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Understanding the response of Indian banks to macro-economic shocks: A strategy perspective

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Abstract

The vulnerability of banks to macroeconomic and financial shocks is an area of growing interest to policymakers, especially in emerging markets. Strong adverse aggregate shocks contribute heavily to loan losses when banks are highly exposed to such shocks. I intend to understand the heterogeneity in Indian bank risk responses to macro shocks. Based on the work of Buch et al. (2010), I intend to discuss how macro factors effect bank risk. Using Factor augmented VAR model, I will allow macroeconomic factors to affect bank risk, when macroeconomic factors themselves are modelled as a function of banking variables. We examine if discriminating strategies impact risk responsiveness of Indian commercial banks to macro-economic shocks using Factor augmented VaR approach for quarterly periods during 2002-13.

Keywords: bank risk, inflation, house-price, FAVAR, Strategy

1 Introduction

The strength of the financial institutions is determined by their investment and funding decisions (Gavin & Hausmann, 1996). Not all banks need to contribute equally to risk parole of stability of banking system (De Jonghe, 2008). Differences in risk may stem from discrimination across its business strategies. When trying to understand a major crisis in which substantial fraction of banking system is endangered, the focus on the characteristics of institutions that may fail is potentially important. It is possible that, banks are correlated in ways that could increase the chance of simultaneous credit losses. This could be because of their similar sized balance sheets; broadly comparable shares of lending and deposits; relatively large shares of housing loans; similar capital positions; and the same credit ratings (RBA, March 2014).

Contagion is rare but can nonetheless wipe out a major part of the banking system. Low bankruptcy costs and an efficient crisis resolution policy are crucial to limit the system wide impact of contagious default events (Elsinger, Lehar, & Summer, 2006). It is hence particularly useful for identifying in advance banks that are vulnerable to downturns in the economy. For example, in the years prior to the crisis of 2007–2009, the risk of a downturn was perceived as low. Market-based measures of bank defaults (such as CDS spreads or the distance-to-default) consequently implied a low probability of default at the time (Knaup & Wagner, 2012).

Even though weakness of individual banks possibly will be a trigger to larger crises, it is mostly deterioration of macroeconomic environment that makes single bank fail and may cause chain reactions in a tightened surrounding (Gavin & Hausmann, 1996). Macroeconomic disturbances of almost any sort can adversely affect bank balance sheets, and if large enough, threaten the solvency of large parts of the banking system (Gavin & Hausmann, 1996).

Banking systems are likely to remain vulnerable to macroeconomic shocks, no matter how well regulated and supervised they are (Gavin & Hausmann, 1996). Most banking panics have been related to macroeconomic fluctuations rather than to prevalent contagion or 'mass hysteria' (Gorton, 1988; Kaminsky & Reinhart, 1999). From the macro-prudential perspective, it is crucial to predict how banks may respond to some adverse macro-financial scenarios considered by central banks and supervision authorities (Hałaj, April 2013).

Macroeconomic shocks have an important impact on bank risk and on other bank level variables (Claudia M. Buch, Eickmeier, & Prieto, 2014). Large heterogeneity of bank loan responses, particularly those to a monetary policy shock, may be attributed to a loan supply side, such as banks' maturity conditions, profitability conditions, and balance sheet conditions (Hirakata, Hogen, Sudo, & Ueda, 2013).

In Section 2, we will discuss the theoretical framework. Section 3 will discuss the gaps of literature. Section 4 contain hypothesis statement. Section 5 contains research methodology. Section 6 has analysis of results which are subsequently discussed and concluded.

2 Theoretical Framework

2.1 Transmission of macroeconomic shocks to bank risk

Macroeconomic shocks have an important impact on bank risk and other bank level variables (Claudia M. Buch et al., 2014). Strong adverse aggregate shocks contribute heavily to loan losses when banks are highly exposed to such shocks (Pesola, 2011). Adverse macroeconomic shocks may make it difficult for bank borrowers to pay their debts in full and on time, thus threatening solvency of banks (Gavin & Hausmann, 1996).

Large macroeconomic disturbance can harm banks' portfolios even when country as a whole benefits from the shock, if the disturbance has large distributional effects. This is because of the Bank loans extended to sectors adversely affected by disturbance are likely to fall into arrears, while increased income that accrues to sectors that receive a windfall from the shock is not captured by banks, which mainly own debt rather than equity claims on firms (Gavin & Hausmann, 1996).

As per literature there are several macro-economic factors like low GDP growth (Asli & Enrica, 1998; Davis & Karim, 2008; Evrensel, 2008; Noy, 2004; Tracey, 2007), high inflation (Asli & Enrica, 1998; Babouček & Jančar, 2005; Mishkin, 1996; Tracey, 2007), interest rates (Altunbas, Gambacorta, & Marques-Ibanez, 2012; Asli & Enrica, 1998; Claudia M Buch, Eickmeier, & Prieto, June 2013; Mishkin, 1999; Tracey, 2007) which were found to influence the stability of banks. Kaminsky and Reinhart (1999) argued shocks like declines in asset prices such as equity and real estate to be associated with episodes of banking sector problems.

In literature, effect of house price changes on banks risk has been discussed. Large share of financial sector assets is tied to housing values. A house is often largest and most important asset of households accounting for a major share of their wealth, immobile can therefore not easily be put out of creditor's reach, commonly used as collateral for loans (Goodhart & Hofmann, 2007). House price fluctuations may therefore have a major effect on economic activity and the soundness of financial system. As a result, house price fluctuations may significantly amplify effects of macroeconomic shocks, like supply, demand, or monetary policy shocks, and non-fundamental movements or bubbles in house prices may give rise to imbalances in economy and the financial system (Goodhart & Hofmann, 2007).

While banks typically do not speculate directly in land or real estate markets, they do make loans to construction companies whose ability to repay is threatened if real estate market takes a dive. And bad real estate loans, associated with poor real estate markets, have in fact been an important feature in many bank crises (Gavin & Hausmann, 1996). Real estate serves as collateral for loans, movement in house prices affect the quality of collateral and thus the strength of borrowers' balance sheet (Claudia M. Buch et al., 2014)

Effect of monetary policy changes on bank risk

↓ **interest rates**	↓ **interest rates**	↓ **interest rates**
(Claudia M Buch, Eickmeier, & Prieto, 2010)	(Claudia M Buch et al., 2010; Rajan, 2006)	(Angeloni & Faia, 2009)
↓ interest rate burden of firms	↑ borrowing capacity of high-risk firm	↓ Bank's funding cost
↓ risk of o/s flexible loan contracts	Banks might engage in riskier, high yield, projects (to offset the negative effects of lower interest rates on profit)	To maximize profits, bank optimally choose to <u>↑ leverage</u>
↑ probability of repayment & value of underlying collateral	↑ Bank risk	Also, ↓ interest rates ⇒ <u>Bank's ↓ ROA</u>
↓ Bank risk		↓ ROA + ↑ leverage
		↑ Bank risk

Our analysis on transmission of shocks is based on a factor-augmented vector autoregressive model (FAVAR) as discussed in previous studies (Bernanke, Boivin, & Eliasz, 2005; Claudia M. Buch et al., 2014). This model extends a standard macroeconomic VAR comprising GDP growth, inflation, house price inflation, and the monetary policy interest rate with a set of factors summarizing a large amount of information from bank-level data, omission of which can yield misleading estimates of impulse responses and monetary policy shock. Shocks to the banking factors matter for macro economy with their explanatory power highest for monetary policy interest rate (Claudia M. Buch et al., 2014).

2.2 Sources of heterogeneity across banks responses (to macro shocks)

The rich structure of our bank data set also allows analyzing bank heterogeneity which has two dimensions. There are idiosyncratic components in bank-level developments, and Heterogeneity may also reflect different responses of banks to the common shocks. The importance of these sources of heterogeneity can be analyzed by looking at the dispersion of the common and the idiosyncratic components of bank-level developments (Claudia M. Buch et al., 2014).

Transmission of common macroeconomic shocks to individual banks can also be visualized using impulse response functions of individual banks. This will help in seeing how an individual bank variable (say risk) reacts to macro-economic shocks.

2.3 What explains differences in individual banks' responses to macroeconomic shocks?

Borrower firms' liability conditions: The sensitivity of bank loan responses to shocks depends on borrower firms' liability conditions, in particular, the ratio of capital to assets. In response to adverse macro shocks, firms with a lower ratio experience a more severe drop in bank loans (Hirakata et al., 2013). Among borrowers' demand side (loan demand side) factors, the firms' substitution motive between bank loans and alternative financial measures explains a portion of sectoral heterogeneity in the response of bank loans to a bank capital shock at a statistically significant level (Hirakata et al., 2013).

Bank’s response to information: Differing views of the bank about economy like effect of interest rate on inflation and the output gap (Hirakata et al., 2013). Each bank has the same public information set but augments this with private information (Hirakata et al., 2013).

