Bank Entry, New Loans, and Misallocation*

Pavel Chakraborty† Nirvana Mitra‡

August 2024

Abstract

How do banking reforms affect the real economy? By utilizing a unique policy change regarding the entry of new domestic private and foreign banks in India, we examine its effect on manufacturing firms' credit received, performance, and misallocation using unique firm-bank matched data. We find robust evidence of *cherry-picking*: entry of new banks resulted in higher loans, but only for the big firms by 4.8–10%. More credit resulted in firm size expansion and improvements in physical or *within-firm* productivity with no change in allocative efficiency or *between-firm* allocation of resources, keeping them at least as constrained as before. Lastly, our counterfactual exercises show that entry of the new banks accounted for *at least* a 5–7% gain in overall manufacturing output. Our findings suggest that unilateral policy change can limit the effect if other reforms, such as incentives for banks to extend loans to small firms in our case, are not simultaneously undertaken.

Keywords: Banking Reforms, Domestic Private and/or Foreign Banks, Big Firms, Cherry Picking, Misallocation, Physical Productivity.

JEL Codes: G1, G21, O47, L25.

---

*We thank Marina Azzimonti, Gabriel Mihalache, Amil Dasgupta, Aprajit Mahajan, and all the seminar participants at Stony Brook University and 1st ABLE Workshop, Indian Institute of Management, Ahmedabad for their helpful comments and suggestions. We also thank Niranjan Kumar for his excellent research assistance.

†Department of Economics, Management School, Lancaster University, LA1 4YX, UK. Email: p.chakraborty1@lancaster.ac.uk

‡CAFRAL (promoted by Reserve Bank of India) & Shiv Nadar IoE. Email: nirvana.mitra@gmail.com. Disclaimer: Views and opinions expressed in this paper are solely the author's and may not necessarily reflect those of CAFRAL.

1 Introduction

Developing countries typically have inefficient public-sector banks resulting in high borrowing costs and limited access to finance for many firms.[1] And, opening up the banking sector to competition is often a proposed way of removing these supply-side constraints. Under the 1998 WTO services trade agreement (GATS – General Agreement on Trade in Services), India opened up its banking sector to both domestic private and foreign banks. We use this policy shift as a quasi-natural experiment to study the impact these new banks had on credit borrowing, performance, and aggregate misallocation of Indian manufacturing firms. We find that entry of the new banks resulted in higher volumes of borrowing and improvement in firm performance, but only for big firms. And, this increase in credit flow to big firms led to improvements in within-firm productivity with no impact on the overall allocation of resources.

There is little microeconomic evidence on the impact of financial liberalization in emerging market economies,[2] in our case introduction of new domestic private and/or foreign banks, on firm credit availability and performance, largely due to (a) data limitations – a significantly large proportion of studies are concentrated on high-income countries that have well-developed credit markets (Bertrand et al., 2007), and (b) the difficulty of isolating banking globalization from contemporaneous macroeconomic shocks (Goldberg, 2009). While there are a few macroeconomic studies that analyze the impact of an increase in competition in the banking sector on the domestic banks in emerging markets, little is known about their real impact.

India's commitment to the WTO for liberalizing the financial sector to allow entry for new domestic private and foreign banks came at a time when the initial waves of liberalization, which had already taken place in the early 1990s started to slow down (Gormley, 2010). **Figure 1** presents the districts in India with new domestic private and foreign bank branches at two different points in time. The left side of the figure shows the cumulative number of domestic private or foreign bank branches in Indian districts until 2000, while the right side shows a snapshot of the same in 2007.

The difference is noticeable and striking. The period between 2001 and 2007 saw

[1] A large proportion of firms in developing countries frequently report access to finance as one of the major impediments to their growth (Bloom et al., 2010).

[2] This is especially after or contemporaneous with the large-scale liberalization programs implemented in Asia and South America from the 1980s and 90s onward.

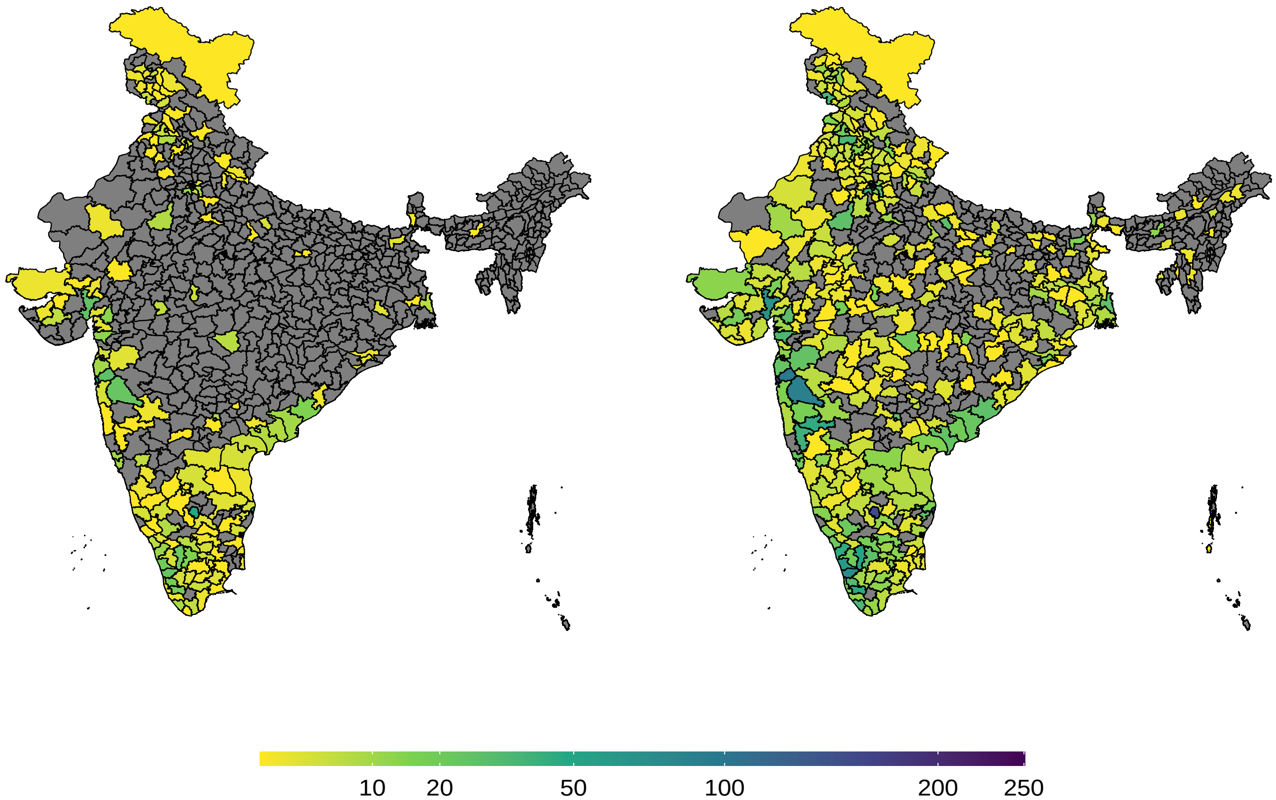
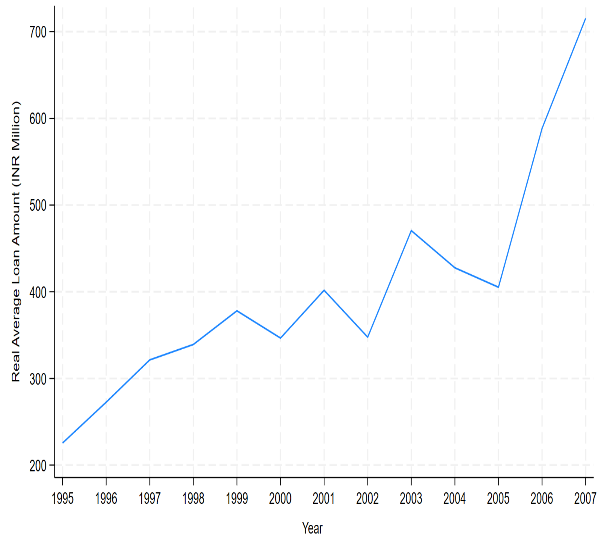


Figure 1: Domestic Private and Foreign Bank Branches, District Level, 2000 and 2007
Notes: The left panel shows the concentration of domestic private/foreign bank branches across Indian districts for the year 2000. The right panel shows the same for 2007.

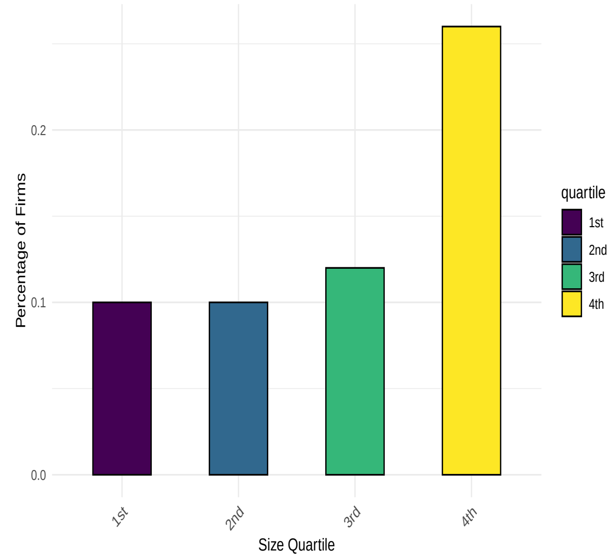
exponential growth in the number of new bank branches in India. In particular, between 1995 and 2000 the average number of bank branches (domestic private, and foreign) was around 150. Between 2001 and 2007, it increased to more than 1000. 12 new private banks and 1,100 new branches of those banks were added; on the other hand, 17 new foreign banks and 89 new foreign bank branches were opened. Therefore, it is the new domestic private bank branches that dominated the overall growth of new bank branches.[3]

To see whether this increase in the number of branches also led to a subsequent increase in the amount of borrowing or loans received by firms, we plot the average amount of borrowing done by firms from all banks in a given year in **Figure 2a**. Commensurate

[3]**Figure A.1** (**Appendix A**) plots the total number of bank branches opened in India across all the districts between 1995 and 2007. It shows a very similar picture.



(a) Total Real Borrowing



(b) Private/Foreign Banking Relationships

Figure 2: Total Bank Borrowing by Firms and Lending Relationships by Firm Size

with **Figure 1**, we find that the amount of borrowing by firms also increased significantly from 2000 onward.[4] However, this increase in the total amount of loans received may not be equitably spread out across the distribution of firms. The new entrants, in our case banks, could 'cherry-pick' their clients, because of a lack of 'soft information' (see Petersen & Rajan (1995) in the context of the U.S.), etc., among others.

Figure 2b plots the percentage of firms having credit relationships with new domestic private or foreign banks by different size quartiles over the period of 1995–2007.[5] The bar graphs clearly point out that as of 2007, 4th quartile or the big firms had the highest share of credit/banking relationships with newly opened domestic private and foreign banks – 26%. And, this average for any other quartile of firms is only about 10%.

These stylized facts pave the way for rigorous empirical investigation to find out the causal effect of the entry of new banks on firm level borrowing, performance, and overall misallocation. In order to carry out such an analysis, we exploit data at the firm-

[4]We run a simple unconditional correlation between the number of new bank branches (sum of domestic private and foreign) opened and average borrowing by firms in a given year in **Figure A.2**. Our plot shows a strong positive correlation between the two paving the way for a possible causal effect of the opening of the new bank branches on firm-level borrowing.

[5]Quartiles are defined according to the total assets of a firm. A firm whose total assets, between 1995–2007, are below the 25th percentile of the total assets of the corresponding industry, that firm belongs to the 1st quartile, and so on.

bank level. In particular, we exploit PROWESS which gives detailed information on the banking or credit relationships of each firm over time.

We use this information on firm-bank relations to construct a variable that takes value 1 if a firm enters into a credit relationship with at least one of the new domestic private and/or foreign banks given that (a) the firm had no previous relationship with that bank; and (b) the bank opened a new branch in that year. Therefore, our control group is the sample of firms who never had any relation with any of the new domestic private and/or foreign banks. However, these firms may have had banking relations with other private (domestic and foreign) and public-sector banks from before. Controlling for such prior relationships, our results show that firms, with relationships with new banks, experience about 5–10% increase in credit received which is around 2% of their assets. And, this finding is completely driven by firms belonging to greater than 75$^{\text{th}}$ percentile of the size distribution.[6] Our results are robust to several selection issues related to the firm characteristics, differential trends, industry, and region unobservables that may confound our estimates.

Our results imply that the introduction of the new banks (private and/or foreign banks) led to what the literature terms as *'cherry picking'* or *'cream skimming'*: A lending strategy that involves extending credit only to the wealthy and transparent segments of the credit market which are primarily the big firms (Detragiache et al. (2008); Beck & Peria (2010)) while excluding segments that comprise of less wealthy and/or marginal borrowers (Berger & Udell, 1998). In particular, Detragiache et al. (2008) in the context of developing countries point out that "countries with larger foreign bank presence have shallower credit markets." Other studies have also found that presence of new private banks (domestic and/or foreign) does not necessarily enhance overall credit availability and may aggravate the conditions of credit constraints rather than alleviating such constraints, mainly for the smaller firms (see Khwaja & Mian (2008) for Pakistan; Beck & Peria (2010) for Mexico; Gormley (2010) for India; Lin (2011) for China).

Having observed that entry of the new banks only increased the credit flow for big firms, we take a step further and examine whether this increase in the volume of credit for the big firms address the issue of resource misallocation in Indian manufacturing or

[6] Following Gormley (2010), we also check our findings at the district level. For the district level, we use a dataset compiled by the Reserve Bank of India, India's Central Bank (RBI, hereafter) to track the opening of all the new branches in a district and compare the amount of borrowing done by firms located in these districts to those where no new branches (of new private and/or foreign bank) were opened. Similar to our firm level finding we find the effect only for firms above the 75$^{\text{th}}$ percentile of the size distribution.

not. We answer this question using the misallocation accounting framework of Hsieh & Klenow (2009). Our measure of misallocation is not just confined to credit. It takes into account the misallocation of other inputs of production which might be affected indirectly through the credit channel. We first disaggregate the overall misallocation into capital and product market distortions. We then estimate them separately for each firm within their corresponding industry (at the 2-digit level), as a function of wedges relative to a frictionless economy. Our measure of misallocation, defined as the total revenue productivity (TFPR), is a combination of all the marginal revenue productivities of inputs (capital and labor in our case) to production.

In a world without misallocation, we would expect TFPR to be equated across firms within the same industry. Using the estimates of capital and product market wedges for firms, we find that although the marginal productivity of capital declined for those firms that established lending relationships with the new banks, the marginal productivity of labor, on the other hand, increased. This resulted in the TFPR distribution across firms to remain unchanged. In other words, the re-weighting of the capital and product market wedges led to a null effect in the allocation of resources. On the other hand, we find significant gains in physical productivity (TFPQ) for the big firms.[7]

We denote this increase in physical productivity as the *within-firm* effect of new banking relationships with no observed gains from reallocation, or the *between-firm* effect. Easier access to credit in an otherwise credit-constrained economy led to an increase in sales, value-added, use of inputs (raw materials, capital, labor), investments (tangible and intangible), and profits for those firms.

Lastly, we use our model to compute aggregate productivity, a combination of both physical productivity and allocative efficiency, which in turn is used to compute the aggregate potential gains in output, similar to Hsieh & Klenow (2009). Then, to find the contribution of entry of the new banks, we follow Bau & Matray (2023) and run a few counterfactual exercises. We find that the new banks are responsible for 5–7% of the overall gain in manufacturing output and these gains are realized when most of the new banking relationships are formed, that is, towards the end of our sample period.

Our findings are consistent with a model in which distortions in bank lending can create artificial barriers to entry in the real sectors of an economy (Sengupta, 2007).[8] We

[7] This may have further neutralized the possible gains, from reallocation of resources, among other firms by increasing the marginal productivities of both capital and labor proportionally for those big firms.

[8] Although our results point towards such direction, our dataset is not suitable to estimate firm entry

have two primary contributions. First, we add to the small literature on how the presence of new banks can lead to an increase in credit availability for firms (Bertrand et al. (2007); Sengupta (2007); Gormley (2010)). However, in our case, we show that such entries do not necessarily add to the increase in credit received for all firms, but only for big firms.[9] To our knowledge, we provide the first evidence of such a finding in the case of a large developing country using unique information on the banking relationships of firms. Our results also show that new banks led to an increase in the overall performance of firms.

Second, our results also contribute to the misallocation literature. A great deal of research has focused on aggregate measures of misallocation using the indirect approaches of Hsieh & Klenow (2009), Ziebarth (2013), Syverson (2004), etc. where the extent of misallocation within an economy is estimated without identifying its plausible sources. While these approaches have several analytical advantages, it does not inform us of the identification and mitigation of such sources which are of first-order concern, especially for low-income countries like India (Collard-Wexler et al. (2011), Kalemli-Ozcan & Sorensen (2014)). Using an alternative approach, Midrigan & Xu (2014) study the effect of financial frictions on misallocation. They find that such frictions make more productive firms switch to internal capital accumulation and therefore do not explain large TFP losses due to misallocation. Greenwood et al. (2010), Buera et al. (2011) and Banerjee & Moll (2010) also provide estimates of financial frictions that explain the extent of misallocation and the resulting loss in productivity.

