Government Put: What Options Market Imply about the Volatility and Left-tail Risk of Indian Public versus Private Banks

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Abstract

We examine the differences in the options implied left-tail risk and volatility of government-owned and private banks in India. We show that left-tail risk and the cost of insurance for protection against it are high for private banks as compared to government-owned banks in general and the difference widens during the high systematic risk period of the COVID-19 crisis. The gap exists despite private banks having better asset quality than their public counterparts. Contrary to our left-tail risk result, we find that government-owned banks have higher near-the-money options implied volatility than private banks, and this gap widens during a period characterized by high policy uncertainty, the central bank's asset quality review. Our findings lend support to the notion that government ownership lower expected downside risk, but riskier lending policies, and subsequent uncertainty about capital infusion lead to higher expected volatility.

Keywords: government guarantee, banks, left-tail risk, implied volatility, options market, India

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1. Introduction

Government support is valuable to firms and particularly to financial institutions, especially in times of a financial crisis. This expected support from the sovereign is priced by financial markets (Kelly and Jiang, 2014; Borisova, Fotak, Holland and Megginson, 2015; Gandhi, Lustig and Plazzi, 2020). Banks with outright government ownership are expected to be supported by the sovereign in times of crisis, whether it is a bank-specific, sector-specific, or a systemic crisis, impacting the banking industry on the whole (Iannotta, Nocera and Sironi, 2013; Sironi, 2003; Borisova and Megginson, 2011). However, government ownership of banks leads to politically motivated loans to connected firms and therefore can lead to inefficient allocation of funds and later, compensation from the sovereign (Faccio, Masulis and McConnell, 2006; Khwaja and Mian, 2005; Gropp, Hakenes and Schnabel, 2011). Therefore, ownership by the sovereign can have two different impacts on the risk of the publicly traded equity of banks. First, it provides protection on the downside and therefore likely reduces the stock price crash risk. Second, it induces uncertainty into the stock price due to inefficient lending to both connected firms (Khwaja and Mian, 2005) and for political gains (Gropp et al., 2011).

In this paper, using Indian banks options data we examine if the ownership by the sovereign leads to two contrasting impacts on the risk characteristics of banks. First, we use left-tail risk measures derived from options implied volatility (IV) and put options portfolio returns to examine if government ownership of banks leads to lower downside risk and lower cost of hedging, especially during a crisis episode. Furthermore, we examine if a likely higher policy uncertainty leads to higher expected volatility in the stock price of the government-owned banks measured by IV of at-the-money options. We employ two natural experiments to further test our hypotheses.

First, we use the COVID-19 crisis, which was a systemic crisis that heightened the downside risk of all firms (Ding, Levine, Lin and Xie, 2021; Ramelli and Wagner, 2020). Therefore it is likely that the implicit downside protection in government banks was valued more during the peak of the crisis. Second, we employ an asset quality review

(AQR) of banks conducted by the Reserve Bank of India (RBI), the Indian central bank (Acharya, 2017; Chopra, Subramanian and Tantri, 2021; Das, Mohapatra and Nigania, 2022). This review, which impacted the asset quality and profitability of government-owned banks or public sector banks (PSBs), was followed by capital infusion into these banks. This period, therefore, is likely to have induced significant policy uncertainty in PSBs and therefore provide a unique opportunity to examine the impact of sovereign ownership of banks on uncertainty.

The likelihood of government support to a firm during a crisis is priced by financial markets. Kelly and Jiang (2014) provide evidence from options markets that the government was unlikely to let the banking system fail, while it was unsure of which institution the support will be directed to. Gandhi et al. (2020) show that expected returns on stocks is cheaper for financial institutions likely to be supported by the government. Outright government ownership can also make the issuance of debt cheaper during crisis (Borisova et al., 2015), reduced their credit spreads' sensitivity to risk (Sironi, 2003), and makes them less prone to failure (Iannotta et al., 2013). We, therefore, employ ownership by the government as a proxy for a higher likelihood of failure insurance from the government.

While government ownership of banks leads to a likely lower left-tail risk, especially in times of crisis, government-owned banks are associated with inefficient lending and consequent sovereign support (Gropp et al., 2011; Gropp, Gruendl and Guettler, 2014; Das et al., 2022; Iannotta et al., 2013). Government ownership of banks is associated with a higher risk-taking (Gropp et al., 2011) and the removal of deposit guarantee by the government, with a lowered risk-taking (Gropp et al., 2014). It is also related to a higher credit spread in normal times (Borisova et al., 2015) and a higher operational risk (Iannotta et al., 2013). Politically connected firms are lent to at favourable terms and in turn, public banks receive government support (Faccio et al., 2006). Therefore, the literature points to a likely increased risk of public banks compared to private ones. However, this risk is likely crash protected, as discussed above.

We examine the twin hypotheses employing measures derived from traded options prices. Using options for estimating perceived risk has several advantages. First, option-derived measures are inherently forward-looking and therefore are an estimate of expected risk, which may not be realized. Second, they allow for the estimation of different aspects of forward-looking risk, from near-the-money volatility (Mayhew, 1995) to the measures of tail risk (Kozhan, Neuberger and Schneider, 2013; Bakshi, Kapadia and Madan, 2003). Therefore, options-derived measures provide ideal means to test our twin hypotheses. In particular, we employ three different option-derived measures of left-tail risk, the slope of the out-of-money put options relative to at-the-money put options (Ilhan, Sautner and Vilkov, 2021), risk-neutral skewness (Kozhan et al., 2013) and the returns on a bear spread strategy that provides downside protection (Lu and Murray, 2019). For near-the-money volatility, we use implied volatility (Mayhew, 1995). Indian single stock options and the underlying futures are extremely liquid, even for the out-of-money options (Jain, Varma and Agarwalla, 2019; Agarwalla, Saurav and Varma, 2022) and therefore can be used to reliably estimate our measures. In addition, options are traded with scheduled commercial banks as underlying and there is a symmetric distribution of available option prices for public sector banks and private sector banks. For instance, in our sample, we have 13 government-owned banks and the same number of private banks. These 26 banks in our sample manage about 86% of the total assets managed by all the banks in India at the end of FY2022. Overall, the Indian options market provides a good setting for examining the different aspects of the forward-looking risk of banks.

With this backdrop, we examine several hypotheses with regard to the difference in the perceived risk of public sector banks (PSBs) and privately held banks ($Non-PSB$s). First, we examine if the left tail risk measures are higher for $Non-PSB$s relative to the PSBs in our sample to establish a baseline. Next, we investigate if this difference is higher in times of crisis, employing the COVID-19 crisis as an exogenous shock that adversely impacted the left-tail risk of most businesses. This is likely because the value of likely government intervention is heightened in times of crisis. Third, we examine if the cost of insuring against the downside risk is higher for $Non-PSB$s relative to the PSBs. This is expected if the investors are willing to pay a higher price for insuring against a steep stock price fall of $Non-PSB$s owing to a lower probability of government intervention, particularly during a crisis. Finally, employing the Reserve Bank of India's AQR, we examine if a heightened policy uncertainty leads to a higher expected near-the-money volatility for PSBs, relative to the un-impacted $Non-PSB$s.

We report several interesting results. First, we find that the left tail risk captured by both the slope of the out-of-money put options (*Put slope*) and the risk-neutral skewness (RNS) are significantly more negative for $Non-PSB$s. This points to a higher anticipated downside risk for $Non-PSB$s. We also find that for the same increase in the non-performing assets, the left tail risk measures indicate a greater downside risk for $Non-PSB$s. Second, we find that during the peak of the COVID-19 crisis, the downside risk measures became significantly more negative for $Non-PSB$s relative to the PSBs. These findings indicate that not only is the downside risk greater in $Non-PSB$s, but the gap is also significantly larger in times of crisis when the value of government protection is likely the highest. Third, we find that the cost of buying downside protection is significantly higher for $Non-PSB$s, relative to the PSBs in times of crisis, indicating that the market pays a premium for buying downside protection for $Non-PSB$s, likely anticipating a government intervention if a crisis hit a PSB. The crisis period results are robust to time-invariant bank fixed effects and day fixed effects, which control for the average difference between the two sets of banks and any unobserved time-series effects. These findings support our hypotheses that the perceived downside risk is greater for private banks relative to government-owned and the gap becomes larger in times of crisis.

Finally, we find that the government ownership of PSBs, while lowering their downside risk, leads to higher anticipated volatility due to policy uncertainty. In particular, we show that the near-the-money implied volatility ($ATM-IV$) is higher for the PSBs relative to $Non-PSB$s. This indicates higher anticipated volatility for PSBs, which is contrary to our findings with respect to the downside risk above. We, therefore, employ the RBI's AQR as an exogenous shock to the policy uncertainty of the PSBs to examine if it is policy uncertainty that leads to a higher anticipated volatility, despite a lower downside risk. We find that while the left tail risk in the review period is not significantly different between the two sets of banks, the difference in the $ATM - IV$ becomes significantly larger. This indicates that while the downside risk was not expected to increase despite a review (see Section 3.1 for the impact of the review on the asset quality and profitability of the PSBs), the volatility was anticipated to be higher. This is likely due to the anticipated capital infusion from the government. Overall, we find two contrasting effects of government ownership of financial institutions on their perceived risk. While the expected support from the sovereign leads to a lower expected downside risk, riskier lending policies and subsequent capital infusion also lead to higher expected volatility.

We contribute to several strands of literature. First, by using options implied left-tail risk measures we show that the perceived downside risk is lower for the PSBs, we contribute to the literature on the impact of government guarantees, implicit or explicit, on the pricing of securities (Kelly, Lustig and Van Nieuwerburgh, 2016; Gandhi et al., 2020; Borisova et al., 2015). We use single stock options, extremely liquid in India, to show that a likely greater downside protection leads to favorable options pricing, particularly for out-of-money put options, that act as downside insurance, extending the work of Kelly et al. (2016) and others. Second, on similar lines, we contribute to the literature on the distortions created by outright government ownership, in financial markets, in our case options markets (Iannotta et al., 2013; Beuselinck, Cao, Deloof and Xia, 2017; Sironi, 2003). We use the fact that approximately half of the Indian scheduled commercial banks are government owned and the other half are privately owned and demonstrate two somewhat contrasting impacts of government ownership of financial institutions. Employing the COVID-19 crisis as a shock to the left tail risk and the RBI's AQR as a shock to PSBs' policy uncertainty, we show that while the government guarantee mitigates the downside risk, it also induces volatility to stock prices due to policy uncertainty. Third, by showing that both the perceived downside risk and the premium for insuring against it is lower with government ownership, we contribute to the literature on the use of options markets to examine different aspects of the risk of traded firms (Ilhan et al., 2021; Lu and Murray, 2019). Finally, we also contribute to the literature on the impact that the COVID-19 crisis had on financial markets (Ramelli and Wagner, 2020; Ding et al., 2021) and how outright government ownership was able to mitigate the downside risk of firms.

The rest of the paper is organized as follows. Section 2 discusses the existing work on the impact of government ownership on financial markets and builds testable hypotheses. Section 3 gives an overview of the banking sector in India, the derivatives market in India, and the RBI's *AQR* of Indian banks. Section 4 discusses the data employed in the empirical analysis and the estimation of dependent variables. Section 5 and 6 discusses the univariate and regressions results, respectively. Section 7 concludes the paper.

