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State-owned banks and credit allocation in India: Evidence from an asset quality review*

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Abstract

This paper examines the role of state-owned banks' presence in allocation of credit to different sectors in India using the central bank's Asset Quality Review (AQR) as a quasi-natural experiment. The AQR resulted in a larger increase in non-performing loans of state-owned banks as compared to other banks. We exploit the heterogeneity in the presence of state-owned and other banks across districts to identify the supply side channels for bank credit reallocation. Using a difference-in-differences analysis, we find that the top-third of districts based on presence of state-owned banks' branches experienced a higher fall in the share of credit to the industrial sector in the post-AQR period compared to other districts. Such districts also experienced a greater increase in retail loans, which are considered less risky compared to industrial loans. Further, an analysis using a panel vector autoregression finds that the AQR, through an increase in non-performing loans of state-owned banks, led to a decrease in economic growth at the district-level. The results of this study suggest that central bank policy reforms can influence bank credit allocation at the sub national level and have real economy effects.

Keywords: Central bank policy reform, asset quality review, bank credit flows, bank ownership, state-owned bank

JEL Classification: E51, E52, E58, E65

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1. Introduction

In the aftermath of global financial crisis of 2008-09, the Indian corporate sector experienced a slowdown and its balance sheet strength deteriorated considerably. Increased corporate distress spilled over to the financial sector and the stressed loans of Indian banks started rising. In response, the Reserve Bank of India (RBI) relaxed the norms for restructuring of such loans and exercised forbearance on recognition of stressed loans as non-performing assets (NPAs) in order to provide relief to Indian banks (Chopra, Subramanian, & Tantri, 2021; Rajan, 2016). However, by 2015, it was evident that banks had resorted to restructuring the loans to postpone the recognition of the NPAs (Vishwanathan, 2016). Banks were relying on forbearance of stressed assets instead of classifying them as non-performing loans (Flanagan & Purnanandam, 2019). The net profits of the Indian commercial banks started declining in 2011-12 and was negative in 2013-14. This decline has been ascribed to higher provisioning for bad loans by banks after the crisis (Mundra, 2016).

The RBI announced an asset quality review (AQR) in April 2015 with the aim to clean up the banks' balance sheets by mandating the recognition of highly stressed assets as bad loans (Singh, 2016). The AQR involved checking violation of regulations relating to classification of loans, evergreening of loans, and assumptions about the recoverability of loans.[1] The policy reform prompted a better recognition of non-performing loans by the Indian banks, resulting in a significant rise in the NPAs (Basu et al., 2017).[2] The effect of the reform on NPAs was more pronounced for the state-owned banks, also known as the public sector banks, which account for the majority of bank lending in India. Approximately one-sixth of the state-owned banks' gross advanced were found to be stressed (non-performing or restructured) after the implementation of the AQR (Acharya, 2017). RBI data shows that NPAs as a percentage of gross advances for the state-owned banks increased from approximately 4.0 percent, on average, in the four years prior to the AQR to 11.5 percent in the subsequent four years, while it increased by a much

[1] Evergreening of loans involved banks' issuing fresh loans to repay maturing debt, in order to prevent a default on the loan (Chopra et al., 2021).

[2] According to RBI data, NPAs of the Indian banking system increased from 5.5 percent of gross advances in March 2015 to 9.3 percent in March 2017.

smaller percentage for other banks (Figure 1).[3]

This paper analyses the changes in lending portfolios of state-owned banks and other banks following the RBI's AQR. The AQR is used as a quasi-natural experiment to measure the changes in credit share of different sectors using district level credit in India. We exploit the heterogeneity in districts based on the concentration of state-owned and other banks to identify the supply side channels for bank credit reallocation. The analysis relies on a difference-in-differences (DID) estimation based on a matched sample. Bank credit to districts with higher share of state-owned banks is expected to be more adversely affected due to the larger increase in their NPAs as a result of AQR as compared to other banks. Therefore, we classify the top third districts with the highest presence of state-owned banks by branch offices as the 'treatment' group. We create a matched sample of treatment districts and control districts (from the remaining two-third districts) based on pre-AQR district characteristics using the 2011 census data for India using the matching methods developed by Abadie and Imbens (2002). This matched sample is employed for the DID analysis.

Our main findings suggest that the districts with the highest presence of state-owned banks experienced a higher fall in the share of outstanding credit to the industrial sector in the post-AQR period, as compared to other districts. While the share of credit to industrial sector reduced, the share of credit to households increased in the post-AQR period for districts with higher share of state-owned banks. This indicates a reallocation of credit from industry to households, the sector with lower risk of loan defaults. We further disaggregate the share of credit to households into two sub-categories: housing (mortgage) loans and non-housing loans to households. The results imply that the increase in the share of non-housing credit to households was higher than that in the housing (mortgage) loans. Finally, we find that the shares of bank credit to services and agriculture is not affected by the AQR.

We conduct a variety of alternate estimations and robustness tests of the main findings. First, we change the classification of districts with high state-owned bank presence by considering the

[3]The NPAs for other banks is a weighted average of NPAs for private banks, regional rural banks and foreign banks, with their respective credit shares.

top quarter (instead of top third) of districts with highest share of state-owned bank branches, to indicate high state-owned bank districts. Next, we use an alternate matching method to create the matched sample for the top third districts with highest presence of state-owned banks. We match the treatment districts with three nearest neighbours (instead of five nearest neighbours) from the remaining sample. We also check the robustness of the baseline results by creating the matched sample for top third districts with highest share of state-owned bank credit (instead of bank branch offices) in overall district credit in the pre-AQR period. The results for the above-mentioned robustness tests are broadly consistent with the baseline findings. We further analyse the change in the aggregate district credit in the districts with higher state-owned bank branches and find that the growth of aggregate district credit slowed down in such districts after implementation of AQR, as compared to other districts. Finally, we conduct a falsification test with a placebo implementation year, which suggests that the baseline results are likely to be driven by the implementation of the AQR.

The findings of the paper show that the AQR resulted in a differential change across state-owned and other banks in the supply of credit to different sectors. This is because the AQR led to changes in the banks' asset classification and thus the need for provisions which created a supply side shock to the ability to extend loans. To account for the changes in the demand for credit by various sectors, following Qian and Strahan (2007), we include the log of district per capita gross value added (GVA) and the year-on-year changes in the district per capita GVA in all our specifications.

We also evaluate the real economy effect of the AQR using a panel vector autoregression (PVAR). Previous studies have observed that fluctuations in the bank credit supply have effects on the real economy by affecting factors such as the GDP, GDP growth rate, and others (Cingano, Manaresi, & Sette, 2016). As alluded to earlier, the AQR resulted in changes in the bank credit supply and banks' lending portfolio. Therefore, we analyse the real economy effect of the implementation of the AQR by studying its effects on the district-level GVA growth rate. We find that the district GVA growth rate was negatively correlated with the steep increase in the state-owned banks' NPA due to the AQR. This suggests that the AQR resulted in lower district GVA growth rates in districts with higher concentration of state-owned banks.

This paper contributes to the literature on policy reforms adopted to improve the quality of bank assets and the implications of rise in non-performing assets on banks' lending behaviour. For instance, Abbassi, Peydró, Iyer, and Soto (2020) study the changes in banks' credit portfolio at the firm-level after the European Central Bank's asset quality review in 2013. Other studies have focused on studying the impact of rise in the non-performing assets on banks' lending behaviour in countries such as Italy (Cucinelli, 2015), Vietnam (Vinh, 2017) and Ghana (Alhassan, Owusu Brobbey, & Effah Asamoah, 2013), among others. It adds to literature by providing evidence of banks' portfolio reallocation in response to the central bank's policy reform in India and studying the effects of banking reforms on banks' lending behaviour and the real economy. While previous studies have provided evidence for the impact of the AQR on lending in India and other countries, this study adds to the literature by documenting the shift in the banks' credit portfolios from riskier credit to less risky credit due to an increase in AQR. We also evaluate the impact of the AQR on real economy through the reduction in the credit supply and credit growth rate. While other studies in the context of the Indian AQR, have assessed the impact of AQR on bank lending, there is not much evidence on its effects on credit reallocation and real economy.

The paper also lends support to the literature focusing on the changes in banks' risk portfolio. Prior studies have documented that banks change the composition of their loan portfolios in response to policy changes and exogenous shocks. For instance, Juelsrud and Wold (2020) study the impact of increase in risk-weighted capital requirements on changes in banks' lending behaviour in Norway. They find that the banks reacted by reducing their risk-weighted assets by increasing the credit supply to households and reducing the credit supply to firms. Further, a cross-country study by Avramova and Le Leslé (2012) provides evidence of higher average risk weights being associated with corporate loans as compared to household loans. In another study covering advanced and developing countries, Mohapatra and Purohit (2021) observe that banks shift their lending portfolio from firm credit to household credit in order to reduce the riskiness of their portfolio in response to a rise in economic uncertainty. The current paper extends support to the previous research by examining the shift in Indian state-owned banks' lending portfolio in response to the exogenous shock created by the AQR and observing a shift in lending from a riskier sector (industry) to a relatively less risky sector (household loans).

The next section discusses the relevant literature. The methodology and the data used for the estimation are discussed in Section 3. Section 4 presents the results for the baseline specification and the test for parallel trends. The next section discusses various alternative specifications and robustness tests. Section 6 presents the real-economy effects of the AQR using a panel VAR estimation and Section 7 concludes.

2. Conceptual background and literature review

This paper relates to the literature on the effects of bank ownership on lending behaviour and the regulatory measures undertaken by the central banks. This section provides a comprehensive review of previous studies and provides a conceptual background of the RBI's asset quality review.

