Banking Reforms, Access to Credit, and Misallocation

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Abstract

New liberalization policies are rapidly globalizing financial services in developing countries, but there is little or no microeconomic evidence on the impact of banking reforms on the real economy. We examine the impact of a banking sector reform, characterized by the introduction of new domestic private and/or foreign banks, on Indian manufacturing firms' access to credit, performance and the resulting misallocation in the Indian economy using a unique firm-bank matched data. We find that the introduction of new banks led to (i) increase in access to credit by 18—23% for big firms (top 25 percentile of size distribution); (ii) reduction in access to loans for small firms (bottom 25th percentile) by around 45%; and (iii) increase in profit, total sales for big firms. Next, we follow Hsieh and Klenow (2009) and estimate the distortions arising out of capital and output market and show that the banking reforms significantly relaxed the credit constraints only for the big and more productive firms, resulting in reduced capital market misallocation. Finally, our counterfactual experiment shows that the reallocation of credit led to an overall gain in manufacturing output by 0.15–1.1%.

Keywords— Banking Reforms, Private and/or Foreign Banks, Big Firms, Cream Skimming, Misallocation

JEL— G1, G21, O47, L25

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1 Introduction

Developing countries typically have inefficient domestic public-sector banks resulting in high borrowing costs and limited access to finance for many firms[1]. Opening up the banking sector to competition is often proposed as a way of inducing competition in the banking sector to remove these supply-side constraints. Entry of the new private and/or foreign banks may increase the supply of credit and improve efficiency, and on the other hand, it may reduce access to credit for some firms because private and/or foreign banks tend to have limited local information and 'cherry-pick' their clients (see Petersen and Rajan (1995) in the context of the U.S.).

New liberalization policies are rapidly globalizing financial services in developing countries[2], but there is little micro-economic evidence on the impact of new private and/or foreign banks on firm growth, largely due to (1) 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 (2) the difficulty of isolating banking globalization from contemporaneous macroeconomic shocks (Goldberg (2009))[3].

We examine the impact of banking sector liberalization on Indian manufacturing firms' access to credit using India as the case study. Our results show that banking reforms led to about 18–23% increase in loans for the big firms (top 25%), while reducing access to loans for small firms (bottom 25th percentile) by around 45%. In addition, we also investigate whether these banking reforms contributed to the overall misallocation problem in the economy arising from any skewed credit allocation due to cream skimming or cherry picking behavior of the banks. We find that the reform reduced the distortions arising out of the capital market, but only for big firms (with opposite effect for small firms). Finally, this increased access to loans/credit led to overall increase in profits as well as sales for big firms.

India opened to the new domestic private and foreign banks from the late 1990s due to its obligations under the WTO's services trade agreement, rather than due to a macroeconomic crisis package (Gormley 2010, Gormley et al., 2018). In particular, new bank entry guidelines were established after the GATS (1998) round of agreement allowing more of domestic private and foreign bank branches to operate across India. We use this policy change, in terms of banking sector reforms, that allowed new domestic private and foreign banks to enter. In addition, public banks were allowed to issue equity up to 49%. This deregulation led to a significant increase in bank entry both by domestic private and foreign banks.

In response to the deregulation policy, 12 new private banks and 1,700 new branches were added between 1993 and 2004. On the other hand, 17 new foreign banks and 89 new foreign bank

[1]Most firms in developing countries report financing problems as constraints to growth (Bloom et al. (2010)).

[2]This is especially after or simultaneously with the large scale liberalization programs implemented in Asia and South America from 80s and 90s onward.

[3]While several macroeconomic studies analyze the impact of increase in competition in the banking sector on the domestic banks in emerging markets, less is known about the their real impact (Goldberg (2009)).

branches were opened in India bringing the total number of foreign banks to 41 with 212 branches as of March 2002. Figure 1 plots the number of new domestic private and foreign bank branches opened in India between 1990 and 2007. The figure points out that between 1995 and 2000, there was virtually no increase in the number of branches across India; it was around 150. However, it started to increase exponentially afterwards, going to more than 1000 by 2007[4].

Given this significant increase in the number of new branches after 2000, we study the effect of this liberalization of banking sector on credit access using a sample of Indian manufacturing firms for the years 1995 to 2007. We carry out the analysis at two different levels.

First, we investigate whether introduction of a new domestic private and/or foreign bank branch led to more credit issued to these firms or not. We do this at two levels: first, at the district level. We track the opening of all the new branches in a district after the year 2000 and compare them against the districts where no new branches (of private and/or foreign bank) were opened. We find that introduction of a private and/or foreign bank led to lower availability of loans, but only for the smaller firms. Our most conservative estimates show that the introduction of new bank branches (private and foreign) in a district led to about 40% drop in accessibility to loans for small firms. This is relative to other small firms in districts where no new domestic private and/or foreign bank branch was opened after the GATS (1998) round.

Second, at the firm level. We estimate what happens to access to credit for firms when it adds a new private and/or foreign bank to its list of banking relationship after 2000 given that the firm had no previous associations with any such bank. Our control group is now the sample of firms who never added any new private and/or foreign bank to its list of lenders. Our previous result (from the district level analysis) stays the same: availability of loans to small firms decrease with having a new private and/or foreign bank compared to firms (small) who never have had such a relationship. On the other hand, access to credit for big firms increased compared to firms (big) who similarly never had any relationship with a domestic private and/or foreign bank. Our results, both at the district and firm level, 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 new banks (private and/or foreign banks) could have engaged in what the literature calls 'cream skimming'. A lending strategy that involves extending credit only to wealthy and transparent segments of the credit market which are primarily the big firms (Detragiache et al. (2008); Beck and Peria (2010)), while excluding segments that comprise less wealthy and/or marginal borrowers (Berger and 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." Many other studies have also found that presence of new private banks (domestic and/or foreign) does not necessarily enhance overall credit availability and

[4]Figures 2 and 3 plot the domestic private and foreign bank branches separately. Although, both the new foreign and domestic private bank branches started to increase after 2000, it is the domestic private bank branches that dominates the overall growth.

may actually aggravate the conditions of credit constraints rather than alleviating such constraints, mainly for the smaller firms (see Khwaja and Mian (2008) for Pakistan; Beck and Peria (2010), 2010 for Mexico; Gormley (2010) for India; Lin (2011) for China). This cream-skimming behavior by the banks can have mixed effects in terms of misallocation of resources. In particular, it may adversely affect the allocative efficiency of firms and aggravate the misallocation of credit problem. On the other hand, an easier access to credit for the more productive firms may reduce the extent of such misallocation.

Therefore, our next step is to understand whether the banking reforms did contribute to the overall growth in total factor productivity (TFP), or there has been credit misallocation leading to an overall reduction in TFP (for the manufacturing sector). We follow Hsieh and Klenow (2009) and use the same misallocation (accounting) method to measure the magnitude of allocative inefficiency in an economy. We find that the capital market distortion, proportional to the firm-specific marginal productivity of capital, is lower and shows a decreasing trend, but only for the big firms with an opposite trend for the small firms.

To understand whether this decline in capital market distortions (for big firms) or increase (for small firms) can be explained by increase in (or not) association with private and foreign banks, we regress the misallocation measures (aggregate, capital market, and output market) on our main variable of interest, 'switch'[5]. We find that switching to new private and/or foreign banks helped the big firms to reduce their distortions arising out of the capital market, with no impact on overall distortion or distortions coming out of the output market. This finding is robust to controlling for several selection issues related to the firm, year, industry, and region that may confound our estimates (using interactions between our main of interest and unobservables at different levels). We use a placebo to check whether pre-reform capital market distortions can explain such relationships with new domestic private and/or foreign banks and this is not the case. Rather, it is the firm size, which plays a significant role. Since firm size is a reasonable proxy for physical productivity, our results can possibly be interpreted as follows: upon entry into the Indian banking industry, the new domestic private and/or foreign banks picked their clients based on size (physical productivity). These new banking relationships then relaxed the credit constraints for those firms, resulting in reduced capital market misallocation which is confirmed by their subsequent increase in sales and profits.

Overall, our results suggest that the introduction of the new domestic private and/or foreign banks reduce capital market misallocation, leading to cheaper and easier access to credit and better performance for the most efficient firms, but the overall manufacturing TFP remained constant for the entire period of our analysis. This possibly suggests that the banking reforms did not contribute significantly towards the overall growth of the economy.

[5] We use the same explanatory variable that we use at the firm level to estimate the effect of banking reforms on access to credit.

Overall, our findings are consistent with a model in which distortions in bank lending can create artificial barriers to entry in the real sectors of the economy (Sengupta (2007))[6]. We have two primary contributions. First, we add to the small literature on how presence of new banks led to overall credit availability of firms (Bertrand et al. (2007); Sengupta (2007); Gormley (2010)).We show that liberalization of banking sector does not necessarily add to the increase in overall credit availability for all firms; our results show significant evidence of re-allocation of loans from small to the big firms. We extend Gormley (2010) to show that that results at the district level also hold at the firm level and both for domestic private and foreign banks[7]. Second, our results also add to the misallocation literature (Hsieh and Klenow (2009), Restuccia and Rogerson (2008)). While Hsieh and Klenow (2009) and Ziebarth (2013) use plant level data to measure misallocation, we use firm level data to link firm performance with their banking relationships. To the best of our knowledge, this is the first paper to show that credit allocation can contribute to the overall misallocation problem of the economy, but heterogeneously. The presence of new banks led to decrease in distortions arising out of capital market for big firms and quite the opposite for small firms.

The rest of the paper is organized as follows: Section 2 describes the dataset we use. Section 3 estimates the aggregate and heterogeneous effect of the introduction of new banks on credit issued to firms both at district and firm level. Section 4 addresses how the banking liberalization affected the misallocation problem. Section 5 discusses our results from the previous section and relates to the behaviour of overall manufacturing TFP in the economy, while Section 6 concludes.

2 Datasets

2.1 Firm level – PROWESS

The sample of firms is drawn from the PROWESS database, constructed by the Centre for Monitoring the Indian Economy (CMIE), a private agency. The database contains information on approximately 27,400 companies, both publicly listed and unlisted, all within the organized sector. 9000+ of them are in the manufacturing sector. We use data for around 3,500+ firms, for which there is consolidated data on banking relationships. We use data for the years 1995 to 2007[8]. Unlike other sources, the PROWESS data is in effect a panel of firms, enabling us to study their behaviour and banking relationships over time.

[6] Although our results point towards such direction, our dataset is not suitable to estimate firm entry and exit effects precisely (Goldberg et al., 2010).

[7] Gormley (2010) using Indian district level data 1994–2002 show that increase in the presence of new foreign banks only led to increase in loans for big firms

[8] We have data till 2015, but we truncate it before 2008 to avoid the period of the North American financial crisis.

The data is classified according to 5-digit 2008 National Industrial Classification (NIC) level. We re-classify it to 4-digit NIC 2004 to facilitate matching with other important industry-level variables; hence, all the categorization made throughout the paper are based on the 2004 NIC classification. The data spans across 108 (4-digit 2004 NIC) dis-aggregated manufacturing industries that belong to 22 (2-digit 2004 NIC) larger sectors. It presents several features that make it particularly appealing for the purposes of our study. Below, we outline two of the most important features that are primarily needed for the paper.