Bank’s condition:

Bank-level features have been studied by (Claudia M. Buch et al., 2014) explaining differences in banks’ exposure to expansionary monetary policy shocks. Size, capitalization, liquidity, riskiness real estate exposure and consumer loans were found to matter for risk and lending responses of banks to monetary policy and house price shocks (Claudia M. Buch et al., 2014).

Capital is the "cushion" that stands between adverse shocks and bankruptcy, and because that cushion is relatively thin for banks, relatively small shocks can drive a bank to insolvency. Capital is, then, a crucial buffer stock for banks and amount that should be held depends upon the volatility of the environment in which the bank is embedded (Gavin & Hausmann, 1996). When banks are allowed to adjust their capital structures, low interest rates increase bank leverage, which in turn lowers the incentives to monitor (i.e. risk increases) (De Nicolò, 2010).

Liquidity: Macroeconomic shocks to banks' funding sources are very large. To prevent such shocks from disrupting the flow of credit upon which the real economy depends, banks hold buffer stocks of liquid reserves which allow them partially to insulate lending from shocks to deposits and other funding sources (Gavin & Hausmann, 1996)

Bank strategy:

From the macro-prudential perspective, it is also crucial to predict how banks strategies may respond to some adverse macro-financial scenarios considered by central banks and supervision authorities. We define strategy/business strategy as any income earning operation of bank which also determine its asset and Income composition. Broadly it includes: Retail banking includes exposures to individuals or small businesses. Previous studies (Claudia M. Buch et al., 2014) have considered the exposure of banks to consumer loans. Wholesale banking includes high ticket exposures primarily to corporates. Treasury operations include investments in debt market (sovereign and corporate), equity market, mutual funds, derivatives, and trading and forex operations.

In this study, the information on bank characteristics can be used to explain different adjustments to macroeconomic shocks. We will focus on House price shocks and Monetary Policy shocks. In a next step, we analyze whether the impact of above shocks differs across individual banks in any systematic way. We regress individual banks' impulse response functions of our two risk measures on several variables capturing long-run structural differences across banks.

3 Research gaps & Contribution

The earlier international empirical studies (Claudia M. Buch et al., 2014) have considered the exposure of banks to real estate and consumer loans. Moving from this premise, in this paper we evaluate whether business strategy differs the impact of monetary policy and house price shocks across individual banks in an emerging market setting such as India. In doing so we are the first in literature to use business strategy as a factor for evaluating heterogeneity in bank risk responses. This study takes that opportunity to posit that strategy lead bank's risk to respond more to macro-economic shocks and also affect their ability to shelter from adverse economic conditions.

4 Objectives & Hypothesis

Based on the above discussions, following are the objectives of this study: How are macroeconomic shocks transmitted to individual banks and, in particular, to bank risk? If there is any heterogeneity across individual bank risk responses? If strategy impact responsiveness of bank's risk to macro-economic shocks?

5 Research Methodology

5.1 Data Source and Period of study

The Financial data has been extracted from CMIE Prowess and DION INSIGHT. The source of Macroeconomic data is DATASTREAM. The sample which we have used in this study constitutes 15 listed Indian banks: ALLBANK, ANDHRABANK, AXISBANK, BOB, BOI, CANARABANK, FEDBANK, INGVYSYA, PNB, SBI, SBT, SYNDIBANK, UCO, UNIONBANK and VIJAYABANK. The time period which will be examined in this study represents 31 MAR 2003 - 31 MAR 2013.

5.2 Research design & estimated approach

5.2.1 Measuring the bank level risk

We will derive two risk indicators for the banks based on accounting approach. The first is the share of nonperforming loans in total assets. This ratio informs about changes in the overall quality of the stock of credit and is thus a backward-looking measure of risk. The second is the share of noninterest income in total income, that is, a flow variable, which is used as a more forward-looking measure of risk (Markus K. Brunnermeier & Sannikov, 2013; DeYoung & Roland, 2001). The higher the share of noninterest income, the higher the volatility of returns, and thus the higher risk (Claudia M. Buch et al., 2014).

5.2.2 Transmission of macroeconomic shocks to bank risk

Our analysis is based on a factor-augmented vector autoregressive model (FAVAR) as proposed by Bernanke et al. (2005) and used in Claudia M. Buch et al. (2014). This model extends a standard macroeconomic VAR comprising GDP growth, inflation, house price inflation, and the monetary policy interest rate with a set of factors summarizing a large amount of information from bank-level data. It allows analyzing the dynamic interaction between bank-specific and macroeconomic developments in a flexible way. It accounts for the endogeneity of both, macroeconomic and banking factors.

The model exploits the comovement between individual banks, and it allows us to model linkages between individual banks, running through the interbank market or through the exposure to common shocks. The need to account for linkages between financial institutions is one key lesson of the recent crisis (Markus K. Brunnermeier, 2009).

Moreover, we model the interaction between different banking variables, including risk and returns of banks because we use a large number of bank-level time series, we can assess the exposure of each individual bank to macroeconomic shocks.

5.2.2.1 Is there a factor structure in the data

Exploiting a rich amount of (bank-level) information can be beneficial in a factor analysis. Our factor model, however, also needs to provide a good description of data. For this to be the case, there needs to be a factor structure among series included, or, put differently, factors can be accurately estimated only if series strongly co-move (Boivin & Ng, 2006).

This issue is particularly relevant for microeconomic data as opposed to (aggregate) macroeconomic data to which factor models have been previously employed and which tend to exhibit a greater co-movement (Claudia M. Buch et al., 2014).

5.2.2.1.1 Assessing the co-movement between banking variables

We will assess to what extent different banking variables are correlated by constructing a correlation matrix of the median banks' variables over the entire sample period i.e.

$$\text{Median banking variable j} =$$

$$\text{Median}\left(Variable_{j,t}^{Bank\ 1}, Variable_{j,t}^{Bank\ 2}, \ldots\ldots Variable_{j,t}^{Bank\ C} \right)$$

Where,
Time t is defined in quarters such that $\mathrm{t} = 1,2, \ldots \mathrm{T}$
Bank i is defined such that $i = 1,2, \ldots \mathrm{C}$
Variable j is defined such that $\mathrm{j} = 1,2, \ldots \mathrm{L}$

We will consider three (risk related) banking variables (NPA/Total Loans, Non-interest Income/Total operating Income, ROA, capital adequacy ratio). If the series strongly co-move (as per the correlation matrix estimated above), we can attempt to accurately estimate the factor structure (Boivin & Giannoni, 2009) that is discussed in the following section.

5.2.2.1.2 Relation between individual banks

We next examine to what extent individual banks are related.

We will perform the Principal component analysis of bank level information which will also determine the dimension of unobserved bank factor (Cut off for principal components H?)

Let $\mathbb{X}_t$ be the bank level dataset for any time t, written in the following matrix $\mathbb{X}_t(i,j)$ with $i = 1,2, \ldots \mathrm{C}$ corresponds to an individual bank and $\mathrm{j} = 1,2, \ldots \mathrm{L}$ corresponds to bank related variables

t	Variable 1			… …	… …	Variable L		
	Bank 1	…	Bank C	… …	… …	Bank 1	…	Bank C
1	$X_{1,1}^{t=1}$	…	$X_{C,1}^{t=1}$	… …	… …	$X_{1,L}^{t=1}$	…	$X_{C,L}^{t=1}$
2	$X_{1,1}^{t=2}$	…	$X_{C,1}^{t=2}$	… …	… …	$X_{1,L}^{t=2}$	…	$X_{C,L}^{t=2}$
⋮	⋮	…	⋮	… …	… …	⋮	…	⋮
⋮	⋮	…	⋮	… …	… …	⋮	…	⋮
T	$X_{1,1}^{t=T}$	…	$X_{C,1}^{t=T}$	… …	… …	$X_{1,L}^{t=T}$	…	$X_{C,L}^{t=T}$

The resulting matrix of principal component is $\mathbb{PC}_t(j,k)$ with row (time) t$=$ 1,2, … T corresponds to time and column $\mathrm{k} = 1,2, \dots \mathrm{H}, \dots \mathrm{CL}$ corresponds to an (PC). The PC have to be taken for the above matrix containing bank level dataset

t	PC_1	…	PC_{CL}
1	$PC_{1,1}^{t=1}$	…	$PC_{CL,1}^{t=1}$
2	$PC_{1,1}^{t=2}$	…	$PC_{CL,1}^{t=2}$
⋮	⋮	…	⋮
⋮	⋮	…	⋮
T	$PC_{1,1}^{t=T}$	…	$PC_{CL,1}^{t=T}$

Each PC value has some proportion of explanation of a variable under each firm that will be added to get a single cumulative variance share for a variable column in the following table.

