Loan Loss Provision: Keeping Too Much or Too Less?

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ABSTRACT

We find evidence of biased belief formation in bank managers' decision on loan loss provision across the commercial banks in the United States. The errors incurred in the provisioning assessment are not only predictable but can be readily explained by diagnostic expectations, a belief formation mechanism where agents increasingly overweigh the future outcomes conditional on the current information. Through this over-reaction channel in expecations of the banking sector, our model can explain the existence of procyclicality of the financial system and the real variables. We use the error in provisioning assessment as a measure of optimism for banks and show that banks with excess optimism have higher loan growth and subsequently, stock of these banks have lower returns. We also show that a statistical provisioning rule, where expected losses over the whole business cycle are accounted for, is welfare improving by mitigating procyclicality.

JEL *classification*: E32, E44, E52, E71, G21

The financial crisis of 2008 has motivated an ongoing research about the possible reasons for failure of traditional models to accomodate many facts surrounding it. Many of the former models which link financial sector and real economy relies on financial frictions introduced by Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) for propagation and amplification of shocks. The failure of these models to account for several facts surrounding the crisis has led to a departure from rationality assumption. Most notable are the works of

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Bordalo, Gennaioli, and Shleifer (2018), Bordalo et al. (2017), and Bordalo et al. (2018) which follow Minsky (1977). Any macroprudential policy designed to improve financial stability needs to take this into account. In this paper, we investigate bank's loan loss provision in light of biased expectation. We find that banks are biased while valuing loans and keeping provision to account for future loss. Then we analyze the impact of this bias on credit growth and output in a general equilibrium model.

Macroeconomic rational expectation approach explains credit cycle using adverse shocks whose effects get amplified by financial frictions. These models can well account for procyclicality of financial system. Following this, national regulators as well as Basel committee has proposed various instrumets like capital conservation buffer, countercyclical capital buffer, dynamic provisioning system to mitigate procyclicality. However, a number of recent research on credit cycle have found existence of bias in the behavior of market participants and financial intermediaries. The financial sector tends to make predictable errors, hard to reconcile with rational expectation theories. So any countercyclical regulatory rule must take this into consideration.

In this paper, we focus on banks' loan loss provision. Loan loss provision has been discussed a lot because of its procyclical impact on bank's regulatory capital and consequent lending activity. The incurred loss model, currently used, allows provisioning for loans which are already impaired. However, the presence of bias in the behavior of banks alters the dynamics of loan loss provision. We show that banks keep less than required provision during good times and keep more than required during bad times. By "good times" we mean periods when banks experience a fall in net charge off or realised loss compared to past and vice versa. In our data, expectations do not appear to be rational in the sense that—both in the aggregate and at the level of individual banks—expectational errors are consistently predictable from recent net charge-offs. The observed excess optimisim during good time can account for banks with high loan growth and poor future performance in stock market. In addition, we find that the extent of bias is not symmetric. We find the extent of underprovisioning during good time to be higher than overprivisioning.

The income smoothening hypothesis for loan loss provision predicts exactly the opposite. As per this, bank managers keep less provision during bad time when incomes are low and more provision during good time when incomes are high. This helps banks in achieving a stable income and better stock market performance. We find evidence which contrasts this. So the question arises why bank managers are behaving in a manner detrimental to their objectives of better stock market performance. It cannot be explained by assuming bankers are more conservative as a conservative banker does not keep less than required provision during good time.

Overall, this existing evidence does not seem to agree with rational expectation. Failure to account for this fact, while designing countercyclical loan loss provisioning rule can fail to generate intended results.

We use a behavioral model to analyze bank's loan loss provision and explain the finding of irrationality. The behavioral approach we use, follows Bordalo, Gennaioli, and Shleifer (2018)'s diagnostic expectation model. According to Tversky and Kahneman (1983) who first propose this idea, a certain event becomes more likely to agents if current news is diagnostic of that event. For example in macroeconomic context, agents overweight those future states whose likelihood increases the most in light of recent news. So a path of good news makes agents overly optimistic and a path of bad news makes agents excessively pessimistic. We introduce diagnostic expectation into the behavior of banks. It affects how banks value loans and keep loan loss provision. We then conduct several experiments to study the implications of a biased banking sector on real economy.

Our paper is related to three strands of research. First, the use of loan loss provision as a macroprudential tool in reducing procyclicality and improving timeliness of loss recognition has been suggested by Beatty and Liao (2011), Laeven and Majnoni (2003), and Bushman and Williams (2015). These research document early recognition of losses leads to better performance of banks. Delay in loss recognition causes capital to fall during economic downturn and reduces lending activity, called as capital crunch effect. To mitigate this, dynamic provisioning system makes banks to recognise losses early(Bikker and Metzemakers (2005),Agénor and Zilberman (2015),Agénor and Pereira da Silva (2017),Bouvatier and Lepetit (2012)). Compared to these works, we exploit the time series variation in banks' provisioning behaviour. We ask when it is more likely that banks delay loss recognition. We find delay in loss recognition happens mostly during good time when banks are experiencing a fall in realised loss on extended loans or net charge-offs. We also extend the analysis of Beatty and Liao (2011) and show that one of their measure for recognising delay in loss increases when banks experience less charge off on loans consistent with biased provisioning behavior induced by diagnostic expectation.

Our second contribution is to the literature on aggregate dynamics in credit market. Overly optimistic belief is often cited as one of the reasons for high leverage prior to the recent financial crisis . When the economy was doing good in 2000s, banks were experiencing less net charge-offs on their loans. Our findings that banks extrapolate based on recent experience, would have led them to become overly optimistic. This manifested in the form of less provision, lower interest rate and excessive growth of credit, making the system fragile. Once the crisis happened, these banks saw a spike in their net charge-offs which made them overly pessimistic. This over pessimism would have led banks to keep more than required provision and charge higher loan rate, making recovery from the crisis difficult and a prolonged affair. We find direct evidence of such extrapolative behavior by banks by analyzing loan loss provision. Our inference can be extended to other aspects of bank's behavior. Presence of bias in loan loss provision shows irrational valuation of loans, existing on bank's balance sheet. Such bias in behavior can be expected to affect the valuation of other assets as well. He, Khang, and Krishnamurthy (2010) presents a model of equity risk based capital constraint for commercial banks. The model shows banks are not willing to lend or buy new asset because of limited capital and expectation of increased chance of distress induced by these new assets. They document such behavior of commercial bank during the financial crisis. The presence of diagnostic expectation can exggagerate the above effect.

Third, our paper is related to the works concerning behavioral approach to explain several issues in financial sector with primary focus on banks. There is evidence of irrational behavior on part of commercial banks (Baron and Xiong (2017), Fahlenbrach, Prilmeier, and Stulz (2017)). Fahlenbrach, Prilmeier, and Stulz (ibid.) shows that banks having high loan growth, perform worse than other banks in future. These banks have a lower return on assets and experience an increase in their loan loss reserve. Baron and Xiong (2017) shows equity market participants fail to anticipate such poor performance. But these papers do not explain the source and mechanism of such bias. These works document predicatability in performance of banks from past credit decisions and justify irrationality. But it is difficult to justify the mechanism of such bias as they do not observe the outcomes when there is no bias. By focusing on loan loss provision, we can observe the actual realization (net charge-off) to which provisions are directly related. So we provide direct evidence for irrationality on part of commercial banks. Our model can explain why stocks of banks with higher loan growth underperforms in future. Periods of excessive optimism make banks to underestimate risks associated with loans and increase their lending activity. Equity Investors fail to recognise this fact and associate high loan growth with good performance. We show that it is irrational optimism which is the main cause for excessive lending. Subsequently equity investors realise this. Given this background, we find our measure of excessive optimism on part of banks can explain excessive lending of past and poor stock return in future.

In section 2, we lay out the model of expectations for the banking sector which forms the basis for our empirical analysis. Section 3 uses bank holding company (BHCs) data to provide evidence that supports extrapolative bias in keeping provision for future loan loss. In section 4, we augment the model of section 2 to incorporate observed biasedness in the behavior of banks. In section 5, we incorporate the model of expectations for the banking sector into a standard New Keynesian model for real economy. Section 6 presents some dynamics of the model and then describes the quantitative properties of the model. In Section 7, we study the outcomes of the model by introducing real financial shocks derived from data. Section 8 provides a brief study on macroprudential policies and its effectiveness in reducing real and financial sector volatility. Section 9 concludes.

I. A Framework for Empirical Analysis

Before proceeding to exploring the data, we motivate our empirical analysis with a simple model which includes a commercial bank and a capital good producer. First we describe the interaction between the bank and the capital good producer, then we conduct our empirical analysis.

A. The Commercial Bank

The commercial bank in our model performs two functions, it collects deposits from the households and provides loan to the capital good producer. In the model, each period corresponds to one quarter. The capital good producer gets a loan of L_t from the bank for one quarter. However the loan is risky and there is a chance of default happening at t+1. In that scenario the bank is expected to lose g_{t+1} fraction of the loan.

Because of this risk in lending activity, the bank needs to keep loan loss provision as per the rules set by the regulator, details of which are described below.

A.1. Loan Loss Provision

Loan loss depends on several borrower specific characteristics as well as macroeconomic environment. We assume, the composition of bank's loan portfolio does not change over time. The borrower specific factors remain constant over time and only the common factors like macroeconomic variables causing loan impairment change over time. So any persistence in these economic characterisitcs gets transferred to loan loss and creates similar persistence. For simplicity, we abstract from modelling all these factors. We assume g_t evolves accroding to the following process with a persistence parameter ρ.

$$g_t = \overline{g}^{1-\rho} g_{t-1}^{\rho} exp(\nu_t^g) \tag{1}$$

where $\overline{g}$ represents the steady state value. ν_t^g is a normally distributed shock with mean zero and constant variance.

While making a loan of L_t at t, the bank needs to estimate the fraction of loan it cannot recover at t+1 based on information available at t.[1] The actual fraction of loan lost by the bank is

$$g_{t+1} = \overline{g}^{1-\rho} g_t^{\rho} exp(\nu_{t+1}^g) \tag{2}$$

Here we assume g follows a logarithmic AR(1) process and later use it for quanitative analysis .

The bank then, needs to keep loan loss provision,

$$LLP_t = E_t g_{t+1} L_t \tag{3}$$

where E_t is the expectation operator. For the purpose of empirical analysis and later for use in general equilibrium model, it is convenient to log-linearize above equations and express it in growth rates. We denote the log linearized variables with a hat on them. So the equations after log-linearization can be written as

1. Loss Fraction or (g_t): $\widehat{g_t} = \rho \widehat{g_{t-1}} + \nu_t^g$
2. Rational Expectation of loss fraction or $(E_t g_{t+1})$: $\widehat{E_t g_{t+1}} = \rho \widehat{g_t}$
3. Unbiased Provision or (LLP_t): $\widehat{LLP_t} = \widehat{E_t g_{t+1}} + \widehat{L_t}$
4. Actual loss or net charge-off in t+1 or$(Loss_{t+1})$: $\widehat{g_{t+1}} + \widehat{L_t}$

To study, whether expectations are rational or not, we focus on the errors made in keeping provision.

The error in keeping provision when expectations are rational is

$$\widehat{Loss_{t+1}} - \widehat{LLP_t} = \widehat{g_{t+1}} - \widehat{E_t g_{t+1}} = \nu_{t+1}^g \tag{4}$$

The error in this case is random.

[1] Repayment happens at the end of period t or begining of period t+1 as the capital goods producer receive its payment from renting capital at the end of period.

II. Empirical Evidence on Expectation of loan loss and Net Charge-off

In this section, we define the data and describe the strategy for assessing bank's provisioning behavior. Our main objective is to create the error term as shown in equation 4 and test predictability of this error term. If expectations are rational, forecast errors should be orthogonal to all information available at the time when the forecast is made. If expectations are systematically biased, then errors would be predictable using information available ex ante.

First we conduct the analysis on aggregate time series, next we provide results at bank level. The results of aggregate time series analysis are later used in general equilibrium modelling.

A. Data Description and Sample Selection

We use *FR Y-9C* reports which provides information on bank holding companies at consolidated level and is used as a primary analytical tool for monitoring these financial institutions. Our sample covers 46,084 bank-quarter observations on 1092 bank holding companies starting from 1987Q1 to 2018Q4. We use *FRED economic research* to get data on macroeconomic variables. Table I provides summary statistics of two variables i.e. loan loss provision and net charge-offs which are used in the analysis.

Summary Statistics

	Mean	Standard Deviation	Median
Loan Loss Provision	49044.76	583955.8	1566.5
Net Charge-offs	46614.25	523309.4	1118
Observations	46,084		

Table I: The table reports summary statistics for loan loss provision and net charge-offs for the whole panel of banks over the full sample period.

B. Construction of variables

Our objective is to compare loan loss provision kept by banks in each quarter and the net charge-offs they experience in future. We follow three different approaches to conduct above analysis. The purpose of taking multiple approaches is: we do not observe the loan loss provision made and the net charge-offs on loans separately, making a direct comparison impossible. Banks report only aggregate value. To overcome this limitation, we perform our analysis using variables constructed from different approaches. In each case we normalise both loan loss provision and net charge-offs by total loans extended in the last quarter. We take log of these variables and calculate the growth rates in line with our log linearised model explained in section 2.

B.1. Approach 1:

In our first approach, we simply take average of the concerned variables. For loan loss provision(llp_{it}) and recent net charge-offs (nco_{it}), we take average these variables over quarter t-3 to quarter t. For future net charge-offs (nco_{it+1}), we take average of net charge-offs from quarter t+1 to quarter t+4.

B.2. Approach 2:

Approach 1 assumes that bank's loan portfolio remains constant over future four quarters or there is no change in the portfolio due to new issuance or default. To take care of this drawback, we need to fix the loan portfolio and then look at future net charge-offs.

We define l as loss rate. For a particular quarter t+k, loss rate can be written as

$$l_{it+k} = \frac{nco_{it+k}}{L_{it+k-1}}$$

l_{it+k} is loss rate for 'i' th bank in quarter t+k. For quarter t+1 to t+4, we create these loss rates. Assuming that composition of bank's loan protfolio does not change drastically over the next four quarters, same loss rate can be used for current loan portfolio. So total realised loss or cl_4 over next four quarters for loan extended at t-1 or L_{it-1} is

$$\begin{aligned} cl_4 = L_{it-1}\Big[& l_{it+1} + (1-l_{it+1})l_{it+2} + (1-l_{it+1})(1-l_{it+2})l_{it+3} \\ & +(1-l_{it+1})(1-l_{it+2})(1-l_{it+3})l_{it+4}\Big] \end{aligned} \tag{5}$$

Then we take average of this cumulative loss and normalise it by L_{it-1} to get the future realised net charge-offs or nco_{it+1}.

