The anatomy of the Indian credit boom of 2004-2008

Ajay Shah*

December 10, 2015

Abstract

This paper documents the biggest bank credit boom in a quarter century in India, from 2004 to 2008, where industrial credit rose by 2.61 times. We examine the non-financial firms who borrowed from banks. The firms where bank credit surged during the credit boom appear to have superior credit quality when compared with the firms that did not. Credit assessment does not seem to have degraded during the boom. A matched difference-in-difference design shows that firm performance was not substantially inferior for the firms where bank borrowing surged during the credit boom. The internal validity of this analysis is, however, limited to older and smaller firms who were not in the fields of infrastructure and construction. The distress of Indian banking from 2013 onwards may, then, potentially be rooted in loans given in the boom years to younger firms, larger firms and firms in infrastructure and construction.

*I thank Josh Felman for numerous valuable discussions. I am grateful to Mohit Desai, Dhananjay Ghei and Pramod Sinha for excellent research assistance. This work was done under the aegis of the NIPFP-DEA Research Program.

Contents

1 Introduction

Bank credit booms have come to prominence in economic thinking of recent decades. Credit booms in emerging markets, where institutional quality is lower, may potentially have particularly harmful consequences. At the same time, in countries with a weak banking system and a significant scale of financial repression, financially constrained firms may benefit from increased access to capital in a credit boom. Empirical evidence is required to identify the overall outcome between these conflicting effects.

In this paper, we examine the biggest boom in bank credit in a quarter century in India. From 2004-05 to 2007-08, bank credit rose by roughly 15 percentage points of GDP. 'Industrial credit' expanded 2.61 times in this boom. Loans in one field, infrastructure and construction, expanded by 4.07 times, while the remainder of industrial credit expanded by 2.3 times.

By 2013, many indicators were showing that Indian banking was showing stress on questions of bad assets. This motivates a careful examination of the relationship between the loans given out in the credit boom and their downstream consequences. Many researchers have looked at credit booms using data about banks. In this paper, we undertake a careful examination of the non-financial corporations who borrowed from banks.

We form a large dataset of non-financial firms who are observed from 2004 to 2013. For each firm, we construct B as the ratio of bank borrowing in 2008 divided by bank borrowing in 2004, and focus on firms with above-median bank borrowing in 2004 so as to emphasise the large accounts who could influence bank fragility. While credit booms are sometimes viewed as generalised outbursts of euphoria on the part of banks and their borrowers, we find that for more than half the firms, bank borrowing *fell* in the period of the credit boom.

The analysis of firm characteristics within B quartiles shows that the credit quality of firms in the top quartile (i.e. the firms where bank credit surged the most in the period of the credit boom) was superior to the other firms. It does not appear that banks picked low quality borrowers at the time of the credit boom. This is borne out by regressions explaining B using firm characteristics, and by comparing the behaviour of banks in the boom years against their behaviour in the preceding normal years. It is hard to suggest that there was a broad-based decline in lending standards, in this dataset.

In order to understand the impact of large B values upon firm performance, we setup a research design where top quartile firms (by B) are matched against firms with below-median values of B. This permits a matched difference-in-difference design which can yield insights into various aspects of firm performance during and after the credit boom. Five alternative research designs are utilised, in order to avoid artifacts of any one methodology.

The matching process is quite successful in identifying paired treatment and control firms in the sense that there is good match balance. However, the firms in the matched dataset are small. The biggest firm has a firm size of Rs.10.85 billion. This is much smaller than the full universe of firms which has firms as large as Rs.933.9 billion. The matched dataset also has few firms from the field of infrastructure and construction, where the strongest credit boom took place.

The estimation results show that the firms who surged bank borrowing fared well from 2004 to 2008, but by 2013, the controls had caught up with the treated firms. By 2013, in some respects, it appeared that the high B firms were somewhat worse than the controls. The results are relatively benign.

How can these results be reconciled against the credit stress in Indian banking from 2013 onwards? We may conjecture that within the support of the matched dataset (i.e. older firms, firms of size below Rs.10.85 billion, and firms in industries other than infrastructure and construction), Indian banking fared reasonably well in making decisions about allocating credit. The problems may lie in the areas not covered in the matched dataset: infrastructure and construction firms, firms larger than Rs.10.85 billion and younger firms.

2 Credit booms and their consequences

In the aftermath of the global crisis of 2008, there has been increased interest in the phenomenon of credit booms. Aikman et al. (2015) show empirical facts about credit booms in the 1880-2008 period for advanced countries. They identify a 'credit cycle' where credit periodically rises substantially above trend, and show empirical facts about macroeconomic dynamics. Arena et al. (2015) identify credit booms in 135 developing countries over the 1960-2011 period. Credit booms are now seen as an important component of our understanding of financial systems and business cycles. Mendoza and Terrones (2008, 2012) identify credit booms in cross country data using systematic procedures, and conduct event studies to establish empirical regularities about macroeconomic aggregates and firm data. All these papers find systematic patterns interlinking credit booms, GDP growth, asset prices, firm leverage, and bank fragility.

While most financial crises are preceded by credit booms, not all credit booms are followed by financial crises. One strand of the literature has explored aggregative data examining different kinds of credit booms when placed under different kinds of initial conditions. Gorton and Ordonez (2015) document the differences between the two kinds of credit booms, and propose a simple model to explain the differences between the two kinds of booms.

Turning to microeconomic studies, the natural areas for examination are banks and the firms which borrow from banks in a credit boom. Do banks, their supervisors and their borrowers behave differently during a credit boom? Were lending transactions unjustified, with the benefit of hindsight? Coricelli et al. (2010) analyse firm data in emerging Europe, and find that TFP growth is increasing in leverage upto a threshold but not beyond.

While credit booms are important in developed countries, they are particularly important in emerging economies. Managed exchange rates, which are more common in emerging economies, are more likely to give credit booms. Weak banking regulation, which is more common in emerging economies, is likely to permit inappropriate lending in the environment of a boom, and also increase the welfare costs of dealing with a banking crisis. Weaknesses in the bankruptcy process, which are more prevalent in emerging economies, are likely to increase the losses for banks once bad loans have been given. Hence, it is important to study credit booms in emerging markets, and obtain insights which can help shape policy thinking into these questions.