# PC’s	Cumulative variance share		
	Variable 1		Variable L
1	⋮	…	⋮
⋮	⋮	…	⋮
H	~ 0.40	…	~ 0.40
⋮	⋮	…	⋮
CL	⋮	…	⋮

To determine the number of principal components H, we will use the criteria of cumulative variance shares. The criteria (cumulative variance > 40%) should be roughly matched for all the variables. In the above table say r=H is the cutoff, where for all the variables (taken for PC over all firms) cumulative variance has approximately exceeded 40%.

With the bank-level variables at hand, we next describe how we use this information to model the dynamic feedback effects between Indian banks and the macro-economy.

5.2.2.2 FVAR to model the dynamic feedback effects between banks and macro-economy

A set of macroeconomic shocks will be identified and based on an impulse response analysis their transmission through the banking system will be assessed (Claudia M Buch et al., 2010).

5.2.2.2.1 Motivating the FVAR structure

Since Bernanke and Blinder (1992) and Sims (1992), a considerable literature has developed that employs vector auto regression (VAR) methods to attempt to identify and measure effects of monetary policy innovations on macroeconomic variables.

The key insight of this approach is that identification of the effects of monetary policy shocks requires only a plausible identification of those shocks (for example, as the un-forecasted innovation of the federal funds rate in Bernanke and Blinder (1992)) and does not require identification of the remainder of the macroeconomic model. These methods generally deliver empirically plausible assessments of the dynamic responses of key macroeconomic variables to monetary policy innovations.

FAVAR framework will considers the set of macroeconomic indicators in our identification of monetary policy shocks, and extends this data by appending a variety of commercial-bank variables that the central banks and financial market participants exploit in practice (Claudia M Buch et al., 2010). While these variables deliver an indication of how bank risk responds to an improved identification of monetary policy shocks. A natural by-product of the estimation is to obtain impulse response functions for any variables included in the dataset.

5.2.2.2.1.1 Macro-economic VAR

We start from a small-scale macroeconomic VAR model which includes GDP growth (Δy_t), inflation (Δp_t) , Repo rate ($\Delta Repo_t$), real house price inflation (Δhp_t) as endogenous variables1. These variable are summarized in m X 1 dimensional vector (m= 4 in this case)

$$G_t = \begin{bmatrix} \Delta y_t \\ \Delta p_t \\ \Delta hp_t \\ \Delta Repo_t \end{bmatrix}_{m \times 1}$$

5.2.2.2.1.2 Augmenting the observed macro-economic VAR with unobserved banking factor

We augment the vector $[G_t]_{m\times 1}$ with a set of unobserved r "banking factors"

$$B_t = \begin{bmatrix} b_{1t} \\ \vdots \\ \vdots \\ b_{rt} \end{bmatrix}_{r \times 1}$$

$$F_t = \begin{bmatrix} \mathrm{G}_t \\ \mathrm{B}_t \end{bmatrix}_{m+r \ \times \ 1}$$

The unobserved vector B_t needs to be estimated

5.2.2.2.1.3 Modeling the joint dynamics of macroeconomic variables and banking factors

5.2.2.2.1.3.1 VAR MODEL

We model the joint dynamics of macroeconomic variables and banking factors as a VAR (p) process

$$A(L)F_t = d + P\ \mathrm{w}_t \qquad (1)$$

Where,

$\mathrm{A(L)} = \mathrm{I} - \mathrm{A_1 L} - \cdots - \mathrm{A_p L^p}$, is a lag polynomial of finite order p

d comprises deterministic terms

[1] GDP growth, inflation, and interest rates represent the standard block of variables included in macro-economic VARs (e.g. Christiano et al. 1996, Peersman 2005); fewer studies also include house prices in such a VAR (Bjørnland and Jacobsen 2008, Jarociński and Smets 2008). We include house prices not only because they may be relevant for the macro-economy but also because they reflect the value of assets that can potentially serve as collateral for bank lending.

P is the coefficient matrix

$\mathrm{w_t}$ is vector of structural shocks (which can be recovered by imposing restrictions on P)

5.2.2.2.1.3.2 DYNAMIC FACTOR MODEL

Let us consider $[\,\mathrm{X}_t]_{N\times 1}$ which is driven by the common factor F_t

X_t with a cross section dimension $\mathrm{N} = (\mathrm{C}\times \mathrm{L}) + \mathrm{L}$ is assumed to include:

Observed 'L' banking variables (say non-performing loans ratio, return on assets, non-interest income ratio, capital adequacy ratio) of C individual banks

Medians of the 'L' banking variables across banks

We will assume that X_t follows2 an approximate dynamic factor model (Bai & Ng, 2002; Stock & Watson, 2005).

$\mathrm{X}_t = \Lambda'\,\mathrm{F}_t + \Xi_t$ (2)

Where,

$\Xi_t = [\xi_{1t} \ldots\ldots \xi_{Nt}]\,'_{N\times 1}$ denotes a vector of idiosyncratic components

$\Lambda = [\lambda_1 \ldots\ldots \lambda_N]_{r+M\,\times N}$ denotes a factor loading matrix

λ_i is of dimension $r + M \times 1 \quad \forall\, i = 1, \ldots N$

F_t is of dimension $r + M \times 1$

X_t is of dimension $N \times 1$

$R + M \ll N$

X_t constitutes common and idiosyncratic components which are orthogonal

The common components are mutually orthogonal

The idiosyncratic components can be weakly mutually and serially correlated (Chamberlain & Rothschild, 1983)

5.2.2.2.1.3.3 FAVAR MODEL

$A(L)F_t = d + P\,\mathrm{w}_t$ (1)

$\mathrm{X}_t = \Lambda'\,\mathrm{F}_t + \Xi_t$ (2)

[2] In matrix form where we have T time points, factor model can be represented as
$X_{N\times T} = \Lambda_{N\times(r+m)} \quad F_{(r+m)\times T} + \Xi_{N\times T}$

Equation (1) and (2) represent a FAVAR model (Bernanke et al., 2005; Claudia M Buch et al., 2010)

5.2.2.2.2 Estimation in FVAR structure

<u>Determining the dimension of factors</u> $[\mathrm{F}_t]_{\ r+m\ \times\ 1}$:

For ‘r’ unobserved banking factors the choice (say r= H) is made under the rule of principal component analysis of X_t (see, e.g., Claudia M Buch et al. (2010))

<u>Estimation of unobserved banking factor B_t:</u>

Using the iterative procedure proposed by Boivin and Giannoni (2009) we will estimate by following the steps given below:

In matrix form where we have T time points, factor model in equation 2 can be represented as :

$$X_{N\times T} = \Lambda_{N\times(r+m)} \quad F_{(r+m)\times T} + \Xi_{N\times T}$$

The above has to be solved for loading (coefficient) matrix $\widehat{\Lambda}_{(r+m)\times N}$. The last m columns of $\widehat{\Lambda}_{(r+m)\times N}$ will yield $\widehat{\Lambda}_G^{(0)}$ which can help in removing the observed factor G_t from the overall factor space F_t and further estimating B_t.

For the estimation of the coefficient matrix we can use multivariate multiple regression (Johnson & Wichern, 2007)

$$\mathcal{X}_{T\times N} = \mathcal{F}_{T\times(r+m+1)}\Lambda_{(r+m+1)\times N} \quad + \Xi_{T\times N} \qquad (2.1)$$

Where,

$\mathcal{X}_{T\times N}$

t	Variable 1			... ...	Variable L			Variable 1	... ...	Variable L
	Bank 1	...	Bank C	... ...	Bank 1	...	Bank C	Median Bank	...	Median Bank
1	$X_{1,1}^{t=1}$	...	$X_{C,1}^{t=1}$	... ...	$X_{1,L}^{t=1}$	...	$X_{C,L}^{t=1}$	$X_{\text{Median},L}^{t=1}$	...	$X_{\text{Median},L}^{t=1}$
2	$X_{1,1}^{t=2}$	...	$X_{C,1}^{t=2}$	... ...	$X_{1,L}^{t=2}$	...	$X_{C,L}^{t=2}$	$X_{\text{Median},L}^{t=2}$	...	$X_{\text{Median},L}^{t=2}$
⋮	⋮	...	⋮	... ...	⋮	...	⋮	⋮	...	⋮
⋮	⋮	...	⋮	... ...	⋮	...	⋮	⋮	...	⋮
T	$X_{1,1}^{t=T}$	...	$X_{C,1}^{t=T}$	... ...	$X_{1,L}^{t=T}$	...	$X_{C,L}^{t=T}$	$X_{\text{Median},L}^{t=T}$	...	$X_{\text{Median},L}^{t=T}$

From the array $\mathcal{F}_t$, G_t is observed. We have to estimate B_t from equation (2.1).