For loan loss provision, we simply use provision kept at quarter t or llp_{it}. For recent net charge-offs or loss experienced by bank on loans, we construct cumulative net charge-offs over past four quarters and then take its average. For example, if we want to know the loss experienced by banks over last k quarters (from quarter t to quarter t-k+1) on provision kept at t, we first calculate past loss rates as we did above. Then we calculate past cumulative loss and take average. So we calculate cumulative loss over last four quarters (including current quarter) as

$$pl_4 = L_{it-1}\Big[l_{it} + (1-l_{it})l_{it-1} + (1-l_{it})(1-l_{it-1})l_{it-2} + (1-l_{it})(1-l_{it-1})(1-l_{it-2})l_{it-3}\Big] \tag{6}$$

where l_{it-k} denotes loss rates for bank i in quarter t-k.[2]

Then we take average of this cumulative loss and normalise it by L_{it-1} to arrive at recent loss (nco_{it}).

B.3. Approach 3:

Here we augment the second approach by looking at how much banks deviate from rational expectation. Instead of using actual loss rate, we construct rationally expected future loss rate conditional on information available at quarter t. After calculating the loss rate for any quarter t+k as l_{it+k}, first we run the following regression.

$$l_{it+k} = \alpha_1 NCO_{it} + \alpha_2 \Delta NCO_{it} + \alpha_3 NPA1_{it} + \alpha_4 NPA2_{it} + \alpha_5 L_{it} + \alpha_6 \Delta GDP_t + \alpha_7 \Delta UNEMP_t + \alpha_8 \Delta CSRET_t + \alpha_6 r_t + \alpha_6 \Delta r_t + \varepsilon_{it} \tag{7}$$

NCO represents net charge-off. NPA1 and NPA2 represents loans past due for 90 days and non-accrual loans respectively. L_{it} represents log of total loans extended which accounts for size of the loanbook. The model includes four measures of economic characteristics that can influence future loss: real gross domestic product (GDP_t), unemployment ($UNEMP_t$), case-shiller real estate index ($CSRET_t$) and federal fund rate as risk free rate (r_t). All the bank level variables except L_t are normalised by last quarter loan. Δ represents growth of the corresponding variable.

The predicted value from the model or $\widehat{l_{it+k}}$ is used as expected loss rate conditional on information available at t. Similar to approach 2, we calculate cumulative loss using these predicted loss rate for next four quarters and take average of it as a measure of realised future net charge-offs.

C. Are Expectations Rational?

In this section, we are going to first show analysis of aggregate time series. We aggregate all the required variables across bank holding companies for each quarter and follow the steps described above, then we provide results at bank holding company level.

[2]While creating average loss rate over last four quarters, we have calculated it backward thus giving more weightage to recent losses and it falls as one moves further in the past. Banks are likely to be affected more by current loss as memory of past losses gradually fades.

C.1. Aggregate Level Analysis: Banking Sector

Figure 1 visually presents the association between the deviation of provision from realised net charge-offs or $(nco_{t+1} - llp_t)$, and current net charge-offs or nco_t for all three approaches. The data suggests predictability. When current net charge-off is high, the expected future charge-off or provision is too high and, when current charge-off is low, the expected future net charge-off is too low. The periods building upto the crisis are associated with a declining net charge-off. This created excessive optimisim and underestimation of future loan loss. So banks kept less than required provision. But actual charge off turned out to be higher and hence error term was increasing and positive. When the global financial crisis happened, the charge- offs were higher and banks became pessimistic. This led to overestimation of future loan loss and more than required loan loss provision. But actual loss turned out to be less than what had been predicted, hence the error term turns negative towards the end of crisis period. Table II presents the empirical analysis for predictability of forecast errors. In line with our log linearised model described above, we calculate the change in realised future net charge-off, change in loan loss provision and change in current net charge-off. The difference between change in realised future net charge-off and change in loan loss provision gives the error term.

$$error_t = \Delta nco_{t+1} - \Delta llp_t \tag{8}$$

The results reaffirms the message of Figure 1. $Error1_t$, $Error2_t$ and $Error3_t$ are the error terms created using first, second and third approach respectively. Banks tend to have belief biased by excessive persistence of current conditions. The estimated parameter for change in loan loss provision is higher than the persistence parameter for change in actual future charge off for all three approaches. If expectations are rational, forecast errors should be unpredictable. But column 3 shows errors are predictable and the signs are consistent with the presence of excess optimism during good time and excess pessimism during bad time. Figure 2 further illustrates these results with scatter plots of expectational errors against recent net charge-offs. It shows that the bias is present throughout the sample period, and not driven by a single outlier event like crisis.

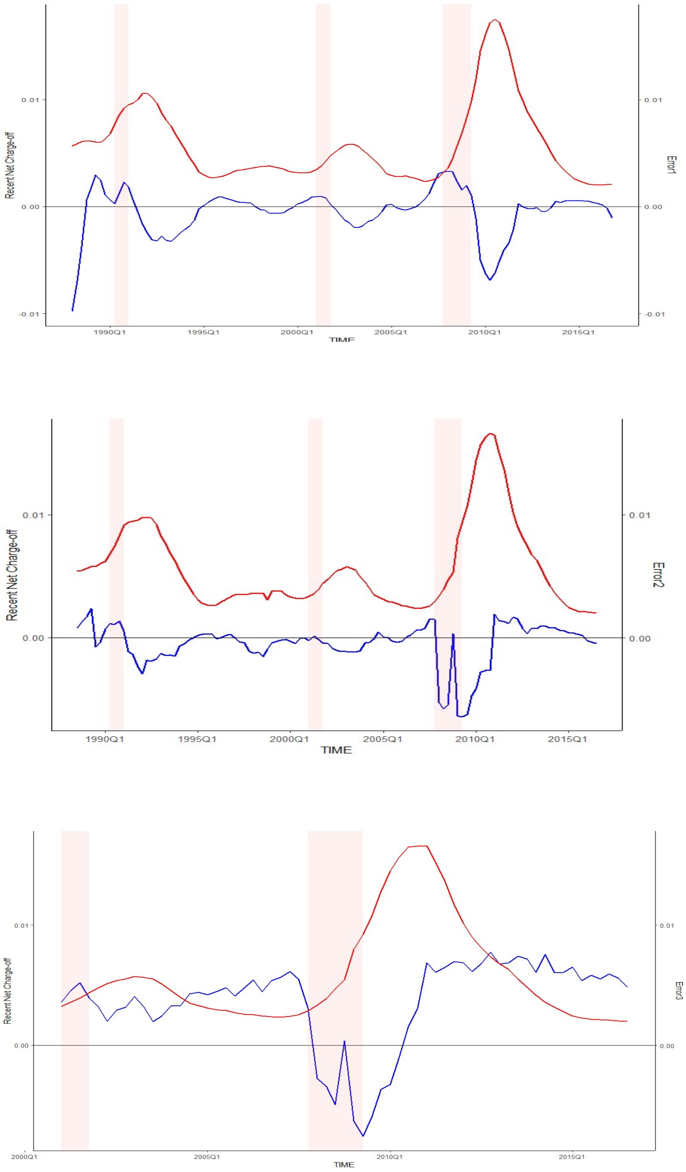

Figure 1: Predictable errors in loan loss provision: The plot shows aggregate errors in expectation of future loan loss or provision and recent net charge offs. The red line plots recent net charge-off and the blue line plots the error which is the difference between realized future charge-off and loan loss provision. Both the time series are constructed using first, second, and third approach and are plotted respectively.

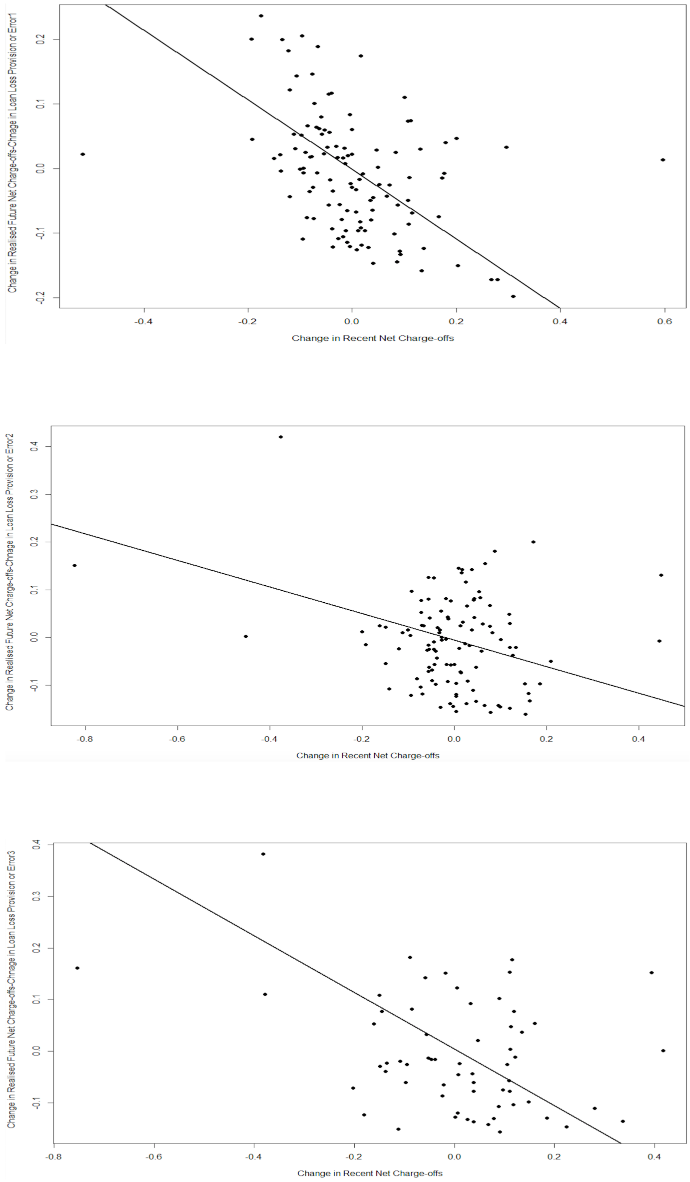

Figure 2: Scatter Plots of errors in loan loss provision: Scatter plots of errors in expectation of future loan loss growth are plotted against growth in recent net charge-offs. Bank level variables are aggregated across banks in a quarter. Variables are constructed using first, second, and third approach and are plotted respectively.

A: Actual, Forecast, and Error of Future Charge-offs

	$\Delta RealizedNCO$ (1)	ΔLLP (2)	$Error1$ (3)
$\Delta CurrentNCO$	0.525 (3.75)	1.06 (8.46)	−0.538 (−5.46)
Constant	−0.008 (−0.59)	−0.007 (−0.56)	−0.001 (−0.09)
Observations	115	115	115
R^2	0.22	0.51	0.15

B: Actual, Forecast, and Error of Future Charge-offs

	$\Delta RealizedNCO$ (1)	ΔLLP (2)	$Error2$ (3)
$\Delta CurrentNCO$	0.503 (4.52)	0.781 (4.02)	−0.278 (−2.25)
Constant	−0.004 (−0.31)	−0.0009 (0.05)	−0.005 (−0.5)
Observations	112	112	112
R^2	0.252	0.213	0.04

C: Actual, Forecast, and Error of Future Charge-offs

	$\Delta RealizedNCO$ (1)	ΔLLP (2)	$Error3$ (3)
$\Delta CurrentNCO$	0.273 (3.38)	0.82 (3.15)	−0.55 (−2.31)
Constant	−0.0005 (−0.06)	−0.004 (−0.15)	0.004 (−0.16)
Observations	62	62	62
R^2	0.093	0.233	0.111

Table II: Quarterly regressions of errors in banks' expectations of future loan loss. The dependent variable is aggregate future realised net charge off growth in the next quarter minus aggregate loan loss provision growth in the current quarter. Independent variables include aggregate current net-chargeoff growth. The variables are constructed using first, second and third approach in panel A, B, and C respectively. Standard errors are Newey-West with four lags. t-statistics in parenthesis.

C.2. Panel Level Analysis:Bank

Table III reports prelimnary analysis done at bank level. Our results from aggregate time series analysis are: when banks experience a fall in net charge-offs, they become overly optimistic and keep less than required provision. Going forward, future net charge-offs turned out to be higher. The opposite happens when banks experience an increase in net charge-offs. For prelimnary analysis, we examine the difference between growth in future net charge-offs and loan loss provision for two sub periods: 1. a pre-crisis period from 2005Q2 to 2007Q2; 2. a post crisis period from 2009Q2 to 2011Q2. During the pre-crisis period, we expect the difference between growth in future net charge-off and provision to be positive as banks were overly optimistic and keeping less provision. During the post crisis period, we expect the difference to be negative since banks had gone through the crisis and were overly pessimistic. So they were keeping more than required provision.

Univariate Analysis

Difference between growth in future net charge-offs and loan loss provision		
	Pre-Crisis	Post-Crisis
Approach 1	0.089***	-0.054***
Approach 2	0.217***	-0.042**
Approach 3	0.26***	-0.008

Table III: The table tests the significance of the difference between growth of future net charge-offs and loan loss provision separately for two sub periods; pre-crisis period from 2005Q2 to 2007Q2 and post crisis period from 2009Q2 to 2011Q2.

As it can be seen from the table III, the results are as expected for all the three approaches. Table IV reports the results of regressions conducted at bank level. To account for any heterogeneity across banks, we include fixed effects. If there are banks which are consistently optimistic or pessimistic due to some prior beliefs, the fixed effect helps in controlling for this. Our results are robust when we include a time fixed effect, which absorb the effect of any variable that does not vary across banks, such as exposure to any common factors. The standard errors are clustred at bank level. The results are qualitatively similar with what we observe from aggregate time series analysis.