2. Literature Review and Hypothesis Development

Through the course of the Global financial crisis and Eurozone crisis, governments have extensively implemented bailout policies for individual banks or for the financial sector. Some policies were explicit guarantees and others came to be seen as concomitant to the implicit prerogative of the sovereign. Government support leads to a reduction in default risk of a bank and the change in default probability is priced in the financial markets (Faeh, Grande, Ho, King, Levy, Panetta, Signoretti, Taboga and Zaghini, 2009; Kelly et al., 2016; Gandhi et al., 2020). In evidence of differential pricing of a possibility of a bailout in the equity market, Gandhi et al. (2020) find that large financial institutions trade at a premium relative to small ones. They attribute this spread to the greater possibility of a bailout of larger institutions in a crisis. They also show that the spread is larger in countries with a greater propensity to bail big financial institutions out. Faeh et al. (2009) show that government intervention during the crisis leads to a lower default risk evidenced by a lower CDS premium. In an evidence from the options market, Kelly et al. (2016) shows that the options market indicates a low probability of a crash of the financial sector on the whole, while it is unsure of which institution(s) the support would be directed to. Overall, the literature finds evidence that government support to financial institutions for protection from downside risk is priced in financial markets.

While the implicit government support to firms lowers the perception of default and therefore a stock price crash, outright government ownership of firms has a similar impact on their left-tail risk (Iannotta et al., 2013; Borisova and Megginson, 2011; Borisova et al., 2015; Beuselinck et al., 2017). Iannotta et al. (2013) show that government ownership leads to higher bank-level operational risk. The reduction of government guarantees is a reason for a higher cost of debt for privatized firms (Borisova and Megginson, 2011). Highlighting the role of the implicit government guarantee due to its equity ownership, Borisova et al. (2015) show that while in normal times, government ownership may lead to a higher cost of debt due to distorted lending decisions, in times of crisis, their cost of debt is significantly lower. This effect is attributed to failure protection due to government ownership. Beuselinck et al. (2017) use the global financial crisis to show that government-owned suffered a lower loss in their value during the turbulent period. In particular, explicit government guarantee to some banks may lead to them providing inter-bank loans to other non-protected banks, in anticipation of a bailout during a crisis (Eisert and Eufinger, 2019). In India, approximately half of the scheduled commercial banks are owned by the Government of India, with their equity ownership percentage much greater than 50% (Bank characteristics are discussed in Section 3). This provides us with a unique opportunity to compare government-owned banks with private banks, with respect to their perceived risk characteristics.

Recent studies have used the options market to study the left-tail risk of firms in various contexts. Kelly et al. (2016) uses the options market to examine the pricing of crash insurance of US financial institutions during the 2007-2009 financial crisis. Similarly, Ilhan et al. (2021) use options implied risk-neutral skewness (RNS) and slope of IV curve to estimate the firm-level left-tail risk caused by the exposure to climate change-related uncertainty. Specific trading strategies can be used to estimate the fear of a crash. For instance Lu and Murray (2019) uses a bear spread strategy to estimate the risk of a market-wide crash using the S&P index options and estimate the exposure of stock returns to this factor. They find that bear beta is a source of risk that is priced by the equity market.

Motivated by these studies, we use options implied left-tail risk measures to examine the impact of the government guarantee on bank's left-tail risk. One benefit of using options-based measures is that they are forward-looking and capture the perceived risk. Options trade at multiple strikes, which allows us to estimate the cost of downside risk insurance. In this paper, we employ three measures of left tail risk estimated from the traded single stock options (SSO) prices. First, we use the slope of the out-of-money put options, relative to the near-the-money put options (*Put Slope*) to estimate crash risk. Second, we follow Kozhan et al. (2013) and estimate the risk-neutral skewness (RNS), which indicates the relative downside risk in comparison with the upside potential. Finally, we follow Lu and Murray (2019) to estimate the loss from a bear spread strategy, which acts as insurance against the downside risk of the underlying. We discuss the details of estimation in Section 4.2.

Overall, government ownership (Iannotta, Nocera and Sironi, 2007; Borisova and Megginson, 2011) and the possibility of rescue during a crisis (Kelly and Jiang, 2014; Gandhi et al., 2020) is priced in both the options market and the equity market. Options market can be used to examine the left tail risk of the underlying (Ilhan et al., 2021; Lu and Murray, 2019). Since in India, the government-owned public sector banks (PSBs) have a majority government ownership and therefore have a greater likelihood of government support if a left tail event occurs, relative to private banks ($Non-PSB$s) we hypothesize:

Hypothesis 1. *The left tail risk of $PSBs$ is lower than that of the $Non-PSBs$, as indicated by the traded options' prices.*

In times of crisis, the value of an implicit or explicit government guarantee is significant and positively priced by financial markets(Borisova et al., 2015; Kelly et al., 2016; Beuselinck et al., 2017). The COVID-19 pandemic led to countries taking steps to check the spread of the virus and extend fiscal and monetary support to businesses (see Ding et al., 2021; Ramelli and Wagner, 2020; Alfaro, Chari, Greenland and Schott, 2020). In India, Bansal, Gopalakrishnan, Jacob and Srivastava (2022) show that firms that had plants located in areas that were severely impacted by the crisis had large negative stock price reactions. To minimize the impact on the Indian banking sector, the Reserve Bank of India took several steps, such as deferment of loan repayments.[1]. Since it is likely that the implicit government guarantee in the PSBs became more valuable in the crisis period, we hypothesize:

Hypothesis 2. *The negative difference between the left tail risk of $Non-PSBs$ and that of the $PSBs$ became larger in magnitude during the months of the COVID-19 crisis.*

Bear spread strategy in the options market help protect against the downside risk of the underlying (Lu and Murray, 2019), with a negative return to the strategy indicating a larger premium for insurance against downside risk. Since the perceived downside risk of $Non - PSB$s is likely to be larger relative to the PSBs, we hypothesize:

Hypothesis 3. *Bear spread returns are significantly more negative for $Non - PSBs$ relative to the $PSBs$.*

Literature has also argued that the policies contributing to an implicit guarantee are not always beneficial to the banks they are meant for. They support the view that state ownership of banks politicizes the allocation of resources for development and renders the banks inefficient and sets the course for slower economic growth. Faccio et al. (2006) argue that banks receive benefits from the state that offset their losses to loans made to politically connected firms. Additionally, banks factor in the eventuality of a bailout of these politically connected firms in an event of economic distress. Gropp et al. (2011) find that banks that have state ownership tend to be more risk-taking than their peers without public ownership, but having government guarantees. Borisova et al. (2015) show that investment distortions by the government lead to a higher cost of debt for government-owned firms during normal times, whereas the guarantee becomes valuable only in times of a crisis.

In addition, government ownership leads to an undiversifiable risk of political uncertainty (Pástor and Veronesi, 2013). They may add to the exposure of the banks to an aggregate risk component that spills over from sovereign risk. For example, bailouts put pressure on the fiscal capacity and add to the fragility of the sovereign, which trans-

[1]Link to a press article.

fers to the bank's risk (Acharya, Drechsler and Schnabl, 2014). Sovereign credit rating downgrades negatively affect the stock returns of banks with an implicit guarantee from the sovereign (Correa, Lee, Sapriza and Suarez, 2014). Therefore, it is likely that while the left tail risk is lowered by the government ownership of PSBs, they have a higher stock price volatility due to political uncertainty, politically motivated lending, and the instability of the sovereign.

Swidler and Wilcox (2002) argue that there can be no consensus on a single proxy for volatility in bank's assets and default risk. They show that implied volatility measures based on option prices of bank's shares are better reflective of riskiness in bank's assets. The strength of the implied volatility measure to reflect riskiness in bank's assets is inversely related to the capital ratio of the bank. Several studies have emphasized the informativeness of the options market in providing better indicators for prudential purposes (see Coffinet, Pop and Tiesset, 2013; Sarin and Summers, 2016, for instance). We, therefore, employ near-the-money implied volatility ($ATM - IV$) estimated from traded option prices as a measure of expected stock price volatility. Since the government ownership of PSBs is likely to expose them to significant stock price volatility, we hypothesize:

Hypothesis 4. *Near the money implied volatility of $PSBs$ is greater than the $Non - PSBs$.*

The Reserve Bank of India (RBI) conducted an Asset Quality Review (AQR) of all Indian commercial banks. The exercise which was announced in FY 2014-15, impacted the asset quality and profitability indicators of the PSBs more than $Non - PSBs$ (see plots (a), (b), and (c) of Figure 1) and also led to subsequent equity infusion into PSBs by the government (We discuss the AQR in detail in Section 3.1). Since the period was characterized by a heightened policy uncertainty for the PSBs, it is likely that the option implied volatility is higher for PSBs relative to $Non - PSB$s in the period of the AQR exercise. We therefore hypothesize:

Hypothesis 5. *Near the money implied volatility of $PSBs$ was higher relative to the*

$Non - PSBs$ *in the months of the AQR*

3. Background and stylized facts

3.1. Banks in India

The Indian banking system is significantly different than other major economies. All Indian commercial banks can be categorized into two parts – Public sector banks ($PSBs$) and Private sector banks ($Non - PSBs$). Both groups are regulated by the Indian central bank which is the Reserve Bank of India (RBI) and have large loan book sizes.

PSBs in India are majority owned by the Government of India. As per an RBI report[2], the average percentage shareholding of the Government of India in 12 major PSBs was approximately 83%, with the highest being 97.1% for Punjab and Sind Bank and the lowest being 56.9% for the State Bank of India. On the contrary, the average Government shareholding in the 21 major scheduled commercial banks other than the PSBs is approximately 17%, varying from 0% (Most major $Non-PSB$s) to 68% (Jammu and Kashmir Bank). These $Non - PSB$s are, in turn, owned by financial institutions, both domestic and foreign and the wider public. For instance, HDFC Bank, India's biggest scheduled commercial bank by market capitalization, is owned to the extent of 72% by foreign institutions, and ICICI Bank, India's second biggest scheduled commercial bank by market capitalization, is approximately 60% owned by foreign institutions and another 22% by domestic institutions. Overall, the ownership of the PSBs is by the Government of India and that of the $Non - PSB$s is not by the sovereign.

As the PSBs are majority owned by the Government of India, the decision-making in these banks is influenced by the sovereign to a greater extent, relative to the $Non-PSB$s. Therefore, despite all scheduled commercial banks being required to participate in social schemes, their actual participation is low.[3]. This is often due to such schemes being high cost and therefore adversely affecting the profitability of the banks.[4]. In addition to

[2] Link to the RBI FY 2020-21 shareholding pattern of scheduled commercial banks
[3] Link to a popular press article on the low participation of private banks in government schemes.
[4] Link to a popular press article

higher participation in government-backed schemes that are often less profitable, PSBs in India have also been plagued by regulatory forbearance and ever-greening of bad loans (Das et al., 2022), which led to the RBI conducting an Asset Quality Review (AQR) of several PSBs in 2015. Plots (a), (b), and (c) of Figure 1 show that $PSBs$ have lower profitability and high non-performing assets than $Non - PSBs$.