A unique dimension in emerging economies is the relatively small size of bank credit when compared with GDP, and the relatively small role of banks in firm financing. If a substantial extent of financial repression is present, banks may face a constrained optimisation when lending to private firms. Many firms may be credit constrained. In such an environment, a credit boom may play a role of easing financing constraints, which could offset some of the effects of lax standards when lending in a boom.

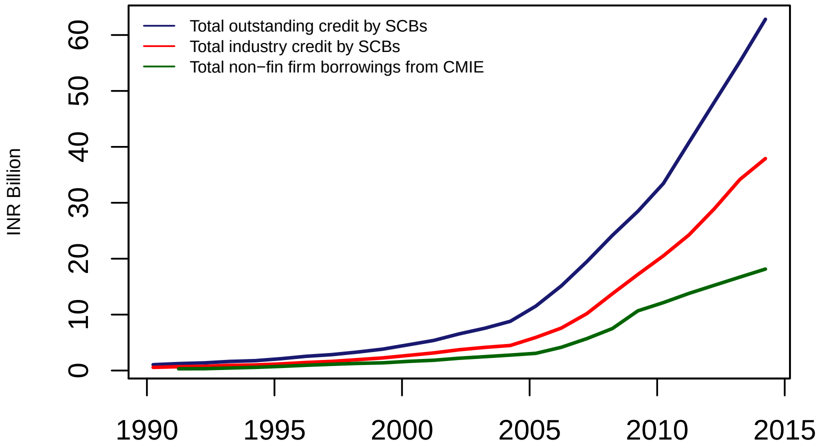
In this paper, we examine the credit boom in India, from 2004-2008, from the viewpoint of the *borrowing firms*. Using micro data, we identify firms who had a sharp expansion of bank credit. We ask three groups of questions:

1. What were the characteristics of the borrowing firms where bank credit expanded sharply during the credit boom?

2. Did banks exhibit lax lending standards in this lending?

Figure 1 Bank credit in India from 1990 onwards

This figure shows three time-sries. The uppermost line is the total lending of banks. The lower line is 'industrial credit' of banks as defined by us. The third line is the bank borrowings of large firms as seen in the CMIE database.



3. How did the firms which borrowed a lot during the credit boom fare, in the years after the boom, when compared with the firms that did not?

3 The credit boom of 2004-2008

In this paper, we focus on a subset of bank lending in India that we term 'industrial credit'.[1]

3.1 Identifying the dates of the credit boom

Figure 1 shows the three important time series of bank credit in India from 1990 onwards. In Figure 2, we display the year-on-year growth of industrial credit. The outstanding fact from this graph is that there were four years where industrial credit grew at a pace which was unlike the remaining 21 years. Based on this, we identify the years of the credit boom as running from 2004-05 to 2007-08.

[1]This is the sum of credit to 'Industry' as defined by RBI, credit to 'Transport operators', credit to 'Professional and other services' and credit to 'Trade'. This excludes lending to individuals, lending to agriculture including the Food Corporation of India.

Figure 2 Identifying the years of the credit boom

This figure shows the year-on-year growth of 'industrial credit' by banks, as defined by us. The 25th, 50th and 75th percentile values are shown as dashed lines. This suggests that there was a credit boom from 2004-05 to 2007-08; this period is shaded.

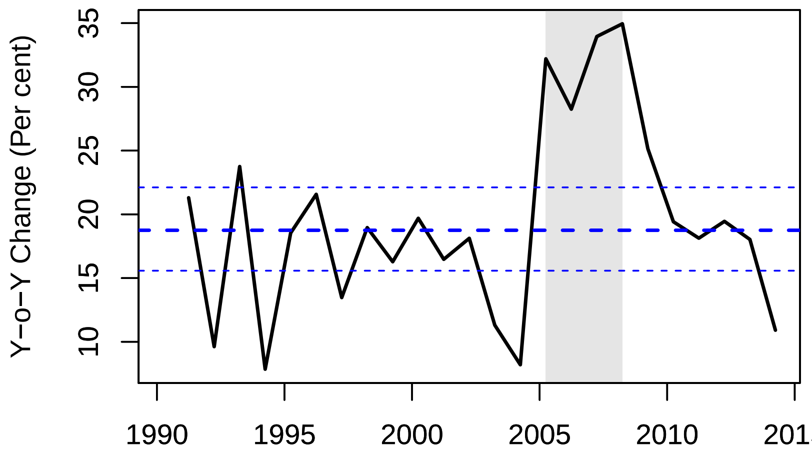


Figure 3 Industrial credit to GDP

This figure shows the time series of industrial credit to GDP. This surged during the credit boom from 2004-05 to 2007-08 (the shaded period); however the values are modest all through the time series.

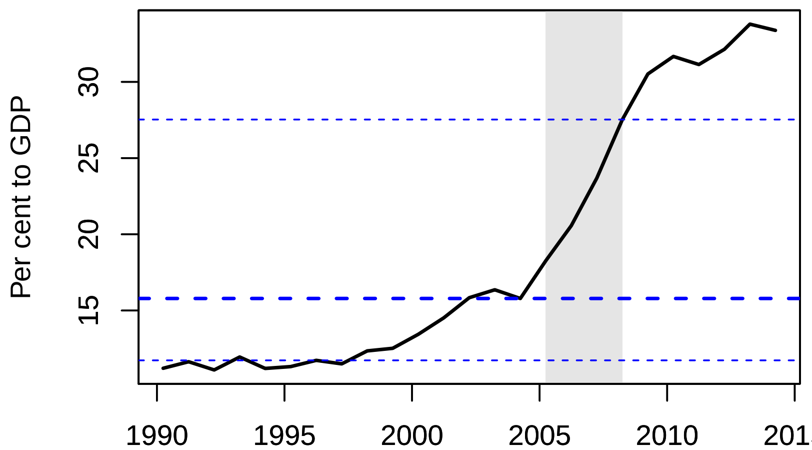


Figure 3 examines the time-series of industrial credit, expressed as per cent to GDP. A substantial increase is seen during the years of the credit boom. At the same time, the values seen are remarkably modest. This reflects a combination of the small size of bank deposits in India, and the system of financial repression through which banks are forced to lend to the government and to certain sectors.