We obtain the first r=H principal components of $\mathcal{X}_{T\times N}$ (with $N = (\mathrm{C} \times \mathrm{L}) + \mathrm{L}$) as an initial estimate of B_t,

$\left[\widehat{\mathrm{B}}_t^{(0)}\right]_{T\times r}$

T	b_1	b_2	… …	… …	b_r
1	$PC_1^{t=1}$	$PC_2^{t=1}$	… …	…	$PC_r^{t=1}$
2	$PC_1^{t=2}$	$PC_2^{t=2}$	… …	…	$PC_r^{t=2}$
⋮	⋮	⋮	… …	…	⋮
⋮	⋮	⋮	… …	…	⋮
T	$PC_1^{t=T}$	$PC_2^{t=T}$	… …	…	$PC_r^{t=T}$

The $\mathcal{F}_{T\times(r+m)}$ formed will be:

T	b_1	… …	b_r	g_1	… …	g_m
1	$PC_1^{t=1}$	… …	$PC_r^{t=T}$	$g_1^{t=1}$	… …	$g_m^{t=1}$
2	$PC_1^{t=2}$	… …	$PC_r^{t=T}$	$g_1^{t=2}$	… …	$g_m^{t=2}$
⋮	⋮	… …	⋮	⋮	… …	⋮
⋮	⋮	… …	⋮	⋮	… …	⋮
T	$PC_1^{t=T}$	… …	$PC_r^{t=T}$	$g_1^{t=T}$	… …	$g_m^{t=T}$

For the estimation of equation 2.1:

$\mathcal{X}_{T\times N} = \mathcal{F}_{T\times(r+m+1)}\Lambda_{(r+m+1)\times N} \quad + \Xi_{T\times N}$

We cannot directly use multivariate multiple regression (Johnson & Wichern, 2007), Since,

$T \ngtr (r + m + 1) + N$

If we consider T=40, r=6, m=4, N= 64 (=15Bank*4variables+4median variables) due to data constraints.

But, given the covariance matrix of error structure in a factor model is a diagonal matrix, we are motivated to consider estimating[3] the above multivariate multiple setup using the collection of univariate estimates.

Simply stating, the $i^{th}\, response\, \mathcal{X}_{(i)}$ follows a linear regression model[4]

$\mathcal{X}_{(i)_{T\times 1}} = \mathcal{F}_{T\times(r+m+1)}\, \lambda_{(i)_{(r+m+1)\times 1}} \quad + \varepsilon_{(i)_{T\times 1}}$

From the above regressions we will obtain

'N' number of $\hat{\lambda}_{(i)_{(r+m+1)\times 1}}$ that we can collect (append) to form $\widehat{\Lambda}^{(0)}_{(r+m+1)\times N}$

The last m rows of $\widehat{\Lambda}_{(r+m)\times N}$ will yield $\widehat{\Lambda}^{(0)}_{G\ \ m\times N}$the coefficients or factor loadings that belong to G_t

'N' number of $\varepsilon_{(i)_{T\times 1}}$ will be collected (appended) to form $\Xi_{T\times N}$

Using $\Xi_{T\times N}$ obtained in the previous step we will also calculate $Trace_{(0)}\ (\Xi_{T\times N} \times \Xi_{T\times N}{}')$

We calculate $\widetilde{\mathcal{X}}^{(0)}_{T\times N} = \mathcal{X}_{T\times N} - \quad G_{T\times m}\ \widehat{\Lambda}^{(0)}_{G\ \ m\times N}$

We estimate $\widehat{\mathrm{B}}^{(1)}_t$ as the first H principal components of $\widetilde{\mathcal{X}}^{(0)}_{T\times N}$ and repeat until convergence[5] to end up with an estimator of B_t, $\hat{B}_t$

Unlike before when $\mathcal{F}_{T\times(r+m+1)}$ has $B^{(0)}_{T\times r}$. we will use $B^{(1)}_{T\times r}$

We will end up with an estimator $\hat{B}_t$, if any iteration the difference between the last and the previous 'trace' is ≤ 0.000001

We can see how much variation in the bank level dataset is explained by observed macro-economic G_t together with the latent banking factors $\hat{B}_t$.

This is done by observing R^2while regressing X_t on G_t and $\hat{B}_t$

The VAR(p) will be fitted to (p will be chosen as per BIC) the following

$$[\hat{\mathrm{F}}_t]_{m+r\times 1} = \begin{bmatrix} \mathrm{G}_t \\ \hat{B}_t \end{bmatrix}_{m+r\ \times\ 1}$$

---

[3] The objective was to regress X_t on $\widehat{\mathrm{B}}^{(0)}_t$ and G_t, ending up with $\widehat{\Lambda}^{(0)}_G$, the coefficients or factor loadings that belong to G_t

[4] The regression model with intercept can be used. The F is constructed to have first columns of 1's. The software is expected to give intercept estimates unless otherwise mentioned

[5] We define the procedure as having converged if the sum of squared residual from a regression of $X_{i,t}$. $i = 1,2 \ldots N$ on $\widehat{\mathrm{B}}^{(k)}_t$ and G_t has hardly changed compared to the sum of squared residual from a regression of $X_{i,t}$ on $\widehat{\mathrm{B}}^{(k-1)}_t$ and G_t (by no more than a small value which we shall set at 0.000001).

$$[\hat{\mathcal{F}}_t]_{m+r\times 1} = \begin{bmatrix} G_t \\ \hat{B}_t \\ bank\ risk_{i,t} \end{bmatrix}_{(m+r+1)\times 1}$$, where i represents an individual or median bank

5.2.2.2.3 Identification of macro-economic shocks in FVAR structure

The idea is that structural economic shocks are linear combinations of the VAR innovations. Identifying the VAR means finding a particular matrix, i.e. choosing one particular representation of F_t in order to recover the structural shocks from the VAR innovations.
Identification is based on qualitative restriction involving the sign of some shocks on some variables.

1. We will impose the following ordering: $\Delta y_t \rightarrow \Delta p_t \rightarrow \Delta hp_t \rightarrow \hat{B}_t \rightarrow \Delta PLR_t$
2. Suppose that $[\hat{u}_t]_{r+m\times 1}$ is the vector of reduced form VAR residuals where the latent $\hat{B}_t$ and observable factors G_t are the endogenous variables

   We will estimate the orthogonalized vector of Cholesky residuals $[\hat{v}_t]_{r+m\times 1}$ as $\hat{v}_t = \hat{A}\,\hat{u}_t$

   Where, $[\hat{A}]_{r+M\times r+M}$ is obtained as a lower triangular Cholesky matrix of $cov\,(\hat{u}_t)$

   a. We will partition $\hat{v}_t$ into two parts i.e. $\hat{v}_t = [\hat{v}_t^{1\ldots 2} \quad \hat{v}_t^{3\ldots r+M}]$

      i. $\hat{v}_t^{1\ldots 2}$: Cholesky residuals associated with GDP growth and GDP deflator inflation

      ii. $\hat{v}_t^{3\ldots r+M}$: Cholesky residuals associated with house price inflation, repo and the latent banking factors

   b. We will label the Cholesky residuals associated with the equations explaining house price inflation, the r latent banking factors' and the bank prime lending rate "house price shock", "banking shocks" and "monetary policy shocks", respectively.[6]

[6] We should note that we cannot be sure that the shocks to the banking factors truly represent shocks that occur in the banking sector or "banking shocks". They may instead also contain shocks that are not modeled explicitly, such as shocks to balance sheets of the non-financial private sector (which may, however, also be propagated through the banking system).

3. The second step aims at separating “aggregate supply shocks” and “aggregate demand shocks”. It involves:
    a. Rotating the Cholesky residuals associated with the equations for GDP growth and GDP deflator inflation
    b. Imposing some theoretically motivated sign restrictions (Claudia M Buch et al., 2010)

    After an aggregate supply shock, GDP and the GDP deflator move in opposite directions whereas after an aggregate demand shock, these two variables as well as the bank PLR rate move in the same direction. The sign restrictions are imposed contemporaneously and on the first four lags after the shock.

