$S(t) = 1 - F(t) = P[T > t] \tag{24}$$

where $S(t=0) = 1$ and $S(t=\infty) = 0$.

Alternatively, the random variable T may be represented by its hazard rate or default intensity.

$$h(t) = \frac{\lim}{\triangle t \to 0} \frac{P(t \leq T < t + \triangle t | T \geq t)}{\triangle t} = \frac{f(t)}{S(t)} \tag{25}$$

which is strictly positive, and can be interpreted as the instantaneous rate of default, conditional on not having defaulted before. Integrating the default intensity function gives the cumulative default intensity function:

$$\Lambda(t) = \int_0^t h(u)\, du \tag{26}$$

from which the survival function can be obtained again as:

$$S(t) = \exp(-\Lambda(t)) = \exp\left(-\int_0^t h(u)\, du\right) \tag{27}$$

It is assumed here that h is integrable over the range of t, given by $(0, \infty)$, and for the function to exist, $\ln S(t)$ is continuous [see Castellacci (2008)]. Given h, S could be obtained by integrating h along with the initial condition $S(0) = 1$. Conversely, if S is differentiable one can obtain the hazard rate from the survival probability function as:

$$h(t) = -\frac{d}{dt} lnS(t) \tag{28}$$

Whilst estimating the default term structure, the hazard rate is assumed constant between subsequent CDS maturities and is assumed to follow a piecewise function of maturity time.

The model is calibrated using observed 5 year CDS spreads for the 6 Indian banks at daily frequency, from 2007.5 - 2024.12. [7] This provided 4,573 observations across all 6 banks.

A hazard rate curve is bootstrapped from observed CDS spreads to construct a default probability curve or default term structure. Bootstrapping requires a default-free discount curve given by the term structure of zero coupon yields. A zero rates curve is generated using the term structure of UK government zero-coupon bond yields, which are obtained at daily frequency, from the Bank of England public domain yield curve data base. [8] As discussed in Section 3, the credit rating of UK government bonds is high enough for their yields to qualify for an approximation of the default-free discount curve. Fourteen different maturities that would broadly cover the maturity spectrum of the yield curve are considered; they are 6-month, 1-,2-,3-,4-5-,6-7-,8-,9-,10-,15-,20- and 25-year bonds.

The value of the put option, based on CDS spreads, can now be computed by subtracting the

[7] The coverage of CDS series for banks is lower than equity prices, both in terms of the cross-section and time-series dimensions. Axis bank had CDS spreads going back only as far as 15 May 2007. To generate a consistent time series across all banks the estimation started from that date.

[8] http://www.bankofengland.co.uk/statistics/pages/yieldcurve/default.aspx

expected discounted payoff from the debt contracts from the discounted face value of debt. The expected discounted payoff from the debt contracts should be equal to:

$$D\exp\left(-\left(r_t + CDS_t\right)T\right) \tag{29}$$

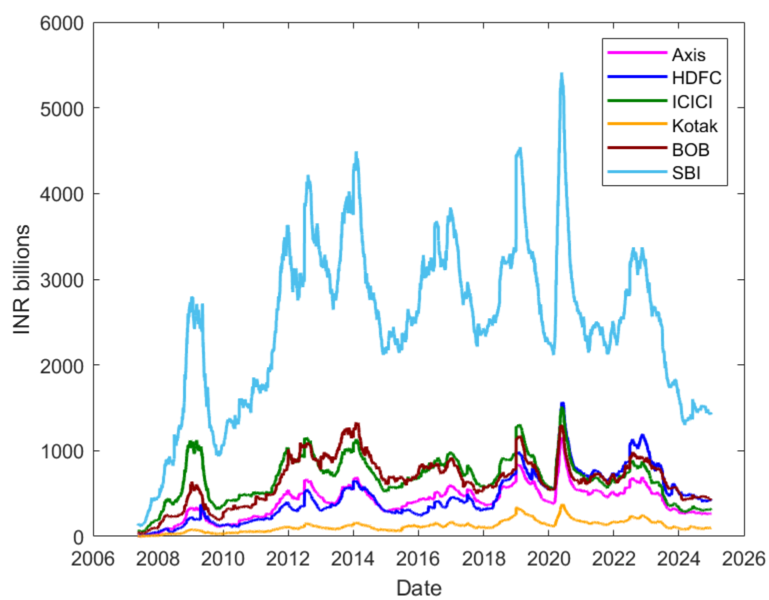
where CDS_t is the price at time t, r_t is the risk-free rate of interest at time t, D is the face value of debt that is due at some point in the future T. In this case $T = 5$ as the CDS spreads have a 5 year maturity. In each period, the creditor would have to pay a premium of CDS to insure the debt. The CDS spread can, therefore, be applied as a discount factor. The put option value based on CDS prices can be expressed as:

$$P_t^{CDS} = D\exp\left(-r_t T\right) - D\exp\left[-\left(r_t + CDS_t\right)T\right] \tag{30}$$