Bank Level Evidence

Error=ΔRealised Future Net Charge-off-ΔLoan Loss Provision

	Panel A				Panel B				Panel C			
$\Delta CurrentNCO$	−0.47 (−25.12)	−0.49 (−24.13)	−0.486 (−25.25)	−0.487 (−21.63)	−1.19 (−32.94)	−0.3 (−14.5)	−1.17 (−31.96)	−1.15 (−23.06)	−1.10 (−21.50)	−0.19 (−4.50)	−1.11 (−21.03)	−1.12 (−20.98)
ΔGDP			−0.66 (−1.45)	−0.4 (−0.69)			4.35 (5.48)	−5.05 (−5.64)			−1.29 (−0.91)	−1.44 (−1.02)
$\Delta CSRET$			−1.46 (−11.04)	−1.65 (−11.56)			−2.4 (−7.65)	−1.12 (−3.36)			−1.91 (−4.38)	−1.79 (−4.08)
Δr			0.117 (0.24)	−1.6 (−2.44)			24.33 (24.21)	26.06 (21.35)			19.39 (11.88)	19.27 (11.81)
$NPA1_t$				0.066 (0.10)				0.3 (0.23)				0 (−0.003)
$NPA2_t$				−1.44 (−4.70)				1.8 (4.45)				3.79 (8.93)
Firm Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time Fixed Effects		Y				Y				Y		
Observations	31,041	31,041	31,041	19,388	29,358	29,358	29,358	18,387	13,218	13,218	13,218	13,218
R^2	0.1345	0.1773	0.1405	0.1452	0.3931	0.7241	0.4041	0.376	0.2849	0.6132	0.2911	0.2940
Number of BHCs	941	941	941	904	926	926	926	885	567	567	567	567

Table IV: Quarterly time series regressions of errors in bank's expectation of future loan loss or loan loss provision on change in recent net charge-offs. The error term and recent net charge-off are constructed using first, second and third approach in Panel A, B, and C respectively. Standard errors are clustred by firms. Within R-square is reported. t-statistics in parenthesis.

Several studies have earlier documented that banks which delay in recognising loan loss and keeping provision, have to reduce their lending going forward. But these studies do not explore the time varying characteristics of this delaying behavior. We pick one such study of Beatty and Liao (2011). The authors have used a market based measure for identifying banks which delay loss recognition. They run the following regression and define C-score as the association between net income and negative equity return.

$$\begin{aligned} NI = \beta_0 + \beta_1 * D + Returns * (\mu_1 + \mu_2 MV + \mu_3 LEV) \\ + D * Returns * (\lambda_1 + \lambda_2 MV + \lambda_3 LEV) + \varepsilon \end{aligned} \tag{9}$$

where

$$NI = \text{net Income normalised by last quarter loan}$$

$$D = \text{an indicator if return on equity is negative}$$

$$MV = \text{Natural log of market value of equity}$$

$$LEV = \text{leverage or Total liability divided by market value of equity}$$

C-score is defined as,

$$\text{C-score} = \widehat{\lambda_1} + \widehat{\lambda_2} MV + \widehat{\lambda_3} LEV \tag{10}$$

Assuming market reflects information about rationally expected loss, association between net income and negative equity return can be a measure for delay in loss recognition. If banks delay in keeping provision, then the association between net income and negative return on equity will decrease as net income will be artificially higher due to low provision. A lower C-score means banks are keeping less provision. We construct C-score for our sample and analyze its relationship with recent net charge-offs. As per the bias we found, banks keep less provision during good time when charge offs are less. During this time we expect C-score to fall.

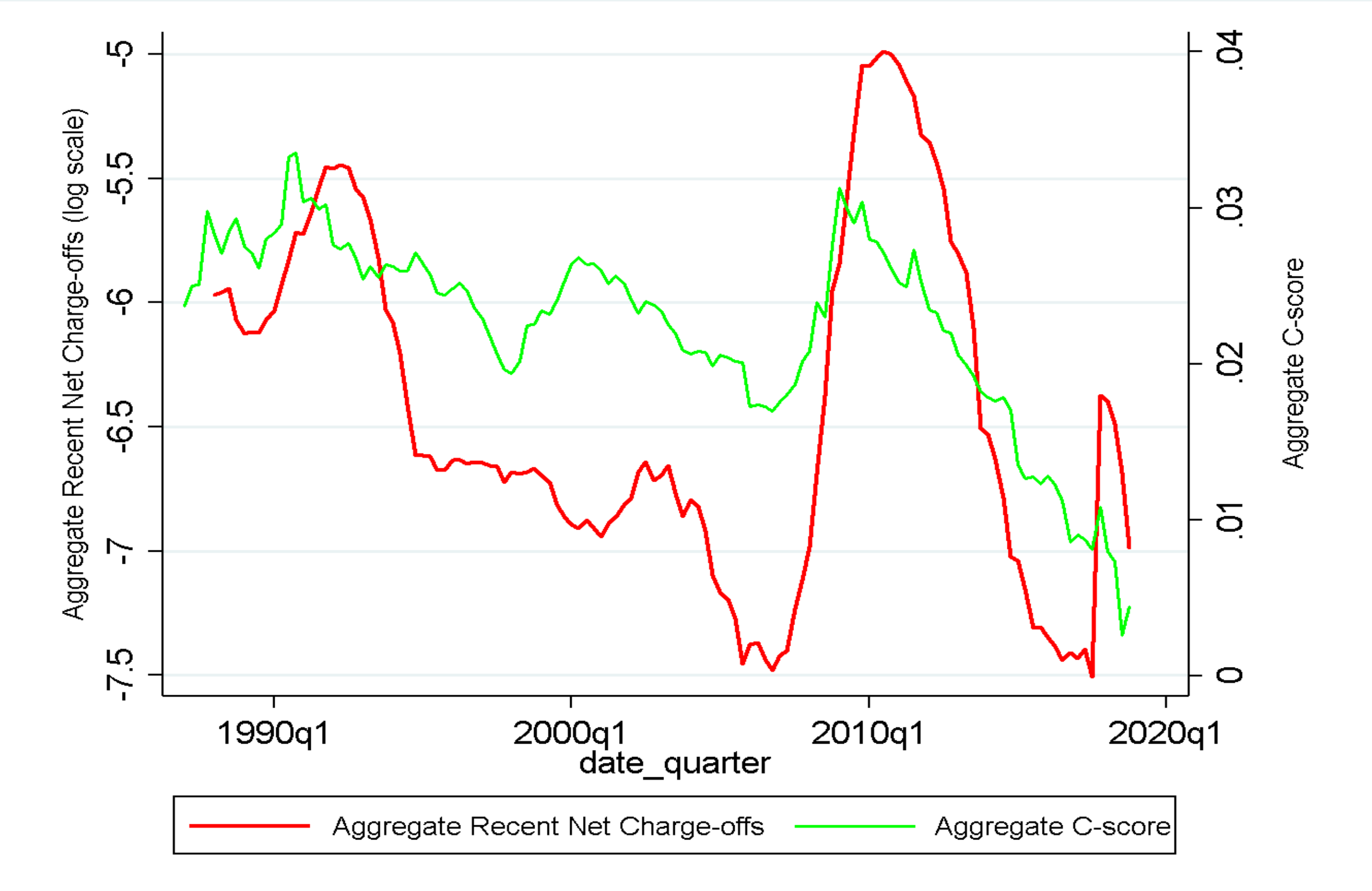

Figure 3: The plot shows aggregate C-score and log of recent net charge-offs. The variables used for the plot are constructed from first approach. Results are robust to use of altervative approaches.

Figure 3 plots the average C-score aggregated across banks and log of aggregated current net charge-offs. Current net charge-off variable is constructed from first approach. As expected, C-score falls when charge offs are less and vice versa. The spearman rank-order correlation between these two aggregate time series is found to be 0.66 and statistically significant.

C.3. Biased Expectation, loan growth and Return

As we show in previous section, banks with excessive optimism tend to underestimate actual loan loss and do not keep enough provision. Because of this optimism, the error which is the difference between average future loss on loans and loan loss provision, turns positive. In this section we use this error as a measure of irrational optimism shown by banks and show how it affects their lending decision as well as future stock return.

We use error term created using first approach and calculate average optimism shown by a bank over past one year, two year and three years. Next we sort banks into quartile based on the degree of optimism.

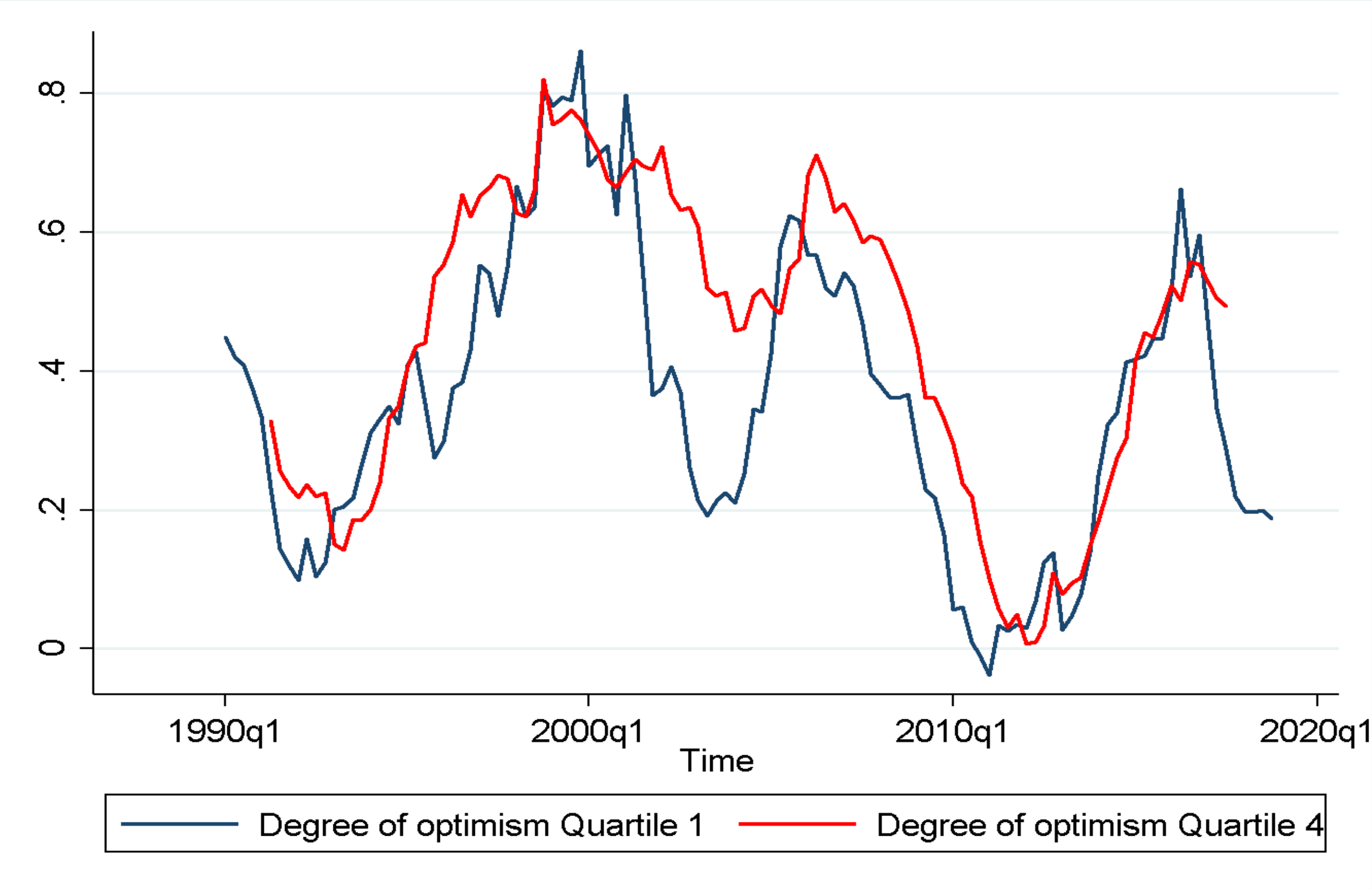

Figure 4: The plot shows the time-series of average loan growth over last three years. For every quarter, we sort banks into four quarters based on degree of optimism over last three years.The red line shows the loan growth of banks in the highest quartile of our optimisim measure. The blue line corresponds to the loan growth of banks in the lowest quartile of our optimisim measure.

Above figure plots average loan growth over last three years for two group of banks. The red line shows the loan growth of banks in the highest quartile of our optimisim measure. The blue line corresponds to the loan growth of banks in the lowest quartile of our optimisim measure. The figure shows that for most of the sample years, loan growth is higher for banks belonging to the highest quartile of optimism group.

We also statistically verify the above inference by running the following probit regression.

$$Probability\ of\ falling\ in\ quartile\ X = Fn(Degree\ of\ optimisim)$$

where X varies from 1 to 4. Below we present the results. Degree of optimism is the average of the error term over past one year, two year and three years panel A, B and C respectively.

Relationship between loan growth and degree of optimism

	quartile 1	**quartile 2**	**quartile 3**	**quartile 4**
A. One-year loan growth				
Degree of optimisim	-0.21^{***} (-6.78)	-0.007 (-0.23)	0.13^{***} (4.21)	0.09^{**} (2.89)
Marginal Effect	-0.067	-0.002	0.042	0.028
Log likelihood	-15803.91	-16144.47	-15971.94	-15,455.13
B. Two-year loan growth				
Degree of optimisim	-0.58^{***} (-9.38)	0.049 (0.81)	0.31^{***} (5.14)	0.21^{***} (3.49)
Marginal Effect	-0.18	-0.016	0.10	0.067
Log likelihood	-13485.25	-13831.53	-13767.01	-13172.28
C. Three-year loan growth				
Degree of optimisim	-0.73^{***} (-7.38)	-0.17^{*} (-1.75)	0.5^{***} (5.12)	0.39^{***} (4.01)
Marginal Effect	-0.23	-0.056	0.16	0.12
Log likelihood	-11544.80	-12002.66	-11792.53	-11394.23

Table V: The table presents the results of probit regression where bank quartile is regressed against Degree of optimisim. Banks are sorted into four quartiles based on past one, two and three year loan growth. Variable 'Degree of optimisim' is the error made in estimating loan loss and keeping provision. Numbers in parenthesis are z-statistics.

Across all panels we see, degree of optimism increases the probability of a bank falling to either quartile

3 or quartile 4 in terms of loan growth. The effects are economically and statistically significant. One unit increase in degree of optimisim increases a bank's probability of falling into highest quartile loan growth group by 9%, 21% and 39% respectively for one year, two year and three year loan growth.

Fahlenbrach, Prilmeier, and Stulz (2017) shows that stocks of banks with loan growth in the top quartile underperforms the common stock of banks with loan growth in the bottom quartile. Their evidence is consistent with extrapolative expectations on part of investors. Investors wrongfully associate good performance with high credit growth. Above we have shown that it is optimisim on part of banks which leads to excess loan growth in the first place. Not only high credit growth, but banks's excess optimism can also reflect in other activities which make investors. Since irrational optimism is the main cause of loan growth, rather good performance, investors realise the same in future and stocks of these banks underperform. Below we show that, our measure of optimism has additional explanatory power over loan growth in explaining poor stock return.

