

Does credit risk persist in the Indian banking industry? Recent evidence

Anju Goswami

University of Petroleum and Energy Studies, Dehradun, India

Abstract

Purpose – This study aims to capture the “persistence effect” of credit risk in Indian banking industry using the bank-level data spanning over the period of 19 years from 1998/1999 to 2016/17. Alongside, the study explored how the bank-specific, industry-specific, macroeconomic variables alongside regulatory reforms, ownership changes and financial crisis affect the bank’s asset quality in India.

Design/methodology/approach – Using two-step system generalized method of moment (GMM) approach, the study derives key factors that affect the bank’s asset quality in India.

Findings – The empirical results confirm the time persistence of credit risk among Indian banks during study period. This reflects that bank defaults are expected to increase in the current year, if it had increased past year due to time lag involved in the process of recovery of past dues. Further, higher profitability, better managerial efficiency, more diversified income from nontraditional activities, optimal size of banks, proper credit screening and monitoring and adherence regulatory norms would help in improving the credit quality of Indian banks.

Practical implications – The practical implication drawn from the study is that nonaccumulation of nonperforming loans (NPLs), higher profitability, better managerial efficiency, more diversified income from nontraditional activities, optimal size of banks, proper credit screening and monitoring and adherence regulatory norms would help in improving the credit quality of Indian banks.

Originality/value – This study is probably the first one that identifies in addition to the current year, whether lag of bank industry-macroeconomic affects the level of NPLs of Indian banks. So far, such an analysis has received less attention with respect to Indian banking industry, especially immediate aftermath of the global financial crisis.

Keywords Credit risk, Persistence effect, Dynamic estimation, Indian banks

Paper type Research paper

1. Introduction

The recent global financial crisis of 2007–08 has stimulated the interest of academicians, policymakers and researchers to the key consequences that banking crisis can have on to the nation’s economy. The situations of financial crisis intensify the banking distress, and in the process, become one of the main obstacles to the stability of the financial system, in general, and banking system, in particular. More specifically, a rapid increases in asset prices, high leverage of borrowers and lenders, a decline in lending standards, coupled with liquidity and/or insolvency problems caused by the increase in nonperforming loans (NPL) and regulation and supervision failures may pace up the risk of an occurrence of such financial crises (Laeven and Valencia, 2008; Castro, 2013; Claessens *et al.*, 2014). Caprio and Klingebiel (1996) concluded that such crises in the past have resulted in severe bank losses or public sector resolution costs, especially in developing countries [1]. Such a consequences of banking crises has raised the concern as to the reasons why such crises occur? The credit risk, which arises



due to bubbling up of NPLs in the bank's balance sheets, generally overlays the other causes for the occurrences of banking crisis since it can seriously undermine the financial soundness of the banking sector.

The level of NPLs or impaired loans is generally used as a critical indicator to quantify the credit risk burden, which represent the risk of loss due to nonpayment by the borrower (RBI, 2007) [2]. Currently, the high level of NPLs in banks has been a matter of grave concern for all nations' policymakers since it creates bottlenecks in the smooth flow of credit in the economy. This underlines the procyclical behavior of the banking system, wherein asset quality get compromised during periods of high credit growth and results in the creation of default risk for banks in the later years. In the Indian context too, the gross and net NPLs as a percentage of advances stood at 15.7 and 8.1% in 1996–1997, which later declined to 2.3 and 1.1% in 2007–08, reflecting an improvement in asset quality in post-reforms period. But, during the crisis year 2008–09, the gross NPLs ratio remained stable for Indian banks, reflecting the success of financial sector deregulation and reforms, regulatory and supervisory process. In particular, banks have made substantial progress in cleaning up the NPLs from their balance sheets during the pre-crisis period (Reserve Bank of India, 2004).

However, the robust credit growth (of more than 30%), followed by economic expansion (of around 10%), in the Indian economy during 2006–2011, has further raised concern with regard to the credit risk. As of March 2015, gross and net NPLs for the Indian banking system as a whole rose at 4.4 and 2.4% of total advances, respectively, doubled from the 2007–08 level. Thus, due to an excessive credit lending to troubled borrowers and mismanaged information regarding borrowers, reduced the likelihood of them to repay their debts and increased the probability of defaults (Reserve Bank of India, 2011). Now, the distressed asset crisis weighed heavily on credit growth in India, which stood at only 4% for public sector banks, compared with 25% for private banks as at end March 2016. The public sector banks now have no ability to take on additional credit risk which poses a serious issue for the economy. From the above discussion, it is clear that the rising NPLs cause a serious concern for the policymakers, regulators, government and the central bank. For minimization of the credit risk, the bank regulators need to undergo deeper investigation of its underlying determinants. The present study is an attempt in this direction.

Against this backdrop, the key objective of this paper is to examine the determinants of credit risk in Indian banking industry for more recent time period, i.e. 1999–2014, covering the period following the global financial crisis. This study intends to provide evidence on the factors determining the credit risk structure in the emerging nation with special reference to Indian banking industry. The contribution of our study to the existing literature on credit risk determinants is threefold. First, this study provides new and most recent evidence on the time persistence in accumulation of NPLs in the Indian banking industry. For the estimation of “persistence effect”, the study employs a two-step system generalized method of moment (GMM) estimation method on an unbalanced panel of bank-level data spanning over the period of 19 years from 1998/1999 to 2016/17. The study further provides the pooled OLS, PCSE, within group fixed effects and two-step difference GMM estimates for robustness check.

Second, this study is probably the first one that identifies in addition to the current year, whether lag of bank-industry-macroeconomic also generates a burden of credit risk in Indian banking industry. This study would perhaps be the first one to consider the role of prudential norms, crisis and ownership structure as additional factors, along with size, profitability, credit growth, diversification, market concentration, bank solvency, among others, underlying the dramatic changes in credit risk structure of Indian banking industry. I believe this study has potential to provide a clear and lag-wise scenario of bank-macro and industry-specific factors for credit risk to regulators and stakeholders of Indian banks. So that they can form the necessary strategy against those factors, which are fully responsible for the generation of NPLs in the banking industry in India.

Finally, our study provides an evidence for a single country with particular reference to the Indian banking industry. Such an analysis bear a great significance due to the fact that the Indian economy has bank-based financial system like Indonesia and Pakistan, where banks play an important role in their financial system, and any shock to banks ultimately impact the entire economy (Demirgüç-Kunt and Levine, 1999). This study seems to have relevance in the current scenario due to surging bad loans in the balance sheets of Indian banks in the recent years. Furthermore, bank's NPLs in India as a percentage of gross loans has been found to be consistently far above the levels seen in other Asian economies [3]. Ahmad and Ariff (2007) concluded that the credit risk in emerging economy banks is higher than that in developed economies, and that risk is formed largely by bank-specific factors in emerging economies compared to their counterparts. In this regard, this study would try to help the bank managers in identifying the factors that may lead to deterioration in credit quality and increase the burden of default risk. So far, such an analysis has received less attention with respect to Indian banking industry, especially in the aftermath of global financial crisis.

The rest of the paper is organized as follows. Section 2 discusses credit risk scenario in in the Indian banking industry. Section 3 presents a relevant literature review on the subject matter. Section 4 encompasses description of databases, methodology and discussion on conceptual framework. Section 5 focuses on results and discussion, while Section 6 concludes the findings of the study.