For a CDS contract, from a buyer's perspective, future cash flows include premium payments and the recovery of the credit loss in the event of default. As these payments are contingent on default, their present values depend on the risk-neutral default term structure (Gray and Malone (2008)).

Figure 4 shows the put option values, estimated by equation (30), for the six Indian banks over the observation period from May 2007 to December 2024.

Figure 4: Indian Banking Sector (6 Largest Listed Banks): Put Option Values based on bank CDS spreads, May 2007 to December 2024 (In INR Billions)



Notes: Put Option values based on CDS spreads surged at the height of the GFC in the second half of 2008 and the Covid-19 pandemic in 2020.
Source: Model Outputs

CDS spreads spiked during the aftermath of the GFC in 2009 and the shock from the Covid-19 pandemic in 2020. However, severe market turmoil during both those periods might also have impeded the efficient pricing of CDS.

6 Estimates of the implicit subsidy

The put option values of banks derived from equity prices, P_t^E (as shown in Figure 2) should capture default risk under the assumption that there are no bailouts. Assuming that equity holders are wiped out in the event of default, equity prices contain information only on the probability of default. Conversely, a CDS only pays out if the bank defaults on its debt. It follows that P_t^{CDS} (as shown in Figure 4) should capture the joint risk of the bank becoming distressed and the government not bailing out creditors. It should, therefore, be lower than P_t^E. For an individual bank, the difference between P_t^E and P_t^{CDS} provides a measure of the implicit subsidy it receives.

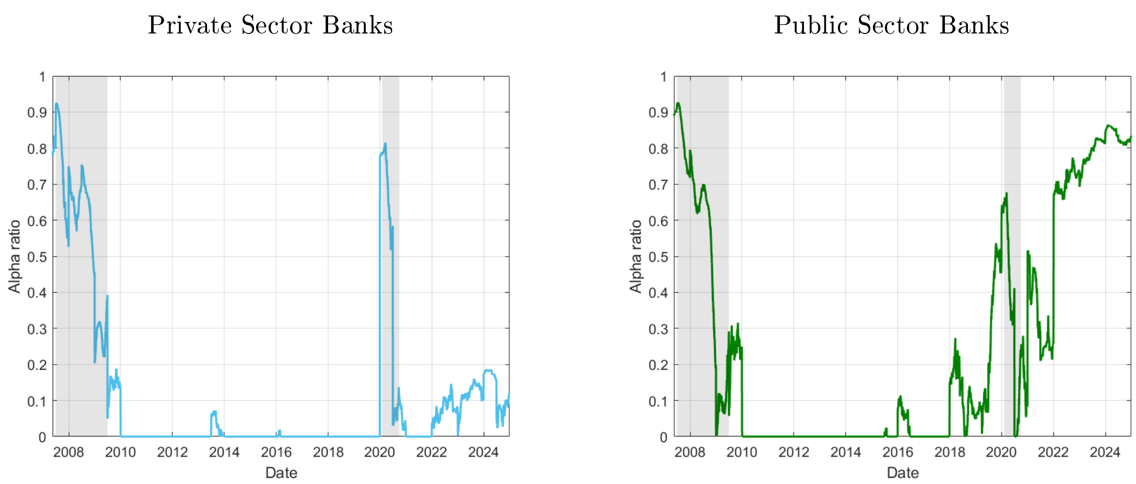
At the height of the GFC, in October 2008, the nominal value of the implicit subsidy to the Indian banking system reached INR 4.75 tn (GBP 60 bn). Given that the total debt of the six banks amounted to roughly INR 22 tn (GBP 270 bn) at the time, this yields a subsidy of about 2000 basis points (bps). At the end of 2024, the implicit subsidy to the Indian banking system had fallen to about 600 bps with a nominal value of INR 9 tn (GBP 82 bn) against a total debt of INR 155 tn (GBP 1.4 tn).