3.2 The macroeconomic context of the credit boom

This analysis shows that there was a credit boom from 2004-05 to 2007-08.

It is useful to examine the stance of monetary policy in this period. Using the methods of Zeileis et al. (2010), India ran an inflexible exchange rate from 28 August 1998 to 16 March 2007.[2]

Patnaik (2005) shows that the implementation of this exchange rate regime induced a loss of autonomy of monetary policy, and low interest rates, a problem which only ended on 16 March 2007 when exchange rate flexibility went up sharply.

The calculations of Pandey and Patnaik (2015) suggest that there was a business cycle expansion from Q1 2003 to Q2 2007. Through the bulk of this period, there was a combination of exchange rate inflexibility and artificially low interest rates in a business cycle expansion.

This forms the macroeconomic backdrop for setting off the largest bank credit boom of the quarter-century. This setting also set off an inflation crisis, which began when headline inflation breached 5% in February 2006, and ran until 2014.

3.3 The credit boom at the level of the banking system

In the period of the credit boom, there was an important shift in the composition of bank landing, in favour of the field of lending to infrastructure and construction. This was a novel direction for banking in India, where such assets were previously not held on the books of banks to a substantial

[2]The structural breaks analysis using Zeileis et al. (2010) shows a first regime with an R^2 of the Frankel-Wei regression of 0.97 from 28/8/1998 till 19/3/2004. This was followed by $R^2 = 0.85$ till 16/3/2007. After that, exchange rate flexibility rose considerably until 2013, which is the period of analysis of this paper.

Table 1 The rise of infastructure and construction lending

In the aggregate, industrial credit by the banking system went up by 2.61 times in the credit boom. This was composed of a 4.07× increase in lending to infrastructure and construction, and a 2.3× increase in lending to other areas.

	2004	2008	B
	(Billion rupees)		(Times)
Infrastructure + Construction	573	2333	4.07
Other areas	2717	6250	2.30
Total industrial credit	3290	8583	2.61

extent. In the period of the boom, infrastructure and construction went up from 17% to 27% of industrial credit.

Figure 4 shows the year-on-year growth of stressed assets of the banking system. As is the case with most credit booms, in the boom years, banks appeared rather healthy. After the credit boom ended, stressed assets surged in the following years.

4 Identifying bank credit booms in firm data

In this paper, we examine the credit boom through an analysis of firm data. We use the CMIE database in order to obtain information about firms. In the years under examination, 57% of the industrial credit is in the firms visible in the database.

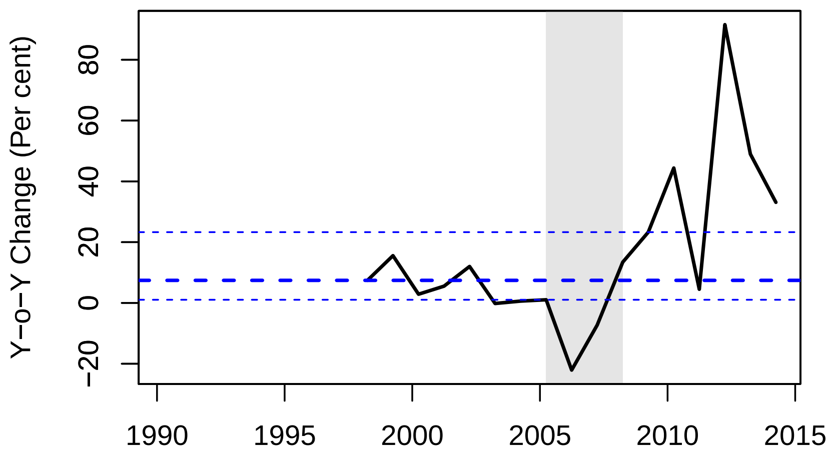
There are 14,500 non-financial firms in the database where assets, borrowings and net worth exceed Rs.10 million. For a firm i, we construct:

$$B_i = \frac{\text{bank borrowing}_{i,2008}}{\text{bank borrowing}_{i,2004}}$$

As an example, $B_i = 2$ is a firm i where bank credit doubled from 2004 to 2008. Many small firms have very large values for B. While there may be a substantial bank credit surge for these firms, these values are unlikely to matter on the scale of the overall health of the banking system. In order to stay focused on the macroeconomic phenomenon of the credit boom, we restrict our attention to the firms with bank borrowing in 2004 which was above the median value (of Rs.46 million). This gives a dataset of 2,519 firms where B is observed and the bank borrowing in 2004 was above median.

Figure 4 Year-on-year growth of stressed assets of banks

This figure shows the year-on-year growth of stressed assets of banks, defined as the sum of gross non-performing loans and the assets which went into 'corporate debt restructuring'. During the boom years (shaded), there were no difficulties on this score. After the credit boom, stressed assets have risen by as much as 80% in one year.



It is important to emphasise the selection bias that is inherent in the construction of this dataset. In order to measure B, we have to measure firms which existed in 2004. Young firms are excluded from this dataset. In order to measure the causal impact of large bank credit surges upon long term firm performance, we will exclude firms where data for 2012 and 2013 are not observed. This induces survivorship bias. The results of this paper thus pertain to the behaviour of banks in the context of older established firms, with an bias induced by the non-observation of firms that failed.

As an illustration, Table 2 shows the 25 firms with the highest B values. At the top is the GMR International Airport in Hyderabad, where B was 121.05. It is interesting to see no simple industry domination at this upper tail of the distribution of B.

Figure 5 shows the kernel density estimator of B. For a large number of firms, bank credit in 2008 was *lower* than that seen in 2004. While the modal value was near 1, there is an upper tail of very high values.

