Journal of
Risk and Financial Management

Systematic Review

A Study of Banks' Systemic Importance and Moral Hazard Behaviour: A Panel Threshold Regression Approach

C. P. Gupta and Arushi Jain *

Department of Finance and Business Economics, University of Delhi, New Delhi 110021, India
* Correspondence: jainarushi74@gmail.com

Abstract: This study has two objectives, first, to investigate if the lending behaviour of banks exhibits moral hazard in the Indian Banking Industry, and second, to investigate whether banks' moral hazard behaviour changes when the systemic importance of the banks is taken into consideration. We studied banks' moral hazard behaviour by observing the impact of their level of Net Non-Performing Loans (NNPL) on their lending behaviour. This study used threshold panel regression by using 1 year lagged values of NNPL as the threshold variable to find its endogenously determined value that impacts the lending behaviour of the banks. The 1 year lagged value of the NNPL (threshold variable) has been used to depict the level of distress faced by a bank. Assuming that loans may turn bad any year after they are granted, a banks' lending behaviour has been shown through the relationship between various lags of Loan Growth Rate (LGR) and the contemporaneous values of Net Non-Performing Loans (NNPL). As per our analysis, the loan growth ratio raises NPLs with a relatively higher value when banks are experiencing prior sizable loan losses as compared to when banks are relatively safe, indicating moral hazard behaviour in the Indian banking industry. However, when the systemic importance of the bank is considered, the systemically important banks are found to be engaged in risky lending irrespective of their level of distress, whereas the opposite results are found for the least important banks.

Keywords: moral hazard; Indian banking industry; systemic importance of the banks; TBTF status; NPLs; LGR; Panel Threshold Regression

JEL Classification: E58; G00; G01; G21; G33; G28; G32

check for updates

Citation: Gupta, C. P., and Arushi Jain. 2022. A Study of Banks' Systemic Importance and Moral Hazard Behaviour: A Panel Threshold Regression Approach. *Journal of Risk and Financial Management* 15: 537. https://doi.org/10.3390/jrfm15110537

Academic Editor: James R. Barth

Received: 15 October 2022
Accepted: 15 November 2022
Published: 17 November 2022

1. Introduction

The Global Financial Crisis (GFC) of 2007–2008 highlighted vulnerabilities in the existing financial system and demonstrated how the failure of large institutions may severely affect the whole economy (Financial Crisis Inquiry Commission 2011; Hett and Schmidt 2017). These financial institutions are so important that their failure may inflict severe harm to both financial markets and the economy as a whole (Dell'Ariccia et al. 2008). To avoid this turmoil in the financial system, governments are reluctant to let Too Big to Fail (TBTF) institutions fail (Mishkin 2006). Thus, the rescue of these banks becomes important due to their importance in the financial system (Moosa 2010; Azgad-Tromer 2017), which requires taxpayers' money. Therefore, it becomes imperative to increase the banks' resilience to losses as the cost involved in their rescue at the time of distress is even higher, which has to be borne by the government and ultimately by the taxpayers (Moosa 2010).

The question is how a single bank can inflict such a systemic disruption. Most clearly, a significant bank's failure can cause systemic disruptions if it raises depositors' concerns about the stability of other banks, forcing them to cause bank runs (Honohan 1997; Schooner and Taylor 2009; Financial Crisis Inquiry Commission 2011). Because the bankruptcy of a major bank will be widely publicized, the chance of runs on other banks, and panics may be relatively greater for larger banks (Schooner and Taylor 2009).

Under normal circumstances, a bank's systemic importance leads to a rise in the vulnerability of other banks due to their bilateral exposure, increasing the likelihood of domino-like failures (Kaufmanh 1996; Schooner and Taylor 2009). This is particularly common if a systemically important bank has a sizable presence in more than one financial market. If a significant bank that is a key player in a specific market fails, the whole market may experience a liquidity crisis. Other financial institutions with exposure to that market may also face liquidity issues as a result. This issue is not limited to the banking industry. The US's Federal Reserve encouraged JP Morgan-Chase to acquire Bear Stearns in March 2008 because it was considered too interconnected to fail and, because of its significant role in the financial market, it was possible that if it failed it would have caused considerable disruption across financial markets (Financial Crisis Inquiry Commission 2011). Later that year, the insurance behemoth American International Group (AIG) was also bailed out, owing in large part to its position in the credit default swap market where it was a key provider of this type of risk insurance. These instances show the relevance of TBTF institutions, and the risk associated with them.

To address this problem, the Financial Stability Board (FSB) advised in October 2010, that all member nations should have a framework in place to reduce the risk associated with Systemically Important Financial Institutions (SIFIs). In response to this, in November 2011 the Basel Committee on Banking Supervision (BCBS) released a framework for identifying Global Systemically Important Banks (G-SIBs) together with an extra level of capital requirement applicable to such G-SIBs. Later, BCBS directed the member nations to come up with a framework for dealing with Domestic Systemically Important Banks (DSIBs) too. In India, the RBI released its framework for dealing with domestic-systemically important banks (D-SIBs) in December 2013 and decided to assign them Too Big to Fail (TBTF) status. It then declared SBI and ICICI as the first D-SIBs in the country in August 2015—RBI releases a list of D-SIBs. Further, in 2017, HDFC was added to this list—RBI releases the 2017 list of D-SIBs (Framework for dealing with D-SIBs 2014).

BCBS provided a framework for dealing with D-SIBs in 2012. However, the framework allows for national discretion in the identification of D-SIBs. The process of assessing the systemic importance of the banks consists of two steps. The first step is to select a sample of banks for systemic importance assessment, which is based on the bank's size as a percentage of Gross Domestic Product (GDP). In the sample, banks that account for more than 2% of GDP are selected. Further, using the indicators of size, substitutability, complexity and interconnectedness, final systemic importance scores for selected banks are computed. These indicators are explained in detail in the methodology section of the study. Based on the combination of the above-explained quantitative analysis, country-specific factors, and the regulatory judgement of RBI, banks with different systemic importance beyond a certain threshold are put into different buckets. These buckets represent extra Common Equity Tier 1 capital (CET1) capital that needs to be maintained by the bank. The bank with the highest systemic importance score is put in bucket 4 and hence has to maintain 0.8% of its risk-weighted assets as an additional capital requirement in the form of CET1 capital. The process is similar for other buckets too. Table 1 shows the additional CET1 capital requirement for DSIBs under different buckets. This computation of scores of all the banks in the sample is done annually and is based on the year-end data. The above discussion shows that the aim behind the introduction of the said criteria was to make them more resilient; however, this criterion also affects other aspects of the banking industry which are often ignored and can lead to severe consequences. According to RBI, TBTF or D-SIB status may lead to the problem of moral hazard, reduced market discipline, a threat to competition and increased chances of distress in the future (Framework for dealing with Domestic Systemically Important Banks (D-SIBs) 2014). However, the current study focuses only on the moral hazard aspect of the systemic importance of the banks.

Table 1. Bucket system.

Bucket	Additional Common Equity Tier1 (CET1) Requirement (as a Percentage of Risk Weighted Assets)
5	1%
4	0.8%
3	0.6%
2	0.4%
1	0.2%

1.1. Moral Hazard

Moral hazard occurs when one party incurs a greater risk knowing that it is protected, and another party will bear the expense (Machina and Viscusi 2013; Cumming and Johan 2013). The underlying cause of moral hazard is information asymmetry, which occurs when the risk-taker in a transaction has relatively more information than the party liable for the risk's consequences. More specifically, moral hazard occurs when the party with more information has an incentive to behave inappropriately towards the party with less information. Moral hazard, adverse selection and information asymmetry are related terms that are often confused with one another. Asymmetric information is the root cause of both moral hazard and adverse selection (Husted 2007; Dionne et al. 2004; Yamamoto et al. 2012). Asymmetric information causes one party to increase their overall risk exposure after the transaction is completed, whereas adverse selection takes place before the transaction takes place (Husted 2007; Cumming and Johan 2013). In the insurance industry, consumers who have insurance are more likely to act carelessly than those who do not, representing moral hazard. Adverse selection, on the other hand, implies that while purchasing insurance, consumers may withhold details about their current medical conditions from the health insurer.

In banking, assuming that the government will step in with financial assistance whenever they need it, bank managers and investors will be less concerned about managing risk than if the bank was forced to rely on their resources (Schooner and Taylor 2009). Because the government protects depositors and other bank creditors from losses (via deposit insurance and capital injections), interest rates on bank deposits and other types of bank debt do not fully reflect the riskiness of the banks' operations. As a result, banks collect an inaccurate pricing signal and eventually end up financing riskier projects than they would otherwise (see Stern 1999; Maclachlan 2001).

In terms of ownership, several studies have sought to identify moral hazard. In comparison to their private-sector counterparts, PSBs make inefficient risk-taking decisions (see Shen and Lin 2012). The reasons presented in the misgovernance theory of businesses (Banerjee et al. 1997) include the political theory of firms (Shleifer and Vishny 1997) and that market discipline under implicit guarantees can be utilised to explain the inefficient risk decisions made by these PSBs (Flannery and Nikolova 2004). According to Shleifer and Vishny's (1997) political theory, officials who represent the state seek private advantages by diverting bank financing into riskier or politically important but inefficient enterprises. As per the market discipline point of view, market discipline is undercut by the regulatory system's implicit assurances on a bank's liabilities (Flannery and Nikolova 2004). Moral hazard also occurs due to the government's implicit and explicit promises (Kornai 1979; Demirgüç-Kunt 1989), which raises their riskiness due to expected support. A similar study was done by Nguyen (2020) on ASEAN nations using quantile regression approach. Their results indicate that first, state and foreign ownership have a beneficial effect on bank risk-taking in high-risk banks but a negative effect in low-risk banks. Second, the link between ownership concentration and risk-taking is inverse across all bank risk distributions. Their findings imply that an appropriate ownership structure can restrain bank risk-taking activities based on each bank's level of risk.