2. Review of the literature

A significant body of the literature has evolved in the past which explored the determinants of credit risk in the banking sector. In particular, there exit two strands of the literature on the determinants of bank credit risk (Castro, 2013; Aver, 2008; Ahmad and Ariff, 2007). The first volume of the literature focused primarily on the factors affecting systematic credit risk (e.g. macroeconomic factors, economic policies, political changes, etc.). The studies that only examined the macroeconomic factors affecting the credit risk include Baboucak and Jancar (2005), which provide the systematic assessment of the links between loan quality and macroeconomic shocks in the Czech banking industry. They found a direct relation between NPLs, rate of unemployment and consumer inflation rate, while an inverse relation with GDP growth in the Czech economy. On the similar grounds, Nkusu (2011) analyzed the credit risk determinants across 26 advanced economies during the period spanning from 1998 to 2009. They found that NPLs were positively explained by macroeconomic variables such as the unemployment rate, policy rate of interest and lagged NPLs, while negatively explained in GDP growth rate, housing price index and equity price index. Beck *et al.* (2013) examined the role of macroeconomic indicators in 75 advanced and emerging economies during the period 2000–2010 and concluded that the bank asset quality significantly affected by a drop in real GDP growth, share prices, the exchange rate and the lending interest rate. Further, exchange rate depreciations have also lead to an increase of NPLs in sampled countries. Similarly, Castro (2013) analyzed the link between the macroeconomic factors and credit risk in the Greece, Italy, Portugal, Spain and Ireland by employing dynamic panel data approaches over the period 1997q1–2011q3. They conclude that the credit risk increases when GDP growth, share price indices and housing prices decrease and rises when the unemployment rate, interest rate and credit growth increase.

In contrast, the second strand of the literature has also considered the role of unsystematic risk factors (e.g. bank-specific, industry-specific, regulatory and institutional, etc.) in generating the default risk. Considering the relationship between bank's efficiency and bad loans, Berger and DeYoung (1997) performed Granger causality analysis for the period 1984–1995 and found that less cost efficient banks wind up having more problem loans. They also

concluded with the importance of four hypotheses explaining the relationship between efficiency and NPLs – bad management, bad luck, moral hazard and skimping hypotheses. [Ahmad and Ariff \(2007\)](#) explored a sample of four advanced and five developing nations and concluded that regulatory capital, management quality and loan loss provisions were significant determinants of potential credit risk. [Louzis *et al.* \(2012\)](#) explored the factors that affect NPLs from three categories of loans mortgage, business and consumer separately. The results show that, for all loan categories, NPLs in the Greek banking system have been explained mainly by GDP, unemployment, interest rates, public debt and management quality. The similar findings have been revealed by [Abid *et al.* \(2014\)](#) for Tunisian banking industry. Using the panel dataset of 80 banks in the GCC region, [Espinoza and Prasad \(2010\)](#) found that lower non-oil real GDP growth and higher interest rates increased the level of NPLs during the period of 1995–2008. Further, a positive relationship has been found between lagged credit growth and NPLs. [Khemraj and Pasha \(2009\)](#) found that real effective exchange rate and real interest rate to have a positive significant impact on NPLs, while GDP growth, loan to assets ratio and loan growth had a negative impact. [Makri *et al.* \(2014\)](#) also found strong correlations between NPL and various macroeconomic (annual GDP growth rate, public debt to GDP ratio and unemployment rate) and bank-specific factors (return on equity and capital adequacy ratio).

Using a dynamic panel analysis, [Chaibi and Ftiti \(2015\)](#) compared the determinants of NPLs of commercial banks in France (a market-based economy), with Germany (a bank-based economy) during 2005–2011. The empirical results reveal that credit risk in France is more susceptible to bank-specific determinants compared to Germany. [Klein \(2013\)](#) observed the persistence of NPLs in 16 Central, Eastern and South Eastern Europe countries during 1998–2011. Further, unemployment, inflation, exchange rate, VIX and loan growth has been found to positively explain the NPLs, while the solvency ratio, ROE and GDP growth rate had a negative association. The similar findings have been reported by [Skarica \(2013\)](#). [Alhassan *et al.* \(2014\)](#) also found the persistence of NPLs in Ghanaian banking sector, with loan growth, bank market structure, bank size, inflation, real exchange rate and GDP growth to have a significant effect on banks' asset quality. Finally, [Ghosh \(2015\)](#) analyzed the persistence effect of credit risk in US banking sector during the period 1984–2013 using dynamic panel estimation method. The results reveal that greater capitalization, liquidity risks, poor credit quality, greater cost inefficiency and banking industry size to significantly increase NPLs, while greater bank profitability lowers NPLs.

In Indian context, [Rajaraman and Vashishtha \(2002\)](#) were the first one to examine the factors influencing the NPLs in the public sector banks during the period 1996–2000. They found that operating profit to working funds has a significant negative impact on asset quality of public sector banks in India. Later, [Ranjan and Dhal \(2003\)](#) also considered a sample of public sector banks and found that bank size in terms of assets has the negative, while in terms of capital has positive impact on gross NPLs. [Das and Ghosh \(2007\)](#) empirically reported the high persistence of credit risk across state-owned banks in India during the period 1994–2005. Using the balanced panel data of 19 private and 26 public sector banks operating in India during 2005–2013, [Satpathy *et al.* \(2015\)](#) found that operating inefficiency, restructured debt and inflation rate have a positive impact on NPLs, while credit growth, priority sector advances, fiscal deficit, GDP growth rate, lending rate, trade balance and advanced to sensitive sector seems to have a negative effect. [Bardhan and Mukherjee \(2016\)](#) find the persistence effect of NPAs in the Indian banking industry. A higher level of capitalization, profitability and GDP growth lowers NPAs level in the following years, while the lagged size of banks and inflation leads to a higher level of NPAs in the Indian banking industry. [Bawa *et al.* \(2019\)](#) find that lagged NPAs level is positively associated with the current NPAs level in the Indian banking industry during the period 2007–2014. In addition, they reveal that a higher intermediation cost and return on assets tend to reduce the level of

NPAs, while aggressive asset growth and solvency induce a rise in the level of NPAs. Using a two-step system GMM approach, [Gulati et al. \(2019\)](#) explore the key determinants of credit risk for the period 1998/99 to 2013/14. They find a persistence effect of credit risk in the Indian banking industry.

From the above survey of literature, following observations have been made. First, it is clear that most existing studies on credit risk determinants in the banking industry relates to either those of developed nations or were conducted in cross-country settings, especially in the aftermath of global crisis. No doubt, the research efforts have also been made to investigate the factors contributing to credit risk in single-country settings, but large majority of studies have focused on European nations. Thus, among the existing studies, there exist only few one whose attention is directed to developing countries. Second, the contemporary literature proves that, in the past, most of the studies concentrated on macroeconomic linkage of credit risk, while few other studies incorporate the role of bank-specific and other factors which may be responsible for the rise in NPL levels. The large majority of studies mainly focused on the macroeconomic and bank-specific factors, but the changes in credit worthiness of borrowers, depth of information sharing, regulatory policies, governance structure which are difficult to examine and left out of consideration. Third, only a handful of studies have accounted for the persistence of credit risk in the banking sector. The large majority of research efforts were only after the global crisis of 2007–08, and that too for US and European banks. However, none of the existing studies tried to identify that whether accumulation of credit risk, bank-macro and industry-specific factors may impact the NPLs level over the last 3 decades in the Indian banking industry or not. The present study aims to attempt in this direction. I believe this study has potential to provide a clear and lag-wise scenario of bank-macro and industry-specific factors for credit risk to regulators and stakeholders of Indian banks. So that they can form the necessary strategy against those factors, which are fully responsible for the generation of NPLs in the banking industry in India.

It is obvious that there is a gap in the contemporary literature, regarding the determinants of NPLs in the developing and emerging nations, particularly India. The studies pertaining to Indian banking sector have mainly looked at the determinants of credit risk in the public sector banks only (see, [Das and Ghosh, 2007](#)), which currently forms only 75% of the business operations in terms of total assets in India. This study is perhaps an effort to consider full range of sample of Indian banks (including public, private and foreign banks) operating in India from 1998–99 to 2016–17. Further, it has been observed that credit risk in emerging economy banks has been found to be higher than that in developed economies ([Ahmad and Ariff, 2007](#)). So, considering the above notion, our study tries to fill this gap for emerging nations by empirically investigating the determinants of credit risk across a bank-based economy like India. The study would not only analyze all the possible factors that may deteriorate the asset quality but also account for the persistence of credit risk in Indian banks.