(i) information on the banking relationships for each firm[9]. The data provides the names and the types of banks (domestic public-sector, domestic private, foreign) that a bank has a relationship for all the firms. An Indian manufacturing firm on average has credit relationships with 5 banks. A public-sector firm is client to about 7 banks, whereas a private and foreign firm is client to 5. Bigger firms on average have more banking relationships than smaller ones[10]. The dataset also reveals all the important information from the balance sheet of the banks. This gives us the unique advantage of utilizing this information for a firm and see the impact of its new banking relationships (due to the bank reforms) on credit access.

However, in spite of all these advantages there are is two potential limitations of this data that must be mentioned: 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. Second, we only observe the aggregate credit/loans (*bank*) issued. We cannot dis-aggregate them by the origin banks. More on this below.

(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 domestic banks, foreign banks, borrowings from domestic private financial institutions, etc.[11] We sum all the different types of loans received by a firm (from *banks*) and use it as our main outcome variable of interest. We also use extensive margin of loans (an indicator variable indicating whether a firm has received a loan or not) as the other outcome of interest.

[9]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 co-operative banks. This is according to the list of major banks (excluding the state-sponsored financial institutions, cooperatives) provided by the RBI.

[10]Same goes for exporters; an average exporter is client to twice the number of banks in comparison to a non-exporter.

[11]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 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 or a number of banks or from a syndicate of banks with some collateral; all of these are a part of secured bank borrowings.

2.2 Others

2.2.1 Branch Level – RBI

For our district level analysis, we use data on the details of new bank branches opened across India from the website of India's central bank (popularly known as *Reserve Bank of India*, or RBI hereafter). The data runs from early 19th century to the present day. We scrape the data for the new branch districts for the period 1995 to 2007 and match it with the information on location of firms (postcodes) from the PROWESS data.

2.2.2 NBER

We also use 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.

3 Banking Reforms and Access to Credit

This section analyzes whether increased proliferation of new domestic private and/or foreign banks, as a result of the new banking reform, have had any effect on the allocation and accessibility to credit issued. We study this along two dimensions: (a) exploiting the location information of firms and new banks, we investigate whether firms located in the same district as the opening of a new bank branch have access to more loans or not[12]; and (b) using firm-bank level data, we estimate whether a new banking relationship (with domestic private and/or foreign) has any effect on the loans they receive. In addition, we also study whether this effect varies by firm size[13]. We start with the former.

3.1 District level

3.1.1 Stylized Facts

To study the spatial effect(s) of increased bank branches, we use postal codes at 3-digit level (denoting districts) for the banks and the corresponding firms. There are 736 districts in India with a median area of approximately 20,000 sq. Km and we have location information of new bank branches for 535 districts[14] from the RBI data.

[12]This is similar to Gormley (2010). But, we extend the period to 2007 and add domestic private banks to the list of banks, whereas Gormley (2010) restricts his analysis only for the foreign banks.

[13]We define firm size by classifying them into four different quartiles according to their corresponding industry; more on this later.

[14]In essence we cover around 75% of all districts across India

Figure 4 plots the state level geographic concentration of new domestic private and foreign banks. The left panel plots the concentration before while the right panel plots the concentration after the year 2000. Darker shades for a state implies increased bank concentration. New bank entry was not uniform across all the states (and districts). The state of Maharashtra shows the greatest increase, followed by Kerela, Tamil Nadu and Karnataka (southern states). The regional bias of new bank(s) is evident from the fact that most of the new entries are concentrated around Mumbai (a metropolis in the western part of the country and the financial capital of India) and other urban and industrial centres. Furthermore, a good proportion of the new entries also happened in districts with already existing private and foreign banks[15].

In order to prevent the effect of the existing private and/or foreign banks from confounding our estimates we filter the data to focus our study only on the districts which received a domestic private and/or foreign bank on or after the year 2000 or never received such a bank branch at all[16]. For our purposes, we define a variable $pfbank_{dt}$ for district d in year t such that it takes a value 1 if district d receives its first domestic private and/or foreign bank in year t after 2000 and 0 otherwise.

Table 1 reports number of firms, number of districts, size distribution of firms, loans they received and their assets according to the following three categories: (a) districts with pre-existing private and/or foreign banks, (b) districts which received private and/or foreign banks after 2000, and finally (c) districts with no private and/or foreign banks (both before and after 2000). Our bank and firm location matched data has 338 districts, 165 of which already had a preexisting private or foreign bank before 2000. 74 districts received a new private and/or foreign bank after 2000 while the remaining 99 districts never received such a bank branch within our sample period.[17]

Overall, it seems that the firm distribution is similar across the districts in columns (2) and (3). However, note that both the asset and loan levels are higher in the districts which received a domestic private and/or foreign bank after 2000. The median asset level is 549.15 Million INR for the districts in column (2) while the same is 342.3 Million INR in column (3). As for the amount of median amount of bank loans, districts with a new private and/or foreign bank report a value of 4.43, while it is 4.05 the districts which never received a new private and/or foreign bank branch.

It is important to point out here that the results in Table 1 may be a consequence of selection issues at the bank level. More specifically, the new domestic private and/or foreign banks may have strategically chosen only those districts where economic activity is relatively higher and political climate is conducive for business and growth. To rule out these possible selection effects, we use a fixed effects regression specification, described in the next subsection.

[15] Other than Mumbai, South Delhi, Chennai, Bangalore are a few other examples.

[16] Note that we use the year 2000 as our threshold year. Using any year from 1998-2002 gives us qualitatively similar results. Since private bank entry in India is a slow moving process we opt not to be too strict regarding the choice of the threshold year.

[17] This reflects the fact that most of the entry entry occurred in districts with preexisting private/foreign banks and portends of a serious endogeneity problem.

3.1.2 Empirical Strategy

Stylized facts in the previous section show that firms in districts that received a new domestic private and/or foreign bank after 2000 have higher access to credit. We now test for the causal effect of the introduction of private and/or foreign banks on bank loans using the following fixed effects OLS specification:

$$\text{Bank Loans}_{it} = \alpha_i + \beta_1 \text{bankbr}_{dt-1} + \mathbf{X}_{it-1} + \theta_{jt} + \omega_{st} + \epsilon_{it} \tag{1}$$

β_1 is our coefficient of interest; a difference-in-differences estimator. We measure *Bank Loans*$_{it}$ along two dimensions: (a) intensive margin – does a firm located in a district with a new domestic private and/or foreign bank branch get *more loans* than a firm located in a district with no new domestic private and/or a foreign bank? (b) extensive margin – do new firms receive bank loans in districts with a new domestic private and/or foreign bank?

As indicated in the stylized facts, banks may self select themselves into districts with higher economic activity, more profit opportunities, better institutions, etc. Districts with better business opportunities are also populated by firms with better financial health or higher assets. To deal with this potential source of endogeneity, we take the following two steps: (a) using a lagged value of $bankbr_{dt}$ as an instrument for new bank entry in district d and period t. This will replace bank entry with pre-entry location characteristics and partially control for the endogenous choice of a bank to enter a district. In other words, this step effectively breaks the correlation between increase in the access to credit and bank entry caused by this selection effect. (b) using a full set of firm fixed effects (α_i). This controls for both district as well as more granular firm level unobserved factors that may have affected bank entry in a district or in other words, the demand side factors. Possible examples of these unobserved factors include firm level lobbying for new banks or district level real estate costs affecting new bank entry.

ω_{st} and θ_{jt} are the interactions between state-year and industry-year fixed effects, respectively. The former controls for variation in state level policies over time that may effectively increase credit access for firms by creating incentives for banks to locate in specific districts. This involves subsidies or tax breaks provided to banks by legislation in the state level industrial policies. The latter, on the other hand, does the same for industry specific time varying demand. If firms in a specific industry are located in clusters and experience a persistent increase in demand, this may encourage banks to locate in districts where firms of a specific industry is operational. $\mathbf{X}_{it-1}$ controls for firm level observable factors that includes age, age squared and assets (measured with a lag). These variables would control for the propensity of banks to locate in districts populated by either younger firms or older firms or, more plausibly by firms with more assets. Additionally, our year fixed effects will control for the factors which would capture the general economic reforms and policy environment in India during our sample time period.

There are a host of other possible supply side factors that can create omitted variable bias in our estimates. To account for those we interact $bankbr_{dt-1}$ with key firm level characteristics, firm, industry and state fixed effects. These variables would control for all possible kinds of banks' operational supply side incentives (not captured by industry or district fixed effects) to operate in specific districts when they enter. For example, this may be the operational plan of a new board of directors or an influx of funds which can only be used if the bank expands its operations in new districts.

3.1.3 Results

Tables 2 and 3 reports the result at the district level for intensive and extensive margins of access to credit. For all the regressions at the aggregate level, we control for interactions between $bankbr_{dt-1}$ and a key firm characteristic, which is firm assets to control for any selection issues at the firm level which drove the banks to open a new bank branch. We start by looking at the intensive margin (Table 2)– whether firms who had access to credit before got more loans.

Column (1) regresses natural logarithm of total loans received by a firm on a lagged value of $bankbr_{dt}$, controlling for firm, state-year fixed effects, and industry-year trends. Our point estimate show that introduction of new bank branches (private and/or foreign) had a dampening effect on the access to loans by firms. In other words, due to the introduction of new banks, firms had lower access to loans/credit – 1 standard deviation increase in bank branches led to about 10.5% decrease in access to credit by firms on an average. And, this is significant at 1% level. Columns (2) and (3) replace industry-year trends and use industry-year fixed effects at 2-digit and 3-digit level. Our benchmark result continues to hold, although the point estimates drop a little.

Column (4) additionally controls for the idea that whether a bank decided to open a branch based on the industries located in those districts. For example, a bank may have preference towards giving credit to certain industrial sectors and some districts have higher concentration of those industries. In order to control for that, we interact our main variable of interest, $bankbr_{dt-1}$ with industry fixed effects (3-digit level). Introducing these new fixed effects does little to our benchmark result. Columns (5) and (6) do the same, but uses interactions of $bankbr_{dt-1}$ with year fixed effects to control for differential time trends and firm unobservables such as managerial ability, respectively. Finally, column (7) interacts $bankbr_{dt-1}$ with state fixed effects to control for any state level policies that may influence a bank's decision to open a new branch. In all these cases, our benchmark result does not change – introduction of new banks led to lower access to credit. Overall, our estimates show that 1 standard deviation increase in bank branches led to around 6.8% - 11% reduction in loans for firms.