The relationship between the two put option prices can also be used to derive the proportion of default risk of a bank that is believed to be insured by the government.

$$\alpha_t = 1 - \frac{P_t^{CDS}}{P_t^E} \tag{31}$$

Figure 5 shows the fraction of default risk of the six Indian banks considered to be insured by the Government. The left-hand side panel plots the average alphas for the 4 private sector banks. The right-hand side panel shows the alpha average for the 2 PSBs.

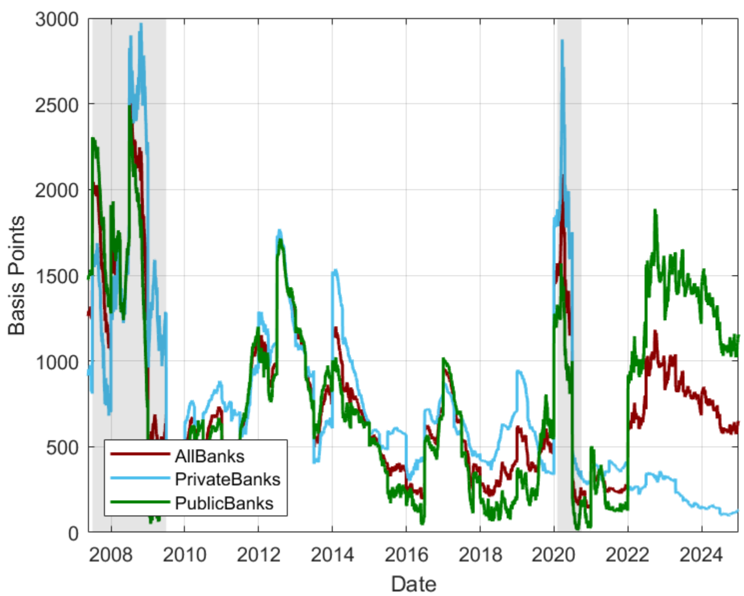
Figure 5: Indian Banking Sector (6 Largest Listed Banks): Fraction of default risk insured by the government



Notes: The left-hand side panel shows time-variation in the average value of alpha for the 4 private sector banks. Alphas for all 4 banks were high during the GFC and the Covid-19 pandemic. Since July 2020 alphas for private sector banks, as a whole, have remained modest. The right-hand side panel shows alphas for the PSBs. As in the case of private sector banks, alphas were high during the GFC. Alphas for these 2 PSBs dropped close to zero over the period from 2010 to 2017. Alphas rose again during the Covid-19 pandemic in 2020. But not to the same degree that they did for private sector banks, Alphas for PSBs increased again in 2022 and have remain elevated since then.
Source: Model Outputs

It can be seen from the left-hand side panel of Figure 5, that the value of alpha was close to 1 across private sector banks, during the onset of the GFC and the shock from the pandemic. This implies that creditors of these banks would have been beneficiaries of heightened government guarantees at the time as highlighted by the shaded vertical bars. Since 2020 H2, the value of alpha for the private sector banks has averaged below 0.1. For some private sector banks, alpha was effectively zero over this period. The right-hand side panel shows that the average value of alpha, for the PSBs, also peaked during the GFC and the Covid-19 pandemic. However, the value of alpha during the pandemic was less for the PSBs than it was for the private sector banks. During the pandemic, PSBs did not witness a fall in the market value of their equity to the same degree that private sector banks did. Within the framework of a structural credit risk model, described in Section 4, a decline in the market value of equity would lead to a rise in default risk, implying a higher implicit subsidy. For much of the intervening period from 2010 to 2017, the average alpha ratio for the PSBs remained close to zero. Alpha values for the PSBs began to rise from January 2022 and remained high until the end of the observation period in 2024.

Figure 6: Indian Banking Sector (6 Largest Listed Banks): Implicit subsidies (In basis points), May 2007 to December 2024



Notes: The figure shows the time series variation in the implicit subsidy for the Indian banking system over the period from May, 2007 to December, 2024. The chart distinguishes between the implicit subsidy to the private sector banks and the public sector banks. Implicit subsidies, expressed in basis points, are obtained by dividing the absolute value of the subsidy by the total debt of the banks. The shaded vertical areas refer to periods of financial stress : the GFC (July 2007 to June 2009) and the Covid-19 shock (February 2020 to September 2020). Implicit subsidies peaked during the GFC and the shock from the Covid-19 pandemic. During these crisis periods implicit subsidies for private sector banks were higher than that for public sector banks.
Source: Model outputs

Implicit subsidies, expressed in basis points, are plotted in Figure 6. The chart shows a decomposition of the overall implicit subsidy to the Indian banking sector between the PSBs and private sector banks. The results displayed in Figure 6, mirror those in Figure 5, in that the level of the implicit subsidy peaked during the GFC and the pandemic when the alphas across banks were high. During these crisis periods, implicit subsidies expressed in basis points, were particularly high for private sector banks. This is notwithstanding the fact that PSBs are more leveraged than private sector banks with higher volumes of debt in their capital structure. Implicit subsidies to the Indian banking system dropped to their lowest levels in the second half of 2021, averaging 200 basis points. But they rose again in 2022 driven increases in implicit subsidies for PSBs.