    The structural shock presented in VAR equation 1, estimated as:
    $\widehat{w}_t = \left[\widehat{w}_t{}^{1\ldots2} \quad \widehat{w}_t{}^{3\ldots r+M}\right]$

    $\widehat{w}_t$ is related to $\hat{v}_t$ as follows: $\widehat{w}_t{}^{1\ldots2} = R\ \hat{v}_t{}^{1\ldots2}$ and $\widehat{w}_t{}^{3\ldots r+M} = \hat{v}_t{}^{3\ldots r+M}$
    (i.e. we will identify a structural shock for GDP and GDP deflator)

    - By construction $cov\ (\widehat{w}_t) = \mathrm{I}_{r+m}$
    - $[\mathrm{R}]_{2\times2}$ is the rotation matrix and R’R = I_2

    - R is chosen such that the identifying restrictions are satisfied (as in table 3 of Claudia M Buch et al. (2010)
    - More than one R (R is not ℝ) may satisfy the sign restrictions. We will choose out of k (=100 say) R’s that satisfy the sign restrictions, the R that leads to impulse response functions which are as close as possible to their median values; for details see Fry and Pagan (2011).
4. Computing a finite number of impulse responses (Martin, Hurn, & Harris, 2013)

    $\psi_0 \widehat{\mathrm{A}}\, R^{`}, \psi_1 \widehat{\mathrm{A}}\, R^{`}, \psi_2 \widehat{\mathrm{A}}\, R^{`}, \psi_3 \widehat{\mathrm{A}}\, R^{`}$ ...
    Where, ψ_i’s are the VMA parameters

5.2.2.3 Understanding the transmission of macroeconomic shocks to the banking sector

To assess the dynamic transmission of macroeconomic shocks to the banking sector, we will look at impulse response functions for the (median) bank level variables. To assess the relative importance of each of the above macroeconomic shocks for the variation in the macroeconomic variables and median banking variables, we will do the forecast error variance decomposition

We believe that banking factors $\hat{B}_t$ capture shocks to banks, but they could also capture shocks to other (financial) factors. Omitting bank-level information would bias estimated impulse response functions of the monetary policy rate. It would also attribute shocks originating in the banking sector (incorrectly) to monetary policy shocks and yield a rather implausible shape of the monetary policy shocks. Therefore, we will assess how omitting information extracted from the micro-level banking dataset would bias our results. This will be done by comparing the Impulse responses of the observable macroeconomic factors derived from our benchmark FAVAR model with Impulse responses obtained from a VAR in which we replace the banking factors $\hat{B}_t$ by the median values of our bank variables (which were considered for estimating unobserved banking factor)

5.2.2.4 Understanding the heterogeneity across banks

So far, we have focused on adjustments of the "median" bank following macroeconomic shocks. However, the rich structure of our dataset also allows analyzing bank heterogeneity. Bank heterogeneity has two dimensions: There may be a substantial idiosyncratic component in bank-level developments, but Heterogeneity may also reflect that banks respond differently to the common shocks.

We want to analyze the importance of these sources of heterogeneity by looking at the dispersion of the common and the idiosyncratic components of bank-level developments. In a final step, we want to use information on bank characteristics to explain different adjustments to macroeconomic shocks.

5.2.2.4.1 Idiosyncratic Shocks versus Asymmetric Transmission of Common Shocks

We will determine the dispersion of idiosyncratic and common components of individual banks' L variables (say L=3 i.e. NPA, Non-interest income, ROA) over the sample period. This is done by regressing X_t on $\hat{F}_t$.

$$\mathrm{X}_t = \begin{bmatrix} \mathrm{X}_1^1 \\ \vdots \\ \mathrm{X}_\mathrm{L}^1 \\ \vdots \\ \vdots \\ \vdots \\ \mathrm{X}_1^C \\ \vdots \\ \mathrm{X}_\mathrm{L}^\mathrm{C} \end{bmatrix}_{(C\times\mathrm{L})\times 1}$$

L corresponds to bank related variables and C corresponds to bank.

We will estimate $\hat{e}_t^{i,j}$ such that i (i=1,2,…C) represents a bank and j (j=1,2,…L) represents the bank variable. The dispersion of the idiosyncratic components of individual bank level variable j can be estimated as $\underset{\boldsymbol{j},T}{\mathrm{Mean}}\left[\sigma_{j,C}\left(\hat{e}_t^{i,\boldsymbol{j}}\right)\right]$ (i.e. standard deviation of idiosyncratic components of all banks, averaged over the sample period).

We can infer common shock component for each bank by subtracting idiosyncratic component from X_j^i and can similarly determine the dispersion of the common shock component of individual bank level variable.

The two shock components will help us in understanding the heterogeneity across banks.
We will also visualize the transmission of common macroeconomic shocks to individual banks using impulse response functions of individual banks. This will help in seeing how an individual bank variable (say risk or lending) reacts to macro-economic shocks.
The VAR model considered for the above is

$$F_t = \begin{bmatrix} \mathrm{G}_t \\ \mathrm{X}_t^{i,1} \\ \vdots \\ \mathrm{X}_t^{i,\mathrm{L}} \end{bmatrix}_{m+\mathrm{L}\,\times\,1}$$

m is the observed macroeconomic variables (i.e. dimension of G_t). $\mathrm{X}_t^{i,j}$ is the bank level information, where i (i=1,2,…C) is the given bank and j (j=1,2,…L) is the bank variable

5.2.2.4.2 Which Bank-Level Features Affect the Exposure of Banks to Monetary Policy and House Price Shocks?

We will analyze whether the impact of (macroeconomic shock) monetary policy and house price shocks differs across individual banks with different characteristics in any systematic way.

If the choice of business strategy reduces the bank risk responsiveness to macro-economic shocks. To analysis the relationship we use data from individual bank's balance sheet and income statements to empirical assess whether business strategies will reduces risk responsiveness. To test the hypotheses following models have been estimated.

Using OLS we will regress individual banks' impulse response functions of risk (these are 2 variables out of L banking variables considered in the study) after two and four quarters on 'U' variables which are intended to capture long run, structural differences across banks.

Our 'U' explanatory variables are size, liquidity, riskiness, capitalization, ownership and differences in banks' loan portfolio structure (Claudia M Buch et al., 2010).

Since the bank-level features included at this stage capture structural differences across different types of banks, instead of short-term adjustments patterns, we will average them over the sample period. We will discuss below the approach followed for the regression:

Dependent variable: $Response^{i,\ j}_{Macro\ shock,\ s}$

Independent variable: $\overline{Bank\ variable^{\mathrm{U}}_{t}}^{\ i}$

Where,

i is an individual bank such that i=1,2…L

U are the variables like size, liquidity, riskiness, capitalization, ownership, Business strategy (related to Wholesale, retail and treasury related banking)

s is the time after which we will see the response (say 1 year and 0.5 year).

Incorporating the above, we write our model as:

IRF Coefficient (Risk response to monetary policy/House price) =f (Business strategy (Treasury, wholesale and retail), Diversification, other control variables)

$IRFCOEFF_i = \alpha + \beta_1 TO_i + \beta_2 WB_i + \beta_3 CAR_i + \beta_4 NPA_i + \beta_5 OWNERSHIP_i + \beta_6 Size_i + \beta_7 Liquidity_i$

(10)

Where,

$IRFCOEFF_i$ represents the coefficient of impulse response (to macro shock) of i^{th} bank and TO_i, WB_i, RB_i represents business strategy (averaged over the sample period) of i^{th} bank. Similarly CAR_i represents capital asset ratio of i^{th} bank, NPA_i represents non-performing assets of i^{th} bank averaged over a sample period, $Size_i$ represents size of i^{th} bank averaged over a sample period and $Liquidity_i$ represents liquidity of i^{th} bank averaged over a sample period. $OWNERSHIP_i$ represents a dummy variable that is 1 if i^{th} bank is a public sector bank and 0 otherwise.

We estimated three regressions separately in order to assess the effect of discriminating business strategies by distinguishing the risk responses after zero, two and four quarters.

Equation (10) analyze under given macro-economic shocks, if discriminating business strategies reduces the responsiveness of bank risk.

5.3 Variables description

5.3.1 Dependent variables

Individual banks' impulse response functions of backward looking risk measure: This has been obtained as a coefficient of impulse risk response to monetary and house price shock. The backward looking risk measure is Gross NPA/ Advances

Individual banks' impulse response functions of forward looking risk measure: This has been obtained as a coefficient of impulse risk response to monetary and house price shock. The forward looking risk measure is Non Interest Income/ Total Income. Non-interest incomes generated from involving non-traditional activities are quite volatile, and thus risky (Stiroh & Rumble, 2006).

5.3.2 Independent variables

In order to analyze the heterogeneity of bank risk responses, we will focus on business strategy.

Business Strategy (TO, WB, RB, DIV) have been used as a principal independent variable. Market may reward the bank for more profitable but risky strategy. Also if market rewards the bank being more diversified in its operations. Well-capitalized banks may react less to output shocks also because their profits could be less sensitive to the business cycle, as their portfolio choices may differ from those taken by less-capitalized banks. If well-capitalized banks are also more risk-averse, they select ex ante a pool of borrowers who are on average less financially fragile, thus containing banks' exposure to default risk when an economic downturn occurs (Gambacorta & Mistrulli, 2004). Diversification Index is measured as defined in Acharya, Hasan, and Saunders (2006)

5.3.3 Control variables

Capital Asset ratio may also influence the way the loan supply reacts to output shocks if banks' profits, and thus banks' capital accumulation, depend on the business cycle. In this case, output shocks affect banks' capacity to lend if the market for equity is not frictionless and banks have to meet regulatory capital requirements.