We use the indirect accounting measure from Hsieh & Klenow (2009), but instead of studying financial frictions in general we use a policy experiment to study the effect of relaxing such financial constraints on misallocation.[10] However, unlike the standard Hsieh & Klenow (2009) framework, we are not worried about the distribution of revenue

and exit effects precisely (Goldberg et al., 2010).

[9] Our work is closest to Gormley (2010) who uses data at the district level for opening of new bank branches for foreign banks in India for the years 1994–2002 and show that the presence of new foreign banks led to an increase in loans only for big firms. We distinguish ourselves from Gormley (2010) in four key ways: (i) our study also investigates the entry of new domestic private banks along with the foreign banks giving a more holistic picture of the banking sector reforms as entry of foreign banks would only give a narrow portrayal of the overall effect of the banking reforms as highlighted by **Figure 1**; (ii) unlike Gormley (2010) we use detailed information on firm-bank credit relations to show that our findings at the firm level (for firms that form relationships with these new entrants) match with Gormley (2010)'s findings at the district level; (iii) unlike Gormley (2010), we find the discernible impact of the new banking relations on the performance of the big firms; and (iv) we show that banking reforms had a significant effect on reduction in capital market distortions and led to overall increase in manufacturing output.

[10] Our approach is not agnostic to the typical issues of measurement error that may bias estimates of misallocation (Bils et al. (2021), Rotemberg & White (2021), Gollin & Udry (2021)).

productivity for a cross-section of plants. We are interested in the changes in revenue productivity of each firm over time which precludes any bias due to measurement error. Similar to Bils et al. (2021) we also find only negligible effect on misallocation which reflects the purging of measurement errors, if any.

Our work is closest to Bau & Matray (2023) which focuses on foreign capital liberalization and its effect on manufacturing industries in India. We differ from them in the following ways: (a) for Bau & Matray (2023), foreign capital liberalization is measured through access to the foreign equity market, while we focus on entry of new banks into the domestic market; and (b) we use a different technique to estimate the market distortions using a monopolistically competitive setup and focus on firm level heterogeneity to credit access as the driving force for our results.[11] Most importantly, unlike us, they find that all the gains of foreign capital liberalization come from improved allocation and not from *within-firm* growth in physical productivity. To the best of our knowledge, our paper is one of the first that isolates the effect of banking sector liberalization and provides new evidence for its heterogeneous impact not only at the micro but at the aggregate level as well.[12]

One of our key findings which shows increase in *within-firm* productivity has its parallels to Bollard et al. (2013), who terms this as India's mysterious manufacturing growth puzzle, and argue this increase in growth does not stem from reduced misallocation. We show that the easing of credit constraints, because of the new banking relationships is one of the reasons for such a growth pattern. The sample period we use for our study also signifies other industrial reforms, such as de-licensing (Alfaro & Chari, 2014) and dismantling of product reservation for small-scale industries (Martin et al., 2017). While the former may have deterred bigger firms from growing further, the latter was a process of taking off support from smaller firms.[13] With such ongoing reforms as our background, it is not unlikely that a policy that aims at reduced capital market distortion can increase the marginal productivity of other inputs because of incomplete reforms, or reforms meant to achieve other targets. While this had triggered physical investment, it only had a neg-

[11] In addition, their sample period runs till 2015.

[12] Bolhuis et al. (2024) in a separate context for India analyzes the effect of land-market distortions on agricultural productivity. They find that these substantial differences across states in rental barriers has large negative effects on agricultural productivity. An efficient reallocation of land would increase agricultural productivity by 65% and by more than 100% in some states, with more than 50% of these effects attributed to those state level rental barriers.

[13] Allcott et al. (2016) show that firms in India faced a shortage of consistent power supply, which severely distorts production.

ligible impact on misallocation.

The rest of the paper is organized as follows: Section 2 describes the datasets we use and presents some stylized facts. Section 3 estimates the effect of the new banking relations on firm level borrowing or credit received and performance using firm-bank matched data. Section 4 addresses how the banking reforms affected the misallocation problem and Section 5 runs some counterfactual estimations to understand the contribution of these new banks on aggregate output. Section 6 concludes.

2 Data and Stylized Facts

In this section, we describe our different data sources and present summary statistics.

2.1 Data

Our data comes from two different sources. First, for our firm-bank level analysis, we draw our sample of firms from the PROWESS database, maintained by the Centre for Monitoring the Indian Economy (CMIE), a private agency. We use data for around 3,500+ manufacturing firms, for which there is consolidated data on banking relationships for the period 1995 to 2007.[14] Unlike other firm level data sources from India (especially where information from the 1990s needs to be used), PROWESS is a panel of firms, enabling us to study their behavior and banking relationships over time.[15]

The data is classified according to the 5-digit 2008 National Industrial Classification (NIC, hereafter) level and spans across 309 (5-digit 2008 NIC) dis-aggregated manufacturing industries that belong to 22 (2-digit 2008 NIC) larger sectors. It presents several features that make it particularly appealing for our study. We outline two of the most important features that are primarily needed for the paper: (i) information on banking relationships for each firm.[16] The data provides the names and the types of banks (domestic

[14]We have data till 2015, but we truncate it before 2008 to avoid the period of the 2008–09 financial crisis.

[15]Chakraborty (2024) has utilized this particular aspect (the firm-bank credit relationships) of the PROWESS dataset to show that bank ownership significantly matters for firms' export performance to which it is connected.

[16]The data provides information on 52 public-sector banks (including state-sponsored financial institutions), 88 private banks (including cooperatives), and 53 foreign banks. Additionally, it gives information on approximately 9000 private Non-Bank Financial Corporations (NBFC), 250 public-sector NBFCs, 173 foreign NBFCs, and 80 other small cooperative banks. This is according to the list of major banks (excluding

public-sector, domestic private, foreign) that a firm has a relationship with. An average representative Indian manufacturing firm has credit relationships with 3 banks. This is a bit higher for firms belonging to the top half of size distribution which has about 5;[17], (ii) details about a firm's borrowing.

It gives detailed information on different types of loans (from banks and/or private financial institutions) received by firms from different sources (domestic or foreign). For example, borrowing from banks, borrowings from domestic private financial institutions, etc.[18] We sum all the different types of loans received by a firm (from *banks* only) and use it as our main outcome variable of interest.[19]

Second, we use the NBER productivity database to estimate our measures of misallocation. It contains information at the industry level for value-added, employment, capital employed, etc. which are used to calculate the industry-time-specific factor shares. We match this dataset with our firm level dataset, PROWESS, at the industry level using concordance tables from the UN classification system. While there is no reason to believe that the factor shares for the U.S. are the same as of India, there are crucial reasons for using this database. First, it provides external validity of our results. Second, in our misallocation exercise, the identification of the wedges will depend on these factor shares. Since the factor shares themselves could be distorted due to misallocation, it is, therefore, crucial to use the same from a relatively less distorted economy as a benchmark. This way, the estimated wedges capture most of the distortions at the firm level.

2.2 Stylized Facts

We now present a few stylized facts using our matched firm-bank level data. **Table 1** reports the number of firms with and without credit relationships with new private

the state-sponsored financial institutions, and cooperatives) provided by India's central bank (popularly known as *Reserve Bank of India* (RBI, hereafter).

[17]However, despite all these advantages there is one potential limitation of this data that needs to be noted: there is no way to understand which bank is the main 'reference bank' for a firm. Therefore, we treat all the banks with equal importance.

[18]The borrowings are further divided into secured and non-secured borrowing. When a firm borrows money from a bank (public-sector or private or foreign) and provides them security in the form of some claim over assets in the event of a default, then such borrowings are termed as secured bank borrowings. A company may borrow from a single bank, several banks, or a syndicate of banks with some collateral; all of these are a part of secured bank borrowings. We only use secured borrowings for our purposes.

[19]Please note that we only observe the aggregate credit/loans for a firm. We cannot disaggregate them by respective banks.

and/or foreign banks and the median loans received by firms, across different size classes, based on their banking relationships. In particular, we compare firms who never had a banking relationship with any of the new private and/or foreign banks with firms who developed such a relationship with banks *after* they appear in the sample.

Table 1: Summary Statistics

	Firm-Bank Level	
	Added New Private and/or Foreign Banks	No New Private and/or Foreign Banks
	(1)	(2)
# of Firms	659	2,383
Bank Loans – All Sizes	48.18	16.61
Quartile 1	0.71	0.88
Quartile 2	3.80	2.21
Quartile 3	7.81	6.27
Quartile 4	79.47	44.28

Notes: Numbers reported are median loans (in Million INR) received by an Indian manufacturing firm.

Overall, 659 firms formed new private banking relationships compared to 2,383 who never form such a relationship. Overall, median loans received by firms that had banking relationships with new entrants are three times higher than firms that had no such relationships, i.e., Million INR 48 vs. 16, respectively. And, this is primarily driven by big firms. The median loans received by big firms are not only noticeably higher compared to big firms who did not, but also compared to other quartile of firms. For example, an average Indian firm belonging to the 3rd quartile of size distribution received one-tenth of what an average firm belonging to the 4th quartile received.[20]

[20]**Table B.1 (Appendix B)** outlines the number of districts (3-digit zip), loans they have received, and their assets according to two categories: (a) districts that received new private and/or foreign banks, and (b) districts with no private and/or foreign banks. For this analysis, we use spatial data on the details of new bank branches opened across India from RBI. We scrape the data for the new branch districts for the period 1995 to 2007 and match it with the information on the location of firms (3-digit postcodes) from our firm-level data. Loans received are higher in the districts that received a new domestic private and/or foreign bank.

3 Bank Entry and Access to Credit

3.1 Empirical Strategy

We now aim to examine whether the increased proliferation of new domestic private and/or foreign banks has had any effect on credit received by firms. We study this using information on banking relationships of firms. In particular, for our empirical analysis, we compare firms with new banking relationships with domestic and/or foreign banks with the ones that had no such relationships. In essence, we drop all such firms that had previous domestic private and/or foreign banking relationships. In addition, we also examine whether the credit received by firms varies by size or not. We use the following fixed effects OLS specification:

$$\text{Ln(Loans + 1)}_{it} = \beta \text{ New Bank Relation}_{i,t-1} + \theta \mathbf{X}_{it} + \alpha_i + \theta_{jt} + \epsilon_{it} \quad (1)$$

Loans is the total amount of secured loans received by a firm i at year t across all banking sources. We add one to loans to include observations with zero loans in our estimation. If we do not use zeros we will end up comparing only the firms that have positive amounts of loans. So, in essence, we put intensive and extensive margins together.

New Bank Relation$_i$ takes a value of 1 if a firm i forms a new credit relationship with one of the new domestic private and/or foreign banks given that the bank opened at least one new branch that year and zero otherwise. Our primary coefficient of interest is β – it measures the differential effect for firms given that it has entered into a new credit relationship with one of the new domestic private and/or foreign banks compared to firms which never formed such relationship. Therefore, it measures the relative effect of adding a new domestic private and/or foreign bank by a firm on total loans received in comparison to firms who never had any such relationship with the new domestic private and/or foreign banks. The firms in our comparison group either have relationships with public sector banks and other private (domestic and foreign) banks, or only have banking relationships with public sector banks.[21]

One of the major problems in estimating the true effect of *New Bank Relation*$_i$ is how the matching happens between firms and banks. There are several reasons why a bank(s) chooses a firm(s) or vice-versa. First, having a pre-existing credit relationship with a sim-

[21] A large proportion of firms in our dataset have a relationship with one public-sector bank.

ilar bank may drive the formation of this new relationship. In addition, firms receiving less credit/loans from other banks can also explain part of the new banking relationships created. To potentially control for all these, we use lagged *New Bank Relation*$_i$. A key assumption for our identification strategy to be valid is that the cross-sectional differences in forming relationship(s) with the new private and/or foreign bank(s) is driven by characteristics of these new banks, but uncorrelated with unobserved firm characteristics that can affect their credit demand and performance during the same period. Nevertheless, to control for such range of issues we interact few key firm characteristics, such as age, sales with *New Bank Relation*$_i$ and present our results; our benchmark results remain the same.

Second, credit relationships may form based on social and professional networks. For example, it may be the case that the CEO of a firm knows somebody in the top management of the bank (private and/or foreign) where it creates the new relationship. Therefore, to control for such type of issues we use firm fixed effects, α_i. Ioannidou et al. (2015) argues that firm fixed effects can only be used when firms have variation in banking relationships.

Overall, a representative Indian manufacturing firm has credit relationships with two different types of banks – domestic private and public-sector bank. About 36% firms have only links to private banks, 60% of firms have connection with only public-sector banks, 55% firms have connection to both, and 20% have connection to foreign banks. Therefore, such within firm variation of *New Bank Relation*$_i$ allows us to use firm fixed effects in our estimation. In addition, presence of firm fixed effects also controls for other unobservable firm characteristics that might influence a bank to choose a firm as its client (including level effects of multiple prior banking relationships). Khwaja & Mian (2008) and Jiménez et al. (2012) point out that once the firm fixed effects are controlled for, the key firm level characteristics that influence the loan demand has only a minor impact on the estimated coefficients.

Third, another important issue which can possibly bias our estimates while estimating the above equation is the issue of multiple banking relationships of firms, irrespective of the bank type(s). The mean and median number of banking relationships of an Indian manufacturing firm is 4 and 3, respectively. Restricting the data to firms with a single banking relationship would force us to drop around 80–85% of the observations leading to a potential loss in external validity. To deal with the multiple banking relationships of firms, we collapse the data to firm level. Please note that, our *New Bank Relation*$_i$ variable takes a value 1 when a firm *adds* one or more new private and/or foreign banks to its portfolio. So, in essence our estimates do not capture the effect of the total number of banking relationships of a firm, but captures an incremental effect. Since our data is at the firm-year level we cannot control for bank specific attributes that may influence a firm's access to loans, including firm-bank fixed effects. Following Petersen & Rajan (1995), we claim that firm-bank fixed effects only matter, for loans, if the banking industry is less concentrated.[22] In particular, we are interested, for our purposes, only in newly formed private banking relationships in a period of increased banking competition. Therefore, it is plausible to assume that firm-bank fixed effects are negligible and will not contaminate our estimates.[23]

Fourth, a related concern could be that the total number of banking relationships for a firm can change over time and drive our results. Therefore, using pre-period banking relationships (relationship with another bank and not the newly opened domestic private and/or foreign bank) for firms could bias our results in a certain way. In order to check whether banking relationships change, especially after the banking competition starts to intensify i.e., for the years 2000–2007, we calculate the mean, median, standard deviation for an average firm for all types of banking relationships, and separately for public-sector, and private banks in **Table B.2**. The numbers, across any type of banking relationship, do not change much over time thereby justifying our choice of using the pre-period banking relationship.

Fifth, different types of firms may choose to form new relationships with different kinds of banks, which is turn could drive how these firms are receiving more credit. **Table B.3** presents a frequency distribution of linkage by firm types for the post-banking competition years, 2000–2007. We divide our sample of firms into the following categories and present the median number of banking relationships for these types of firms over time – by industry (end-use category), by ownership, by age, and by size. While there are some obvious differences in the number of banking relationships by their size, such as big firms, especially above the median having higher number of relationships

[22]Petersen & Rajan (1995) point out that with increased banking competition, banking relationships are less valuable.

[23]Berger et al. (2005) argue that large banks with a complex organizational structure rely more on hard financial information for extending loans. The new domestic private and foreign banks are big banks with significant foreign equity holdings. We control for all the firm-specific information that may be of interest to the new banks to establish new relationships. More on this later.

than the rest – there is no systematic differences for any other category.[24]

Sixth, is there political influence on which firms banks can lend to and how much they can lend? This is unlikely as the process of newly-established domestic private and foreign bank branches was undertaken following India's 1994 commitment to the World Trade Organization (WTO) to allow for greater banking liberalization. As discussed before, entry of banks was also staggered. Even if such is the case (maybe for a handful of the firms), the interaction between firm characteristics with *New Bank Relation*$_i$ will control for such unobservables. In addition, banks can choose where they can open their new branches and location of firms can significantly drive this choice. In order to control for such types of unobservables, we use state fixed effects interacted *New Bank Relation*$_i$.

$\mathbf{X}_{it}$ is a vector of control variables at the firm level – age and age squared. Additionally, we use the interaction between industry and year fixed effects, θ_{jt}, to control for other simultaneous demand and supply side factors that may affect the access to credit for firms, such as any kind of subsidies given by the Indian Government towards any industrial sector, increase in demand for certain products leading to increased demand for credit, industry exposure of banks, etc. For example, some banks can choose to give credit only to certain set of industries, which can help the firms to have more access to them. We cluster our standard errors two-way – at firm and year level.

However, one should still be careful in interpreting the basic estimates as conclusive evidence of the causal effect of the new banking relationships, with new domestic private or foreign banks, on firm level credit because of the possible omitted variable bias. We address this by sequentially interacting different fixed effects, such as industry, state and its interaction with *New Bank Relation*$_i$ dummy to our baseline specification. These interactions would control for all possible kinds of banks' operational supply-side incentives, such as factors influencing a new private or foreign bank to open a new relationship with a firm who belongs to certain key industries and/or states, etc. Nonetheless, we first check for endogenous formation of new banking relations.