Table 2 The 25 firms with the highest B values

Blah

Company	Industry	B ratio
G M R HYDERABAD INTL. AIRPORT LTD.	Transport services	121.05
B S E S RAJDHANI POWER LTD.	Electricity distribution	112.00
ELECTROTHERM (INDIA) LTD.	Metals and metal products	104.06
JAI BALAJI INDS. LTD.	Metals and metal products	86.23
ERA INFRA ENGG. LTD.	Industrial and infrastructural construction	85.94
I L AND F S ENGG. AND CONSTRUCTION CO. LTD.	Industrial and infrastructural construction	77.76
SPENTEX INDUSTRIES LTD.	Textiles	59.39
RANBAXY LABORATORIES LTD.	Chemicals and chemical products	57.58
PURAVANKARA PROJECTS LTD.	Housing construction	54.19
GUJARAT N R E COKE LTD.	Coal and lignite	49.61
PARSVNATH DEVELOPERS LTD.	Housing construction	48.99
S B I GLOBAL FACTORS LTD.	Miscellaneous services	47.20
INDIAN POTASH LTD.	Wholesale and retail trading	46.90
TATA POWER CO. LTD.	Electricity generation	43.84
MAWANA SUGARS LTD.	Food and agro-based products	41.31
RUCHI WORLDWIDE LTD.	Wholesale and retail trading	38.31
KOUTONS RETAIL INDIA LTD.	Textiles	38.06
JET AIRWAYS (INDIA) LTD.	Transport services	37.55
KINGFISHER AIRLINES LTD.	Transport services	34.68
INDUS FILA LTD.	Textiles	32.79
POLYCAB WIRES PVT. LTD.	Machinery	32.40
DHARAMPAL SATYAPAL LTD.	Food and agro-based products	32.35
CORPORATE ISPAT ALLOYS LTD.	Metals and metal products	31.71
C C L PRODUCTS (INDIA) LTD.	Food and agro-based products	31.04
BANNARI AMMAN SPG. MILLS LTD.	Textiles	30.86

Figure 5 Density of B

B is bank borrowing by a firm in 2008 divided by its bank borrowing in 2004. The kernel density estimator shows that bank credit *fell* for a large number of firms in this period. While the modal value is near 1, a small number of firms have very large values.

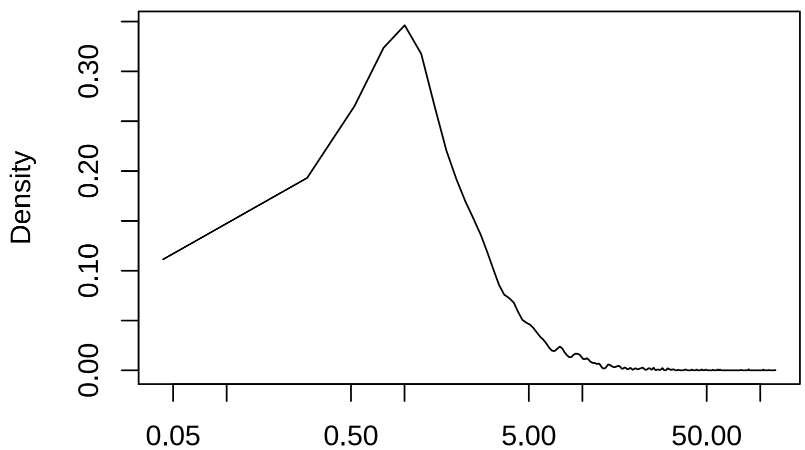


Table 3 Firm characteristics in 2004 by B quartiles

All firms are classified into quartiles based on their B value. The highest B values are placed in the 'High' quartile and the lowest B values are placed in the 'Low' quartile. Within each set, median values of certain firm characteristics are reported here. The 'High' quartile is not starkly dissimilar from the 'Low' quartile, and appears to show superior credit risk characteristics.

Variable	All firms	Low	Q2	Q3	High
Age (Years)	30.00	30.00	31.00	30.00	28.00
Size (INR Million)	831.00	741.90	782.10	840.70	940.85
Operating Profit Margin (Percent)	8.93	8.39	8.65	8.91	9.74
Debt/Total assets (Ratio)	0.41	0.45	0.43	0.41	0.38
Interest Cover (Ratio)	1.85	1.32	1.50	2.01	2.43
Exports/Sales (Ratio)	0.12	0.10	0.11	0.12	0.12
Liquidity (Ratio)	0.21	0.15	0.22	0.24	0.21

5 What was different about the firms where bank credit enlarged greatly?

Table 3 shows median values for firm characteristics in 2004, within B quartiles. This shows that B does not appear to vary by firm age. In terms of size, the top quartile by B is somewhat larger than the low quartile.

The credit risk of high B firms does not seem greater. The firms in the top B quartile had a higher operating profit margin, superior interest cover and better liquidity when compared with the bottom quartile.

In order to explore these firm characteristics of high B firms further, we estimate an OLS regression where B is on the left hand side and firm characteristics are on the right hand side. These results are shown in Table 4.

The impact of age is not statistically significant. There is a quadratic in log size which penalises very large firms. Firms with a higher return on capital employed are much more likely to increase bank borrowing. Enhanced levels of debt exerts a negative influence. Enhanced liquidity helps increased bank credit in model 2.

These estimates reinforce the idea that credit quality of high B firms was not inferior to those with lower B. Large surges of bank credit seem to have taken place for firms with higher profitability, higher liquidity. Even in an environment of the credit boom, when faced with a comparison between established firms with poor credit risk characteristics and established firms with healthier credit risk characteristics, banks appear to have favoured the

Table 4 OLS regressions with B on the left hand side: Credit boom period

For each firm, B shows the expansion of bank credit from 2004 to 2008. This table shows OLS regressions explaining B based on firm characteristics. Two variants are shown: using firm characteristics in 2004 and another using firm characteristics which are the median value from 2002 to 2004.