2.1. Bank ownership and lending

In India the commercial banks are categorised into the following major types of banks: state-owned banks, private banks, foreign banks, and regional rural banks.[4] The literature concerning the bank ownership and bank lending behaviour is well researched. Studies have provided evidence for the procyclical nature of bank credit growth with respect to economic growth. For instance, Gonzales (2009) finds that the banking sector tends to increase the impact of a business cycle by intensifying lending during economic booms and by imposing loan restrictions during economic downturns. Prior to the global financial crisis, the high GDP growth rate in India, corresponded to a very high bank credit growth (see Figure 3). Bank credit in India grew by 27.4 percent during 2005-06. However, there was a sharp decline in the bank credit growth in the following years. The growth rate of overall bank credit declined from 27.4 percent in 2005-06 to 4.15 percent in 2009-2010. This significant decline in bank credit growth

[4] The regional rural banks, which operate at the regional level, are sponsored by state-owned banks only.

can be ascribed to the global financial crisis in 2007-08. While the banking sector as a whole experienced a slowdown in credit growth, the decline was not uniform – private sector banks were affected to a larger extent as compared to the state-owned banks (Gulati & Kumar, 2016). Credit growth for state-owned banks decreased from 25.1 percent prior to the crisis to 7.1 percent in 2009-10, while the decline in credit growth for other banks was significantly larger, from around 35 percent to -4.9 percent (Figure 4).

Research also shows that the ownership of banks by the government influences their lending behaviour to a great extent. Bertay, Demirgüç-Kunt, and Huizinga (2015) show that the lending behavior of the state-owned banks is less pro-cyclical compared to private and other banks. While some studies favour the involvement of government in state-owned banks' lending, others provide evidence against it. For instance, Stiglitz (1989) highlights the role of government ownership of banks in reducing market failures that leads to a better allocation of credit. On the other hand, using a cross-country analysis, Shleifer and Vishny (1994) show that political meddling resulting due to the involvement of government in bank lending increases state-owned banks' inefficiency. A study by Qian and Yeung (2015) also support the claim of a sub-optimal efficiency of state-owned banks. They demonstrate that the reason for poorer allocation of credit by the state-owned banks' is the greater presence of agency conflicts. Research has also found evidence of the influence of political meddling where there is higher presence of state-owned banks (Carvalho, 2014). Using information on individual loan contracts, Sapienza (2004) establishes the relationship between political situation and state-owned banks' lending. The author shows that the lending behavior of state-owned banks is positively affected by the electoral results of the party affiliated with the bank. Similarly, Dinç (2005) provides evidence of an increase in lending by the state-owned banks in election years highlighting the political influences on banks. These studies complement the finding of La Porta, Lopez-de Silanes, and Shleifer (2002) that countries with higher presence of state-owned banks in the credit market experience lower economic growth.

Studies suggest that during an economic boom banks tend to be overly optimistic and extend higher credit (Gonzales, 2009). Relatively lower decline in credit growth by the state-owned banks during the financial crisis suggests that the state-owned banks continued to extend high credit assuming that the pre-crisis trends in economic growth would persist. Therefore, it was presumed that they would not be required to account for the higher risks of loan defaults. However, a sharp decline in economic growth following the crisis led to a twin-balance sheet problem involving over-leveraged corporate balance sheets and deteriorating asset quality of state-owned banks (Subramanian & Felman, 2019). Bhaumik, Dang, and Kutan (2011) study the impact of bank ownership on banks' reaction to monetary policy shocks. They find that during periods of tight monetary policy, state-owned banks, old private banks, and foreign banks curtail credit in response to an increase in interest rate. By contrast, during easy money periods, a fall in interest rates leads to an increase in the growth of credit disbursed by old private banks, with no significant reactions from other types of banks.

As a consequence of excessive lending by the state-owned banks coupled with the slow down of economic growth during the financial crisis, there was an accumulation of bad loans and increase in NPAs (Mundra, 2016). Further, owing to the economic slowdown, there was a subsequent decline in demand for credit. The decline in demand for credit along with the increased NPAs explains the decline in overall credit growth observed in the period following 2010-11. Figure 4 shows that there was a sharp decline in the credit growth for the state-owned banks during FY2015 to FY2017. In November, 2016, the government of India announced demonetization which led to a liquidity crunch, further reducing the credit growth (Chodorow-Reich, Gopinath, Mishra, & Narayanan, 2020). The decline in the credit growth became more prominent with the introduction of the goods and services tax (GST) in 2017-18. Therefore, we observe a sharp fall in credit growth in the years following the global financial crisis, especially for the state-owned banks. Alongside the broader trends in overall credit growth, the implementation of the asset quality review (AQR) in 2015-16 which required banks to declare their NPAs likely created a divergence in the credit growth of state-owned and other banks.

2.2. *Non-performing loans and bank clean-up exercises by central banks*

In a review of the determinants of the non-performing loans of banks in the United States, Ghosh (2015) suggests that these are affected by bank specific characteristics such as credit growth, loan loss provision, banks' portfolio diversification, profitability of banks, amongst other things. Vinh (2017) assesses the impact of non-performing loans on bank lending behaviour and profitability. He employs a generalised methods of moments on a dynamic panel dataset for 34 Vietnamese commercial banks and conclude that an increase in the level of non-performing loans of the Vietnamese banks result in a reduction in overall bank lending and commercial bank profitability. Alhassan et al. (2013) observe similar results for banks in Ghana. They examine the impact of reduced bank asset quality measured as the ratio of non-performing loans to gross advances, on the bank lending behaviour in Ghana. They employ a random effects model with AR(1) to find a negative impact of deteriorating bank asset quality on banks' lending. Additionally, their findings suggest that the negative impact on bank credit supply is persistent and not just contemporaneous.

Several studies have examined the effects of bank clean-up exercises during crisis period (see for instance, Acharya, Eisert, Eufinger, and Hirsch (2019); and Cortés, Demyanyk, Li, Loutskina, and Strahan (2020)). Further, increased banking supervision has been shown to be linked to a reduction in bad loans. For instance, Balakrishnan, De George, Ertan, and Scobie (2021) study the economic consequences of increased role of bank auditors across 28 EU countries after the global financial crisis to expand information exchange. Their results suggest that, due to increased auditing and supervision, there is a reduction in non-performing loans and risk-weighted assets after the introduction of this mandate. They also observe improvements in provision for bad loans by the banks. However, studies have also linked increased supervision, such as the AQR, to a decrease in overall bank credit. Furfine (2001) uses bank-level data to estimate the changes in bank lending behavior due to stricter bank monitoring. He finds that an increase in monitoring scrutiny reduces the banks' credit lending by 7.23 percent. Along with regulatory changes and stricter supervision practices by bank, studies have found that even the perception of regulatory uncertainty in the banking system leads to a decrease in lending and credit reallocation (Gissler, Oldfather, & Ruffino, 2016). Finally, Hirtle (2020) reviews the literature on banking supervision and regulations. He finds that although supervision reduced the risk undertaken by the banks, it does not have a significant impact of banks' profitability. He also observes that the impact of bank supervision activities on bank credit supply is more diverse as some banks reduce the risk by decreasing credit while others manage to reduce risk without significantly decreasing lending.

Studies have evaluated the effects of regulatory changes similar to India's AQR in other countries, especially within the European Union. A study by Abbassi et al. (2020) examines a regulatory asset quality review undertaken by the European Central Bank (ECB) in 2014. They evaluate the impact of the AQR on banks' lending decisions and the changes in the risk composition of banks' credit portfolio. They find that post-AQR, the banks that were reviewed increase their share of securities that have top-tier rating and reduce the share of supply of credit to riskier firms. However, they observe that after the AQR compliance period, the banks' increase the level of riskier securities again. These results suggest that although the banks reduce the risk of their credit profile after the announcement of the AQR, they undo the exercise later. Similarly, Accornero, Alessandri, Carpinelli, and Sorrentino (2017) analyse the impact of an increase in non-performing loans due to the asset quality review by the ECB. The findings lend support to the evidence suggesting a negative impact of increase in non-performing loans due to an exogenous shock such as the supervisory intervention, on bank credit supply.

2.3. Asset Quality Review of Indian banks

The RBI introduced the AQR in April 2015 to address the issue of rising non-performing assets in the Indian banking system. The primary aim of the AQR was to end the asset classification forbearance for restructured assets introduced after the global financial crisis. The objective of the central bank was to recognise the stressed assets in the banking system and reclassify them as NPAs (Acharya, 2017). Such banking regulatory measures have been adopted by various central banks to increase supervisions and clean-up bank balance sheets. The Indian AQR, however, is different from the asset quality reviews conducted by other countries in the

European Union, United States, and others since it was a preemptive measure in a non-crisis period and did not have any structural capital infusion (Chopra et al., 2021).

NPAs are used as a measure of efficiency of the banking system (Bawa, Goyal, Mitra, & Basu, 2019). They also attribute regional and national economic conditions such inflation and interest rates to NPAs. Swami, Nethaji, and Sharma (2019) examine the factors determining NPAs for the Indian banks. They report that banks with lower level of capital, reduced profitability, less diversified portfolio, poor operating and managerial efficiency are at greater risk of having diminished asset quality, whereas the size of the bank is positively linked with the higher level of NPAs.

The accumulation of NPAs for state-owned banks in India was much higher than other banks. State-owned banks account for the majority of bank lending in India. After the introduction of the AQR, one-sixth of the state-owned banks' gross advanced were found to be stressed (non-performing or restructured) (Acharya, 2017). This resulted in an increase of the state-owned banks NPAs from 4.0 percent, on average, in pre-AQR, to 11.5 percent, post-AQR (Figure 1). While the NPAs as a whole increased for the banking sector, some sectors were more affected than the others. RBI reports show that the gross NPAs for the industrial sector was the highest followed by the services and agriculture sectors, and finally the retail sector (Vishwanathan, 2016). This suggests that the credit to industrial sector is likely to be riskier as compared to loans to households. Since the accumulation of bad loans was higher for the state-owned banks, there was a greater reduction in their credit growth rate. Figure 5 shows that the average credit growth rate for private and other banks during 2005-06 to 2019-20 was approximately 13 percent while the average credit growth for state-owned banks during the same period was 7.2 percent. The average credit growth rate for the state-owned banks reduced from 9.2 percent in the pre-AQR period (2008 to 2015) to -2.8 percent after AQR. On the other hand, the average credit growth rate for the other banks increased for the same time period.