3. Database and methodology

3.1 Database

Our study considers all the banks operating in the industry during the period from 1998/99 to 2016/17. The bank-level data pertaining to all the variables have been obtained from the various issues of “Statistical Table Relating to Banks in India”, an “*annual publication of Reserve Bank of India (RBI)*” and “*Performance Highlights of Public Sector Banks*”, “*Performance Highlights of Private Banks*” and “*Performance Highlights of Foreign Banks*”, an “*annual publications of Indian Banks’ Association*” (IBA). The real GDP growth rate (%) and inflation rate (%) for each sample year has been obtained from the World Bank database. Finally, the mergers and acquisitions, and exit of some banks from the industry have left us with the unbalanced panel of banks for the above mentioned period.

3.2 Dynamic panel model estimation

This study adopts the two-step system generalized method of moments (GMMs) technique of [Blundell and Bond \(1998\)](#) to test the time persistence in credit risk structure in the Indian banking industry for the following reasons: (1) in the presence of the lagged dependent variable, $Y_{i,t-1}$, the traditional panel estimators are seriously biased (see, Baltagi, *Econometric Analysis of Panel Data*, 5th edition, 2013 and Roodman, D., through the looking glass, and what OLS found there: on growth, foreign aid and reverse causality. Unpublished working paper, Center for Global Development, 2008); (2) fixed effects model's accuracy deteriorates when the panels are unbalanced. Therefore, the use of system GMM method appears to outperform than the fixed effects model in the presence of endogeneity and lagged dependent variable in unbalanced panels (see, [Arellano and Bond, 1991](#); [Blundell and Bond, 1998](#)) and (3) one-step GMM estimation can produce consistent estimates under the assumption of independent and homoscedastic residuals (both cross-sectional and over time). However, its standard error is largely downward biased in small samples. Therefore, [Windemeijer's \(2005\)](#) correction for small sample is applied to rectify the standard error bias. Consequently, the two-step GMM estimator is used which provides more accurate estimates than the robust one-step GMM estimator, especially for the system GMM ([Roodman, 2006](#)). In addition, the study uses the [Arellano and Bover \(1995\)](#) forward orthogonalization procedure and collapsing method of [Holtz-Eakin et al. \(1988\)](#) to limit the number of instruments (for more details, see [Roodman, 2009](#)).

The factors that determine credit risk have been examined based on the generalized method of moments. The dynamic panel data specification used is given by:

$$Y_{it} = \alpha + \delta Y_{i,t-1} + \sum_{j=1}^J \beta_j X_{it-s}^j + \sum_{z=1}^Z \gamma_z X_{it-s}^z + \sum_{k=1}^K \theta_k X_{it-s}^k + \sum_{d=1}^D \eta_d X_{it}^d + \mu_{it} \quad (1)$$

where $|\delta| < 1$, $i = 1, \dots, N$, $t = 1, \dots, T$, $s = 0, 1, \dots, L$

where the subscripts i and t denote the cross-sectional and time-dimensions of the panel, respectively. The dependent variable, Y_{it} , used is the logit transformation of the net nonperforming loans to total advances, a proxy for credit risk for i th bank in the t th year. As suggested by [Espinoza and Prasad \(2010\)](#), [Klein \(2013\)](#), [Wenzel et al. \(2014\)](#) and [Ghosh \(2015\)](#), such transformation ensures the dependent variable to span over the interval $[-\infty, +\infty]$ and is distributed symmetrically. Further, it allows the assumption of normality in the error term and accounts for nonlinearities in a way that larger shocks to the explanatory variables may cause a large, nonlinear response in the transformed dependent variable. The value of δ lies between 0 and 1 implies persistence of credit risk. $\beta_j X_{it-s}^j$ denotes bank-specific variables in $t-s$ period, $\beta_z X_{it-s}^z$, $\beta_k X_{it-s}^k$ and $\beta_d X_{it-s}^d$ macroeconomic, industry-specific and dummy variables (see, [section 4](#) for more details). Further, $\mu_{it} = \eta_i + \nu_{it}$, where η_i represents the unobserved bank-specific effects, and ν_{it} is the error term.

The overall validity of the instruments has been tested by using the Hansen J specification test, which under the null hypothesis of joint validity of the moment conditions (the presence of over-identification) is asymptotically distributed as chi-square ([Arellano and Bond, 1991](#); [Arellano and Bover, 1995](#); [Blundell and Bond, 1998](#)). Furthermore, we assess the fundamental assumption of serially uncorrelated errors, i.e. ν_{it} using Arellano–Bond tests for Autoregression AR(1) and AR(2) by testing the hypothesis that $\Delta \nu_{it}$ is not second order autocorrelated. The rejection of the null hypothesis of no second order autocorrelation of the differenced errors implies serial correlation for the level error term and thus, inconsistency of the GMM estimates.

4. Variable(s) specification

4.1 Dependent variable

In the present study, we use the ratios of net nonperforming loans (NNPLs) to total advances as proxies for credit risk. Much of the literature on credit risk (see, for example, [Salas and Saurina, 2002](#); [Das and Ghosh, 2007](#); [Espinoza and Prasad, 2010](#); [Klein, 2013](#)) has considered the dependent variable in dynamic panel data regression using logit transformation of either GNPLs or NNPLs. Similarly, we define the dependent variable as of the following: $\ln[\text{NNPLS}_{i,t}/(1 - \text{NNPLS}_{i,t})]$ in case of net NPLs specification. It is important to note that this transformation ensures the dependent variable to span over the interval $[-\infty, +\infty]$ (as opposed to between 0 and 1 in case of NPLs ratio) and is distributed symmetrically.

The rest of systematic (macroeconomic) and unsystematic factors that are expected to form credit risk in the Indian banking industry are listed in [Table 1](#). However, the brief description of each independent variable(s) is given below.

4.2 Systematic (macroeconomic) variables

4.2.1 Real GDP growth rate (RGDP). The real GDP growth rate (RGDP) is used to control the effect of macroeconomic business activity. The literature suggest that during the periods of expansion, growth in real GDP usually increase the income which ultimately enhances the loan payment capacity of the individual and corporate borrowers which in turn contribute to lower default. As the expansion period continues, credit is then extended to lower quality debtors and subsequently results in increase in NPLs in the recession period. Thus, considering the above notion, the literature suggest that a negative relationship between economic activity and NPLs (see for, e.g. [Ranjan and Dhal, 2003](#); [Khemraj and Pasha, 2009](#); [Nkusu, 2011](#); [Beck et al., 2013](#); [Castro, 2013](#); [Chaibi and Ftiti, 2015](#)).

4.2.2 Inflation rate (INF). The literature spells an ambiguity in the relationship between NPLs and inflation. The studies by [Baboucek and Jancar \(2005\)](#), [Klein \(2013\)](#) and [Alhassan et al. \(2014\)](#) have found that an increase in inflation rate (INF) characterized by uncertain business conditions worsens the loan payment capacity by eroding the purchasing power of consumers and reducing the real income of borrowers, and thus reduces the debt servicing capacity resulting in increased risk of nonpayment of loans. On the contrary, a rise in inflation rate in the current period could see a reduction in the level of NPLs. This is because it can enhance the loan repayment capacity of borrower by reducing the real value of outstanding debt ([Shu, 2002](#); [Khemraj and Pasha, 2009](#)).