3.1.1 Endogeneity Checks

We do a series of endogeneity checks in **Table 2**. We start by showing that new banking relationships in period t are not driven by previous period firm characteristics,

[24] As discussed above, we also control for size-dependent banking relationships by interacting sales (a size indicator) with *New Bank Relation*$_i$.

such as loans received by firms or firm ownership, etc. Secondly, we also show that state characteristics in the initial period also did not drive the new relationships with firms who are located in those states where the new bank branches are opened. In essence, we use the following equation:

$$New\ Bank\ Relation_{i,t} = \pi\ X_{it-1} + \alpha_i + \theta_{jt} + \epsilon_{it} \tag{2}$$

where X is a vector of total loans received by a firm (previous loans issued may indicate the credit worthiness of a firm), total number of banking relationships of a firm (previous relationships may drive the formation of new relationships; for example bad experiences with public sector banks may incentivize firms to form new relationships with new banks), firm age (young firms may want to form relationships with new banks), economic conditions of the state where the new bank branches are opened, such as per capita NSDP (Net State Domestic Product), total grants received, etc.

All our specifications control for firm (α_i), and industry-year (θ_{jt}) fixed effects. In addition, the regressions on state level characteristics also use state fixed effects interacted with year trends. We cluster our standard errors at year level. All our coefficients indicate no statistical correlation between formation of new banking relationships and any of the previous firm and/or state characteristics.

3.2 Results

Table 3 reports the result for the amount of loans/credit received by firms due to new banking relations. **Panel A** does it at the aggregate level while **Panel B** checks for size heterogeneity. Overall our results show that there is no effect at the aggregate level, but when we divide firms by size, into four different quartiles, the entire effect is completely driven by firms belonging to 4th quartile or big firms. Our estimates show that relationships with new private and/or foreign banks aided firms, belonging to 4th quartile, to receive 1.8–10% more loans compared to firms with no relationships to new domestic private

Table 2: Endogeneity Checks of New Banking Relationship

	New Bank Relation$_{i,t}$					
	Firm Characteristics			State Characteristics		
	(1)	(2)	(3)	(4)	(5)	(6)
Loans Received$_{it-1}$	0.001					
	(0.004)					
No. of Banking Relations$_{it-1}$		–0.003				
		(0.007)				
Firm Age$_{it-1}$			0.025			
			(0.021)			
NSDP$_s$				–0.058		
				(0.072)		
Total Grants Received$_s$					–0.055	
					(0.071)	
Total Development Expenses$_s$						–0.125
						(0.154)
R-Square	0.66	0.76	0.66	0.08	0.08	0.08
N	13,815	13,815	13,804	11,774	11,774	11,774
Firm FE	✓	✓	✓	X	X	X
Industry FE (2-digit) × Year FE	✓	✓	✓	✓	✓	✓
State FE × Year Trends	X	X	X	✓	✓	✓

Notes: We use *New Bank Relation* as the dependent variable. It represents when a new credit relationship with a new domestic private and/or foreign bank. In particular, it takes a value of 1 if a new relationship with a new domestic private, and/or foreign bank is formed by firm i in year t and 0 otherwise. *Loans Received$_{it-1}$* is the natural logarithm of the amount of loans received by a firm i at period $t-1$. $No.of\ Banking\ Relations_{it-1}$ is the total number of banking relationships of firm i at year t. This is sum of public and private banks. *Fimr Age$_{it}$* is the natural logarithm of a firm age. $NSDP_s$ is the natural logarithm of the Net State Domestic Product of a state s. *Total Grants Received$_s$* is the natural logarithm of total grants received by a state s from Central Govt. *Total Development Expenses$_s$* is the natural logarithm of total expenditure made by a state s towards development objective. Intercepts are not reported.

and/or foreign banks.[25]

We start by controlling only for firm and industry-year fixed effects in column (1). Our diff-in-diff estimate shows that firms which formed relationships with new domestic private and foreign banks received 10% more loans than other firms which never had such relationships. Column (2) introduces firm controls – age and age squared. We do not find any difference in our estimate.

[25]For our quartile level regressions we use the following equation:

$$\text{Ln(Loans + 1)}_{it} = \sum_{q=1}^{4} \beta_q(\text{New Bank Relation}_{i,t-1} \times Q_q) + \theta \mathbf{X}_{it} + \alpha_i + \theta_{jt} + \epsilon_{it} \tag{3}$$

These β_q's measure the differential effect for firms belonging to that particular size quartile given that it has entered into a new relationship with one of the new domestic private and/or foreign banks or not.

Table 3: Banking Competition and Loans Received: Firm Level Analysis

	Ln(Loans + 1)							Ln(Loans/Assets)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Aggregate								
New Bank Relation$_{i,t-1}$	0.032	0.032	0.031	–0.005	0.013	0.013	0.019	0.006*
	(0.023)	(0.023)	(0.023)	(0.024)	(0.019)	(0.020)	(0.023)	(0.003)
R-Square	0.96	0.96	0.96	0.96	0.96	0.96	0.97	0.82
Panel B: Size Heterogeneity								
New Bank Relation$_{i,t-1}$ × *Quartile*$_1$	0.084	0.088	0.093	0.062	0.107	0.092	0.149	0.022
	(0.071)	(0.074)	(0.076)	(0.077)	(0.106)	(0.119)	(0.142)	(0.024)
New Bank Relation$_{i,t-1}$ × *Quartile*$_2$	–0.023	–0.022	–0.023	–0.013	–0.047**	–0.039	–0.089	–0.008
	(0.019)	(0.019)	(0.020)	(0.032)	(0.024)	(0.034)	(0.075)	(0.006)
New Bank Relation$_{i,t-1}$ × *Quartile*$_3$	–0.047	–0.046	–0.047	–0.035	–0.071*	–0.042	0.010	–0.004
	(0.041)	(0.039)	(0.039)	(0.053)	(0.040)	(0.045)	(0.057)	(0.006)
New Bank Relation$_{i,t-1}$ × *Quartile*$_4$	0.100**	0.099**	0.097**	0.039***	0.085**	0.062**	0.048*	0.018**
	(0.047)	(0.047)	(0.046)	(0.011)	(0.040)	(0.030)	(0.030)	(0.009)
R-Square	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.81
N	7,685	7,685	7,681	5,471	7,652	6,928	6,194	6,928
Firm Controls	X	X	✓	✓	X	X	X	X
Control for Public Bank	X	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE (2-digit) × Year FE	✓	✓	✓	✓	✓	✓	X	✓
Firm Controls × *New Bank Relation*$_{i,t}$	X	X	X	✓	X	X	X	X
Industry FE (2-digit) × *New Bank Relation*$_{i,t}$	X	X	X	X	✓	✓	X	✓
State FE × *New Bank Relation*$_{i,t}$	X	X	X	X	X	✓	✓	✓
Industry FE (5-digit) × Year FE	X	X	X	X	X	X	✓	X
Industry FE (5-digit) × *New Bank Relation*$_{i,t}$	X	X	X	X	X	X	✓	X

Notes: All the regressions are for the years 1995–2007. Columns (1) – (7) use logarithm of total loans received by a firm plus 1 as the dependent variable. Column (8) use logarithm of total loans received as a ratio of the total assets of a firm. *New Bank Relation*$_{i,t}$ takes a value 1 when a firm i forms a new credit relationship with a domestic private or foreign bank branch year t. We use *New Bank Relation*$_{i,t-1}$ as a proxy for *New Bank Relation*$_{i,t}$ to control for the potential endogeneity due to selection issues. Quartiles $Qr_{i=1,2,3,4}$ are defined according to the total assets of a firm. Firm Controls include age and age squared of a firm. Loans are corrected for inflation. Standard errors in parentheses are clustered two-way at the firm and year level. Intercepts are not reported. * , **, *** denotes 10%, 5% and 1% level of significance, respectively.

Next, in column (3), we control for credit relationships of these firms with public-sector banks. A crucial factor which can play an important role in the credit access of a firm is its relationship with other *type(s)* of bank(s) – the public-sector banks in our case. 81% of all the firms in our sample have pre-existing relationship with public-sector bank. Maintaining credit relationships with public-sector banks is ubiquitous in India owing to some level of social skepticism towards the private banks. Credit relationships with public-sector banks are also common across all firm types, irrespective of their financial health. On the other hand, omitting this variable can also create an upward bias in our estimates. We therefore, use a variable which takes a value 1 if a firm has an existing relationship with a public-sector bank and/or adds a public sector bank in its banking portfolio in year *t* and 0 otherwise and interact it with our quartile dummies. Our coefficients did not change – big firms continue to receive 9.7% more loans from new private and/or foreign banks.

Column (4) controls for different firm characteristics that may affect the amount of credit received by firms. Even though we control for firm fixed effects, our estimates could still be affected due to the following problem: domestic private and/or foreign banks may lend to firms by observing their fundamentals, such as age, sales. To control for such issues, we interact two key firm characteristics, size (measured through average real sales between 1995–2000) and age with $New\ Bank\ Relation_i$. The coefficient of interest, which is the coefficient for firms belonging to fourth quartile, continues to remain positive and significant.

Columns (5) and (6) in addition interacts our treatment variable $New\ Bank\ Relation_i$ with industry and state fixed effects, respectively; column (7) estimates the required effect at the most dis-aggregated level possible, which is 5-digit industry level; column (8) controls for size by using the ratio of loans received to total assets of a firm as the outcome variable of interest. In all these cases, our benchmark finding continues to hold. Big firms, which had relationships with new private and foreign banks, received about 1.8–10% more loans than firms which did not have any such relationships. These results indicate strong evidence of cherry-picking or cream-skimming by the new domestic private and/or foreign banks in India (Gormley (2010); Sarma & Prashad (2014)).

Even though we control for all possible demand and supply side factors to establish a causal effect of banking reforms on credit received, one problem could still plague our results: credit received by firms with new domestic private and/or foreign bank branches may be on different trends before forming relationship with new banks compared to firms with no new relations.

To tackle this problem, we interact year fixed effects with $New\ Bank\ Relation_i$ and plot the yearly coefficients for all firms and firms belonging to fourth quartile in **Panels A** and **B** of **Figure 3**, respectively. We plot the coefficients of credit received by firms for 5 years preceding and 5 years after the formation of a new credit relationship with domestic private and/or foreign bank. And, these coefficients are plotted relative to the year when a new banking relation started. So, in essence, our coefficient plot is a staggered event-study plot. Our control group continues to remain the same – firms with no relationships with new banks. Likewise our results from the regressions, the overall effect is significantly driven by fourth quartile of firms with little pre-trends before a relationship is formed with a new domestic private and/or foreign bank.[26,27,28]

3.2.1 Industry and Firm Characteristics

Our findings regarding the size effect of higher credit received due to entry of new banks may be masking other types of heterogeneity, such industry and firm characteristics. For example, our indicator for fourth quartile of firms may be acting as a proxy for R&D-intensive industries where firms across the size distribution may have got more loans than non R&D-intensive industries. Similarly, for the export-intensive and non export-intensive industries. It could also be that all firms which have high financial leverage received more credit than firms with low financial leverage and our aggregate results conceal the true reason behind why fourth quartile of firms received more loans.

To explore whether it is only the size of a firm that is playing a crucial role or there are other industry and/or firm characteristics that can also explain our findings we slice our data into five key industry characteristics, such as R&D intensive, export intensive, high external dependence on finance, downstream industries (as India has a comparative advantage in such industries), skill intensive and three key firm characteristics such as high financial leverage, listed in major stock exchanges of India, and Business Group firms. We present our results in **Table 4**.

[26] **Figure A.3** do the coefficient plots separately for all the other three quartiles of firms. We do not find any pattern for all the other three quartiles of firms.

[27] **Figure A.4** checks the robustness of the results for the fourth quartile of firms by plotting the yearly coefficients in two different ways. In **Panel A**, we drop all the covariates from the regression to avoid any sort of correlation between the covariates and our outcome variable of interest; in **Panel B**, we use a different control group. In particular, we substitute firms that never forms a new relationship with a new private and/or foreign bank with firms that are in the first quartile of the distribution of forming new bank relations as the control group. In both cases, the yearly coefficients remain the same as **Panel B** of **Figure 3**.

[28] Gormley (2010) show that opening of new foreign bank branches in different districts of India resulted in higher amount of loans received by big firms located in those districts. As an additional check, we extend his exercise by including new domestic private along foreign banks opened in those districts and its effect on the amount of credit received by firms. Results remain the same as the firm level – only the fourth quartile of firms received credit (results available on request). We repeat the event study plots for all firms and firms of the fourth quartile in **Figure A.5**.

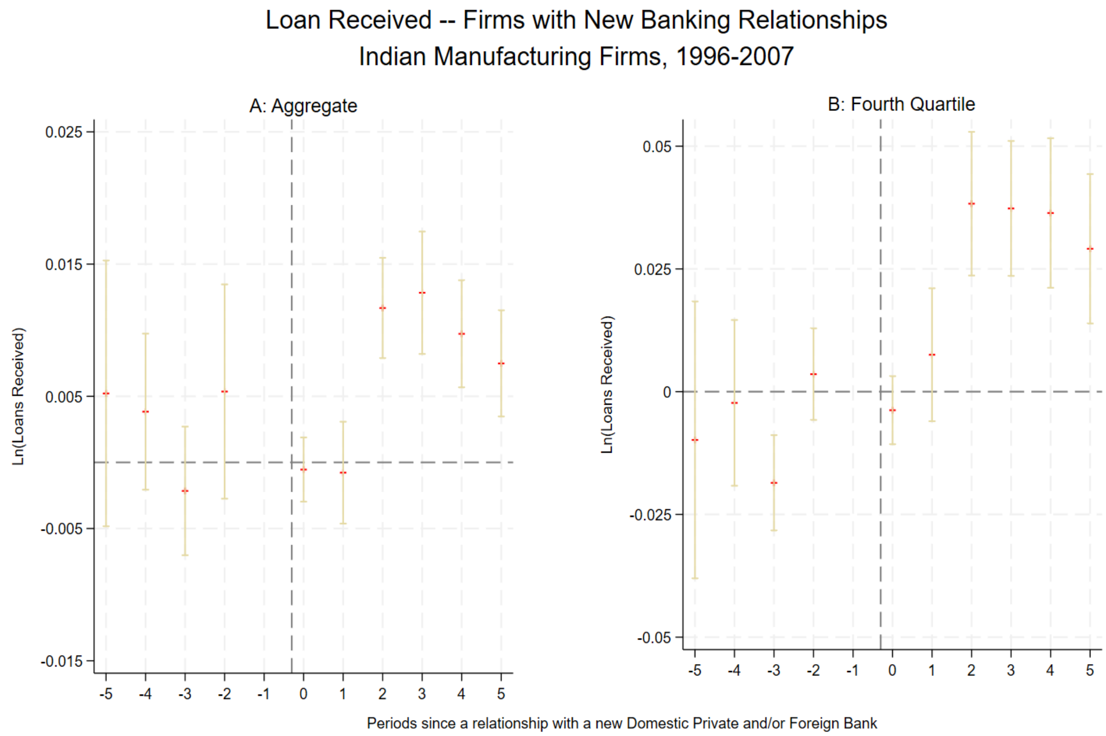


Figure 3: Loans Received – Aggregate and 4th Quartile Firms with New Relationships
Notes: The coefficient plots represent the differences in the amount of loan received by firms both at the aggregate level and 4th quartile of firms when forming new banking relationships with a new domestic private and/or foreign bank compared to firms which did have any relation with a new domestic private and foreign bank throughout all the years of our sample. In effect, we plot a staggered differences-in-differences graph as different firms formed new credit relationships with new domestic private and foreign bank branches at different points in time. Our coefficient estimates are controlled for covariates (age and age-squared of a firm) firm, industry-year fixed effects, and public-sector bank branch trends. Standard errors clustered at the year level.

