An Empirical Inquiry into the Distortionary Effect of Bank Bailout Policies in India with Special Focus on the Financial Fragility

Author Note

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Abstract

By utilizing forward looking behavior of banks and their proclivity to risk, we provide an econometric and empirical perspective that provision of bailouts in banking industry leads to additional risk taking by these financial institutions. The sample includes stratified levels of 131 banks with their capital levels and additional covariates. The study is undertaken for the time period of 2008-2020 with exhaustive study into the bailout and exit of banks through this time period. We conclude that, for change in the expected bailout probability of the banks by two standard deviation leads to additional risk from 5.3% to 10.7% and a movement is highly significant. We also conclude that, the distinction of the size of banks seem to have lesser that known impact in risk taking behavior. CAMELS strength show expected sign and plausible results.

JEL, C30, C78, G21, G28, L51

Keywords: Banks, Bailout, Financial Fragility, State intervention, Financial Regulation, Moral Hazards

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The banking sector, through its pivotal role in intermediating the savings of households, defines the financial health of an economy. Sound banks are able to lend out to better projects and expand whereas distressed banks are a liability on both depositors and the government. In traditional Keynesian literature government intervention in the free economy is stressed as an important factor to combat a wide array of economic problems and crises. However, there are certain intrinsic and implicit costs that are caused because of such interventions (Laeven & Valencia, 2013). While proponents for the bailouts advocate that bailouts instil overall confidence in the economy and provide for the shortcomings from misallocation, there is no clear consensus regarding its effects.

Predicting financial distress is generally tricky and there are no defined methods to deem an entity as distressed in a most definitive sense. Prediction of financial distress of a bank using statistical methods uses the available and current data to deem whether a bank is distressed or not (Sun.J, Li, Huang, & He, 2014). Ever since the work of Beaver (1966) and Altman (1968) in pioneering a framework for classification of entities into distressed and otherwise, many attempts have been made to replicate and improve on the methodology. In Indian context, studies often rely on computations of rating agencies which are futuristic in nature and fail to accommodate the behavioral trails in question.

The Financial Stability Report (RBI, 2019&20) cited moderate levels of NPAs after re-defining the NPA framework, but this is a stop gap policy action that may not have inherent solution to the problems of the Indian Banking system. Reports on Banking trend published on an annual basis by the Reserve Bank of India (2016 to 2019) also have highlighted banks of different stratum failing as a part of a chain reaction. With the Indian Banking system intertwined at a greater degree, there is a great possibility of system wide collapse. But to prevent that and enable confidence, regulatory authorities have a spectrum of policies and instruments in place to prevent such harmful chain reactions like that happened in 2008-09 Global Financial Crisis. This paper attempts to explore the effect of the bailout policies on the real economy through empirically analysing the impact of such infusions on the fragility of the banking sector.

Literature Review

Early literature on the moral hazard problem focused on episodes of crisis fuelled by financial intermediaries taking on excessive debt. Akerlof & Romer (1990) investigate the phenomenon of ‘bankruptcy for profit’ where a firm decides to take unsustainable financial positions and make profits in the short-run with the reassurance that the government will bail them out. This leads firms to maximize current extractable value and leads to cycles of credit booms and busts. At the heart of such issues is the presence of inefficient contracts which lead to ‘looting behavior’ where neither the lender nor borrower have incentives to operate according to the standard principles of value maximization.

Similarly, Boyd et. al (1998) identify another institutional source of such moral hazard problems i.e. costly procedures for evaluation and verification of projects. Since only investors know the true value of their projects, they are likely to withhold information. Under such circumstances, bankers find it profitable to lend out money since they have the safety net of the DGIC backing them. The authors use this analysis to show why universal banking creates more moral hazard problems. Even when it is assumed that bankers do not rely on DGIC backing, as Bernanke & Gertler (1989) show, high agency costs due to informational asymmetry lead to banks lending out only to borrowers with higher net worth. Greater availability of funds, in turn, translates to real investment and further increases the net worth of the borrowers, thereby reinforcing the bank's belief. Combined with the institutional constraint previously discussed, it can be observed that borrowers with higher net worth have a greater ease of obtaining funds and a subsequent leeway in utilizing them.