1.2. Systemic Importance and Moral Hazard Behaviour

A systemically important bank may indulge in risky lending due to the mere expectation that being a systemically important bank, it would be entitled to the government's support if it fails (Evaluation of the effects of too-big-to-fail reforms by the Financial Stability Report, 2020; Framework for Dealing with Domestic Systemically Important Banks by RBI 2014). Such an assumption of government support can encourage moral hazard due to a bank's systemic importance, and thus, due to the expectation of being bailed out in case of insolvency, moral hazard becomes even more apparent (Refer Jeanne and Korinek 2020; Boyd and Graham 1998; Nier and Baumann 2006). Although with systemic importance a higher capital obligation also comes in the form of a higher common equity tier 1 capital (CET1) to make them more resilient in the economy, the prospect of systemically important banks (SIBs) taking higher risks to gain an incremental return on capital negates the purpose of added capital (Urjit R. Patel, Governor, 32nd Annual G30 International Banking Seminar, 15 October 2017, Inter-American Development Bank, Washington, D.C.).

Non-performing loans (NPL) are an unwanted by-product of the lending activity in the banking industry. They incur either due to bad luck or bad management (Berger and DeYoung 1997). The former relates to macroeconomic conditions or borrowers' inability to repay, whereas the latter depicts the moral hazard behaviour. No doubt, moral hazard cannot be directly observed; nonetheless, it can be inferred from the banks' conduct. Excessive risk-taking in lending is one of the key indications of moral hazard problems according to Jensen (1976). However, there is a certain level of risk involved in every loan investment undertaken by the bank, thus, in this study, moral hazard has been identified by observing the lending behaviour of the banks when they are under the pressure of a high level of impaired loans (investment part is not considered in this study). The moral hazard principle suggests that if the bank is under distress, its management would attempt to offset losses by increasing lending to maximise prospects of recovery. Bank managers can be forced to relax their criteria or accept riskier applications to increase loan growth, thus raising their overall risk exposure. This behaviour could also be motivated if the bank is under the implicit assumption that it would be supported by the government even if it incurs losses with additional risky lending. If taking on more risk finally pays off, the shareholders will receive the gains, while depositors will bear the brunt of any potential losses. Thus, by employing Panel Threshold Regression, we examine whether banks' lending practices are sensitive to the level of NPL exceeding a certain threshold and, more importantly, whether banks with higher NPL ratios tend to adopt a more aggressive and riskier lending approach. If the banks indulge in risky lending when it is already beyond the threshold level of NPL, it would depict moral hazard behaviour. The effect of loan growth rate on the level of NNPL has been observed to study the lending behaviour of the banks. If NPL increases with a rise in the LGR, this shows that the bank is engaged in risky lending. This study also explores the relevance of the capital adequacy ratio (CRAR) as an alternative to regulatory measures in addition to NPLs, inspired by recent substantial regulatory reforms in India through Basel requirements.

The existing literature fails to consider the systemic importance of the banks while checking for the existence of moral hazard in the lending behaviour of banks, which is the main focus of this study. This study attempts to check for the existence of moral hazard in the Indian Banking Industry, and thereafter considers systemic importance of banks as the possible cause by creating different dummies to depict banks with different systemic importance. To our best knowledge, no study has been done which accounts for systemic importance of banks in determining moral hazard behaviour of banks. This study has the following structure. The state of the Indian banking sector during the selected period is briefly covered in the next section. Section 3 provides a summary of pertinent research in this field. Section 4 relates moral hazard to lending behaviour and its relevance in the Indian banking industry. Section 5 describes hypothesis development, and Section 6 discusses the data under consideration and the related variables. In Section 7, the technique and empirical strategy are explained, while Section 8 provides empirical findings. Section 9 presents findings based on CRAR measurements and contrasts, and analyses the efficacy of CRAR and NPLs ratio as alternative regulatory metrics. The conclusion and policy ramifications of the findings are discussed in the final part of the study.

2. Overview of the Indian Banking Industry and History of Government Support

With an average GDP growth rate of 6.57% each year from 2012 to 2020, India ranks 7th among the world's top economies, 70th with 54.65% of GDP as bank credit to the private sector and 20th in terms of NPA among Morgan Stanley Capital International (MSCI) emerging markets (Data bank: World Bank indicators).

The history of the Indian banking industry demonstrates that both public and private banks in India have benefited greatly from state backing, either explicitly, as in the case of public sector banks, or implicitly, as occurred in Yes Bank (2019) and IDBI Bank (2019). The State Bank of India, the largest lender in the nation, led a consortium to inject Rs 7250 crore in additional capital for Yes Bank, which had been trying to cope with huge, bad loans. Other lenders also contributed to the rescue effort, with HDFC Ltd. and ICICI Bank both spending Rs 1000 crore, while Axis Bank and Kotak Mahindra Bank announced respective capital investments of Rs 600 crore and Rs 500 crore. Similar to this, the government devised a rescue plan for IDBI, which had 55,000 crores in non-performing assets and another 60,000 crores in stressed assets. With the help of Life Insurance Corporation (LIC), which invested a staggering '216.24 billion and acquired a 51% stake in IDBI bank, IDBI had 55,000 crores in NPAs and another 60,000 crores in stressed assets. Theoretically and experimentally, academic research contends that capital injections and bailouts could persuade a bank to take on more risk, leading to moral hazard (Haq and Heaney 2012). Chavan and Gambacorta (2016), argue that a decrease in asset quality in the Indian banking industry is a result of bank recapitalization backed by public money. Their findings are consistent with research on bank recapitalization and bailout programmes (Flannery 1989; Samantaraya 2016). These instances are evidence that the Indian banking industry has been receiving government support through various means, and there is a high probability that the government would continue to do so, especially for systemically important banks, due to their possible severe effect on the whole economy.

3. Review of Literature

The literature on moral hazard is substantial, with a concentration on commercial banks in the United States. Some studies focus on the Indian economy, but they are few. Jensen (1976) employed a division in their definition of the systemic risk problem and explained the relationship between the systemic risk problem, credit expansion, and NPAs. As per the study of Jensen (1976), moral hazard appears when bankers have a propensity to receive private benefits due to vested interests. Managers who have vested interests in particular projects are more likely to invest in those projects and may neglect to properly monitor their loans, which can lead to investments in those projects even if they involve high risk. Secondly, bank stock owners can decide to engage in riskier loans, which then puts pressure on bank depositors. The prime indication of moral hazard, according to Jensen (1976), is unjustifiably increased risky loans. According to Foos et al. (2010), the Loan Growth rate was found to be a significant indicator of riskier lending decisions. Over 10,000 different banks from 14 major Western nations were examined from 1997 to 2005 to see how loan growth affected asset riskiness. According to the authors, credit expansion is a significant factor in bank risk.

According to Foos et al. (2010), loan growth is a significant determinant of bank riskiness. Using data from banks in the United States, Canada, Japan, and Europe from 1997 to 2007, Foos et al. (2010) found that a rise in loan losses is caused by loan growth, which lowers interest income and the capital ratio. Demirgüç-Kunt (1989), Barr et al. (1994), Berger and Udell (1994), Gorton and Rosen (1995), and Shrieves and Dahl (2003) conducted additional research on the link between NPLs, loan growth, and bank risk-taking.

According to Bruche and Llobet (2011), when banks encounter the possibility of insolvency they usually transfer problematic loans to facilitate recovery. Nguyen and Dang (2022) also conducted an empirical assessment of theories concerning bank stability, audit committee structures, and national institutional quality. According to their primary findings, audit committee effectiveness can improve bank stability by increasing bank performance and capitalization levels. These relationships, however, are found to be dependent on the institutional quality of each country and the level of stability of each bank.

Clair (1992) studying Texas banks, found that while loan growth initially enhances the credit quality of the lending portfolio, when assessed with time the credit quality degrades. This observation implies that it is difficult for bankers to identify a decline in credit quality quickly, especially when credit quality first rises positively. Clair (1992) discovered an exception to this rule for banks with strong equity positions. Banks with high capital ratios and rapid growth did not exhibit signs of deteriorating asset quality. Thus, Berger and DeYoung (1997) empirically established that for low-capitalised banks, a decline in capital ratios typically precedes a rise in NPLs. In the belief that greater risks may result in greater profits, and according to Clair (1992), banks with low capital ratios may be more vulnerable to systemic risk concerns. For banks that are deemed too large to fail, Nier and Baumann (2006) ascribe increased problem loans to implicit government guarantees. The authors conclude that for a specific equity ratio (capital adequacy), public sector banks select assets with a higher risk of default.

In addition to endogenous variables that are directly connected to assets, there exist other factors that connect management theory, theory of the firm, and agency ideas with the rising NPA issue in banking. Gorton and Rosen (1995) concluded that loans with poor returns choices in financially unsound banks were due to corporate control issues. According to the authors, such bad lending choices cause bank capital to erode, and when enough capital is lost, a tipping point is reached, and when moral hazard concept predicts, a wave of needless risky lending occurs. According to them, the presence of moral hazard in the setting of significant US banks may be experimentally attributed to issues with corporate control. Another body of literature, however, examines the moral hazard issue in banks from the perspectives of risk shifting and bank financial structure. According to Duran and Lozano-Vivas (2015), any change in the bank and loan portfolio would indicate that the owners are transferring the risk to the debt holders to increase profits. Higher risk-taking eventually pays off, and stockholders reap the majority of the rewards. Deposit holders, however, are largely responsible for any potential losses. Building on the idea that stockholders in undercapitalized banks have a higher propensity to accept excessive risks, Duran and Lozano-Vivas (2015) made the additional observation that investors have a higher willingness to shift risk if they have relatively small ownership interests. When banks are undercapitalized and have increased riskier lending, the moral hazard conflict between depositors and shareholders eventually becomes more acute.