One of the channels through which increased bank supervision leads to a decrease in credit supply is through an increase in declared NPAs by banks, that might have previously been falsely classified. Goyal and Verma (2018) use bank-level panel data from India to study the determinants of credit and NPAs. They also establish a link between implementation of the AQR and an increase in the declared NPAs. Therefore, some studies have gauged the effects of an increase in NPAs on credit supply by banks. Studies have found evidence of reduction in bank lending due to increased NPAs for other countries.

Previous studies assessing the impact of the AQR in India have focused more on the effects on the overall credit supply. Chopra et al. (2021) examine the asset quality review conducted by the RBI and study its effects on bank recapitalization and credit lending. They find that a higher exposure of banks to the asset quality review measured in terms of additional provisions made by the banks in response to the AQR, lead to a 25 percent reduction in the loan supply by the banks. Further, they also observe that the banks affected by AQR do not resort to recapitalising by raising capital from the market after the review.

This paper attempts to study the impact of the increase in NPAs in the Indian banking sector due to the implementation of the AQR by the RBI on banks' lending behavior, credit reallocation, and effects on the real economy. Other studies in the context of the Indian AQR have assessed the impact of AQR on bank lending. However, there is not much evidence on its effects on credit reallocation and real economy. While previous studies have provided evidence for the implications of regulatory changes in other countries and the impact of RBI's AQR on credit lending in India, this study adds to the literature by documenting the shift in the banks' credit portfolios from riskier credit to less risky credit due to the implementation of the AQR. For instance, Vishwanathan (2016) predicts a shift from industrial loans to personal loans as one of the consequences of the AQR. We attempt to provide empirical evidence for the same and examine the link between credit reallocation and the asset quality review. Further, we also evaluate the impact of the AQR on real economy through a reduction in bank credit growth.

3. Data and empirical approach

In this section we describe the methodology and data used to analyze the impact of the AQR on banks' lending portfolio.

3.1. *Difference-in-differences analysis*

To analyse the changes in the allocation of sectoral credit by the state-owned banks as compared to other banks, pre- and post-AQR, we employ a difference-in-differences (DID) estimation (Donald & Lang, 2007; Meyer, 1995). A district level matched sample is used for the analysis. The construction of the matched sample is discussed in the next section. The DID regression equation is as follows:

$$\begin{aligned} \mathit{CreditShare}_{i,j,t} = \beta_0 + \beta_1 \mathit{HighPSBdist}_{i,t} + \beta_2 \mathit{Post\text{-}AQR}_{i,t} * \mathit{HighPSBdist}_{i,t} \\ + \delta X_{i,t-1} + \mu_t + \eta_i + \varepsilon_{i,t} \end{aligned} \tag{1}$$

The dependent variable $\mathit{CreditShare}_{i,j,t}$ is the percentage share of outstanding credit of sector j in overall credit in district i in year t. The dependent variable includes the following sectoral credit shares: industry, other sectors (agriculture and services), and credit to households (housing loans and other loans to households).[5] $\mathit{Post\text{-}AQR}_t$ is an indicator for the years following the AQR as discussed in the next section. $\mathit{HighPSBdist}_{i,t}$ is an indicator variable for the top-third districts with the highest presence of PSBs (state-owned banks) in terms of branch offices. Our main variable of interest is the interaction between the AQR indicator and indicator for districts with high state-owned bank presence, $\mathit{Post\text{-}AQR}_{i,t} * \mathit{HighPSBdist}_{i,t}$. A negative coefficient of β_2, which represents the DID effect of the AQR, would imply that the share of credit in districts with high PSB (state-owned banks) presence reduced post-AQR as compared to other districts. η_i represents district fixed effects which account for the unobserved time invariant heterogeneity across districts. Year fixed effects, μ_t, account for common time varying factors at the national level. Additionally, we conduct a test of parallel trends in credit share of districts with high state-owned bank presence and other districts to test if there is any difference between the treatment and control groups in the pre-treatment period (see subsection 4.2).

$X_{i,t}$ is a vector of district-level control variables at for district i at time t. The control variables include district gross value added (GVA) per capita, year-on-year growth of per capita district

[5] The variables are defined in Table 1.

GVA, share of the industrial sector in district GVA and the share of services sector in district GVA. Similar variables have been used in earlier studies on bank credit to households and firms. For instance, Beck, Büyükkarabacak, Rioja, and Valev (2012) find that the share of credit to households is associated with the size of manufacturing sector in the economy. To account for this, we include the contribution of industry and services sector in district per capita GVA as control variables (contribution of the agriculture sector is taken as the reference group). Following Bahadir and Valev (2021), who show that the share of household and firm credit is correlated with GDP per capita, we use the district-level per capita GVA as a control for differences in economic activities across districts. The per capita district GVA measures the level of economic activities in the district and thus account for the financial and economic development in a district. Further, we use growth in the district per capita GVA to account for the changes in credit to households and other sectors due to economic growth (Meng, Hoang, & Siriwardana, 2013). District per capita GVA and GVA growth account for unobserved variation in demand for credit (Qian & Strahan, 2007). All the control variables are lagged by one time period.

3.2. Data and matched estimation sample

To analyse the impact of the asset quality review by the RBI on the credit portfolio of districts with higher state-owned bank share, we use the Reserve Bank of India's database on Indian Economy (DBIE). The RBI collects and publishes annual time-series data on bank performance indicators and banking statistics under the Basic Statistical Return (BSR) series. We use the district level credit data by bank groups which are categorized by sectors.[6] The groups include credit to industry, other sectors (services and agriculture) and households loans which include housing (mortgage) loans and non-housing household credit.

Every year, the RBI checks selected banks' books as a part of the Annual Financial Inspection (AFI). However, in the financial year 2015-16, the RBI carried out the AQR from August to November with a much large sample size and evaluating almost all the large borrowers. The

[6]The bank groups include State-owned banks (public sector banks), private banks, regional rural banks and foreign banks.

banks were then given the next two quarters until March, 2016, to reclassify their most stressed assets as non-performing loans. This resulted in a steep rise in the aggregate bank NPAs (see Raj, Rath, Mitra, and John (2020) and Goyal and Verma (2018)). Therefore, we classify the four financial years prior to the AQR implementation as the pre-AQR period and FY2016-17 to FY2019-20 as post-AQR period. The year of implementation is excluded from the analysis. The post-AQR indicator takes on the value 1 for four years post-AQR from 2016-17 to 2019-20, and zero for the four years prior to the AQR (2010-11 to 2014-15).

The matched sample used in the difference-in-differences analysis is created using the nearest neighbour matching technique (Abadie & Imbens, 2002).[7] We use the matching technique to match the districts with higher share of state-owned bank offices (treatment) with the remaining districts using the 5 nearest neighbours method. The matched sample is created using the pre-AQR year FY2010-11 for which data on district-level attributes is available from the 2011 census by the Indian government. The treatment districts are matched with other districts based on district-level characteristics. These characteristics include average family size, gender ratio, literacy rate, average number of households in a district, total population, urbanization rate and log of district per capita GVA.

The initial district level sample consists of 632 Indian districts comprising of 210 districts that are in the top third by share of state-owned bank branch offices, and 422 other districts. The matched sample includes 177 districts in the treatment group and 272 districts in the control group. A balancing test is performed for the district-level variables used for the matching estimation for the raw and matched sample.[8] The lower standardised differences for the matched sample suggest that the difference between the covariates reduced and the matched sample now consists of districts with similar characteristics.

Table 1 provides variable description and the sources of the outcome variables and the regressors used for the analysis. Table 2 presents the summary statistics for the full sample period which suggests that the share of industry credit is 14.7 percent and share of credit to households

[7]The NNMatch command in Stata is used for creating the matched sample.
[8]The result for the balancing test is presented in appendix Table A1.

(housing and other loans) is 30.6 percent. The share of credit to other sectors (agriculture and services) constitutes the remainder. The average district per capita GVA growth for the sample was approximately 3 percent. The contribution of services to the district GVA was higher at 46.5 percent as compared to the contribution of the industrial sector at 26.2 percent. All the variables are winsorized at the 1st and 99th percentile.

Figure 2 shows the changes in the credit shares in the pre- and post-AQR period. We find that the share of credit to industries declines, the share of credit to other sectors does not change substantially, and the share of credit to households increases. However, the average values presented in the Figure 2 do not control for district characteristics or common time varying factors. The findings for the relationship between the AQR and credit shares to different sectors after controlling for a variety of covariates are presented in the next section.

4. Findings and discussion

In this section we present the results for the difference-in-differences estimation measuring the impact of the AQR on banks' credit portfolios and the parallel trends assumption. The first sub-section describes the baseline result. The next section presents the test for parallel trends and the last sub-section provides results for disaggregated credit shares.

4.1. Baseline Results

The results for baseline specification using the matched sample for the top-third districts with highest number of state-owned bank branches are presented in Table 3. The results suggest that high state-owned bank districts experienced a larger fall in the percentage share of industry credit post-AQR (column 1 in Table 3). The percentage share of credit to the industrial sector reduced by 2.29 percentage points post-AQR in the top-third districts with highest state-owned bank presence as compared to other districts. Column 3 in Table 3 shows that post-AQR, the percentage share of credit to households increased by 1.95 percentage points in the top-third districts with highest presence of state-owned banks as compared to other districts.

We also observe that the districts with higher per capita GVA experience a rise in the credit share of housing credit and a decrease in the share of non-housing credit to households. This decrease in the share of non-housing credit to households could be attributed to a higher household income corresponding to higher per capita GVA and in turn a lower need to borrow for non-housing household consumption.

The results imply that there was a shift in the banks' credit portfolio post-AQR. The share of credit for industry loans, which are usually at a higher risk of default decreased while the share of credit to households, which are at lower risk of default, increased. This suggests that the districts with higher share of state-owned banks and thus the districts affected more by the AQR, shifted their credit portfolio away from sectors with higher default rates to those with lower default rates.

4.2. Test for parallel trends

An assumption underlying a DID analysis is that the treatment and control groups should be on parallel trends prior to the policy reform. Following the methodology employed by D'Acunto, Liu, Pflueger, and Weber (2018), we regress the share of credit to the industrial sector, other sectors and households on the interaction of an indicator for the top third districts with highest state-owned bank offices and year dummies for the pre-AQR period (FY2012 to FY2015). The reference category is FY2011. If the treated (high state-owned bank districts) and other matched districts are on parallel trends, the coefficients of the interaction terms are expected to be insignificant.