Dam & Koetter (2012) highlight the key challenge with the modelling of moral hazards, namely the identification problem. Since banks that are bailed out already exhibit high levels of distress, any econometric relationship between the two is likely to have biased conclusions. In their paper, however, using German data from 1995-2006, the authors model banks' expectations of bailouts by the regulator and find clear evidence for moral hazard in the German banking sector. By defining bailout expectations as being conditioned by the past behaviour of the regulator, the paper is able to capture the unobserved moral hazard effects.

The microeconomic foundations of our paper can be found in Myerson (2012), where long-term relationships with investors allow bankers to collect moral hazard rents which accumulate over their lifetime and lead to a large reward towards the end of their careers. The paper shows that an investor's trust in a financial intermediary is contingent on future profits in banking. The better relationship that investors are able to form with bankers, the higher is the chance of some form of a moral hazard occurring. The same behaviour can be transposed to regulators and bankers, where long-term relationships between regulators and bankers may create perverse incentives for banks as a whole.

Such risk taking behaviour by banks often varies according to the business cycle as shown by Reichlin & Siconolfi (2004) in their analysis of optimal debt contracts. They argue that during times of boom, banks are more prone to pooling debt contracts since they are competing with other banks to lend out money. Pooling as a strategy minimizes bank risk through aggregation. Such behaviour induces taking up more ‘bad projects’ and leads to default and bad loans. During such times, political pressures also compound the problem. Ming & Sung (2003), in a study of 6764 financial institutions in Korea, find that firms that were distressed had largely similar characteristics. These were political connections, a higher leverage rate and a lower return on assets. This indicates that a large part of why inefficient projects get access to loans is due to banks being forced to lend due to the prevalence of cronyism.

In the Indian context, the biggest implication of the moral hazard problem has manifested in the form of rising bad loans in banks. Muniappan (2002) emphasises on internal and external factors in causing an ‘overhang’ of NPAs in Indian banks. The paper identifies internal factors such as borrowers diverting funds taken for projects for other purposes or even using them for newer projects. Much like the international literature, the external factors include changes in the business cycle and specifically recessions.

The moral hazard problem also has important welfare implications for India. If banks are indeed reliant on bailouts and continue existing practices which lead to a buildup of NPAs, borrowers might ultimately bear the cost. Selvarajan & Vadivalagan (2013) find priority sector lending of banks to be the main cause of the bad loan problem. Especially for PSBs, since priority sector lending is dictated by politicians and bureaucrats, this forms an adverse political-banking nexus which leads to banks to continue such unsustainable practices with the backing of political office. However, the underlying causes for unsustainable banking practices are not yet explored. There is no empirical evidence in the Indian context of the moral hazard problem.

Research Objectives

After the thorough perusal of the literature and developing the hypothesis, the objectives for the current study are as follows,

1. To compute bank-level expectation-formation of bailout probabilities and employing the same to understand the strategic response of banks to regulatory behavior.
2. To estimate the underlying relationship between adaptability of the banking sector to a shock such as a financial bailout using an expectations model.

Structural Model and Econometrics

The moral hazard problem cannot be identified by regressing the bank's propensity to risk on the observed bailouts of the distressed banks due to an endogeneity problem. This approach also does not distinguish between bad luck and bad behavior of risk-taking. Therefore, we use simultaneous, static two-player game (Cordella & Yeyati, 2003) between individual bank and the regulator (Central Bank, Governmental authorities, Insurance companies etc.) to provide the structure, and the game is described in Figure 1. Regulators can neither offer unlimited bailouts nor publicly commit to providing support to a specific bank owing to the potential for higher fragility and risky behavior on part of banks.