Despite the possible adverse influence of government ownership, the PSBs often benefit from capital infusion from the government. The aggregate amount of capital infusion planned for a year is often declared in the annual budget, however, it is often not known how it will be distributed between the banks.[5]. This infusion is either out of the budget of revenue for the fiscal year or by the issuance of government bonds. Effectively, this implies that it is more likely that equity capital will be infused by the owner in the PSBs should they face a distress situation. Moreover, this infusion will be financed by either sovereign revenues or it borrowing on its own account by issuing recapitalization bonds, both of which are default risk free. This is the distinctive feature of the PSBs that distinguishes them from $Non - PSB$s. Therefore, in this paper, we use the government ownership of PSBs as a proxy for the increased likelihood of capital infusion in distress.

3.1.1. Asset Quality Review of Banks

Indian banks were not directly impacted by the global financial crisis (GFC), but RBI allowed Indian banks to restructure loans without downgrading and providing provisions for them as a part of the forbearance policy. The policy continued for seven years even after the strong economic recovery in the interim period. In April 2015 RBI ended the forbearance policy and launched the Asset Quality Review (AQR) with the aim to recognize the hitherto masked non-performing assets in banks balance sheet (Acharya, 2017). The AQR initiated by RBI is different from the asset quality reviews initiated in European Union and the United States because it was preemptive in nature as it is done in a non-crisis period with no capital infusion plan (Chopra et al., 2021).

During AQR the non-performing assets of $PSBs$ increased disproportionately more

[5]Link to a popular press article on budgeted capital infusion.

than $Non - PSBs$. As can be observed in plots (b) and (c) of Figure 1 both gross and net non-performing assets of $PSBs$ zoomed more with respect to $Non - PSBs$ in the post-AQR implementation period. As the AQR was not accompanied by a capital infusion plan for the $PSBs$ from the government's side, it lead to an increase in policy uncertainty regarding the $PSBs$.

3.2. Derivatives market in India

Indian financial market is highly liquid and well-regulated. In terms of the market capitalization of the listed firms, it ranks fifth in the world according to data from the World Bank. There are two major exchanges in India out of which the National Stock Exchange (NSE) is the largest one where all the major financial instruments like equity, index options, index futures, single stock options (SSO), and single stock futures (SSF) trade. The existence of liquid equity, SSO, and SSF makes NSE unique. It has almost 99.9% market share in derivatives trading in India and is one of the world's leading stock exchanges in terms of derivatives volume (WFE, 2022). All the options contracts traded on NSE post-January 2011 are European in nature. Both SSO and SSF follow a maximum of three-month expiry cycle and expire on the same day – the near month (mature on the last Thursday of the same month), the next month (mature on the last Thursday of the next month), and the far month (mature on the last Thursday of the third month). Almost all the volume in the equity derivatives is concentrated in the near-month contracts. Recent studies have demonstrated that the Indian equity options market is micro-efficient and has low mispricing (Jain et al., 2019; Agarwalla et al., 2022).

Not all listed bank stocks have equity derivatives traded against them in India. Only banks with large market capitalization and high liquidity act as underlying for the derivatives (both SSO and SSF). Indian derivatives market also shows a very high expiry day effect (Vipul, 2005; Agarwalla and Pandey, 2013). Our sample has 26 banks, all of which have exchange-traded options contracts. These banks consist of 13 $PSBs$ and 13 $Non - PSBs$. It is important to note that not all commercial banks in India have exchange-traded options contracts. These selected banks represent a significant portion of the Indian banking sector, collectively managing over 86% of the total assets held by all banks in India at the end of FY 2022. Table A1 reports the name and classification of all the banks in our sample.

4. Data and Variable Construction

4.1. Data

Our sample consists of all the banks for which derivatives trade on the National Stock Exchange (NSE), which is one of the leading stock exchanges in the world in terms of derivatives trading volume (FIA, 2021). The sample period spans from January 2013 to December 2021. The data used in the study come from various sources. The single stock options (SSO) and single stock futures (SSF) price data are taken from the trading book of the National Stock Exchange (NSE). The accounting, stock price, and volume data are obtained from CMIE $Prowess_{dx}$. The risk-free rate is taken from the Reserve Bank of India's website. The daily Fama and French (1993) and Carhart (1997) four-factor return for idiosyncratic skewness estimation is taken from the Indian Institute of Management Ahmedabad's (Agarwalla, Jacob and Varma, 2014) online library.[6]

The NSE trade book data consists of tick-by-tick high-frequency traded prices of index options, index futures, SSO, and SSF. We use some standard filters to select the daily option series. First, we exclude all option contracts for a day that are traded less than five times on that day to eliminate infrequent options whose traded price may reflect spurious information (Chan, Chung and Johnson, 1993). Second, we exclude options contracts with less than a day to expiry to eliminate any expiration day effects from our data. Lastly, since to measure slope, we require option contracts of a fixed maturity, we consider near-month options and futures that expire on the last Thursday of every month (near-month options). To obtain the daily closing price of options and futures contracts we match the last traded price of an option contract with that of the underlying single stock futures price, to the nearest minute. We do not use high-frequency data for our analysis otherwise. Our final sample has 26 banks with 13 each belonging to PSB and Non-PSB groups (see Table A1 for more details).

[6] https://faculty.iima.ac.in/~iffm/Indian-Fama-French-Momentum/

4.2. Volatility and Left-Tail Risk Measures

We measure volatility risk by using the implied volatility of at-the-money options ($ATM - IV$). To measure left-tail risk, we employ two different left-tail risk measures – the difference in implied volatility of the out-of-money put options with respect to the at-the-money options which captures the slope of the put side of the IV curve ($Put\ Slope$) and skewness of the risk-neutral density (RNS). These two measures are widely used in literature for measuring the left-tail risk of a stock. In this section, we discuss the estimation of these measures.

For the estimation of the $Put\ Slope$ and $ATM - IV$ measures, we first require the implied volatility (IV) of each option contract for each trading day. We, therefore, employ the high-frequency single stock option trading data and the high-frequency futures trading data provided by the NSE to obtain the daily IV for the eligible option contracts. We discuss the filters we employ to select our option series in Section 4.1. We then match the last traded price of an option contract with that of the underlying futures contract, nearest to a minute. India has a very liquid single stock futures market (SSF), which allows us to use Black (1976) model instead of Black and Scholes (1973) for IV estimation.[7] The use of Black's model does not require an estimation of dividend yield. We take the annualized 91-day treasury rate as the risk-free rate. This gives us the daily IV for each underlying stock corresponding to the option contracts of a series of strike prices.

ATM-IV: For the estimation of the $ATM - IV$, we select the put option that is nearest to the money for a firm-day combination. We require that the option has a moneyness greater than 0.98 and less than 1. This gives us 32,551 firm-day observations for ATM-IV, which we employ in our empirical analysis. This is constituted by 15,898 observations of 13 $PSBs$ and 16,653 observations from 13 $Non - PSBs$. Then, we take the IV of this put option as $ATM - IV$ for a firm day.

Put Slope: For the estimation of our $Put\ Slope$ measure, we first remove the IV for the strikes that are greater than the current price of the underlying. We do this

[7] Many previous India studies have used Balck's model for IV estimation (Agarwalla, Varma and Virmani, 2021b,a; Agarwalla et al., 2022; Saurav, Agarwalla and Varma, 2023).

because the slope we estimate is a proxy for the crash risk, which is captured by the strikes that are substantially lower than the current trading price. Further, in order for a firm-day to be eligible for estimation of the slope, we require that it has at least 3 values of IV with at least one of them corresponding to a strike that is lower than 95% of the closing price of the stock on a trading day. We do this to have at least one out-of-money IV observation to estimate the slope for a firm day. We take the IV of the furthest out-of-money option as IV_{OTM} and the nearest-to-the money option as IV_{ATM}. We then estimate the moneyness slope employing the equation below:

$$Put\ Slope = \frac{IV_{OTM} - IV_{ATM}}{Moneyness_{OTM} - Moneyness_{ATM}} \tag{1}$$

where $Moneyness_{OTM}$ and $Moneyness_{ATM}$ are respectively the moneyness of the out-of-money and at-the-money options, given by the ratio of the strike price, K and the price of the underlying futures price (F).

This leaves us with 26,973 firm-day observations of the put slope measure. This comprises 12,481 observations from 13 public sector banks (PSBs) and 14,492 observations from 13 non-public banks. This is the sample we employ in our empirical analysis.

Since, for most of the underlying $IV_{OTM} > IV_{ATM}$ and $Moneyness_{OTM} < Moneyness_{ATM}$, the $Put\ Slope$ on an average is a negative number with a larger negative value indicating higher left-tail risk.

Risk Neutral Skewness (RNS): We estimate the risk neutral skewness (RNS) using the model-free approach of Kozhan et al. (2013). For the estimation of RNS of underlying j on date t, we use the prices of all the OTM call and put options and the SSF price that expire on the last Thursday of every month (T). Further, in order for a firm-day to be eligible for estimation of the RNS, we require that it has at least 3 OTM call (strike > SSF Price) and 3 OTM put (strike < SSF Price) option contracts. Next, we follow Kozhan et al. (2013) and implement their technique of RNS estimation for discrete and limited option strike prices. The formula used is mentioned below:

$$\Delta I(K_i) \equiv \begin{cases} \frac{K_{i+1}-K_{i-1}}{2}, & \text{for } 0 \leqslant i \leqslant N \text{ (with } K_{-1} \equiv 2K_0 - K_1,\ K_{N+1} \equiv 2K_N - K_{N-1}), \\ 0, & \text{Otherwise} \end{cases}$$

$$v\,^{L}_{t,T} \equiv 2\sum\nolimits_{K_i \leqslant F_{t,T}} \frac{P_{t,T}(K_i)}{B_{t,T}K_i^2}\Delta I(K_i) + 2\sum\nolimits_{K_i > F_{t,T}} \frac{C_{t,T}(K_i)}{B_{t,T}K_i^2}\Delta I(K_i) \tag{2}$$

$$v\,^{E}_{t,T} \equiv 2\sum\nolimits_{K_i \leqslant F_{t,T}} \frac{P_{t,T}(K_i)}{B_{t,T}K_iF_{i,t}}\Delta I(K_i) + 2\sum\nolimits_{K_i > F_{t,T}} \frac{C_{t,T}(K_i)}{B_{t,T}K_iF_{i,t}}\Delta I(K_i) \tag{3}$$

$$RNS_{j,t,T} = \frac{3(v\,^{E}_{t,T} - v\,^{L}_{t,T})}{(v\,^{L}_{t,T})^3/2} \tag{4}$$

where $N+1$ shows the total number of different strike prices K_i for a firm-day pair at date t that matures at T. $B_{t,T}$ is equal to $(1+r_f)^{(T-t)/365}$. $P_{t,T}(K_i)$ and $C_{t,T}(K_i)$ is the price of the put and call options at time t that matures at T and have strike price K_i. $RNS_{j,t}$ is the risk-neutral skewness of of firm j at day t. A larger negative RNS value indicates a high left-tail risk.

Our final RNS sample has 26,400 firm-day observations. This comprises 12,142 observations from 13 $PSBs$ and 14,258 observations from 13 $Non-PSBs$.