A few more studies use managerial competition theory to the NPA issues in banks. Boyd and Nicolo (2005) investigate the impact of bank rivalry and incentives to take on risk. They claim that less competition among banks results in risky lending behaviour. This occurs because banks have a tendency to raise interest rates when markets grow more consolidated and there is less competition. Bank debtors eventually face a greater danger of bankruptcy as a result of increasing interest rates. When borrowers optimally raise their own risk of failure, systemic risk incentives on their behalf become apparent.

Threshold panel data regression was used in more recent works by Piatti and Cincinelli (2018) and Bardhan et al. (2019). To determine whether credit management performance leads to NPLs attaining a particular threshold, Piatti and Cincinelli (2018) used a dataset of 298 Italian banks from the years 2006 to 2014. They discovered that improving credit quality and loan monitoring reduces the number of problematic loans as long as NPLs stay below a predefined level, but if the bad loans ratio rises over the predetermined threshold, the link breaks down. Bardhan et al. (2019) applied the threshold regression model described by Hansen (1999) to panel data of 82 Indian banks spanning between 1996 and 2011 to assess the influence of bank-related endogenous variables on NPLs. They found that, beyond a predetermined level, both the CRAR and LGR had adverse effects on defaulted loans. According to the aforementioned brief literature review, banks' behaviour may be significantly predicted by the amount of NPLs they have. The banks may act differently, leaning toward more hazardous assets in their investment portfolios, when faced with larger problem loan levels than are typically acceptable. As a result, the size of bad loans stands out as a key indicator for spotting moral hazards in bank lending choices. Thus, by analysing threshold levels of bank NPLs, this study checks for the existence of moral hazard through their lending behaviour.

4. Hypotheses Development

- **Existence of Moral Hazard in the Indian banking industry.**

Following Thomas and Thakur (2020) and Zhang et al. (2016), the moral hazard principle suggests that management would attempt to offset losses by increasing lending to maximise their prospects of recovery. Bank managers can be forced to relax their criteria or accept riskier applications to increase loan growth, thus raising their overall risk exposure. This behaviour could also be motivated if the bank is under the implicit assumption that it would be supported by the government even if they incur losses with additional risky lending.

H1. *When a bank is under distress, it engages in risky lending activities.*

If it is concluded that when the bank is under huge stress of impaired loans it engages in riskier lending, it would be conclusive proof that the bank is willing to take on more risk even when it is already under distress and thus exhibiting moral hazard behaviour.

- **Existence of Moral Hazard with respect to the systemic importance of the banks.**

In this study, the existence of moral hazard is tested across banks with different systemic importance. Moral hazard may or may not exist at all levels of systemic importance. However, a systemically important bank might participate in riskier activities due to the implicit assumption of government assistance in times of difficulty, as its failure might have a negative influence on the whole economy (Evaluation of the effects of too-big-to-fail reforms by the Financial Stability Report, 2020; Framework for Dealing with Domestic Systemically Important Banks by RBI 2014). In this study the lending behaviour of these banks is examined. Thus, following Thomas and Thakur (2020) and Zhang et al. (2016) the lending behaviour of the banks is observed across different systemic importance categories of banks, especially when the bank is burdened with a high level of impaired loans.

H2. *When a bank is under distress, a systemically important bank engages in riskier lending activities.*

5. Data and Variables

Data was taken from 1 April 2012, through 31 March 2020. RBI announced its SBI as the first TBTF bank in 2013 and hence with a 1-year lag, the data was obtained from 2012. After 2020 major bank mergers took place which would have made the sample size smaller, hence the limits to 2020. The study is based on all the public and private sector banks with 38 banks in total. This study is based on all the public and private sector banks. Data relating to the bank's fundamentals were collected from the RBI database, "Database on Indian Economy (DBIE)". The data obtained is balanced and outliers were removed for data analysis.

5.1. Systemic Importance (Moderating Variable)

The process of determining the systemic importance of banks uses five sets of indicators, which are the same as those used by BRI for assigning TBTF status. These indicators are classified into further sub-categories as shown in Tables 2 and 3. Based on this set of indicators, a composite score indicating systemic importance for each bank is computed.

Table 2. Systemic Importance Indicators and their weightage.

S. No.	Indicator	References	Variable	References	Weightage
1	Size (20%)	BCBS approach & DSIB criteria by RBI	Total assets	Chen et al. (2014)	20%
2	Interconnectedness (20%)	BCBS approach & DSIB criteria by RBI	Intra-financial system assets	BCBS approach & DSIB criteria by RBI	6.67%
			Intra-financial system liabilities	BCBS approach & DSIB criteria by RBI	6.67%
			Securities outstanding	BCBS approach & DSIB criteria by RBI	6.67%
3	Substitutability (20%)	BCBS approach & DSIB criteria by RBI	Bank branches	Author's choice	6.67%
			Payments made in INR using RTGS and NEFT systems	BCBS approach & DSIB criteria by RBI	6.67%
			Number of ATMs	Author's choice	6.67%
4	Complexity (20%)	BCBS approach & DSIB criteria by RBI	Cross-Jurisdictional assets	Chen et al. (2014)	6.67%
			Cross-Jurisdictional Liabilities	BCBS approach & DSIB criteria by RBI	6.67%
			Liability on forward contracts	Author's choice	6.67%
5	Ownership (20%)	(Sironi 2003)	Public		20%
			Private		0%

Table 3. Systemic Importance Variables and their Sub-categories.

Variable	Sub-Categories
Intra financial system assets	Lending to financial institutions Investments in India
Intra-financial system liabilities	Borrowings from other financial institutions Deposits of other financial institution
Cross Jurisdictional assets	Advances outside India Foreign currency assets Invest outside India
Cross Jurisdictional Liabilities	Deposits from branch outside India Borrowings outside India Foreign currency liabilities

5.2. Indicators

Size. The size of a bank is observed as a significant measure of systemic risk. According to Basel III, in the official BCBS approach, the size category is measured through the "total exposure" of a bank. However, the indicator "total exposures" needs both on-balance sheet and off-balance sheet items, which are not available in a concise manner in any software. Therefore, "total assets" on the balance sheet are adopted as a proxy for size.

Interconnectedness. Systemic risk can rise through connectivity and interlinkages between various other banks, both directly and indirectly. If one bank defaults, then it might not be able to pay its interbank liabilities and, thereby, the probability of distress for other banks or other financial institutions may increase, which could lead to domino effects of default contagion within the system. This variable is measured by the size of intra-financial system assets, intra-financial system liabilities, and total marketable securities of the bank. They are further classified into sub-categories, which are given in Table 3.

Non-substitutability. This denotes a bank's systemic importance within the system by analysing the difficulty for other banks to provide parallel services in case of a default. The three sub-categories used under this category are bank branches, number of ATM's and payments made using RTGS and NEFT.

Complexity. This category of systemic importance concerns the "too-complex-to-fail" theory. The idea behind the variable is that a complex bank is more difficult to dissolve than a less complex one in the event of a failure, as it requires greater costs and time.

Cross-jurisdictional assets, liabilities on forwarding contracts and cross-jurisdictional liabilities are used with equal weights. These variables are further classified, and are given in Table 3. The two indicators: cross-jurisdictional assets and cross-jurisdictional liabilities, indicate the bank's activities outside India to define how much international bearing would occur from its distress or failure. The idea is that the greater the global reach of a bank, the more widespread the spillover effect would be from its failure.

Ownership. This study, apart from the indicators of the systemic importance as given by BCBS and RBI, also considers ownership due to its high significance in the context of the Indian banking industry. As discussed in the earlier section, ownership plays a significant role in influencing the lending behaviour of the managers and hence the NPA level.

Table 4 presents list of variables with their respective definition and abbreviation. Table 5 presents a summary of all the variables used in this study and Table 6 presents the Correlation matrix.

Table 4. List of variables with their respective definition and abbreviation.

Variables	Description	Abbreviation	Period
Systemic importance	Dummy variable with M1—most important banks. M3- least important bank.	m1 m2 m3	2011–2020
Asset quality	The ratio of net NPA To net advances	NNPL	2011–2020
LGR	$(\text{loans}_t - \text{loans}_{t-1})$*100/loans of PY	LGR	2011–2020
Deposit growth	deposits of the current year − deposits of previous year*100/deposits of the previous year.	Deposit growth	2012–2020
Capital Adequacy	The capital adequacy ratio includes both tier 1 and tier 2 capital	CRAR	2011–2020
Equity Ratio	(Tier 1 + Tier 2 capital)/Total assets	Equity ratio	2011–2020

Table 5. Summary of variables.

Variable	Observations	Mean	Std. Dev.	Min	Max
M1	380	0.326	0.469	0	1
M2	380	0.368	0.483	0	1
M3	380	0.305	0.461	0	1
NNPL	380	13.201	15.011	−31.215	116.89
LGR	380	12.772	14.69	−31.215	116.89
Deposit Growth	380	9.078	15.690	−56.91	132.074
CRAR	380	13.011	2.657	9.5	23.2
Equity Ratio	380	13.568	1.235	10.2	22

Table 6. Correlation matrix of the variables.

	M1	M2	M3	NNPL	LGR	Deposit Growth	CRAR
M1	1.0000						
M2	−0.5316	1.0000					
M3	−0.4613	−0.5063	1.0000				
NNPL	−0.0696	−0.1014	0.1771	1.0000			
LGR	−0.1004	−0.0911	0.1976	0.9671	1.0000		
Deposit Growth	−0.0526	−0.0549	0.1111	0.4840	0.5373	1.0000	
CRAR	−0.0668	−0.1848	0.1255	0.4699	0.4681	0.3282	1.0000

5.3. Quantifying Moral Hazard Behaviour through Lending Behaviour

Lending Behaviour. The relationship between LGR and NPLs was used to depict the lending behaviour of the banks. If with an increase in the LGR, the NPL also increases, this shows that the bank is indulging in risky lending activities and vice-versa.