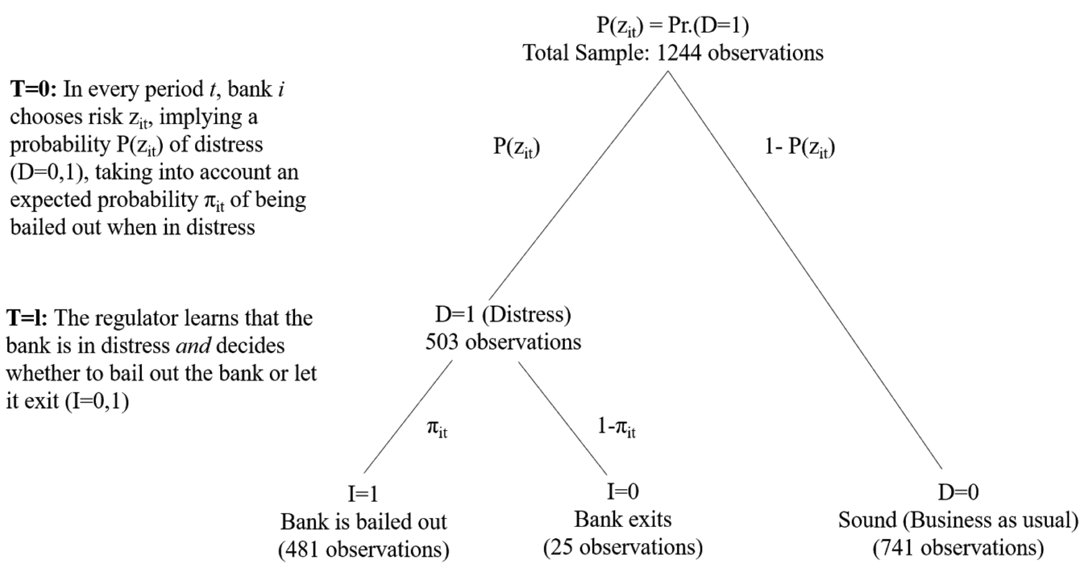

Figure 1: Game tree

We use the streamlined version of Generic Two Player lagged game model (Dam & Koetter, 2012) to construct the model for our study.

To capture the expectations of an individual bank *i* in year *t* about the behavior of the regulator, we construct the model of expected bailout probability π_{it} conditional on a bank is in distress as

Equation 1: Expected Probability of Bailout, conditional on bank being distressed

$$\boldsymbol{\pi_{it}} \equiv \boldsymbol{E}\left[\boldsymbol{I_{i,t}} \middle| \boldsymbol{D_{i.t}} = \mathbf{1}\right]$$

$$= \boldsymbol{\alpha_{year}} + \boldsymbol{\alpha_{group}} + \boldsymbol{\beta_1 X'_{i,t-1}} + \boldsymbol{\beta_2 G'_{i,t-1}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .\ \textit{(1)}$$

In the above equation, $\boldsymbol{I_{i,t}}$ is an indicator equal to 1, if the authorities choose to bail out the bank conditional on the indicator $\boldsymbol{D_{i.t}} = \mathbf{1}$, which indicates the bank is in a state of distress. $\boldsymbol{\alpha}$ is the coefficient of fixed effects for year and group. $\boldsymbol{X'_{i,t-1}}$ and $\boldsymbol{G'_{i,t-1}}$ are lagged vectors of bank specific covariates and control variable, i.e. indicator of decision that explains bailouts, but not the propensity to risk.

At *T = 0*, individual banks decide on a specific level of risk $Z_{i,t}$, the level in which the expected values are maximized constrained on the expected probability of bailout in case if the bank faces distress. The bank thus faces a trade-off between maximizing the expected cash flows in future, which again depend on the choice of the level of risk and a terminating value (Dam & Koetter, 2012). Thus from the Eq (1), the expected value of bank bailout conditional on distress is utilized as a covariate in the following risk to under the risk taking behavior of the individual bank.