4.3 Unsystematic (bank-specific) variables

Return on assets (ROAs) is expressed as a proxy for bank's profitability. It is expected that better bank's performance in terms of profitability lowers the level of NPLs. [Louzis et al. \(2012\)](#), [Castro \(2013\)](#) and [Chaibi and Ftiti \(2015\)](#) found that more profitable bank reflect better management quality in terms of efficiency in borrower's application screening and credit granting procedures, which may likely to lower the risk of defaults as supported by the "bad management" hypothesis. Thus, ROA is hypothesized to have a negative relationship with the level of NPLs. On the contrary, [Rajan \(1994\)](#) model suggests that higher profits may also lead to rise in NPLs. This may be due to "liberal credit policy" adopted by banks' management to maximize banks' earnings to maintain the short-term reputation. This view has been empirically tested by [Ghosh \(2015\)](#).

4.3.1 Non-interest income (NONIT). The ratio of non-interest income (NONIT) to total assets is used as a measure of income diversification which may expect to lower the risk from traditional lending. Banks earnings not only depend on loans and advances but also rely on NONIT like fee-paying and commission paying services, investment banking, assets management, etc. It leads to reduction in the bank credit risk from loans due to bank's

Variables	Symbol	Definition	Testable hypotheses	Expected sign
<i>Dependent variable</i>				
Net nonperforming loans	NNPL	Logit (ratio of net nonperforming loans to total advances/1- ratio of net nonperforming loans to total advances)		
<i>Independent variable(s)</i>				
Credit growth	CREDIT	Ratio of loans to total assets (in %)	Bad management	(+)
Size	SIZE	Log of total assets	Diversification or Too big to fail	(-) (+)
non-interest income	NONIT	Ratio of non-interest income over total assets (in %)	Diversification	(-)
Intermediation cost	IC	Ratio of operating expenses to total assets (in %)	Inefficiency Bad management Skimping	(+) (+) (-)
Return on assets	ROA	Ratio of return to average assets (in %)	Bad management or procyclical credit policy	(+) (-)
Solvency ratio	SOLVENCY	Ratio of equity to total assets (in %)	Moral hazard	(-)
Real GDP growth rate	RGDP	Real GDP growth rate at 2004–05 constant prices	–	(-)
Inflation	INF	Annual inflation rate (as a % change in GDP deflator)	–	(+/-)
Bank concentration	CR10	Concentration of top 10 banks in terms of advances	Tight control	(-)
Prudential norms	PNORMS	1 for the period 1998–99 to 2003–04 and 0 otherwise	–	(-)
Ownership effect	PUBLIC	1 if public bank, and 0 otherwise	–	(+/-)
	PRIVATE	1 if private bank, and 0 otherwise	–	(+/-)
Financial crisis	CRISIS	1 for the period 2007–2009 and 0 otherwise	–	(+)

Source(s): Author's elaboration

Table 1.
Specification of
variable(s)

diversified sources of income. Following [Alhassan et al. \(2014\)](#), [Chaibi and Ftiti \(2015\)](#) and [Louzis et al. \(2012\)](#), a negative association is hypothesized between NONIT and credit risk.

4.3.2 Credit growth (CGROWTH). The literature suggests that growth in advances of a bank also helps in determining the credit risk. It is expected that higher loan growth leads to higher NPLs. It is argued that increase in supply of loans may reduce the credit standards, thereby increase the chances of loan defaults by borrowers ([Keeton, 1999](#)). Following, [Espinoza and Prasad \(2010\)](#), [Messai and Jouini \(2013\)](#) and [Alhassan et al. \(2014\)](#), the study proxied credit growth by total loan growth, i.e. percent change in the current year loans and advances with previous year's by an individual bank.

4.3.3 Bank size (SIZE). This variable is proxied by natural logarithm of bank's total assets. Empirical evidences on the relationship between NPLs and bank size (SIZE) is ambiguous. The large banks are assumed to have better risk management techniques, which ensure proper screening of loan applicants and lower default rate and better diversification opportunities. In this line of research, [Salas and Saurina \(2002\)](#), [Ranjan and Dhal \(2003\)](#) and [Alhassan et al. \(2014\)](#) reported a negative impact of SIZE on asset quality. Some of the empirical studies that have argued that as banks become too large, monitoring and

evaluation become difficult as they take on increased risk and may lead to “too big to fail” (Louzis *et al.*, 2012).

4.3.4 Inefficiency (INEFF). The credit risk may also be determined by bank’s inefficiency (INEFF) defined by a ratio of total operating expenses to total assets, i.e. intermediation cost of bank. The empirical literature suggests an ambiguity in the relationship between INEFF and NPLs. Berger and DeYoung (1997) argued that problem loans may arise either due to the events beyond the bank’s control (“bad luck”) or management’s INEFF to control lending risk (“bad management”). Either of the two situations will lead to increase future NPLs, implying a negative effect of INEFF on NPLs (see for, e.g. Chaibi and Ftiti, 2015 for French banks, Ghosh, 2015; Louzis *et al.*, 2012; Podpiera and Weill, 2008). On the contrary, the “skimping hypothesis” of Berger and DeYoung (1997) suggest that defaults are likely to increase with cost efficiency. This may be due to the fact that banks decide not to spend sufficient resources to ensure higher loan quality would appear to be efficient. This view has been empirically supported by Chaibi and Ftiti (2015) for German banks. Thus, the effect of inefficiency on NPLs may be expected to be negative or positive.

4.3.5 Bank solvency (SOLVENCY). Following the Louzis *et al.* (2012), Klein (2013), Makri *et al.* (2014), Chaibi and Ftiti (2015) and Ghosh (2015), this study determines the effect of bank’s solvency on asset quality by using a ratio of bank’s equity to total assets. The literature suggests that managers of thinly capitalized banks have moral hazard incentives to engage in risky lending practices, along with poor credit screening and monitoring of borrowers (Keeton and Morris, 1987). The inverse relation between solvency and NPLs validates the existence of “moral hazard” hypothesis in the Indian banking industry.

4.4 Industry-specific variable

4.4.1 Concentration ratio (CR_{10}). Only few studies have determined the impact of bank concentration on the credit risk. This variable measures a concentration of top ten banks in terms of advances in the industry during a particular year. The literature suggests that a higher concentration in lending by top ten banks increases the likelihood of credit risk. It is argued that banks with high degree of concentration may aggressive lend to specific sectors (such as agriculture and commerce) as a strategic choice to gain market power and earn higher profits which lead to high level of NPLs in future. Following Louzis *et al.* (2012), we hypothesized the concentration to have a positive impact on credit risk.

4.5 Dummy variables

4.5.1 Prudential norms (PNORMS). This variable is included in the econometric model as a dummy variable for a policy change. It represents a role of prudential norms in the improving the assets quality across Indian banks. The Reserve Bank of India has implemented a reform measure pertaining to classification of an asset as nonperforming and defined an asset to be a nonperforming when it remained not paid for 90 days, as on end of 2004. It is hypothesized that regulatory reforms has led to the improvement in the asset quality of Indian banks.

4.5.2 Ownership dummy (PUBLIC or PRIVATE). The study estimates the differences in level of credit risk across distinct ownership groups using two ownership dummies – PUBLIC and PRIVATE. Higher coefficient value of PUBLIC relative to PRIVATE reflects greater credit risk among public sector banks.

4.5.3 Financial crisis (FINCRISIS). In addition, we also incorporated the dummy to capture the influence of global financial crisis of 2007–09 on the credit risk structure of Indian banks.