When they are faced with an increase in the number of impaired loans, the banks either adopt safe lending practices or indulge in risky lending activities with the expectation of high returns to maximise their prospects of recovery. It is expected that a systemically important bank, under the impression of government support in times of distress, may indulge in riskier lending activities whereas a least systemically important bank might adopt a safe lending path. This is consistent with a study by Bruche and Llobet (2011), according to which banks, to maximise their prospects of recovery when they are threatened with bankruptcy, may act differently and skew their asset portfolios toward risky assets. Thus, the lending choices made by these banks are a key indicator for spotting moral hazard behaviour in banks' lending decisions.

The Loan Growth Rate (Regime-Independent Variable) is computed as (Loans of the current year − Loans of the previous year)*100/Loans of the previous year. Loans include unsecured advances and the term loans made by the bank in the respective year. It is crucial to include lags of LGR in the models. According to Clair (1992), a higher LGR results in a decline in loan quality, but only with some delays, whereas the contemporaneous relationship between LGR and NPLs ratio should be negative. This variable is the regime variable in the threshold regression, as this would be divided between two regimes (in a single threshold model) based on the threshold value determined endogenously. In the context of threshold regression, the regime variable refers to the variable which is categorised into different categories based on the threshold variable value.

Net Non-Performing Loans. One-year lagged values of Net-NPLs ratio ($NNPL_{t-1}$) were used as the threshold variable denoting the level of financial distress faced by the bank. Contemporaneous values ($NNPL_t$) were used as the dependent variable.

Control Variables. The control variables vary according to different models in the study and have been listed in the next section with their respective models.

6. Research Methodology

6.1. Systemic Importance of the Banks

The study is based on panel data with 38 banks in total, varying from 2012 to 2020. Using the above-mentioned indicators, systemic importance scores for each bank were calculated. Based on the weights assigned to each variable as mentioned in Table 2, scores for each bank were calculated. After obtaining the scores for all the banks for the period 2012–2020, the banks were arranged in descending order based on their systemic importance scores to get the year-wise sequence of most important to least important banks. Then dummies were created by dividing the banks into three categories: m1, m2 and m3; where, m1 represents the set of most important banks, m2 represents banks with a medium level of importance; and m3 represents the least important set of banks. It is to be noted that the scores of the banks are time-variant and, therefore, a bank's category may change, implying the changing systemic importance of the bank across different years.

6.2. Evidence of Moral Hazard through Threshold Regression

Non-performing loans (NPL) are an unwanted by-product of the lending activity in the banking industry. They occur either due to bad luck or bad management (Berger and DeYoung 1997). The former relates to macroeconomic conditions or the borrower's inability to repay, whereas the latter depicts the problem of moral hazard. Moral hazard cannot be directly observed; nonetheless, it can be inferred from the banks' conduct. Excessive risk-taking in lending is one of the key indications of the moral hazard problem according to Jensen (1976). However, there is a certain level of risk involved in every loan given by the bank; thus, in this study moral hazard was identified by observing the lending behaviour of the banks when they were already under the pressure of a high level of impaired loans. The moral hazard principle suggests that if the bank is under distress, its management would attempt to offset the losses by increasing lending to maximise its prospects of recovery. Bank managers can be forced to relax their criteria or accept riskier applications to increase loan growth, thus raising their overall risk exposure. This behaviour could also be motivated if the bank is under the implicit assumption that it would be supported by the government even if it incurs losses with additional risky lending. If taking on more risk finally pays off, the shareholders will receive the gains, while depositors will bear the brunt of any potential losses. Thus, by employing Panel Threshold Regression, we examine whether banks' lending practices are sensitive to NPL levels exceeding a certain threshold and, more importantly, whether banks with higher NPL ratios tend to adopt a more aggressive and riskier lending approach that eventually worsens the NPL ratio. If the banks indulge in risky lending when it they already beyond the threshold level of NPL, it would depict the problem of moral hazard. The effect of loan growth rate on the level of NNPL was observed to study the lending behaviour of the banks. If NNPL increases with a rise in the LGR, this shows that the bank is engaged in risky lending.

Jensen (1976) suggest that managers have strong incentives to act contrary to the interests of both investors and the regulator, and that moral hazard may lead to excessive risk-taking, reducing asset quality and ultimately causing the organisation to fail. According to Keeley (1990), agents can fully benefit from profitable results but have only minimal obligations when they fail. According to a study by Kahneman and Tversky (1979), agents are risk-averse when presented with certain benefits, but risk-seeking when they face certain losses. It is thus acceptable to suggest that in a troubling scenario, the bank management has an incentive to enhance risk-taking (Keeley 1990; Hellman 2000; Allen and Gale 2001). As a result, this article employs a threshold regression model to identify moral hazard issues. It is intended to categorize individual observations based on the value of a predetermined variable.

The model depicted in Figure 1 explains the model framework employed in this study. As per our hypotheses, lagged values of NPA as the threshold variable and systemic importance of banks as the moderating variable affect the lending behaviour of banks. This is explained in further sections of the study by Panel Threshold Regression Approach.

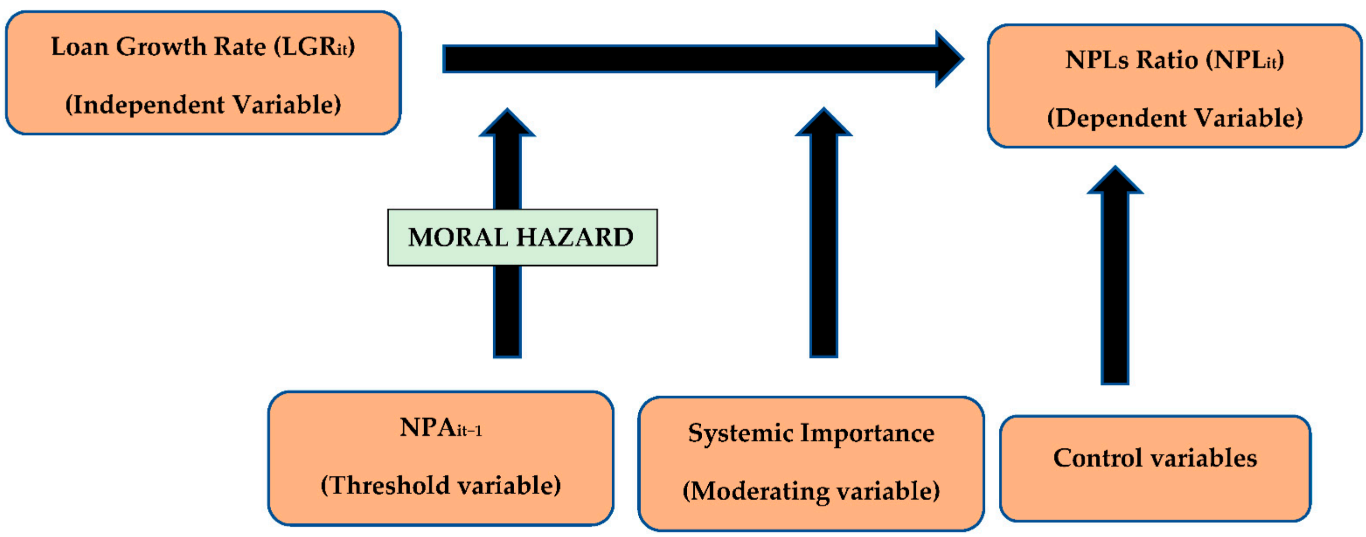

Figure 1. Model framework. Source: Authors.

6.3. Panel Threshold Regression

In this study, threshold regression was employed for a non-dynamic panel model with individual fixed effects. Whether regression models belong to discrete classes or are uniformly applied to all data in a sample remains to be seen. The answer lies in threshold regression. The jumping behaviour, or structural break in the relationship between variables, is described by the threshold model. The threshold autoregressive (TAR) model is one of the most common examples of this model type in nonlinear time series (Tong 1983). Given a balanced panel of data (*i* for the cross-sectional index and *t* for the time series part), the structural equation can be written as:

$$Y_{it} = \alpha + \beta 1 X_{it}\ I(q_{it} < \gamma) + \beta 2 X_{it}\ I(q_{it} \geq \gamma) + \mu_i + \in_{it} \tag{1}$$

where, q_{it} is the threshold variable, and γ is the threshold parameter that segregates the regression into two regimes with coefficients $\beta 1$ and $\beta 2$. u_i is the individual effect, I is the indicator function, which equals 1 if the statement in the bracket is true and 0 if it is false, and e_{it} is the error term. This model permits a partial threshold effect as well as the endogenous selection of the threshold value. Depending on whether q_{it} is lower or higher than γ (threshold parameter), the observations are split into two regimes. These regimes may be identified by the $\beta 1$ and $\beta 2$ different regression slopes and, accordingly, the relevant slope is selected. The components of X_{it} and q_{it} must not be time-invariant for $\beta 1$ and $\beta 2$ to be identified. It is assumed that the error e_{it} has an independent and identically distributed (iid), a mean of zero, and a finite variance σ^2. Chan (1993) and Hansen (1999) advocate least squares estimation of the threshold variable. The concentrated sum of squared errors can be minimised to the greatest extent to obtain this. As a result, the least squares estimator is $\hat{\gamma}$ where

$$\hat{\gamma} = \text{argmin}\gamma \text{S1}(\gamma)\gamma \tag{2}$$

According to Hansen (1999), $\hat{\gamma}$ is a consistent estimator for γ, the easiest way to determine if it is true is to construct the confidence interval using the "no-rejection region" technique and the likelihood-ratio (LR) statistic, as shown below

$$\text{LR1}(\gamma) = \{\text{LR1}(\gamma) - \text{LR1}(\gamma)\}/\sigma^2 \overset{Pr}{\to} \xi \tag{3}$$

$$\Pr(\text{x} < \xi) = (1 - \text{e}^{-\text{x}/2})^2$$

Testing if the coefficients are identical in each regime and looking for a threshold effect are equivalent tests. The linear model vs the single-threshold model is the alternative to the null hypothesis.