Equation 2: Levels of Risk and risk taking behavior of Individual Bank

$$\boldsymbol{P}\left(\boldsymbol{Z_{i,t}}\right) = \boldsymbol{E}[\boldsymbol{D_{i,t}}]$$

$$= \boldsymbol{\delta_{year}} + \boldsymbol{\delta_{group}} + \boldsymbol{\varphi E}\left[\boldsymbol{I_{i,t}} \middle| \boldsymbol{D_{i.t}} = \mathbf{1}\right] + \boldsymbol{\rho X'_{i,t-1}} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .\ \textit{(2)}$$

Again, in the above equation $\boldsymbol{D_{i,t}}$ indicates, whether a bank is in the verge of failure, i.e. distress or financially sound. Similarly, $\boldsymbol{\delta}$ explains the fixed effects of the model. Similarly, $\boldsymbol{X'_{i,t-1}}$ is the bank-specific covariates same as earlier equation Eq (1). The coefficient (parameter) of interest for our study is **φ,** which is the coefficient for the expected probability of bailout for a bank given a certain financial performance in the past time period *t-1*. The distinction between bank-specific covariates and expected bailout is important to observe the medium of the effect's pass through, whether direct effect through **ρ** (in simple language, are large banks taking higher risks simply because they are large?) or indirect effect through **φ** (are banks taking higher risk because they are more likely to be bailed out?)

The expected bailout probabilities are not observable values and since all the banks that are bailed out are distressed by default, it poses problems to computation of the models. To avert the problem of endogeneity we use the lagged variables for econometric modelling purpose. The logic behind whether a bank is bailed out depends on the past financial performance. Simply put, we will be able to deem a bank as distressed only in the time period t+1 based on the financial performance of the same bank in t=0. Hence, if Yes Bank Ltd., is deemed distress in 2020, then the decision is based on the financial performance of the bank in the year ended 31st March 2019. We control for the effects of the heterogeneity by imposing a uniform restriction that banks must have $\boldsymbol{D_{i.t} = 1}$ to distinguish banks included in the first equation from the banks included in the second equation.

As we can see, the Eq (1) corresponds directly to the left branches of lower levels of the game tree in Figure 1, thus empirically restricting the sub-sample to 503 observations over 11 years. The Eq (2) corresponds directly to the model's top branches, i.e., the whole sample (1244 observations). To compute the second equation, we need the expected bailout probabilities of all 1244 observations when they are in distress. However, the expected bailout probabilities are latent. Hence we employ a two-step procedure for computing Eq (2). The employed restriction for empirical purposes, i.e., sub-sample of 503, helps calculate the behavior of regulators conditional on the fact that a bank is distressed and whether or not they are bailed out.

Of the two-step procedure, the first step is estimating the Eq (1) and obtaining the $\hat{\alpha}$ and $\hat{\beta}$ to estimate the expected values of bailout probabilities, $\hat{\pi}_{i,t}$ which is latent and is calculated from the Eq (1) for all banks individually for the entire sample of banks, both sound - unexpected banking problems during the year - and distressed. In simpler words, we use out-of-sample prediction to obtain the estimates of $\hat{\pi}_{i,t}$ from the parameters estimated in the Eq (1) where, if $\boldsymbol{E}\left[\boldsymbol{I}_{i,t}\middle|\boldsymbol{D}_{i.t}=\mathbf{1}\right]$ for all the banks. Thus using the expected probability calculated through Eq (1), we run the second equation and thereby completing the second step of the procedure.

The first step-estimation will yield true and consistent parameters if the standard regularity conditions are met. (Murphy & Topel, 2002). In both the equations specified above, we utilize a Probability model, specifically a Probit Regression Model[1], for estimation purposes. We make two inherent assumptions for our estimation. There is no way to know, without a supervisory bailout, whether a bank would have survived. Hence, we assume the banks would have exited otherwise without any relief support. Second, we assume that the estimated parameters reflect ex-post measures; that is, the decision will be in subsequent time period t+1 and not on t=0.

Data and Summary Statistics

Bailouts and Risks

We define bailouts as a bank receiving a capital injection either through the bank's insurance fund or through guided capital infusion from the regulatory authorities or guided regulatory

[1] We use robust standard error throughout the model to calculate the estimated parameters (Dam & Koetter, 2012).

action that control the deterioration of the banks distress like Protective Corrective Framework, dismissal of the bank's board or any other action. RBI does not have a definitive definition for a bank's distress, but intuitively distress is defined as an event in which a bank's survival is seriously endangered. In the event of distress, in India, there can be only two outcomes for the distressed banks, i.e., survival through distress or bank exit because of distress. The bank exits are restructuring measures like mergers, acquisitions, and amalgamation or a simple exit by ceasing to exist.