The coefficient of interaction between indicator for high state-owned bank districts and pre-AQR year dummies (FY2012 to FY2015) are provided in Table A2. The results for credit share to industry confirm that the interaction coefficients are insignificant at the 5 percent level of significance.[9] The interaction terms for credit to other sectors and households are also insignificant at the 5 percent level. These suggest that districts with high state-owned bank shares

[9]The coefficient for the interaction term is marginally significant for only one year (FY2015) out of the four pre-AQR years.

and other districts are broadly on parallel trends prior to the AQR implementation.

4.3. Disaggregated credit shares results

Table 4 represents the results for disaggregated credit shares for other sectors and household credit. Columns 1 and 2 suggest that the shares of credit towards services and agriculture experienced no change or statistically insignificant change in the top-third districts with the highest presence of state-owned bank in the post-AQR period, compared to other districts. Table 4 also presents the disaggregated increase in shares of housing (mortgage) credit and non-housing loans to households (columns 3 and 4). The regression coefficients for housing (mortgage) loans and non-housing credit suggest that the increase in the share of overall credit to household was dominated by the increase in share of non-housing loans. The share of housing credit increased by 0.7 percentage point while the increase in non-hosing credit share was 1.28 percentage points in top-third districts with highest presence of state-owned banks.

4.4. Alternative specifications and robustness tests

This subsection presents several robustness tests for the baseline findings and an alternate specification. We test the robustness of the baseline results using a different threshold for high state-owned bank presence (top quarter of districts instead of top third), use of a different matching method (three nearest neighbours matching), use of pre-AQR bank credit share to define state-owned bank presence, and for a shorter time period (two years pre- and post-AQR). Additionally, we also study the effect of the AQR in districts with higher presence of state-owned banks by bank offices on the aggregate district-level credit (in constant rupees). We also conduct a falsification test with a placebo implementation year to confirm that the baseline results are driven by the AQR implementation.

4.4.1. Robustness to a different threshold for high state-owned bank presence

A robustness was performed for alternate *HighPSBdist* for top-quarter districts with highest state-owned bank presence, instead of the top third of districts used in the baseline. The matched sample for this analysis includes 132 treatment districts and 252 matched control districts.

The regression results for this alternate definition of *HighPSBdist* are presented in panel A of Table 5. The analysis reveals that the percentage share of credit to the industrial sector was lower for districts with higher presence of state-owned banks (column 1). Column 3 shows that the share of credit to households increased in the post-AQR period for districts with higher state-owned banks. The findings of this robustness test show that districts with a higher share of state-owned bank experienced a higher fall in the share of credit to the industrial sector and a larger increase in the share of credit to the household sector in the post-AQR period compared to other districts, consistent with the baseline findings.

4.4.2. Use of a different matching method

The next robustness test conducts an analysis using a matched sample for the top-third districts with highest share of state-owned bank branches using 3 nearest neighbours matching instead of 5 nearest neighbours matching. The final matched sample for the top third districts with highest share of state-owned bank offices with 3 nearest neighbours matching includes 157 treatment and 214 matched control districts.

The results for this alternate sample are presented in panel B of Table 5. The findings corroborate the baseline findings. The results indicate that the percentage share of industry credit reduced more for districts with a high presence of state-owned banks (column 1). Consistent with the baseline results, the share of credit to households increased more in districts with high state-owned bank branches as compared to other districts in the post-AQR period and there was statistically insignificant change in share of credit to other sectors (columns 2 and 3).

4.4.3. Use of pre-AQR state-owned bank credit share

We conduct another robustness test by altering the definition of districts with a high share of state-owned banks. In this section, high state-owned bank districts are defined based on the share of outstanding credit by the state-owned banks in overall credit extended by all the banks in the district, pre-AQR. We create a matched sample similar to the baseline sample using the matching technique described in section 2.1. Here, the treatment district consists of the top third districts with the highest share of state-owned bank credit in overall district credit. The matched sample for this analysis 197 treatment districts and 313 control districts.

The results for the estimation using pre-AQR state-owned bank credit share are presented in panel C of Table 5. Column 1 shows that the percentage share of industry credit in the top third districts with highest share of state-owned bank credit pre-AQR, compared to other districts, in the post-AQR time period. Similar to the baseline results, the findings confirm that the share of credit to households increased post-AQR and the change in share of credit to other sector was statistically insignificant (columns 2 and 3).

4.4.4. Use of a shorter time period

This robustness test analyses the baseline DID regression for a shorter time period. Here, we trim the sample period to include two pre-AQR years (FY 2014 and FY2015) and two post-AQR years (FY2017 and FY2018). The results for this estimation are presented in panel D of Table 5. The share of industry credit in the top-third districts with highest share of state-owned bank by branch offices declined compared to other districts in the post-AQR time period (columns 1). The findings confirm that the share of credit to households increased post-AQR and the change in share of credit to other sector was statistically insignificant (columns 2 and 3). The findings with a shorter time window for the estimation are broadly consistent with the baseline results.

4.4.5. AQR and aggregate district-level credit

In addition to analysing the impact of AQR in districts with higher presence of state-owned banks on the share of credit to different sectors, we also study the changes in the overall district credit for districts with higher state-owned banks compared to other districts. Table A3 presents the DID regression result using an alternate specification with the outcome variable as the log of aggregate district credit (in constant 2010 rupees). The aggregate district credit is measured as the sum of credit extended by all bank groups to all the sectors in a district. As evident from the regression coefficients in Table A3, the DID coefficient is negative suggesting that the aggregate district credit for high state-owned bank districts decreased by 6.3 percentage points in the post-AQR period as compared to other districts. Together with the findings from Table A3 where the decline in industry credit more than offset the increase in credit to households in the high state-owned banks districts, this suggests a substantial reallocation of bank credit away from industries and towards households in the post-AQR period.

4.4.6. Placebo estimation

This section presents the results from a falsification test with a placebo treatment year. The placebo treatment year is taken as 2013-14, two years before the actual AQR implementation year. The time period considered for the estimation is the pre-AQR time period from 2010-11 to 2014-15. Other studies that have used similar placebo estimations include D'Acunto et al. (2018) and Acharya and Xu (2017), among others. The results for the placebo estimation are presented in Table 6. The interaction term for high cases districts and the treatment indicator variable, is insignificant. This implies that there is no differential impact of the placebo treatment on bank credit allocation in districts with higher presence of state-owned banks as compared to other districts. Therefore, the results from the falsification test indicate that the change in the credit allocation from industry credit to households is likely to be driven by the implementation of the AQR.

5. Real effects of the AQR reform: Panel VAR analysis

The DID results discussed in the previous section provide evidence of reallocation of credit from industry to households after the implementation of the AQR. Changes in bank credit supply can have adverse effects on the real economy (Cingano et al., 2016). In this section, we examine the effects of the AQR reform on district-level economic growth using a panel vector autoregression (PVAR) estimation.

5.1. Panel VAR methodology

A panel VAR approach treats all the variables in the system as endogenous. The specification includes district-level fixed effects γ_i to account for unobserved heterogeneity across districts. Following Love and Zicchino (2006), we use the forward orthogonal differencing to correct for Nickell bias, which suggests that the estimates would be biased with the presence of lagged dependent variables in the right-hand side of the equations even with a large N (Nickell, 1981). In this procedure, all the variables in the model are transformed by taking the deviation from average of all future observations. This transformation preserves the orthogonality between the lagged regressors and the transformed variables, and differences out the fixed effects. Therefore, we use lagged regressors as instruments to estimate the coefficients using a generalised method of moments (GMM) estimator (see Abrigo and Love (2016)).

We also present orthogonalized impulse-response functions which present the response of one variable to an orthogonal shock in another variable. This allows us to isolate the shocks in the variables and to identify the effect of one shock at a time while the other shocks are taken as constant. To create the impulse response functions (IRF), we use Cholesky decomposition to specify the ordering of impulse and response variables. Cholesky decomposition assumes that the variables appearing earlier in the system affect the other variables contemporaneously while those appearing later affect the earlier variables only with a lag suggesting that the variables appearing earlier in the system are more exogenous. The specification for the first order panel VAR used for the analysis is as follows:

$$Y_{it} = \beta_0 + \beta_1 Y_{it-1} + \gamma_i + \varepsilon_{it} \tag{2}$$

where Y_{it} is a vector of the dependent variables and Y_{it-1} are the lagged values of the dependent variable. The specification includes district-level fixed effects γ_i as discussed earlier. The variables in the panel VAR system include the following:

$$Y_{it} = \{NPAPSB, GVAgr, CredGr, InCrSh, OthCrSh, PerCrSh\} \tag{3}$$

The variables are listed in order as the most exogenous to least exogenous. *NPAPSB* is computed as the national-level non-performing assets of the state-owned banks weighted by the district-level bank credit share of state-owned banks.[10] *GVAgr* is the annual growth of real gross value added at the district-level. *CredGr* is the overall growth in real bank credit (in 2010 prices) at the district level. *InCrSh*, *OthCrSh* and *PerCrSh* refer to the share of district-level bank credit to industry, other sectors, and households, respectively. A panel unit root test shows that all the variables used in the panel VAR estimation are stationary (Table A4).

In equation (2), we assume that the shocks to state-owned banks' non-performing assets (*NPAPSB*) to be the most exogenous variable. As shown earlier, the NPA of the state-owned banks increased significantly after the introduction of the RBI's AQR reforms. The variables that are considered relatively more endogenous are the district GVA growth, and credit share to industry, other sectors, and households.