Following Fahlenbrach, Prilmeier, and Stulz (ibid.), we estimate

$$r_{i,t+k} = \beta_1 * I_{loangrowth_{i,t} \in Q_2} + \beta_2 * I_{loangrowth_{i,t} \in Q_3} + \beta_3 * I_{loangrowth_{i,t} \in Q_4}$$
$$+ \beta_4 * I_{loangrowth_{i,t} \in Q_2} * Optimism + \beta_5 * I_{loangrowth_{i,t} \in Q_3} * Optimism + \beta_6 * I_{loangrowth_{i,t} \in Q_4} * Optimism + \varepsilon_{it}$$

Optimism is an indicator variable which is 1 if the bank is overoptimistic or the average error term is positive during las one, two or three years. $r_{i,t+k}$ is the k year ahead return for bank i, $I_{loangrowth_{i,t} \in Q_j}$ is a dummy variable equals to 1 if the loan growth of bank i is in j th quartile. Table 6 presents the results. Across panel we observe returns are decreasing across growth quartiles. In addition to this, when quartile dummy is interacted with optimism, the coefficient turns out to be negative. This shows within each quartile, banks showing excess optimism have lower return going forward.

Relationship between loan growth, degree of optimism and subsequent returns						
A.One-year loan growth						
	1-year returns		**2-year returns**		**3-year returns**	
Growth quartile 2	−0.0045 (−4.5)	−0.0041 (−4.2)	−0.01 (−6.61)	−0.009 (−6.38)	−0.012 (−6.23)	−0.012 (−6.19)
Growth quartile 3	−0.0055 (−4.98)	−0.0048 (−4.45)	−0.013 (−7.57)	−0.012 (−7.15)	−0.016 (−7.82)	−0.016 (−7.68)
Growth quartile 4	−0.0053 (−4.88)	−0.0043 (−4.10)	−0.015 (−8.29)	−0.013 (−7.85)	−0.020 (−9.22)	−0.019 (−9.13)
Growth quartile 2*optimism	−0.011 (−6.01)	−0.011 (−6.10)	−0.015 (−5.36)	−0.015 (−5.35)	−0.011 (−3.42)	−0.011 (−3.47)
Growth quartile 3*optimism	−0.007 (−3.80)	−0.008 (−4.04)	−0.008 (−3.07)	−0.008 (−3.20)	−0.002 (−0.69)	−0.002 (−0.71)
Growth quartile 4*optimism	−0.01 (−4.08)	−0.01 (−4.14)	−0.011 (−3.10)	−0.01 (−3.31)	−0.002 (−0.68)	−0.003 (−0.90)
No. of Observations	27,468	27,468	24,749	24,749	22,284	22,284
R-squared	0.30	0.31	0.36	0.36	0.40	0.38
B.Three-year loan growth						
Growth quartile 2	−0.006 (−5.35)	−0.006 (−5.51)	−0.009 (−4.61)	−0.009 (−4.75)	−0.011 (−4.58)	−0.011 (−4.69)
Growth quartile 3	−0.008 (−6.09)	−0.007 (−6.21)	−0.014 (−6.49)	−0.013 (−6.66)	−0.017 (−6.34)	−0.016 (−6.48)
Growth quartile 4	−0.012 (−8.02)	−0.0114 (−8.22)	−0.020 (−8.15)	−0.019 (−8.33)	−0.025 (−7.80)	−0.024 (−7.94)
Growth quartile 2*optimism	−0.009 (−1.08)	−0.0103 (−1.26)	0.005 (0.45)	0.003 (0.32)	0.020 (1.37)	0.219 (−1.48)
Growth quartile 3*optimism	−0.019 (−2.46)	−0.021 (−2.63)	−0.011 (−0.96)	−0.012 (−1.07)	0.011 (0.82)	0.0104 (−0.76)
Growth quartile 4*optimism	−0.033 (−2.91)	−0.037 (−3.17)	−0.0252 (−1.55)	−0.027 (−1.68)	0.013 (0.81)	0.013 (−0.87)
No. of Observations	20,287	20,287	18,288	18,288	16,458	16,458
R-squared	0.28	0.29	0.36	0.367	0.42	0.42
Time FEs	Y	Y	Y	Y	Y	Y
Bank FEs	Y	N	Y	N	Y	N

Table VI: The table presents results from regressions of bank stock returns on bank's loan growth. Based on loan growth over past one year and three years, we sort the banks into quartiles. Variable Optimisim takes a value of 1 in panel A and panel B, if for that bank-quarter observation, the average error is estimating loan loss is positive during the previous one years and three years respectively. Indicator variables representing loan growth quartile are included in the regression and also interacted with Optimisim variable. Lowest loan growth quartile forms the base group. t-statistics are in parenthesis.

C.4. Asymmetry in Bias and Size effect

We extend our panel level analysis and study whether the extent of bias is symmetric across periods and size of banks. As per the bias observed, banks keep less than rationally expected provision during good time or when they experience relatively less loss on loans and vice versa. Here we qunatify the extent of under provisioning during good time and over provisioning during bad time. To do so, we measure the extent of the negative relationship between error term and net charge-offs during good time and bad time separately. We create a dummy variable 'B' for bad period and interact it with recent charge-off experienced by banks. We take the first approach in constructing the required variables and use all controls. Table VII shows the results.

Asymmetry in Bias

	$Error1_t$ = ΔRealised Net Charge-offs- ΔProvision		
$\Delta CurrentNCO$	-0.621 (-20.51)	-0.627 (-20.63)	-0.637 (-16.20)
B*$\Delta CurrentNCO$	0.265 (6.28)	0.25 (5.86)	0.263 (5.21)
ΔGDP		-0.213 (-0.46)	0.06 (0.10)
$\Delta CSRET$		-1.43 (-10.99)	-1.62 (-11.53)
Δr		0.23 (0.48)	-2.13 (-1.37)
$NPA1_t$			-0.033 (-0.05)
$NPA2_t$			-1.33 (-4.38)
Firm Fixed Effects	Y	Y	Y
Observations	31,041	31,041	19,388
R^2	0.1345	0.1461	0.1514
Number of BHCs	941	941	904

Table VII: Quarterly time series regressions of errors in bank's expectation of future loan loss or loan loss provision on change in recent net charge-offs. The error term and recent net charge-off is constructed using first approach. Dummy variable B stands is one for quarters in which banks experience an increase in net charge off compared to previous quarter. Standard errors are clustred by firms. Within R-square is reported. t-statistics in parenthesis.

The association between the error and recent loss experienced, which is magnitude of the coefficient of recent net charge-off is stronger during good time. A one unit fall in net charge-off growth makes banks to under provision by 0.63 units. The extent of over provisioning during bad time is comparatively less. When banks experience a unit increase in growth of recent loss, they over provision by 0.37 units. Although banks are keeping provision in a biased manner, the distortion caused by bias is stronger during good time.

We also run the above regression separately for banks depending on their size. Table VIII reports the extent of under provisioning and over provisioning. For brevity, only coefficients are reported. We report the results separately for banks below 90th percentile, above 90th percentile and above 95th percentile. The extent of underprovisioning is still higher than overprovisioning across size groups. As the coefficients suggest, large banks seem to be biased more while keeping provision.

Asymmetry in Bias across size groups

Association between error term and chaneg in recent net charge-off

	Extent of Over Provisioning	Extent of Under provisioning
All banks	-0.37	-0.63
$Size < 90th percentile$	-0.36	-0.63
$Size > 90th percentile$	-0.53	-0.80
$Size > 95th percentile$	-0.48	-0.71

Table VIII: The table reports the coefficients of recent net charge-off from running regression of errors in bank's expectation of future loan loss or loan loss provision on change in recent net charge-offs. Variables are constructed using first approach and all control variables are included. Under Provisioning column reports the association between error term and recent net charge-off when period is good. Periods are defined good when there is a fall in net charge-offs and vice-versa.

Since these large banks are a major source of credit to the economy, the bias in their behavior is more harmful. Under provisioning during good time makes the financial system more fragile and overprovisioning during bad time makes recovery from crisis more difficult. Our results favour earlier studies which advocates more regulations for large financial institutions.

III. Modelling Expectation

Now we are going to lay out the potential mechanism to incorporate the observed bias in the provisioning behavior of banks. All variables which are biased have a superscript of θ on them. We follow Bordalo, Gennaioli, and Shleifer (2018) and model this bias as deviation from rational expection. While estimating the loss fraction i.e. g_{t+1}, the bank gives more weightage to realized current conditions defined by g_t. Expectation formation by such process is termed as diagnostic expectation. The bias in believes of the bank gives rise to,

$$E_t^{\theta} g_{t+1} = E_t g_{t+1} \left(\frac{E_t g_{t+1}}{E_{t-1} g_{t+1}} \right)^{\theta} \tag{11}$$

The intuition behind above formulation is: Compared to quarter t-1, any new information about g_{t+1} the bank gets at t from g_t, is given more weightage. As per equation 1, when bank revises its expectation about g_{t+1} at t, it recieves new information in the form of $exp(\nu_t^g)$, which is given more importance. ν_t^g is the random shock on loan loss experienced at t. If this shock ν_t^g is positive, bank revises its expectation of the future loss at t+1 to be higher than what could be supported by fundamentals. Here θ measures extra weightage given to this new information. Because of this bias, loan loss provision becomes,

$$LLP_t^{\theta} = E_t^{\theta} g_{t+1} L_t \tag{12}$$

Log linearising the above two equations,

1. Biased Expectation of loss fraction or $(E_t^{\theta} g_{t+1})$: $\widehat{E_t^{\theta} g_{t+1}} = \rho \widehat{g_t} + \theta \left(\widehat{E_t g_{t+1}} - \widehat{E_{t-1} g_{t+1}} \right)$
2. Biased Provision or (LLP_t^{θ}): $\widehat{LLP_t^{\theta}} = \widehat{E_t^{\theta} g_{t+1}} + \widehat{L_t}$

If banks keep provision in a biased manner as described, the expectational error is

$$\widehat{Loss_{t+1}} - \widehat{LLP_t^{\theta}} = \widehat{g_{t+1}} - \widehat{E_t^{\theta} g_{t+1}} = \nu_{t+1}^g + \theta \left(\widehat{E_t g_{t+1}} - \widehat{E_{t-1} g_{t+1}} \right) \tag{13}$$

The last term in above equation is $\theta \rho \nu_t^g$. The error in this case contains this ν_t^g term which makes it predictable from current loss on loans experienced by the bank, which we observe in the empirical analysis.

As per diagnostic expectation, when banks overreact to recent good or bad innovations denoted by ν_t^g, it introduces excess volatility. Consistent with this, we find the variance of loan loss provision is 36% higher than net charge-offs and the difference is statistically significant.

IV. A model of banking sector with biased belief

In section 3, we have established the hypothesis that banks extrapolate current conditions and keep provision in a biased manner. This concurs well with the biased provision model described in section 4. To study the implications of such bias on economy, we augment the standard New Keynesian model (Agénor and Zilberman (2015)) with a banking sector which has diagnostic expectation (Bordalo, Gennaioli, and Shleifer (2018)). The model economy has three sectors: households, firms and bank. The firms are further sub divided into final good firms, intermediate good (IG) firms and a capital good (CG) producer. The households and the firms are modelled in the standard rational expectation set up.

We start with describing the bank's activities as this is where our model differs from the standard model. Then we present firms, household sector and define general equilibrium.

A. Formulation of bank's objective

We have already explained the mechanism for actual loss on loans and observed bias in loan loss provision in section 2 and section 4 respectively. Here we are going to explain the remaining parts of the role the bank plays in the model. The bank finances the loan of capital good producer using deposit and if there is any shortfall, it borrows from the central bank. The supply of loan is perfectly elastic at the prevailing loan rate. The bank's balance sheet in real terms can be written as

$$(L_t - LLR_t^{\theta}) + B_t^B = D_t + L_t^B \tag{14}$$

where the first term in the parenthesis is total credit extended by the bank L_t net of loan loss reserve LLR_t^{θ}. B_t^B is the amount invested in government bonds which pays an interest of i_t^B. On liability side, apart from deposit D_t, the bank borrows L_t^B from the central bank at a rate of i_t^r.

The bank invests entire amount of loan loss reserves in safe assets i.e. $LLR_t^{\theta} = B_t^B$ and earns an interest i_t^B on it.

We use the specification used by Agénor and Zilberman, 2015 for defining loan loss reserve as follows.

$$LLR_t^{\theta} = (LLR_{t-1})^{\rho_{LR}} (LLP_t^{\theta})^{1-\rho_{LR}} \tag{15}$$

where ρ_{LR} is the persistence parameter.[3]

[3]The specification assumes bank builds provisions up gradually over the period. Also we do not model charge offs and loan recoveries for simplicity.

The commercial bank in each period sets deposit rate and lending rate to maximize the expected value of profit realised at the end of the period. The expected value of the end of the period profit is

$$E_t J^B_{t+1} = (1 - E^\theta_t g_{t+1})(1 + i^L_t)L_t + (1 + i^B_t)LLR^\theta_t - (1 + i^D_t)D_t \\ -(1 + i^R_t)L^B_t - LLP^\theta_t \tag{16}$$

Here, the first term is the fraction of cash flow from the loan the bank is expecting to receive. The second term represents loan loss reserve which are invested in government bonds. Loan loss provision i.e. LLP^θ_t is deducted from the bank's profit. Maximising the profit subjected to loan loss estimated by equation 15 and balance sheet constraint equation 14, yields the following first order conditions.

$$1 + i^D_t = \frac{1 + i^R_t}{1 + \eta_D^{-1}} \tag{17}$$

where η_D is constant interest elasticity of deposit.

$$1 + i^L_t = \frac{(1 + \eta_L^{-1})^{-1}}{1 - E^\theta_t g_{t+1}} \left\{ (1 + i^R_t) + \frac{\partial LLP^\theta_t}{\partial L_t} - (1 + i^B_t)\frac{\partial LLR^\theta_t}{\partial L_t} \right\} \tag{18}$$

where η_L is constant interest elasticity of loan demand. Equation 18 indicates the bias in belief generated by diagnostic expectation affects loan rate in two ways. First, risk arising out of default must be compensated. Through the risk premium channel, the fraction of loss estimated adds to the cost of borrowing. However, with diagnostic expectation, the effect is exaggerated. During bad time, the bank is overly pessimistic and a higher $E^\theta_t g_{t+1} \left(> E_t g_{t+1} \right)$ reduces the expected marginal return from each unit of loan which is $(1 + i^L_t)(1 - E^\theta_t g_{t+1})$. This increases the cost borrowing for the capital good producer.