India, and many other jurisdictions, experienced a notable shift in its interest rate environment in 2022 marked by the re-emergence of high interest rates against a background of high inflation. The RBI increased it's policy rate, known as the Repo rate, four times in 2022, raising it from 4 percent in April to 6.25 percent in December 2022. Banks are generally more profitable in a high interest rate environment as they benefit from increased net interest margins if loan interest rates rise faster than funding costs. At the same time, higher rates reduce the present value of assets with fixed payments, including government bonds and other fixed-rates securities. Domestic banks have traditionally been important players in sovereign bond markets, in emerging economies, both as investors and market makers. In India, banks are required to hold large buffers of government securities (20.5 percent of assets), with loans accounting for about 60 percent of bank assets [IMF and Bank (2018)]. PSBs tend to hold a much larger proportion of government securities than their private sector peers, and as such are likely to be more sensitive to interest rate risk and asset price revaluation. That may help explain why the implicit subsidy for PSBs, has risen since 2022, and by substantively more than that for the private sector banks.

7 Conclusion

This paper provides a market-based estimate of the size of the implicit subsidy, to the Indian banking system, by comparing measures of default risk based on equity prices and CDS spreads. A bank's market value of equity reflects investor sentiment about its future profitability, while CDS speads indicate the market's assessment of the bank's credit risk and potential for default, both providing insights into the financial soundness of a bank. An implicit government guarantee compromises market discipline by reducing creditors' incentive to monitor and price the risk-taking activities of banks. If debt investors perceive that the government will protect them from bearing the full cost of failure, they will provide funding without paying sufficient attention to the bank's risk profile. The extent of this distortion and associated moral hazard depends on the size of the implicit subsidy given to banks, which is why quantifying the subsidy is important.

The size of the implicit subsidy to the Indian banking system peaked during periods of financial stress associated with the GFC and the shock from the Covid-19 pandemic. However, during the intervening tranquil periods the implicit subsidy remained at low levels. Since the beginning of 2021 the proportion of default risk insured by the government, for the private sector banks, have remained at modest levels. For some private sector banks they have been neglible over this period. But from 2022 onwards, implicit subsidies have increased for PSBs and remain elevated.

A key lesson from the recent crises has been that regulatory capital instruments in the future must be able to absorb losses in order to help banks remain 'going concerns'. During the GFC, equity constituted a small proportion of regulatory requirements. The going concern loss absorption achieved by bank debt during the financial crisis was revealed to be weak. Since then bank capital levels have risen. Indeed in India between 2008 and 2024, the aggregate Tier 1 capital of these six major Indian banks increased eightfold from INR 1.8 tn (GBP 22 bn) to INR 14.6 tn (GBP 133 bn). That chimes with the general fall in the estimated implicit subsidy over that period.

The implicit subsidy does, however, appear to rise during periods of financial stress. A resolution framework - beyond standard insolvency and bankruptcy procedures - could reduce it further. Options like bail-in of senior creditors however remain contentious, and such tools would need to be carefully calibrated in the Indian context, given past public concerns and the strong emphasis on protecting depositors. Notably it would require careful consideration of the prioritised order in which the investors of the bank would be required to recapitalise the institution.