5.2. *Panel VAR results*

The results presented in Table 7 show that the response of industry credit share to a shock in state-owned banks' NPA is negative, suggesting that an increase in NPAs reduces lending to industry (see column 4). The credit share of other sectors is also negatively affected by a shock to state-owned banks' NPAs (column 5). By contrast, household credit share shows a positive response to a shock in NPAs (column 6). These results are in the expected direction and confirm the earlier DID results of evidence of credit reallocation from industry to households when there is an increase in state-owned banks' NPAs. An increase in credit shares of industry and other sectors is associated with higher credit growth. We observe that the response of district-level GVA to a shock in overall credit growth as well as the credit shares of industry, other sectors, and households is positive (column 2). This suggests that as overall credit growth and the credit share of any sector increases, there is a positive effect on the real output. District

[10] This variable represents the exposure of a district to the non-performing assets of state-owned banks. Since NPA information is not available at the district level, this variable is computed using data on the national-level NPAs and the district credit share of state-owned banks. For example, if the NPA of the state-owned banks is 10 percent of gross loans at the national level, and these banks account for 75 percent of a district's overall bank credit, this variable would take on a value of 7.5 percent (10% * 0.75) for that district.

GVA growth is negatively related to the increase in NPAs of state-owned banks, although the effect is statistically insignificant (column 2).[11] However, the results suggest an indirect effect of banking sector stress on real activity, since the state-owned banks' NPAs affect the allocation of bank credit, which, in turn, influences real output.

The impulse response function graphs presented in Figure 6 show that although the district-level GVA growth increases with a one standard deviation increase in industry credit share initially, it gradually starts decreasing after two time periods. Similarly, a shock to the household credit share has a positive effect on the district-level GVA growth initially. However, the district GVA growth gradually decreases in response to a shock in household credit share after four time periods. The Figure 6 confirms a decrease in industry and other sectors' credit shares and an increase in household credit share, with a one standard deviation increase in state-owned banks' NPAs, consistent with the DID results presented earlier.

6. Conclusion

This paper analyses the effects of the RBI's AQR on reallocation of credit to different sectors in districts with a high presence of state-owned banks as compared to other districts. We use DID analysis for a matched sample created using the nearest neighbours matching technique. It finds that owing to a steep rise in the NPAs for the state-owned banks as a result of the AQR, the share of credit towards industries in districts with high state-owned bank presence declined and the share of household credit increased in the post-AQR period. On the other hand, the share of other sectors credit did not experience a statistically significant change.

Further, we disaggregate the shares of household credit to find that the share of non-housing loans increased to a greater extent as compared to the share of housing credit in districts with a high share of state-owned banks. The findings are robust to change in the threshold for measuring high state-owned banks districts, use of a different matching method, an alternate definition of state-owned banks presence by pre-AQR credit share and shortening the pre- and post-AQR time periods. Additionally, this paper finds that the aggregate district credit (in

[11]Note that the shock to each variable in the panel VAR system is considered independently.

constant rupees) reduced in the districts with high state-owned bank presence post-AQR as compared to other districts. Further, the study analyses the real economy effects of the AQR using Panel Vector Autoregression (PVAR). The findings confirm the reallocation of credit post-AQR and a negative effect on the district real GVA growth rate.

The observed shift in the banks' lending portfolio from industry credit to household credit and the established higher riskiness of loans to industries, contribute to the understanding of banks' lending behaviour in case of higher NPAs. Overall, the results of this study suggest that central bank policy reforms do influence bank credit allocation at the sub national level and have strong real economy effects. Our study has implications on the effectiveness and consequences of banking policy reforms adopted by the central banks and other governing bodies.

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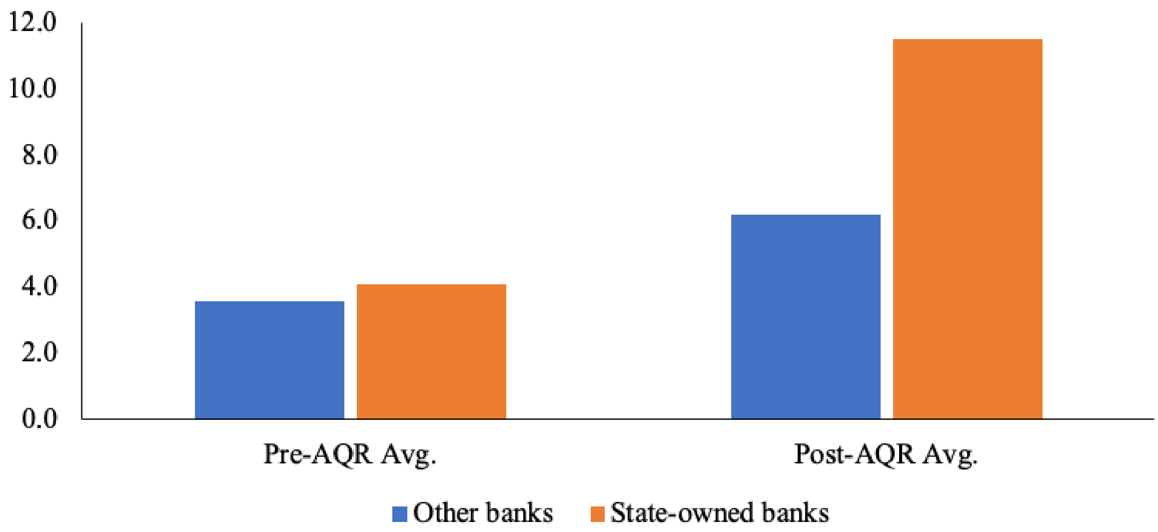
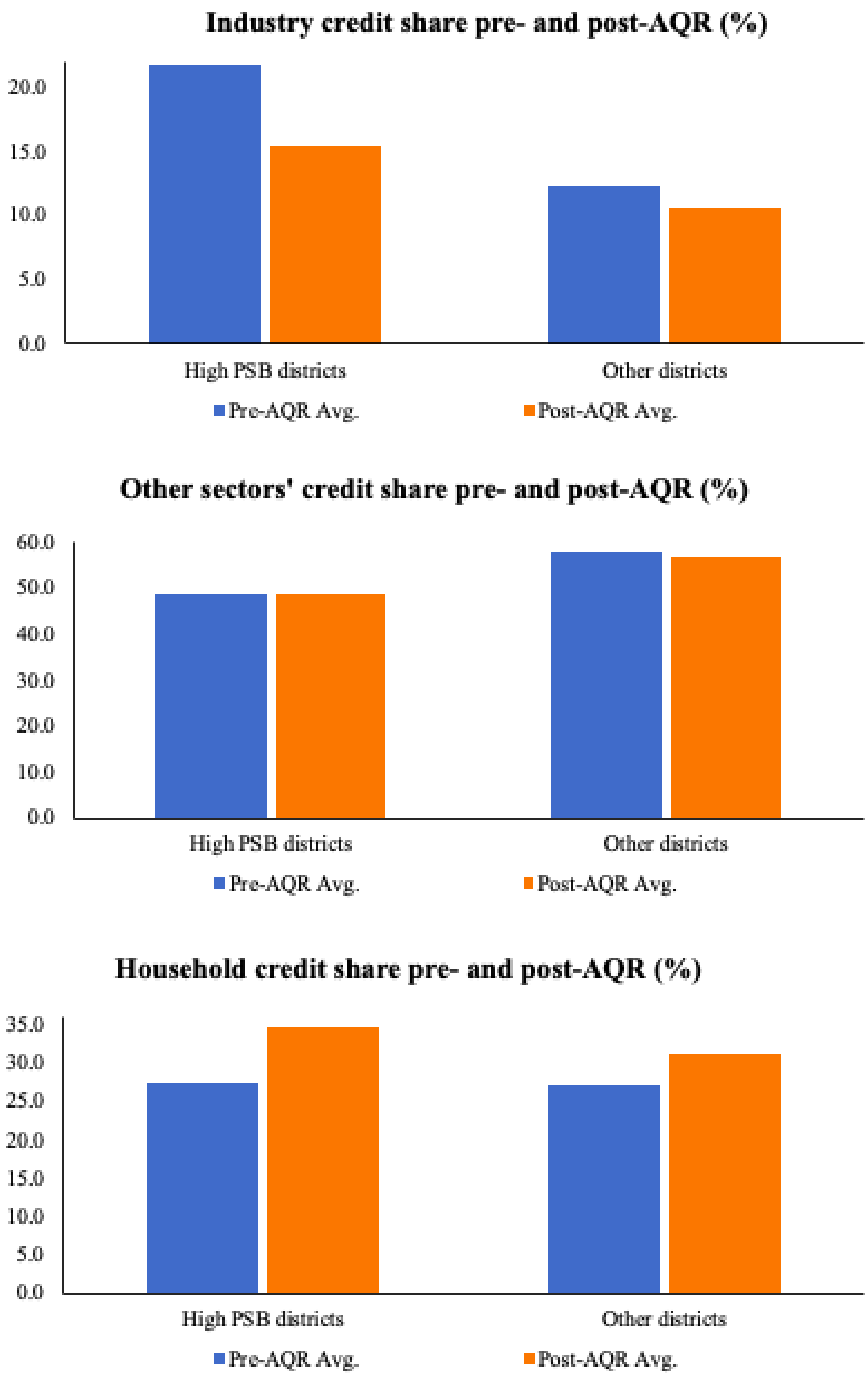
Figure 1: State-owned and other banks' non-performing assets (NPA) pre- and post-AQR (% of loans)