It may be the case that our aggregate results are driven by certain groups of firms or is valid for a particular group of firms only. In order to understand, whether size heterogeneity plays a role in explaining our results, we divide our sample of firms into four different quartiles, according to their total assets. We consider total assets as the size indicator of the firms. The different size categories of firms are indicated by a dummy variable. For example, if the total assets of a particular firm falls below the 25th percentile of the total assets of the corresponding industry, then that firm belongs to the first quartile and the variable would indicate 1 for that particular firm, and zero otherwise. Likewise, if a firm's total assets fall between 25th percentile to 50th percentile, 50th percentile to 75th percentile and above 75th percentile, the firm belongs to the categories of second, third and fourth quartile, respectively. We interact different quartile dummies with $bankbr_{dt-1}$ in order to measure the required effect on that particular quartile of firms. We use the following specification:

$$\text{Bank Loans}_{it} = \alpha_i + \sum_{q=1}^{4} \beta_q (\text{bankbr}_{dt-1} * \text{Quartile}_q) + \mathbf{X}_{it-1} + \theta_{jt} + \omega_{st} + \epsilon_{it} \tag{2}$$

Columns (8) – (11) run the quartile level regressions. Our estimates show that the aggregate result is completely driven by small firms or firms belonging to 1st quartile. We do not find any effect of increase in bank branches on any other quartile of firms. Introduction of new bank (private and/or foreign) branches lead to significant reduction of credit for small firms. These results seem to indicate evidence of cream skimming by new banks in India (Gormley (2010); Sarma et al. (2014)). On other hand, we do not find any effect on the extensive margin of credit (Table 3).

Even though we control for all possible demand and supply side factors to establish a causal effect of banking reforms on access to credit, there could still be two possible drawbacks. First, the way we construct our sample. We only compare districts that receive their first domestic private and/or foreign bank after 2000 with districts that never receive such a bank. This may have a significant impact on our sample size. This is because 165 districts in our sample already had a private or foreign bank before the year 2000. Second, Petersen and Rajan (2002) points out that over time distance between the lenders and firms becomes insignificant as communication between them turns out to be more impersonal. If this hypothesis holds true, then firms can borrow from banks located in different districts without even physically travelling to the bank. This can potentially attenuate our estimate. In order to get our way around these drawbacks, we move our analysis to the firm level, described in the next subsection.

3.2 Firm level

3.2.1 Stylized Facts

In this section, we take a step ahead and take our analysis to the firm level. We investigate how the relationships with new domestic private and/or foreign banks affect a firm's access to loans. Unlike the previous section, the data here is no longer restricted by the limited number of districts that received a domestic private and/or foreign bank after 2000. We now compare firms who never had a domestic private and/or foreign banking relationship with firms who develop such a banking relationship *after* they appear in the sample.

To carry out such a comparison, we define $pfswitch_{it}$. It takes a value 1 for firm i in year t if it is associated with a domestic private and/or foreign bank, and 0 otherwise. Table 4 reports the mean and median of loans received by all firms and also dis-aggregated by $pfswitch_{it}$. We start with the entire sample of firms in columns (1) – (2), and distinguish them by their size. We use a firm's assets to classify them into their respective quartiles. Columns (4) – (5) calculate the same for the firms who are associated with private and/or foreign banks and columns (7) – (8) do the same for the firms who never form a relationship with private and/or foreign banks.

Overall, 768 firms create new private banking relationships after they appear in the sample as opposed to 2316 firms who never form such a relationship. Both the mean and median loans received is noticeably higher for the big firms who *switched* as opposed to the big firms who did not. For example, the median value of loans received by the fourth and third quartile of firms who do not have a private and/or foreign relationship is 5.13 and 3.95, respectively. And, the same is 5.80 and 4.19 for firms who form a new relationship.

However, we observe quite the opposite for the firms belonging to the 1st quartile or small firms. The median loans received by them who form a new private relationships is 0.55 in comparison to 1.39 for the firms (small) who do not form such a relationship.[18] Columns (3), (6), and (9) of Table 4 report the number of firms by size quartiles for the entire sample, for the firms who *switch* and for the firms who never *switch*. Only 13.4% of the Q1 firms form new private and/or foreign relationships; 16.2% of the Q2 firms, 21.6% of the Q3 firms and 42.3% of the Q4 in our sample form domestic private/foreign relationships. This shows clear evidence of the bias of the new domestic private and foreign banks towards bigger firms.

This bias is also evident from Figure 5. It plots the number of firm-years where $pfswitch_{it}$ is equal to 1. 26% of firm-years associated with fourth quartile added one private and/or foreign banks to their portfolio after they start operating. It was followed by 12% firms in Q3, 10% in Q2, and 9% in Q1. Since $pfswitch_{it}$ varies within firms, this figure reveals that on an average, a big firm has a significantly higher chance of associating with a private/foreign bank, closer to the first year they appear in the sample. [19]

Since higher loans can result from any new banking relationship (not necessarily private), it is imperative to look into how an average firm receives loan from its new public sector banking relationship(s) as well. We define $public_{it}$ as a binary variable that takes the value 1 if a firm increases its public sector banking relationships relative to the year it first appears in the sample, and 0 otherwise. This variable is fundamentally different from the way $pfswitch_{it}$ is defined. While a zero value for $pfswitch_{it}$ means no domestic private and/or foreign banking relationships, a zero value for $public_{it}$ means that the number of public banking relationships for firm i has not increased relative to the year it first appears in the sample. Table 5 reports the descriptive statistics for loans

[18] A similar effect is observed if we compare the means.

[19] Figure 6 shows that among the firms who *switch* to a private and/or foreign bank, the chances are significantly higher for firms belonging to the fourth quartile to be associated with more than one private and/or foreign banks compared to any other size quartiles.

extended to firms with $public_{it}$ equal to 1 compared to those with $public_{it}$ equal to 0. The patterns of the loan statistics and percentages of firms connected to banks by size, are similar to that observed in Table 4. Big firms are favourably treated and a higher number of firms belonging to fourth quartile also increase their relationships to public-sector or state-owned banks.

In addition, 279 firms increase both of their public-sector and private and/or foreign banking relationships. Of these 279 firms, 4, 25, 58 and 192 firms belong to the first, second, third and fourth quartile, respectively. To summarize, increase in the number of relationships with private and/or foreign banks appears to have resulted in an increase in the loans extended to the big (Q4) firms. However, many of these firms may have also increased their banking relationships with existing public-sector banks, thus confounding the impact of domestic private and/or foreign banks alone. In what follows, we describe the empirical technique used to causally estimate the effect of domestic private and/or foreign banks on credit access by firms.

3.2.2 Empirical Strategy

As the summary statistics suggest, big firms connected to domestic private and/or foreign banks received more loans than firms belonging to other size quartiles. We now test this hypothesis using the panel structure of our firm level loan data to estimate the causal effect of introduction of new domestic private and/or foreign banking relationships on loans using the following fixed-effects OLS specification:

$$\begin{aligned} \text{Bank Loans}_{it} &= \alpha_i + \beta_1 \text{pfswitch}_{it-1} + \beta_2 \text{public}_{it-1} \\ &+ \mathbf{X}_{it-1} + \theta_{jt} + \omega_{st} + \epsilon_{it} \end{aligned} \tag{3}$$

Similar to the district level regression, we measure *Bank Loans*$_{it}$ for firm i in year t along two dimensions of credit access: intensive margin and extensive margin.

Our primary coefficient of interest is β_1. It measures the effect of adding a new private and/or foreign bank by a firm to its list of bankers on its access to credit or total loans in comparison to firms who never had a relationship with domestic private and/or foreign bank. In other words, β_1 measures the relative difference between firms' access to credit when it is connected to new private and/or foreign banks vs. a public-sector bank[20].

One of the major problems in estimating the true effect of $pfswitch_{it}$ is how the matching happens between firms and banks. There are several reasons why a bank(s) chooses a firm(s) to provide credit. Relationships may even be 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 where it creates a new relationship. In order to potentially control for this, we use lagged values of $pfswitch_{it}$ as a proxy for current value. Our identifying assumption here is that we assume the

[20]Almost all firms in our data have a public sector banking relationship.

pre-reform banking relationships of a firm drives its post-reform relationships[21], which eventually have an effect on its credit access. More specifically, firms having access to more credit/loans may be due to some favouritism by some banks and thus can explain part of the new banking relationships created; lagged regressors will potentially remove that effect. However, it is true that the relationship between a firm and a bank even in the pre-reform years is not random. But, our goal here is to control for the fact that the relationship (between a firm and a bank) is not influenced due to the reform, but due to independent past events. We control for all the other possible reasons of the matching as required robustness checks. We explain this in detail below.

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.[22] Since, omitting this variable can create an upward bias in our estimates of interest, we control for public_{it-1} in all of our specifications. public_{it-1} takes a value 1 if the firm i adds a public sector bank in its banking portfolio in year t and 0 otherwise.

Another important issue which can possibly bias our estimates in 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 5 and 4, respectively. Restricting the data to firms with a single banking relationship would force us to drop around 95% of the observations leading to a potential loss in external validity. To deal with the multiple banking relationships of firms, we do the following:

(a) we collapse the data to firm level. Please note that, our $\textit{pfswitch}_{it}$ 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. We cannot control for bank specific attributes that may influence a firm‘s access to loans, including firm-bank relationship fixed effects. But, following Petersen and Rajan (1995), we claim that firm-bank fixed effects only matter (for access to loans) if the banking industry is less concentrated[23].

Following the same line of argument, for our purposes, we are interested only in newly formed private banking relationships in a period of increased banking competition[24]. Therefore, it is plausible to assume that firm-bank relationship specific fixed effects are negligible and will not contaminate our estimates[25].

[21] $\textit{pfswitch}_{it}$ takes value 0 in the periods before the firm starts a relationship with a private/foreign bank. But it may have had a positive number of public-sector banking relationships.

[22] 279 of the 618 firms who increase their public banking relationships also create at least one domestic private and/or foreign banking relationship.

[23] Petersen and Rajan (1995) argues that with increased banking competition, banking relationships are less valuable.

[24] Most of the new relationships are created after 2000.

[25] Berger et al. (2005) argues 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 organizations 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.

(b) we use firm fixed effects, α_i. Ioannidou et al. (2015) argues that firm level fixed effects can only be used when firms have variation in banking relationships. Within firm variation of $pfswitch_{it}$ allows us to use firm fixed effects in our estimation. In addition, presence of firm fixed effects also controls for unobservable firm characteristics that might influence a bank to choose a firm as its client (including level effects of multiple prior banking relationships). Khwaja and Mian (2008) and Jiménez et al. (2012) point out that once the firm level fixed effects are controlled for, the key firm level characteristics that influence the loan demand has only a minor impact on the estimated coefficients.

$\mathbf{X}_{it-1}$ is a vector of control variables at the firm level – age, age squared and firm size. We use total assets of a firm in real terms in period (t-1) as its size indicator. Additionally, we use interaction of industry fixed effects (at both 2-digit and 3-digit level) 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. ω_{st} are interactions of state-year fixed effects to control for any state level credit supply policies[26]. Lastly, the year fixed effects will pick up any year specific trend or fluctuations that impact loans[27]

However, one should still be careful in interpreting the basic estimates as conclusive evidence of the causal effect of increased number of domestic private or foreign banking relationships on firm level credit access because of possible omitted variable bias. We address this by sequentially interacting different fixed effects, year, industry, state, and other observable characteristics and its interaction with the $pfswitch_{it-1}$ dummy to our baseline specification. This controls for more granular supply side factors, such as factors influencing a new private or foreign bank to target industries or states.

3.2.3 Results

Results are reported in Tables 6 and 7 for intensive and extensive margin of access to credit, respectively. Like before, we start by looking at intensive margin in Table 6. Our results, at the aggregate level, in columns (1) – (5) show no effect of new banking relationships of firms on their access to credit. Our estimations control for the interactions between $pfswitch_{it-1}$ with year, industry, and state fixed effects in addition to industry-year and state-year.