H0: $\beta 1 = \beta 2$
H1: $\beta 1 \neq \beta 2$

In the case of H0, the threshold doesn't exist, and the asymptotic distribution is irregular. To examine the importance of the threshold effect, we apply bootstrapping to the crucial values of the F statistic. A bootstrap method to assess the statistical significance of the threshold effect is also described. Our empirical study begins by determining if threshold effects exist and setting the threshold level for each model. We compute bootstrap *p*-values since the Likelihood Ratio statistics are typically non-standard. According to the bootstrap *p*-values, the Likelihood Ratio test statistics are often significant. In contrast to the linear model, these data support the presence of the threshold effect. The threshold-effect test is also sequential, that is, if we reject the null hypothesis in a single-threshold model, then we must test the double-threshold model. The null hypothesis is a single-threshold model, and the alternative hypothesis is a double-threshold model. Using the above explanation, the following model is proposed to test the existence of Moral Hazard.

Model 2 to 5

$$\begin{aligned} NNPL_{it} = \alpha + \beta 1 \sum_{j=0}^{k} LGR_{i,t-j}(NPL_{i,t-1} \leq \gamma) \\ + \beta 2 \sum_{j=0}^{k} LGR_{i,t-j}(NPL_{i,t-1} > \gamma) + \delta X_{i,t} + \in_{it}) \end{aligned} \tag{4}$$

where LGR = Loan Growth Rate = ($loans_t - loans_{t-1}$)*100/loans of PY; NNPL = Net-Non performing loan ratio. Vector X represent other explanatory variables. i refers to the bank and t refers to the year. $\beta 2$ needs to be considered when banks face severe loan losses (performing over the threshold value), otherwise $\beta 1$.

Model 2 sets k = 0, contemporaneous LGR.
Model 3 sets k = 1
Model 4 sets k = 2
Model 5 combines models 2, 3 and 4.

It is crucial to include the lags of LGR in the models. While the contemporaneous connection between LGR and NPL ratio should be negative, Clair (1992) asserts that a greater LGR causes a drop in loan quality, but with certain delays. While the contemporaneous connection between LGR and NPL ratio should be negative, Clair (1992) asserts that a greater LGR causes a drop in loan quality, but only with some delays. For banks with sizable prior losses (or NPLs), dilution of loans (greater loan growth) may temporarily lower the ratio of NPLs. However, to increase loan growth, banks may need to reduce their lending rates, reduce their requirements, or approve riskier applicants, which might result in greater upcoming losses. Therefore, we anticipate that delayed LGR and NPLs will have a positive relationship. Only the sign of the coefficient between LGR_{t-1} and the NPL ratio is examined in this hypothesis. However, if all the banks despite the difference in their systemic importance are found to be engaged in risky lending beyond the threshold level of NPL, the value of coefficients is also considered. Thus, different models with different year-lag values are taken for LGR as the regime variable.

Control Variables

- Capital Adequacy (CRAR) is measured by the ratio of capital to risk-weighted assets. It has a negative relationship with the riskiness of the banks. It is used as one of the potential NPA determinants, with a detrimental effect anticipated. This assumption is based on the claims made by Swami et al. (2019) and Salas and Saurina (2002) that a bank with a greater capital adequacy ratio (CRAR) (or equity ratio) will typically have fewer NPLs (NPAs) and be viewed as a safer organisation when compared to its peers.
- Deposit growth is calculated as (deposits of the current year − deposits of the previous year)*100/deposits of the previous year. Deposits here include demand deposits (other than inter-bank), term deposits, and savings deposits.

Model 6 to 8

$$\begin{aligned} NPL_{it} = \alpha + \beta 1 \sum_{j=0}^{k} LGR_{i,t-j}(NPL_{i,t-1} \leq \gamma) \\ *\text{systemic importance category}_{it-1} \\ + \beta 2 \sum_{j=0}^{k} LGR_{i,t-j}(NPL_{i,t-1} > \gamma) \\ *\text{systemic importance category}_{it-1} + \delta X_{i,t} + \in_{it} \end{aligned} \quad (5)$$

where LGR = Loan Growth Rate = ($loans_t$- $loans_{t-1}$)*100/loans of PY; NNPL = Net-Non performing loan ratio. Systemic importance category is a dummy variable with three categories—m1, m2, and m3, wherein m1 represents the set of banks with the highest systemic importance, and m3 shows the least important banks.

Model 6 sets k = 0 which includes no lags of the LGR but just the contemporaneous LGR.
Model 7 sets k = 1 includes the lagged LGR.
Model 8 sets k = 2 includes the lagged LGR

Control Variables

- Capital Adequacy (CRAR)
- Deposit growth

Models 6–8 use different categories of banks based on their systemic importance scores to evaluate the impact of a bank's systemic importance in creating moral hazard. The existence of moral hazard can be traced to the nature of the relationship between the dependent variable (NNPL) and the interaction terms of the bank's category and the LGR (both contemporaneous relations and with lagged values). This is indicated by the sign of the coefficients in the regression results. Details of each model with their respective dependent variable, Regime Dependent variable and Threshold variable is given in Table 7.

Table 7. Estimation Parameters.

Estimation Model	Dependent Variable	Independent Variables (Like Control Variables)	Regime Dependent Variable	Threshold Variable
Model 2–5	NNPL ratio	Deposit growth, CRAR (Capital adequacy ratio)	LGR with 0, 1 and 2 lagged periods	NPL_{t-1}
Model 6–8	NNPL ratio	Deposit growth, CRAR (Capital adequacy ratio)	LGR, LGR*m1, LGR*m3 with 0, 1 and 2 lagged periods	NPL_{t-1}
Model 9–12	NNPL ratio	Deposit growth, equity ratio	LGR with 0, 1 and 2 lagged periods	$CRAR_{t-1}$
Model 13–15	NNPL ratio	Deposit growth, equity ratio	LGR, LGR*m1, LGR*m3 with 0, 1 and 2 lagged periods	$CRAR_{t-1}$

According to threshold panel regression, empirical research must start by identifying threshold effects and defining a threshold for the respective models. Therefore, this study first checked for the existence of a threshold for each of the models stated above by employing threshold estimations based on Hansen (1999). The significance of each of the threshold values was determined using their respective p-value with the null hypothesis linear regression model or no threshold effect and a single threshold as the alternative hypothesis. Tests for second or third threshold effects may be run if a single-threshold effects model is shown to be significant. In our analysis, the second threshold effect were overall insignificant and hence they have not been reported.

7. Empirical Results

This section evaluates whether the Indian banking system demonstrates moral hazard across different systemic importance ratings of the banks. This section also checks for the difference in the behaviour of different sets of banks in times of high NPLs based on their systemic importance scores. Threshold panel regression was used to study the behaviour of banks in times of distress. Since models 6–8 include interaction terms, the adjusted t statistic was computed using the linear combination of the interaction terms and is presented in Table 10 The same was used to compare the coefficients of interaction terms (variables of interest) to check for the degree of moral hazard. The following conclusions are made based on these adjusted t statistics only. All the tables regarding the results are presented in the appendix.

- **Existence of Moral Hazard in the Indian banking industry**

<u>Threshold effects</u>. Models 2–5 study the lending behaviour of all banks taken together in the Indian banking industry. Model 2 uses no lags for LGR, and thus studies its contemporaneous relationship with NPLs. The null hypothesis in the testing for threshold effects (linear relationship) was rejected in model 2 only due to the significant p-values. Thus, in contrast to the linear model, these results support the hypothesis that the threshold effect is present with k = 0. The null hypothesis cannot be rejected for the other models. The threshold values for all models and consequent p-values are listed in Table 8. Before discussing regression findings, we examine the characteristics of banks that are either over

or below the NPL ratio criteria. On average, 62.8% of banks had NPL ratios lower than the average threshold figure in models 2 to 5. As expected, banks may be influenced by moral hazard issues, but only a very small number of those with substantial issues will respond accordingly. We now assess how banks behave on both sides of the threshold after establishing the presence of a nonlinear threshold effect.

Table 8. Estimation of Single-Threshold Effects Model.

Model	NNPL (Threshold Variable)	Confidence Interval (95%)	Residual Sum of Squares	*p*-Value
2	2.96	[2.44%–3.08%]	1171.2312	0.040 **
3	0.75	[0.73%–0.76%]	11800	0.140
4	4.48	[3.74%–4.72%]	10200	0.160
5	2.88	[2.42%–2.93%]	918.39	0.088 *
6	2.9	[2.53%–2.96%]	1036.7931	0.000 ***
7	5.73	[5.68%–6.16%]	11500	0.041 **
8	4.48	[4.07%–4.72%]	9660.5425	0.01 ***

Note: The confidence interval is computed using the 5% critical value for the non-rejection area, and the *p*-values are produced using 400 bootstraps. *** Statistical significance at 1% level. ** Statistical significance at 5% level. * Statistical significance at 10% level.

Regression results. Table 9 shows the regression results for the above-mentioned five models. Model 1 illustrates that when no threshold impact is permitted, the only critical components are LGR with k = 0 and deposit growth. The threshold effect and the current LGR level are included in Model 2. In model 2, we note that the contemporaneous impact of LGR on distressed banks is adverse. Model 2 demonstrates that the LGR raises NPLs when banks previously had losses (NNPL ratio is higher than the threshold value) and also when they are reasonably safe (NNPL ratio is less than the threshold value). However, by comparing the t values, it can be observed that the value of this increase in NNPL ratio is quite low when banks are safe compared to when banks are troubled (comparing the standardised values of the coefficients). These results are in accordance with the empirical findings of Clair (1992) and Zhang et al. (2016). These results demonstrate that the loan growth ratio raises NPLs with a higher value when banks are experiencing prior sizable loan losses as compared to when banks are relatively safe. For banks with higher NPL ratios, reckless lending by those struggling banks might result in major difficulty given that the yearly LGR on average is 12.72% and 13% for NPLs. The aforementioned data and results confirm our theory that bank managers act poorly under pressure caused by prior losses, perhaps setting up an even worse situation.