Second, as shown by equation 12 diagnostic expectation also affects loan loss provision. Loan loss provision affects the cost of borrowing through the composite term $\frac{\partial LLP^\theta_t}{\partial L_t} - (1 + i^B_t)\frac{\partial LLR^\theta_t}{\partial L_t}$. This provisioning cost channel's impact as defined by Agénor and Zilberman (2015) depends on the relative magnitude of opportunity cost associated with $\frac{\partial LLP^\theta_t}{\partial L_t}$ and return earned from $\frac{\partial LLR^\theta_t}{\partial L_t}$. The impact of diagnostic belief by the commercial bank affects the cost of borrowing and thus the investment by the capital good producer. The above channels establish the link between the banking sector which is irrational and the real side of the economy.

B. Capital good producer

The capital good producer uses final good to produce new capital. To do so, it has to pay for these goods in advance by borrowing from the commercial bank. To invest I_t it needs to borrow from the commercial bank L_t, where $L_t = I_t$. Assuming linear production technology, the new stock of capital after investment is

$$K_{t+1} = I_t + (1-\delta_k)K_t - \frac{\Theta_k}{2}\left(\frac{K_{t+1}}{K_t} - 1\right)^2 K_t \tag{19}$$

where δ_k is the constant rate of depreciation and Θ_k is the adjustment cost parameter. So capital for the next period is sum of existing stock of capital after depriciation and new investment net of adjustment cost. The bank charges the capital good producer i_t^L for financing the new investment. The repayment is done at the begining of period t+1 (which is similar to end of period t). However the repayment is uncertain and it can pay back only $(1-g_{t+1})$ fraction. The capital goods producer chooses the level of capital stock to maximize the value of discounted profit subjected to equation 19. The end of period profit is

$$E_t J_{t+1}^k = r_t^k K_t - (1-E_t g_{t+1})(1+i_t^L)L_t$$

where r_{t+1}^k is the rental rate for capital goods. The optimization problem of the CG producer is

$$\begin{aligned}\max_{K_{t+s+1}} E_t \sum_{s=0}^{\infty} \Delta_{t,t+s} \Bigg[r_{t+s}^k K_{t+s} - (1-E_t g_{t+1})(1+i_{t+s}^L)\Bigg\{ & K_{t+s+1} - (1-\delta_k)K_{t+s} \\ & + \frac{\Theta_k}{2}\left(\frac{K_{t+s+1}}{K_{t+s}} - 1\right)^2 K_{t+s}\Bigg\}\Bigg]\end{aligned} \tag{20}$$

where $\Delta_{t,t+s}$ is the stochastic discount factor. The first order condition yields

$$\begin{aligned}E_t r_{t+1}^k = {} & (1-E_t g_{t+1})(1+i_t^L)E_t\left[\left\{1+\Theta_k\left(\frac{K_{t+1}}{K_t}-1\right)(1+i_t^B)\frac{P_t}{P_{t+1}}\right\}\right] \\ & -(1-E_t g_{t+2})E_t\left[(1+i_{t+1}^L)\left\{(1-\delta_k)+\frac{\Theta_k}{2}\left[\left(\frac{K_{t+1}}{K_t}\right)^2 - 1\right]\right\}\right]\end{aligned} \tag{21}$$

C. Intermediate good firms

A continuum of IG firms indexed by $j \in (0,1)$ operate in a monopolistic environment. They use capital and labor to produce the intermediate good as follows:

$$Y_{j,t} = A_t N_{j,t}^{1-\alpha} K_{j,t}^{\alpha} \tag{22}$$

where $K_{j,t}$ is the capital used after renting from the capital good producer. $N_{j,t}$ is the amount of labor employed and A_t denotes a common technology parameter. A_t follows AR(1) process,

$$\frac{A_t}{\overline{A}} = \left(\frac{A_{t-1}}{\overline{A}}\right)^{\rho_A} exp(\nu_t^A)$$

where ρ_A is the persistence parameter and ν_t^A is a normally distributed random shock with zero mean and constant variance. $\overline{A}$ is the steady state value.
The IG firm first minimizes the cost of production and decides on capital and labor.

$$min_{N_{j,t},K_{j,t}} W_t^R N_{j,t} + r_t^k K_{j,t} \tag{23}$$

where r_t^k is the rent paid on each unit of capital and W_t^R is the wage rate. The minimization excercise leads to the optimal capital to labour ratio as

$$\frac{K_{j,t}}{N_{j,t}} = \alpha(1-\alpha)^{-1}\left(\frac{W_t^R}{r_t^k}\right)$$

The real marginal cost is given by

$$MC_{j,t} = \frac{(W_t^R)^{1-\alpha}(r_t^k)^{\alpha}}{\alpha^{\alpha}(1-\alpha)^{\alpha} A_t}$$

Next, the IG firms set the optimal price for maximizing profit. Here we use Calvo type pricing contracts, where a fraction ω_p of firms keep their prices fixed while the rest of firms adjust their price. The profit maximization excercise yields the following price equation

$$\frac{P_t^*}{P_t} = \left(\frac{\theta_p}{\theta_p - 1}\right)\frac{E_t \sum_{s=0}^{\infty} \omega_p^s \beta^s C_{t+s}^{-\tau} Y_{t+s} MC_{t+s}\left(\frac{P_{t+s}}{P_t}\right)^{\theta_p}}{E_t \sum_{s=0}^{\infty} \omega_p^s \beta^s C_{t+s}^{-\tau} Y_{t+s}\left(\frac{P_{t+s}}{P_t}\right)^{\theta_p - 1}} \tag{24}$$

where P_t^* is the optimal price chosen by firms adjusting their prices in period t.

D. Final good firm

Final good firm opertates in a perfectly competitive environment. It combines the goods received from a continuum of intermediate firms [0,1] and produces the final good as,

$$Y_t = \left[\int_0^1 Y_{j,t}^{\frac{\theta_p - 1}{\theta_p}} dj \right]^{\frac{\theta_p}{\theta_p - 1}} \tag{25}$$

where θ_p is the elasticity of substitution between intermediate goods. It buys goods from the intermediate firm at price $P_{j,t}$ and sells the final good at P_t. The optimisation problem determines the familiar conditions for demand of intermediate good,

$$Y_{j,t} = Y_t \left(\frac{P_{j,t}}{P_t} \right)^{-\theta_p} \tag{26}$$

The price of the final good in the competitive environment is obtained by imposing zero profit condition,

$$P_t = \left[\int_0^1 P_{j,t}^{1-\theta_p} dj \right]^{\frac{1}{1-\theta_p}} \tag{27}$$

E. Households

There is a continuum of homogenous households maximizing expected life time utility

$$U_t^i = E_t \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{1-\tau}}{1-\tau} - \frac{H_t^{1+\gamma}}{1+\gamma} + \eta_x ln \left\{ \left(M_t^H \right)^{\nu} D_t^{1-\nu} \right\} \right] \tag{28}$$

where C_t is consumption, H_t is labour supply, D_t and M_t^H are deposits and cash respectively. η_x presents household preference for liquidity and ν presents relative preference between cash and deposit. Parameter τ and γ stands for intertemporal elasticity of substitution and marginal disutility for labor respectively. The representative household's budgest constraint is

$$\begin{aligned} C_t + D_t + B_t^H + M_t^H \leq (1 + i_{t-1}^D) D_{t-1} \frac{P_{t-1}}{P_t} + (1 + i_{t-1}^B) B_{t-1}^H \frac{P_{t-1}}{P_t} \\ + M_{t-1}^H \frac{P_{t-1}}{P_t} + \frac{W_t H_t}{P_t} + \int_0^1 J_{j,t}^{IG} dj + J_t^K + J_t^B - T_t \end{aligned} \tag{29}$$

Here bank deposits pay a return of i_t^D and investing in bonds B_t^H pay a return of i_t^B. Gross repayments include wage payments W_t, profit from IG fims J_t^{IG}, from CG producer J_t^K, and from bank J_t^B. In addition, they also pay a lump sum tax denoted by T_t. Payments from deposit,bond and cash holdings are adjusted to real terms in period t

Maximising equation 28 subject to equation 29 yields,

$$C_t^{-\tau} = \beta E_t \left[C_{t+1}^{-\tau} (1 + i_t^B) \frac{P_t}{P_{t+1}} \right] \tag{30}$$

$$D_t = \frac{\eta_x (1 - \nu) C_t^{\tau} (1 + i_t^B)}{i_t^B - i_t^D} \tag{31}$$

$$M_t^H = \frac{\eta_x (\nu) C_t^{\tau} (1 + i_t^B)}{i_t^B} \tag{32}$$

$$H_t = \left(W_t^R C_t^{-\tau} \right)^{1/\gamma} \tag{33}$$

where W_t^R is the real wage. The first three conditions determine household's consumption, deposit and cash holding. The last condition determines the labour supply.

F. Central Bank

The central bank is assigned with the responsibility of conducting moneatry policy, using a Taylor-type rule:

$$\frac{1 + i_t^R}{1 + \overline{\overline{i^R}}} = \left(\frac{1 + i_{t-1}^R}{1 + \overline{\overline{i^R}}} \right)^{\phi} \left[\left(\frac{Y_t}{\overline{\overline{Y}}} \right)^{\phi_Y} \left(\frac{\pi_t}{\pi_T} \right)^{\phi_\pi} \right]^{1-\phi} \tag{34}$$

where π_T is target inflation rate. $\frac{Y_t}{\overline{\overline{Y}}}$ is cyclical component of output. Central Bank's balance sheet contains loans given to the commercial bank L_t^B and holdings of government bonds B_t^C on asset side. On liability side, there is only money supply given by M_t^s,

$$L_t^B + B_t^C = M_t^S \tag{35}$$

Any income generated by the central bank is transferred to the government at the end of the period.

G. Government

The government spends G_t on final goods, pays back to all entities holding government bonds at the end of the period. It finances this expenditure by issuing new bonds, collecting lump-sum taxes from households and, using profit transferred from the central bank. Thus, the budget constraint of the government in real terms can be written as

$$T_t + i^R_{t-1} L^B_{t-1} \frac{P_{t-1}}{P_t} + i^B_{t-1} B^C_{t-1} \frac{P_{t-1}}{P_t} + B_t = G_t + (1 + i^B_{t-1}) B_{t-1} \frac{P_{t-1}}{P_t} \tag{36}$$

where $B_t = B^H_t + B^B_t + B^C_t$ is the total bond issued. Government spending is fixed as a constant fraction of total output,

$$G_t = \mu Y_t \tag{37}$$

where $\mu \in (0,1)$

H. Market clearing conditions

All the households as well as the IG firms are identical. So in equilibrium $K_{j,t} = K_t$, $N_{j,t} = N_t$, $Y_{j,t} = Y_t$ and $P_{j,t} = P_t$ for all $j \in \left(0,1\right)$. The goods market clearing condition is$Y_t = C_t + I_t + G_t$. Loans are made in cash. In equilibrium currency market satisfies $M^S_t = M^H_t + L_t$. We assume total stock of government bond is constant at $\overline{B}$ and total holding of government bond by the central bank is constant at $\overline{B^C}$. The government maintains a balanced budget by varying the tax imposed on households.

V. Quantitative Analysis

In this section, we evaluate the quantitative effects of financial shocks when the commercial bank has diagnostic belief. To do so, we log-linearize the model. First we provide some dynamics of the model. Then through the simulation of the model, we capture the response of various macroeconomic as well as financial variables in response to a financial shock.

A. Steady State and Log-linearization

In the appendix, we have provided the details of steady states and log-linarized versions of the model. Here, we focus on some key variables important to our model. In the steady state, loan loss reserve and loan loss provisions are equal to,

$$\overline{LLR} = \overline{LLP} = \overline{g}\overline{L} \tag{38}$$

The fraction of loan loss in steady state is denoted by $\bar{g}$. The cost of borrowing for the capital goods producer in the long run is

$$1 + \overline{i^L} = \frac{\left(1 + \eta_L^{-1}\right)^{-1}}{1 - \overline{g}} \left[\left(1 + \overline{i^R}\right) - \overline{i^B}\overline{g}\right] \tag{39}$$

Many of the log linearized equations are similar to those from a standard New Keynesian model, which are given in the appendix. Below we only present the equations relevant to the commercial bank. The log-linearized equations representing fraction of loan loss is given by

$$\widehat{g_{t+1}} = \rho \widehat{g_t} + \nu_{t+1}^{g}$$

The log-linear equations that define bank's estimation of fraction of loan loss is given by

$$\widehat{E_t^{\theta} g_{t+1}} = \widehat{E_t g_{t+1}} + \theta \left(\widehat{E_t g_{t+1}} - \widehat{E_{t-1} g_{t+1}} \right) \tag{40}$$

where

$$\widehat{E_t g_{t+1}} = \rho \widehat{g_t}$$

The log-linear equations for loan loss provisions and loan loss reserves are

$$\widehat{LLP_t^{\theta}} = \widehat{L_t} + \widehat{E_t^{\theta} g_{t+1}}$$

$$\widehat{LLR_t^{\theta}} = \rho_{LR} \widehat{LLR_{t-1}} + \left(1 - \rho_{LR} \right) \widehat{LLP_t^{\theta}}$$

Using the above, the log-linearized version of the loan rate can be written as

$$\begin{aligned} (1-\overline{g})(1+\overline{i^L})\widehat{i_t^L} &= (1+\overline{i^R})\widehat{i_t^R} + \left\{ 1 - (1+\overline{i^B}) \right\} \overline{g} \left(\frac{\partial \widehat{LLP_t^{\theta}}}{\partial L_t} \right) \\ &- (1+\overline{i^B})\overline{g} \left\{ \widehat{i_t^B} - \rho_{LR} \left(\widehat{LLP_t^{\theta}} - \widehat{LLR_{t-1}} \right) \right\} + \overline{g} \widehat{E_t^{\theta} g_{t+1}} (1+\overline{i^L}) \end{aligned} \tag{41}$$

B. Parameterization

The baseline parameters such as discount factor, preference of households, price stickiness etc. are standard in the literature. The preference parameter of housholds for cash and deposit are set at 0.4 and 0.01 respectively. The persistence parameter for loan loss reserve is taken to be 0.8. (see Agénor and Zilberman (2015)). Below we explain the procedures used to estimate the parameters new to our model.