We classify an industry as R&D intensive if the initial (between 1995–1998) R&D expenditure of that industry (at the 4-digit level) is greater than the median R&D expenditure of the manufacturing sector. Similarly for export intensive, externally dependent on finance (using Rajan & Zingales (1998) index), downstream industries (where we use Antràs et al. (2012) index), skill intensive (= ratio of non-production workers to total employees). As for high financial leverage, if the average tangible net worth of a firm is greater than than median tangible net worth of the corresponding industry that firm is identified as a high leverage firm. Lastly, PROWESS gives information on if a firm is listed in at least one of the major stock exchanges of India and whether a firm belongs to a Business Group or not. In all of the cases (across industry and firm characteristics) where we find significant effects, the effect is visible only for the fourth quartile of firms

Table 4: Banking Competition and Access to Credit: Firm Level Analysis – Industry and Firm Characteristics

	Ln(Loans + 1)							
	Industry Characteristics					Firm Characteristics		
	R&D Intensive	Export Intensive	External Fin Dep	Down-stream	Skill Intensive	High Fin Leverage	Listed	Business Group
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
New Bank Relation$_{i,t-1}$ × *Quartile*$_1$	–0.010	–0.030	0.322	0.116	0.173	0.080	0.006	–0.006
	(0.020)	(0.024)	(0.199)	(0.124)	(0.144)	(0.135)	(0.065)	(0.065)
New Bank Relation$_{i,t-1}$ × *Quartile*$_2$	–0.017	–0.020	–0.026	0.017	0.007	–0.027	–0.028	–0.012
	(0.021)	(0.022)	(0.022)	(0.020)	(0.017)	(0.017)	(0.027)	(0.041)
New Bank Relation$_{i,t-1}$ × *Quartile*$_3$	0.018	0.005	–0.076	–0.021	0.014	–0.042	–0.040	–0.099
	(0.047)	(0.046)	(0.056)	(0.033)	(0.019)	(0.073)	(0.059)	(0.070)
New Bank Relation$_{i,t-1}$ × *Quartile*$_4$	0.064	0.130*	0.136**	0.099**	0.163**	0.161***	0.137**	0.130**
	(0.045)	(0.069)	(0.052)	(0.047)	(0.067)	(0.060)	(0.062)	(0.055)
R-Square	0.95	0.95	0.95	0.96	0.96	0.95	0.96	0.95
N	3,780	4,346	4,884	3,072	4,193	4,762	4,028	3,561
	Not R&D Intensive	Not Export Intensive	Not External Fin Dep	Up-stream	Not Skill Intensive	Low Fin Leverage	Not Listed	Stand-alone Private
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
New Bank Relation$_{i,t-1}$ × *Quartile*$_1$	0.041	0.238	–0.026*	0.115	0.029	0.032	0.187	0.043
	(0.229)	(0.171)	(0.016)	(0.124)	(0.022)	(0.093)	(0.119)	(0.058)
New Bank Relation$_{i,t-1}$ × *Quartile*$_2$	–0.047	–0.027	–0.025	–0.039	–0.022	–0.014	–0.013	–0.018
	(0.026)	(0.020)	(0.026)	(0.052)	(0.029)	(0.026)	(0.017)	(0.019)
New Bank Relation$_{i,t-1}$ × *Quartile*$_3$	–0.099	–0.092	0.030	–0.022	–0.011	–0.020	–0.060	0.004
	(0.068)	(0.058)	(0.062)	(0.033)	(0.065)	(0.018)	(0.037)	(0.032)
New Bank Relation$_{i,t-1}$ × *Quartile*$_4$	0.044	0.067**	0.010	0.099**	0.029	–0.009	0.019	–0.011
	(0.055)	(0.034)	(0.052)	(0.047)	(0.034)	(0.032)	(0.036)	(0.046)
R-Square	0.96	0.96	0.95	0.95	0.95	0.96	0.95	0.96
N	3,609	3,382	2,834	3,044	2,987	2,962	3,663	4,096
Control for Public Bank	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE (2-digit) × Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: All the regressions are for the years 1995–2007. Columns (1) – (16) use logarithm of total loans received by a firm plus 1 as the dependent variable. $NewBankRelation_{i,t}$ takes a value 1 when a firm i forms a new credit relationship with a domestic private or foreign bank branch year t. We use $NewBankRelation_{i,t-1}$ as a proxy for $NewBankRelation_{i,t}$ to control for the potential endogeneity due to selection issues. Quartiles $Qr_{i=1,2,3,4}$ are defined according to the total assets of a firm. Loans are corrected for inflation. Standard errors in parentheses are clustered two-way at the firm and year level. Intercepts are not reported. *, **, *** denotes 10%, 5% and 1% level of significance, respectively.

thereby suggesting that size continues to play a crucial role in explaining the amount of credit received by firms due to new banking relationships.

3.3 Selection Bias

Even though our firm-level estimations control for the presence of public banks in the overall banking relationships of firms, the above estimations may still be biased due to selection effects.[29] In particular, initial relationships with public-sector banks, especially for big firms, can also drive the formation of these relationships with the new domestic private and/or foreign banks. It could be possible that the credit supply from the public-sector banks falls short of the overall credit demand for those firms, and this forces the firms to form relationships with the newly opened banks to meet the remaining demand for credit. Or the firms may want to diversify their credit portfolio as the price of the loans from public-sector banks was unsuitable. If these are the reasons, relationships with public-sector banks will then result in a lower amount of the loan received. To check whether such is the case or not, we estimate the following placebo specification:

$$\text{Ln(Loans + 1)}_{it} = \beta \text{Prior–Rel Govt. Bank}_{i,t-1} + \theta \mathbf{X}_{it} + \alpha_i + \theta_{jt} + \epsilon_{it} \tag{4}$$

$Prior - Rel\ Govt.\ Bank$ indicates whether a firm had prior credit relation with atleast one public-sector bank before it forms a relationship with a new domestic private and/or foreign bank. It takes value 1 if firm i in year t had any prior credit relation with atleast one public-sector bank and 0 otherwise. The rest of the specification continues to the same as before. If there is no selection bias, we expect β to be equal to 0.

Table B.3 presents the required results. Column (1) uses firm and industry-year fixed effects and interaction of industry fixed effects with $Prior - Rel\ Govt.\ Bank$; column (2) adds firm controls to this specification; column (3) introduce interactions of state fixed effects and $Prior - Rel\ Govt.\ Bank$; column (4) in addition interacts $Prior - Rel\ Govt.\ Bank$ with year trends; column (5) estimates at the most disaggregated level of industry classification (5-digit). Overall, our coefficient of interest in columns (1) – (5) show no effect of prior relationships with public-sector banks on credit received.

Columns (6) and (7) divide the firms according to their size quartiles and repeat columns (3) and (2), respectively. We find no effect of relationships with public-sector banks on credit received for big firms demonstrating that our benchmark results are not contaminated by selection bias. On the other hand, we find positive effect for small firms or firms belonging to Quartile 1 due to their banking relationships with public-sector

[29] see DiNardo & Pischke (1997) for an excellent discussion on selection bias.

banks.

3.4 Firm Performance

Higher amount of credit can significantly impact firm performance across many dimensions (Alfaro et al., 2021). We now examine whether the new banking relations have had any effect on firm outcomes using the following specification:

$$Y_{it} = \sum_{q=1}^{4} \beta_q (\text{New Bank Relation}_{i,t-1} \times Q_q) + \theta \mathbf{X}_{it} + \alpha_i + \theta_{jt} + \epsilon_{it} \tag{5}$$

where Y is either the logarithm of total sales, gross value added (GVA), raw materials expenditure, capital employed, labor compensation, intangible investments (sum of investments on research and development, advertising, distribution, and marketing), tangible investments (sum of investments on plant and machinery, land and buildings, transport and communication infrastructure, and net fixed assets), and profits. All the other variables remain the same as in Eqn. (3). Additionally, we control for (a) relations with public-sector banks by interacting the respective quartile dummies; (b) interactions between industry fixed effects and *New Bank Relation*$_i$ (to control for whether certain industry characteristics are driving the new banking relationships); and (c) interactions between state fixed effects and *New Bank Relation*$_i$ (to control for the fact that the location of a firm may help the firm to form a new banking relationship). Results are presented in **Table 5**.

We start by using the total sales (column (1)) and gross value-added (column (2)) of a firm as the outcomes of interest, respectively. We find that the banking relations with new domestic private and/or foreign banks helped firms, but only the ones belonging to the 4th quartile, to earn 25% more from sales and increasing their value-addition by 22%.

Next, we check whether these new banking relations led to higher use of productive factors or not. We use three different production factors (i) raw materials in column (3), (ii) capital employed in column (4), and (iii) labor compensation in column (5), respectively as our outcome variables of interest. Our estimates show that new banking relations led to a significant impact on all three counts: use of raw materials, capital, and labor increased by 30%, 26%, and 15%, respectively.

Table 5: Bank Entry and Firm Performance

	Total Sales (1)	Gross Value-added (2)	Raw Materials (3)	Capital Employed (4)
New Bank Relation$_{i,t-1}$ × *Quartile*$_1$	0.051	0.031	0.003	0.043
	(0.237)	(0.208)	(0.251)	(0.179)
New Bank Relation$_{i,t-1}$ × *Quartile*$_2$	0.001	–0.061	–0.047	–0.006
	(0.083)	(0.075)	(0.155)	(0.043)
New Bank Relation$_{i,t-1}$ × *Quartile*$_3$	–0.003	–0.034	0.103	0.079
	(0.073)	(0.071)	(0.109)	(0.057)
New Bank Relation$_{i,t-1}$ × *Quartile*$_4$	0.245***	0.218**	0.304***	0.264***
	(0.070)	(0.074)	(0.112)	(0.061)
R-Square	0.95	0.94	0.90	0.97
	Labour Compensation (5)	Intangible Investments (6)	Tangible Investments (7)	Profits after Tax (8)
New Bank Relation$_{i,t-1}$ × *Quartile*$_1$	0.003	0.028	0.069	–0.216
	(0.099)	(0.154)	(0.220)	(0.168)
New Bank Relation$_{i,t-1}$ × *Quartile*$_2$	0.028	–0.154	–0.022	0.049
	(0.052)	(0.158)	(0.069)	(0.167)
New Bank Relation$_{i,t-1}$ × *Quartile*$_3$	0.007	0.035	0.121*	–0.050
	(0.038)	(0.064)	(0.072)	(0.154)
New Bank Relation$_{i,t-1}$ × *Quartile*$_4$	0.153***	0.451***	0.179***	0.303***
	(0.041)	(0.123)	(0.061)	(0.108)
R-Square	0.98	0.79	0.79	0.85
N	5,016	5,016	5,016	5,016
Firm FE	✓	✓	✓	✓
Industry FE (2-digit) × Year FE	✓	✓	✓	✓
Industry FE (2-digit) × *New Bank Relation*$_{i,t}$	✓	✓	✓	✓
State FE × *New Bank Relation*$_{i,t}$	✓	✓	✓	✓

Notes: All the regressions are for the years 1995–2007. Columns (1) – (8) use the logarithm of total sales, gross value-added, raw materials consumed, capital employed, labor compensation, intangible investments (e.g., R&D investments, advertising, distribution, and marketing), tangible investments (plant and machinery, land and building, transport and communication infrastructure, and net fixed assets), capital employed, and profits of a firm as the dependent variable. *New Bank Relation*$^{PF}_{i,t}$ takes a value of 1 when a firm i forms a new credit relationship with a domestic private or foreign bank branch year t. We use *New Bank Relation*$^{PF}_{i,t-1}$ as a proxy for *New Bank Relation*$^{PF}_{i,t}$ to control for the potential endogeneity due to selection issues. Quartiles $Qr_{i=1,2,3,4}$ are defined according to the total assets of a firm. The dependent variables are corrected for inflation. Standard errors in parentheses are clustered two-way at the firm and year level. Intercepts are not reported. *, **, *** denotes 10%, 5% and 1% level of significance, respectively.

Columns (6) and (7) look at two different types of investments – intangible and tangible. Intangible investments increased by 45%, whereas tangible by 18%. Lastly, we use profits in column (8) – new banking relations also lead to an increase in profits of firms by

30%. Based on these results and following Banerjee & Duflo (2014), we argue that Indian manufacturing firms were credit-constrained and opening of the new banks gave them access to higher amount of credit which eventually increased their sales, use of productive factors, investments, profits. In other words, introduction of new banks led to overall firm expansion. But, all of these changes were limited only to the big firms.[30]

4 Misallocation and Productivity

4.1 Analytical Framework

Our results so far provides robust evidence of new domestic private and/or foreign banks being engaged in *cherry picking* or *cream skimming*. In other words, it is only the big firms who received credit, while nothing changed for firms of other sizes.

One can plausibly argue that this may have led to an increase in inequality (in terms of credit received, performance, etc.) among firms on the one hand, but created a conducive environment for the operation and growth of the bigger firms on the other.[31] To this, we now take a step further and ask whether such favorable treatment to big firms by the new banks is efficient in aggregate or not. To check this, we first estimate a measure of misallocation at the firm level, link it causally to the newly established banks, and then aggregate it up to the entire manufacturing sector.

We follow the methodology proposed by Hsieh & Klenow (2009, 2013) to create a measure of resource misallocation at the firm level. This is a direct measure that does not account for the source of allocative inefficiency.[32] We start by describing the analytical

[30]One of the reasons for this improved performance of the fourth quartile firms could be due to the fact that they may have got higher amount of loans at low interest rates. And, this may have facilitated them to invest more in productive factors, tangible, and intangible assets which eventually resulted in higher sales, GVA, and profits. To check whether such is the case or not, we examine what happened to interest paid by a firm. Unfortunately, we do not have data on interest rates for each of the loan received by a firm from the respective banks. But, our dataset provides information on total amount of interest expenses paid out by a firm against the total amount of loan it has received. We use Eqn. (5) with interest expenses as the outcome of interest. Result is presented in **Table B.4**. The estimates show that this hypothesis is not true in our case. We do not observe any drop in interest rate paid by firms due to new banking relationships, but the opposite. Higher amount of credit led to higher interest expenses paid.

[31]This may have also skewed the size distribution of firms. However, investigating such issues is outside the scope of our current work.

[32]A similar measure was used by Ziebarth (2013) to compare 19th century U.S. level of development with recent levels of development in India and China.

framework.

Let the aggregate manufacturing output in the economy be produced by a representative firm in a perfectly competitive market using a Cobb-Douglas production technology. The firm uses J inputs and the production technology is given by:

$$Y = \prod_{j=1}^{J} Y_j^{\theta_j}, \text{ where } 0 < \theta_j < 1 \text{ and } \sum_{j=1}^{J} \theta_j = 1 \tag{6}$$

Assume that there are M_j firms in each industry j that produce differentiated products. Aggregate output, Y_j, is produced following a CES production function:

$$Y_j = \left(\sum_{i=1}^{M_j} Y_{ij}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{7}$$

where σ is the elasticity of substitution which only affects aggregate efficiency as opposed to misallocation at the firm level (more on this later). The profit of a firm producing a differentiated product is given as

$$\pi_{ij} = (1 - \tau_{ij}^{Y}) P_{ij} Y_{ij} - wL_{ij} - (1 + \tau_{ij}^{K}) RK_{ij} \tag{8}$$

where $P_{ij}Y_{ij}$ is the revenue net of the cost of intermediate goods, or, the value added by the firm. τ_{ij}^{Y} is the level of product market distortion faced by a firm i in industry j. This distortion affects the marginal productivity of capital and labor of the firm simultaneously. This could be a result of preferential treatment given to a firm within an industry because of say, entry restrictions, government regulations, etc. τ_{ij}^{K} is the level of distortion faced by a firm due to capital market (K) imperfections; for example, due to differential access to bank or any other sources of credit. This distortion affects the firm's marginal productivity of capital relative to labor.[33] We are interested in the behavior of τ_{ij}^{K} across firms and within industries. We hypothesize that the introduction of new domestic private and/or foreign banks would increase the amount of credit received by more productive firms and thus, reduce the extent of misallocation.

Each firm combines capital and labor using a Cobb-Douglas production production

[33] In this model, we treat the labor market wedge as a numeraire. Our results are robust to treating any one of the wedges as a numeraire.

technology.

$$Y_{ij} = A_{ij} K_{ij}^{\alpha_j} L_{ij}^{1-\alpha_j} \tag{9}$$

Notice that the capital share of output, α_j does not vary across firms within an industry. Following Foster et al. (2008) and Hsieh & Klenow (2009), we focus on the following two measures indicating the extent of misallocation:

$$\mathrm{TFPQ}_{ij} = A_{ij} = \frac{Y_{ij}}{K_{ij}^{\alpha_j} L_{ij}^{1-\alpha_j}} \tag{10}$$

$$\mathrm{TFPR}_{ij} = P_{ij} A_{ij} = \frac{P_{ij} Y_{ij}}{K_{ij}^{\alpha_j} L_{ij}^{1-\alpha_j}} \tag{11}$$

Equation (10) is the Solow residual and is a measure of the physical productivity of a firm. It is typically computed using firm-level price deflators which we do not observe. However, our model allows us to compute it relative to the respective industry-level physical productivity. TFPR in Equation (11) is the revenue productivity of a firm; this is calculated using industry-level deflators to deflate the firm-level variables. Variation of TFPR_{ij} across firms within an industry j is an indicator of misallocation. To see this, note that if a firm i in industry j has high physical productivity, A_{ij}, then it employs more capital and labor and produces more output. In a frictionless world, this firm would charge a lower price P_{ij}. Labor and capital allocation increases for the firm with higher physical productivity until TFPR_{ij} is equalized across all the firms within an industry j.