Columns (6) – (8) divide the firms according to the size quartiles and repeat columns (3), (4), and (5) respectively. Like the district level analysis, we find that new banking relationships or introduction of new banks led to a significant reduction in access to credit for small firms (Q1),

[26]Every state in India has its own Industrial policy that may influence bank incentives as well as firm demand to extend loans.

[27]A relevant example in this regard is the growth in number of private bank branches in our data.

whereas it has quite the opposite effect for big firms (Q4). Access to credit increased for big firms with new banking relationships compared to firms of the same quartile who did not switch to a new private and/or foreign bank. As for the small firms, access to credit dropped with new relationships relative to firms who did not have a new domestic private and/or foreign banking relationship.

In case of extensive margin of credit, we do find some negative effect for firms belong the lower half of the size distribution and opposite effect for firms belonging to Q3, but the effects are not robust across different specifications.

Although our benchmark results match with that of district level analysis, the above estimations still cannot control for any time-varying unobserved firm or bank attributes that may influence access to loans. To check whether our estimates are biased due to selection effects[28], we estimate a placebo using the following specification:

$$\begin{aligned}\text{Bank Loans}_{it} = \alpha_i + \beta_1 \text{pre-public}_{it-1} + \mathbf{X}_{i,t-1} \\ + \delta_{jt} + \omega_{st} + \epsilon_{it}\end{aligned} \tag{4}$$

pre-public$_{it-1}$ takes the value 1 if firm i in year t had a pre-existing relationship with a public-sector bank or experience an increase in the number of public bank relationships and 0 otherwise. The rest of the specification continues to be the same as before.

The reason to run the above estimation is the following: 81.3% of the firms in our sample have either a pre-existing public-sector banking relationship or increased its number of public banking relationships within the sample period. Maintaining a public banking relationship is ubiquitous in India owing to some level of social skepticism towards the private banks. Public banking relationships are also common across all firm types, irrespective of their financial health. So, it is difficult to imagine that *pre-public*$_{it-1}$ will be causal for increased loans. If there is no selection bias, we should expect β_1 to be equal to 0.

Similarly, in a specification with *pre-public*$_{it-1}$ interacted with firm quartile dummies as our explanatory variables, we should expect no effect on the big (Q4) firms' loan access. This is because the argument in the last paragraph is definitely true for the bigger firms[29]. If our estimates have selection bias, the β_1 for the Q4 firms will be positive and significant. More specifically, if there is selection bias, a positive estimate will reflect that the bigger firms who increase their private banking relationships are more likely to maintain their public relationships as well, and enjoy more loans. However, this argument may not be entirely true for the smallest of firms. They are more marginal and the test cannot say anything conclusive for the smallest firms [30].

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

[29] Public banking relationships are common among all kinds of big and average sized firms.

[30] We are not sure what results to expect for the smallest firms. Maintaining or increasing a public banking relationship is not as common among them as the big firms

Table 8 summarizes the results of the test for selection bias. Columns (1) – (4) present the results for the intensive, while columns (5) – (8) present the results for the extensive margin. The coefficients of $pre\text{-}public_{it-1}$ are not significant for both the intensive as well as the extensive margin at the aggregate level. However, when we use firm size interactions, only the small (Q1) firms have a positive coefficient; all other quartiles are insignificant. This confirms that our benchmark results are not contaminated by sample selection.

4 Banking Reforms and Misallocation

4.1 Analytical Framework

So far we show some robust evidence that the new domestic private and/or foreign banks engage in what we call 'cream skimming' or 'cherry picking' behavior. In other words, they only choose less risky or wealthy clients and provide them with more credit. Based on this, one can plausibly argue that this has may have led to an increase in inequality among firms and created an environment conducive for the operation and growth of big firms only[31]. In relation to this, we now take a step ahead and ask whether such a behavior (favourable treatment of the big firms) by the new banks is efficient (in terms of the gains in overall productivity) for the economy. To check whether such is the case, we estimate different measures of misallocation and ask if these new domestic private and/or foreign banking relationships, or banking reforms per se, had an effect on misallocation in the Indian economy.

We follow the methodology proposed by Hsieh and Klenow (2009) and Hsieh and Klenow (2013) to create a measure of resource misallocation at the firm level. This is a direct measure which does not account for the source of allocative inefficiency. 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. We start by describing the model.

Let the aggregate 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:

$$\mathrm{Y} = \prod_{j=1}^{J} \mathrm{Y}_j^{\theta_j}, \text{ where } 0 < \theta_j < 1 \text{ and } \sum_{j=1}^{J} \theta_j = 1 \tag{5}$$

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

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:

$$Y_j = \left(\sum_{i=1}^{M_j} Y_{ij}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma-1}{\sigma}} \tag{6}$$

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

$$\pi_{ij} = (1 - \tau_{ij}^{Y})P_{ij}Y_{ij} - wL_{ij} - (1 + \tau_{ij}^{K})RK_{ij} \tag{7}$$

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 output distortion (Y) 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 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; say, 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. 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 should ease the access to credit across the more productive firms (at least) and thus, reduce misallocation.

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

$$Y_{ij} = A_{ij}K_{ij}^{\alpha_j}L_{ij}^{1-\alpha_j} \tag{8}$$

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

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

$$\text{TFPR}_{ij} = P_{ij}A_{ij} = \frac{P_{ij}Y_{ij}}{K_{ij}^{\alpha_j}L_{ij}^{1-\alpha_j}} \tag{10}$$

Equation (9) is the Solow residual and is a measure of physical productivity of a firm. TFPQ, or total factor productivity (TFP hereafter), is computed using plant level deflators for plant specific variables. TFPR in equation (10) is the revenue productivity of a firm; this is calculated using industry level deflators to deflate the firm level variables. Variation of the 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 monopolistic competitive framework and, in the absence of distortions, a 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

$$\mathrm{TFPR}_{ij} \propto (\mathrm{MRPK}_{ij})^{\alpha_j}(\mathrm{MRPL}_{ij})^{1-\alpha_j} \propto \frac{(1+\tau_{ij}^K)^{\alpha_j}}{1-\tau_{ij}^Y} \tag{11}$$

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

$$\mathrm{MRPK}_{ij} = \mathrm{R}(\frac{1+\tau_{ij}^K}{1-\tau_{ij}^Y}) \tag{12}$$

$$\mathrm{MRPL}_{ij} = \frac{\mathrm{w}}{1-\tau_{ij}^Y} \tag{13}$$

A higher value of TFPR_{ij} for a firm, within any industry, implies a higher level of distortion. This is because a high TFPR_{ij} implies either a high τ_{ij}^K or a high τ_{ij}^Y or both. For our case, we are interested in the variability of τ_{ij}^K, since it directly measures the distortions due to credit access. TFP for industry j can be expressed as

$$\mathrm{TFP}_j = \left(\sum_{i=1}^{\mathrm{M}_j}\left[\mathrm{A}_{ij}\frac{\overline{\mathrm{TFPR}_j}}{\mathrm{TFPR}_{ij}}\right]^{\sigma-1}\right)^{\frac{1}{\sigma-1}} \tag{14}$$

where $\overline{\mathrm{TFPR}_j}$ is the geometric mean of the average the marginal revenue product of capital and labor in sector j, defined as

$$\frac{1}{\overline{\overline{\mathrm{MRPL}_j}}} = \sum_{i=1}^{\mathrm{M}_j}\frac{1}{\mathrm{MRPL}_{ij}}\frac{\mathrm{P}_{ij}\mathrm{Y}_{ij}}{\mathrm{P}_j\mathrm{Y}_j} \tag{15}$$

$$\frac{1}{\overline{\overline{\mathrm{MRPK}_j}}} = \sum_{i=1}^{\mathrm{M}_j}\frac{1}{\mathrm{MRPK}_{ij}}\frac{\mathrm{P}_{ij}\mathrm{Y}_{ij}}{\mathrm{P}_j\mathrm{Y}_j} \tag{16}$$

and

$$\overline{\mathrm{TFPR}_j} = (\overline{\mathrm{MRPK}_j})^{\alpha_j}(\overline{\mathrm{MRPL}_j})^{1-\alpha_j} \tag{17}$$

Evidently, 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 rate respectively. This will result an equal value of TFPR within an industry.

In a world with distortions, firms with higher A_{ij} are expected to have a higher $TFPR_{ij}$ than the industry average. This may reflect size dependent policies or, it could be that more productive firms are credit constrained. For our purposes, we first compute $TFPR_{ij}$ for each firm using equation (11). Our measures of misallocation (at the firm-year level) are $\log(TFPR_{ij})$, scaled by the industry $\log(TFPR_j)$[32] and $\log(1 + \tau_{ij}^K)$ scaled by $\log(1+\tau_j^K)$. The latter measures the extent of capital market distortions only.

In order to estimate our measure of distortion, we need to specify the parameter values, R, σ and the share of capital α_j. We adopt the parameter values from Hsieh and Klenow (2009) and set (a) $R = 0.1$[33]; (b) $\sigma = 3$[34].

Finally, 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 perfections. Since we estimate a measure of misallocation from our sample of Indian manufacturing firms, capital and labor shares cannot be identified from our data.

Using the assumptions of profit maximization (of a firm) and monopolistic competition in the product market (firms take these as given, even though they have market power on their own product) we derive the expressions for capital and output distortions:

$$1 + \tau_{ij}^K = \frac{\alpha_j}{1-\alpha_j} \frac{wL_{ij}}{RK_{ij}} \tag{18}$$

$$1 - \tau_{ij}^Y = \frac{\sigma}{\sigma - 1} \frac{wL_{ij}}{(1-\alpha_j)P_{ij}Y_{ij}} \tag{19}$$

Intuitively, capital distortion in equation (18) is high when the share of labor with respect to capital is higher than what one would expect from the profit maximization problem of firm i. This distortion is amplified when the share of α_j is high. Please note that a high capital distortion implies a low labor distortion (since capital distortion is measured with respect to labor distortion).

[32] $\log(TFPR_j)$ is the geometric mean of $TFPR_{ij}$ across all firms in industry j.

[33] 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.

[34] We follow the literature and use the lower bound of the estimates, which range from 3 to 10. Please 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.

The output distortion in equation (19) is positive if the labor share is lower than expected 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.[35]

Finally, in order to construct an aggregate value of manufacturing TFP and the potential gains from reducing distortions over the sample period, we need TFPQ_{ij} from the data. Since we do not use plant level deflators, we observe only value added, $\mathrm{P}_{ij}\mathrm{Y}_{ij}$, and not real outlay, Y_{ij}. We use the demand for intermediate goods for the aggregate final goods producer (equation (5)) and compute:

$$\mathrm{A}_{ij} = \kappa_j \frac{(\mathrm{P}_{ij}\mathrm{Y}_{ij})^{\frac{\sigma}{\sigma-1}}}{\mathrm{K}_{ij}^{\alpha_j}\mathrm{L}_{ij}^{1-\alpha_j}} \tag{20}$$

κ_j is normalized to 1 since we are interested in the values of A_{ij} scaled by industry averages which cancels 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 limitations. First, the model we use is not dynamic. Second, it assumes that the capital stock for each period is exogeneously given. Third, it assumes that the number of firms in each industry is constant for every period and ignores the effect of misallocation on extensive margin.[36]. However, one advantage of the measures of misallocation that we use is that it relies on the dispersion of several firm level variables within an industry. This allows us to identify the wedges easily from the data ignoring the level differences across industries.