4.3. Bear Spread Return Estimation

A bear spread protects the buyer from left-tail risk and is very frequently used by options traders. It consists of holding opposite positions in two put options. A typical bear spread position includes a long position in OTM put option, denoted by PUT_1 having strike price (K_1) and delta Δ_1 and a simultaneous short position in DOTM put option denoted by PUT_2 having strike price (K_2) and delta Δ_2 ($K_1 > K_2$ & $\Delta_1 < \Delta_2$). The bear spread pay-off is K_1 - K_2 if the stock/futures price on the day of expiry is below K_2 and zero if the stock/futures price on the day of expiry is above K_1. When the stock/futures price remains between K_1 and K_2 on the day of expiry the payoff decreases linearly from K_1 - K_2 to zero.

Choosing PUT_1 and PUT_2 requires careful empirical considerations. As equity options have sparse strike prices compared to index options we can't set K_1 and K_2 to be certain standard deviations below the futures price as done in Lu and Murray (2019). To circumvent this issue, we use options delta instead of strike price to identify put options in the bear spread.[8] Typically, the delta of the OTM put option ranges between $[-0.45, -0.30)$ and the same for DOTM put option ranges from $[-0.30, 0]$. We construct a bear spread by taking a long position in OTM put option (PUT_1) with delta (Δ_1) between $[-0.45, -0.30)$, and have the highest volume amongst all the contracts whose delta lies in this range. Simultaneously, we take a short position in DOTM put option (PUT_2) with delta (Δ_2) between $[-0.30, 0]$, and have the highest volume amongst all the contracts whose delta lies in this range.[9] The average delta value of OTM and DOTM put thus selected are -0.375 and -0.218, respectively.

An unhedged bear spread has a negative delta ($\Delta_1 - \Delta_2$) and is exposed to the movement in the underlying price. So, to remove the exposure to underlying price movement we delta-hedge the bear spread. Specifically, we use static delta hedge as done in various options studies (Goyal and Saretto, 2009; Bali and Murray, 2013; Byun and Kim, 2016).

As stated earlier, we use near-month contracts that expire on the last Thursday of every month in our analysis. So, we construct a delta-hedged bear spread on the first trading day immediately after the expiry in month t and close the position at the next options maturity date in month T. India has a very liquid single stock futures market, therefore we use futures to do delta hedging instead of stock. Our delta-hedged bear return over [t,T] is given by the formula mentioned below:

[8] Various previous studies have used options delta to identify options contracts with the same moneyness across underlying (Bollen and Whaley, 2004; Driessen, Maenhout and Vilkov, 2009; Jin, Livnat and Zhang, 2012; Bali and Murray, 2013; Kelly et al., 2016).

[9] We select the options having the highest volume because sometimes OTM/DOTM options contracts are illiquid in the Indian market.

$$Ret\ Bear\ Spread = \frac{(\Delta_{2,t} - \Delta_{1,t})F_T + max(K_1 - F_T, 0) - max(K_2 - F_T, 0)}{(\Delta_{2,t} - \Delta_{1,t})F_t + P_1 - P_2} - 1$$

where P_1, P_2, $\Delta_{1,t}$, $\Delta_{2,t}$, K_1, and K_2 are price, delta, and the strike price of OTM and DOTM put options at time t, respectively. F_t, and F_T are SSF price at time t and T i.e at the time of maturity.

For some of the bank month pairs, none of the DOTM/OTM put options satisfy our liquidity filter mentioned in section 4.1 in that case we drop those bank month pairs. This gives us an unbalanced panel of monthly delta-hedged bear spread returns having 1,619 observations which we use in our empirical tests.

A negative bear spread return means that an investor who takes a long position on the bear spread loses money, suggesting that the protection against left tail risk is expensive.

4.4. Control Variables

We construct two sets of control variables – the first set includes accounting variables that capture the quality of assets of the banks, and the second set includes stock market variables that are known to explain left-tail and volatility risk.

We use three accounting variables, these variables are available at an annual frequency and we use their one-year lagged value in the regression specifications. The two variables that are proxies of the asset quality of banks are – Net NPA ($NNPA$), Capital to Risk (Weighted) Assets Ratio ($CRAR$). The two measures capture the percentage of non-performing assets of a bank and the extent to which the capital reserves of a bank can absorb losses arising out of bad loans. To control for the size of the banks, we use the total assets ($Total\ assets$). We use these measures to capture any systematic difference between public and private banks in their perceived risk, arising out of bank-specific characteristics, other than ownership.

We construct six stock market variables that are known to explain the left-tail and volatility risk. Idiosyncratic skewness ($Iskew$), is the skewness of idiosyncratic return which is estimated by regressing daily stock return on Fama and French (1993)-Carhart (1997) four-factor daily return within a year and then estimating skewness of the residuals at the monthly level. It is likely that the realized tail measures are correlated with the expected tail risk and therefore we attempt to isolate expectation from realization by controlling for realized skewness. Market Capitalization is the natural logarithm of the market size of the firm in INR million at the end of a month. Market-to-Book Ratio (M/B) is the ratio of the market value of the firm at the end of a month and the book value of the total asset at the end of the previous fiscal year. Rev(-1) is the stock return over the previous month. Momentum is the cumulative return of stock over the previous six months (t-6 to t-1). Illiquidity is the natural logarithm of the average ratio of the absolute daily stock return to its daily Indian rupee trading volume multiplied by 10^8 in a month. We refer the reader to Table A2 for a detailed definition of control variables and their source.

4.5. Summary Statistics

Table 1 reports the summary statistics of all the variables used in the study. As expected the mean value of both the left-tail risk measures – *Put Slope* (-1.296) and RNS (-0.135) are negative. It shows that on average OTM put options are more expensive than the ATM put options (Xing, Zhang and Zhao, 2010). $ATM - IV$ has a mean value of 0.428 which is comparable to the average volatility reported in other Indian studies (Agarwalla et al., 2022). *Ret Bear Spread* has a negative mean (-0.514 %) and median (0.925 %) value, which is consistent with the risk premium paid by buyers of the bear spread to insure against left-tail risk. The 75^{th} percentile bear return is positive (6.195 %) showing at least 25% of the bear returns are positive.

5. Univariate Results

Figure 2 shows the quarterly average of *Put Slope* (Plot (a)), and $ATM - IV$ (Plot (b)) for the two sets of banks ($PSBs$ and $Non - PSBs$). As can be observed in plot (a), the average value of *Put Slope* of $PSBs$ is less negative than that of $Non - PSBs$

in almost every financial quarter. Since a more negative value of the put slope implies a greater overpricing of the OTM put relative to the ATM put option, the preliminary evidence indicates a greater fear of a crash for $Non-PSBs$ relative to the $PSBs$. Out of thirty-six quarters in twenty-eight quarters, the average value of $Non-PSB's$ *Put Slope* is either below or equal to $PSB's$ *Put Slope*. This trend indicates that in our sample on average $Non-PSBs$ have higher unconditional left-tail risk than $PSBs$. One potential reason behind the narrowing of the gap between $PSB's$ and $Non-PSB's$ *Put Slope* after the first quarter of 2014 is the Asset Quality Review (AQR) that RBI conducted for all the banks in India. This exercise resulted in a drastic increase in non-performing assets for $PSBs$ and a drop in their interest income. We plot the key performance indicators of the $PSBs$, namely the Net Interest Margin, Net NPA, and Gross NPA, and compare them with those of the $Non-PSBs$ in plots (a), (b), and (c) of Figure 1, respectively. One can clearly observe that the key performance measures diverge in FY 2014. The net interest margin drops substantially for the $PSBs$ while the NPA levels rise, relative to the $Non-PSBs$. Later in our analysis, we use the AQR as an exogenous shock to the perceived asset quality of the PSBs.

Contrary to the plot for the left tail risk, in the plot (b) we observe that the average values of $ATM-IV$ for $Non-PSBs$ are lower than $PSBs$ across all quarters. This trend indicates that in our sample on average $Non-PSBs$ have lower unconditional implied volatility than $PSBs$. Therefore, while the options market indicates that the fear of a stock price crash is lower in the $PSBs$, it also provides evidence that the fear of near-the-money volatility is higher, relative to the $Non-PSBs$. Furthermore, the difference in the ATM-IVs of $PSBs$ and $Non-PSBs$ diverges even more during the AQR. This indicates a greater perceived near-the-money volatility for the stock price of $PSBs$ relative to the $Non-PSBs$ after the policy intervention. Overall, we find preliminary evidence of two different impacts that government ownership has on the perceived risk of banks. While it helps in alleviating the fears of a price crash, it also induces the fear of a higher near-the-money volatility in stock prices. In the subsequent sections, we use regression analysis to test these two key ideas.

6. Regression Analysis and Results

In this section, we use multivariate analysis to examine our hypotheses.

6.1. Left tail risk

In this section, we examine the differences in the tail risk between the public sector ($PSBs$) and non-public sector banks ($Non-PSBs$). We first examine if in our sample there is evidence of the tail risk being higher for the $Non-PSBs$. Next, we examine if the difference increases in times of crisis as it is likely that a greater probability of government support during the crisis for a PSB is valued more in such times. Finally, we examine if the fear of higher crash risk in a $Non-PSB$ leads to a lower return for a bear spread strategy, which is often used for downside protection. For each of the above, we first present the model employed for testing the hypothesis and then discuss the results of the estimation.

To further examine the difference in the left-tail risk between the public sector ($PSBs$) and non-public sector banks ($Non-PSBs$), we estimate the panel data regression mentioned below:

$$Var_{i,t} = \beta_1 \; Private_i + \sum_{j=1}^{n} \alpha_j \; Control_{j,i,t} + \gamma_t + \epsilon_{i,t} \tag{5}$$

where, $Var_{i,t}$ represents a vector of dependent variables for bank i on date t. We estimate the above equation for two different dependent variables – *Put Slope* and RNS, representing the slope of the IV of the OTM with respect to the ATM put option estimated using Equation 1, and the risk-neutral skewness estimated using Equation 4 respectively. The term $Private_i$ represents a bank dummy that takes the value 1 for a $Non-PSBs$ and zero for a $PSBs$. $Control_{j,i,t}$ includes $Total\ assets$, $NNPA$, $CRAR$, and $Iskew$ (see Table A2 for variables definition). γ_t is day-level fixed effects. It captures the effect of policy uncertainty that may affect the banks' crash risk.

β_1 is our coefficient of interest. It captures the difference in the mean of dependent variables between a $Non-PSBs$ and a $PSBs$. A negative value of β_1 would mean that on average $Non - PSBs$ have higher left-tail risk than $PSBs$.

We present the results of the estimation of Equation 5 in Table 2. Columns (1)-(4) present the results with *Put Slope* as the dependent variable and columns (5)-(8), with RNS as the dependent variable.

The coefficient of $Private$ is negative and significant in all specifications as in columns (1)-(4). This indicates that the *Put Slope* for $Non - PSB$s is significantly more negative, implying a greater crash risk for private banks. The difference is economically significant. For instance, in column (4), the coefficient value is approximately 16% lower than the unconditional mean of *Put Slope*, which is -1.296, as reported in Table 1. This indicates a significantly larger crash risk perceived by the options market, for $Non - PSB$s relative to the PSBs. The finding is consistent with Hypothesis 1.