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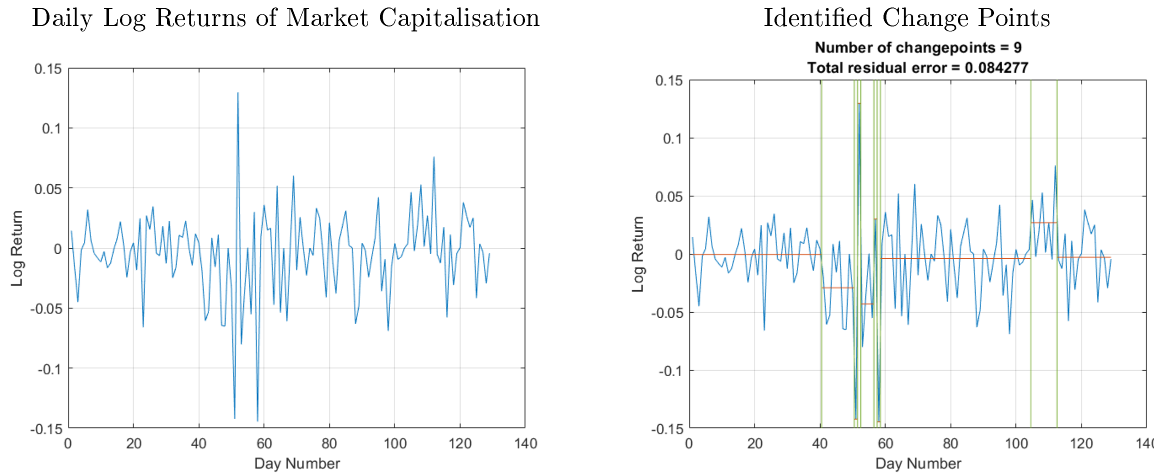
Appendix A - Estimating Change Points

In this section we describe the optimisation process involved in identifying the structural breaks in the mean of the time series of log returns of the observable market capitalisation. For illustration purposes, we consider the daily market capitalisation of SBI during the observation period January to June 2020 which consists of 130 observations. The purpose of the optimisation is to determine the precise time when the mean changes abruptly, which we call change points.

Let x_i denote the log returns in the market capitalisation of Barclays bank at time t where $1 \leq i \leq n$ and $n = 130$ days. We assume that these log returns fluctuate around some underlying signal m that could be associated with the factors driving the market capitalisation of the bank. x_i can be expressed as

$$x_i = m(t_i) + e_i, \tag{32}$$

Figure 7: Daily Log Returns of Market Capitalisation of SBI with Identified Change Points, January-June 2020



Notes: It is assumed the log returns fluctuate around some underlying signal that could be associated with the factors driving the market capitalisation of the bank. The figure in the right-hand side panel shows that the mean of the series does not change during some time periods, which implies that the signal remains constant during any of these "distinct states". The horizontal lines capture these distinct states or regions whose starting and end date are identified by a distinct change point.The horizontal lines capture these distinct states or regions whose starting and end date are identified by a distinct change point. During the course of these 130 trading days between Jan-June 2020, there are nine "change points" where the mean changes abruptly. The algorithm also returns the residual error of the signal against the modeled changes which, in this case, is 0.0843.

where e_i is a sequence of residual errors of the signal against the modelled changes. Figure 1 shows that the mean does not change during some time periods, which implies that m is piecewise constant within any of these "distinct states." The horizontal lines in Figure 1 capture those distinct states whose starting and end dates are identified by a distinct change point. The objective of this detection method is to determine these change points. For the log-return time series data $x_1, ..., x_n$ if a change point occurs at τ, then $x_{1,...,}x_\tau$ will differ from $x_{\tau+1,...,}x_n$ in some way. Following Lavielle (2005) and Killick et al. (2012), we assume that log-returns x_i follow a normal distribution, where the means m_i are piecewise constant through time. Moreover, we assume that there exists discontinuity instants

$\mu_1, \mu_2, ...\mu_K$ such that

$$m(t) = \mu_k \text{ if } \tau_{k-1} < i \leq \tau_k, \tag{33}$$

where $k-1$ is the number of change points, which gives k homogeneous intervals where the mean of the log-returns are constant, and where $\tau_0 = 0$ and $\tau_k = n$. Thus, for any $\tau_{k-1} < i \leq \tau_k$,

$$x_i = \mu_k + e_i. \tag{34}$$

The sequence of residual errors $e_i, 1 \leq i \leq n$ is a sequence of random variables with zero mean. So x_i is a sequence of random variables with piecewise constant mean

$$E(x_i) = \mu_k \text{ if } \tau_{k-1} < i \leq \tau_k. \tag{35}$$

Assuming that the sequence of residual errors is a sequence of independent and identically distributed Gaussian variables $e_i \sim N(0, \sigma^2)$. It follows that

$$x_i \sim N(0, \sigma^2) \text{ if } \tau_{k-1} < i \leq \tau_k. \tag{36}$$

Therefore, identifying the number and sequence of jumps in the time series of log asset value returns would involve estimating (i) the number of K segments, (ii) the location of the discontinuities (τ_k, where $1 \leq k \leq K-1$) and (iii) the value of the underlying signal or mean in each segment ($\mu_k, 1 \leq k \leq K$). We derive these estimates by minimising the residual errors, which is equivalent to maximising the likelihood. Adding change points decreases the residual error but can result in overfitting. In the extreme case, every point becomes a change point, and the residual error vanishes.