4.2 Stylized Facts: Misallocation

We start by computing TFPR_{ij} for all firms and compare the mean and median values of across the size quartiles[37]. Since dispersion in TFPR_{ij} signifies misallocation, we demean the estimate using the industry-year TFPR_j (geometric mean within an industry-year). Second, we decompose TFPR_{ij} into capital and output distortions and analyze similar demeaned measures for both of them. Demeaning makes these measures of misallocation comparable across all industries and years. It precludes the need to control for inflation and any other fixed or time varying factors at the industry level that may deem these measures non-comparable.

Figures 7 and 8 plot the mean and median log values of the demeaned TFPR_{ij}. Firms belonging to Q4 have the highest TFPR_{ij}. This indicates that the big firms face the highest level of overall

[35] Note that, like Hsieh and Klenow (2009), 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 $\mathrm{wL}_{ij} = \mathrm{w}_{ij}\mathrm{N}_{ij}$, where L_{ij} is the number of effective workers and w is the wage per effective worker.

[36] Misallocation along the lines of entry and exit of firms due to financial frictions has been analyzed before in Midrigan and Xu (2014).

[37] 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.

distortion[38,39]. The figures also show that the TFPR for big firms (Q3 and Q4) remains almost constant for the entire sample period, whereas, the same shows a downward trend for the smaller firms (Q1 and Q2).

Figures 9 and 10 plot the mean and median of the $\log(1 + \tau_{ij}^{K})$. This captures the effect of factors that can possibly distort a firm's marginal product of capital. Both the figures show that the measure of capital distortion is low for the Q4 firms and has a downward trend throughout the sample period. This downward trend is clearer for the mean, reported in Figure 10. The opposite is true for the small (Q1 and Q2) firms.

Table 9 reports the mean and median of capital market distortion for the years 1996, 2000 and 2007. It shows that over time the capital distortions tend to increase for the small firms (median of -0,19 to 0.23 for the Q2 firms) while it decreases for the large firms (0.05 to -0.15). The fact that Q4 firms have a smaller value of capital market distortions from the beginning of the sample is intuitive. As pointed out by Atack (1986), large firms adopt higher levels of technology and more dependent on capital. In our case, we are interested in understanding whether this downward trend for the capital distortions of the Q4 firms can be explained by their newly established relationships with domestic private and/or foreign banks.

Figures 11 and 12 plot the mean and median of $\log(1 - \tau_{ij}^{Y})$[40] For this measure, a higher value means a lower level of distortion. Contrary to capital market distortion measure, output distortion is highest for the large firms (Q4 and Q3) and the opposite for the Q1 and Q2 firms. In particular, this measure shows a downward trend for the the large (Q4) firms and an upward trend for the small (Q1) firms. This implies that output distortions increased for the large firms, with the opposite being true for the small firms. Table 10 confirms this observation. From 1996 to 2007, the values of output distortion decreased from 0.16 to -0.10 for the big firms while it increased from 0.08 to 0.61 for the small firms.

4.3 Empirical Methodology and Results

Our discussion in the previous section (Section 4.2) points out towards a positive correlation between capital market distortions and financial market liberalization, but only for the big firms. In this section, we aim to find a causal effect of the reform (regarding the new relationships with domestic private and/or foreign banks).

The new banking relationships can affect the capital market distortion positively (this means leading to a decrease in distortions) in the following two ways. On the one hand, the newly formed

[38]Q3 and Q4 firms also have the highest TFPQ.

[39]One word of caution on the industry-year mean is worthy of mention here. As noted before, our sample consists of a higher proportion of firms belonging to Q4 relative to Q1 and Q2. Without appropriate weighting, this may result in a bias of our estimations towards the big firms. However, this will not still change the fact that big firms face more distortions, resulting in having on impact any of our benchmark results.

[40]The values are scaled by industry-year geometric mean of firms.

relationships can directly reduce the capital market distortion through easier and improved access to loans. Our results from Sections 3.1 and 3.2 provide robust evidence that firms which formed new domestic private and/or foreign banking relationships obtained more loans. On the other, overall reforms may be responsible for this cheap and easy access to credit for the big firms. In that case, the new private and/or foreign banks were merely associating with firms who benefited from the wave of economic reforms in general without creating a real impact.

We use the following specification to test the direct effect of domestic private and/or foreign banking relationships on misallocation of firm i:

$$\begin{aligned} \mathrm{Y}_{it} &= \alpha_i + \beta_1 \mathrm{pfswitch}_{it-1} + \beta_2 \mathrm{public}_{it-1} \\ &+ \mathbf{X}_{it-1} + \delta_t + \omega_{jt} + \epsilon_{it} \end{aligned} \tag{21}$$

where Y_{it} represents the following three measures of misallocation: (i) capital market distortions relative to labor market distortions, $\log(\frac{1+\tau_{ij}^K}{1+\tau_j^K})$; (ii) output market distortion $\log(\frac{1-\tau_{ij}^Y}{1-\tau_j^Y})$; and (iii) overall distortion, $\log(\frac{\mathrm{TFPR}_{ij}}{\mathrm{TFPR}_j})$. Our main outcome of interest is the measure on capital market distortions because banking relationships are more likely to impact the marginal productivity of capital of a firm and β_1 is our coefficient of interest.

The regression specification we use in this case is similar to the one we use to determine the effect of banking relationships on access to loans in Section 3[41]. The only difference here is that we use year fixed effects (δ_t) instead of industry-year fixed effects (at the 2-digit level). This is because all the measures of misallocation are already scaled by their industry level geometric means.

Table 11 reports the results for equation (21). Columns (1) – (5) use capital market distortions relative to labor market distortions, $\log(\frac{1+\tau_{ij}^K}{1+\tau_j^K})$ as the outcome of interest. All the columns control for state-year fixed effects along with interactions between $pfswitch_{it-1}$ and a key firm characteristic. Column (1) additionally uses interactions between $pfswitch_{it-1}$ and year effects to control for differential time trends of the different banks forming the new relationships; (2) uses interaction between $pfswitch_{it-1}$ and industry fixed effects to control whether the new relationships are due to any unobservable characteristic of the corresponding industry of a firm; and (3) controls for interaction between $pfswitch_{it-1}$ and state level unobservables. Our estimates show that new relationships with private and/or foreign banks do not have an effect on the misallocation at the aggregate level.

Columns (4) and (5) divides the firms according to their size classification. Our coefficients of interest here are the interaction terms between $pfswitch_{it-1}$ and Q_i, where i=1,2,3,4. Classifying firms according to their size quartiles show that new relationships (with private and/or foreign) reduce the capital market misallocation measure only for firms belonging to Q4, or the big firms (who got more access to loans), whereas it increased the capital market distortions for the small firms (Q1). Overall, our results show that banking reforms had a dampening effect on the capital

[41]Similar to the firm level regressions, we continue to use lagged values of $pfswitch_{it}$ as our main variable of interest to identify the causal effect of the newly formed banking relationships.

market distortions for big firms, reducing it by around 10%; it worsens the same for the small firms, increasing it by around 20%.

Columns (6) – (9) do the same for the aggregate measure of misallocation, $\log(\frac{\text{TFPR}_{ij}}{\text{TFPR}_j})$. However, we do not find any effect of the banking relationships on the aggregate measure of misallocation[42]. Lastly, in column (10) we use output market distortions as one of the explanatory variables; the effect on Q4 turns out to be negative with Q1 as positive.

Combining our results form Section 3 and this section, we hypothesize that cream-skimming or cherry picking behavior by the new domestic private/or foreign banks led to biased allocation of loans towards big firms and this eventually reduced their distortions arising from the capital market. In what follows, we check whether it is the lower capital market distortions in the previous period which led to these associations between the banks and the big firms using the following specification:

$$\begin{aligned} \text{Prob}(\text{pfswitch}_i) = \beta_0 + \beta_1 \log(\frac{1+\tau_{ij}^K}{1+\tau_j^K}) \\ + \mathbf{X}_i + \epsilon_i \end{aligned} \tag{22}$$

The above specification tests whether the marginal productivity of capital of firms, before they form a domestic private or foreign banking relationship, can explain the new banking relationships. The data we use for this regression is a firm level cross-section. Our outcome of interest is the probability of forming a new domestic private and/or foreign banking relationship at any time within our sample period. The main variable of interest is the capital market distortion measure in the year when a new relationship is formed. For all the other firms, who never form a domestic private or foreign relationship, it takes the value of capital market distortion in the latest possible year. The coefficient of interest, β_1, measures the association of firms with banks on the basis of prior credit availability. More specifically, a negative β_1 would mean that the new private and/or foreign banks were biased towards firms who already had easy access to other sources of funding. In other words, this regression tests whether the association between domestic private and/or foreign banks with firms is based on capital market distortion. Additionally, we control for firm size and industry fixed effects.

Table 12 reports the results for specification (22). Column (1) runs a linear probability model, while columns (2) and (3) use logit and probit regressions. Capital market distortion does not come out to be significant in any of the regressions. However, firm size appears to be a significant determinant of the new banking relationships.

To summarize, we find that the new banking relationships cause the capital market distortions to fall for the big firms. And, these new relationships are not determined by prior access to credit.

[42]We also use output market measure as the outcome variable of interest, but find no effect.

The new banks chose firms based on their size and supplied more credit reducing their capital market distortions.

4.4 Banking Reforms and Firm Performance

Lastly, we investigate if the new domestic private and/or foreign banking relationships imply any significant changes in firm performance. We use sales and profits as the indicators for firm performance.[43]. We use the following OLS specification to estimate the effect of new banking relationships on firm performance:

$$\begin{aligned} \mathrm{Y}_{it} &= \alpha_i + \beta_1 \mathrm{pfswitch}_{it-1} + \beta_2 \mathrm{public}_{it-1} \\ &\quad + \mathbf{X}_{it-1} + \delta_{jt} + \omega_{st} + \epsilon_{it} \end{aligned} \tag{23}$$

where Y is either logarithm of profits or total sales of a firm. The left hand side of the specification continues to be same what we use before in Section 3. Investigating the effect of $pfswitch_{it-1}$ on firm profits and sales can help us relate intangible measures of misallocation to tangible measures of firm performance.

Results of this specification are presented in Table 13. Columns (1) – (6) and (7) – (12) use real profits and sales of a firm as the outcome of interest, respectively. All the regressions control for industry(3-digit)-year and state-year fixed effects along with interactions for $\mathrm{pfswitch}_{it-1}$ and a key firm characteristic, size (assets). Overall, our results show that the new banking relationships have had a positive effect on the profits and sales for big firms, with the opposite for firms belonging to the lower half of the size distribution. New banking relationships increased the profits of the big firms by 25–28% and sales by 18-25%.