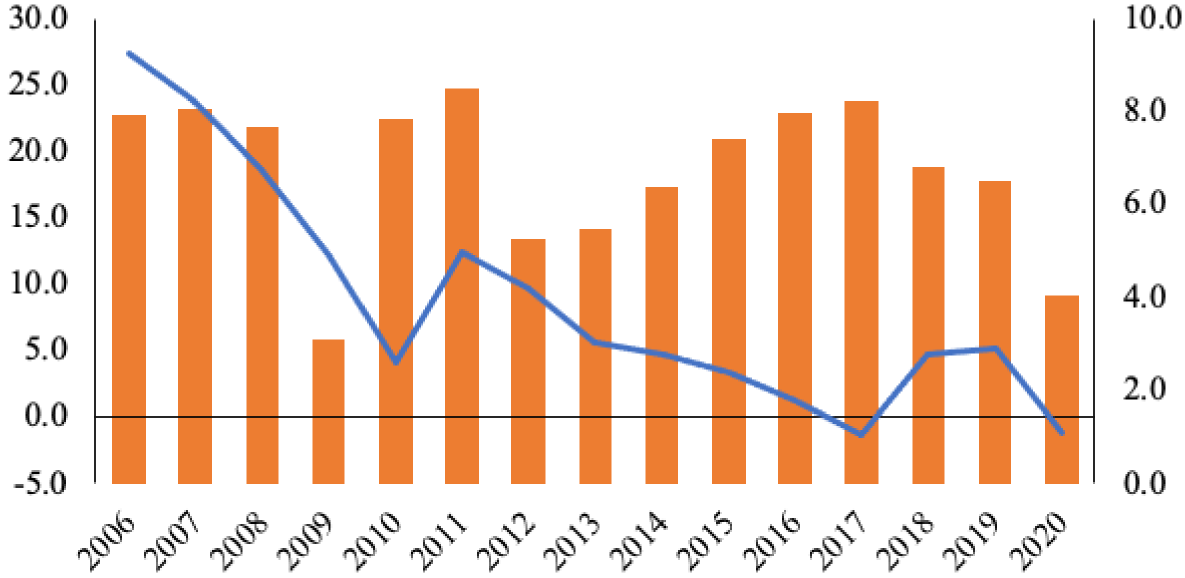
The figure represents the changes in the average non-performing assets declared by the state-owned and other banks in India in the pre- and post-AQR periods. The pre-AQR average includes the NPAs for the years from 2010-11 financial year (FY2011) to FY2015. The post-AQR average includes NPAs for the years from FY2017 to FY2020, following the Reserve Bank of India's Asset Quality Review (AQR) of commercial banks in FY2016.

Figure 2: Credit shares of industry, household and other sectors pre- and post-AQR



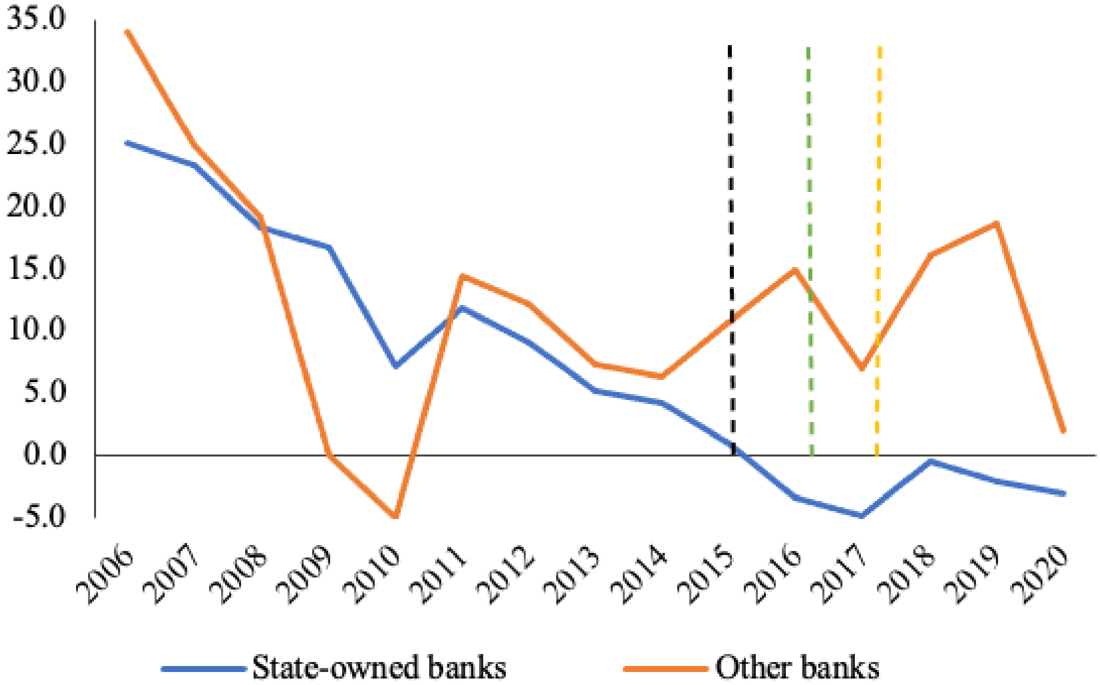
The figure represents the average share of district-level credit in the pre- and post-AQR periods for high PSB (state-owned banks) districts and other districts as defined in Table 1. The pre-AQR period includes the years from 2010-11 financial year (FY2011) to FY2015 and the post-AQR period includes the years from FY2017 to FY2020.

Figure 3: Real GDP growth and real bank credit growth (%)



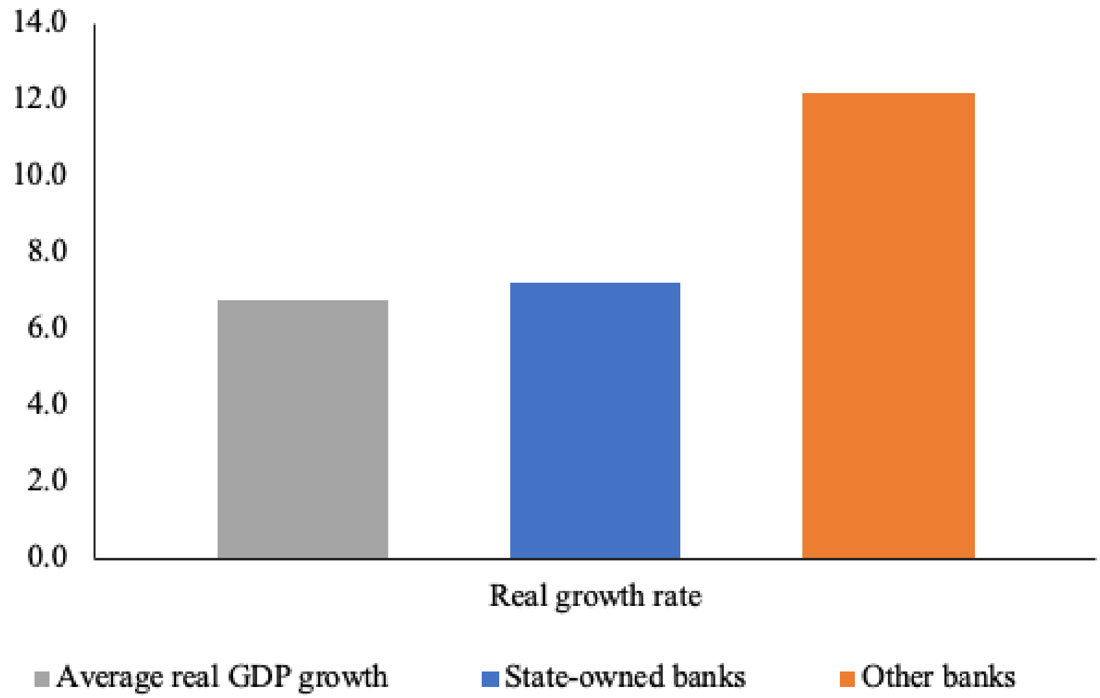
The figure presents trends in real GDP and real credit growth rates. The bars represent growth in real GDP. The y-axis on the right correspond to the real GDP growth. Credit growth rate is represented by the line chart and corresponds to the y-axis on the left. The year 2020 indicates the financial year 2019-20.

Figure 4: Real bank credit growth rates for state-owned banks and other banks (%)



The figure presents the credit growth rate for state-owned banks and other banks from 2005-06 financial year (FY2006) to FY2020. The black line represents the implementation of the AQR in FY2016 and the green and yellow lines represent the introduction of demonetization (in FY2017) and GST (FY2018), respectively.

Figure 5: Average real GDP growth and real bank credit growth rate for state-owned banks and other banks, 2005-06 to 2019-20 (%)



The figure represents the average rate of growth for real GDP and real credit growth by state-owned banks and other banks. The time period between 2005-06 financial year (FY2006) to FY2020 is considered.

Table 1: Description of variables

Variable	Description	Source
Post-AQR	This is a dummy variable which takes the value 1 for the years following the RBI's asset quality review (AQR), from the 2016-17 financial year (FY) until FY2019-20, and 0 for the pre-AQR period.	Authors' calculations.
High PSB Dist.	The variable High PSB Dist. takes the value 1 for the top third districts with the highest share of state-owned bank (public sector bank) branch offices, and 0 otherwise.	Authors' calculations based on RBI's DBIE.*
Industry Credit Share (%)	The percentage share of industry credit represents the share of industry loans in overall credit extended by the all the banks in a district.	Authors' calculations based on RBI's DBIE.
Other business Credit Share (%)	The percentage share of credit to other businesses represents the sum of the shares of services and agriculture loans in overall credit extended by the all the banks in a district.	Authors' calculations based on RBI's DBIE.
Serv. Credit Share (%)	The percentage share of credit to services represents the share of industry loans in overall credit extended by the all the banks in a district. This includes loans to services, transport operators, professionals, trade and finance.	Authors' calculations based on RBI's DBIE.
Agri. Credit Share (%)	The percentage share of agriculture credit represents the share of agriculture loans in overall credit extended by all the banks in a district.	Authors' calculations based on RBI's DBIE.
Household Credit Share (%)	The percentage share of household credit represents the sum of share of both housing (mortgage) and non-housing loans in overall credit extended by all the banks in a district.	Authors' calculations based on RBI's DBIE.
Housing Credit Share (%)	The percentage share of housing credit represents the share of housing (mortgage) loans in overall credit extended by all the banks in a district.	Authors' calculations based on RBI's DBIE.
Non-housing Credit Share (%)	The percentage share of non-housing credit represents the share of other household loans (excluding mortgage loans) in overall credit extended by all the banks in a district. This includes loans towards credit cards, vehicles, education and consumer durables.	Authors' calculations based on RBI's DBIE.
Log Dist. GVAPC	This variable is the logarithm of annual per capita district gross value added (GVA). The per capita district GVA is measured in 2010 constant rupees.	District GDP of India database.
GVAPC Growth (%)	This variable represents the percentage change in annual per capita district GVA (measured in constant 2010 rupees) for each district.	District GDP of India database.
Ind. GVA as % of Dist. GVA	This variable measures the percentage contribution of the industrial sector in the overall district GVA.	District GDP of India database.
Serv. GVA as % of Dist. GVA	This variable measures the percentage contribution of the services sector in the overall district GVA.	District GDP of India database.