5. Empirical results

5.1 Descriptive statistics and preliminary evidences

Table 2 reports the descriptive statistics of the sample data set. For the estimation purpose, the study used net NPLs to net advances as a proxy for credit risk. The dependent variable,

Variables	Mean	Std. Dev.	Min	Max	SWILK (Z-statistics)	SFRANCIA (Z-statistics)	Observations
<i>Dependent variable NNPLs</i>							
NNPL	-2.903	2.675	-10.67	4	13.83***	13.03***	1,361
<i>Bank-specific variables</i>							
SOLVENCY	-1.053	0.450	-5	0.049	12.50***	11.86***	1,361
SIZE	4.899	0.996	2.478	7.253	7.219***	6.785***	1,361
ROA	0.0043	0.0093	-0.176	0.052	7.006***	6.708***	1,361
NONIT	0.0086	0.0097	-0.011	0.100	8.258***	7.763***	1,361
IC	-1.641	0.242	-5	-0.492	13.05***	12.35***	1,361
CREDIT	-0.385	0.314	-5	-0.078	14.86***	14.01***	1,361
<i>Industry-specific variables</i>							
CR10	1.760	0.006	1.746	1.770	8.342***	7.904***	1,361
<i>Macroeconomic variables</i>							
RGDP	0.812	0.147	0.590	1.011	10.84***	10.23***	1,361
INF	0.698	0.154	0.491	0.954	9.998***	9.437***	1,361

Note(s): *** Denotes significance levels at 1 %, respectively

Source(s): Author's calculations

Table 2.
Descriptive statistics of
variables

the logit transformed ratio of net nonperforming loans to net loans (NNPLs), reports a mean value of -1.83, respectively. The negative mean values indicate that there has been a decline in impaired loans after write-offs over time. The average equity to total assets ratio is about -1.06, and log of total assets is about 4.89, respectively. The mean NONIT to total assets is approximate at 0.0085, and average ROA is 0.004 with SD 0.009. Broadly similar mean values have been observed for all the macroeconomic and industry-specific variables. The SWILK and SFRANCIA tests of normality indicate that all the variables are not normally distributed at the 1% level of significance.

Table 3 shows the cross-correlations between all the independent variables which are used in the study for estimation purpose. The results indicate that, except inflation and CR10, no significant indication of multicollinearity is observed among the independent variables [4]. Following the empirical literature, we also performed unit root tests for individual variables using the Fisher Augmented Dickey-Fuller (ADF) and the Phillips-Peron (PP) tests to establish the degree of data integration. Assuming the individual unit root process, the results reported in Table 4 reveals that all the individual variables are stationary at level.

5.2 Dynamic estimation

As noted above in Section 3, the study employs dynamic panel estimation method to account for “persistence effect” in credit risk along with the set of potential systematic and unsystematic factors responsible in the formation of credit risk in Indian banking industry. For the estimation purpose, we employed two-step system GMM approach and presented the empirical findings in Table 5.

5.2.1 Persistence effect. In order to account the persistence of credit risk in Indian banking industry, we included the first lag of NNPLs in the econometric model. The empirical findings, as reported in Table 5, reveals the existence of “persistence effect” in credit risk among Indian banks with persistence coefficient (δ) to vary from 0.15 to 0.18% across different model specifications. This confirms that bank defaults are expected to increase in the current year, if it had increased past year due to time lag involved in the process of recovery of past dues. The results thus clearly provide an evidence of time persistence in accumulation of bad loans in the Indian banking industry. Further, the effect on NPLs has prolonged in the aftermath of

Table 3.
Correlation matrix of
independent variables

Variables	SOLVENCY	Size	ROA	NONIT	IC	CREDIT	CR10	RGDP	INF
SOLVENCY	1.000								
SIZE	-0.461	1.000							
ROA	0.303	-0.121	1.000						
NONIT	0.164	-0.199	0.385	1.000					
IC	0.102	-0.257	0.381	0.011	1.000				
CREDIT	-0.135	0.378	-0.098	-0.110	-0.083	1.000			
CR10	-0.127	-0.167	0.093	-0.122	0.074	-0.054	1.000		
RGDP	0.028	0.049	-0.071	0.023	-0.002	0.009	-0.442	1.000	
INF	0.134	0.229	-0.116	0.141	-0.125	0.081	-0.783	0.475	1.000

Source(s): Author's calculations

Table 4.
Panel unit root tests

Dependent variables Variables	Fisher-ADF	Dependent variable: NNPLs Fisher-PP
Logit NNPL	465.28*** (0.000)	501.63*** (0.000)
Log of SOLVENCY	748.13*** (0.000)	826.52*** (0.000)
Log of SIZE	311.20*** (0.000)	357.14*** (0.000)
Log of ROA	483.47*** (0.000)	531.01*** (0.000)
Log of NONIT	430.69*** (0.000)	460.08*** (0.000)
Log of IC	396.22*** (0.000)	408.39*** (0.000)
Log of CREDIT	418.61*** (0.000)	424.66*** (0.000)
Log of CR10	507.32*** (0.000)	510.46*** (0.000)
Log of RGDP	493.99*** (0.000)	495.79*** (0.000)
Log of INF	266.32*** (0.000)	240.41*** (0.000)

Note(s): *** denotes significance levels at 10%

Source(s): Author's calculations

the financial crisis of 2007, and it would take time to reduce at a significant level. The plausible reason for this may be that the Indian bank has followed a procyclical pattern of credit growth (during 2004–2007), in which they gave aggressive loans to stressed sectors (namely, infrastructure, coal mining and aviation, etc.), which grossly compromised their credit quality in 2011 due to economy slowdown and ultimately contributed to higher defaulters. The significant positive effects of lagged NNPLs in all the estimated models in Table 5 are similar to the findings of Louzis *et al.* (2012), Ghosh (2015) and Bardhan and Mukherjee (2016).

5.2.2 Bank-specific effects. Bank's profitability (ROA): On discussing the effect of profitability on bank's asset quality, we note that current year rise in ROA by 1% leads to decline in risk of future accumulation of NPLs by (–) 0.0079 to (–) 0.0120%. This suggests that if the profitability of Indian bank(s) increases, they engage themselves in more prudent lending, with more careful screen and monitors the borrowers, which may lead a reduction in the risk of defaults. This empirical finding is consistent with Ghosh (2015) and validates the existence of “moral hazard” hypothesis in Indian banking industry. If one period lag of ROA is considered, the sign of the coefficient changes significantly. It indicates that past year's profitability of Indian banks on an average generate 0.0018–0.028% higher level of NPLs, signifying the fact that Indian banks have not followed prudent lending practices in the past years. This may be due to “liberal credit policy” adopted by banks' management to increase the credit supply and maximize banks' earnings, thus supporting “bad management” hypothesis. This finding of our study is consistent with Makri *et al.* (2014), Messai and Jouini (2013), Abid *et al.* (2014), Chaibi and Fiti (2015) and Klein (2013). Further, it has been noted that in many