In columns (5)-(8), we present the results with RNS as the dependent variable. The variable assumes a large positive value if the options market expects a large upside jump relative to a downside jump and vice versa. Therefore, while the *Put Slope* estimates the perceived downside risk irrespective of the perception of the upside, RNS estimates the same with reference to the upside expectations. For instance, it is likely that the risk-neutral distribution has fat tails on both ends of the distribution. While this will result in a large negative value of *Put Slope*, it will not result in a large negative value of RNS. Therefore, we employ RNS as an alternative measure of downside risk. The coefficient of $Private$ is negative and significant in all specifications, indicating that the $Non - PSB$s have a larger negatively skewed risk-neutral density, relative to the PSBs. This is in line with our findings with *Put Slope* as the dependent variable and indicates that $Non - PSB$s have both a relatively more negative *Put Slope* and a relatively more negatively skewed risk-neutral density compared to the PSBs.

6.1.1. The impact of NPAs

The non-performing asset is an important measure of a bank's risk profile. A higher percentage of non-performing assets for banks signals poor asset quality, and hence higher downside risk (Swidler and Wilcox, 2002). In this subsection, we examine if government ownership in the bank moderates the relation between net non-performing assets ($NNPA$) and left-tail risk. We specifically check if for the same level of $NNPA$ non-public sector banks have higher left-tail risk than public sector banks. We do so by adding an interaction term between $NNPA$ and $Private$ dummy in our baseline panel data regression. We estimate the model below:

$$Var_{i,t} = \beta_1 \ Private_i + \beta_2 \ NNPA_{i,t} + \beta_3 \ Private_i \times NNPA_{i,t} + \sum_{j=1}^{n} \alpha_j \ Control_{j,i,t} + \gamma_t + \epsilon_{i,t} \tag{6}$$

We estimate the above equation for two different dependent variables – $Put\ Slope$, and RNS. All other variables are defined the same as in the baseline regression model (see Table A2 for variables definition). β_3 is our variable of interest. It captures the difference in left-tail risk between PSBs and $Non - PSB$s for the same level of $NNPA$. A negative β_3 means for the same level of $NNPA$ $Non - PSB$s have a higher level of left-tail risk.

The estimated coefficients of Equation 6 are presented in Table 3. As before, columns (1)-(4) ((5)-(8)) show the results of the estimation with $Put\ Slope$ (RNS) as the dependent variable. The coefficient of $Private \times NNPA$ is negative and significant. This indicates that government ownership of the PSBs reduces the adverse impact of a larger NPA level on the left tail risk. Economically, a 1% increase in $NNPA$ of a $Non - PSB$ leads to an increase in the $Put\ Slope$ by approximately 3 times, relative to PSBs (column (4)). Similarly, while the RNS of PSBs remains positive despite an increase in $NNPA$, it is significantly reduced if the bank is a $Non - PSB$ (column (8)). These findings indicate a lower impact of an increase in bad loans on the perceived downside risk of the PSBs.

6.1.2. COVID 19 Analysis

During a period of high systematic risk, government guarantee becomes very salient, hence government ownership can reduce the tail risk (Kelly et al., 2016). One such example of a systematic risk event is the COVID-19 pandemic which increased the systematic risk of the banking sector across the world including India (Duan, El Ghoul, Guedhami, Li and Li, 2021). We use COVID-19 as an exogenous shock that increased the systematic risk and examine how the left-tail risk of the two sets of banks (PSBs and $Non-PSB$s) was impacted in this period. For the same, we estimate the panel data regression model mentioned below:

$$\begin{aligned} Var_{i,t} = {} & \beta_1\ Private_i + \beta_2\ COVID\ period + \beta_3\ Private_i \times COVID\ period \\ & + \sum_{j=1}^{n} \alpha_j\ Control_{j,i,t} + \gamma_t + \theta_i + \epsilon_{i,t} \end{aligned} \tag{7}$$

We estimate the above equation for two different dependent variables – *Put Slope*, and RNS, both of which measure left-tail risk. A smaller value of both measures indicates high left-tail risk, as before. *COVID period* is a dummy variable that takes the value one for the time period between February 2020 to July 2020, and zero otherwise. We also include θ_i, which represents bank-level fixed effects and controls for time-invariant, unobserved heterogeneity among banks, including the difference in ownership. Therefore, the average impact of government ownership is controlled for, while the observed effect is only for the crisis period. All other variables are defined the same as in the baseline regression model (see Table A2 for variables definition).

β_3 is our coefficient of interest. It captures the average difference in the left-tail risk between PSBs and $Non-PSB$s during the COVID-19 period. A negative value of β_3 would indicate that the left-tail risk of $Non-PSBs$ is higher than the $PSBs$ during the COVID period.

The results of the estimation of Equation 7 are presented in Table 4. As shown, the crisis significantly reduces the *Put Slope* and RNS of $Non-PSB$s (both the measure are negatively associated with left-tail risk), relative to their values in the normal period. For instance, column (3) indicates that during the months of the crisis, the *Put Slope* of $Non-PSB$s was approximately 80% lower than the normal period. Similarly, while the *COVID period* impacted the *Put Slope* of the $Non-PSB$s, the PSBs were relatively unaffected. The results remain unaffected if the time-invariant bank fixed effects are introduced (column (4)). Similar results are observed with RNS as the dependent variable. The findings indicate that in times of crisis, government ownership of banks leads to a more significant positive impact on the perceived left tail risk, consistent with Hypothesis 2.

6.1.3. Cost of insurance against left-tail risk: PSB V/S Non-PSB

Our results so far are suggestive of a greater perceived left tail risk of $Non-PSB$s relative to the PSBs. In this section, we examine the impact that government ownership has on the cost of insurance against downside risk. As discussed in Section 4.3, a large negative return on a bear spread strategy indicates insurance premium, with a larger negative value indicating a larger premium being paid to insure against the downside risk. Since the premium is expected to be larger if the downside risk is perceived to be more severe, it is likely that the bear spread return is more negative for $Non-PSB$s relative to the PSBs, as hypothesized in Hypothesis 3. To examine this, we use the empirical specification below:

$$Var_{i,t-T} = \beta_1 \; Private_i + \sum_{j=1}^{n} \alpha_j \; Control_{j,i,t} + \gamma_{t-T} + \epsilon_{i,t-T} \tag{8}$$

where, $Var_{i,t-T}$ represents return of delta hedged bear spread (*Ret Bear Spread*) of bank i between trading day t to T. The term $Private_i$ represents a bank dummy that takes the value 1 for $Non-PSB$s and zero for PSBs. $Control_{j,i,t}$ includes $Size$, M/B, $Rev(-1)$, $Momentum$, and $Illiquidity$ (see Table A2 for variables definition). γ_{t-T} are day-level fixed effects.

β_1 is the coefficient of interest. It captures the average difference in bear spread return between $Non-PSBs$ and $PSBs$. A negative value of β_1 shows that investors incur higher losses on the bear spread formed on $Non-PSBs$ than on $PSBs$. It implies that hedging left-tail risk in the options market is more expensive for $Non-PSBs$ than $PSBs$.

We present the results of the estimation of Equation 8 in Table 5. The coefficient of $Private$ is negative and significant in columns (1)-(3) and negative and insignificant in column (4). This provides weak evidence that the insurance cost of $Non-PSB$s is greater than that of PSBs in the full sample.

To further examine the impact of government ownership on the cost of insurance against downside risk, we choose a period when the fear of a crash and therefore the cost of insurance is likely to be high. The COVID-19 period was a period with high macroeconomic uncertainty and therefore a significantly higher fear of stock price crash (Ding et al., 2021; Bansal et al., 2022). We, therefore, expect that in $COVID\ period$, as defined in earlier specifications, the difference in the cost of insurance will be greater between the PSBs and $Non-PSB$s. This expectation is in line with our findings in Section 6.1.2. Since the fear of a crash is greater in the $Non-PSB$s, relative to the PSBs in this period, it is likely that the cost of insurance will also be higher for the $Non-PSB$s, as in Hypothesis 3. To test this, we employ the panel data regression specification mentioned below:

$$\begin{aligned} Var_{i,t-T} = \beta_1\ Private_i + \beta_2\ COVID\ period + \beta_3\ Private_i \times COVID\ period \\ + \sum_{j=1}^{n} \alpha_j\ Control_{j,i,t} + \gamma_t + \theta_i + \epsilon_{i,t-T} \end{aligned} \tag{9}$$

The above equation is the same as Equation 7, with the exception that the dependent variable is the monthly bear spread return, $Ret\ Bear\ Spread$. The control variables are the same as in Equation 8.

The results of the estimation of Equation 9 are presented in Table 6. The coefficient of $Private \times Covid\ period$ is negative and significant in all specifications. This indicates a lower return for a delta-hedged bear spread return strategy for $Non-PSB$s relative to the PSBs. Economically, during the months of the crisis, the strategy gave 0.086% lower returns (column (4)) for $Non - PSB$s relative to the PSBs on a monthly basis. This translates to an annualized difference of approximately 1%, a significantly higher premium to pay to protect against the downside risk of $Non - PSB$s relative to the PSBs.

Overall, we find that the stock price crash risk is significantly higher in $Non-PSB$s relative to the PSBs as indicated by the options market. This difference is larger in times of crisis and in such times, the cost of insuring against the crash of $Non - PSB$s is significantly larger, relative to the PSBs. These findings indicate that the left tail risk is indeed viewed differently for government-owned banks, relative to the private banks.

6.2. Risk of near-the-money volatility ($ATM - IV$)

Our findings so far have indicated that the left tail risk is higher for $Non - PSB$s relative to the PSBs. In this section, we examine the possible difference that government ownership makes to the expected volatility of stock returns, as indicated by the options market. We first examine the difference in the implied volatility (IV) of PSBs and $Non - PSB$s at an overall level in our sample. Thereafter, we employ the Asset Quality Review conducted by the Reserve Bank of India as an exogenous shock to the policy uncertainty of PSBs, to examine the impact that policy uncertainty may have on near-the-money option implied volatility.

6.2.1. Difference in IV

To examine the difference between the near the money IV of the two sets of banks, we employ the empirical specification as in Equation 5, with $ATM-IV$ as the dependent variable. We present the results of the estimation in Table 7. The coefficient of $Private$ is negative and significant in all columns. This indicates lower expected volatility in the stock returns of $Non - PSB$s relative to the PSBs, consistent with Hypothesis 4. Economically, the $ATM - IV$ of PSBs is approximately 16% higher relative to the $Non - PSB$s on an annualized basis indicating a significantly higher priced near-the-money options and therefore a higher perceived risk of near-the-money stock price volatility.

Next, we employ RBIs Asset Quality Review as an exogenous shock to the policy uncertainty of the government regarding the PSB (see Section 3.1 for a discussion on the AQR and its consequences for the PSBs) to examine its impact on the IV of the PSBs relative to the $Non-PSB$s. To examine this, we use the empirical specification below:

$$Var_{i,t} = \beta_1\ Private_i + \beta_2\ AQR + \beta_3\ Private_i \times AQR + \sum_{j=1}^{n} \alpha_j\ Control_{j,i,t} + \gamma_t + \epsilon_{i,t} \quad (10)$$

We estimate the above equation for the dependent variable $ATM-IV$. AQR is a dummy variable that takes the value one for the time period between April 2015 and April 2020, and zero otherwise. All other variables are defined the same as in the baseline regression model (see Table A2 for variables definition). We expect β_3 to be negative and significant as it would indicate that the policy uncertainty induced by the AQR impacted the IV of the PSBs adversely, further increasing their risk of near-the-money volatility.