B.1. Estimating ρ and θ

Our results are robust to whichever approach we take in estimating parameters ρ and θ empirically. Although the value of these two parameters will change across the three different approaches, the results are qualitatively similar. So we continue with the first approach. For estimating ρ which is the persistence parameter in fraction of loan loss,

$$\widehat{g_t} = \rho \widehat{g_{t-1}} + \nu_t^g \tag{42}$$

we run the following regression:

$$\Delta nco_t = \beta_1 \Delta nco_{t-1} + \nu_t^g \tag{43}$$

where nco_t is the log of net charge-off normalised by last quarter loan. For estimating θ, the bias parameter, we first create the error term.

$$\widehat{g_{t+1}} - \widehat{E_t^\theta g_{t+1}} = \nu_{t+1}^g + \theta \left(\widehat{E_t g_{t+1}} - \widehat{E_{t-1} g_{t+1}} \right) \tag{44}$$

The right hand side equals to $\nu_{t+1}^g + \rho \theta \nu_t^g$. To estimate θ, we regress this error on recent loan loss fraction $\widehat{g_t}$. The coefficient of the regressor $\widehat{g_t}$ is given by

$$\frac{Cov\left(\widehat{g_{t+1}} - \widehat{E_t^\theta g_{t+1}}, \widehat{g_t} \right)}{Var\left(\widehat{g_t} \right)} \tag{45}$$

In estimation of θ, we regress the following error term on recent change in loan loss or Δnco_{t+1}

$$error_t = \Delta nco_{t+1} - \Delta llp_t \tag{46}$$

We use aggregate time series for running both the regressions. The results of both these regressions are already presented in Table I. The value of ρ comes out to be 0.525 and the coefficient of regressor recent net charge-off on error term is -0.538. Using results from both the regression and expanding equation 45, θ is given by

$$\theta = \frac{0.538 * var(\widehat{g_t})}{0.525 * Var(\nu_t^g)}$$

Expanding the above and substituting the estimated parameters, θ is estimated to be 1.04. $\bar{g}$ is taken to be 0.006 which is consistent with observed net charge-offs to last quarter loan ratio.

Details of parameter values are provided in Table IX.

Table IX: Parameter Values

Discount factor	β=0.99	Elasticity of intertemporal substitution	τ=2
Inverse of the frisch elasticity of labour supply	γ=2.5	Preference parameter for liquidity holdings	η_x=0.01
Share parameter in index of money holdings	ν=0.4	Elasticity of demand for intermediate goods	θ_p=6
Degree of price stickiness	ω_p=0.75	Share of capital in intermediate goods output	α=0.3
Depriciation rate of capital	δ_k=0.03	Adjustment cost parameter for investment	Θ_k=10
Persistence parameter in LLR	ρ_{LR}=0.8	Share of government spending in output	μ=0.3
Degree of persistence in Taylor rule	ϕ=0.8	Response of policy rate to inflation deviation	ϕ_π=1.5
Response of policy rate to output deviation	ϕ_Y=0.2	Persistence parameter for loss causing events	ρ_{jj}=0.92
Persistence parameter for loan loss fraction	ρ=0.525	Steady state value for fraction of loan loss g	$\bar{g}$=0.006
Bias Parameter	θ=1.04		

C. Diagnostic Expectation in Banks and Proporties of Equilibrium

The goal of this section is to provide some basic insights into the effect of bias caused by diagnostic expectation on bank's lending activity. To do so analytically, we have made some simplifying assumptions.

In our model, commercial bank is the only channel through which the effect of financial shock ν_t^g is transmitted to the real side. Diagnostic expectation operates through this financial shock. After experiencing an increase in loan loss, the commercial bank extrapolates the bad situation and accordingly sets the interest rate. Below we present some results regarding the extent of distortion caused by diagnostic expectation.

We start from time t when the commercial bank observes the financial shock ν_t^g. It adjusts the interest rate which is governed by equation 18. It is difficult to analytically derive any result as all the variables are simultaneously determined. So we make the following simplifying assumptions.

1. The policy rate i.e. i_t^R is constant.

2. The persistence parameter in loan loss reserve equation i.e. ρ_{LR} is 0.

When i_t^R is constant, $\widehat{i_t^R} = 0$. Since, bond rate i_t^B mimicks policy rate, $\widehat{i_t^B}$ is also 0. The loan rate equation can now be written as

$$1 + i_t^L == \frac{\left(1+\eta_L^{-1}\right)^{-1}}{1 - E_t^\theta g_{t+1}} \left\{ 1 + \overline{i^R} - \overline{i^B} \frac{\partial LLP_t^\theta}{\partial L_t} \right\} \tag{47}$$

The log linearized version of the equation which shows the adjustment made to the loan rate by the bank after observing the financial shock is,

$$(1-\overline{g})(1+\overline{i^L})\widehat{i_t^L} = \overline{g}(1+\overline{i^L})\widehat{E_t^\theta g_{t+1}} - \overline{g}\overline{i^B}\frac{\partial \widehat{LLP_t^\theta}}{\partial L_t} \tag{48}$$

where $\frac{\partial LLP_t^\theta}{\partial L_t} = E_t^\theta g_{t+1}$. So equation 48 can be written as

$$(1-\overline{g})(1+\overline{i^L})\widehat{i_t^L} = \overline{g}\widehat{E_t^\theta g_{t+1}}(1+\overline{i^L}-\overline{i^B})$$

After the economy is hit by an adverse financial shock v_t^g equivalent to an increase in g_t,

PROPOSITION 1: *Diagnostic expectation induced bias which is measured by θ, causes more than required deviation in loan rate.*

$$\frac{\partial \widehat{i_t^L}}{\partial \theta} > 0 \tag{49}$$

See the Appendix for all derivations. After a negative financial shock, the bank increases loan rate. But the actual change is higher than the required change which can be supported by the underlying financial shock. The higher the θ, the deviation caused by any shock is larger. This gets passed on to the capital goods producer's investment decision and finally output.

The extent of distortion $\left(\frac{\partial \widehat{i_t^L}}{\partial \theta}\right)$ caused by θ depends on several parameters. The effect of some of these parameters are straighforward. For example, persistence parameter ρ increases the extent of distortion. A higher persistence parameter means present outcomess contain more information for future. So any bias in formulating expectation about future gets amplified by ρ.

PROPOSITION 2: *The average loan loss $\overline{g}$ amplifies the distortion caused by diagnostic expectation.*

$$\frac{\partial^2 \widehat{i_t^L}}{\partial \overline{g} \partial \theta} > 0 \tag{50}$$

The steady state value of loan loss inflates the increase in cost for the bank after a negative shock and reduces the benefit of extending one unit of loan. This is clear from equation 48. So the impact of θ which operates through change in cost (right hand side of equation 48) gets inflated when $\overline{g}$ is higher. This suggests a better credit equilibrium condition where loan recovery for banks is high, lessens the impact of diagnostic expectation.

PROPOSITION 3: *In the presence of diagnostic expectation, when steady state loan loss fraction or $\overline{g}$ increases, the adjustment to loan rate is higher.*

$$\frac{\partial \widehat{i_t^L}}{\partial \overline{g}}|_{\theta=\widehat{\theta}} = \left[1+\widehat{\theta}\left(1-\frac{\widehat{E_{t-1}g_{t+1}}}{\widehat{E_t g_{t+1}}}\right)\right]\frac{\partial \widehat{i_t^L}}{\partial \overline{g}}|_{\theta=0} \tag{51}$$

The term in the square bracket is always positive after a negative financial shock or an increase in g_t. Diagnostic expectation only amplifies the effect of financial shocks. It does not have any impact on steady state equilibrium. But when steady state equilibrium value for fraction of loan loss increases, banks adjust their loan rate upward[4] after a negative financial shock. Because of bias, this upward adjustment gets amplified. In this way diagnostic expectation exaggerates the impact of change in any steady state value. To sum up,

1 Adjustment to loan rate after a financial shock is higher in the presence of diagnostic expectation.

2 Improvement in credit market equilibrium condition which gets reflected in better recovery from impaired loans by banks, helps in reducing the effect of diagnostic expectation.

3 Effect of any institutional changes to credit market scenario, on interest rate and credit supply gets amplified if banks have diagnostic expectation while evaluating loans.

D. Findings

D.1. Impact of a negative macroeconomic shock

In this section, we examine the response of major variables after the economy is hit by a negative shock. The negative shock, we study, is a relative increase in g_t. We compare the response of variables in two cases: 1. When bank forms its expectation about loan loss rationally, 2. When bank suffers from diagnostic expectation bias. For the second case, we take the value of θ which is the bias parameter to be 1.04 as estimated.

[4] $\frac{\partial \widehat{i_t^L}}{\partial \overline{g}}$ is greater than zero.

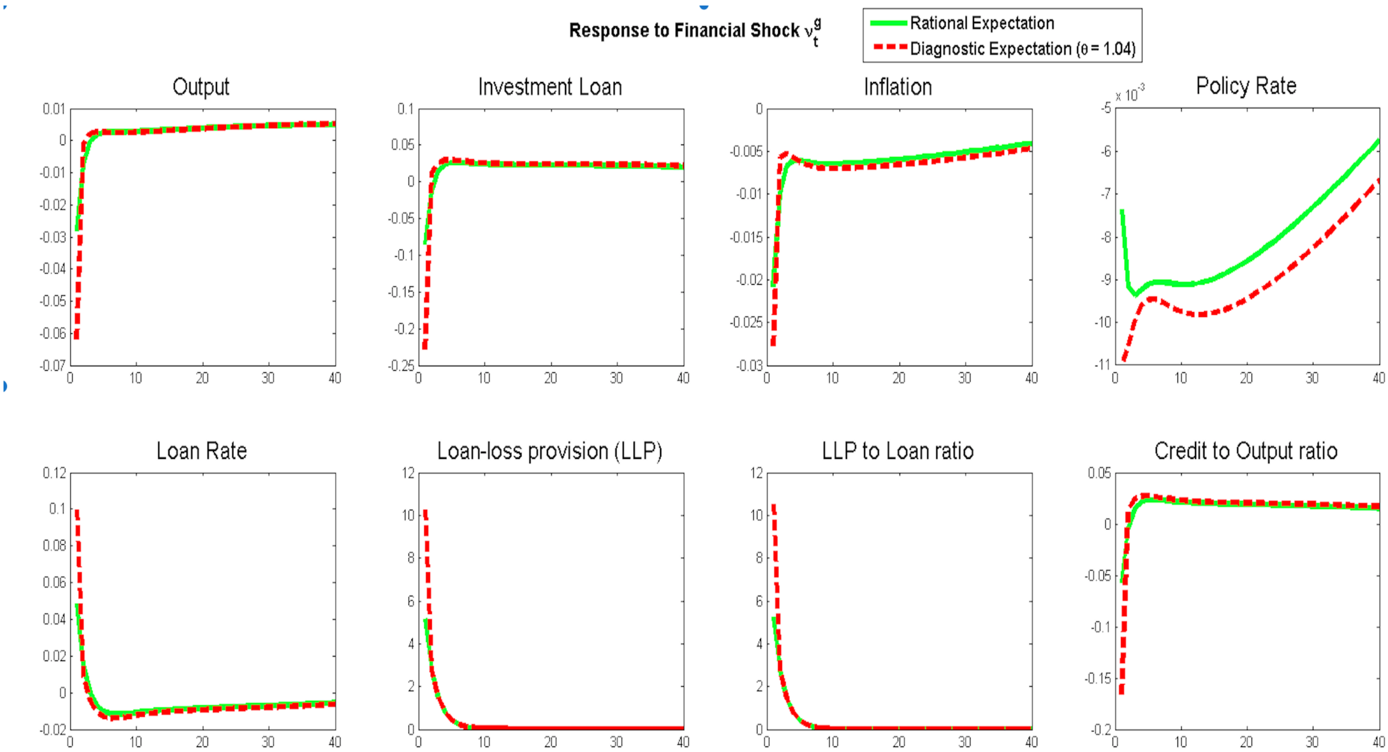

Figure 5: Response of variables when g_t rises by 10% through v_t^g: The green line plots the response of variables when there is no bias and the red line plots the response of variables when there is bias or $\theta = 1.04$

As we can see from Figure 5, a negative financial shock that increases g_t by 10%, increases the loan rate. The direct channel through which the shock affects the loan rate is the risk premium channel. Experience of higher than expected loss makes bank pessimistic about future and leads to a conjecture of higher loan loss. To compensate for this expected loss, it charges a higher rate ex-ante. Secondly, the bank is mandated to keep higher provision to account for the increase in expected loan loss. Since these provisions are invested in safe assets only, there is an indirect cost channel which affects the loan rate. The higher provision negatively affects bank's profit and makes the bank to pass these costs to the borrower.

Through loan rate, the effect is transmitted to the real economy. Because of an increase in loan rate, the capital goods producer invests less, which causes a fall in output. Overall the economy enters into a contraction phase with reduced output, less investment and a fall in credit to output ratio. In line with Taylor rule, the central bank reduces the policy rate to counter the negative effect.

The impact of bias as shown by the dashed red line, is to exaggerate the above effects. After the negative shock, the bank overreacts by expecting higher fraction of loan loss to happen at the end of the period. This more pessimistic conjecture by the bank increases the loan rate by a higher amount as indicated in the figure and causes a further reduction in loan extended as well as the output. So this bias caused by diagnostic expectation makes the bank's activities of extending loan as well as keeping loan loss provision more procyclical.

D.2. Statistical Provisioning

This incurred loss model for keeping loan loss provision[5] has been criticised after the crisis because of its pro-cyclical nature. It recognises the loss too late i.e. after the loss causing event happens. If bank keeps extra provision during good time, it can be used later when the loss causing event actually takes place. In this case the bank needs to estimate the expected loan loss over the whole business cycle. Specifically, this statistical provisioning rule can be written as

$$LLP_t^{\theta,Statistical} = E_t^{\theta} g_{t+1} L_t + \lambda \left(\overline{g} - E_t^{\theta} g_{t+1} \right) L_t \tag{52}$$

Here λ is the smoothening parameter.

We conduct the same experiment by increasing g_t 10% with smoothening parameter λ=0.8. Figure 6 shows that results from statistical provisioning indicated by black dashed line mitigate the procyclicality of loan loss provisioning significantly. The two variables, loan loss provision and loan loss provision to loan ratio show substantial change. Output, Investment, credit to output ratio also show improvement compared to incurred loss scenario. However statistical provision can only affect these variables through provisioning cost channel. It diminishes the effect of bias on loan loss provision. But the impact of bias through risk premium channel still remains.