	Dependent variable:	
	Log change of B - ratio	
	(1)	(2)
Age	-0.003	-0.002
	$p = 0.130$	$p = 0.348$
Log Size	1.169^{**}	1.109^{**}
	$p = 0.034$	$p = 0.021$
Log Size Square	-0.082^{**}	-0.084^{**}
	$p = 0.040$	$p = 0.017$
ROCE	3.429^{**}	3.945^{***}
	$p = 0.019$	$p = 0.002$
Debt/Total assets	-0.951^{***}	-0.723^{**}
	$p = 0.005$	$p = 0.012$
Interest cover	0.024	0.049
	$p = 0.615$	$p = 0.232$
Liquidity	0.505	0.554^{**}
	$p = 0.108$	$p = 0.047$
Interest incidence	-0.001	-0.004
	$p = 0.961$	$p = 0.763$
Cash-flow generated from operations	-0.0003	0.0002
	$p = 0.247$	$p = 0.347$
Observations	796	1,050
R^2	0.133	0.144
Adjusted R^2	0.101	0.121
Residual Std. Error	0.991 (df = 767)	1.014 (df = 1021)
F Statistic	4.204^{***} (df = 28; 767)	6.152^{***} (df = 28; 1021)
Note:		*p<0.1; **p<0.05; ***p<0.01

latter.

6 Was bank behaviour in the credit boom different from that in normal times?

In order to assess how bank credit growth during the boom was unlike conventional times, we repeat the OLS regression for Table 4 (explaining B in the credit boom) with the identical specification in pre-credit-boom times. These results are shown in Table 5.

The results do not support the idea that banks are much more lax in their lending standards in a credit boom. In the older period, return on capital mattered more, but more leveraged firms seemed to get higher B, the interest cover did not matter, and enhanced liquidity seems to adversely affect B. If anything, banks seem to be more discriminating in the period with the credit boom.

7 How did the firms with large increases in bank credit fare in the following years?

We now take up the question about firm performance from 2008 to 2013, and how high B firms fared over this period. This was a period of macroeconomic turbulence, starting with the Lehman crisis of 2008 and ending with the Indian currency defence of 2013 (Patnaik and Shah, 2009-10; Shah, 2015). These phenomena would shape firm performance in substantial ways. Our research design proceeds through the following steps:

1. We identify a set of high B firms as the 'treatment' firms. These are the firms which took the treatment of large increases in bank credit.

2. We use matching techniques to identify controls which have similar firm characteristics as the treatment firms, using firm characteristics in 2004, i.e. at the start of the credit boom.

3. We setup a matched-difference-in-difference regression explaining firm performance in the future.

Within the constraint of matching on observables, this allows us to obtain a causal estimate of the impact of the treatment upon firm performance.

Table 5 OLS regressions with B on the left hand side : Pre-credit-boom period

For each firm, B shows the expansion of bank credit from 1999 to 2004. This table shows OLS regressions explaining B based on firm characteristics. Two variants are shown: using firm characteristics in 1999 and another using firm characteristics which are the median value from 1997 to 1999.

	Dependent variable:	
	Log change of B - ratio	
	(1)	(2)
Age	−0.001	−0.001
	$p = 0.703$	$p = 0.352$
Log Size	0.730	0.311
	$p = 0.114$	$p = 0.436$
Log Size Square	−0.045	−0.018
	$p = 0.188$	$p = 0.547$
ROCE	4.581***	4.120***
	$p = 0.00000$	$p = 0.00001$
Debt/Total assets	0.393	0.486**
	$p = 0.130$	$p = 0.042$
Interest cover	−0.063	−0.020
	$p = 0.187$	$p = 0.653$
Liquidity	−0.597**	−0.555**
	$p = 0.032$	$p = 0.022$
Interest incidence	0.016*	0.007
	$p = 0.093$	$p = 0.418$
Cash-flow generated from operations	−0.001**	−0.0003
	$p = 0.042$	$p = 0.269$
Observations	699	914
R^2	0.115	0.088
Adjusted R^2	0.077	0.058
Residual Std. Error	0.747 (df = 669)	0.757 (df = 884)
F Statistic	3.010*** (df = 29; 669)	2.927*** (df = 29; 884)
Note:		*p<0.1; **p<0.05; ***p<0.01

The matched difference-in-difference regression is setup as:

$$\Delta y_{i,t} - \Delta y_{j,t} = b_0 + e_{ij}$$

where, y is the firm characteristic of interest in year t; i is the treated firm and j is the matched control firm. In all cases, we show estimates for $\hat{b}_0$ from a robust MM-type estimator for the linear regression.

From the viewpoint of statistical methodology, it is possible to envision a simple observational econometrics strategy of regressing firm performance upon B and other covariates which influence firm performance. This approach would suffer from two limitations. First, there are nonlinearities and extreme values amidst the covariates; such regressions are often unstable with parameter estimates that change substantially across alternative specifications. Second, the lack of match balance between the treated and the control firms would imply that the regression is being used to extrapolate from observed values to unobserved values. Regression models work poorly with extrapolation. The advantage of our design is that the final matched difference-in-difference regression is just a regression of outcome on dummy variable, as there is good matching in a large number of covariates. The matching process is also useful in that it tends to eliminate influential observations which are unlikely to be a nearest neighbour in the matching process.

7.1 Research designs

In order to obtain more robust results, we establish four alternative research designs:

1. *Definition of treatment firms*: Top quartile by B.

   Control pool: Q1 and Q2 by B.

   Matching technique: Propensity score matching with the constraint that treatment and control have to be in the same industry.

2. Instead of using quartiles, we break the dataset into three tertiles. The top tertile are the treatment firms, and the bottom tertile are the control pool.

3. Instead of using propensity score matching, we use Mahalanobis distance matching in three dimensions: Log size, return on capital employed, and debt/assets.

4. Instead of using constrained matching within the same industry, we do matching without the constraint of the industry.
5. In the fifth variant, we combine two changes: the shift to tertiles instead of quartiles, and the use of unconstrained matching instead of within-industry matching.

In all cases, a caliper of 0.25 is employed to reject low quality matches. In all cases, observations with a propensity between 0 and 0.1, and a propensity between 0.9 and 1, are rejected. All our estimation will be done with four alternative research designs; hence we will obtain four estimates of each parameter of interest.