Other things being equal, well capitalized banks are in a better position, with respect to less-capitalized banks, to absorb output shocks. Since they hold more capital in excess of the minimum required to meet prudential regulation standards, well-capitalized banks need to adjust lending less during economic downturns in order to avoid regulatory capital shortfalls. Thus, if for institutional reasons banks hold a different amount of capital in excess of regulatory requirements, this may in turn imply cross-sectional differences in lending responses to output shocks (Gambacorta & Mistrulli, 2004).

SIZE represents Log of banks' real gross total assets, that is, assets divided by the GDP deflator

Non-Performing assets has been controlled as an accounting measure of risk. The increased NPA level is likely to have adverse impact on the bank business as well as profitability thereby the shareholders do not receive a market return on their capital and sometimes it may erode their value of investments. Rising NPAs are a double whammy as they put pressure on P&L (profit & loss account), which in turn puts pressure on capital requirements. And lack of capital curtails growth." (Kishore & Kumar, 2014). NPA is measured as Gross non-performing assets to advances.

$\mathbf{OWNERSHIP_i}$ represents a dummy variable that is 1 if i^{th} bank is a public sector bank and 0 otherwise.

Liquidity is defined as cash divided by current liabilities. A stock of liquid assets helps the banking system withstand a sudden drop in deposit demand or in international credit without an abrupt and potentially very costly contraction of lending. However, holding liquid assets is costly for banks, because the interest rate earned on such assets is lower than could be earned on loans and other non-liquid investments. It is costly to society as well, in the sense that the long-term investments that are foregone when banks hold high levels of liquidity are those that are required for growth and development (Gavin & Hausmann, 1996)

6 Preliminary Empirical results

6.1 Results Analysis based on bank risk response

6.1.1 Impulse response function of Individual banking variables (FAVAR with restrictions)

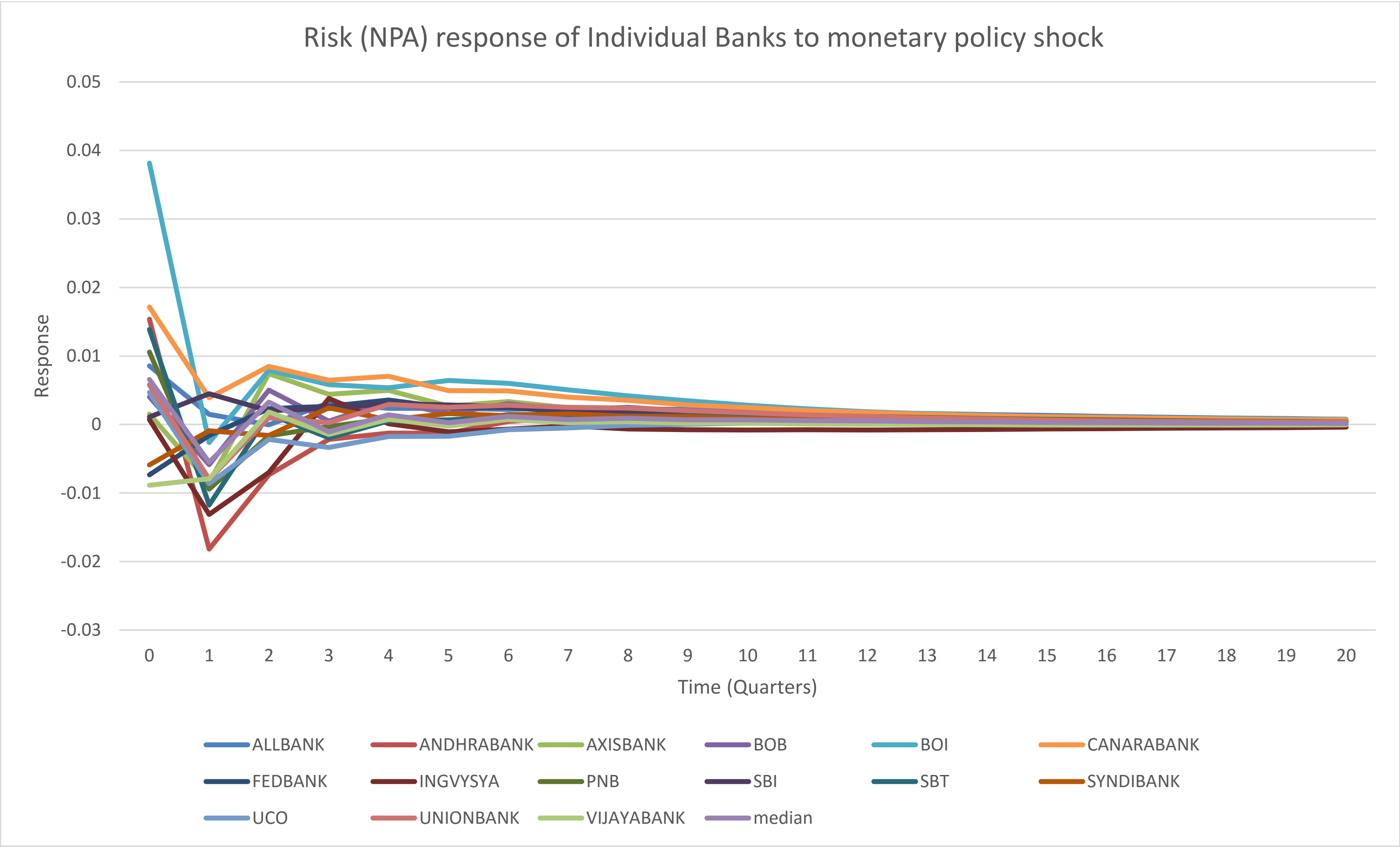
6.1.1.1 Variable definition

Macro: GDP, GDP Deflator, House Price, Unobserved banking factors, Repo rate
Banking: NPA (backward looking risk), Non-Interest Income (Forward looking risk)