[5] Also called specific provisioning (See Agénor and Zilberman (2015),Saurina (2009))

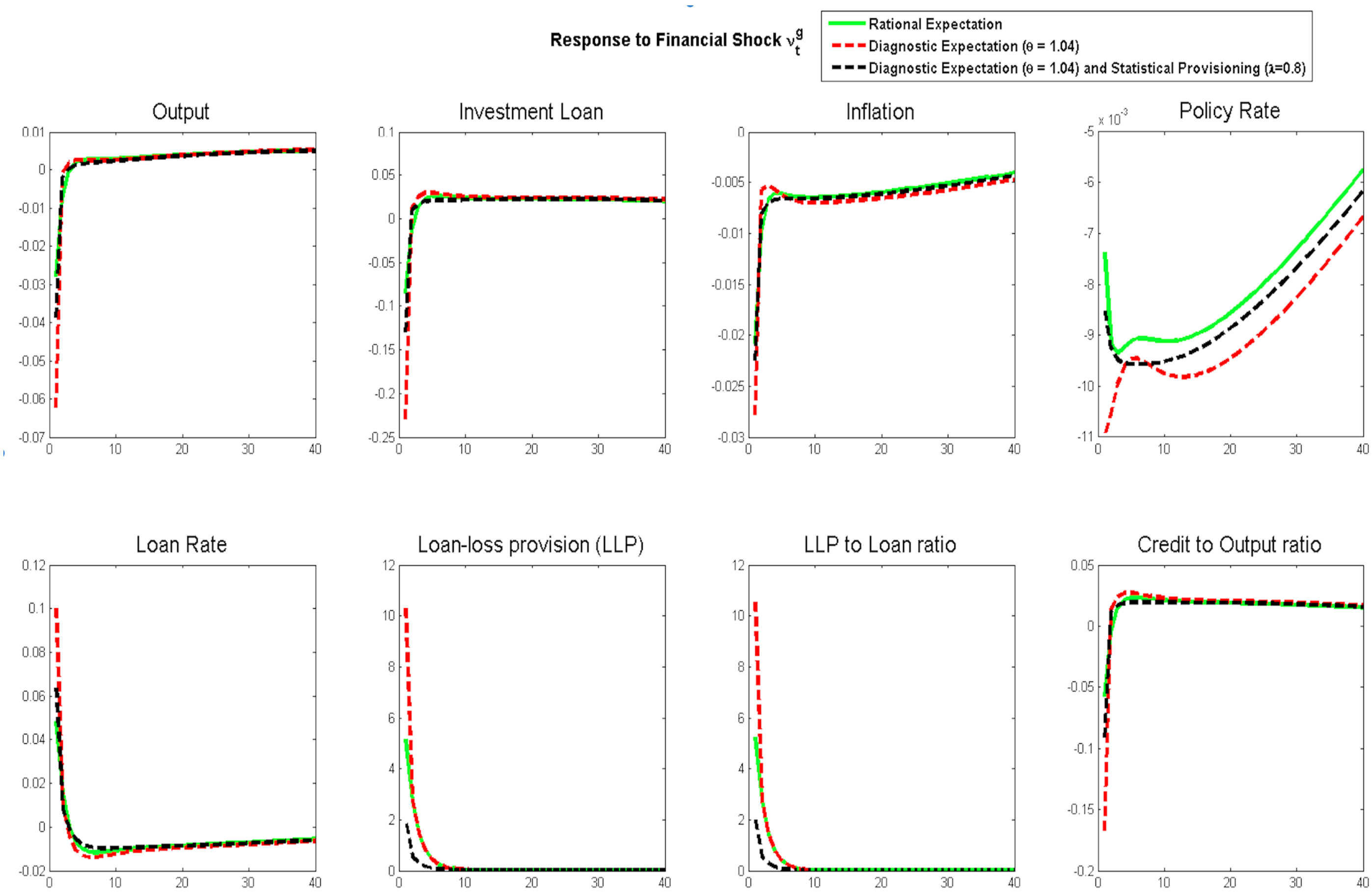

Figure 6: Response of variables when g_t rises by 10% **through** ν_t^g: The green line plots the response of variables when there is no bias and the red line plots the response of variables when there is bias or $\theta = 1.04$. The black line plots the response where there is bias and banks follow statistical provisioning with $\lambda = 0.8$

To reach at an optimal value of smoothening parameter λ, it is essential to consider the presence of bias in bank's behavior. Below we conduct an excercise to quantify the effect of λ in presence of bias, θ and a negative financial shock to g_t as above. The objective of the regulator, we consider, is to reduce volatility in output, inflation as well as credit to output ratio, a measure for financial sector health. We consider the following loss function for the regulator,

$$Loss_t = V\left(\widehat{\pi}_t\right) + 0.25V\left(\widehat{Y}_t\right) + 0.1V\left(\widehat{L}_t - \widehat{Y}_t\right) \tag{53}$$

Here $V(x_t)$ denotes the volatility of the deviation of a variable x_t from its steady state.

Figure 7 plots the loss function against degree of biasedness θ and smoothening parameter λ. We vary smoothening parameter λ and bias parameter θ in step of 0.1 while restricting the value of λ between $\left(0,1\right)$. As shown in the figure, with θ the volatility of financial sector as well as real sector increases. To make loan loss provision less procyclical and achieve a certain target for loss, the smoothening parameter λ that needs to be set by regulators, is required to be higher than the one calculated without taking into account the bias induced by diagnostic expectation.

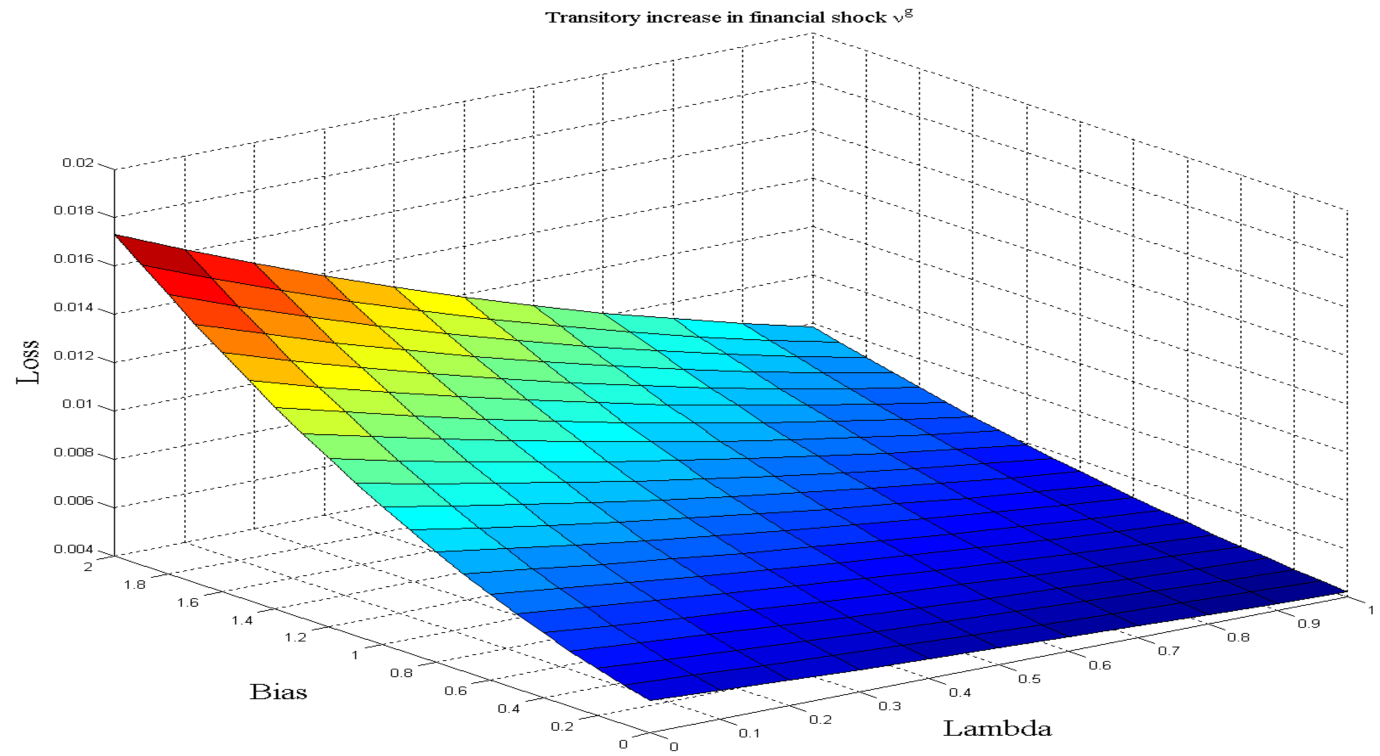

Figure 7: Loss Function when g_t rises by 10% through v_t^g

VI. Dynamics of the model with actual financial shocks

In this section, we study the dynamics of the model by feeding actual shocks estimated from data. We construct the financial shock series v_t^g from data and subject the economy with these shocks. Then we compare the response of key macroeconomic variables between two scenarios: 1. when there is no bias 2. when there is bias. For loan loss provision, we use only incurred loss approach which is currently followed by banks.

A. Estimation

The variables g_t which represents fraction of loan loss follows

$$\widehat{g_{t+1}} = \rho \widehat{g_t} + v^g_{t+1}$$

As explained in section 2.1.1, we use net charge-off to run this regression. The variables are constructed using first approach. The residuals of the above regression is used to construct the series for the financial shock.

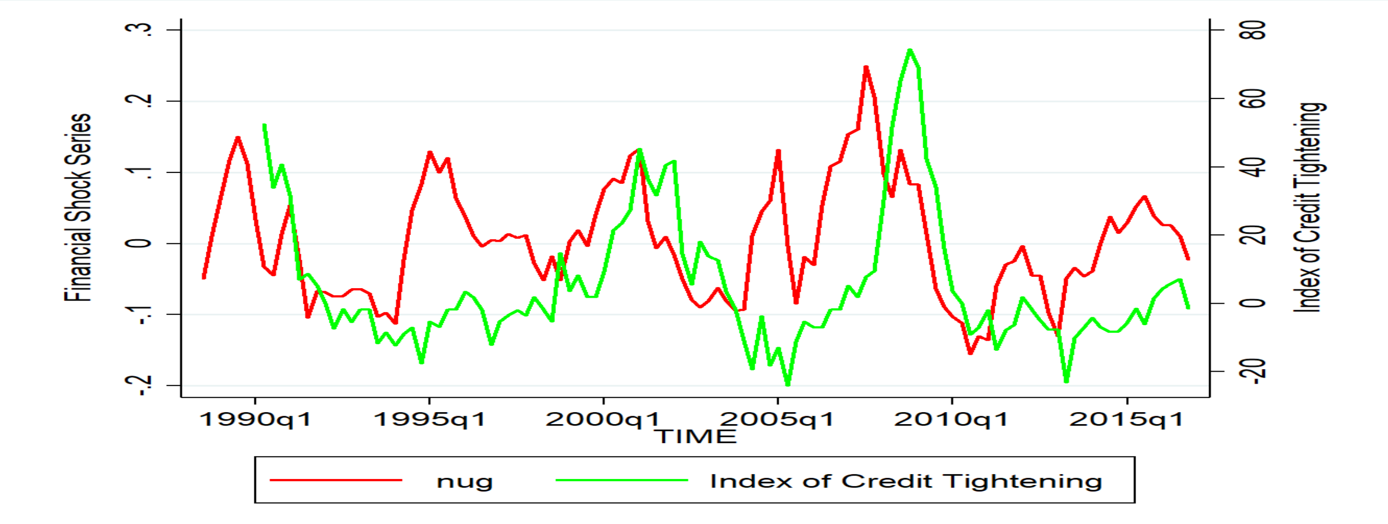

Figure 8: Financial Shock (Red Line) and Credit Tightness index (Green Line) Time Series

Figure 8 plots the financial shock series v^g_t against credit tightness index, which shows net percentage of banks tightening credit standard to small firms.[6] Starting with the steady state, we feed the innovations into the model and compute the response of model variables. Figure 9 reports the results. The top row plots real GDP growth and unemployment growth. Bottom row plots change in loan supply and change in interest rate charged by the bank.

The response of the variables in no bias case seems more stable compared to the scenario where bias is present. In case of diagnostic expectation, the short term extrapolative behavior creates abrupt reversals of credit cycle than what could be accounted from fundamentals. This over reaction amplifies the volatility of macroeconomic as well as financial variables making the system more unstable. The presence of bias in the behavior of banks also tends to deepen the procyclicality.

[6]Data is taken from Federal Reserve's Senior Loan Officer Opinion Survey.