7.2 Description of the matched dataset for Research Design 1

In this section we undertake a detailed description of the matched dataset obtained under Research Design 1. Descriptions of the other three datasets are omitted in the interests of brevity, and are available from the author on request.

While we started with a very large dataset, Research Design 1 yields a matched dataset of 165 pairs of firms. Table 6 shows that the matching process is successful in removing the lack of match balance in the raw data. On the five covariates displayed, the distribution of the subset of firms is equal, between treated firms and the controls.

Sound match balance is achieved in all the other designs also. The details are available on request from the author.

It is important to emphasise that the results shown ahead are local estimates in the sense that they have validity within the support of the data. Summary statistics for the matched dataset are presented in Table 7, and the industry characteristics are presented in Table 8.

The matched dataset differs from the full database is in the industry composition. As Table 8 shows, the matched dataset is primarily comprised of firms in chemicals, textiles, food, metals, machinery and transport equipment. As Table 1 had shown, the strongest credit boom took place in the fields of infrastructure and construction. These are, largely, not represented in the matched dataset.

In terms of firm characteristics, Table 7 shows that the matched dataset is

Table 6 Match balance achieved through matching under Research Design 1

Under research design 1, the raw data shows substantial differences between treatment and control firms. The matched dataset has a high quality match balance, as evidenced by the standardised differences, and by the non-rejection of the null in the Kolmogorov-Smirnov tests.

Standardised differences

	Before Matching	After Matching
Propensity Score	0.86	0.01
ROCE$_{t-1}$	0.52	-0.04
Debt/Total assets$_{t-1}$	-0.20	0.07
Log(Size)$_{t-1}$	0.04	0.04
Asset Tangibility$_{t-1}$	-0.05	0.00

Kolmogorov-Smirnov tests for equality of distributions

	Before Matching	After Matching
Propensity Score	0.3667	0.0303
	(0)	(1)
ROCE$_{t-1}$	0.2681	0.0606
	(0)	(0.9223)
Debt/Total assets$_{t-1}$	0.1062	0.0788
	(0.0669)	(0.6851)
Log(Size)$_{t-1}$	0.0866	0.0848
	(0.2083)	(0.5925)
Asset Tangibility$_{t-1}$	0.0719	0.1091
	(0.4181)	(0.2799)

Table 7 Support of the matched dataset

Variable	Category	Mean	SD	Min	25th	Median	75th	Max
Age (Years)	All firms	35.90	19.64	10.00	23.00	30.00	42.00	152.00
	Matched	35.15	18.10	11.00	24.00	30.00	40.00	136.00
Size (INR Million)	All firms	4425.49	27948.50	20.10	348.70	800.60	2128.15	933910.60
	Matched	1639.46	2077.90	176.30	415.30	805.30	1981.10	10850.50
Op. Profit Margin (Percent)	All firms	-2.35	340.55	-12500.00	3.38	8.55	14.68	5450.00
	Matched	10.61	5.39	0.72	6.77	9.92	14.20	23.12
Exports/Sales (Ratio)	All firms	0.30	1.86	0.00	0.03	0.12	0.39	72.91
	Matched	0.21	0.20	0.00	0.04	0.14	0.31	0.71
Debt/Total assets (Ratio)	All firms	0.61	1.31	0.01	0.29	0.43	0.59	47.62
	Matched	0.40	0.12	0.17	0.31	0.40	0.49	0.73
Interest Cover (Ratio)	All firms	0.42	147.07	-6108.00	0.68	1.82	3.71	1508.76
	Matched	2.64	1.50	-0.45	1.50	2.25	3.39	7.28
Liquidity (Ratio)	All firms	0.20	0.27	-4.83	0.07	0.22	0.35	0.98
	Matched	0.26	0.12	-0.04	0.18	0.27	0.34	0.46

Table 8 Number of firms in each industry

Industry	Entire dataset	Matched pairs
Crude oil and natural gas	1	0
Irrigation	2	0
Coal and lignite	5	0
Electricity distribution	11	0
Minerals	12	0
Communication services	20	0
Information technology	39	0
Hotels and tourism	42	0
Electricity generation	43	0
Housing construction	48	0
Transport services	52	0
Diversified	60	3
Industrial and infrastructural construction	73	2
Consumer goods	80	3
Construction materials	85	4
Miscellaneous manufacturing	99	8
Miscellaneous services	117	1
Transport equipment	148	15
Wholesale and retail trading	171	4
Machinery	177	16
Metals and metal products	255	20
Food and agro-based products	286	19
Textiles	317	39
Chemicals and chemical products	376	31
Total	2519	165

Table 9 Impact on asset growth

The table shows the coefficient b_0 in the matched difference-in-difference regression across various time horizons and across the five different research designs. In all cases, the value in brackets is the p value.

	Design 1	Design 2	Design 3	Design 4	Design 5
2003	-0.011(0.67)	0.065(0)	-0.033(0.31)	0.004(0.84)	0.012(0.6)
2004	0.013(0.5)	0.019(0.37)	0.005(0.86)	0.032(0.07)	0.032(0.09)
2005	0.154(0)	0.167(0)	0.209(0)	0.159(0)	0.148(0)
2006	0.237(0)	0.236(0)	0.344(0)	0.216(0)	0.218(0)
2007	0.267(0)	0.265(0)	0.273(0)	0.26(0)	0.242(0)
2008	0.184(0)	0.151(0)	0.14(0)	0.161(0)	0.129(0)
2009	0.049(0.07)	0.064(0.03)	0.035(0.36)	0.058(0.01)	0.046(0.1)
2010	0.028(0.12)	0.018(0.5)	0.044(0.45)	0.005(0.82)	0.049(0.12)
2011	0.002(0.94)	0.043(0.22)	-0.053(0.44)	-0.029(0.28)	-0.008(0.77)
2012	0.017(0.47)	0.013(0.69)	0.039(0.2)	0.022(0.41)	0.061(0.11)
2013	-0.046(0.14)	-0.097(0.14)	-0.03(0.68)	-0.021(0.48)	-0.041(0.09)

about smaller firms, with size going out to a maximum of Rs.10.8 billion. The largest firms – with a size going all the way out to Rs.933.9 billion – are not found in the matched dataset.