Dependent variable: Logit NNPL						
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-2.878 (2.483)	-81.16*** (29.85)	-3.759 (2.705)	-3.260 (3.243)	12.24** (5.463)	-0.0345 (3.693)
NNPL _{<i>t-1</i>}	0.1802*** (0.0584)	0.1679*** (0.0516)	0.1538*** (0.0520)	0.1534*** (0.0538)	0.1524*** (0.0453)	0.1623*** (0.0552)
Size	0.6801 (0.5040)	0.5619 (0.5850)	0.7983* (0.4698)	0.7535* (0.4380)	1.186** (0.5751)	0.7322 (0.5065)
Size _{<i>t-1</i>}	-0.4525* (0.2726)	-0.4323* (0.2564)	-0.5288** (0.2362)	-0.4027* (0.2264)	-0.5230** (0.2366)	-0.4947** (0.2274)
ROA	-0.0183 (0.0040)***	-0.0153 (0.0046)***	-0.0123** (0.0050)	-0.0156*** (0.0044)	-0.0102** (0.0049)	-0.0130** (0.0052)
ROA _{<i>t-1</i>}	0.0038** (0.0016)	0.0038** (0.0016)	0.003** (0.018)	0.0034** (0.0016)	0.0028* (0.0015)	0.0033** (0.0014)
NONIT	0.0047*** (0.0012)	0.0042*** (0.0013)	0.0032** (0.0013)	0.0033** (0.0015)	0.0029 (0.0017)	0.0037** (0.0015)
NONIT _{<i>t-1</i>}	-0.0012** (0.0005)	-0.0012** (0.0005)	-0.0009** (0.0004)	-0.0010** (0.0005)	-0.0011** (0.0005)	-0.0011** (0.0005)
IC	-0.9398 (1.637)	-1.840 (1.677)	-1.637 (1.638)	-0.9134 (1.629)	-0.8981 (1.857)	-1.537 (1.642)
IC _{<i>t-1</i>}	0.6516 (0.8696)	0.7934 (0.7580)	0.5073 (0.7714)	0.2859 (0.7127)	0.3733 (0.5755)	0.3684 (0.6334)
CREDIT	-0.7372 (1.020)	-0.3574 (0.9592)	-0.1809 (1.053)	-0.0317 (1.040)	-0.0818 (0.8176)	-0.0419 (0.9527)
CREDIT _{<i>t-1</i>}	0.5017 (0.4374)	0.2934 (0.3865)	0.2448 (0.4347)	0.3133 (0.4780)	0.2931 (0.3934)	0.3245 (0.4512)
CR10		25.58** (10.84)				
CR10 _{<i>t-1</i>}		18.27 (13.99)				
RGDP			0.4018 (0.4441)	0.3693 (0.5280)		0.4466 (0.5905)
RGDP _{<i>t-1</i>}			0.3300 (0.6019)	0.4015 (0.6303)		0.6021 (0.7123)
INF			-1.095** (0.5487)			-1.058** (0.5056)
INF _{<i>t-1</i>}			-1.707** (0.6806)	-0.6866** (0.3473)		-1.596* (0.9254)
PNORMS						-0.1341 (0.4071)
PUBLIC						-1.505 (1.740)
PRIVATE						-1.076 (1.206)
CRISIS						-0.0364 (0.2826)
Time dummies					Yes	
No. of observations (groups)	1,255	1,255	1,255	1,255	1,255	1,255
No. of groups	97	97	97	97	97	97
Wald χ^2	74.80***	81.81***	86.44***	83.86***	129.95***	93.54***
AR(1)	-5.36*** (0.000)	-5.41*** (0.000)	-5.43*** (0.000)	-5.46*** (0.000)	-5.49*** (0.000)	-5.43*** (0.000)
AR(2) test	0.98 (0.328)	1.13 (0.261)	1.23 (0.220)	0.97 (0.332)	1.37 (0.170)	1.16 (0.247)
Hansen / test	83.78 (0.182)	82.70 (0.205)	78.34 (0.313)	81.06 (0.242)	80.72 (0.251)	79.03 (0.294)

Note(s): (1) Figures in parentheses are robust standard errors, (2) AR(1) and AR(2) are the Arellano–Bond test for first and second order autocorrelation of the residuals, (3) in case of AR(1), AR(2) and Hansen test, we reported the *p*-values and (4) ***, **, * and * denotes significance levels at 10, 5 and 1%, respectively

Source(s): Author's calculations

Table 5.
Dynamic panel
estimates using two-
step system GMM

developing countries, accounting standards have not been rigorous enough to prevent banks and their borrowers from concealing the true size of their NPAs portfolio. Most often, bad loans were made to look good by additional lending to troubled borrowers (“*ever-greening*”) (Reserve Bank of India, 1999).

Surprisingly, the current year’s 1% rise in NONIT to total assets (*NONINs*), increases the default risk by 0.0032–0.0047%, indicating that a higher the share of NONIT of banks, higher the risk for banks. This reflects risk-taking behavior of banks where they rely more on other risky investment portfolios with a view to diversify source of income rather to still depend upon the interest income incurred from loan repayment. This is also found by Ghosh (2015). As expected, the previous year coefficient of NONIT has been found to be negative, implying that if past years’ investment portfolio of banks generate good source of income from nontraditional activities then banks rely less on the interest income from loan repayment, which ultimately leads to reduction in the bank credit risk (Louzis *et al.*, 2012; Ghosh, 2015; Alhassan *et al.*, 2014; Chaibi and Ftiti, 2015).

The large sized banks, on an average, generate higher NPLs by 0.753–1.186% in Indian banking industry. The other studies suggesting the positive relation between size and risk are Khemraj and Pasha (2009), Louzis *et al.* (2012) and Chaibi and Ftiti (2015). This reflects that large banks take excessive risk and extend their credit without proper screening and monitoring of the borrower’s creditworthiness. This is also supported by an incident happened in the year 2010–11, where State Bank of India, the India’s biggest lender bank, extended loans to troubled corporate borrower(s) which in turn led to deterioration in the asset quality of this bank. The lagged size effect has been found to be significantly negative in all the models (similar to Alhassan *et al.*, 2014; Ghosh, 2015). This shows that the smaller bank may have greater managerial efficiency than larger banks in terms of screening and monitoring of loans, leading to lower defaults.

The intermediation cost found to have expected negative sign for gross NPLs (see, Table 5), suggesting that Indian Banks had been very economical in making expenses on credit screening and monitoring to remain cost efficient, but it led to rise in gross NPLs in future. However, the inefficiency does not seem to have any significant impact on net NPLs adjusted for provisions.

5.2.2.1 Industry-specific effects. The impact of bank’s concentration in terms of advances (CR10) in terms of market power is positively significant positive on asset quality. This is in contrast with the prediction of “*tight control*” hypotheses (Louzis *et al.*, 2012). As the market concentration increases, the market power of top ten concentrated banks will also increase and they make more lending mainly to the stressed sector may be due to political or regulatory pressures. This is evident from the fact that Indian banks had high levels of stressed assets from five stressed sub-sectors including infrastructure, iron and steel, textiles, mining (including coal) and aviation, resulting in increased chances of future defaults (Reserve Bank of India, 2014).

5.2.2.2 Macroeconomic effects. Our results suggest that lower probability of risk of default during the periods of inflation in Indian banking industry. This may be due to adjustments in policy rates by the central bank as a step to contain inflation which reduces the real value of outstanding loans and make debt servicing easier for the borrowers. This is line with Chaibi and Ftiti (2015), Khemraj and Pasha (2009), and Makri *et al.* (2014). Finally, the coefficient estimate of RGDP has not shown any significant impact of economic activity during the analyzed period.

5.2.2.3 Dummies effect. The implementation of prudential regulatory reforms in 2004–05 has revealed a significant decline in nonperforming loans. On an average, net NPLs have lowered by (–)0.6866% annually during the sample period. Further, the study also examined the time-specific effects by including yearly dummies on NPLs in the model 5. We note a significant decline in NPLs due to implementation of prudential norms. An attempt has also been made to ascertain the diversify behavior of NPLs across distinct ownership groups.

This ownership effect is captured by including PUBLIC and PRIVATE dummies in the model. It was found that risk of defaults is significantly lower in case of private banks and foreign banks as compared with public sector banks due to effective write-off (see, Table 5).

This study has empirically tested the overall validity of the instruments using the Hansen J specification test, i.e. to test the null hypothesis of joint validity of the moment conditions (the presence of over-identification), is asymptotically distributed as chi-square (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998). The test is based on null hypothesis, i.e. whether all the instruments are valid in the panel data model or not?, which is consistent with the empirical findings of Table 5 and confirmed the acceptability of two-step system GMM model in the dynamic panel framework.