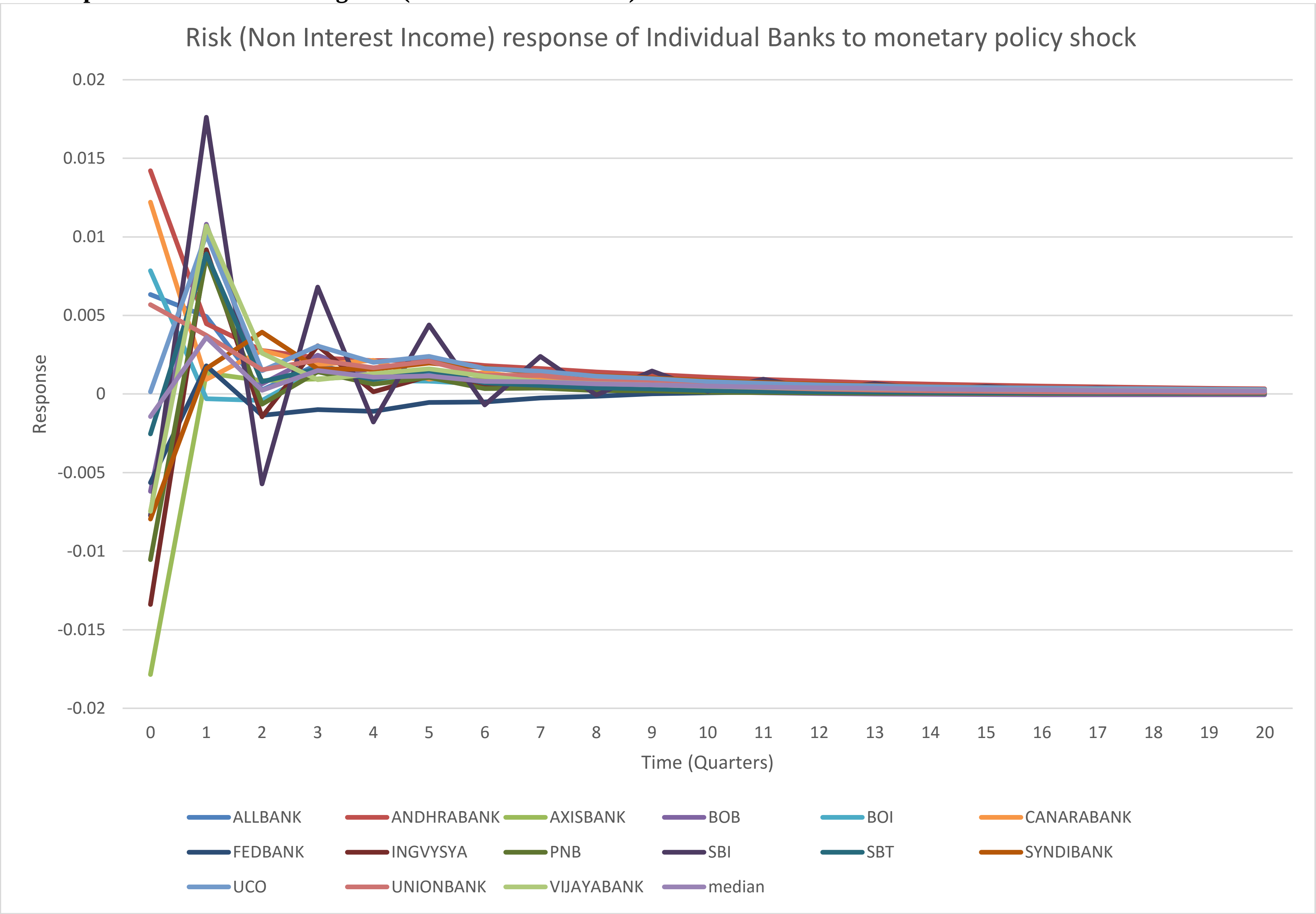
6.1.1.2 Results

6.1.1.2.1 Monetary Policy shock

6.1.1.2.1.1 Response of Backward looking risk (NPA)

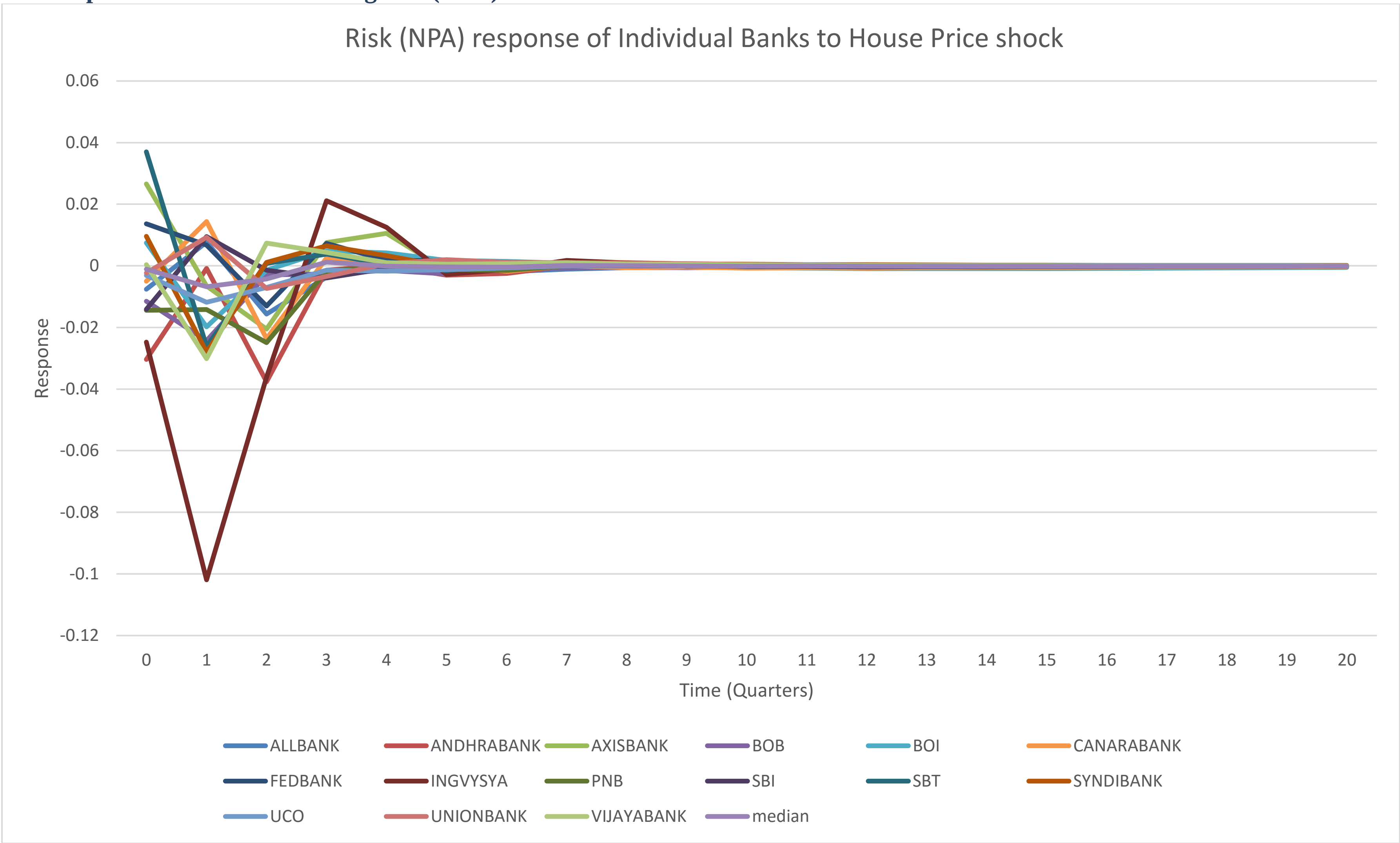


6.1.1.2.1.2 Response of forward looking risk (Non-Interest Income)

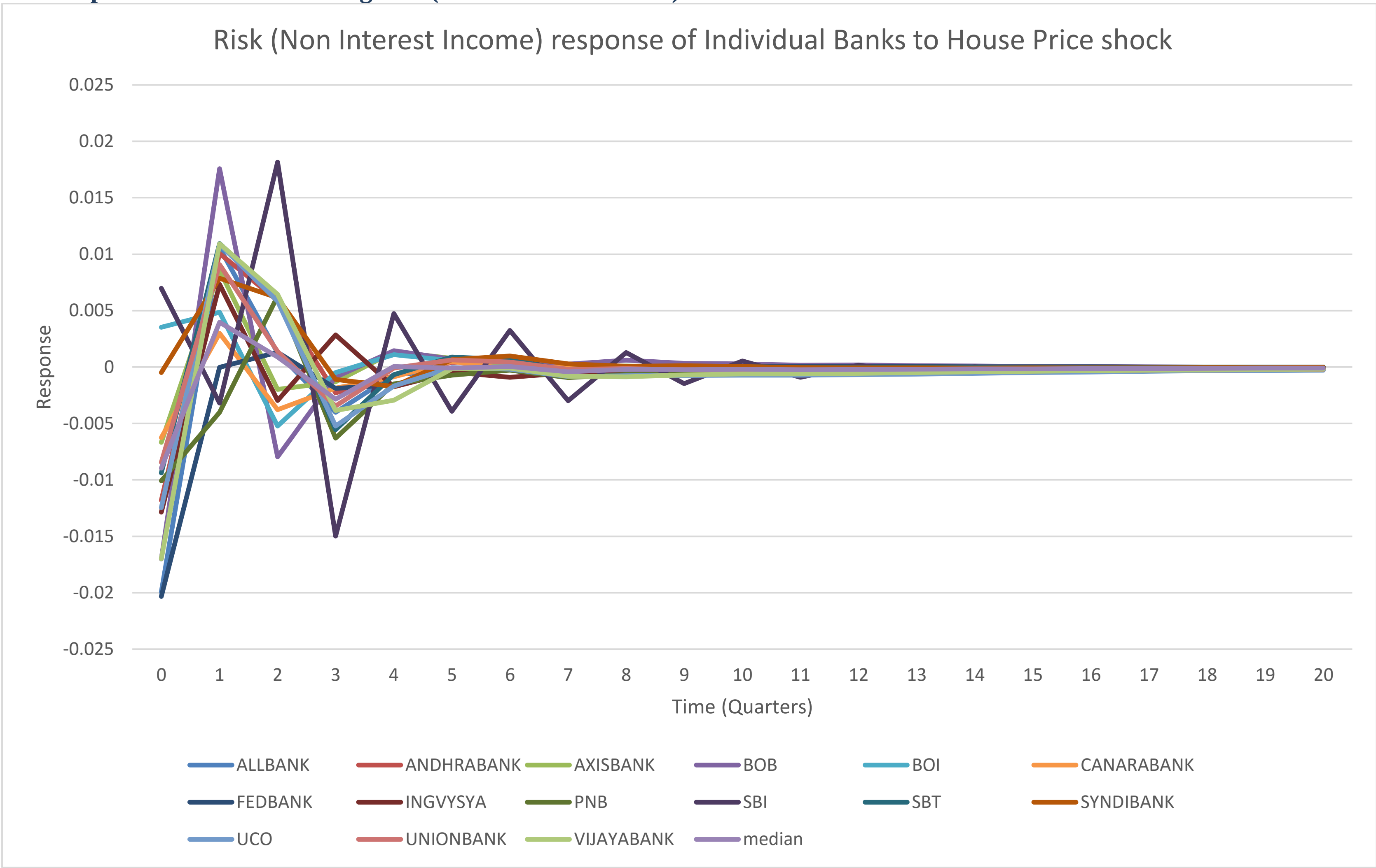


6.1.1.2.2 House Price Shocks

6.1.1.2.2.1 Response of Backward looking risk (NPA)



6.1.1.2.2.2 Response of forward looking risk (Non-Interest Income)



6.2 Relevance of macro-economic shocks for banking sector

The variance decomposition is done to answer the question how relevant the macro-economic shocks are for banking sector developments.