Table 9. Panel Threshold Regression Results. Threshold Variable—NNPL. Net NPLs—Dependent Variable.

Explanatory Variables	1	2	3	4	5
Intercept	−0.4528 (0.8498)	−0.7728 (0.8185)	−2.5010 (2.5781)	−3.7149 (2.7747)	−1.0054 (0.8448)
LGR	0.9487 *** (0.0187)				
LGR_{t-1}	0.0142 ** (0.0067)				
LGR_{t-2}	0.0165 (0.0107)				
Deposit growth	0.0569 *** (0.0196)	0.0308 (0.0195)	0.8609 *** (0.0349)	0.8209 *** (0.0373)	0.0312 (0.0207)
CRAR	−0.0218 ** (0.0107)	0.0287 * (0.0147)	0.2711 ** (0.1055)	0.3218 (0.2172)	0.01587 (0.0665)

Table 9. *Cont.*

Explanatory Variables	1	2	3	4	5
LGR ($NNPL_{t-1} < \gamma$)		0.0026 ** (0.0013)			0.9954 *** (0.0239)
LGR ($NNPL_{t-1} > \gamma$)		1.0137 *** (0.0202)			0.9255 *** (0.0202)
LGR_{t-1} ($NNPL_{t-1} < \gamma$)			−0.0315 (0.0428)		0.0225 ** (0.0147)
LGR_{t-1} ($NNPL_{t-1} > \gamma$)			0.0681 ** (0.0324)		0.0135 * (0.007)
LGR_{t-2} ($NNPL_{t-1} < \gamma$)				0.0662 ** (0.0351)	0.0060 (0.0124)
LGR_{t-2} ($NNPL_{t-1} > \gamma$)				−0.1858 *** (0.0828)	0.0251 (0.0185)
No. of Observations	304	342	342	304	304
R^2	0.9701	0.9733	0.7317	0.6858	0.9716

*** Statistical significance at 1% level. ** Statistical significance at 5% level. * Statistical significance at 10% level.

For models 3 and 4, the presence of a threshold effect could not be determined by the threshold estimation. According to regression results, deposit growth is the only significant independent variable with a positive relation to the NPL ratio. The NPA ratio of a bank increases with its deposit growth. For model 5, when we evaluate the lagged and the contemporaneous impact combined, we see that the contemporaneous impact of LGR and the lagged effect for those struggling banks stay positive, but the lagged effect with k = 2 remains minor. Clair (1992) would approve of this behaviour Banks that have previously suffered big losses attempt to mitigate the impact of NPLs by expanding loans.

In other words, because of the larger denominator, the contemporaneous NPLs ratio with delayed data is the most significant. Banks may be forced to take excessive risks or become less careful when issuing loans, worsening the problem in the future. As a result, our findings imply that in order to prevent the continued deterioration of already troubled banks and their eventual collapse, which would cause further system instability, authorities must pay particular attention to banks with NPLs over the threshold value.

- **Existence of Moral Hazard with respect to the different systemic importance of the banks.**

Threshold effects. Models 6–8 studied the lending behaviour of banks with respect to their systemic importance. The null hypothesis in the testing for threshold effects (linear and non-linear relationships) was rejected in models 6–8 due to the significant *p*-values. In contrast to the linear model, these results support the hypothesis that the threshold effect is present with k = 0 and 1, even when the systemic importance of the banks is considered in place of the whole banking industry. The null hypothesis was rejected in model 8, also, unlike in model 4 with k = 2, after the systemic importance of the banks was taken into consideration. We now assess how banks behave on both sides of the threshold after establishing the presence of a nonlinear threshold effect.

Regression results. Table 10 shows the threshold panel regression results for 6–8 models. The threshold effect of lagged values of NNPL on the LGR with k = 0 and 1, is shown in Models 6 and 7. Models 6 and 7 exhibit a positive relationship between LGR and NNPL ratio for both m1 category of banks whether they are distressed or not; however, the m3 category of banks signifies an opposite relation. The least important banks (m3 category) display a negative relationship when they are distressed and a positive relationship when they are relatively safer. These findings are in line with our hypothesis that systemically important banks indulge in riskier lending when they are distressed.

These results were expected due to the implicit assumption of government support by the systemically important banks (m1 category banks). The results for medium-importance banks were not found to be significant in the regression results. Similar results were found for model 7 with k = 1 further supporting the hypothesis of the existence of risky lending behaviour by systemically important banks.

Table 10. Panel Threshold Regression Results. Threshold Variable—NNPL. Net NPLs—Dependent Variable.

Explanatory Variables	6	7	8
LGR ($NPL_{t-1} < \gamma$)	0.0579 ** (0.0245)		
LGR ($NPL_{t-1} > \gamma$)	−0.0763 ** (0.0321)		
LGR*m1 ($NNPL_{t-1} < \gamma$)	0.1100 *** 0.1679 (0.0263)		
LGR*m1 ($NNPL_{t-1} > \gamma$)	0.1246 *** 0.0483 (0.0388)		
LGR*m2 ($NNPL_{t-1} < \gamma$)	0.0255 0.0834 (0.0242)		
LGR*m2 ($NNPL_{t-1} > \gamma$)	−0.0147 −0.091 (0.0413)		
LGR_{t-1} ($NPL_{t-1} < \gamma$)		0.0874 * (0.0517)	
LGR_{t-1} ($NPL_{t-1} > \gamma$)		−0.4511 * (0.2669)	
LGR_{t-1}*m1 ($NPL_{t-1} < \gamma$)		0.1865 ** 0.2739 (0.0883)	
LGR_{t-1}*m1 ($NPL_{t-1} > \gamma$)		0.5607 ** 0.1096 (0.1241)	
LGR_{t-1}*m2 ($NPL_{t-1} < \gamma$)		0.2062 *** 0.2936 (0.0766)	
LGR_{t-1}*m2 ($NPL_{t-1} > \gamma$)		−0.4710 −0.9221 (0.3321)	
LGR_{t-2} ($NPL_{t-1} < \gamma$)			0.0553 (0.0560)
LGR_{t-2} ($NPL_{t-1} > \gamma$)			0.7007 *** (0.1932)
LGR_{t-2}*m1 ($NPL_{t-1} < \gamma$)			0.0434 (0.0878)
LGR_{t-2}*m1 ($NPL_{t-1} > \gamma$)			0.7862 (0.2337)
LGR_{t-2}*m2 ($NPL_{t-1} < \gamma$)			0.0052 (0.0764)

Table 10. *Cont.*

Explanatory Variables	6	7	8
LGR_{t-2}*m2 ($NPL_{t-1} > \gamma$)			0.5072 *** (0.2324)
Intercept	0.4239 (1.2068)	2.5469 (4.1363)	1.7171 (4.5505)
Deposit growth	0.0380 ** (0.0186)	0.8528 *** (0.0354)	0.8077 *** (0.0378)
CAR	−0.0442 * (0.0226)	0.2596 ** (0.1124)	0.3287 *** (0.1183)
M1	−1.3739 (1.4935)	−6.7135 (5.0530)	−8.9486 (5.6063)
M2	−0.7973 (1.3816)	−7.3072 (4.6206)	−6.7416 (5.1461)
No. of observation	342	342	304
R^2	0.9763	0.7379	0.7016

*** Statistical significance at 1% level. ** Statistical significance at 5% level. * Statistical significance at 10% level.

To our surprise, in model 8, the m3 and m2 categories of the banks demonstrated moral hazard when they experienced prior sizable loan losses with k = 2, whereas the results of the m1 category banks were not significant. These results were not expected because even the least important banks (m3 category banks) are engaged in risky lending when they are under the stress of a high NPL ratio. The aforementioned information and results support the hypothesis that banks act poorly while under pressure from previous losses, perhaps creating a worse scenario. Since there exists no prior research on the systemic importance of the banks and Moral hazard, these results could not be supported by the existing literature. However, robustness analysis was performed to further support our finding of risky lending behaviour by systemically important banks.

8. Robustness Analysis

So far, empirical findings suggest that the lagged values of NPLs might be a significant regulatory variable for monitoring moral hazard issues and avoiding asset quality degradation in the Indian banking sector. Given that RBI has already implemented the Basel Accord, estimating the same econometric model by using Capital Adequacy Ratio (CRAR) would be interesting to see if it may also be an effective regulatory tool. For example, can moral hazard be recognised using the CRAR with the regulatory requirement of 8% (9% in India as mandated by RBI)? Therefore, we substitute the NNPL ratio in our regressions with the CRAR as our new threshold variable.

Louzis et al. (2012) argue that the bank's capital structure acts as an additional factor influencing the level of NPLs, arguing that a greater percentage of liabilities might promote riskier behaviour and hence raise NPLs, depending on bank size. We consider the equity ratio (capital/total assets) as one of the potential predictors of NPLs, and we expect it to have a negative influence as a greater level of CRAR or equity ratio indicates that a bank would have fewer NPAs and is seen as a safer organisation when compared to its peers (Swami et al. 2019; Salas and Saurina 2002). This may also be related to capital adequacy concerns, since a higher CRAR or equity ratio indicates that the bank is relatively secure and will have fewer NPLs (Berger and DeYoung 1997; Salas and Saurina 2002).

As done earlier with NNPL as the threshold variable, we first test for the existence of a threshold and estimate the threshold value. Table 11 summarises the findings. Except for model 12 with k = 2, the bootstrap *p*-values indicate the presence of a threshold effect, while the projected threshold values vary slightly. All four models have very loose bottom limits, but their upper values are nearly identical and close to the threshold value. The discovery of a 12.27% threshold has significant policy implications since, as per the Basel Accord, 8% CRAR is required and 9% as per RBI, both signify a possible moral hazard concern. Model 9 results remain the same as in Table 12. The signals for LGR and its lag are, as predicted, contrary to those for NPL regressions. When just LGR from the current period is incorporated in the threshold model, LGR has a considerable influence on the NPLs ratio in both regimes, albeit with opposing signs. Secure banks have a lower NPL ratio, whereas distressed banks have a higher NPL ratio. When delayed LGR is incorporated in calculations, we can observe that the contemporaneous effect of LGR decreases the struggling banks' loan ratios, which is quite similar to the process outlined in the earlier threshold regression with NNPL. However, the higher the degree of the delayed NPL coefficient, the greater the short-term effect.