The results of the estimation are presented in Table 8. As shown, the coefficient of $Private \times Post\ AQR$ is negative and significant in all specifications, except in column (3) where it is negative but insignificant. This suggests that in the period likely characterized by high policy uncertainty for the PSBs, the $Non-PSB$s had a significantly lower expected near-the-money volatility, consistent with Hypothesis 5. Economically, this translates to a decrease of approximately 9% over the sample average IV of 0.42.

The AQR simultaneously increased the policy uncertainty and impacted the asset quality and performance of PSBs adversely. Therefore, it is likely that it also increased the perceived crash risk of the PSBs. We examine this by employing Equation 10 and using $Put\ Slope$ and RNS as dependent variables. The findings of the estimation are reported in the annexure (Table A3), we find that the left tail risk is not impacted by the AQR, for the PSBs. Therefore, this provides further evidence that while the policy intervention increases the near-the-money risk, it does not impact the left tail risk, despite adversely impacting the performance parameters of the PSBs.

Overall, we find two different impacts of government ownership on perceived bank risk. While the expected support from the sovereign in bad times reduces their tail risk, expected policy uncertainty leads to a higher near-the-money risk of their stock returns. The impact on the left tail risk is more prominent on bad macroeconomic conditions and the impact on the near-the-money volatility is enhanced in times of high policy uncertainty.

7. Conclusion

We examine the impact of government ownership on two different dimensions of risk i.e. volatility and left-tail risk for Indian banks using options prices. The Indian market provides us with this unique opportunity because it has a banking sector that has large private and public banks with exchange-traded option contracts that are very liquid for a range of strike prices.

Using options implied left-tail risk measure, we find that the perceived downside risk of PSBs is substantially lower than $Non-PSB$s. Moreover, we also find that for the same level of NPA, the options implied left-tail risk for $PSBs$ is lower than $Non-PSBs$. Our COVID-19 period analysis evinces that during the period of high systematic risk, the gap between the options implied left-tail risk between $PSBs$ and $Non-PSBs$ became even wider. Lastly, we find that the cost of buying downside protection (measured by the return of bear spread) is significantly higher for $NonPSBs$, relative to the $PSBs$ in general, and particularly at the time of high systematic risk. Our results imply that investors of public sector banks enjoy a sizable amount of government guarantee in the form of protection against the collapse in public sector bank stock prices. Contrary, to our left-tail risk findings, analysis of the behavior of IV of near-the-money options ($ATM-IV$) contracts indicates that $PSBs$ have higher anticipated volatility than $Non-PSBs$. This difference widens in the period of high policy uncertainty like AQR.

The findings of our study suggest that the impact of government ownership of financial institutions (banks) on perceived risk can be divided into two contrasting effects. On one hand, the assurance of support from the government reduces the anticipated risk of large negative outcomes, which reduces left-tail risk. However, on the other hand, the adoption of riskier lending strategies and the subsequent injection of capital into these institutions also contribute to an increased expectation of volatility.

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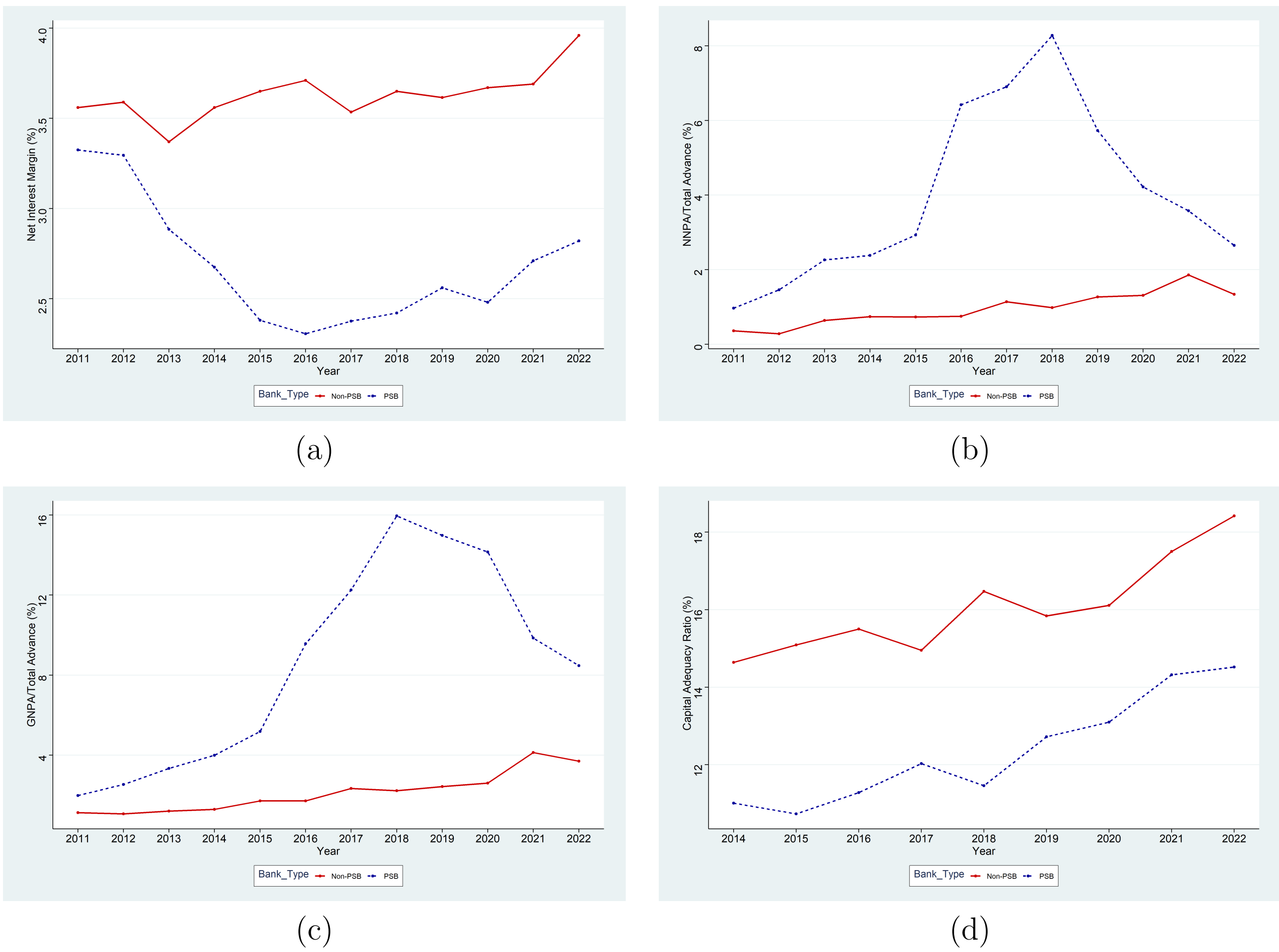
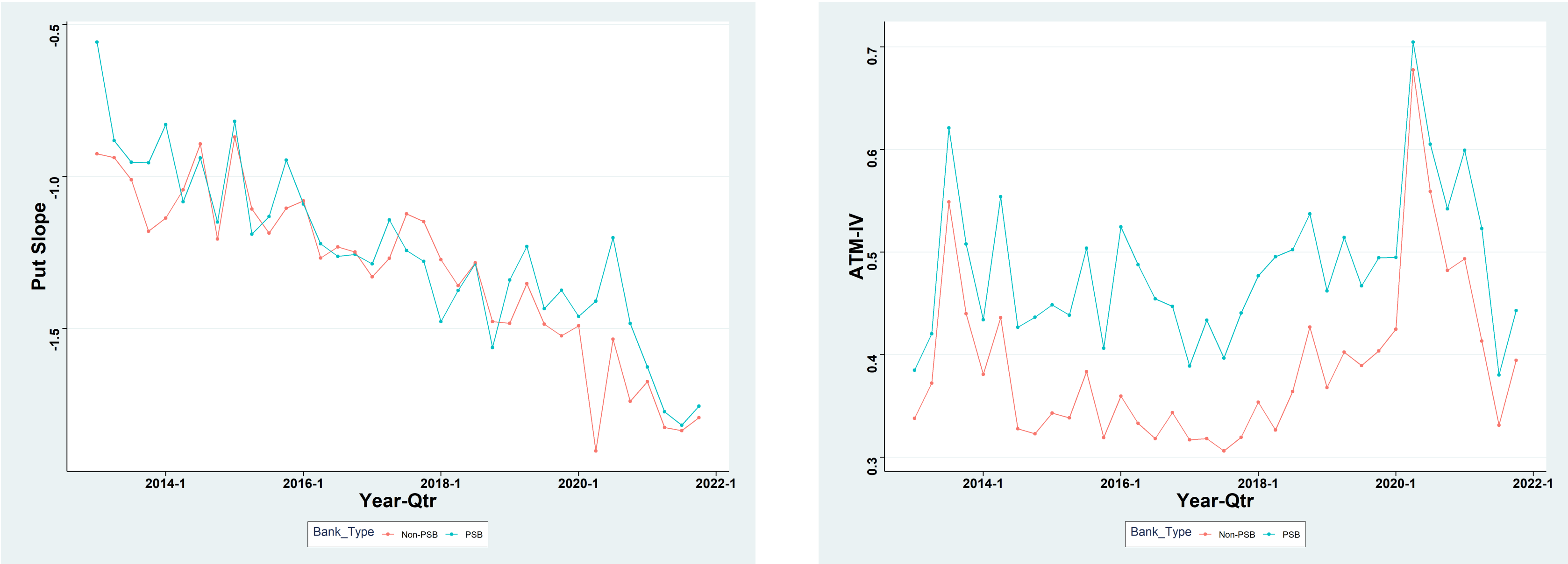
Figure 1: Key bank performance indicators: PSB V/S Non-PSB



(a) (b) (c) (d)

The plots show the key performance indicators of public and non-public banks. Plots (a), (b), (c), and (d) show the yearly median value of net interest margin, net non-performing assets to total advance, gross non-performing assets to total advance, and capital adequacy ratio of public and non-public banks.

Figure 2: Left-Tail Risk and Implied Volatility of ATM Options: PSB V/S Non-PSB



(a) (b)

Plots (a) and (b) of the figure show the average value of $Put\ Slope$, and $ATM - IV$ of public sector and non-public sector banks, respectively. Each plot shows the mean value of the variables estimated at the quarterly frequency. $Put\ Slope$ is the ratio of the difference between implied volatility (IV) of OTM and ATM put options and the difference in their moneyness (strike price/futures price). $ATM - IV$ is the implied volatility of the put option whose moneyness is nearest to one and greater than 0.98. The sample period spans from January 2013 to December 2021 and contains data from 26 banks out of which 13 are public sector banks and 13 non-public sector banks.

Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Put Slope	26,973	−1.296	1.283	−4.901	−1.627	−0.845	−0.436	−0.062
RNS	26,400	−0.135	0.991	−53.511	−0.362	−0.074	0.192	12.384
ATM-IV	32,551	0.428	0.133	0.228	0.331	0.410	0.506	0.724
Total assets	26,973	15.189	0.918	13.509	14.517	15.346	15.795	16.837
CRAR	26,973	14.180	2.493	10.540	12.130	13.740	16.450	18.830
NNPA	26,973	2.709	2.279	0.270	0.810	2.000	3.820	7.810
Iskew	26,973	0.263	0.778	−2.970	−0.165	0.261	0.667	3.829
Ret Bear Spread	1,619	−0.514 %	9.729 %	−67.726 %	−6.776 %	−0.925 %	6.197 %	49.957 %
Market Cap.	1,619	12.737	1.463	9.563	11.626	12.561	14.063	15.994
M/B	1,619	1.810	1.620	0.219	0.619	1.098	2.518	8.986
Rev(-1)	1,619	0.033 %	0.566 %	−3.309 %	−0.293 %	0.020 %	0.347 %	2.668 %
Momentum	1,619	0.001 %	0.292 %	−1.427 %	−0.141 %	0.040 %	0.177 %	0.793 %
Illiquidity	1,619	0.003	0.004	0.00005	0.0004	0.001	0.003	0.034

The table reports the summary statistics of all the variables used in the study. Put Slope is the ratio of the difference between implied volatility (IV) of OTM and ATM put options and the difference in their moneyness (strike price/spot price). RNS is risk-neutral skewness and the same is estimated following Kozhan et al. (2013). ATM-IV is the implied volatility of the put option whose moneyness is nearest to one and greater than 0.98. Total Asset is the natural logarithm of the total assets of a bank. CRAR is the capital-to-risk-weighted assets ratio of a bank. NNPA is the net non-performing assets of a bank. Iskew is the idiosyncratic skewness of a bank's return distribution. Ret Bear Spread is the return of a delta-hedged bear spread formed by taking a delta-hedged long position on an OTM Put option and a delta-hedged short position on a DOTM Put option on the first trading day after expiry (last Thursday of every month) and holding the position up until next expiry day. Market Cap. is the natural logarithm of a firm's market capitalization observed at the end of every month. M/B is the ratio of the market value of the firm at the end of a month and the book value of the total asset at the end of the previous fiscal year. Rev(-1) is the stock return over the previous month. Momentum is the return of stock over the previous six months. Illiquidity is the natural logarithm of the average ratio of the absolute daily stock return to its daily Indian rupee trading volume multiplied by 10^8 in a month. Table A2 provides variable definition. The sample period spans from January 2013 to December 2021 and contains data from 26 banks out of which 13 are public sector banks and 13 non-public sector banks.

Table 2: Left-Tail Risk: PSB V/S Non-PSB

Dependent variable:	Put Slope				RNS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Private$	-0.143^{***}	-0.035^{***}	-0.336^{***}	-0.207^{***}	-0.209^{***}	-0.204^{***}	-0.171^{***}	-0.195^{***}
	(0.016)	(0.007)	(0.033)	(0.016)	(0.012)	(0.012)	(0.026)	(0.028)
$NNPA$			-0.053^{***}	-0.015^{***}			0.028^{***}	0.014^{***}
			(0.005)	(0.003)			(0.004)	(0.005)
$CRAR$			-0.030^{***}	0.004^{*}			-0.013^{***}	-0.022^{***}
			(0.005)	(0.002)			(0.004)	(0.004)
$Total\ assets$			-0.182^{***}	-0.121^{***}			-0.131^{***}	-0.135^{***}
			(0.011)	(0.004)			(0.008)	(0.009)
$Iskew$			-0.022^{**}	-0.007			-0.071^{***}	-0.080^{***}
			(0.010)	(0.005)			(0.008)	(0.008)
Constant	-1.219^{***}		2.227^{***}		-0.022^{**}		2.077^{***}	
	(0.011)		(0.148)		(0.009)		(0.116)	
Day fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Day level clustering	No	Yes	No	Yes	No	Yes	No	Yes
Observations	26,973	26,973	26,973	26,973	26,400	26,400	26,400	26,400
Adjusted R^2	0.003	0.848	0.026	0.854	0.011	0.271	0.031	0.292

The table reports the estimated coefficient of regression Eq. (5). In columns (1-4) and (5-8) Put Slope and Risk Neutral Skewness (RNS) are the dependent variables, respectively. Put Slope is the ratio of the difference between implied volatility (IV) of OTM and ATM put options and the difference in their moneyness (strike price/spot price). RNS is risk-neutral skewness and the same is estimated following Kozhan et al. (2013). *Private* is a dummy variable that takes the value one for non-public sector banks and zero otherwise. All the dependent variables are defined in Table A2 . Standard errors clustered at day level are reported in parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from January 2013 to December 2021 and contains data from 26 banks out of which 13 are public sector banks and 13 non-public sector banks.

Table 3: Non-Performing Assets and Left-Tail Risk: PSB V/S Non-PSB

Dependent variable:	Put Slope				RNS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Private	-0.219^{***}	0.027^{**}	-0.305^{***}	-0.154^{***}	-0.048^{**}	-0.042	-0.145^{***}	-0.151^{***}
	(0.031)	(0.013)	(0.041)	(0.018)	(0.024)	(0.028)	(0.032)	(0.035)
NNPA	-0.040^{***}	0.005	-0.050^{***}	-0.008^{***}	0.039^{***}	0.035^{***}	0.031^{***}	0.020^{***}
	(0.005)	(0.003)	(0.005)	(0.003)	(0.004)	(0.005)	(0.004)	(0.005)
CRAR			-0.031^{***}	0.004			-0.013^{***}	-0.023^{***}
			(0.005)	(0.002)			(0.004)	(0.004)
Total assets			-0.180^{***}	-0.118^{***}			-0.130^{***}	-0.132^{***}
			(0.011)	(0.004)			(0.008)	(0.009)
Iskew			-0.022^{**}	-0.007			-0.071^{***}	-0.080^{***}
			(0.010)	(0.005)			(0.008)	(0.008)
$Private \times NNPA$	-0.039^{***}	-0.038^{***}	-0.015	-0.023^{***}	-0.031^{***}	-0.039^{***}	-0.012	-0.019^{**}
	(0.011)	(0.004)	(0.011)	(0.004)	(0.009)	(0.009)	(0.009)	(0.009)
Constant	-1.044^{***}		2.192^{***}		-0.193^{***}		2.047^{***}	
	(0.026)		(0.151)		(0.021)		(0.118)	
Day fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Day level clustering	No	Yes	No	Yes	No	Yes	No	Yes
Observations	26,973	26,973	26,973	26,973	26,400	26,400	26,400	26,400
Adjusted R^2	0.007	0.849	0.026	0.854	0.014	0.273	0.031	0.293

The table reports the estimated coefficient of regression Eq. (6). In columns (1-4) and (5-8) Put Slope and Risk Neutral Skewness (RNS) are the dependent variables, respectively. Put Slope is the ratio of the difference between implied volatility (IV) of OTM and ATM put options and the difference in their moneyness (strike price/spot price). RNS is risk-neutral skewness and the same is estimated following Kozhan et al. (2013). *Private* is a dummy variable that takes the value one for non-public sector banks and zero otherwise. *NNPA* is the net non-performing assets of a bank. All the dependent variables are defined in Table A2 . Standard errors clustered at day level are reported in parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from January 2013 to December 2021 and contains data from 26 banks out of which 13 are public sector banks and 13 non-public sector banks.

Table 4: COVID-19 Crisis and Left-Tail Risk: PSB V/S Non-PSB

Dependent variable:	Put Slope				RNS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Private	-0.123^{***}		-0.311^{***}		-0.179^{***}		-0.131^{***}	
	(0.016)		(0.034)		(0.012)		(0.026)	
Covid period	-0.222^{***}		-0.100		0.256^{***}		0.365^{***}	
	(0.064)		(0.063)		(0.049)		(0.049)	
NNPA			-0.053^{***}	-0.029^{*}			0.029^{***}	0.009
			(0.005)	(0.016)			(0.004)	(0.027)
CRAR			-0.030^{***}	0.017			-0.015^{***}	0.010
			(0.005)	(0.012)			(0.004)	(0.019)
Total assets			-0.177^{***}	-0.195			-0.131^{***}	0.123
			(0.011)	(0.129)			(0.008)	(0.248)
Iskew			-0.020^{**}	-0.010			-0.070^{***}	-0.081^{***}
			(0.010)	(0.008)			(0.008)	(0.016)
Private × *Covid period*	-0.175^{**}	-0.316^{***}	-0.253^{***}	-0.254^{***}	-0.565^{***}	-0.664^{***}	-0.644^{***}	-0.683^{***}
	(0.076)	(0.107)	(0.076)	(0.089)	(0.059)	(0.106)	(0.058)	(0.091)
Constant	-1.212^{***}		2.152^{***}		-0.031^{***}		2.091^{***}	
	(0.012)		(0.149)		(0.009)		(0.116)	
Day fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Bank fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Day level clustering	No	Yes	No	Yes	No	Yes	No	Yes
Observations	26,973	26,973	26,973	26,973	26,400	26,400	26,400	26,400
Adjusted R^2	0.007	0.859	0.029	0.860	0.015	0.315	0.036	0.318

The table reports the estimated coefficient of regression Eq. (7). In columns (1-4) and (5-8) Put Slope and Risk Neutral Skewness (RNS) are the dependent variables, respectively. Put Slope is the ratio of the difference between implied volatility (IV) of OTM and ATM put options and the difference in their moneyness (strike price/spot price). RNS is risk-neutral skewness and the same is estimated following Kozhan et al. (2013). *Private* is a dummy variable that takes the value one for non-public sector banks and zero otherwise. *Covid period* is a dummy variable that takes the value one for the time periods from February 2020 to July 2020 and zero otherwise. All the dependent variables are defined in Table A2 . Standard errors clustered at firm and day levels are reported in parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from January 2013 to December 2021 and contains data from 26 banks out of which 13 are public sector banks and 13 non-public sector banks.

Table 5: Bear Spread Return: PSB V/S Non-PSB

Dependent variable:	Ret Bear Spread			
	(1)	(2)	(3)	(4)
Private	-0.014^{***}	-0.012^{*}	-0.010^{*}	-0.010
	(0.005)	(0.007)	(0.006)	(0.007)
Size			0.001	0.001
			(0.003)	(0.002)
M/B			-0.002	-0.002
			(0.002)	(0.002)
Rev(-1)			-0.839	-0.839
			(0.606)	(0.836)
Momentum			0.215	0.215
			(1.404)	(1.718)
Illiquidity			-0.243	-0.243
			(0.866)	(0.858)
Constant	0.002			
	(0.004)			
Day fixed effects	No	Yes	Yes	Yes
Day level clustering	No	Yes	No	Yes
Observations	1,619	1,619	1,619	1,619
Adjusted R^2	0.004	0.210	0.209	0.209

The table reports the estimated coefficient of regression Eq. (8) with Ret Bear Spread as the dependent variable. Ret Bear Spread is the return of a delta-hedged bear spread formed by taking a delta-hedged long position on an OTM Put option and a delta-hedged short position on a DOTM Put option on the first trading day after expiry (last Thursday of every month) and holding the position up until next expiry day. All the dependent variables are defined in Table A2 . Standard errors clustered at bank and day levels are reported in parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from January 2013 to December 2021 and contains data from 26 banks out of which 13 are public sector banks and 13 non-public sector banks.