Information about the distress of a particular bank is held by the Reserve Bank of India and is not published to the minute detail by RBI to avoid public panic. When a regulatory authority announces a bank as distressed without any protective measure in place, it will cause a huge public panic, which in itself will endanger the position the bank is facing. This poses a methodological hurdle to the undertaken study. Even if the bank's risk-taking behavior is latent, it still can be observed through the policies that reveal the specificity of the times in which the regulator deems the risk that a bank might fail is too high and triggers protective protocol to avoid such scenarios.

The study's risk measure is derived through a combination of U.S. Bank hazard studies that estimate the risk of a bank failure conditional on multiple sources of evaluation of the exposure to risk and its ability to withstand the risk (Wheelock & Wilson, 1995). In, 1988 the Basel Committee on Banking Supervision proposed following Bank of International Settlements' CAMEL framework for evaluating financial institutions of their riskiness. The CAMEL framework stands for five critical elements of banking operations viz Capital adequacy, Asset quality, Management soundness, Earnings and profitability, and Liquidity and later on with 1997, the Sensitivity to market risk was included, thus making CAMELS framework for evaluation of the financial stability and soundness of financial institutions (Gilbert, Alton, Meyer, & Vaughan, 2000).

To conduct our study, we have utilized a mixed CAMELS model to compute the probability of distress in line with Preemptive Risk theory (Lipe, 1998) as widely used Central Banks across the world, notably Bundesbank, Federal Reserve, and the RBI with slight variations. The data is collected and compiled for a mix of Scheduled Commercial Banks (PSU, Private, Small Finance and Foreign Banks) and Scheduled Urban Co-Operative banks. The following table shows the compilation of distressed and sound banks over 2008-2020 as computed using the CAMELS framework based on the CMIE Prowess database.

Financial Year ended 31st March	Number of Banks financially Sound	Number of Banks under Distress		Number of Banks under consideration
		Bailed out	Exit	
2008	95	2	0	97
2009	39	57	2	98
2010	47	45	1	93
2011	67	25	0	92
2012	26	68	0	94
2013	32	55	3	90
2014	51	39	4	94
2015	90	9	0	99
2016	79	23	2	104
2017	41	63	1	105
2018	48	60	4	112
2019	89	13	8	110
2020	37	19	0	56
Total	741	478	25	1244

Table 1- Source: Author's Calculations based on CMIE Prowess data on Annual Financial Statements on Bank Superset vintage 30th September,2020.

From the above table we see that out of the distressed banks, most of the banks have been bailed out through some mechanism and only selective banks have exited the market. The distinction of the distress is made in accordance with the model of probability of distress adopted by many central banks. And as the official notification of distress in avoided by central banks and regulatory authorities, we rely on benchmarks set by prior academic studies in this field to distinguish banks that are distressed and otherwise (Dam & Koetter, 2012). Insurance funds, regulators, and position auditors of the bank evaluate the position of riskiness and trigger the protocol for support measure if they are deemed distress. The support mechanisms are activated simultaneously. The decision of bank rescue like capital injection and bailout package is evaluated against the cost of letting the bank exit the market. If the bailouts seem profitable and necessary, it is initiated and if not the banks' license is simply revoked. For our study, we do not need the specifics of the decision making of the bailout, but rather only whether they are bailed out or not. The aim of the study is to solely evaluate if the precedence of safety nets like bailouts and insurance protection trigger a moral hazard problem and to that extent we simply evaluate the decision based on available information.

Covariates

For our study we use the following covariates carefully selected based on extensive literature review and specification tests.