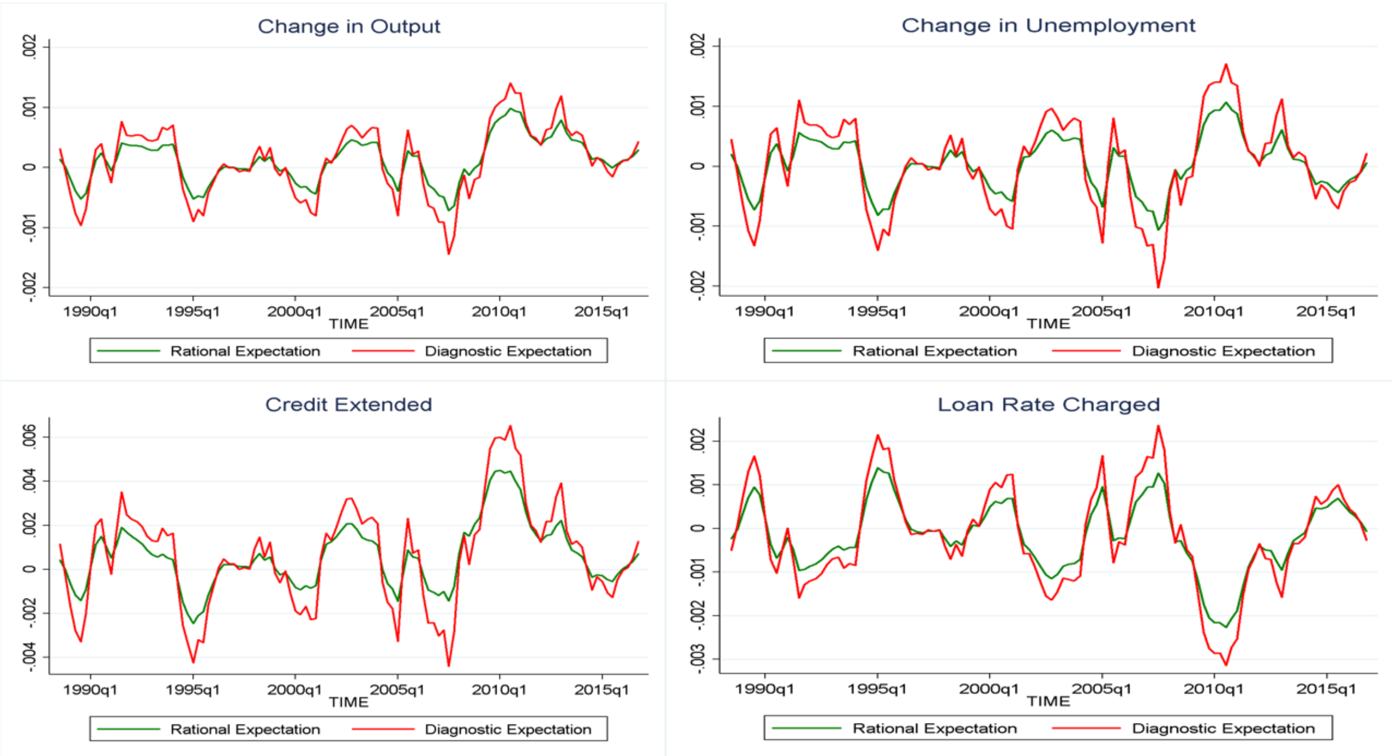

Figure 9: Model generated dynamics with financial shocks from 1988:Q3 to 2016:Q4

Our model economy has a financial system with only a banking sector and its associated financial shock coming only from loan loss provision. Incorporating a richer financial sector could help to understand effect of extrapolative expectation in explaining procyclicality in a better way.

VII. Implications for Monetary and Macroprudential Policies

In this section, we study the effectiveness of macroprudential policies in mitigating procyclicality in the presence of a biased banking sector. For macroprudential instruments, we consider an augmented Taylor rule and statistical provisioning system. An augmented Taylor considers financial sector stability while deciding policy rate. The two measures of financial stability we use, are credit to output ratio, and spread (difference between loan rate charged by bank and policy rate). We analyze different scenarios combining an augmented Taylor rule or standard Taylor rule with either specific provisioning or statistical provisioning system. The augmented Taylor rule, we use can be written as,

$$\frac{1+i_t^R}{1+\overline{i^R}} = \left(\frac{1+i_{t-1}^R}{1+\overline{i^R}}\right)^{\phi} \left[\left(\frac{Y_t}{\overline{Y}}\right)^{\phi_Y} \left(\frac{\pi_t}{\pi_T}\right)^{\phi_\pi} \left(\frac{FS_t}{\overline{FS}}\right)^{\phi_{mp}}\right]^{1-\phi} \tag{54}$$

where FS is financial stability indicator. It is either credit to output ratio $\left(\frac{L_t}{Y_t}\right)$ or spread $i_t^L - i_t^R$.
To study optimal policy, we consider the following loss function,

$$Loss_t = V(\widehat{\pi}_t) + 0.25 * V(\widehat{Y}_t) + 0.1 * V(\widehat{FS}) \tag{55}$$

The above loss function considers volatility of deviation of variables from their steady state. We define sum of volatility of inflation and volatility of output as monetary policy loss[7],volatility of credit to output ratio or spread as macroprudential loss[8] and the sum of all three as combined loss.

We compute loss under four different scenarios as reported in Table X. We normalise the loss function values at specific provisioning rule with no bias to 100 and losses in other cases are reported as percentage of this. Presence of bias increases loss under all cases. This is expected as banks overreact to financial shock causing more volatility. This reaffirms the results of Figure 9 where output and investment are more volatile when the banking sector is biased. The above conclusion holds under both financial stability measures we use.

For statistical provisioning case, the optimal value for λ is found to be one. Statistical provisioning seems to help in reducing volatility. When statistical provisioning is in place, use of augmented monetary policy seems to cause only marginal improvement. This can happen as monetary policy uses the same instrument i.e. policy rate, to control financial stability along with output and inflation. This might reduce the effectiveness of monetary policy.

Our model does not have a full-fledged finanical sector, so we do not suggest any firm recommendation for improving financial stability. Given the objective of our paper, at best we can conclude that presence of bias in the banking sector induces more volatility, deepens procyclicality, and leads to suboptimal results. Use of statistical provisioning delivers better outcomes. Use of augmented monetary policy rule does not give any significant improvement when statistical provisioning rule is already in place.

[7]Monetary Policy Loss= $0.25 * V(\widehat{\pi}_t) + 0.25 * V(\widehat{Y}_t)$

[8]Macroprudential Loss= $0.1 * V(\widehat{L}_t - \widehat{Y}_t)$ or $0.1 * V(\widehat{spread_t})$

		Credit to Output Ratio		Spread	
		No Bias	Bias	No Bias	Bias
		$\theta = 0$	$\theta = 1.04$	$\theta = 0$	$\theta = 1.04$
Statistical Provisioning with Augmented Monetary Policy	Moneytary Policy Loss	57.98	112.19	52.42	96.33
	Macroprudential Loss	39.37	108.66	0.315	0.67
	Combined Loss	55.27	112.58	45.44	83.41
Specific Provisioning with Augmented Monetary Policy	Moneytary Policy Loss	100.83	224.85	86.86	177.51
	Macroprudential Loss	91.33	245.66	0.63	1.57
	Combined Loss	98.97	226.4	75.23	153.73
Statistical Provisioning	Moneytary Policy Loss	58.22	112.3	52.54	96.8
	Macroprudential Loss	39.37	117.32	0.315	0.63
	Combined Loss	55.37	112.59	45.54	83.83
Specific Provisioning	Moneytary Policy Loss	100	224.85	87.1	177.51
	Macroprudential Loss	100	311	0.63	1.57
	Combined Loss	100	225.18	75.43	153.73

Table X: We estimate optimal policy parameters as well as the minimum loss for the regulator under different policy regimes. Two majors i.e. Credit to Output ratio and Spread between loan rate and policy rate are used as financial stability measure.The first row reports the results for an augmented monetary policy rule with financial stability objective and statistical provisioning. Second row reports the results for an augmented monetary policy rule with specific provisioning. The third and fourth rows present results for a normal Taylor type monetary policy rule for statistical provisioning and specific provisioning respectively. For reporting results under bias in the commercial banking sector, we use bias paramenter $\theta = 1.04$. We report values in percentage of loss in case of Specific Provisioning after normalising it to 100. Details of loss parameters as well as loss values are available upon request.

VIII. Conclusion

In this paper, we show that banks are biased and affected by diagnostic expectation. Using loan loss provision and net charge off, we find that banks keep less provision during good times and more than required provision during bad times. This deepens the procyclicality induced by capital requirement rules. The effects are economically significant and robust to alternative specifications. Statistical provisioning system, being dynamic in nature, allows banks to keep provision based on expected loss over the whole business cycle. This is highly effective in mitigating the procyclicality. In the final section, we show statistical provisioning system helps in reducing volatility in the financial as well as real sector.

Our analysis extends the diagnostic expectation theory of Bordalo, Gennaioli, and Shleifer (2018) to commercial banking sector. Use of loan loss provision and the realization of this expectation in the form of net charge-off helps us to provide direct evidence and mechanism of bias in the behavior of commercial banks. In future research, it would be helpful to investigate whether this diagnostic expectation is present in other activities of banks. To improve resilience of the banking sector, it is, thus necessary to look how different banking regulations and macroprudential policies are going to perform when bank's behavior is not rational.

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Appendix A

Log-Linearized Equations

The log-linearized equations of the model represents deviations of the variables from their respective steady states. With hat, we list the log linearized variables below.

Euler Equation

$$\widehat{C_t} = E_t\widehat{C_{t+1}} - \tau\left(\widehat{i_t^B} - E_t\widehat{\pi_{t+1}}\right)$$

Deposits

$$\widehat{D_t} = \tau\widehat{C_t} + \frac{1+\bar{i^d}}{\bar{i^b} - \bar{i^d}}\left(\widehat{i_t^D} - \widehat{i_t^B}\right)$$

Household real money balances

$$\widehat{M_t^H} = \tau\widehat{C_t} - \left(\frac{\beta}{1-\beta}\right)\widehat{i_t^B}$$

Real wages

$$\widehat{W_t^R} = \gamma\widehat{H_t} + \tau\widehat{C_t}$$

Employment

$$\widehat{N_t} = \frac{1}{1-\alpha}\widehat{Y_t} - \frac{\alpha}{1-\alpha}\widehat{K_t} - \frac{1}{1-\alpha}\widehat{A_t}$$

Capital-labor ratio

$$\widehat{K_t} - \widehat{N_t} = \widehat{W_t^R} - \frac{1+\bar{r^k}}{r^k}\widehat{r_k}$$

Marginal Cost

$$\widehat{mc_t} = \left(1-\alpha\right)\widehat{W_t^R} + \alpha\frac{1+\bar{r^k}}{\bar{r^k}}\widehat{r^k} - \widehat{A_t}$$

Phillips curve for price inflation

$$\widehat{\pi_t} = \beta E_t$$

Deposit Rate

$$\widehat{i_t^D} = \widehat{i_t^R}$$

Rental price of capital

$$\left(1+\overline{r^k}\right)E_t\widehat{r_{t+1}^k} = \left(1-\overline{g}\right)\left(1+\overline{i^L}\right)\left(1+\overline{i^B}\right)\left[\widehat{i_t^L}+\widehat{i_t^B}-E_t\widehat{\pi_{t+1}}+\Theta_k E_t\left(\widehat{K_{t+1}-\widehat{K_t}}\right)\right]$$

$$-\left(1+\overline{i^L}\right)\left(1+\overline{i^B}\right)\overline{g}E_t\widehat{g_{t+1}}-\left(1-\overline{g}\right)\left(1+\overline{i^L}\right)\left[\left(1-\delta\right)\widehat{i_{t+1}^L}+\Theta_k E_t\left(\widehat{K_{t+2}}-\widehat{K_{t+1}}\right)\right]$$

$$+\left[\left(1+\overline{i^L}\right)\left(1-\delta\right)\right]\overline{g}E_t\widehat{g_{t+2}}$$

Evolution of capital

$$E_t\widehat{K_{t+1}} = \delta\widehat{L_t}+\left(1-\delta\right)\widehat{K_t}$$

Borrowing from the central bank

$$\bar{L^B}\widehat{L_t^B} = \bar{L}\widehat{L_t}-\bar{D}\widehat{D_t}$$

Loan loss provision

$$\widehat{LLP_t} = E_t^{\theta}\widehat{g_{t+1}}+\widehat{L_t}$$

Loan loss reserves

$$\widehat{LLR_t} = \rho_{LR}\widehat{LLR_{t-1}} + \left(1 - \rho_{LR}\right)\widehat{LLP_t}$$

Loan rate

$$\left(1-\bar{g}\right)\left(1+\overline{i^L}\right)\widehat{i_t^L} = \left(1+\overline{i^R}\right)\widehat{i_t^R} + \left[1-\left(1+\overline{i^B}\right)\right]\bar{g}\left(\frac{\partial\widehat{LLP_t}}{\partial L_t}\right) - \left(1+\overline{i^B}\right)\bar{g}\left[\widehat{i_t^B} - \rho_{LR}\left(\widehat{LLP_t} - \widehat{LLR_{t-1}}\right)\right]$$

where,

$$\frac{\partial\widehat{LLP_t}}{\partial L_t} = E_t^{\theta}\widehat{g_{t+1}}$$

Government Expenditure

$$\widehat{G_t} = \widehat{Y_t}$$

Goods market equilibrium

$$\overline{Y}\widehat{Y} = \overline{C}\widehat{C_t} + \overline{I}\widehat{I_t} + \overline{G}\widehat{G_t}$$

Log-linear money market equilibrium condition

$$\overline{D}\widehat{D_t} + \overline{M^H}\widehat{M_t^H} = 0$$

Actual fraction of loan loss

$$\widehat{g_{t+1}} = \rho\widehat{g_t} + \nu_{t+1}^g$$

Rational expectation of future loan loss fraction

$$\widehat{E_t g_{t+1}} = \rho\widehat{g_t}$$

Biased expectation of future loan loss fraction

$$\widehat{E_t^\theta g_{t+1}} = \rho \widehat{g_t} + \theta \left(\widehat{E_t g_{t+1}} - \widehat{E_{t-1} g_{t+1}} \right)$$

$$= \rho \widehat{g_t} + \theta \rho v_t^g$$

Appendix B

PROOF OF PROPOSITION 1:

Differentiating loan rate deviation i.e. equation 48 from text with respect to bias parameter θ yields,

$$\frac{\partial \widehat{i_t^L}}{\partial \theta} = \frac{\overline{g} \rho v_t^g \left(1 + \overline{i^L} - \overline{i^B}\right)}{\left(1 - \overline{g}\right)\left(1 + \overline{i^L}\right)} \tag{56}$$

PROOF OF PROPOSITION 2:

$$\frac{\partial^2 \widehat{i_t^L}}{\partial \overline{g} \partial \theta} = \frac{\overline{i^L}}{\left(1 + \overline{i^L}\right)\left(1 - \overline{g}\right)^2} + \frac{\overline{g} \frac{\partial \overline{i^L}}{\partial \overline{g}}}{\left(1 + \overline{i^L}\right)^2 \left(1 - \overline{g}\right)} \tag{57}$$

where $\frac{\partial \overline{i^L}}{\partial \overline{g}} = \frac{\left(1 + \eta_L^{-1}\right)^{-1} \left(1 + \overline{i^R} - \overline{i^B}\right)}{\left(1 - \overline{g}\right)^2}$ which is always positive.

PROOF OF PROPOSITION 3:

$$\frac{\partial \widehat{i_t^L}}{\partial \overline{g}} = \widehat{E_t^\theta g_{t+1}} \left[\left\{ \frac{1}{\left(1 - \overline{g}\right)^2} \right\} \left(1 - \frac{\overline{i^B}}{1 + \overline{i^L}} \right) + \frac{\overline{g} \overline{i^B}}{\left(1 - \overline{g}\right)\left(1 + \overline{i^L}\right)^2} \frac{\partial \overline{i^L}}{\partial \overline{g}} \right] \tag{58}$$

Replacing $\widehat{E_t^\theta g_{t+1}}$ with equation 40 will give the required expression.