Table 6: COVID-19 and Bear Spread Return: PSB V/S Non-PSB

Dependent variable:	Ret Bear Spread			
	(1)	(2)	(3)	(4)
Private	−0.008		−0.004	
	(0.005)		(0.007)	(0.000)
Private × *Covid period*	−0.072***	−0.074*	−0.067***	−0.086**
	(0.024)	(0.043)	(0.024)	(0.041)
Size			0.002	0.005
			(0.003)	(0.010)
M/B			−0.003	−0.021***
			(0.002)	(0.007)
Rev(−1)			−1.002**	−0.028
			(0.433)	(0.697)
Momentum			−0.513	2.783
			(0.926)	(1.719)
Illiquidity			−0.760	−2.561*
			(0.914)	(1.477)
Covid period	−0.030		−0.039*	
	(0.020)		(0.021)	
Constant	0.003		−0.010	
	(0.003)		(0.034)	
Day fixed effects	No	Yes	No	Yes
Bank fixed effects	No	Yes	No	Yes
Day level clustering	No	Yes	No	Yes
Bank level clustering	No	Yes	No	Yes
Observations	1,619	1,619	1,619	1,619
Adjusted R^2	0.040	0.211	0.042	0.219

The table reports the estimated coefficient of regression Eq. (9) with Ret Bear Spread as the dependent variable. Ret Bear Spread is the return of a delta-hedged bear spread formed by taking a delta-hedged long position on an OTM Put option and a delta-hedged short position on a DOTM Put option on the first trading day after expiry (last Thursday of every month) and holding the position up until next expiry day. *Covid period* is a dummy variable that takes the value one for the time periods from February 2020 to July 2020 and zero otherwise. All the dependent variables are defined in Table A2 . Standard errors clustered at bank and day levels are reported in parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from January 2013 to December 2021 and contains data from 26 banks out of which 13 are public sector banks and 13 non-public sector banks.

Table 7: At the money implied volatility: PSB V/S Non-PSB

Dependent variable:	ATM-IV			
	(1)	(2)	(3)	(4)
Private	-0.086^{***}	-0.099^{***}	-0.105^{***}	-0.071^{**}
	(0.001)	(0.025)	(0.003)	(0.027)
CRAR			0.004^{***}	-0.006
			(0.0005)	(0.007)
NNPA			0.007^{***}	0.015^{***}
			(0.0004)	(0.003)
Total assets			-0.036^{***}	-0.045^{***}
			(0.001)	(0.010)
Constant	0.472^{***}		0.958^{***}	
	(0.001)		(0.013)	
Day fixed effects	No	Yes	No	Yes
Day level clustering	No	Yes	No	Yes
Bank level clustering	No	Yes	No	Yes
Observations	32,551	32,551	32,551	32,551
Adjusted R^2	0.103	0.541	0.157	0.668

The table reports the estimated coefficient of regression Eq. (5) with ATM-IV as the dependent variable. ATM-IV is the implied volatility of the put option whose moneyness is nearest to one and greater than 0.98. *Private* is a dummy variable that takes the value one for non-public sector banks and zero otherwise. All the dependent variables are defined in Table A2 . Standard errors clustered at day level are reported in parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from January 2013 to December 2021 and contains data from 26 banks out of which 13 are public sector banks and 13 non-public sector banks.

Table 8: Asset Quality Review and At the money implied volatility: PSB V/S Non-PSB

Dependent variable:	ATM-IV			
	(1)	(2)	(3)	(4)
Post AQR	−0.002		−0.028***	
	(0.002)	(0.000)	(0.002)	(0.000)
Private	−0.081***		−0.091***	
	(0.002)	(0.000)	(0.004)	(0.000)
CRAR			−0.001***	−0.005
			(0.001)	(0.003)
NNPA			0.011***	0.012***
			(0.0005)	(0.004)
Total assets			−0.038***	0.056
			(0.001)	(0.053)
Private × *Post AQR*	−0.032***	−0.049***	−0.003	−0.038**
	(0.003)	(0.013)	(0.003)	(0.016)
Constant	0.466***		1.034***	
	(0.002)		(0.013)	
Day fixed effects	No	Yes	No	Yes
Bank fixed effects	No	Yes	No	Yes
Day level clustering	No	Yes	No	Yes
Bank level clustering	No	Yes	No	Yes
Observations	27,040	27,040	27,040	27,040
Adjusted R^2	0.181	0.714	0.261	0.722

The table reports the estimated coefficient of regression Eq. (10) with ATM-IV as the dependent variable. ATM-IV is the implied volatility of the put option whose moneyness is nearest to one and greater than 0.98. *Private* is a dummy variable that takes the value one for non-public sector banks and zero otherwise. *Post AQR* is a dummy variable that takes the value one for time periods between April 2015 to April 2020 and zero otherwise. All the dependent variables are defined in Table A2 . Standard errors clustered at bank and day levels are reported in parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from January 2013 to December 2021 and contains data from 26 banks out of which 13 are public sector banks and 13 non-public sector banks.

Table A1 : Details of Banks

Serial No.	NSE Symbol	Bank Name	Category
1.	ALBK	ALLAHABAD BANK [MERGED]	PSB
2.	AXISBANK	AXIS BANK LTD.	Non-PSB
3.	BANKINDIA	BANK OF INDIA	PSB
4.	ICICIBANK	I C I C I BANK LTD.	Non-PSB
5.	KTKBANK	KARNATAKA BANK LTD.	Non-PSB
6.	PNB	PUNJAB NATIONAL BANK	PSB
7.	SBIN	STATE BANK OF INDIA	PSB
8.	YESBANK	YES BANK LTD.	Non-PSB
9.	CANBK	CANARA BANK	PSB
10.	BANKBARODA	BANK OF BARODA	PSB
11.	HDFCBANK	H D F C BANK LTD.	Non-PSB
12.	UNIONBANK	UNION BANK OF INDIA	PSB
13.	ANDHRABANK	ANDHRA BANK [MERGED]	PSB
14.	SYNDIBANK	SYNDICATE BANK [MERGED]	PSB
15.	INDUSINDBK	INDUSIND BANK LTD.	Non-PSB
16.	KOTAKBANK	KOTAK MAHINDRA BANK LTD.	Non-PSB
17.	ORIENTBANK	ORIENTAL BANK OF COMMERCE [MERGED]	PSB
18.	UCOBANK	UCO BANK	PSB
19.	IOB	INDIAN OVERSEAS BANK	PSB
20.	FEDERALBNK	FEDERAL BANK LTD.	Non-PSB
21.	SOUTHBANK	SOUTH INDIAN BANK LTD.	Non-PSB
22.	DCBBANK	D C B BANK LTD.	Non-PSB
23.	INDIANB	INDIAN BANK	PSB
24.	RBLBANK	R B L BANK LTD.	Non-PSB
25.	IDFCFIRSTB	I D F C FIRST BANK LTD.	Non-PSB
26.	BANDHANBNK	BANDHAN BANK LTD.	Non-PSB

The table reports the NSE Symbol and Name of banks in our sample. Banks are got merged with other banks anytime in our sample are marked as "MERGED" after their name. The 26 banks in our sample manage more than 86% of the total assets managed by all the banks in India at the end of FY 2022.

Table A2 : Variable Construction Details

Variable Name	Variable Definition	Source
Private	A dummy variable that takes the value 1 for private banks and zero otherwise.	CMIE $Prowess_{dx}$
Put Slope	Ratio of the difference in the implied volatility of out-of-the-money and at-the-money put options and the difference in their moneyness ($\frac{IV_{OTM}-IV_{ATM}}{Moneyness_{OTM}-Moneyness_{ATM}}$).	NSE Trading File
RNS	Skewness of the risk neutral distribution estimated following Kozhan et al. (2013).	NSE Trading File
ATM-IV	Implied volatility of the put option whose moneyness is nearest to one and greater than 0.98.	NSE Trading File
Total assets	Natural logarithm of total asset of the banks in INR million.	CMIE $Prowess_{dx}$
CRAR	Capital-to-risk-weighted assets ratio of a bank.	CMIE $Prowess_{dx}$
NNPA	Net non-performing assets of a bank	CMIE $Prowess_{dx}$
Iskew	Idiosyncratic skewness of the bank's return distribution estimated by first regressing daily equity return on Fama and French (1993)-Carhart (1997) four-factor returns within a year, and then estimating skewness of the residuals every month.	CMIE $Prowess_{dx}$

Table A2 : Variable Construction Details

Variable Name	Variable Definition	Source
Ret Bear Spread	Return of a delta-hedged bear spread formed by taking a delta-hedged long position on an OTM Put option and a delta-hedged short position on a DOTM Put option on the first trading day after expiry (last Thursday of every month) and holding the position up until the next expiry day (last Thursday of next month).	NSE Trading File
Market Cap.	Natural logarithm of the bank's market capitalization at the end of every month.	CMIE $Prowess_{dx}$
M/B	Ratio of the market value of the bank at the end of the month and the book value of the assets at the end of the previous fiscal year.	CMIE $Prowess_{dx}$
Rev(-1)	Bank's equity return in the previous month.	CMIE $Prowess_{dx}$
Momentum	Bank's equity return in the previous six month.	CMIE $Prowess_{dx}$
Illiquidity	Natural logarithm of the average ratio of the absolute daily stock return to its daily Indian rupee trading volume multiplied by 10^8 in a month.	CMIE $Prowess_{dx}$

Table A3 : Asset Quality Review and Left-Tail Risk: PSB V/S Non-PSB

Dependent variable:	Put Slope		RNS	
	(1)	(2)	(3)	(4)
Total assets		-0.240^{*}		0.033
		(0.136)		(0.248)
CRAR		0.019		0.017
		(0.012)		(0.020)
NNPA		-0.017		0.013
		(0.016)		(0.024)
Iskew		-0.009		-0.081^{***}
		(0.008)		(0.016)
Private × *Post AQR*	0.120	0.126	0.076	0.091
	(0.070)	(0.082)	(0.086)	(0.099)
Day fixed effects	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes
Day level clustering	Yes	Yes	Yes	Yes
Bank level clustering	Yes	Yes	Yes	Yes
Observations	26,973	26,973	26,400	26,400
Adjusted R^2	0.859	0.860	0.310	0.314

The table reports the estimated coefficient of regression Eq. (10). In columns (1-2) and (3-4) Put Slope and Risk Neutral Skewness (RNS) are the dependent variables, respectively. Put Slope is the ratio of the difference between implied volatility (IV) of OTM and ATM put options and the difference in their moneyness (strike price/spot price). RNS is risk-neutral skewness and the same is estimated following Kozhan et al. (2013). *Private* is a dummy variable that takes the value one for non-public sector banks and zero otherwise. *Post AQR* is a dummy variable that takes the value one for time periods between April 2015 to April 2020 and zero otherwise. All the dependent variables are defined in Table A2 . Standard errors clustered at bank and day levels are reported in parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from January 2013 to December 2021 and contains data from 26 banks out of which 13 are public sector banks and 13 non-public sector banks.