These differences between the matched dataset and the overall database have important implications for the interpretation of the results. We have internal validity within the support of the data and not outside it.

7.3 Impact of large bank credit surges upon firm performance

For an array of measures of firm performance, we report the coefficient b_0 of the difference-in-difference regression. Each table is a compact presentation of only this one coefficient across various time horizons and across the five alternative research designs. All values shown in brackets are p values.

Table 9 shows that in terms of total assets, the treatment firms show substantially larger total assets from 2005 to 2008. All these coefficients are statistically significant, with a difference in log size as large as 0.264 in 2007. This is not surprising: firms that greatly expanded bank credit from 2004 to 2008 had larger balance sheets from 2005 to 2008. From 2009, however, this difference petered away. From 2010 onwards, statistical significance is lost and in 2013 the point estimate is negative (though the p value is only 0.14). By 2013, it appears that the controls, which did not grow bank credit

Table 10 Impact on gross fixed asset growth

The table shows the coefficient b_0 in the matched difference-in-difference regression across various time horizons and across the five different research designs. In all cases, the value in brackets is the p value.

	Design 1	Design 2	Design 3	Design 4	Design 5
2003	0.012(0.43)	0.014(0.4)	0.027(0.19)	0(0.99)	0.014(0.34)
2004	0.021(0.22)	0.045(0.01)	0.003(0.88)	0.054(0)	0.038(0.01)
2005	0.074(0)	0.084(0)	0.042(0.08)	0.061(0)	0.071(0)
2006	0.176(0)	0.133(0)	0.258(0)	0.156(0)	0.127(0)
2007	0.17(0)	0.157(0)	0.209(0)	0.194(0)	0.138(0)
2008	0.208(0)	0.197(0)	0.135(0.01)	0.172(0)	0.171(0)
2009	0.071(0)	0.069(0)	0.094(0.03)	0.087(0)	0.073(0)
2010	0.037(0.04)	0.049(0.02)	-0.023(0.59)	0.024(0.21)	0.018(0.16)
2011	0(1)	0.025(0.42)	0.053(0.43)	0.001(0.95)	0.005(0.81)
2012	0.02(0.15)	0.015(0.44)	0.023(0.79)	0.012(0.54)	0.013(0.55)
2013	-0.005(0.71)	0.015(0.43)	0.052(0.26)	-0.015(0.63)	0.023(0.46)

Table 11 Impact on sales growth

The table shows the coefficient b_0 in the matched difference-in-difference regression across various time horizons and across the five different research designs. In all cases, the value in brackets is the p value.

	Design 1	Design 2	Design 3	Design 4	Design 5
2003	0.039(0.24)	0.066(0.03)	-0.029(0.53)	0.031(0.39)	0.038(0.23)
2004	0.077(0.01)	0.073(0.01)	0.073(0.04)	0.082(0.01)	0.047(0.11)
2005	0.11(0)	0.123(0)	0.141(0)	0.142(0)	0.085(0)
2006	0.098(0)	0.179(0)	0.153(0)	0.117(0)	0.109(0)
2007	0.184(0)	0.181(0)	0.15(0)	0.163(0)	0.217(0)
2008	0.133(0)	0.124(0)	0.079(0.03)	0.079(0.01)	0.091(0)
2009	0.039(0.12)	0.054(0.12)	0.076(0.17)	0.057(0.05)	0.036(0.37)
2010	0.045(0.23)	0.032(0.41)	-0.016(0.83)	0.055(0.1)	0.03(0.4)
2011	0.022(0.53)	0.09(0.09)	0.083(0.46)	0.003(0.94)	0.079(0.05)
2012	-0.055(0.13)	-0.025(0.62)	-0.007(0.9)	-0.061(0.13)	-0.084(0.04)
2013	-0.022(0.56)	-0.046(0.36)	-0.002(0.98)	-0.022(0.63)	-0.028(0.62)

Table 12 Impact on operating profit margin

The table shows the coefficient b_0 in the matched difference-in-difference regression across various time horizons and across the five different research designs. In all cases, the value in brackets is the p value.

	Design 1	Design 2	Design 3	Design 4	Design 5
2003	-0.344(0.43)	-0.03(0.96)	-0.228(0.71)	-0.224(0.63)	0.287(0.58)
2004	-0.313(0.34)	0.247(0.46)	0.057(0.92)	-0.006(0.98)	0.342(0.31)
2005	-0.046(0.92)	0.794(0.13)	0.932(0.06)	0.458(0.17)	0.436(0.3)
2006	-0.234(0.45)	-0.694(0.06)	0.185(0.68)	-0.081(0.83)	0.15(0.77)
2007	1.009(0.01)	0.292(0.56)	1.205(0.07)	0.573(0.13)	0.021(0.96)
2008	-0.603(0.22)	-0.166(0.76)	-0.719(0.37)	-0.134(0.73)	-0.201(0.69)
2009	-0.745(0.19)	-0.328(0.53)	0.226(0.84)	-0.694(0.17)	-0.401(0.44)
2010	0.493(0.48)	0.58(0.4)	-0.21(0.79)	0.705(0.23)	0.156(0.73)
2011	-0.646(0.46)	0.173(0.88)	0.758(0.35)	0.286(0.68)	1.007(0.04)
2012	-0.451(0.58)	0.816(0.17)	0.862(0.37)	0.226(0.77)	0.268(0.69)
2013	0.289(0.68)	-0.781(0.31)	-0.541(0.59)	0.664(0.3)	-0.746(0.49)

Table 13 Impact on return on capital employed

The table shows the coefficient b_0 in the matched difference-in-difference regression across various time horizons and across the five different research designs. In all cases, the value in brackets is the p value.