Our results suggest that access to higher amount of loans at cheaper rates increased profits for big firms. And, in addition, higher amount of credit may have also led to increase in production, resulting in increase in sales revenue. Combining our result with Banerjee and Duflo (2014), we can hypothesize that the Indian manufacturing firms were credit-constrained and access to more credit, due to the banking reforms, increased profits and sales, but only for the big firms.

5 Discussion: Potential Gains from Reallocation

In essence, this paper analyzes the effects of banking industry globalization. More specifically, we are interested in quantifying the effect of the new banking relationships on the efficiency of resource allocation across Indian manufacturing firms. Resource allocation is only efficient, if the firms with higher physical productivity can have access to more credit, such that it can reach its potential. This might as well require a reallocation from relatively unproductive firms to the productive ones.

[43] We plan to elaborate on the firm performance section in the next version of the paper.

Let us summarize the main results of our empirical analysis, and provide some further interpretations. Our results can be described at three different levels. First, as a result of the increase in the number of domestic private and foreign banks in India, especially after the GATS (1998) agreement, access to credit for big firms increased by 18-23% (relative to firms who never formed any new relationships). These new relationships also reduced the loans for the small firms by 45-46%[44]. Our results also show that it is size that plays a major role in driving such relationships rather than any other factors, such as lower distortions in the capital market. Our results are robust to any selection issues that may influence the outcome. Our results provide possible evidence of reallocation of resources from the small to the big firms.

Second, we ask if this reallocation of resources is efficient. To answer this question, we compute two measures of misallocation – output and capital. We find that the capital market distortions reduced by 10% for the big firms (who added a domestic private and/or foreign bank to its portfolio) and increased by around 20% for the small of firms. Third, we look at the effect of new banking relationships on firm profits and sales. Both increase by approximately 22-24% for firms belonging to top 25% percentile and decreased by similar percentage points for bottom 25%. This suggests that the elasticity of sales and profits to the change (increase in our case) in loans is more than 1. Typically, this indicates that a firm is credit constrained (see Banerjee and Duflo (2014)). If sales did not turned out to be responsive, this may have meant that firms were only substituting other sources of credit with the new credit.

Cherry picking the big firms as clients and the resulting increase in loans is only efficient if the their physical productivity (TFPQ) is higher[45]. On the other hand, big firms, who are the most productive face the highest distortion. Therefore, any reallocation resulting in reduced distortions for these firms should improve aggregate TFP.

If resources within industry j is reallocated to equalize the TFPR across all firms (within that industry in any given year), TFP_j must equal $(\sum_{i=1}^{M_j} A_{ij}^{\sigma-1})^{\frac{1}{\sigma-1}}$. Therefore, combining equation (5) and (14), the ratio of the actual output to the efficient output could be written as:

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

where $\overline{\mathrm{A}_j} = (\sum_{i=1}^{M_j} A_{ij}^{\sigma-1})^{\frac{1}{\sigma-1}}$. Then, the potential gains from reallocation (expressed in percentage terms), is given as $(\frac{\mathrm{Y}^{\mathrm{eff}}}{\mathrm{Y}} - 1)$*100. The solid line in Figure 13 plots the possible percentage gains from reallocation for the years 1996 to 2007. The numerical values are reported in the *Benchmark*

[44] This result is supplemented by the district level regressions which indicate presence of new banks led to drop in the access of loans for the small firms.

[45] Using equation (20) we compute the TFPQ and find that the correlation between TFPQ and TFPR is 0.80.

row of Table 15. The numbers vary from 46.8-66.1 percentage points, except for the years 1999 and 2000[46].

Having this as our background, we now quantify the effect of new domestic private and/or foreign banking relationships on aggregate manufacturing TFP. In order to do so, we run a counterfactual experiment where we assume that the capital market distortions did not get affected for firms who created a new domestic private and/or foreign banking relationship. We follow the estimates from Table 11 and do the opposite. In particular, we increase the capital market distortions for the Q4 firms (those who switched) by 9.8% and decrease that of the Q1 firms (those who switched) by 19.24%.

Using this, we recompute the potential gains possible from reallocation. The dotted blue line in Figure 13 and the *Counterfactual* row of Table 15 reports the results of this experiment. The difference in the possible gains between the *Counterfactual* and the *Benchmark* ranges between 0.15-1.10%. The difference tends to increase as we move closer to 2007; this is intuitive as firms add more new banking relationships as the number of years increase post-2000. Our result shows that these relationships are solely responsible for the difference between the *Benchmark* and the *Counterfactual* situations.

Our estimates for potential gains are lower than that of Hsieh and Klenow (2009). In their paper, the latest year for which they do this exercise is 1994. It could be that the allocative efficiency, over the years in our sample period, improved as a result of the overall environment of economic reforms. It could also be possible that our results represent the lower bound of the effect. However, this underestimation does not impact the estimates of the effect of domestic private and/or foreign banking relationships of aggregate manufacturing TFP.

6 Conclusion

This paper studies the real effect of banking industry globalization, characterized by the introduction of new domestic private and/or foreign banks in India. We use PROWESS data supplemented by bank branch statistics from the RBI to specifically address three specific questions: (a) the impact of the introduction of domestic private and foreign bank branches on the supply of credit across manufacturing firms?; (b) how does the new bank branches affect misallocation and firm performance?; and (c) the effect of the banking reforms on the overall possible gains for the economy.

Our results indicate that the introduction of new banks led to a skewed allocation of loans towards the big firms. To test whether this cherry-picking behavior reduces capital market inefficiencies (common in emerging market economies), we follow Hsieh and Klenow (2009) and estimate the measures of misallocation. Results indicate a declining trend in capital market distortions for the big firms and this can be explained by their association with domestic private and/or foreign

[46] Table 14 also confirms this result showing that Of the three years reported, 1999 has the highest standard deviation of TFPR (0.83), compared to 1996 and 2007.

banks. And, vice-versa for small firms. This reduction in capital market distortions got reflected in the increased sales and profits for the big firms.

Next, we use our model to measure potential gains possible from reallocation. We run a counterfactual exercise, where we equalizes TFPR within industries and reports that possible gains is in the range of 0.15–1.1%. An agenda for future research would be to study the other sources of misallocation and quantify the effects of policies that may have caused it.

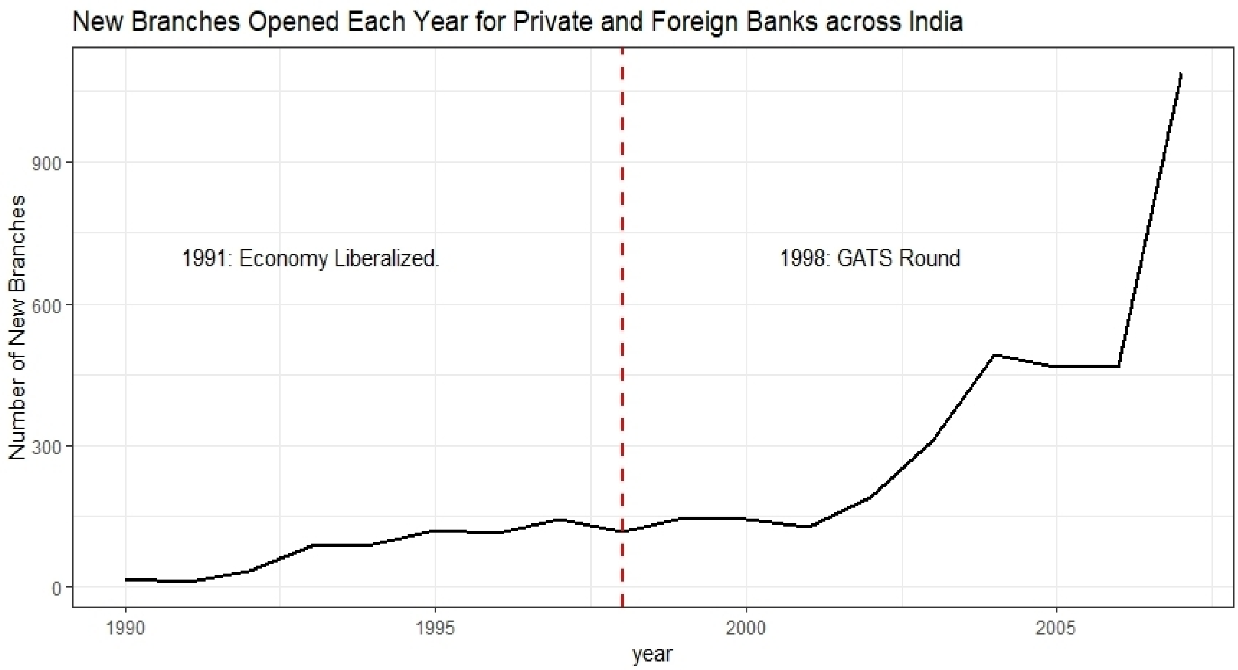

Figure 1: Number of new domestic private and foreign bank branches opened in India (Yearly Numbers).

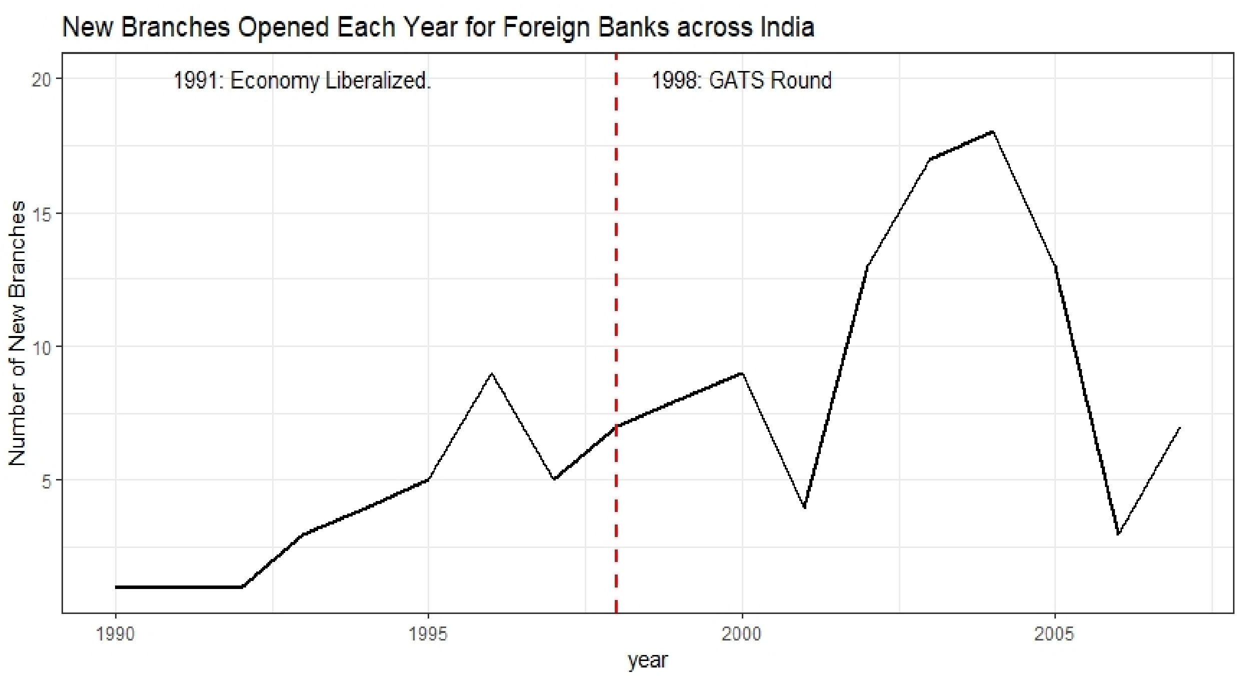

Figure 2: Number of new foreign bank branches opened in India (Yearly Numbers).