Table 2: Summary statistics

The table contains summary statistics for the matched sample used for the baseline estimation.

	Obs.	Mean	Std. dev.	Min.	Max.
Post-AQR	3,138	0.57	0.49	0.00	1.00
High PSB Dist.	3,138	0.39	0.49	0.00	1.00
Industry Credit Share (%)	3,138	14.71	12.72	0.03	62.89
Other Sectors Credit Share (%)	3,138	52.49	17.73	7.83	86.45
Serv. Credit Share (%)	3,138	17.66	7.99	1.80	45.65
Agri. Credit Share (%)	3,138	34.83	20.10	1.35	77.61
Household Credit Share (%)	3,138	30.53	16.29	6.13	86.56
Housing Credit Share (%)	3,138	11.25	6.31	0.00	33.96
Non-housing Credit Share (%)	3,138	19.28	14.95	2.95	80.78
Log Dist. GVAPC	3,138	10.98	0.53	9.56	13.08
GVAPC Growth (%)	3,138	2.82	4.43	-19.44	54.69
Ind .GVA % of Dist. GVA	3,138	26.24	11.92	2.00	68.00
Ser. GVA % of Dist. GVA	3,138	46.48	12.41	10.00	82.00

Table 3: RBI's AQR, state-owned bank presence, and allocation of credit

Industry, other sectors (services and agriculture), and household credit (housing and other loans) share is the percentage of the sector's credit in overall district credit. The *Post-AQR* indicator takes the value one for the years from FY2017 to FY2020, following the Reserve Bank of India's Asset Quality Review (AQR) of commercial banks in FY2016, and zero for the years between FY2011 and FY2015. *HighPSB Dist.* takes the value 1 for districts with the highest 33% of PSB (state-owned bank) branches share. All columns include district and time fixed effects. The standard errors are clustered at the district level. ***, ** , * indicate significance at the 1%, 5% and 10% levels, respectively.

	Industry Credit Share (%) (1)	Other Sectors Credit Share (%) (2)	Household Credit Share (%) (3)
High PSB Dist.	2.089***	-2.400***	0.035
	(0.714)	(0.710)	(0.647)
High PSB Dist. x Post-AQR	-2.293***	0.313	1.953***
	(0.768)	(0.737)	(0.672)
Log Dist. GVAPC	3.800	-5.408	-4.382
	(4.115)	(4.453)	(3.763)
GVAPC Growth (%)	-0.042	0.039	0.016
	(0.031)	(0.033)	(0.028)
Ind. GVA % of Dist. GVA	-0.118	-0.109	0.105
	(0.106)	(0.102)	(0.117)
Serv. GVA % of Dist. GVA	0.064	-0.135	0.113
	(0.111)	(0.137)	(0.134)
Constant	29.154***	46.442***	9.784
	(10.498)	(11.563)	(11.185)
Time fixed effects	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes
Observations	3,138	3,138	3,138
Adj. R-squared	0.797	0.877	0.865

Table 4: Disaggregated credit shares for household and other sectors

Industry, other sectors (services and agriculture), and household credit (housing and other loans) share is the percentage of the sector's credit in overall district credit. The *Post-AQR* indicator takes the value one for the years from FY2017 to FY2020, following the Reserve Bank of India's Asset Quality Review (AQR) of commercial banks in FY2016, and zero for the years between FY2011 and FY2015. *High PSB Dist.* takes the value 1 for districts with the highest 33% of PSB (state-owned bank) branches share. All columns include district and time fixed effects. The standard errors are clustered at the district level. ***, ** , * indicate significance at the 1%, 5% and 10% levels, respectively.

	Other sectors credit		Household credit	
	Serv. Credit Share (%)	Agri. Credit Share (%)	Housing Credit Share (%)	Non-housing Credit Share (%)
	(1)	(2)	(3)	(4)
High PSB Dist.	-0.597	-1.641***	0.081	-0.049
	(0.466)	(0.604)	(0.291)	(0.538)
High PSB Dist. x Post-AQR	0.089	0.193	0.701**	1.280**
	(0.449)	(0.631)	(0.320)	(0.616)
Log Dist. GVAPC	-2.575	-2.287	4.569***	-10.111***
	(3.132)	(3.354)	(1.716)	(3.054)
GVAPC Growth (%)	-0.028	0.067**	-0.020	0.044*
	(0.023)	(0.030)	(0.015)	(0.026)
Ind. GVA % of Dist. GVA	-0.039	-0.063	0.059	-0.005
	(0.069)	(0.090)	(0.049)	(0.087)
Serv. GVA % of Dist. GVA	0.028	-0.174**	-0.016	0.139
	(0.088)	(0.087)	(0.051)	(0.134)
Constant	11.641	36.162***	21.942***	-13.545
	(8.100)	(8.922)	(4.925)	(9.551)
Time fixed effects	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Observations	3,138	3,138	3,137	3,138
Adj. R-squared	0.766	0.927	0.847	0.863

Table 5: Robustness tests

Panel A presents robustness test for a use of different threshold to measure high PSB (State-owned Banks) districts i.e *High PSB Dist.* takes the value 1 for districts with the highest 25% of state-owned bank branch share. Panel B uses a different matching method created using 3 nearest neighbours matching (instead of 5 nearest neighbours matching). Panel C represents results for an alternate measure of high state-owned bank presence, with *High PSB Dist.* taking the value 1 for districts with the highest 33% of PSB (state-owned bank) credit share (instead of bank branches). Panel D conducts the baseline estimation for a shorter time frame, with the time period restricted to two year pre-AQR (FY2014 and FY2015) and two years post-AQR (FY2017 and FY2018). All columns include district and time fixed effects. The standard errors are clustered at the district level. ***, ** , * indicate significance at the 1%, 5% and 10% levels, respectively.

	A: Alt. High PSB threshold			B: Different matching method		
	Industry Credit Share (%)	Other Sectors Credit Share (%)	Household Credit Share (%)	Industry Credit Share (%)	Other Sectors Credit Share (%)	Household Credit Share (%)
	(1)	(2)	(3)	(4)	(5)	(6)
High PSB Dist.	1.149	-1.422*	0.224	1.725**	-1.550**	-0.324
	(0.998)	(0.837)	(0.835)	(0.784)	(0.767)	(0.720)
High PSB Dist. x	-2.034**	-0.138	2.018***	-1.903**	-0.512	2.385***
Post-AQR	(0.855)	(0.820)	(0.719)	(0.840)	(0.776)	(0.691)
Constant	28.551**	50.157***	8.323	30.272**	41.770***	13.181
	(11.820)	(13.568)	(12.946)	(12.187)	(12.683)	(11.908)
District controls	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Dist. fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,697	2,697	2,697	2,592	2,592	2,592
Adj. R-squared	0.813	0.877	0.868	0.774	0.875	0.866

	C: Alt. PSB measure (credit share)			D: Shorter time-period		
	Industry Credit Share (%)	Other Sectors Credit Share (%)	Household Credit Share (%)	Industry Credit Share (%)	Other Sectors Credit Share (%)	Household Credit Share (%)
	(1)	(2)	(3)	(4)	(5)	(6)
High PSB Dist.	1.531**	-1.620**	-0.183	1.447**	-1.681**	0.196
	(0.647)	(0.717)	(0.662)	(0.665)	(0.718)	(0.615)
High PSB Dist. x	-1.100*	-0.809	1.905***	-1.870**	0.209	1.602**
Post-AQR	(0.645)	(0.746)	(0.690)	(0.742)	(0.756)	(0.695)
Constant	29.311***	49.232***	5.353	35.994***	39.186***	8.982
	(10.015)	(14.219)	(13.597)	(12.547)	(13.976)	(15.102)
District controls	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Dist. fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,562	3,562	3,562	1,795	1,795	1,795
Adj. R-squared	0.808	0.863	0.846	0.839	0.901	0.875

Table 6: RBI's AQR, state-owned bank presence, and allocation of credit: Placebo estimation

Industry, other sectors (services and agriculture), and household credit (housing and other loans) share is the percentage of the sector's credit in overall district credit. The placebo treatment year is taken as FY2014 instead of FY2016. The time period considered for the analysis is from FY2011 to FY2015. *High PSB dist.* takes the value 1 for districts with the highest 33% of PSB (state-owned bank) branches share. All columns include district and time fixed effects. The standard errors are clustered at the district level. ***, ** , * indicate significance at the 1%, 5% and 10% levels, respectively.