	Design 1	Design 2	Design 3	Design 4	Design 5
2003	0.003(0.73)	-0.001(0.91)	0.012(0.29)	0.001(0.88)	0.006(0.34)
2004	0.005(0.23)	0(1)	0.002(0.69)	0.005(0.21)	-0.001(0.88)
2005	0.006(0.19)	0.01(0.08)	0.012(0.01)	0.008(0.05)	0.007(0.13)
2006	0(0.94)	0.003(0.61)	-0.006(0.45)	-0.005(0.34)	-0.006(0.35)
2007	-0.007(0.2)	-0.007(0.4)	0.001(0.95)	-0.012(0.02)	0(0.98)
2008	-0.015(0.01)	-0.017(0.02)	-0.018(0.05)	-0.016(0.01)	-0.011(0.2)
2009	-0.01(0.17)	-0.006(0.52)	0.005(0.55)	0(0.96)	0.003(0.68)
2010	-0.008(0.26)	-0.002(0.86)	-0.004(0.75)	-0.001(0.93)	0.003(0.75)
2011	-0.001(0.92)	0.005(0.65)	0.001(0.88)	0.01(0.13)	0.011(0.22)
2012	-0.015(0.13)	-0.023(0.08)	0.008(0.4)	-0.016(0.12)	-0.014(0.19)
2013	0.012(0.18)	0.017(0.3)	-0.019(0.3)	0.013(0.22)	0.001(0.95)

sharply in the credit boom, caught up with the treated firms.

The same pattern is seen with gross fixed assets (Table 10). The difference in logs is as large as 0.206 in 2008. The differences are significant for all years from 2005 to 2009. However, the difference petered away by 2011. By 2011, it appears that the controls caught up with the treated firms.

In terms of output, the treated firms had statistically significantly larger sales in all the years from 2004 to 2008 (Table 11). The difference in logs was as large as 0.183 in 2007. However, by 2010, the difference between the treated firms and the controls had petered out. In 2012 and 2013, the point estimates were actually negative.

Table 12 shows that the operating profit margin was superior for the treatment firms in 2007, with a difference of 1.068 percentage points. However, in most other years, point estimates were negative though not statistically significant. From the viewpoint of shareholders, the strategy of sharply increasing bank credit was not useful in terms of increasing the operating profit of the business.

In terms of return on capital employed (i.e. profit after tax expressed as per cent of equity capital), there was no year in which the treated firms did better (Table 13). There is one statistically significant point estimate, or -0.014, in 2008. From the viewpoint of shareholders, the strategy of sharply adding bank credit was not successful.

8 Conclusions

In the conventional wisdom, credit booms are a period where borrowers and banks embrace a certain optimism, and poor decisions are made all around. Most financial crises are preceded by a credit surge. There are significant problems with asset quality in Indian banking in 2015, and they appear to be related to improper credit risk decisions of the credit surge years.

In a setting like India, on one hand, we may expect banks and their supervisors to have low skills. At the same time, we may expect firms to face credit constraints, and hence obtain a substantial marginal product when bank capital becomes available in a credit boom.

The novel strategy of this paper is the examination of a large credit boom – the singular episode in the last 25 years in India – through information about non-financial firms who borrowed from banks. We identified a set of firms with very high B values, and a set of controls with similar characteristics with low B values. This permitted a matched difference-in-difference design to explore future firm performance.

The results are surprisingly muted. By 2012 and 2013, the firms which greatly added bank credit in the credit boom seem to do slightly worse when compared with their matched controls. What is surprising, however, is the extent to which the problems are muted.

It is important to understand the limited statements which can be made, based on this work. The analysis has internal validity in a certain class of firms: older and established firms, in traditional industries (i.e. largely not infrastructure or construction), with firm size of below Rs.10.8 billion in 2004. The analysis suggests that when faced with such borrowers, Indian banks fared reasonably well in making credit decisions, and their borrowers fared reasonably well in utilising the increased bank credit. Our analysis is likely to overstate the health of treatment firms, owing to survivorship bias, if it is the case that some high-B firms failed between 2008 and 2013.

The analysis indirectly sheds light on banks lending into a class of firms which are *not* present in this dataset. Younger firms are under-represented in the matched dataset which requires firms that are observed from 2004 to 2013. As emphasised in Table 1 in Section 3.3, the strongest credit boom was in bank lending to infrastructure and construction, where $B = 4.07$; these firms are significantly under-represented in the matched dataset. The difficulties seen in Indian banking today may be derived from lending which took place in the credit boom to infrastructure and constructions, and to young firms.

References

Aikman, David, Andrew G. Haldane, and Benjamin D. Nelson, "Curbing the credit cycle," *The Economic Journal*, June 2015, *125*, 1072–1109.

Arena, Marco, Serpil Bouza, Era Dabla-Norris, Kerstin Gerling, and Lamin Njie, "Credit booms and macroeconomic dynamics: Stylised facts and lessons for low income countries," Technical Report WP/15/11, IMF January 2015.

Coricelli, Fabrizio, Nigel Driffield, Sarmishta Pal, and Isabelle Roland, "Microeconomic implications of credit booms: Evidence from emerging Europe," Technical Report, EBRD October 2010.

Gorton, Gary and Guillermo Ordonez, "Good booms, bad booms," Technical Report, NBER June 2015.

Mendoza, Enrique G. and Marco E. Terrones, "An anatomy of credit booms: Evidence from macro aggregates and micro data," Technical Report 14049, NBER May 2008.

_ **and** _ , "An anatomy of credit booms and their demise," Technical Report 18379, NBER September 2012.

Pandey, Radhika and Ila Patnaik, "Dating business cycles in post reform emerging economies," Technical Report, NIPFP 2015.

Patnaik, Ila, "India's experience with a pegged exchange rate," *India Policy Forum*, 2005, pp. 189–226.

_ **and Ajay Shah**, "Why India choked when Lehman broke," *India Policy Forum*, 2009-10, *6.*

Shah, Ajay, "Lessons from the Indian currency defence of 2013," *Ajay Shah's blog*, June 27 2015.

Zeileis, Achim, Ajay Shah, and Ila Patnaik, "Testing, Monitoring, and Dating Structural Changes in Exchange Rate Regimes," *Computational Statistics and Data Analysis*, June 2010, *54* (6), 1696–1706.