Furthermore, we also assess the fundamental assumption of serially uncorrelated errors ν_{it} in Table 5, using Arellano–Bond tests for Autoregression. The test statistics are reported of AR(1) and AR(2) in Table 5, test the null assumption that $\Delta\nu_{it}$ are not first and second order autocorrelated. The rejection of the null hypothesis in first and second order autocorrelation in the differenced errors, implying no serial correlation for the level error term and thus again support the consistency of the GMM estimates.

5.3 Robustness check

To test the sensitivity of two-step system GMM estimates, we have also obtained pooled OLS (POLS), panel corrected standard error (PCSE) and fixed effects (FE) estimates. The results are reported in Table 6. We note that the empirical results obtained using POLS, PCSE and FE confirms the findings of the two-step system GMM estimation. It has been restated that larger the size of bank, more engagement of bank in nontraditional activities, lower profitability and higher concentration of banks' in lending in the current year seems to increase the risk of defaults in future. Some additional findings of POLS, PCSE and FE estimates include (1) equity to total assets ratio exhibits a negative and significant impact on NPLs, especially in case of pooled OLS and fixed effects estimations which are in parallel to the findings of Chaibi and Fiti (2015), Klein (2013) and Louzis *et al.* (2012). This suggest that low capitalized bank face increased credit risk and validates the “solvency” hypothesis in Indian banking industry and (2) previous year credit growth seems to have a significant positive impact on asset quality (as consistent with Ghosh, 2015; Espinoza and Prasad, 2010; Klien, 2013). It supports the “pro-cyclical” [5] nature, wherein credit quality can get compromised during the periods of high credit growth which lead to the creation of NPLs for banks in the future years. The macroeconomic variable INFLATION too exhibits the same sign and significance in case of POLS, PCSE and FE estimation as the system GMM. However, surprisingly current year's RGDP shows positive significant impact on NPLs. It may be due to poor credit standards adopted by Indian banks during the boom period (as supported by Beck *et al.*, 2013). Finally, a clear comparison of the expected sign between different estimation methods used in the present study are reported in Table 6. It is observed that the results are similar for different estimation methods. The results thus provide strong justification for the use of two-step system GMM estimation as the results are over estimated when OLS is applied and underestimated for fixed effects estimation.

6. Conclusion and policy implications

In order to enhance the banking stability, it is vital to monitor the deterioration in credit quality which may increase the risk of defaults in the economy. With this, the present study is an effort to capture the “persistence effect” of credit risk and assess the factors that influence the asset quality in the Indian banking industry. In particular, we test for the persistence effect of credit risk in Indian banking industry during the period 1999–2014. To achieve this objective, the study

Table 6.
OLS, fixed effects and
PCSE estimates

Model estimates Variables	OLS			Fixed effects (FEs)				Panel corrected standard error (PCSE)				
	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18
Constant	-1.239 (1.155)	-1.062 (1.156)	-15.67 (49.66)	-21.56 (47.68)	0.1151 (1.388)	0.5562 (1.289)	-12.40 (48.70)	-19.50 (46.65)	-1.085 (0.9784)	-0.8101 (0.9894)	-4.250 (43.13)	-18.27 (43.88)
NNP _{L-1}	0.2364*** (0.0390)	0.2294*** (0.0404)	0.2115*** (0.0391)	0.2053*** (0.0412)	0.1423*** (0.0400)	0.1401*** (0.0420)	0.1364*** (0.0397)	0.1339*** (0.0418)	0.2230*** (0.0352)	0.2121*** (0.0357)	0.1962*** (0.0354)	0.1845*** (0.0357)
SOLVENCY		-1.174*** (0.3669)		-0.7332*** (0.3496)		-0.6556* (0.3718)		-0.5127 (0.3759)		-1.122*** (0.1970)		-0.7346*** (0.2086)
SOLVENCY _{L-1}		-0.5053** (0.2095)		-0.1424 (0.2056)		-0.0953 (0.2101)		-0.0334 (0.2044)		-0.4160*** (0.1751)		-0.1047 (0.1805)
Size	0.7060*** (0.1404)		0.5337*** (0.1578)		0.5231*** (0.1585)		0.4642*** (0.1712)		0.7090*** (0.1197)		0.5345*** (0.1281)	
Size _{L-1}	-0.0051 (0.1277)		-1.615 (0.1262)		-0.1097 (0.1440)		-0.1147 (0.1360)		-0.0166 (0.1251)		-0.1319 (0.1304)	
ROA	-0.0080*** (0.0012)	-0.0074*** (0.0013)	-0.0075*** (0.0013)	-0.0072*** (0.0013)	-0.0076*** (0.0014)	-0.0072*** (0.0015)	-0.0073*** (0.0014)	-0.0070*** (0.0015)	-0.0075*** (0.0009)	-0.0069*** (0.0009)	-0.0072*** (0.0009)	-0.0068*** (0.0009)
ROA _{L-1}	0.0021* (0.0011)	0.0028** (0.0012)	0.0023** (0.0011)	0.0027** (0.0011)	0.0015 (0.0012)	0.0020 (0.0012)	0.0017 (0.0012)	0.0021* (0.0012)	0.0017* (0.0009)	0.0024*** (0.0009)	0.0016* (0.0009)	0.0020** (0.0009)
NONIT	0.0006 (0.0004)	0.0009** (0.0004)	0.0008 (0.0004)	0.0011** (0.0004)	0.0005 (0.0004)	0.0008* (0.0004)	0.0005 (0.0004)	0.0082* (0.0004)	0.0004 (0.0003)	0.0007*** (0.0003)	0.0006* (0.0003)	0.0009*** (0.0003)
NONIT _{L-1}	-0.0009** (0.0004)	-0.0011*** (0.0004)	-0.0007** (0.0003)	-0.0009** (0.0003)	-0.0009** (0.0003)	-0.0011*** (0.0003)	-0.0009** (0.0003)	-0.0011*** (0.0003)	-0.0009*** (0.0003)	-0.0010*** (0.0003)	-0.0007*** (0.0003)	-0.0009*** (0.0003)
IC	0.5443 (0.3557)	0.2834 (0.3597)	0.5387 (0.3636)	0.3102 (0.3710)	0.5530 (0.4124)	0.3351 (0.4095)	0.6528 (0.4189)	0.4368 (0.4239)	0.6028** (0.3132)	0.3528 (0.3172)	0.5961** (0.3147)	0.3660 (0.3144)
IC _{L-1}	-0.3004 (0.4473)	-0.3490 (0.4144)	-0.2893 (0.4355)	-0.2573 (0.4078)	-0.1719 (0.4357)	-0.1259 (0.4117)	-0.0785 (0.4252)	-0.0179 (0.4066)	-0.2938 (0.3698)	-0.3294 (0.3651)	-0.2023 (0.3728)	-0.1986 (0.3676)
CREDIT	0.3078 (0.2103)	0.6854*** (0.2143)	0.2000 (0.1942)	0.4687** (0.2159)	0.1509 (0.2301)	0.4369* (0.2419)	0.1766 (0.2276)	0.4136* (0.2464)	0.3351* (0.2026)	0.6651*** (0.2262)	0.2542 (0.2070)	0.4617** (0.2322)
CREDIT _{L-1}	0.4951* (0.2673)	0.5521** (0.2738)	0.4169 (0.2644)	0.3886 (0.2760)	0.3905 (0.3022)	0.4008 (0.3132)	0.4198 (0.2986)	0.4061 (0.3100)	0.5927*** (0.2049)	0.7243*** (0.2336)	0.5323*** (0.2089)	0.5624** (0.2348)
CR10			36.73*** (14.17)	32.07*** (14.24)		36.03*** (13.59)		33.43*** (13.51)			28.85*** (12.92)	26.51** (13.13)
CR10 _{L-1}			-30.36 (20.86)	-22.21 (20.98)		-30.96 (20.53)		-24.14 (19.92)			-28.61 (17.89)	-18.24 (17.99)
RGDP	0.5424 (0.4856)	0.1641 (0.4841)	1.228*** (0.5787)	0.8958 (0.5754)	0.4675 (0.4721)	0.3088 (0.4709)	1.221** (0.5794)	0.9762* (0.5777)	0.4021 (0.4123)	0.0454 (0.4134)	0.9769** (0.4656)	0.6135 (0.4631)
												(continued)

(continued)

Table 6.