Table 11. Estimation of Single-Threshold Effects Model.

Model	CRAR (Threshold Variable)	Confidence Interval (95%)	Residual Sum of Squares	*p*-Value
9	12.92	(12.91%–13.00%)	1224.63	0.04 **
10	15.36	(13.81%–15.46%)	11.7	0.06 *
11	12.32	(12.29%–12.38%)	10400	0.67
12	12.84	(12.78%–12.86%)	953.652	0.09 *
13	10.14	(9.97%–10.22%)	1211.9013	0.04 **
14	10.70	(10.63%–10.78%)	11500	0.09 *
15	12.78	(12.73%–12.84%)	10100	0.61

*** Statistical significance at 1% level. ** Statistical significance at 5% level. * Statistical significance at 10% level.

Table 12. Panel Threshold Regression Results. Net NPLs—Dependent Variable. Capital to Risk weighted Assets—Threshold Variable.

Model	9	10	11	12
Variables				
Intercept	−1.605 (0.7591)	−2.9737 (2.3309)	−2.2206 (2.5231)	−0.3653 (0.7774)
LGR ($CAR_{t-1} < \gamma$)	0.9656 *** (0.0192)			0.9598 *** (0.0201)
LGR ($CAR_{t-1} > \gamma$)	−0.9229 *** (0.0224)			−0.9304 *** (0.0247)
LGR_{t-1} ($CAR_{t-1} < \gamma$)		0.0621 * (0.0361)		0.0336 * (0.0177)
LGR_{t-1} ($CAR_{t-1} > \gamma$)		−0.0561 ** (0.0257)		0.0159 ** (0.0075)
LGR_{t-2} ($CAR_{t-1} < \gamma$)			−0.0231 (0.0507)	0.0288 * (0.0158)
LGR_{t-2} ($CAR_{t-1} > \gamma$)			0.0657 * (0.0393)	0.0066 (0.0141)
Equity Ratio	−0.0068 (0.0663)	−0.3374 * (0.2045)	0.2280 (0.2181)	−0.0234 (0.0673)
Deposit growth	0.0754 *** (0.0196)	0.8569 *** (0.0345)	0.8358 *** (0.0374)	0.0641 (0.0210)
No. of observation	342	342	304	304
R^2	0.9720	0.7337	0.6785	0.9705

*** Statistical significance at 1% level. ** Statistical significance at 5% level. * Statistical significance at 10% level.

When the banks' systemic importance is taken into account, the findings are identical to those in Table 13, with the NNPL ratio as the threshold variable reflecting the hazardous lending behaviour of the systemically significant banks. However, when CRAR is used as the threshold variable, the findings for the m2 and m3 categories are not statistically significant.

Table 13. Panel Threshold Regression Results. Net NPLs—Dependent Variable. Capital to Risk weighted Assets—Threshold Variable.

Model	**13**	**14**	**15**
Variables			
Intercept	0.2606 (1.2765)	2.2677 (3.9168)	1.8071 (4.5208)
LGR ($CAR_{t-1} < \gamma$)	0.9596 *** (0.0604)		
LGR ($CAR_{t-1} > \gamma$)	−0.9344 *** (0.0251)		
LGR*m1 ($CAR_{t-1} < \gamma$)	−0.3301 ** 0.6295 (0.1429)		
LGR*m1 ($CAR_{t-1} > \gamma$)	0.0342 −0.9002 (0.0262)		
LGR*m2 ($CAR_{t-1} < \gamma$)	−0.0429 (0.1211)		
LGR*m2 ($CAR_{t-1} > \gamma$)	0.0222 (0.0244)		
LGR_{t-1} ($CAR_{t-1} < \gamma$)		0.1034 (0.1363)	
LGR_{t-1} ($CAR_{t-1} > \gamma$)		−0.0823 (0.0584)	
LGR_{t-1}*m1 ($CAR_{t-1} < \gamma$)		−0.0893 (0.1914)	
LGR_{t-1}*m1 ($CAR_{t-1} > \gamma$)		0.1522 * (0.0886)	
LGR_{t-1}*m2 ($CAR_{t-1} < \gamma$)		−0.3703 * (0.2122)	
LGR_{t-1}*m2 ($CAR_{t-1} > \gamma$)		0.2086 *** (0.0747)	
LGR_{t-2} ($CAR_{t-1} < \gamma$)			−0.0839 (0.0867)
LGR_{t-2} ($CAR_{t-1} > \gamma$)			0.0668 (0.0611)
LGR_{t-2}*m1 ($CAR_{t-1} < \gamma$)			0.1033 (0.1175)
LGR_{t-2}*m1 ($CAR_{t-1} > \gamma$)			0.1298 (0.1127)
LGR_{t-2}*m2 ($CAR_{t-1} < \gamma$)			0.1518 (0.1114)
LGR_{t-2}*m2 ($CAR_{t-1} > \gamma$)			−0.0773 (0.0876)
M1	−0.6382 (1.6102)	−7.1093 (5.0551)	−8.0352 (5.7457)

Table 13. *Cont.*

Model	13	14	15
Variables			
M2	−0.7996 (1.4891)	−7.4321 (4.6099)	−5.5077 (5.2895)
Deposit growth rate	0.0641 *** (0.0191)	0.8547 *** (0.0353)	0.8445 *** (0.0383)
Equity Ratio	−0.0023 (0.0689)	0.3236 (0.2074)	0.2665 (0.2235)
No. of observation	342	342	304
R^2	0.9723	0.7378	0.6877

*** Statistical significance at 1% level. ** Statistical significance at 5% level. * Statistical significance at 10% level.

9. Conclusions

Systemically important banks play a significant role in a country's financial system due to their connectivity, complexity, lower substitutability, and size. Their collapse raises the possibility of a domino effect that could severely impact the country's economy. For instance, if a large bank fails, and other banks are dependent on it, they may also fail, as well as the organisations to which they are financially linked. The failure of a major bank could lead to a recession in the whole economy if the spillover effects produced by this process are significant enough. The TBTF policy's unanticipated by-product is the development of a moral hazard issue. These banks take on excessively risky projects and generally behave less responsibly than they would if they had to bear full responsibility for their actions due to the implicit assumption of government support in case of distress. On the other hand, a large number of bank creditors who depend on the government to safeguard their loans have little motivation to keep an eye on bank behaviour, or choose partnerships with banks that make wise choices demonstrating weak market discipline. Using panel threshold regression, the existence of moral hazard was tested by observing the lending behaviour of the banks in times of high levels of impaired loans. This study is based on 38 banks including both Public and Private sector banks. Our empirical results are evidence of the moral hazard behaviour that emerges due to the systemic importance of the banks in terms of their risky lending behaviour. These results are further supported by our robustness analysis using CRAR as the threshold variable. Overall, our results reflect the negative consequences of the high systemic importance of a bank and stress the need for policy modification regarding this criterion. RBI should closely monitor the NNPL ratio and the CRAR of the banks to control moral hazard behaviour, together with determining the threshold level of NNPL and CRAR that alters the lending behaviour of the banks. If continued for a long time, moral hazard behaviour could impact the solvency of these banks despite the higher capital norms laid down by RBI for these banks. Thus, it is concluded that despite the additional requirement of common equity Tier 1 capital, the systemic importance of the banks may harm the resilience of the banks instead of increasing it, as postulated by the Basel norms and the RBI. This study has several limitations which can be improved for further research. First, this study is based on the Indian Banking sector only, and thus the sample size is small. Inclusion of more nations can severely alter the results and present an improved version of this study. Second, this study calculates systemic importance scores using the RBI D-SIB criteria with few alterations due to data unavailability. This can be improved, and Principal Component Analysis (PCA) can be employed to build the index for systemic importance of banks. This would better reflect the systemic importance of each bank and further improve the results.

Author Contributions: Conceptualization, C.P.G. and A.J.; methodology, C.P.G. and A.J.; software, A.J.; validation, C.P.G.; formal analysis, C.P.G.; investigation, C.P.G. and A.J.; resources, A.J.; data curation, A.J.; writing—original draft preparation, A.J.; writing—review and editing, C.P.G.; visual-

ization, C.P.G.; supervision, C.P.G.; project administration, C.P.G. and A.J.; funding acquisition, C.P.G. and A.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data is available at the RBI's Database on Indian Economy.

Conflicts of Interest: The authors declare no conflict of interest.

References

Allen, Franklin, and Douglas Gale. 2001. *Comparative Financial Systems: A Survey*. Philadelphia: University of Pennsylvania, Wharton School Center for Financial Institutions.

Azgad-Tromer, Shlomit. 2017. Too important to fail: Bankruptcy versus bailout of socially important non-financial institutions. *Harvard Business Law Review* 7: 159. [CrossRef]

Banerjee, Saugata, Benoit Leleux, and Theo Vermaelen. 1997. Large shareholdings and corporate control: An analysis of stake purchases by French holding companies. *European Financial Management* 3: 23–43. [CrossRef]

Bardhan, Samaresh, Rajesh Sharma, and Vivekananda Mukherjee. 2019. Threshold effect of bank-specific determinants of non-performing assets: An application in Indian banking. *Journal of Emerging Market Finance* 18: S1–S34. [CrossRef]

Barr, Richard S., Lawrence M. Seiford, and Thomas F. Siems. 1994. Forecasting bank failure: A non-parametric frontier estimation approach. *Recherches Économiques de Louvain/Louvain Economic Review* 60: 417–29. [CrossRef]

Berger, Allen N., and Gregory F. Udell. 1994. Did risk-based capital allocate bank credit and cause a "credit crunch" in the United States? *Journal of Money, Credit and Banking* 26: 585–628. [CrossRef]

Berger, Allen N., and Robert DeYoung. 1997. Problem loans and cost efficiency in commercial banks. *Journal of Banking & Finance* 21: 849–70.