From the model, TFPR_{ij} is computed as

$$\mathrm{TFPR}_{ij} \propto (\mathrm{MRPK}_{ij})^{\alpha_j} (\mathrm{MRPL}_{ij})^{1-\alpha_j} \propto \frac{(1+\tau_{ij}^{K})^{\alpha_j}}{1-\tau_{ij}^{Y}} \tag{12}$$

where (MRPK_{ij}) and (MRPL_{ij}) are the marginal revenue products of capital and labor respectively:

$$\mathrm{MRPK}_{ij} = R\left(\frac{1+\tau_{ij}^{K}}{1-\tau_{ij}^{Y}}\right) \tag{13}$$

$$\text{MRPL}_{ij} = \frac{w}{1 - \tau^Y_{ij}} \tag{14}$$

A higher value of TFPR_{ij} for a firm i, relative to the industry level average, implies a higher level of misallocation. This is because a high TFPR_{ij} implies either a high τ^K_{ij} or a high τ^Y_{ij} or both. For our purposes, we are interested in the variability of τ^K_{ij}, since it directly measures the distortions due to credit received. Working through some algebra, TFP for industry j can be expressed as

$$\text{TFP}_j = \left(\sum_{i=1}^{M_j} \left[A_{ij} \frac{\overline{\text{TFPR}_j}}{\text{TFPR}_{ij}} \right]^{\sigma-1} \right)^{\frac{1}{\sigma-1}} \tag{15}$$

where $\overline{\text{TFPR}_j}$ is the geometric mean of the average MRPL and MRPK in sector j, defined as[34]

$$\frac{1}{\overline{\text{MRPL}_j}} = \sum_{i=1}^{M_j} \frac{1}{\text{MRPL}_{ij}} \frac{P_{ij} Y_{ij}}{P_j Y_j} \tag{16}$$

$$\frac{1}{\overline{\text{MRPK}_j}} = \sum_{i=1}^{M_j} \frac{1}{\text{MRPK}_{ij}} \frac{P_{ij} Y_{ij}}{P_j Y_j} \tag{17}$$

and

$$\overline{\text{TFPR}_j} = (\overline{\text{MRPK}_j})^{\alpha_j} (\overline{\text{MRPL}_j})^{1-\alpha_j} \tag{18}$$

In the absence of firm-level distortions, all the firms in an industry would equate their marginal revenue products of capital and labor with the wage and rental rates, respectively. This will result in an equal value of TFPR within an industry.

With distortions, if firms with higher A_{ij} have a higher TFPR_{ij} than the industry average, this reflects that firms with higher productivity are subject to higher distortions. This may reflect size-dependent policies, that create disincentives for a firm to grow to its

[34]These weighted means are defined the way they are for convenience with the algebraic calculations necessary for aggregation.

optimal size, or inefficiency in credit allocation, which is a by-product of targeted lending practices ubiquitous in emerging market economies. For our purposes, we first compute TFPR_{ij} for each firm using Equation (18). Our measures of misallocation (at the firm-year level) are $\ln(\text{TFPR}_{ij})$, scaled by the industry $\ln(\text{TFPR}_{j})$[35] and $\ln(1+\tau_{ij}^{K})$ scaled by $\ln(1+\tau_{j}^{K})$. The latter measures are the extent of capital market distortions only.

To estimate our measure of distortion, we need to specify the parameter values, R, σ, and the share of capital α_j. For the first two we adopt the parameter values from Hsieh & Klenow (2009) and set (a) R $= 0.1$[36] and (b) $\sigma = 3$[37]. We use the NBER database on "Manufacturing and Industry Productivity" and use the industry-specific labor shares from the U.S. industries. We then match the 2-digit SIC codes (of the U.S. industries) with the 2-digit NIC codes for Indian manufacturing industries using a UN classification system. The estimated labor shares are then multiplied by 1.5 to account for labor fringe benefits and social security contributions. The underlying assumption is that the U.S. industries face no distortions due to market imperfections. Since we estimate a measure of misallocation from our sample of Indian manufacturing firms, capital and labor shares cannot be identified from our data.

Assuming monopolistic competition in the product market we derive the expressions for capital and output distortions:

$$1+\tau_{ij}^{K} = \frac{\alpha_j}{1-\alpha_j}\frac{\text{wL}_{ij}}{\text{RK}_{ij}} \tag{19}$$

$$1-\tau_{ij}^{Y} = \frac{\sigma}{\sigma-1}\frac{\text{wL}_{ij}}{(1-\alpha_j)\text{P}_{ij}\text{Y}_{ij}} \tag{20}$$

Intuitively, capital distortion in Equation (19) is high when the wage bill to rental bill ratio is high. This implies that less capital is used than the optimal level. This distortion is amplified when α_j is high. Note that a high capital distortion implies a low labor distortion (since capital distortion is measured relative to labor distortion). The output

[35] $\ln(\text{TFPR}_j)$ is the geometric mean of TFPR_{ij} across all firms in industry j.

[36] The value of R does not influence the measure of misallocation since it does not impact the dispersion of TFPR_{ij} from the industry average.

[37] We follow the literature and use the lower bound of the estimates, which range from 3 to 10. Note that σ does not impact the firm-level measure of misallocation. However, it still influences the impact of misallocation on aggregate TFP – a lower value of σ underestimates the effect of misallocation on aggregate TFP.

distortion in Equation (20) is positive if the wage bill is lower than optimal for firm i. Given the parameter values mentioned above, we can now easily estimate the capital and output distortions for firm i belonging to industry j.[38]

Finally, to construct the aggregate value of manufacturing TFP and the potential gains from reducing distortions over the sample period, we need to estimate TFPQ_{ij} from the data. Since we do not use firm-level deflators, we observe only sales (or value added), $P_{ij}Y_{ij}$, and not real outlay, Y_{ij}. We use the demand for intermediate goods for the aggregate final goods producer (Equation (7)) and compute:

$$A_{ij} = \kappa_j \frac{(P_{ij}Y_{ij})^{\frac{\sigma}{\sigma-1}}}{K_{ij}^{\alpha_j} L_{ij}^{1-\alpha_j}} \tag{21}$$

κ_j is normalized to 1 since we are interested in the values of A_{ij} scaled by industry averages which cancel the industry level constant.

However, the methodology we use to compute the overall measure of misallocation and its components (capital and output market distortion) is not without its limitations. First, the model we use is not dynamic, hence silent about firms' evolution of capital. Second, it ignores the extensive margin completely.[39] However, our method has several advantages. We are only interested in the measure of firm-level misallocation relative to the industry average and in its change over time due to new private/foreign banking relationships. The former normalization rules out industry-specific measurement errors, while the latter gets rid of systematic within-firm measurement errors. The unconditional TFPR dispersion within an industry can also be used as an aggregate measure of misallocation. With errors, the TFPR dispersion can portray a blown-up version of reality which we could safely avoid while dealing with our question.

[38]Note that, we assume the wage rate to be a constant across all firms in the model. This controls for variation in human capital across firms. The implicit assumption is $wL_{ij} = w_{ij}N_{ij}$, where L_{ij} is the number of effective workers and w is the wage per effective worker.

[39]In our analysis, we only use firms that we observe for at least five periods. In our data, when a firm is not observed there is no way to tell if the firms are dropping out of the sample or exiting the market. Goldberg et al. (2010) point out that PROWESS data is not well suited to understand entry and exit of Indian firms. Misallocation along the lines of entry and exit of firms due to financial frictions has been analyzed before in Midrigan & Xu (2014).

4.2 Stylized Facts: Misallocation

We start by computing TFPR$_{ij}$ for all firms and compare the median values across the size quartiles.[40] We decompose TFPR$_{ij}$ into capital and output distortions. **Figures 4a, 4b**, and **4c** plot these estimates. Each of them is plotted as ratios to the industry-level averages. This makes these measures comparable across industries.

The measure of capital distortion ($\ln(\frac{1+\tau_{ij}^K}{1+\tau_j^K})$) declines throughout the sample period for the big or fourth quartile (Q4) firms. As for the others: the measure does not show any trend movement for the Q3 firms; for Q2 firms it rises; and for Q1 or the smallest firms, the measure is higher than the rest and is extremely unstable. This shows that while capital market misallocation has dropped over time for the biggest firms, it has either remained the same or increased for others. This observation stands even if we club all the Q1, Q2, and Q3 firms together and compare them with the biggest firms.[41]

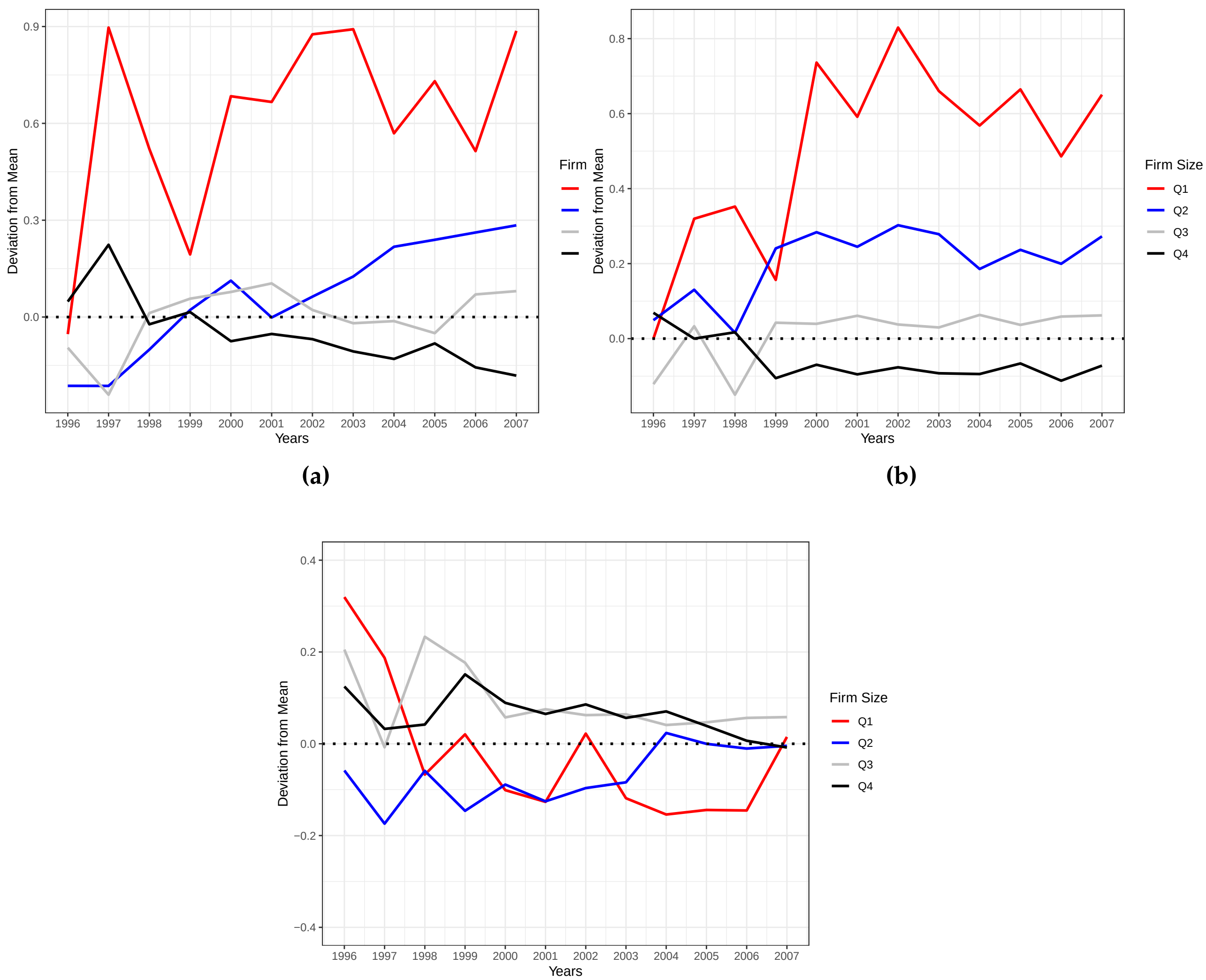
As seen from **Figure 4b**, product market distortions ($\ln(\frac{1-\tau_{ij}^Y}{1-\tau_j^Y})$) (the lowest in the plot refers to the maximum distortions) are the highest for the big firms. This pattern reflects the fact that the big firms received higher amount of credit, but were subject to a high degree of product market distortions. It shows an increase towards the beginning of the sample period but stays the same from 1999 onward.[42]

Figure 4c reports the TFPR ratio ($\ln(\frac{TFPR_{ij}}{TFPR_j})$) across firm size quartiles. Overall, the distribution appears to be converging towards the mean implying that there is an overall reduction of misallocation in the economy. One of the reasons for this observation could be the implementation of economic reforms in India during that period. As expected, throughout the sample period, the $TFPR_{ij}$ is greater than the mean for both the Q4 and Q3 firms and the opposite for the rest. Since $TFPR$ is an average of $MRPK$ and $MRPL$, a higher value implies either or both of them could be higher. For the Q4 firms, these numbers combined with Equations (13) and (14) indicate that the effect on $MRPK$

[40]Our data consists of 4059 firms and covers the period from 1995 to 2007. For our purpose, we only use the data for firms that appear in our sample for at least 3 years. 361 firms belong to the first quartile of the size classification; 955, 1221, and 1520 firms belong to the second, third, and fourth quartiles, respectively.

[41]Recall that PROWESS does not record any information for the smallest manufacturing firms or micro-enterprises. Therefore, since our results are based on the fairly big firms of the Indian manufacturing industry, a representative sample which includes the small and/or micro enterprises would only strengthen our results.

[42]For both Q3 and Q2 firms, the product market distortions are lower than the industry mean. This is similar for the Q1 firms, although the measure is volatile as before.



(a) (b) (c)

Figure 4: Capital market, Product market distortions, and TFPR from 1996 to 2007

Notes: Panel (a) plots the deviation of the median value of $\ln(1+\tau^K_{ij})$ from the log of the industry mean. Panel (b) plots the same for $\ln(1-\tau^Y_{ij})$. Panel (c) plots the same deviation for $\ln(TFPR_{ij})$. Industry means are computed as per 2-digit industry classifications.

is ambiguous, while $MRPL$ has unambiguously increased.

Table 6: Capital Market Distortion

	Years		
	1996	2000	2007
Quartile 1	–0.15	0.62	0.86
Quartile 2	–0.25	0.03	0.25
Quartile 3	–0.09	0.09	0.11
Quartile 4	0.23	–0.03	–0.13
All Sizes	–0.04	0.03	0.03

Notes: Numbers reported are the measures of capital market distortion/misallocation.

To fix ideas, we calculate capital market distortion (at the aggregate and by different size quartiles) for three years: 1996, 2000, and 2007 and present it in **Table 6**. The numbers show a decline only for the Q4 firms. On the other hand, the measure shows an increasing trend for all other quartiles, with smallest firms recording the highest. This is consistent with the fact that over the sample period, big firms faced the maximum distortion in both capital and product markets, while capital distortions tend to fall over time without much change in product market distortions. In what follows, we plan to investigate if the evolution in these wedges across firm quartiles can be causally linked to the new banking relationships.

4.3 Empirical Methodology and Results

Our discussion from the last section shows that there had been a reduction in capital market with no perceived changes in product market distortions. New banking relationships can affect these wedges through two distinct channels: (1) better access to capital can result in gain in allocative efficiency by bringing the TFPR of the firms closer to their respective industry means, with no impact on TFPQ. We call this the *between-firm* effect, since the gains in efficiency is due to reallocation of resources between firms.

Table 7: Banking Competition and Access to Credit: Misallocation

	Misallocation				
Panel A: Capital Market					
	(1)	(2)	(3)	(4)	(5)
New Bank Relation$_{i,t-1}$	–0.084***	–0.077***	–0.067**		
	(0.031)	(0.025)	(0.032)		
New Bank Relation$_{i,t-1}$ × *Quartile*$_1$				–0.016	–0.013
				(0.162)	(0.174)
New Bank Relation$_{i,t-1}$ × *Quartile*$_2$				0.006	0.021
				(0.054)	(0.049)
New Bank Relation$_{i,t-1}$ × *Quartile*$_3$				–0.079	–0.085
				(0.054)	(0.055)
New Bank Relation$_{i,t-1}$ × *Quartile*$_4$				–0.109***	–0.102***
				(0.041)	(0.041)
R-Square	0.91	0.91	0.93	0.91	0.91
Panel B: Product Market					
	(6)	(7)	(8)	(9)	(10)
New Bank Relation$_{i,t-1}$	–0.028	–0.026	–0.033		
	(0.022)	(0.023)	(0.029)		
New Bank Relation$_{i,t-1}$ × *Quartile*$_1$				0.001	0.004
				(0.097)	(0.098)
New Bank Relation$_{i,t-1}$ × *Quartile*$_2$				0.069	0.075
				(0.047)	(0.050)
New Bank Relation$_{i,t-1}$ × *Quartile*$_3$				–0.025	–0.024
				(0.039)	(0.040)
New Bank Relation$_{i,t-1}$ × *Quartile*$_4$				–0.058*	–0.059*
				(0.035)	(0.036)
R-Square	0.84	0.84	0.87	0.90	0.91
N	4,343	4,019	3,593	4,019	4,019
Control for Govt. Bank	X	✓	✓	X	✓
Firm FE	✓	✓	✓	✓	✓
Industry FE (2-digit) × Year FE	✓	✓	X	✓	✓
Industry FE (2-digit) × *New Bank Relation*$_{i,t}$	X	✓	X	✓	✓
State FE × *New Bank Relation*$_{i,t}$	X	✓	✓	✓	✓
Industry FE (5-digit) × Year FE	X	X	✓	X	X
Industry FE (5-digit) × *New Bank Relation*$_{i,t}$	X	X	✓	X	X

Notes: All the regressions are for the years 1995–2007. Panel A, Columns (1) – (5) use a measure of capital market distortion, $\ln(\frac{1+\tau^K_{ij}}{1+\tau^K_j})$; columns (6) – (10) of Panel B use an output market distortion, $\ln(\frac{\text{TFPR}_{ij}}{\text{TFPR}_j})$, respectively as the dependent variable. *New Bank Relation*$_{i,t}$ takes a value of 1 when a firm i forms a new credit relationship with a domestic private or foreign bank branch year t. We use *New Bank Relation*$_{i,t-1}$ as a proxy for *New Bank Relation*$_{i,t}$ to control for the potential endogeneity due to selection issues. Quartiles $Qr_{i=1,2,3,4}$ are defined according to the total assets of a firm. Firm Controls include age and age squared of a firm. Standard errors in parentheses are clustered two-way at the firm and year level. Intercepts are not reported. *, **, *** denotes 10%, 5% and 1% level of significance, respectively.