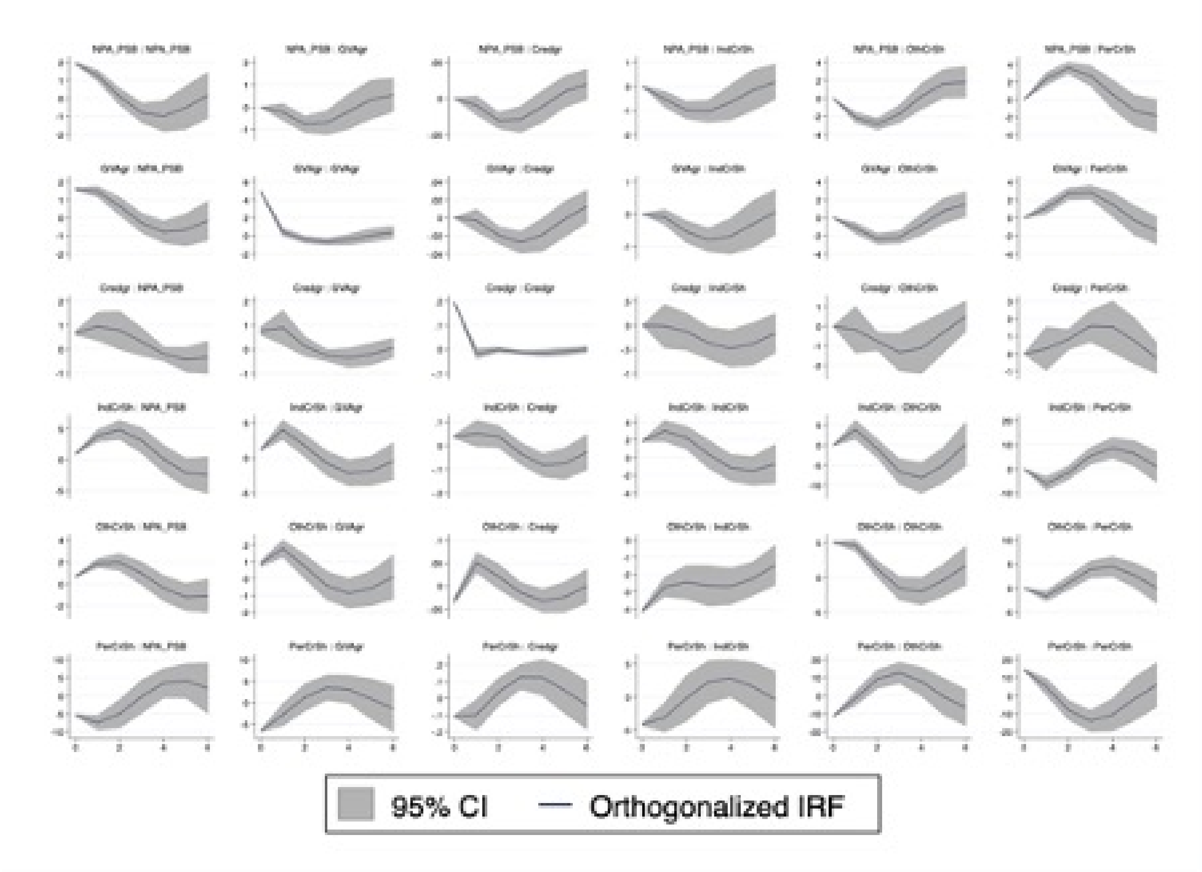
	Industry Credit Share (%)	Other Sectors Credit Share (%)	Household Credit Share (%)
AQR Indicator	-2.028***	3.487***	0.512
	(0.586)	(0.580)	(0.609)
High PSB Dist.	0.373	0.174	1.319
	(0.850)	(0.987)	(1.336)
High PSB Dist. x Post-AQR	-0.970	-0.832	1.244
	(0.804)	(0.808)	(0.812)
Log Dist. GVAPC	15.195***	-12.540**	-0.013
	(5.580)	(4.935)	(6.167)
GVAPC Growth (%)	-0.066	-0.111	0.071
	(0.052)	(0.068)	(0.068)
Ind. GVA % of Dist. GVA	0.482***	-0.117	-0.286*
	(0.128)	(0.134)	(0.148)
Ser. GVA % of Dist. GVA	0.215	-0.133	-0.035
	(0.135)	(0.130)	(0.167)
Constant	39.767***	24.303*	35.438**
	(12.148)	(13.677)	(15.252)
Time fixed effects	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes
Observations	1,346	1,346	1,346
Adj. R-squared	0.901	0.892	0.859

Table 7: Panel VAR

The five variable panel VAR is estimated using GMM. Reported numbers show the coefficients of regressing the row variables on lags of the column variables. GVA growth is the year-on-year percentage change in the district level GVA. Industry, other sectors (services and agriculture), and household credit (housing and other loans) share is the percentage of the sector's credit in overall district credit. Overall credit growth is the percentage change in overall district credit. The standard errors are clustered at the district level. ***, ** , * indicate significance at the 1%, 5% and 10% levels, respectively.

Variables	State-owned banks NPA (1)	GVA Growth (2)	Cred. Growth (3)	Ind. Cred. Share (4)	Oth. Cred. Share (5)	HH Cred. Share (6)
State-owned banks NPA(t-1)	0.653***	-0.111	-0.005	-0.273***	-1.088***	1.217***
	(0.077)	(0.099)	(0.003)	(0.083)	(0.153)	(0.187)
GVA Growth(t-1)	0.087***	0.127***	0.001	0.069***	0.120**	-0.173***
	(0.027)	(0.039)	(0.001)	(0.026)	(0.051)	(0.059)
Cred. Growth(t-1)	2.309	4.543**	-0.077	0.583	2.359	-2.016
	(1.501)	(1.812)	(0.056)	(1.203)	(2.935)	(3.230)
Ind. Cred. Share(t-1)	1.643***	2.027***	0.031*	1.697***	2.479***	-3.743***
	(0.279)	(0.394)	(0.016)	(0.347)	(0.625)	(0.784)
Oth. Cred. Share(t-1)	1.614***	2.012***	0.035**	0.864***	3.054***	-3.495***
	(0.253)	(0.357)	(0.015)	(0.312)	(0.565)	(0.700)
HH Cred. Share(t-1)	1.522***	2.019***	0.028	0.889**	2.690***	-3.119***
	(0.294)	(0.412)	(0.017)	(0.356)	(0.649)	(0.809)
Observations	4,316	4,316	4,316	4,316	4,316	4,316

Figure 6: Impulse-response function



The figure represents the impulse response functions for the variables in the panel VAR system. The first row represents the response in shock to the NPAs of state-owned banks. The second row represent IRFs w.r.t. to a shock in the GVA growth. Third row presents the IRFs for a shock in the overall credit growth variable. The last three rows represents the response in shock to credit share variables (industry, other sectors and household). 95% confidence level bands are presented. The errors are generated by Monte-Carlo with 200 repetitions.

Appendices

Table A1: Balancing test for matched and raw sample

The table provides results of a balancing test conducted after creating the matched sample. The standardised differences measures the average difference between the treatment and control districts in the matched sample. A lower standardised difference means that the covariates for treatment and control districts are similar.

	Standardised Differences	
	Raw	Matched
Avg. family size	-0.214	-0.074
Gender ratio	-0.350	-0.111
Literacy rate	0.705	0.228
Avg. no. of households	0.189	0.017
Total population	0.147	0.004
Urbanisation rate	0.748	0.272
Log GVAPC	0.975	0.320

Table A2: Parallel trends test for the matched sample

The table presents results from the following linear equation:$CreditShare_{i,jt} = \sum_{(t=2012)}^{2015} \beta_t * HighPSBdist + \gamma * HighPSBdist. + \mu_t + \epsilon_{it}$. Credit share is regressed on the year dummies for the pre-AQR period (FY2012 to FY2015) and interactions between the years dummies and High PSB Dist. The reference category is FY2011. The outcome variable is the percentage share of industry loans, other sectors credit share and share of credit to households. *High PSB Dist.* takes the value one for the top-third districts with the highest share of PSB (state-owned banks) offices. The table represents the coefficients of interaction between the high PSB share Dist. and pre-AQR years (FY2012 to FY2015) for industry credit share in overall district credit. FY2011 is omitted in the regressions and taken as the base category. The regressions include district fixed effects. The standard errors are clustered at the district level. ***, ** , * indicate significance at the 1%, 5% and 10% levels, respectively.

	Industry Credit Share (%) (1)	Other Sectors Credit Share (%) (2)	Household Credit Share (%) (3)
High PSB Dist. x 2012	-0.613	1.013	0.095
	(0.806)	(0.956)	(0.919)
High PSB Dist. x 2013	-0.375	-1.270	1.098
	(0.972)	(1.203)	(1.100)
High PSB Dist. x 2014	-1.421	-0.681	1.732*
	(0.933)	(1.020)	(1.041)
High PSB Dist. x 2015	-1.744*	-0.461	1.772*
	(1.005)	(0.952)	(1.020)
High PSB Dist.	0.977	0.183	0.408
	(0.970)	(1.082)	(1.038)
Constant	18.259***	48.940***	28.418***
	(0.399)	(0.557)	(0.464)
Time fixed effects	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes
Observations	2,243	2,243	2,243
Adjusted R-squared	0.857	0.848	0.813

Table A3: RBI's AQR and aggregate district-level credit analysis

The outcome variable is the log of aggregate district credit (in constant rupees). The *Post-AQR* indicator takes the value one for the years from FY2017 to FY2020, following the Reserve Bank of India's Asset Quality Review (AQR) of commercial banks in FY2016, and zero for the years between FY2011 and FY2015. *HighPSBdist.* takes the value 1 for districts with the highest 33% of PSB (state-owned bank) credit share. All columns include district and time fixed effects. The standard errors are clustered at the district level. ***, ** , * indicate significance at the 1%, 5% and 10% levels, respectively.

	Log of aggregate district credit (1)
High PSB Dist.	0.068**
	(0.033)
High PSB Dist. x Post-AQR	-0.063**
	(0.031)
Log Dist. GVAPC	-0.000**
	(0.000)
GVAPC Growth (%)	-0.002
	(0.002)
Ind.GVA % of Dist. GVA	-0.008**
	(0.004)
Ser.GVA % of Dist. GVA	0.004
	(0.006)
Constant	23.863***
	(0.334)
Time fixed effects	Yes
District fixed effects	Yes
Observations	3,139
Adj. R-squared	0.975

Table A4: Unit roots test

The table presents results for the Fisher- Dickey-Fuller test for panel unit roots. The values in the parentheses represent the p-values. The null hypothesis suggests that the panel contains unit roots. Therefore, a p-value less than 0.05 suggests stationarity of the panels.

Variables	Inverse chi-squared (P) (1)	Inverse normal (Z) (2)	Inverse logit (L^*) (3)	Modified inv. chi-squared (Pm) (4)
PSB NPA	1435.35	-6.11	-6.08	4.00
	(0.001)	(0.00)	(0.00)	(0.00)
GVA Growth	3011.61	-25.50	-29.13	35.71
	(0.00	(0.00)	(0.00)	(0.00)
Overall Credit Growth	3436.89	-23.93	-30.82	44.27
	(0.00)	(0.00)	(0.00)	(0.00)
Indus. Credit Share	3786.46	-14.98	-28.39	51.30
	(0.00)	(0.00)	(0.00)	(0.00)
HH Credit Share	1371.22	14.46	13.49	2.72
	(0.004)	(1.00)	(1.00)	(0.003)