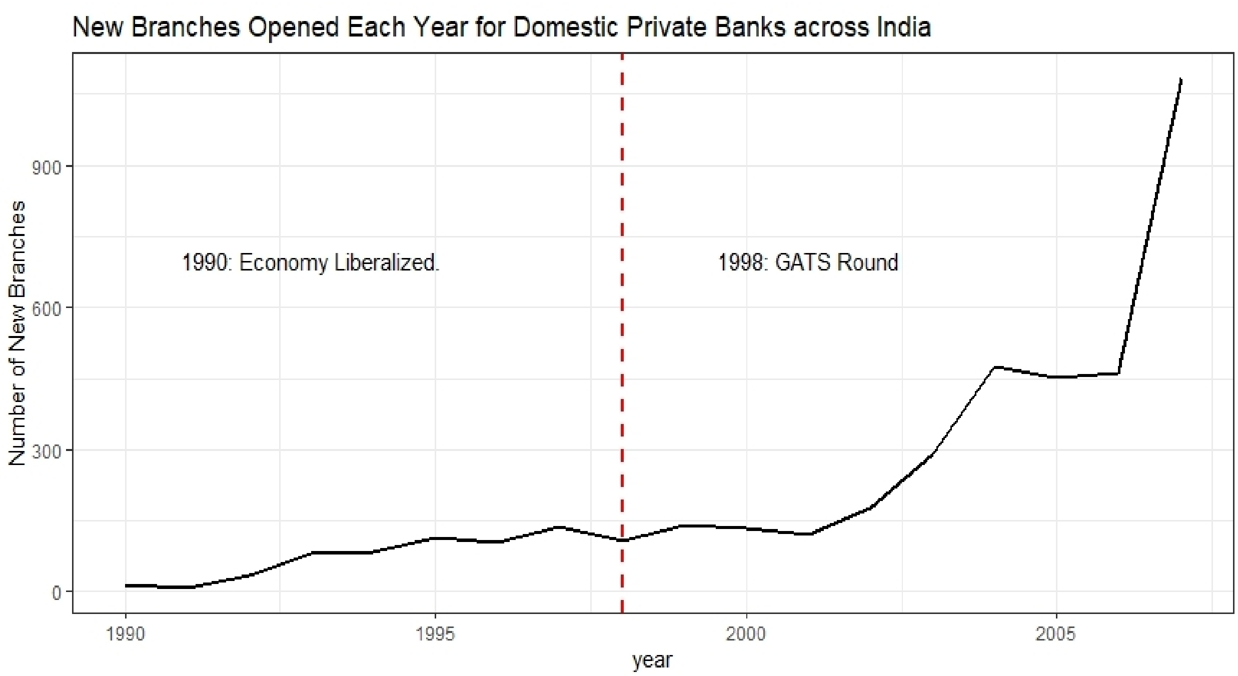

Figure 3: Number of new domestic private bank branches opened in India (Yearly Numbers).

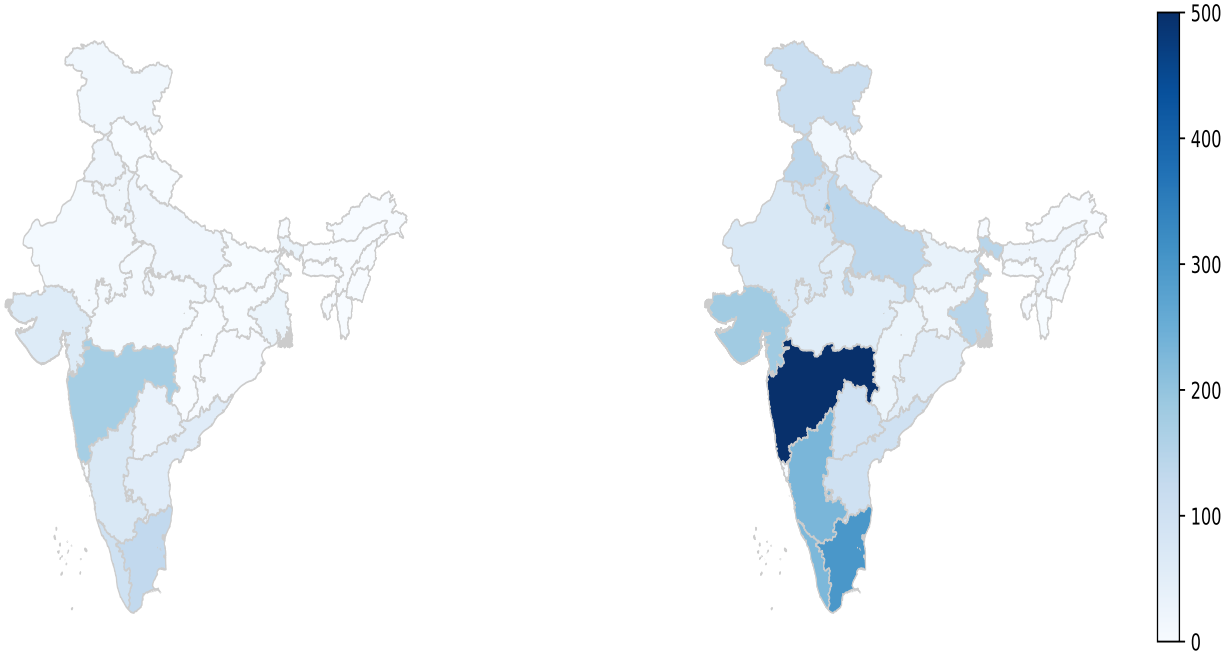

Figure 4: State Level Concentration of the new domestic private/foreign bank branches opened in India. The map on the left hand side shows the cumulative number of bank branches opened from 1993 to 2000. The map on the right shows the same for the period from 2001 to 2007.

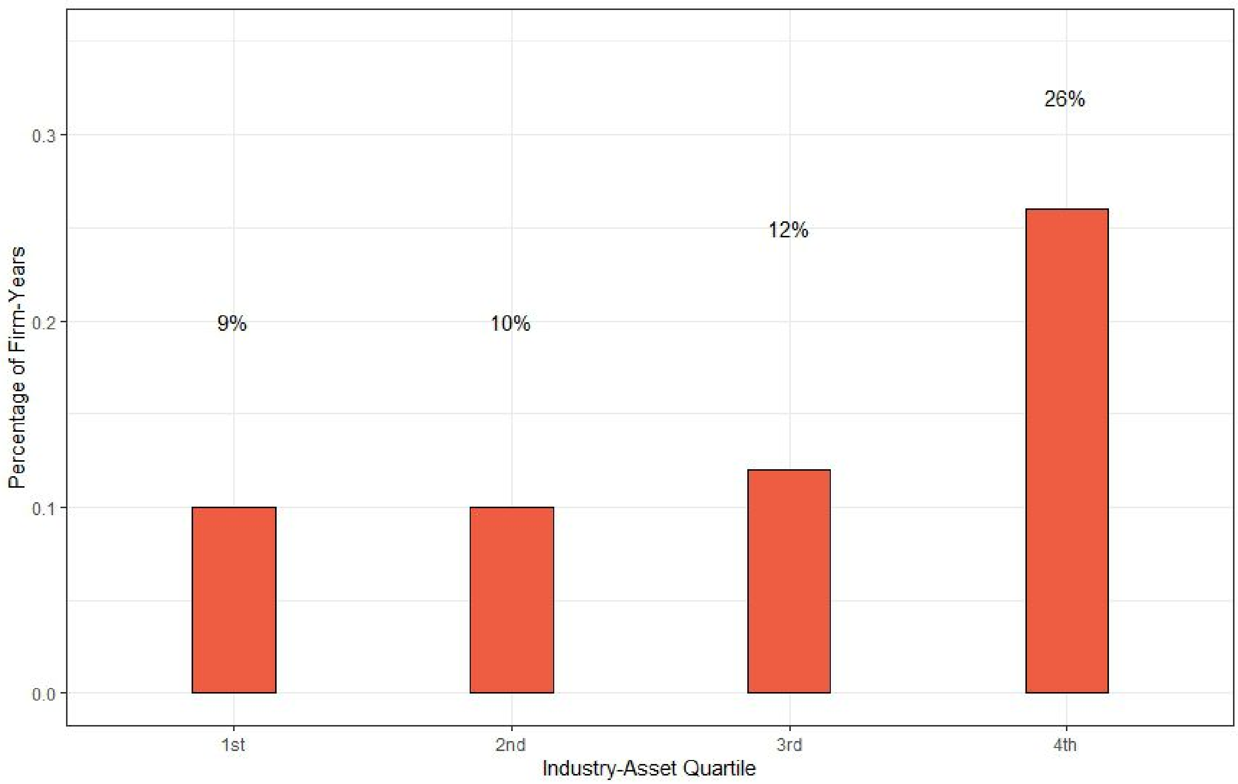

Figure 5: Percentage of Firms with a Domestic Private/Foreign Bank to their Banking Portfolio (by Industry-Asset Quartiles).

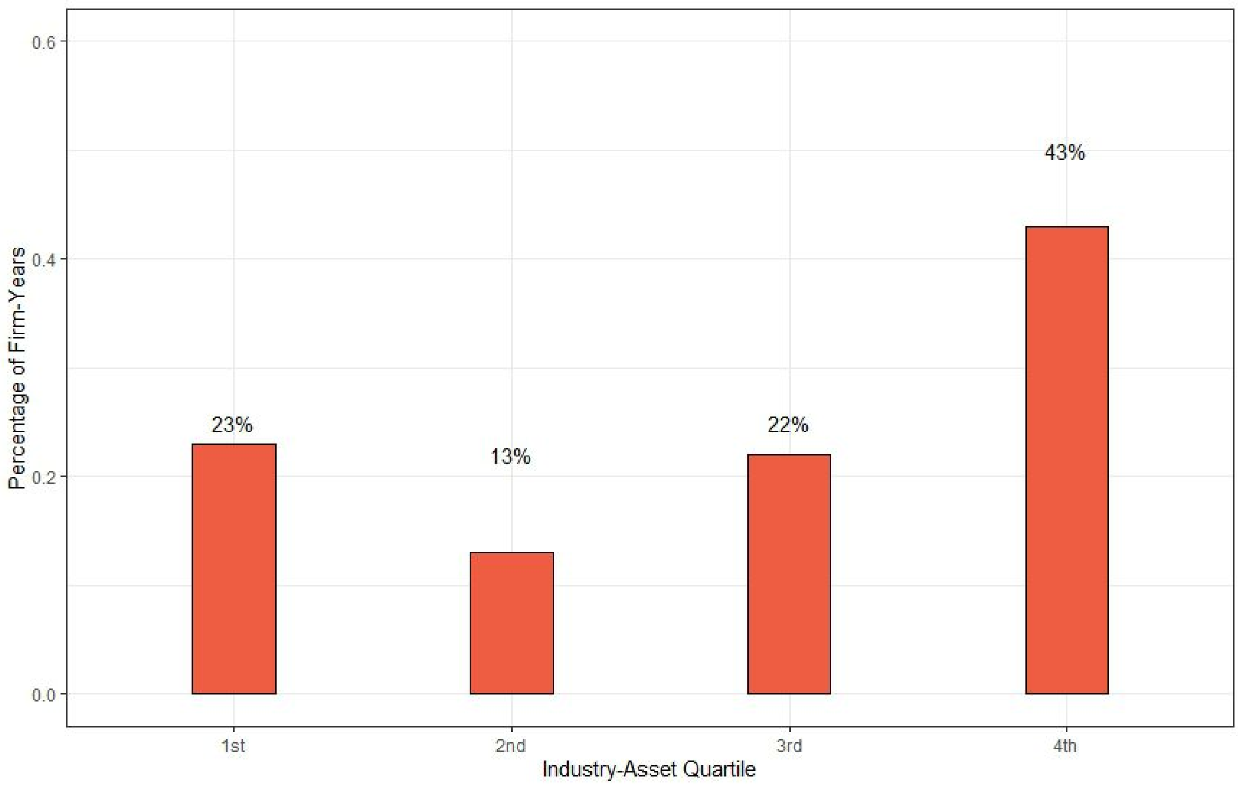

Figure 6: Percentage of firms-years in the sample with **more than one** domestic private/foreign bank to their banking portfolio (by industry-asset quartiles) **among those who established a private/foreign relationship**.