(2) improved access to capital can trigger new investments, which may be long due, leading to a gain in TFPQ. This can increase marginal productivity of other inputs disproportionately so as to reverse the gains in allocative efficiency. In the extreme case, it can increase both MRPK and MRPL leading to a loss in allocative efficiency (a more spread out TFPR distribution). We call this the *within-firm* effect since this regards to efficiency gains from within-firm improvements in production technology. The aggregate effect is a combination of both.

In what follows, we first compute capital and product market distortions, then disentangle the *within-* and *between-firm* components of distortions separately, and provide the first evidence on how these are influenced due to these new banking relationships of firms. We use the following specification:

$$Y_{it} = \sum_{q=1}^{4} \beta_q (\text{New Bank Relation}_{i,t-1} \times Q_q) + \theta \mathbf{X}_{it} + \alpha_i + \theta_{jt} + \epsilon_{it} \tag{22}$$

where Y_{it} represents the following: (i) capital market distortion, $\ln(\frac{1+\tau_{ij}^K}{1+\tau_j^K})$; (ii) product market distortion, $\ln(\frac{1-\tau_{ij}^Y}{1-\tau_j^Y})$, (iii) physical productivity, $\ln(\frac{TFPQ_{ij}}{TFPQ_j})$, and (iv) revenue productivity, $\ln(\frac{TFPR_{ij}}{TFPR_j})$. Our measures of misallocation are scaled by their industry level geometric means. β_q's are our coefficient of interest, especially when $q = 4$ which corresponds to the fourth quartile of firms. Other variables continue to be the same. We continue to control for the relationship(s) with public-sector banks in all our specifications. **Table 7** reports the findings on the different measures of distortion.

Panel A uses capital market distortion, $\ln(\frac{1+\tau_{ij}^K}{1+\tau_j^K})$, as the outcome variable. Overall, our estimates show that new relationships with private and/or foreign banks negatively and significantly affect capital market misallocation. In particular, the new banking relationships led to about 6.7–8.4% reduction in capital market distortions. And, this is driven by firms belonging to Q4, or the big firms who received higher amounts of loans. The magnitude of such reduction is around 11%. And, this is compared to other big firms which did not have any relationships with new domestic and/or foreign banks. **Panel B** replaces capital market with product market misallocation measure. Our results show that relations with new banks led to an increase in the product market distortion.[43] And,

[43] A negative coefficient in this case means an increase in the degree of distortion.

this is true only for big firms.

Reduced capital market distortion accompanied by increased product market distortion is expected with an improved access to capital. But, did this result in an improved allocation or physical productivity or both? **Table 8** reports the regression results for the physical (*within-firm*) and revenue (*between-firm*) productivity, and answers this question.

Table 8: Banking Competition and Gains from Access to Credit

	Physical Productivity (TFPQ) (1)	Revenue Productivity (TFPR) (2)
$New\ Bank\ Relation_{i,t-1} \times Quartile_1$	–0.076	–0.013
	(0.119)	(0.080)
$New\ Bank\ Relation_{i,t-1} \times Quartile_2$	–0.083	–0.076
	(0.081)	(0.052)
$New\ Bank\ Relation_{i,t-1} \times Quartile_3$	0.021	–0.028
	(0.047)	(0.029)
$New\ Bank\ Relation_{i,t-1} \times Quartile_4$	0.107*	–0.004
	(0.061)	(0.028)
R-Square	0.91	0.82
N	3,977	4,019
Control for Govt. Bank	✓	✓
Firm FE	✓	✓
Industry FE (2-digit) × Year FE	✓	✓
Industry FE (2-digit) × $New\ Bank\ Relation_{i,t}$	✓	✓
State FE × $New\ Bank\ Relation_{i,t}$	✓	✓

Notes: All the regressions are for the years 1995–2007. Columns (1) and (2) use physical and revenue productivity as the dependent variable, respectively. Quartiles $Qr_{i=1,2,3,4}$ are defined according to the total assets of a firm. Standard errors in parentheses are clustered two-way at the firm and year level. Intercepts are not reported. *, **, *** denotes 10%, 5% and 1% level of significance, respectively.

We report only the results for firm size quartiles.[44] It is only the coefficient for Q4 that displays a higher TFPQ or physical productivity. In particular, the new banking relationships led to about 11% gain in *within-firm* productivity for the big firms. And, such effects are absent for any other quartile of firms. Similar for the case of revenue productivity or *between-firm* effect and this is irrespective of their size.

This shows that all the gains in productivity are concentrated only for the big firms and are due to *within-firm* channel. This happened because big firms received significantly higher amount of credit in compare to all other firms who had new relations with these banks implying that the new banks were indulged in cherry-picking. But, what led to this

[44] We use the same control variables as the last two columns of **Table 8**.

choice? It might be the case that the new banks choose to be associated with only those firms which had ex-ante better access to credit. In other words, ex-ante lower capital market distortions of the big firms led to the formation of new lending relationships. To check whether such is the case or not, we run the following regression:

$$\text{Prob}(\text{New Bank Relation}_{i,t}) = \beta[ln(\frac{1+\tau_{ij}^K}{1+\tau_j^K})]_{t-1} + \lambda\textbf{Size}_{i,t-1} + \theta_j + \epsilon_i \quad (23)$$

Our outcome of interest for Equation (23) is the probability of entering into a new domestic private and/or foreign banking relationship at any time within our sample period. In particular, it takes a value 1 when a firm forms a new relationship with a new domestic private and/or foreign bank and 0 otherwise. Our main variable of interests are the ex-ante capital market distortion faced by a firm and its size. Additionally we also control for industry fixed effects (θ_j).

Table B.5 presents the required result. Column (1) runs a linear probability model, while columns (2) and (3) use logit and probit regressions. Our estimates show that previous period capital market distortion is not significantly correlated with the probability of forming a new banking relationship. On the other hand, firm size appears to be a significant determinant. This points out that the new banks chose firms based on their size, supplied more credit, and in the process reduced their capital market distortions. Subsequently, those firms responded by investing more and it resulted in improvement of their physical productivity. On the other hand, entry of these banks did not result in any improvement of allocation of resources in the manufacturing sector leaving revenue productivity unaffected.

5 Did the New Banks Matter on Aggregate?

Lastly, we use our analytical framework to aggregate the estimates of $TFPR_{ij}$ and $TFPQ_{ij}$ and carry out few counterfactual exercises to estimate aggregate gains in output. The maximum possible output from reallocation, Y^{eff} is computed counterfactually by assuming that TFPR is equalized across all firms within a 2-digit industry. After working through some algebra, we computed the ratio of current to efficient output as follows and plot in **Figure 5**:

$$\frac{\mathrm{Y}}{\mathrm{Y}^{\mathrm{eff}}} = \prod_{j=1}^{J} \left(\sum_{i=1}^{\mathrm{M}_j} \left[\frac{\mathrm{A}_{ij}}{\overline{\mathrm{A}_j}} \frac{\overline{\mathrm{TFPR}_j}}{\mathrm{TFPR}_{ij}} \right]^{\sigma-1} \right)^{\frac{\theta_j}{\sigma-1}} \tag{24}$$

where $\overline{\mathrm{A}_j} = (\sum_{i=1}^{M_j} A_{ij}^{\sigma-1})^{\frac{1}{\sigma-1}}$. The potential gains from reallocation (expressed in percentage terms) are given as $(\frac{\mathrm{Y}^{\mathrm{eff}}}{\mathrm{Y}} - 1)$*100. The solid blue line in **Figure 5** plots the possible percentage gains from reallocation between 2000 and 2007.[45] The line slopes downwards implying that potential gains from reallocation decreases with time.

Now, how much do the new banking relationships have impacted this change? To do this, we first run year-wise regressions using the following specification:[46]

$$\mathrm{Y}_{ijt} = \sum_{q=1}^{4} \beta_q (\text{New Bank Relation}_{i,j,t-1} \times Q_q) + \theta \mathbf{X}_{it} + \epsilon_{it} \tag{25}$$

Here, Y_{ijt} is equal to $\frac{A_{ij}}{\overline{A_j}}$ and $\frac{\overline{TFPR_j}}{TFPR_{ij}}$. We include firm characteristics, industry, and state-fixed effects as controls. This regression captures the cumulative effect of new private/foreign banking relationship in year t, for a relationship that was established on or before year $t-1$.[47] The effect of prior relationships is important to capture the effect of banking relationships in a given year as such lending relationships usually last longer than a year. Using the estimated coefficients from this regression, we predict ΔY_{ijt}, given as:

$$\Delta Y_{ijt} = \sum_{q=1}^{4} \hat{\beta}_q (\text{New Bank Relation}_{i,j,t-1} \times Q_q) \tag{26}$$

where $\Delta Y_{ijt} = \Delta \frac{\overline{TFPR_j}}{TFPR_{ij}}$ which is the adjustment in reallocation, and $= \Delta \frac{A_{ij}}{\overline{A_j}}$ which is the adjustment in improvement of TFPQ due to new banking relationships. We deduce both the TFRP and TFPQ expressions from Equation (24) using our estimates in Equation (26). This gives us the corresponding ratios without the effect of the new private/foreign banking relationships. We aggregate these adjusted estimates in the same way to arrive

[45]We use firm-level sales for this figure.

[46]In essence, we run repeated cross-section regressions.

[47]This is different from an event study estimation where triple a triple difference-in-differences are usually used.

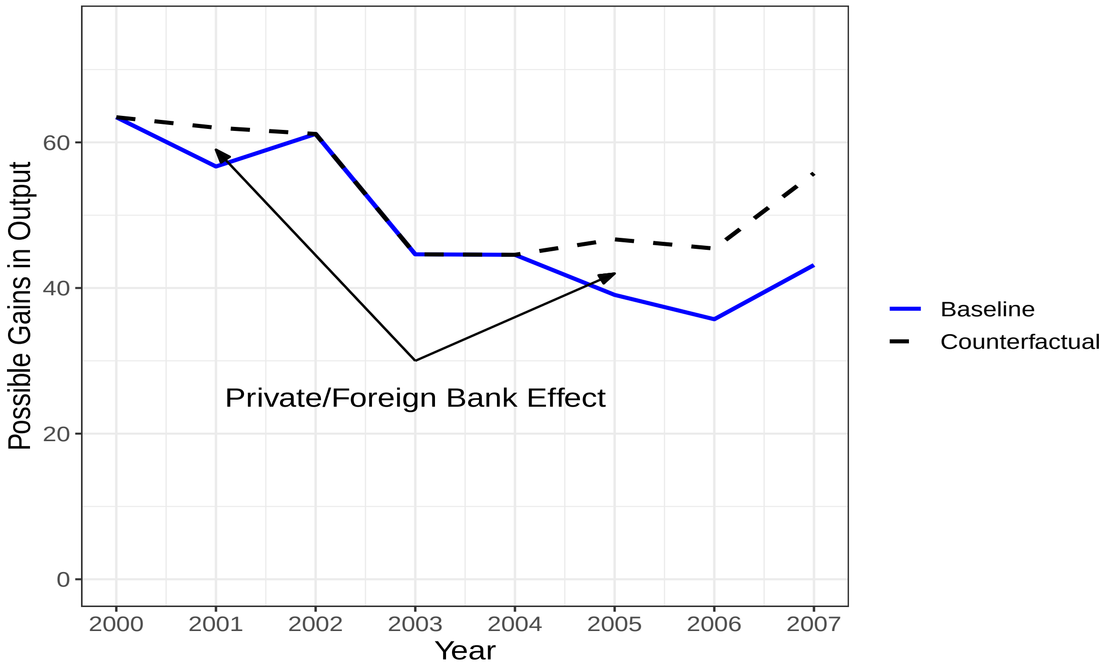


Figure 5: Aggregate Potential Gains in Manufacturing Output over Time

Notes: The blue (solid) line plots the $(\frac{Y^{\text{eff}}}{Y} - 1) \cdot 100$, including the effect of the new banking relationships. The black (dashed) line plots the result of a counterfactual experiment without the effect of the new relationships.

at the *counterfactual* plot given by the black dashed line in **Figure 5**.

As can be observed from the graph, the dashed line or the *counterfactual* is at least as high as the *baseline*. However, it starts to become significantly different, higher in our case, from 2004 onward, i.e., in the latter part of the sample.[48] Our estimates convey that the new bank relationships can explain about 5–7% of the overall gain in manufacturing output.

Table B.6 shows the contribution of reallocation and physical productivity in the aggregate gains as observed in the data. We find that most of the gains come from improvement in *within-firm* changes in TFPQ for the Q4 firms, and especially from 2004 onward. And, this could be due to their association with the new banks. This is consistent with Bollard et al. (2013) which finds that most of the *mysterious* growth in India's manufacturing productivity are coming from within-plant changes in productivity as opposed to across-plants.[49] Combining this with our firm performance estimates point towards the

[48]This is because the branch expansions or new relationships were starting after 2001 and the effect on output began to show a couple of years after the new relationships were formed.

[49]They use plant level data from the Annual Survey of Industries(ASI).

fact that firms in the Quartile 4 were credit-constrained ex-ante reform. The new loans helped them to invest and expand production which led to improvement in physical productivity.

6 Conclusion

We analyze the impact of banking sector liberalization on credit received by firms and misallocation in the Indian manufacturing sector. Utilizing new banking relationships for firms, we find that the new banks led to increase in the amount of loans received by firms. However, the effect is overwhelmingly driven by big firms or firms in the fourth quartile of size distribution indicating towards strong evidence of *cherry-picking* by the banks. We also find that relationships with new banks led to improvement in investments, increased use of productive factors, and higher sales for firms.

Our results also show no evidence for improvement in the aggregate allocative efficiency. Big firms who received more loans only used it to *catch-up* on their productive investments. And, this led to higher or *within-firm* improvements in physical productivity. This gain in physical productivity because of the new banking relationships also led to 5–7% of the overall gain in manufacturing output.

Our findings have important policy implications. Although these new banks led to increased access to loans and *within-firm* increase in physical productivity, but misallocation continues to persist. One of the reasons for such is that the banking reforms relaxed credit constraints only for certain sets of firms, the fourth quartile. This may have lead to increase in labour market misallocation, if labour regulation(s), on the other hand, make it prohibitively expensive for firms to hire more workers. In an economy with high degrees of misallocation, such as India, it is likely that mitigating one aspect of misallocation by undertaking an single array of reform, such as the banking in our case could aggravate the other. While the literature has shown that significant improvements in physical productivity can also result in lowering of misallocation, we should be mindful of the fact that several factors of production also contribute to misallocation. Therefore, policymakers should be aware that undertaking only one set of reforms, rather than a package, where misallocation is high to being with may partially undo the first order gains from such policies, as in our case from the banking sector liberalization.

References

Alfaro, L. & Chari, A. (2014). Deregulation, misallocation, and size: Evidence from India. *The Journal of Law and Economics*, 57(4), 897–936.

Alfaro, L., Garcia-Santana, M., & Enrique, M.-B. (2021). On the direct and indirect real effects of credit supply shocks. *Journal of Financial Economics*, 139(3), 895–921.

Allcott, H., Collard-Wexler, A., & O'Connell, S. D. (2016). How do electricity shortages affect industry? Evidence from India. *American Economic Review*, 106(3), 587–624.

Amiti, M. & Weinstein, D. E. (2011). Exports and financial shocks. *The Quarterly Journal of Economics*, 126(4), 1841–1877.

Amiti, M. & Weinstein, D. E. (2018). How much do idiosyncratic bank shocks affect investment? Evidence from matched bank-firm loan data. *Journal of Political Economy*, 126(2), 525–587.

Antràs, P., Chor, D., Fally, T., & Hillberry, R. (2012). Measuring the upstreamness of production and trade flows. *American Economic Review*, 102(3), 412–416.

Banerjee, A. V. & Duflo, E. (2014). Do firms want to borrow more? Testing credit constraints using a directed lending program. *The Review of Economic Studies*, 81(2), 572–607.

Banerjee, A. V. & Moll, B. (2010). Why does misallocation persist? *American Economic Journal: Macroeconomics*, 2(1), 189–206.

Bartelsman, E., Haltiwanger, J., & Scarpetta, S. (2013). Cross-country differences in productivity: The role of allocation and selection. *American Economic Review*, 103(1), 305–334.

Bau, N. & Matray, A. (2023). Misallocation and capital market integration: Evidence from India. *Econometrica*, 91(1), 67–106.

Beck, T. & Peria, M. S. M. (2010). Foreign bank participation and outreach: Evidence from Mexico. *Journal of Financial Intermediation*, 19(1), 52–73.

Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G., & Stein, J. C. (2005). Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics*, 76(2), 237–269.