Variables	Definition	Level	Measurement Variable	Unit
Total Assets	All assets or items of value owned by the bank	Bank	Financial Position	Crore INR
Capital to Risk-Weighted Assets Ratio (CRAR)	Bank's capital expressed as a proportion of risk-weighted assets	Bank	Capital Adequacy	%
Gross Non Performing Assets (GNPA)	Summation of all assets classified by the RBI as NPAs (principal or interest overdue for over 90 days)	Bank	Asset Quality	%
Business per Employee (BPE)	Revenue generated per individual employee at the bank	Bank	Management Soundness	%
Operating Profit to Working Capital Ratio	Operating profit expressed as a proportion of the difference between current assets and liabilities	Bank	Profitability	%
Liquid Asset Share	Proportion of assets that can be easily converted to cash	Bank	Liquidity	%
Customer Loan Share	Retail loans expressed as a proportion of total assets of the bank	Bank	Market Share	%

Table 2: List of Covariates as defined and used in the study. Source: Reserve Bank of India's Statistical Tables relating to Banks; CMIE Prowess Database collection of Annual Statements for Banks Superset

CAMELS Methodology

Each CAMELS factor were considered individually for the banks and the ratios were computed for the following list of variables. The Variables were normalized using the formula $z = \frac{x - \min(x_t)}{\max(x_t) - min(x_t)}$ and ranks were assigned in the following rates, 1 = 0.0 - 0.2, 2 = 0.21 – 0.4, 3 = 0.41 – 0.6, 4 = 0.61 – 0.8, 5 = 0.81 – 1.0 for Capital adequacy, Liquidity, Business Per Employee, Operating Profit, Customer Loan Share and the vice versa for GNPA. The following table provides summary statistic for the selected covariates of the study.

Bank Specific Covariates	Mean	SD	Max	Min	Count
CRAR	17.50	10.12	60.27	-53.70	1244
GNPA	5.39	9.01	122.37	0.00	1243
Liquid Asset Share	11.65	9.25	97.68	1.31	1244
Customer Loan Share	54.79	13.07	87.75	0.04	1244
Business per Employee (in Rs. Million)	130.81	113.21	645.21	0.00	1244
Operating Profit to Working Capital Ratio	2.13	1.77	8.60	-21.45	1244
Total Assets in Rs. Million	1119420	2811489	39500000	309	1244

Table 3- Descriptive Statistics of Bank Specific Covariates; Author's Calculation

Results and Interpretation

First-Stage results

Table 4 shows the estimation results for the Probit model with robust standard errors for the Eq (1). The Prob. value of the whole model is around 0.001 which is highly significant for a model of this scale. The First column shows that GNPA, Customer Loan share and Liquidity Ratio of the banks are highly significant. Most bank specific covariates exhibit expected and plausible signs. The distinction of Large banks vs small banks seems to be absent when it comes to decision of bailout by the regulator. CRAR and liquidity exhibit a positive relationship bailout expectations which is consistent with available literature. Asset quality measured by GNPA has a negative relationship signaling that banks perform better when it comes to lending operations. Management soundness and profitability signified using Business per employee and Operating Profit to Working capital ratio seems to have no relationship in expected bailout probability.

First Stage Bailout regression, identification of Bailout probabilities

		Number of obs =	490
Group variable:	Name of the Bank	**Number of groups =**	101
Model	Probit	**Obs per group: min =**	1
Family:	Binomial	**Avg =**	4.9
Correlation:	Exchangeable	**Max =**	11
		Wald chi^2(7) =	253.77
Scale parameter:	1	**Prob > chi2 =**	0.001

	Coefficient (1)	Std. Err (2).	Z (3)	P>z (4)	[95% Conf. Interval] (5)	
Total assets in Rs Million$_{t-1}$	6.07E-08	7.85E-08	0.77	0.440	-9.33E-08	2.15E-07
CRAR $_{t-1}$	8.99E-03	0.0093055	9.70E-01	0.034**	-0.00925	0.027226
GNPA $_{t-1}$	-0.0209855	0.0089103	-2.36	0.019**	-0.03845	-0.00352
Liquid Asset Share $_{t-1}$	0.1235522	0.0353793	3.49	0.000*	0.05421	0.192894
Customer Loan Share $_{t-1}$	0.0142393	0.0059198	2.41	0.016**	0.002637	0.025842
Business per employee in $_{t-1}$	-0.0015176	0.0022517	-0.67	0.500	-0.00593	0.002896
Operating Profit to Working Capital Ratio $_{t-1}$	-0.0287441	0.0661739	-0.43	0.664	-0.15844	0.100954

Probit model with indicator variable equal to one if a bank is bailed out and zero if it exited. Between 2008 and 2020 there are total of 490 observations with recorded bailouts or exits. The standard errors are robust clustering and *, **, *** - represents 1%, 5% and 10% significance respectively.