Model estimates Variables	OLS			Fixed effects (FEs)				Panel corrected standard error (PCSE)				
	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18
RGDP _{<i>t-1</i>}	0.0909 (0.6018)	-0.1145 (0.6080)	0.6107 (0.6230)	0.4228 (0.6219)	0.1177 (0.5932)	0.0266 (0.5895)	0.6117 (0.6142)	0.4778 (0.6010)	-0.0077 (0.4638)	-0.0712 (0.4619)	0.4755 (0.4737)	0.3760 (0.4759)
INF	-0.9776** (0.4595)	-0.5268 (0.4706)			-0.9837** (0.4576)	-0.8192* (0.4529)			-1.023** (0.5274)	-0.6126 (0.5236)		
INF _{<i>t-1</i>}	-2.310 (0.8258)	-1.390* (0.7960)			-2.129** (0.8330)	-1.667** (0.7929)			-2.231*** (0.7233)	-1.272* (0.7082)		
PNORMS	-0.5338* (0.2886)	-1.642 (0.2781)	-1.291*** (0.3415)	-0.8667*** (0.3017)	-0.5558* (0.2925)	-0.3561 (0.2820)	-1.3691*** (0.3730)	-1.041*** (0.3383)	-0.4176 (0.2649)	-0.1130 (0.2669)	-1.173*** (0.2813)	-0.7382*** (0.2665)
PUBLIC			1.070*** (0.2901)	1.174*** (0.2232)			1.0483* (0.6031)	1.114* (0.6521)			0.9514*** (0.2650)	1.125*** (0.2459)
PRIVATE			1.003*** (0.2364)	0.8945*** (0.2162)			1.0238* (0.5512)	1.061** (0.5365)			0.9467*** (0.2176)	0.9301*** (0.2336)
CRISIS	0.2660 (0.2270)	0.0485 (0.2272)	-0.0717 (0.2650)	-0.1129 (0.2640)	0.2109 (0.2365)	0.0974 (0.2346)	-0.0760 (0.2655)	-1.039 (0.2632)	0.2350 (0.2072)	-0.0022 (0.2082)	-0.1223 (0.2183)	-0.1720 (0.2193)
No. of observations (groups)	1,255	1,255	1,255	1,255	1,255	1,255	1,255	1,255	1,255	1,255	1,255	1,255
No. of groups	97	97	97	97	97	97	97	97	97	97	97	97
<i>F</i> -statistics	37.95***	35.82***	47.53***	47.55***	13.12***	12.09***	13.26***	13.15***	490.78***	407.73***	576.52***	546.68***
Wald χ^2									0.4759	0.4665	0.4554	0.4416
R^2	0.3241	0.3206	0.3404	0.3362	0.3073	0.2959	0.3353	0.3289				
AR(1)	-0.40 (0.691)	-0.05 (0.963)	-0.08 (0.936)	0.30 (0.767)								
AR(2)	1.11 (0.265)	0.64 (0.251)	0.86 (0.389)	0.69 (0.489)								
BP-CW Htest	238.93***	178.29***	255.36***	241.51***								

Note(s): (1) Figures in parentheses are robust standard errors, (2) AR(1) and AR(2) are the Arellano-Bond test for first and second order autocorrelation of the residuals, (3) in case of AR(1), AR(2) and BP-CW Htest, we reported the *p*-values and (4) ***, ** and * denotes significance levels at 10, 5 and 1 %, respectively

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employs two-step system GMM estimation approach and explored how the bank-specific, industry-specific, macroeconomic variables alongside regulatory reforms, ownership changes and financial crisis affects the bank's asset quality in India. Such an analysis would help the policymakers to clearly quantify the degree of credit risk persistence and identify the key factors which might be responsible in the formation of credit risk in Indian banks.

Following observations have been made from the empirical results. First, the study found the persistence in credit risk among Indian banks during 1999–2014. This confirms that bank defaults are expected to increase in the current year, if it had increased past year due to time lag involved in the process of recovery of past dues. Second, higher the profitability of Indian bank(s), lower is a risk of defaults in the current year. However, the past year's lower profitability, on an average, generate higher level of NPLs, signifying the fact that Indian banks may have not followed prudent lending practices in the past years. This may be due to "liberal credit policy" adopted by banks' management to increase the credit supply and maximize banks' earnings, thus supporting "*bad management*" hypothesis. Third, with the higher share of income from nontraditional activities in the past year, the probability of default risk gets lowered for Indian banks. This is due to the fact that if past years' investment portfolio of banks generate good source of income from diversified sources then banks rely less on the interest income from loan repayment. Fourth, large banks found to have taken excessive risk and extended their credit without proper screening and monitoring of the borrower's creditworthiness. This finding is also supported by the concentration effect. As the market concentration increases, the market power of concentrated banks will also increase, and they make more lending mainly to the stressed sector may be due to political or regulatory pressures which increases the risk of default. Fifth, probability of risk of default declines during the periods of inflation in Indian banking industry. Sixth, regulatory reforms in terms of prudential norms found to have improved the asset quality in Indian banks. However, the financial crisis of 2007–08 had no significant impact on credit quality of Indian banks. This might have been due to effective write-off done by the banks under distinct ownership groups, especially new private and foreign banks.

In all, the empirical results suggest that both systematic (macroeconomic) and unsystematic (bank-specific and regulatory factors) have been found to be crucial in monitoring the level of credit risk and preventing the deterioration in the asset quality. Further, higher profitability, better managerial efficiency, more diversified income from nontraditional activities, optimal size of banks, proper credit screening and monitoring, and adherence regulatory norms would help in improving the credit quality and minimizing the likelihood of default risk. The study found significant time persistence in the accumulation of NPLs, so adequate attention is required to these bank-specific factors to solve the problem of rising future NPLs. Further, to combat the impact of inflation on NPLs, regulatory authorities need to adjust the real value of outstanding loans, so that borrowers can easily repay back their dues on time.

Notes

1. It has been observed that such costs amounted to 10 percent or more of GDP in more than a dozen of developing country episodes during the past 15 years ([Reserve Bank of India, 1999](#)).
2. [Reserve Bank of India \(2015\)](#) defined non-performing loans as a loan or an advance where interest and/or installment of principal remain overdue for a period of more than 90 days in respect of a term loan.
3. The information has been reported based on the ratio of non-performing loans to gross loans of banks across Asian countries. According to the IMF data as of 2015, NPLs in India are around 6% of gross loans followed by Thailand (under 3%) and Indonesia (a little over 2%).
4. According to [Kennedy \(2008\)](#) and [Alhassan et al. \(2014\)](#), correlation coefficients of below 0.70 represents weaker relationship associated among variables.

5. It is noteworthy that in the year 2009–10, the growth in NPAs of Indian banks has largely followed a lagged cyclical pattern with regard to credit growth.

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About the author

Anju Goswami is currently working as an Assistant Professor at the Department of Economics and International Business, University of Petroleum and Energy Studies, Dehradun, India. She received the MHRD Assistantship to pursue her doctoral research. During her doctoral research, she is trained with the skills in constructing models using mathematical programming approaches to benchmark the performance of decision-making units. Currently, her key research interest includes efficiency and productivity analysis and banking institutions. Anju Goswami can be contacted at: anju.iit15@gmail.com

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