VARIANCE DECOMPOSITION TABLE

VARIABLE	Supply Shocks	Demand Shocks	House Price Shocks	Shocks to latent banking factors	Monetary Policy shocks	Idiosyncratic Shocks
1-YEAR HORIZON						
GDP	0.66408	0.03554	0.13254	0.06083	0.01521	
GDP_DEFLATOR	0.07092	0.6684	0.02676	0.12032	0.04033	
HOUSE_PRICE	0.13215	0.09113	0.68332	0.03995	0.01198	
REPO_RATE	0.00242	0.2979	0.02778	0.47555	0.18907	
NPA	0.11132	0.05965	0.01507	0.63788	0.01708	0.13986
NON-INTEREST INCOME	0.11271	0.06156	0.06479	0.69218	0.01211	0.04863
5-YEAR HORIZON						
GDP	0.63346	0.03905	0.12758	0.09282	0.01701	
GDP_DEFLATOR	0.06902	0.6463	0.02644	0.1457	0.04014	
HOUSE_PRICE	0.12722	0.089	0.65081	0.07891	0.01379	
REPO_RATE	0.00762	0.18459	0.01902	0.66031	0.12262	
NPA	0.11163	0.06784	0.0149	0.63509	0.01749	0.13396
NON-INTEREST INCOME	0.10855	0.0634	0.06191	0.69741	0.01322	0.0477

6.3 Explaining differences in individual banks' responses to macroeconomic shocks

Regression Results

	Monetary policy Shock						House Price Shock					
	Non-Performing Loans			Non-Interest Income			Non-Performing Loans			Non-Interest Income		
	0 year	1/2 year	1 year	0 year	1/2 year	1 year	0 year	1/2 year	1 year	0 year	1/2 year	1 year
Intercept												
Estimate	-0.00193	-0.00763	-0.0012	-0.00572	0.00323	0.00154	-0.00127	-0.03227	0.0091	-0.02132	-0.00567	-0.00555
SE	0.0142	0.00489	0.00249	0.00924	0.00178	0.000641	0.02313	0.01483	0.00197	0.00864	0.00586	0.0016
P > |t|	0.895	0.1532	0.6415	0.5512	0.1033	0.0397	0.9574	0.0576	0.0013	0.0358	0.3585	0.0069
CAR												
Estimate	-0.00074	0.00339	0.00202	0.00297	-0.00043	-0.00028	-0.00314	-0.00055	-0.00244	-0.00228	-0.00098	0.000731
SE	0.00507	0.00175	0.00089	0.0033	0.000636	0.000229	0.00826	0.0053	0.000704	0.00309	0.00209	0.00057
P > |t|	0.8865	0.084	0.049	0.392	0.5195	0.2585	0.7129	0.9191	0.0071	0.4786	0.6503	0.2315
VIF	1.48948	1.48948	1.48948	1.48948	1.48948	1.48948	1.48948	1.48948	1.48948	1.48948	1.48948	1.48948
NPA												
Estimate	-0.00379	0.00131	0.000299	-0.00338	-0.00261	-0.00115	0.00272	0.01067	-0.00117	0.00501	0.00648	0.00118
SE	0.00639	0.0022	0.00112	0.00416	0.000801	0.000288	0.0104	0.00667	0.000887	0.00389	0.00264	0.000718
P > |t|	0.5671	0.5664	0.7956	0.4367	0.0098	0.0031	0.7998	0.1442	0.2205	0.2298	0.0363	0.1343
VIF	1.51687	1.51687	1.51687	1.51687	1.51687	1.51687	1.51687	1.51687	1.51687	1.51687	1.51687	1.51687
Ownership												
Estimate	0.01069	0.01102	0.00422	0.00441	-0.00336	-0.00078	2.59E-05	0.02511	-0.00893	0.0148	0.01017	0.00648
SE	0.01723	0.00594	0.00303	0.01122	0.00216	0.000779	0.02808	0.01801	0.00239	0.01049	0.00712	0.00194
P > |t|	0.5504	0.0966	0.1968	0.7035	0.1541	0.3401	0.9993	0.1967	0.0047	0.192	0.1869	0.0086

VIF	4.14259	4.14259	4.14259	4.14259	4.14259	4.14259	4.14259	4.14259	4.14259	4.14259	4.14259	4.14259
Treasury Rev												
Estimate	0.01226	0.05238	0.02207	-0.02469	-0.00983	-0.00074	0.05408	0.05997	0.00557	0.04919	0.00873	0.01656
SE	0.07145	0.02463	0.01254	0.0465	0.00896	0.00323	0.1164	0.07465	0.00993	0.04351	0.0295	0.00803
P > |t|	0.8676	0.0624	0.1124	0.6083	0.3014	0.8231	0.6532	0.4424	0.5884	0.2875	0.774	0.0693
VIF	3.06147	3.06147	3.06147	3.06147	3.06147	3.06147	3.06147	3.06147	3.06147	3.06147	3.06147	3.06147
Wholesale Rev												
Estimate	0.00959	-0.00422	-0.00182	0.05671	0.02483	0.01171	-0.02782	-0.03796	-0.00149	-0.04387	-0.04471	-0.02341
SE	0.07628	0.02629	0.01339	0.04964	0.00957	0.00345	0.12427	0.07969	0.0106	0.04645	0.03149	0.00857
P > |t|	0.9027	0.876	0.8947	0.2828	0.029	0.0079	0.8279	0.6452	0.8914	0.3696	0.1894	0.0232
VIF	2.72852	2.72852	2.72852	2.72852	2.72852	2.72852	2.72852	2.72852	2.72852	2.72852	2.72852	2.72852
RSQR	0.20539	0.42827	0.447	0.48619	0.68381	0.81947	0.09955	0.37158	0.88031	0.36605	0.5501	0.60798

Note: The dependent variables are the impulse response functions for the nonperforming loans ratio, noninterest income ratio, and loans to expansionary monetary policy and house price shocks. Explanatory variables are demeaned bank characteristics

7 Discussion on results

7.1 Response of median bank risk to macro-economic shocks (VAR)

Shocks	**Non-Performing Assets (Backward Looking risk)**	**Non-Interest Income ratio (Forward looking ratio)**
Supply Shock	Insignificant	Insignificant
Demand Shock	Significant	Insignificant
House price shock	Insignificant	Insignificant
Monetary policy Shock	Significant (Contractionary shocks lead to fall in risk)	Significant (Contractionary shocks lead to increase in risk)

7.2 Relevance of macro-economic shocks (including banking factor) for banking sector

As per the variance decomposition we find more than 50% variation in bank risk explained by the shocks in latent (banking) factors.

7.3 Response of individual bank risk to macro-economic shocks (FAVAR)

Preliminary results show homogeneity across individual bank risk responses to macroeconomic (Monetary and house price) shocks.

7.4 Result Analysis based on heterogeneity

Under monetary policy shock, for backward looking risk (NPA), at lag ½ year treasury operation have positive coefficient. For forward looking risk (Non-interest income), at lag ½ year and 1 year wholesale operations have positive coefficient.

Under house price shock, for forward looking risk (Non-interest income), at lag 1 year treasury operation have positive coefficient and wholesale operations has negative coefficient.

8 Hypothesis analysis summary

How are macroeconomic shocks transmitted to individual banks and, in particular, to bank risk?

Monetary policy shocks have an important impact on bank risk.

The response of bank risk depends on the measure of risk used. Nonperforming loans of the median bank and thus backward-looking risk decline after Contractionary monetary shocks. *(This is in consistent with the argument of Claudia M. Buch et al. (2014) & Angeloni and Faia (2009)*

The forward-looking risk, measured through the share of 'noninterest income' rise, following contractionary monetary policy shocks. *(This is also in consistent with the argument of Claudia M. Buch et al. (2014))*

Shocks to the banking factors also matter for bank risk and also the policy rate

If there is any heterogeneity across individual bank risk responses?
The graphs reveal substantial heterogeneity after monetary and house price shocks

If strategy decrease responsiveness of bank's risk to macro-economic shocks?
Business strategy was found to matter for risk responses of banks to monetary policy and house price shocks
Wholesale and treasury dominates in contrast to retail banking. *This is in contrast to Claudia M. Buch et al. (2014) who found exposure to consumer loans as one source of heterogeneity*

Capital adequacy ratio and ownership were also found to be the source of heterogeneity

9 Policy Implication

This study may provide bank regulators or supervisors with important insights about how they should change or improve the regulations related to bank strategies. If the choice of business strategy reduces the systemic then it also reduces the need to impose BASEL norms.

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