Boyd, John H., and Gianni De Nicolo. 2005. The theory of bank risk taking and competition revisited. *The Journal of Finance* 60: 1329–43. [CrossRef]

Boyd, John H., and Stanley L. Graham. 1998. Consolidation in US banking: Implications for efficiency and risk. In *Bank Mergers & Acquisitions*. Boston: Springer, pp. 113–35.

Bruche, Max, and Gerard Llobet. 2011. *Walking Wounded or Living Dead? Making Banks Foreclose Bad Loans*. London: London School of Economics, Financial Markets Group.

Chan, Kung-Sik. 1993. Consistency and limiting distribution of the least squares estimator of a threshold autoregressive model. *The Annals of Statistics* 21: 520–33. [CrossRef]

Chavan, Pallavi, and Leonardo Gambacorta. 2016. *Bank Lending and Loan Quality: The Case of India*. BIS Working Papers 595. Basel: Bank for International Settlements.

Chen, Yibing, Yong Shi, Xianhua Wei, and Lingling Zhang. 2014. Domestic systemically important banks: A quantitative analysis for the Chinese banking system. *Mathematical Problems in Engineering* 2014: 819371. [CrossRef]

Clair, Robert T. 1992. Loan growth and loan quality: Some preliminary evidence from Texas banks. *Economic and Financial Policy Review* 1992: 9–22.

Cumming, Douglas J., and Sofia A. Johan. 2013. *Venture Capital and Private Equity Contracting: An International Perspective*. Cambridge: Academic Press.

Dell'Ariccia, Giovanni, Paolo Mauro, Andre Faria, Jonathan D. Ostry, Julian Di Giovanni, Martin Schindler, Ayhan Kose, and Marco Terrones. 2008. *Reaping the Benefits of Financial Globalization*. Washington, DC: International Monetary Fund, pp. 1–50.

Demirgüç-Kunt, Asli. 1989. Deposit-institution failures: A review of empirical literature. *Economic Review* 25: 2–19.

Dionne, Georges, Pierre-Carl Michaud, and Maki Dahchour. 2004. *Separating Moral Hazard from Adverse Selection in Automobile Insurance: Longitudinal Evidence from France*. Tilburg: Tilburg University.

Duran, Miguel A., and Ana Lozano-Vivas. 2015. Moral hazard and the financial structure of banks. *Journal of International Financial Markets, Institutions and Money* 34: 28–40. [CrossRef]

Financial Crisis Inquiry Commission. 2011. *The Financial Crisis Inquiry Report: The Final Report of the National Commission on the Causes of the Financial and Economic Crisis in the United States Including Dissenting Views*. New York: Cosimo Inc.

Flannery, Mark J. 1989. Capital regulation and insured banks choice of individual loan default risks. *Journal of Monetary Economics* 24: 235–258. [CrossRef]

Flannery, Mark, and Stanislava Nikolova. 2004. Market discipline of US financial firms: Recent evidence and research issues. In *Market Discipline across Countries and Industries*. Cambridge: MIT Press, pp. 87–100.

Foos, Daniel, Lars Norden, and Martin Weber. 2010. Loan growth and riskiness of banks. *Journal of Banking & Finance* 34: 2929–40.

Gorton, Gary, and Richard Rosen. 1995. Corporate control, portfolio choice, and the decline of banking. *The Journal of Finance* 50: 1377–420. [CrossRef]

Hansen, Bruce E. 1999. Threshold effects in non-dynamic panels: Estimation, testing, and inference. *Journal of Econometrics* 93: 345–68. [CrossRef]

Haq, Mamiza, and Richard Heaney. 2012. Factors determining European bank risk. *Journal of International Financial Markets, Institutions and Money* 22: 696–718. [CrossRef]

Hellman, Joel S. 2000. *Measuring Governance, Corruption, and State Capture: How Firms and Bureaucrats Shape the Business Environment in Transition Economies*. Washington, DC: World Bank Publications, vol. 2312.

Hett, Florian, and Alexander Schmidt. 2017. Bank rescues and bailout expectations: The erosion of market discipline during the financial crisis. *Journal of Financial Economics* 126: 635–51. [CrossRef]

Honohan, Patrick. 1997. Banking System Failures in Developing and Transition Countries: Diagnosis and Predictions. Available online: https://www.bis.org/publ/work39.htm (accessed on 14 October 2022).

Husted, Bryan W. 2007. Agency, information, and the structure of moral problems in business. *Organization Studies* 28: 177–95. [CrossRef]

Jeanne, Oliver, and Anton Korinek. 2020. Macroprudential regulation versus mopping up after the crash. *The Review of Economic Studies* 87: 1470–97. [CrossRef]

Jensen, Michael C. 1976. Reflections on the State of Accounting Research and the Regulation of Accounting. *Stanford Lectures in Accounting* 1976: 11–19. [CrossRef]

Kahneman, Daniel, and Amos Tversky. 1979. On the interpretation of intuitive probability: A reply to Jonathan Cohen. *Cognition* 7: 409–11. [CrossRef]

Kaufmanh, George G. 1996. Bank failures, systemic risk, and bank regulation. *Cato Journal* 16: 17.

Keeley, Michael C. 1990. Deposit insurance, risk, and market power in banking. *The American Economic Review* 80: 1183–200.

Kornai, Janos. 1979. Economists and Economic Thought: The Oeuvre of Kenneth J. Arrow. *Acta Oeconomica* 23: 193–203.

Louzis, Dimitrios P., Angelos T. Vouldis, and Vasilios L. Metaxas. 2012. Macroeconomic and bank-specific determinants of NPLs in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of Banking & Finance* 36: 1012–27.

Machina, Mark, and Kip Viscusi, eds. 2013. *Handbook of the Economics of Risk and Uncertainty*. Newton: Newnes.

Maclachlan, Fiona C. 2001. Market discipline in bank regulation: Panacea or paradox? *The Independent Review* 6: 227–34.

Mishkin, Frederic S. 2006. How big a problem is too big to fail? A review of Gary Stern and Ron Feldman's too big to fail: The hazards of bank bailouts. *Journal of Economic Literature* 44: 988–1004. [CrossRef]

Moosa, Imad. 2010. The myth of too big to fail. *Journal of Banking Regulation* 11: 319–33. [CrossRef]

Nguyen, Quang Khai. 2020. Ownership structure and bank risk-taking in ASEAN countries: A quantile regression approach. *Cogent Economics & Finance* 8: 1809789.

Nguyen, Quang Khai, and Van Cuong Dang. 2022. Does the country's institutional quality enhance the role of risk governance in preventing bank risk? *Applied Economics Letters* 2022: 1–4. [CrossRef]

Nier, Erlend, and Ursel Baumann. 2006. Market discipline, disclosure and moral hazard in banking. *Journal of Financial Intermediation* 15: 332–61. [CrossRef]

Piatti, Dpmenico, and Peter Cincinelli. 2018. Does the threshold matter? The impact of the monitoring activity on NPLs: Evidence from the Italian banking system. *Managerial Finance* 45: 190–221. [CrossRef]

Salas, Vicente, and Jesus Saurina. 2002. Credit risk in two institutional regimes: Spanish commercial and savings banks. *Journal of Financial Services Research* 22: 203–24. [CrossRef]

Samantaraya, Amaresh. 2016. Procyclical credit growth and bank NPAs in India. *Economic and Political Weekly* 51: 112–19.

Schooner, Heidi Mandanis, and Michael W. Taylor. 2009. *Global Bank Regulation: Principles and Policies*. Cambridge: Academic Press.

Shen, ChungHua, and Chih-Yuan Lin. 2012. Why government banks underperform: A political interference view. *Journal of Financial Intermediation* 21: 181–202. [CrossRef]

Shleifer, Andrei, and Robert W. Vishny. 1997. The limits of arbitrage. *The Journal of Finance* 52: 35–55. [CrossRef]

Shrieves, Ronald E., and Drew Dahl. 2003. Discretionary accounting and the behavior of Japanese banks under financial duress. *Journal of Banking & Finance* 27: 1219–43.

Sironi, Andrea. 2003. Testing for market discipline in the European banking industry: Evidence from subordinated debt issues. *Journal of Money, Credit and Banking* 35: 443–72. [CrossRef]

Stern, Gary H. 1999. Managing Moral Hazard with Market Signals: How Regulation Should Change with Banking (No. 153). Available online: https://www.minneapolisfed.org/article/1999/managing-moral-hazard-with-market-signals-how-regulation-should-change-with-banking (accessed on 14 October 2022).

Swami, Onkar Shivraj, Arindam Sarkar, and Jyoti Prakash Sharma. 2019. Bank Consolidation in India: An Empirical Study to Identify Leading Indicators of Acquired Banks. *Prajnan* 48: 179–94.

Thomas, Robin, and Shailesh Singh Thakur. 2020. NPLs and Moral Hazard in the Indian Banking Sector: A Threshold Panel Regression Approach. *Global Business Review* 2020: 0972150920926135.

Tong, Howell. 1983. Threshold models. In *Threshold Models in Non-linear Time Series Analysis*. New York: Springer, pp. 59–121.

Yamamoto, Shinichi, Takau Yoneyama, and W. Jean Kwon. 2012. An Experimental Study on Adverse Selection and Moral Hazard. *Hitotsubashi Journal of Commerce and Management* 46: 51–64.

Zhang, Dayong, Jing Cai, David G. Dickinson, and Ali M. Kutan. 2016. NPLs, moral hazard and regulation of the Indian commercial banking system. *Journal of Banking & Finance* 63: 48–60.