The model is specified as a parametric model which depends on a vector of paramaters $\theta = (\mu_{1,...,}\mu_K, \sigma^2, \tau_1, ..., \tau_{K-1})$. Since the data from each segment represent an independent set of random variables, the overall likelihood function is a product of local likelihood functions. The overall likelihood function is denoted by $L(\theta \mid x_{1,}x_2, ..., x_n)$ and is obtained by multiplying all the local probability distributions $p(x_1, x_2, ..., x_n; \theta)$ so that

$$L(\theta \mid x_1, x_2, ..., x_n) = p(x_1, x_2, ..., x_n; \theta)$$

$$= \prod_{k=1}^{K} p(x_{\tau_{k-1}+1,...,}x_{\tau_k} : \mu_k, \sigma^2)$$

$$= \prod_{k=1}^{K} (2\pi\sigma^2)^{\frac{-(\tau_k - \tau_{k-1})}{2}} \exp\left\{-\frac{1}{2\sigma^2} \sum_{i=\tau_{k-1}+1}^{\tau_k} (x_i - \mu_k)^2\right\} \tag{37}$$

The ML estimation of θ can be decomposed into two steps:

(i) the means (μ_k) and change points (τ_k) are estimated by minimising

$$J\left(\mu_1,...,\mu_K,\tau_1,...,\tau_{K-1}\right)=\sum_{k=1}^{K}\sum_{i=\tau_{k-1}+1}^{\tau_k}\left(x_i-\mu_k\right)^2, \tag{38}$$

(ii) the variance σ^2 is estimated as the empirical variance of the estimated residuals

$$\hat{\sigma}^2=\frac{1}{n}\sum_{k=1}^{K}\sum_{j=\hat{\tau}_{K-1}+1}^{\hat{\tau}_k}(x_i-\hat{\mu}_k)^2. \tag{39}$$

We will focus on the critical first step, i.e., the minimisation of $J\left(\mu_1,...,\mu_K,\tau_1,...,\tau_{K-1}\right)$. For a given sequence of change points $\tau_1,...,\tau_{K-1}$, J can be minimised with respect to $1;...;K$. This is described below:

$$\hat{\mu}_k\left(\tau_{k-1},\tau_k\right)=\overline{x}_{\tau_{k-1}+1:\hat{\tau}_k}$$

$$=\frac{1}{\tau_k-\tau_{k-1}}\sum_{i=\tau_{k-1}=1}^{\tau_k}x_i$$

minimises $\sum_{j=\tau_{k-1}+1}^{\tau_k}\left(y_j-\mu_k\right)^2$.

We insert the estimated mean values $\left(\mu_k\left(\tau_{k-1},\tau_k\right)\right)$ into J so that

$$U\left(\tau_1,...,\tau_{K-1}\right)=J\left(\hat{\mu}_1\left(\tau_0,\tau_1\right),...,\hat{\mu}_K\left(\tau_{K-1},\tau_K\right),\tau_1,...,\tau_{K-1}\right)$$

$$=\sum_{k=1}^{K}\sum_{i=\tau_{k-1}+1}^{\tau_k}\left(x_i-x_{\tau_{k-1}+1:\tau_k}\right)^2.$$

The ML estimation process involves minimises

$$U\left(\tau_1,...,\tau_{K-1}\right)=\sum_{k=1}^{K}\sum_{j=\tau_{k-1}+1}^{\tau_k}\left(x_i-\overline{x}_{\tau_{k-1+1:\tau_k}}\right)^2. \tag{40}$$

We use a dynamic programming algorithm for solving this optimisation problem, which is explained in Lavielle (2017). In our analysis, we select the optimum number of change points k (where $k=1,2,3,....,10$) to minimise the residual returned by the model. Specifying a maximum number of k change points does not guarantee that k change points will be found. Rather, any number of change points from 1 up to k could be found.

The output from the algorithm is shown in Figure 1, and specifies the number of times the mean of the log returns series x_i changes most significantly and also the dates at which those changes occur. In this case there were 7 such identified change points, which indicate the number of jumps in the time series of the log returns for the period under observation. The algorithm also returns the residual error of the signal against the modelled changes which, in this case, is 0.31935. The right hand-side panel in Figure 1 shows the results from the algorithm for a UK bank between July and December 2008.