Berger, A. N. & Udell, G. F. (1998). The economics of small business finance: The roles of private equity and debt markets in the financial growth cycle. *Journal of Banking & Finance*, 22(6-8), 613–673.

Bertrand, M., Schoar, A., & Thesmar, D. (2007). Banking deregulation and industry structure: Evidence from the French banking reforms of 1985. *The Journal of Finance*, 62(2), 597–628.

Bils, M., Klenow, P. J., & Ruane, C. (2021). Misallocation or mismeasurement? *Journal of Monetary Economics*, 124, S39–S56.

Bloom, N., Mahajan, A., McKenzie, D., & Roberts, J. (2010). Why do firms in developing countries have low productivity? *American Economic Review*, 100(2), 619–623.

Bolhuis, M., Rachapalli, S., & Restuccia, D. (2024). Misallocation in Indian agriculture. *Mimeograph*, University of Toronto.

Bollard, A., Klenow, P. J., & Sharma, G. (2013). India's mysterious manufacturing miracle. *Review of Economic Dynamics*, 16(1), 59–85.

Buera, F. J., Kaboski, J. P., & Shin, Y. (2011). Finance and development: A tale of two sectors. *American economic review*, 101(5), 1964–2002.

Chakraborty, P. (2024). Bank ownership and firm performance. *Economica*, 91(361), 238–267.

Collard-Wexler, A., Asker, J., & De Loecker, J. d. (2011). Productivity volatility and the misallocation of resources in developing economies. *NBER Working Paper No. 17175*, NBER, Massachusetts.

Detragiache, E., Tressel, T., & Gupta, P. (2008). Foreign banks in poor countries: Theory and evidence. *The Journal of Finance*, 63(5), 2123–2160.

DiNardo, J. E. & Pischke, J.-S. (1997). The returns to computer use revisited: Have pencils changed the wage structure too? *The Quarterly Journal of Economics*, 112(1), 291–303.

Foster, L., Haltiwanger, J., & Syverson, C. (2008). Reallocation, firm turnover, and efficiency: Selection on productivity or profitability? *American Economic Review*, 98(1), 394–425.

Goldberg, L. S. (2009). Understanding banking sector globalization. *IMF Staff Papers*, 56(1), 171–197.

Goldberg, P., Khandelwal, A., Pavcnik, N., & Topalova, P. (2010). Imported intermediate inputs and domestic product growth: Evidence from India. *The Quarterly Journal of Economics*, 125(4), 1727–1767.

Gollin, D. & Udry, C. (2021). Heterogeneity, measurement error, and misallocation: Evidence from African agriculture. *Journal of Political Economy*, 129(1), 1–80.

Gormley, T. A. (2010). The impact of foreign bank entry in emerging markets: Evidence from India. *Journal of Financial Intermediation*, 19(1), 26–51.

Greenwood, J., Sanchez, J. M., & Wang, C. (2010). Financing development: The role of information costs. *American Economic Review*, 100(4), 1875–1891.

Hsieh, C.-T. & Klenow, P. J. (2009). Misallocation and manufacturing TFP in China and India. *The Quarterly Journal of Economics*, 124(4), 1403–1448.

Hsieh, C.-T. & Klenow, P. J. (2013). Misallocation and manufacturing TFP in China and India: Correction Appendix. *Mimeograph*, Stanford University.

Ioannidou, V., Ongena, S., & Peydró, J.-L. (2015). Monetary policy, risk-taking, and pricing: Evidence from a quasi-natural experiment. *The Review of Finance*, 19(1), 95–144.

Jiménez, G., Ongena, S., Peydró, J.-L., & Saurina, J. (2012). Credit supply and monetary policy: Identifying the bank balance-sheet channel with loan applications. *American Economic Review*, 102(5), 2301–2326.

Kalemli-Ozcan, S. & Sorensen, B. E. (2014). Misallocation, property rights, and access to finance: Evidence from within and across Africa. *In African Successes, Volume III: Modernization and Development*, 183–211.

Khwaja, A. I. & Mian, A. (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, 98(4), 1413–1442.

Lin, H.-F. (2011). An empirical investigation of mobile banking adoption: The effect of innovation attributes and knowledge-based trust. *International Journal of Information Management*, 31(3), 252–260.

Martin, L. A., Nataraj, S., & Harrison, A. E. (2017). In with the big, out with the small: Removing small-scale reservations in India. *American Economic Review*, 107(2), 354–386.

Midrigan, V. & Xu, D. Y. (2014). Finance and misallocation: Evidence from plant-level data. *American Economic Review*, 104(2), 422–458.

Petersen, M. A. & Rajan, R. G. (1995). The effect of credit market competition on lending relationships. *The Quarterly Journal of Economics*, 110(2), 407–443.

Rajan, R. & Zingales, L. (1998). Financial dependence and growth. *American Economic Review*, 88(3), 559–586.

Rotemberg, M. & White, T. K. (2021). Plant-to-table (s and figures): Processed manufacturing data and measured misallocation. *Working Paper.*

Sarma, M. & Prashad, A. (2014). Do foreign banks in India indulge in cream skimming? In *Annual International Studies Convention, Jawaharlal Nehru University, and New Delhi* (pp. 10–12).

Sengupta, R. (2007). Foreign entry and bank competition. *Journal of Financial Economics*, 84(2), 502–528.

Syverson, C. (2004). Product substitutability and productivity dispersion. *The Review of Economics and Statistics*, 86(2), 534–550.

Ziebarth, N. L. (2013). Are China and India backward? Evidence from the 19th century us census of manufactures. *Review of Economic Dynamics*, 16(1), 86–99.

Online Appendix for
Bank Entry, Access to Credit, and Misallocation

Pavel Chakraborty
Lancaster University

Nirvana Mitra
CAFRAL, RBI

A Graphs

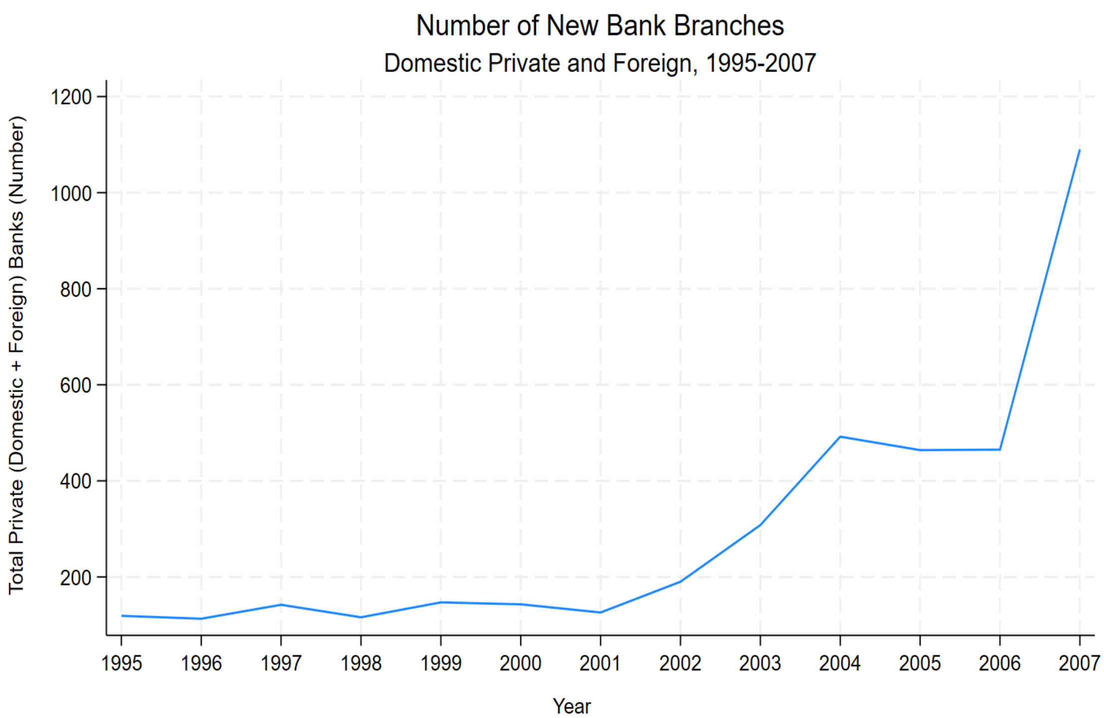


Figure A.1: Number of New Bank (Domestic Private and Foreign) Branches

Notes: Figure represents the total number of bank branches opened across all districts in India in a given year. The total number of bank branches is equal to the number of domestic private and foreign bank branches.

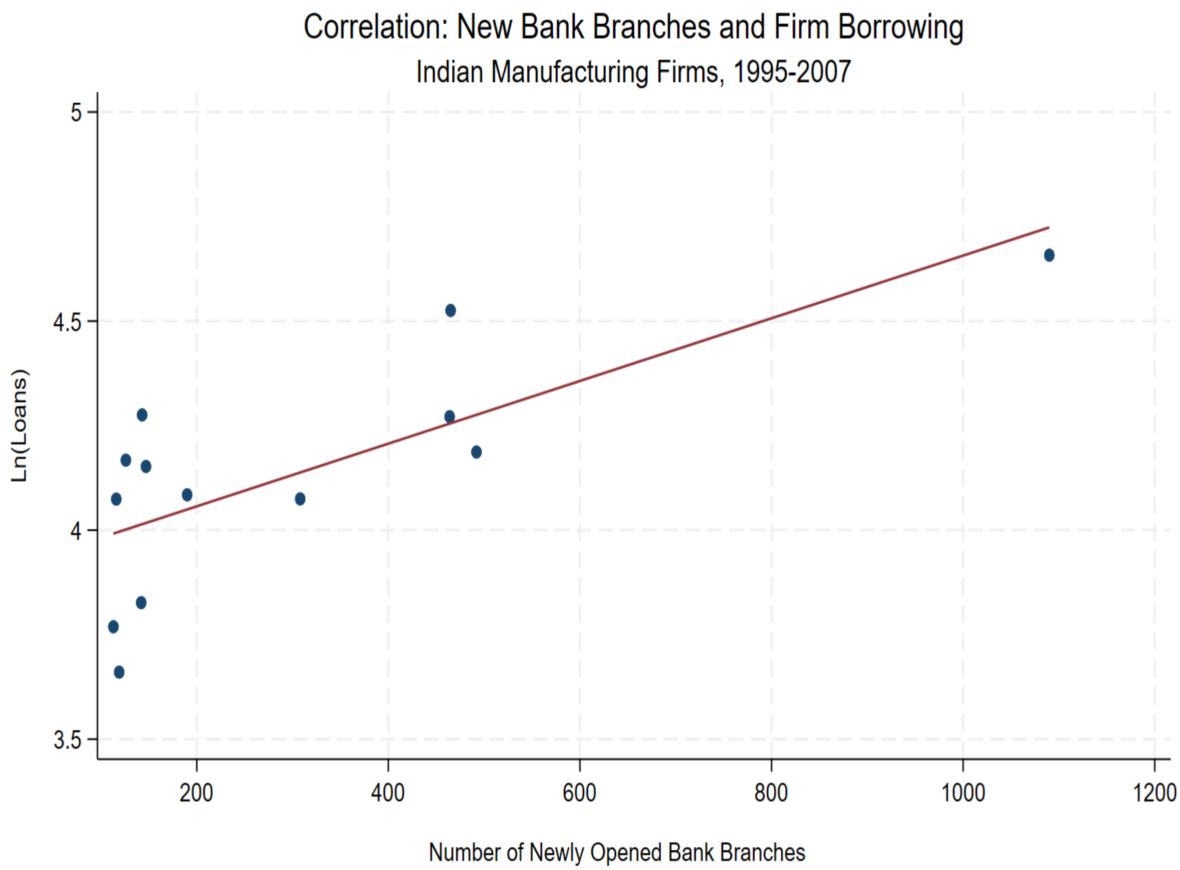


Figure A.2: Unconditional Correlation – Newly Opened Bank Branches and Borrowing by Firms, 1995–2007

Notes: The figure plots the unconditional correlation between number of new bank branches (domestic private and foreign) opened and the amount of borrowing done by firms across the period 1995 to 2007.

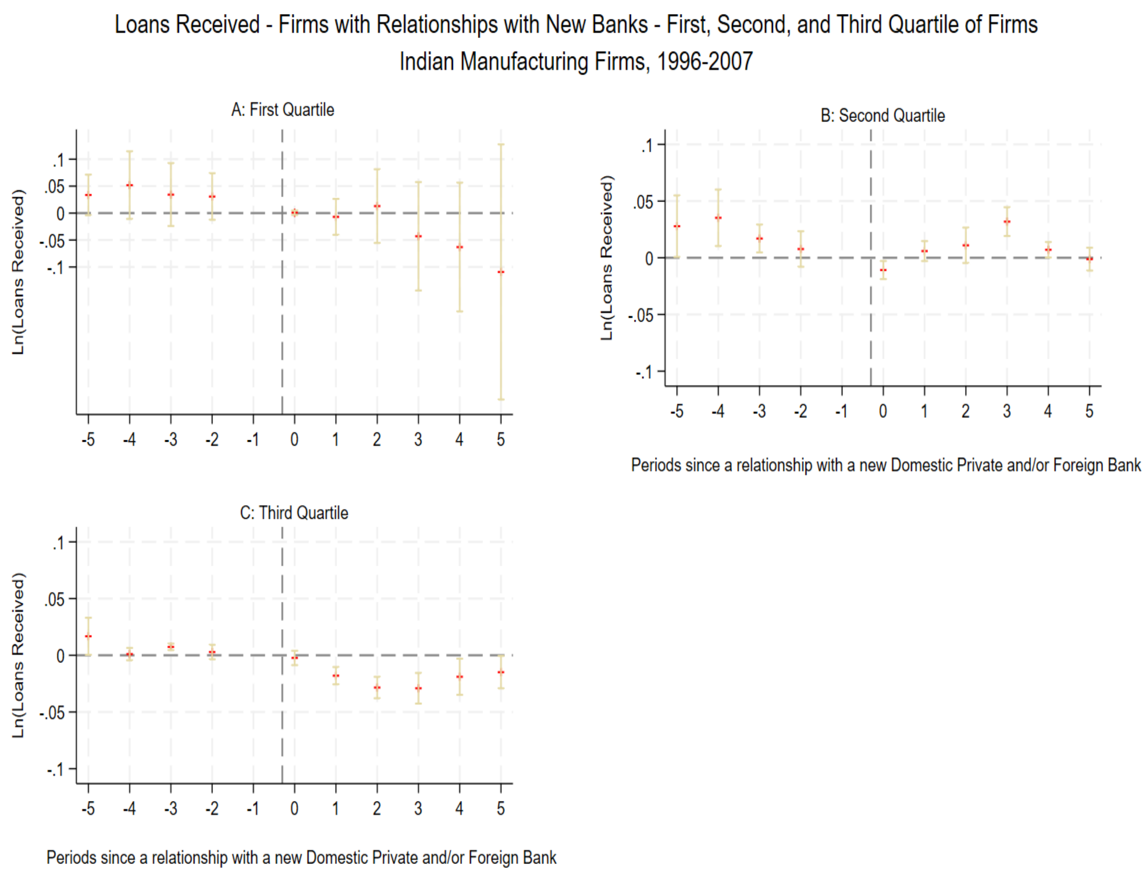


Figure A.3: Loans Received – Firms with Relationships with New Banks – First, Second, and Third Quartile Firms

Notes: The coefficient plots represent the differences in the amount of loan received by First Quartile (Panel A), Second Quartile (Panel B), and Third Quartile (Panel C) of firms who has relationships with new domestic private and/or foreign banks compared to firms who never formed such relationships throughout all the years of our sample. In effect, we plot a staggered differences-in-differences graph as different firms formed these new relationships at different points in time. Our coefficient estimates are controlled for covariates (age and age-squared of a firm) firm, industry-year, state-year fixed effects, and bank branch trends. Standard errors clustered at the firm-year level.