Table 4: Expected Probability of Bailout; Author's Calculation

Second-Stage results: The Effect of Bailout Expectation on Risk Taking

Moral Hazard and bailout expectations

The following table shows the results of estimation of Probit Regression on Eq (2). From the table we are able to see the overall Prob value of the whole mode is around 0.002, which is highly significant. The coefficient of interest $\hat{\pi}_{it}$ **is** significant at 1% level, which confirms the existence of moral hazard problem due to safety measures such as bailout. An increase in the expectation of the bailout probability by 1% increases the likelihood of distress by ~0.36 times the original levels of distress. To scale the magnitude, an increase in bailout expectations by one standard deviation above and below the mean results in increase in the risk of risk by 5.3% (0.3589*2*0.075). Signs of other covariates are in line with evidence available from different countries. Size of the bank does not influence the decision of risk taking, i.e. it does not significantly impact the risk taking behavior.

Second stage risk regression: Out of sample prediction of bailout Expectations

		Number of obs =	1094
Group variable:	Name of the Bank	Number of groups =	137
Model	Probit	Obs per group: min =	1
Family:	Binomial	avg =	8
Correlation:	Exchangeable	max =	12
		Wald chi^2(8) =	187.38
Scale parameter:	1	Prob > chi2 =	0.002

	Coefficient	Std. Err.	z	P>z	[95% Conf.Interval]	
$\hat{\pi}_{it}$	0.35839	0.59405	6.03000	0.00*	2.41	4.74
Total assets in Rs Million $_{t-1}$	-1.37E-08	1.73E-08	-0.79000	0.43	-4.76E-08	2.01E-08
CRAR $_{t-1}$	-0.68844	0.01003	-6.86000	0.00*	-0.89	-0.49
GNPA $_{t-1}$	0.73092	0.04550	6.99000	0.00*	0.05	0.09
Liquid Asset Share $_{t-1}$	-0.07583	0.01246	-6.09000	0.00*	-1.00	-0.05
Customer Loan Share $_{t-1}$	-0.00803	0.00698	-1.15000	0.25	-0.02	0.01
Business per employee in Rs Mill $_{t-1}$	-0.00816	0.00100	-8.02000	0.00*	-0.01	-0.01
Operating Profit to Working Capital Ratio $_{t-1}$	-0.30322	0.04592	-6.60000	0.00*	-0.39	-0.21

Probit model with indicator variable equal to one if a bank was distressed out and zero if it otherwise. Between 2008 and 2020 there are total of 1244 observations which were either recorded as financially sound or distressed. The standard errors are robust clustering and
*, **, *** - represents 1%, 5% and 10% significance respectively.

Statistic	Expected Bailout Probability	Probability of Distress
Standard Deviation	0.0752455	0.302386
Variance	0.0056619	0.0914373
Interquartile Range	0.0581533	0.5363696
Standard Error (Mean)	0.0022749	0.0091422

Table 5:Probability of Distress, Author's calculation

Conclusion

We verify through empirical methods, whether there exists a problem of moral hazard in Indian Banking industry, specifically in the risk taking behavior of banks. The first stage Eq (1) results calculated estimates the expected probability of bailout if the banks are distressed. And using the expectations, we estimate the Eq (2) that measures the risk taking propensity of banks. Moral hazard is thus identified and interpreted as the sensitivity of banks to additional risk taking in response to change in expected bailout probability. Estimations across different groups does not show any heterogeneity.

The study has utilized only distress as represented using probability of distress; allowing for internal variation of distress and exploring the inter-bank risk is a possible corridor for further research. Finally, the research is limited by the availability of uniform data for banks that are operating. With restructuring and free entry and exit hindering the effectiveness, the study can be expanded to fields of behavioral theory of bank competition, banking sector elasticity and much more.

The results from the estimation validates the problem of existence of moral hazard problem in the banking industry. The safety nets, though used to provide confidence and support to the overall financial system, instead increases the propensity of banks to undertake additional risks.

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