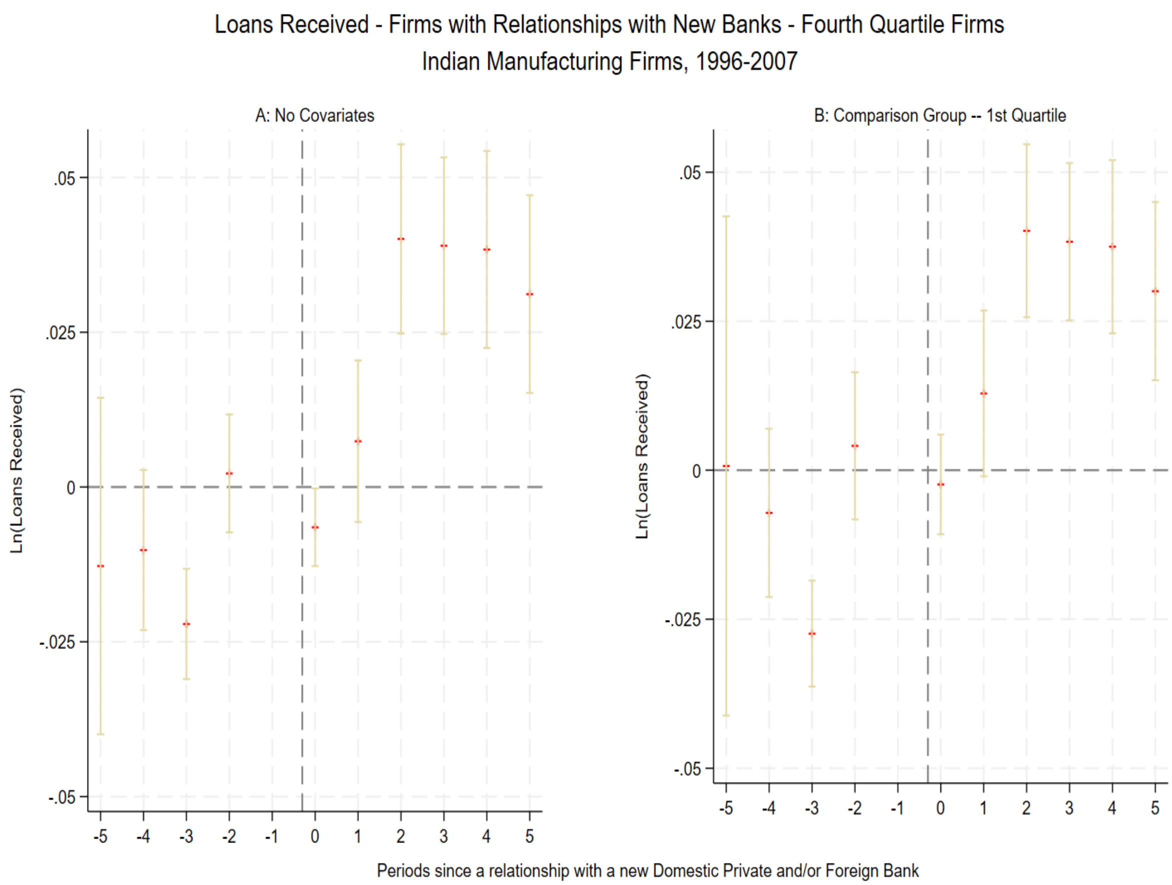


Figure A.4: Loans Received – Firm with Relationships with New Banks – Fourth Quartile Firms: No Covariates (Panel A) and Different Comparison Group (Panel B)

Notes: The coefficient plots represent the differences in the amount of loan received by the Fourth Quartile of firms who has relationships with new domestic private and/or foreign banks compared to firms which never formed such relationships throughout all the years of our sample. In effect, we plot a staggered differences-in-differences graph as different firms formed these new relationships at different points in time. Our coefficient estimates are controlled for covariates (age and age-squared of a firm) firm, industry-year, state-year fixed effects, and bank branch trends. Standard errors clustered at the firm-year level.

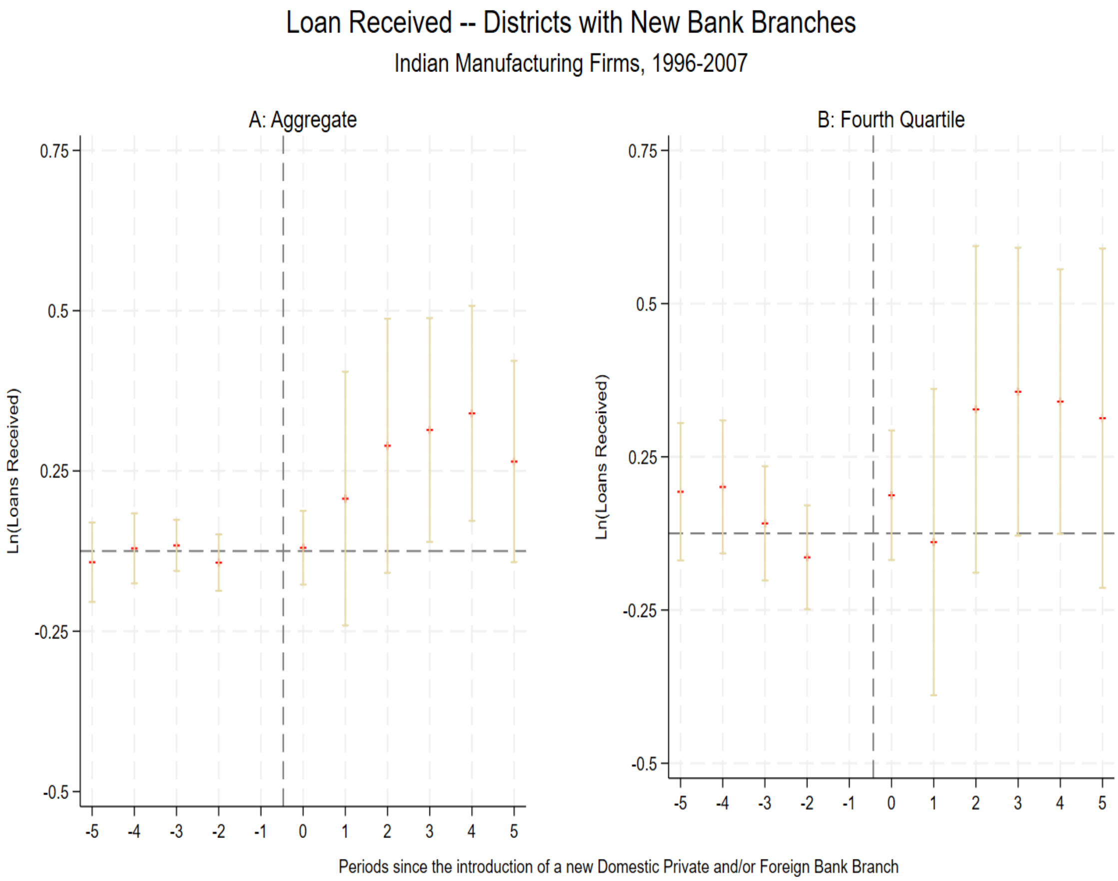


Figure A.5: Loans Received – Aggregate and 4th Quartile Firms in Districts with New Bank Branches

Notes: The coefficient plots represent the differences in the amount of loan received by firms both at the aggregate level and 4th quartile of firms in districts where a new domestic private and/or foreign bank branch was introduced compared to districts which received no such treatment throughout all the years of our sample. In effect, we plot a staggered differences-in-differences graph as different districts received new branches at different points in time. Our coefficient estimates are controlled for covariates (age and age-squared of a firm) firm, industry-year, state-year fixed effects, and bank branch trends. Standard errors clustered at the district-year level.

B Tables

Table B.1: Summary Statistics: District Level

	District Level	
	No Pre-existing Private and/or Foreign banks	
	New Banks	No New Banks
	(1)	(2)
# of Firms	265	391
# of Districts	74	99
Bank Loans	105	56.45
Assets	549.15	342.3

Notes: Bank loans reported are the median loans received by an average manufacturing firm. Both bank loans and firm assets are reported in Million INR.

Table B.2: Summary Statistics: Relationships with Banks'

	Mean	Median	Std. Deviation
Panel A: Aggregate			
2000	4.51	4	3.51
2001	4.47	4	3.56
2002	4.41	4	3.44
2003	4.52	4	3.56
2004	4.76	4	3.75
2005	5.00	4	3.98
2006	5.20	4	4.36
2007	5.48	4	4.64
Panel B: Public-Sector Banks			
2000	2.77	2	2.19
2001	2.72	2	2.25
2002	2.73	2	2.26
2003	2.80	2	2.39
2004	2.87	2	2.50
2005	3.05	2	2.71
2006	3.10	2	2.83
2007	3.19	2	2.97
Panel C: Private Banks			
2000	0.79	1	1.06
2001	0.85	1	1.10
2002	0.90	1	1.13
2003	0.98	1	1.17
2004	1.11	1	1.27
2005	1.18	1	1.30
2006	1.30	1	1.45
2007	1.38	1	1.51

Notes: Numbers represent the mean, median, and standard deviation of number of credit relationships of an individual firm across different kinds of banks. All the values expressed are in numbers.

Table B.2: Summary Statistics: Relationships with Banks' by Firm Type

	2000	2001	2002	2003	2004	2005	2006	2007
Panel A: By Industry								
Consumer Durable	3	3	3	3	3	4	4	4
Consumer Non-Durable	4	4	4	4	4	4	5	5
Intermediate	4	4	4	4	4	4	4	4
Basic	3	3	3	3	4	4	4	4
Capital	4	4	3	3	4	4	4	4
Panel B: By Ownership								
Domestic Private	3	3	3	3	4	4	4	4
Foreign	5	5	5	5	5	4	4	5
Domestic Govt.-owned	5	5	6	6	6	6	6	6
Panel C: By Age								
$<= 10$ *years*	2	2	3	3	3	4	4	4
> 10 & $<= 25$ *years*	3	3	3	3	3	3	4	4
> 25 *years*	4	4	4	4	4	5	5	5
Panel D: By Size								
$< 25th$ *percentile*	2	2	2	2	2	2	2	2
$> 25th$ & $<= 50th$ *percentile*	3	3	3	3	3	3	3	3
$> 50th$ & $<= 75th$ *percentile*	5	5	5	5	5	5	5	5
$> 75th$ *percentile*	8	8	7	8	8	8	9	9

Notes: Numbers represent the median number of credit relationships of an individual firm across different kinds of banks. Size of a firm is defined according to the total assets of a firm. If a firm's total asset falls below the 25th percentile of the total assets of the corresponding industry to which the firm belongs, then the firm belongs to the 1st quartile. Similarly, if a firm's asset is within 25–50th, 50–75th and over 75th percentile then it would fall into 2nd, 3rd and 4th quartile respectively. All the values expressed are in numbers.

Table B.3: Banking Competition and Access to Credit: Test for Selection Effects

	Ln(Loans + 1)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Prior - Rel\ Govt.\ Bank_{i,t-1}$	0.036	0.037	0.046	–0.030	0.062		
	(0.059)	(0.059)	(0.062)	(0.066)	(0.068)		
$Prior - Rel\ Govt.\ Bank_{i,t-1} \times Quartile_1$						0.830***	0.765***
						(0.311)	(0.260)
$Prior - Rel\ Govt.\ Bank_{i,t-1} \times Quartile_2$						–0.016	–0.026
						(0.106)	(0.153)
$Prior - Rel\ Govt.\ Bank_{i,t-1} \times Quartile_3$						–0.169	–0.094
						(0.127)	(0.180)
$Prior - Rel\ Govt.\ Bank_{i,t-1} \times Quartile_4$						0.108	0.089
						(0.110)	(0.111)
R-Square	0.80	0.80	0.79	0.79	0.84	0.79	0.84
N	13,744	13,739	12,511	12,511	12,648	12,511	12,648
Firm Controls	X	✓	X	X	X	X	X
Firm FE	✓	✓	✓	✓	✓	✓	✓
Industry FE (2-digit) × Year FE	✓	✓	✓	✓	X	✓	X
Industry FE (2-digit) × $Prior - Rel\ Govt.\ Bank_{i,t}$	✓	✓	✓	✓	X	✓	X
State FE × $Prior - Rel\ Govt.\ Bank_{i,t}$	X	X	✓	✓	X	✓	X
$Prior - Rel\ Govt.\ Bank_{i,t}$ × Year Trends	X	X	X	✓	X	X	X
Industry FE (5-digit) × Year FE	X	X	X	X	✓	X	✓
Industry FE (5-digit) × $Prior - Rel\ Govt.\ Bank_{i,t}$	X	X	X	X	X	X	✓

Notes: All the regressions are for the years 1995–2007. Columns (1) – (7) use logarithm of total loans received by a firm plus 1 as the dependent variable. $Pre - Govt.\ Bank_{it}$ takes the value 1 if firm i had a pre-existing relationship with any public-sector bank or experience an increase in the number of public banking relationships. We use lagged value of $Pre - Govt.\ Bank_{it}$ to counter for endogeneity reason. Quartiles $Qr_{i=1,2,3,4}$ are defined according to the total assets of a firm. Firm Controls include age and age squared of a firm. Loans are corrected for inflation. Standard errors in parentheses are clustered two-way at the firm and year level. Intercepts are not reported. *, **, *** denotes 10%, 5% and 1% level of significance, respectively.

Table B.4: Bank Entry and Interest Paid

	Interest Expenses (1)
New Bank Relation$_{i,t-1}$ × *Quartile*$_1$	0.057
	(0.105)
New Bank Relation$_{i,t-1}$ × *Quartile*$_2$	0.188
	(0.133)
New Bank Relation$_{i,t-1}$ × *Quartile*$_3$	0.110
	(0.099)
New Bank Relation$_{i,t-1}$ × *Quartile*$_4$	0.188**
	(0.086)
R-Square	0.95
N	5,016
Firm FE	Yes
Industry FE (2-digit) × Year FE	✓
Industry FE (2-digit) × *New Bank Relation*$_{i,t}$	✓
State FE × *New Bank Relation*$_{i,t}$	✓

Notes: The regression is for the years 1995–2007. Column (1) use logarithm of real interest expenses paid by a firm as the dependent variable. *New Bank Relation*$^{PF}_{i,t}$ takes a value 1 when a firm i forms a new credit relationship with a domestic private or foreign bank branch year t. We use *New Bank Relation*$^{PF}_{i,t-1}$ as a proxy for *New Bank Relation*$^{PF}_{i,t}$ to control for the potential endogeneity due to selection issues. Quartiles $Qr_{i=1,2,3,4}$ are defined according to the total assets of a firm. The dependent variables are corrected for inflation. Standard errors in parentheses are clustered two-way at the firm and year level. Intercepts are not reported. *, **, *** denotes 10%, 5% and 1% level of significance, respectively.

Table B.5: Capital Market Distortion and New Banking Relations

	New Bank Relation$_i$		
	OLS	Logit	Probit
	(1)	(2)	(3)
Capital Market Distortion	0.009	0.057	0.034
	(0.007)	(0.055)	(0.031)
Size$_i$	0.080***	0.599***	0.325***
	(0.010)	(0.077)	(0.041)
R-Square	0.16	0.10	0.10
N	2,337	2,006	2,006
Industry FE	✓	✓	✓

Notes: Columns (1) – (3) use *New Bank Relation*$_i$ as the dependent variable. *New Bank Relation*$_{i,t}$ takes a value of 1 when a firm i forms a new credit relationship with a domestic private or foreign bank branch year t. Capital Market Distortion is measured through $\ln(\frac{1+\tau_{ij}^K}{1+\tau_j^K})$. Size$_i$ is the size of firm i. We use the initial assets of a firm as the size indicator. Standard errors in parentheses are robust standard errors. Intercepts are not reported. *,**, *** denotes 10%, 5% and 1% level of significance, respectively.

Table B.6: Gains Analysis (Using Sales)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2000	2001	2002	2003	2004	2005	2006	2007
	Panel A: TFPQ Ratio							
Quartile 1	0.000	0.139	0.077	0.061	0.004	0.099	0.091	–0.009
	(0.000)	(0.091)	(0.098)	(0.066)	(0.056)	(0.050)	(0.048)	(0.050)
Quartile 2	0.000	0.076*	–0.042	–0.036	–0.034	–0.005	–0.039	–0.042*
	(0.000)	(0.035)	(0.035)	(0.029)	(0.029)	(0.029)	(0.023)	(0.020)
Quartile 3	0.000	0.056	–0.007	–0.006	–0.002	0.030	0.023	–0.013
	(0.000)	(0.029)	(0.026)	(0.024)	(0.019)	(0.021)	(0.019)	(0.017)
Quartile 4	0.045	0.071**	0.024	–0.010	0.009	0.031*	0.041**	0.041**
	(0.047)	(0.026)	(0.021)	(0.020)	(0.017)	(0.016)	(0.016)	(0.015)
R-Square	0.75	0.63	0.59	0.62	0.60	0.63	0.63	0.65
	Panel B: TFPR Ratio							
Quartile 1	0.000	1.019**	–0.322	0.181	0.741*	0.343	0.014	–0.600*
	(0.000)	(0.372)	(0.426)	(0.328)	(0.319)	(0.282)	(0.309)	(0.295)
Quartile 2	0.000	–0.228	0.130	–0.009	0.180	0.233	0.229	- -0.000
	(0.000)	(0.145)	(0.154)	(0.144)	(0.166)	(0.161)	(0.146)	(0.120)
Quartile 3	0.000	–0.185	0.048	–0.129	–0.035	0.133	0.055	0.065
	(0.000)	(0.121)	(0.114)	(0.118)	(0.111)	(0.117)	(0.125)	(0.103)
Quartile 4	–0.029	–0.044	0.063	0.024	0.046	0.103	0.061	–0.129
	(0.361)	(0.106)	(0.091)	(0.100)	(0.099)	(0.088)	(0.100)	(0.090)
R-Square	0.77	0.70	0.62	0.59	0.52	0.57	0.52	0.55
N	83	524	547	553	571	565	544	565
Industry FE (2-digit) × New Bank $Relation_{i,t}$	✓	✓	✓	✓	✓	✓	✓	✓
State FE × New Bank $Relation_{i,t}$	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Columns (1) – (6) of Panel A use physical or *within-firm* productivity and Panel B uses revenue or *between-firm* productivity as the outcome variables of interest, respectively. Quartiles $Qr_{i=1,2,3,4}$ are defined according to the total assets of a firm. Standard errors in parentheses are robust standard errors. Intercepts are not reported. *,**, *** denotes 10%, 5% and 1% level of significance, respectively.