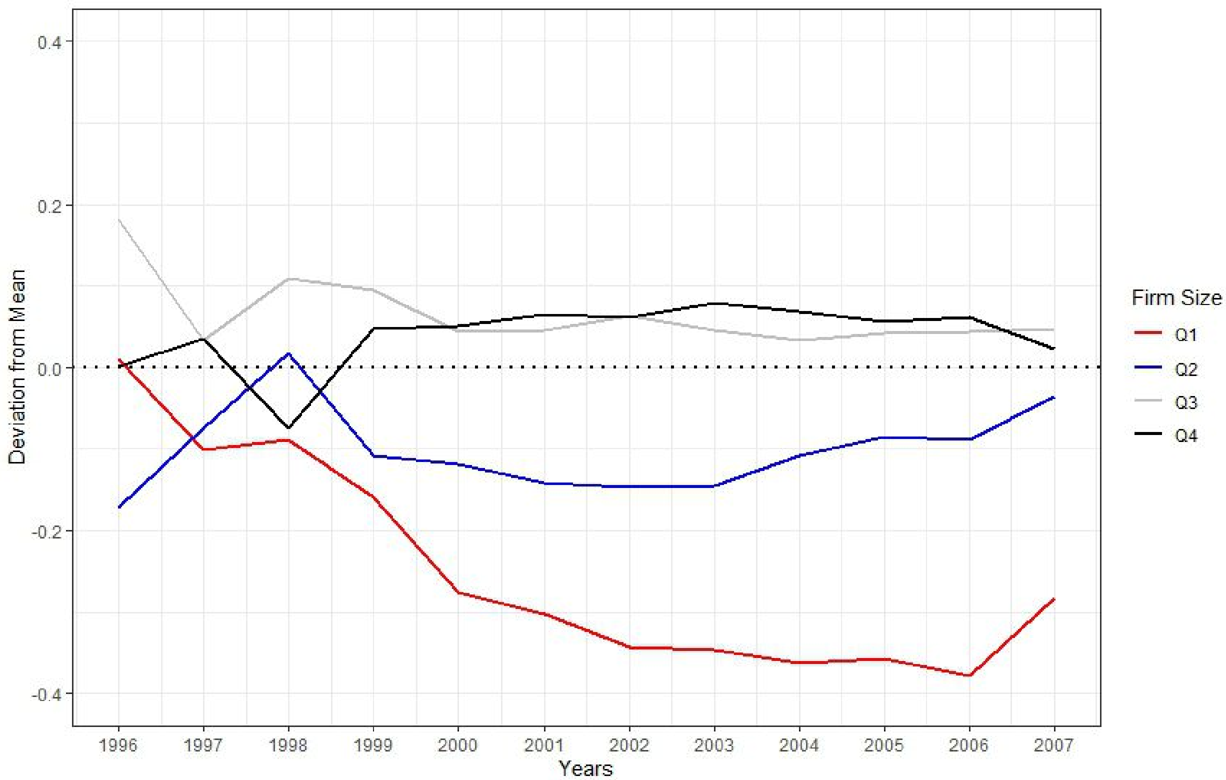

Figure 7: Mean Deviation from Industry-year geometric mean of log(TFPR) for each year from 1996 to 2007.

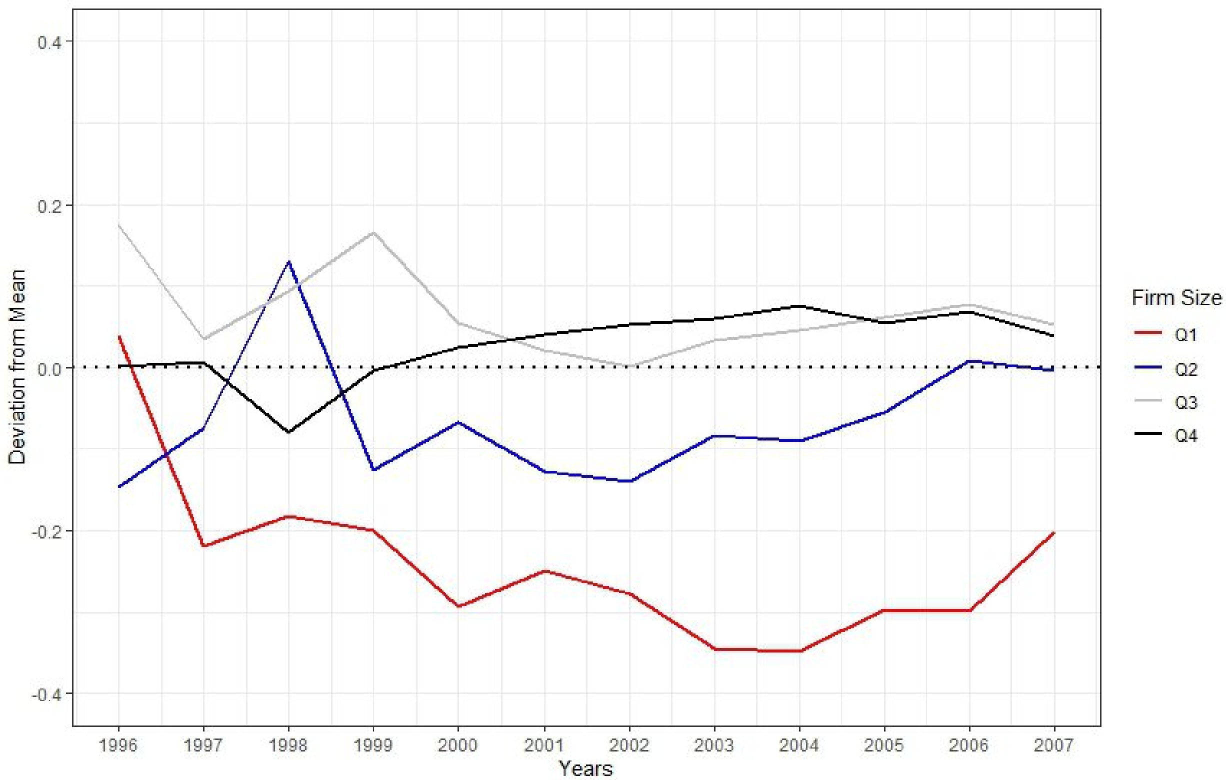

Figure 8: Median Deviation from weighted Industry-year geometric mean of log(TFPR) for each year from 1996 to 2007.

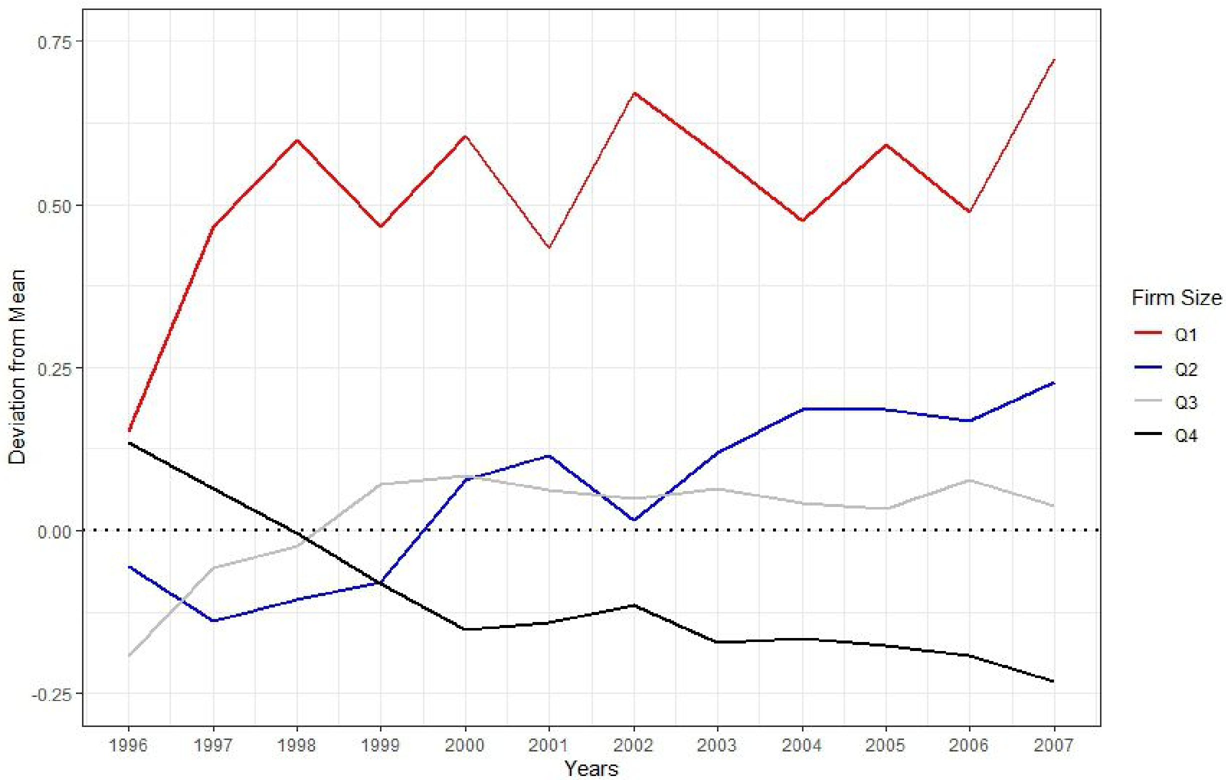

Figure 9: Mean Deviation from weighted Industry-year geometric mean of $\log(1+\tau_{Ksi})$ for each year from 1996 to 2007.

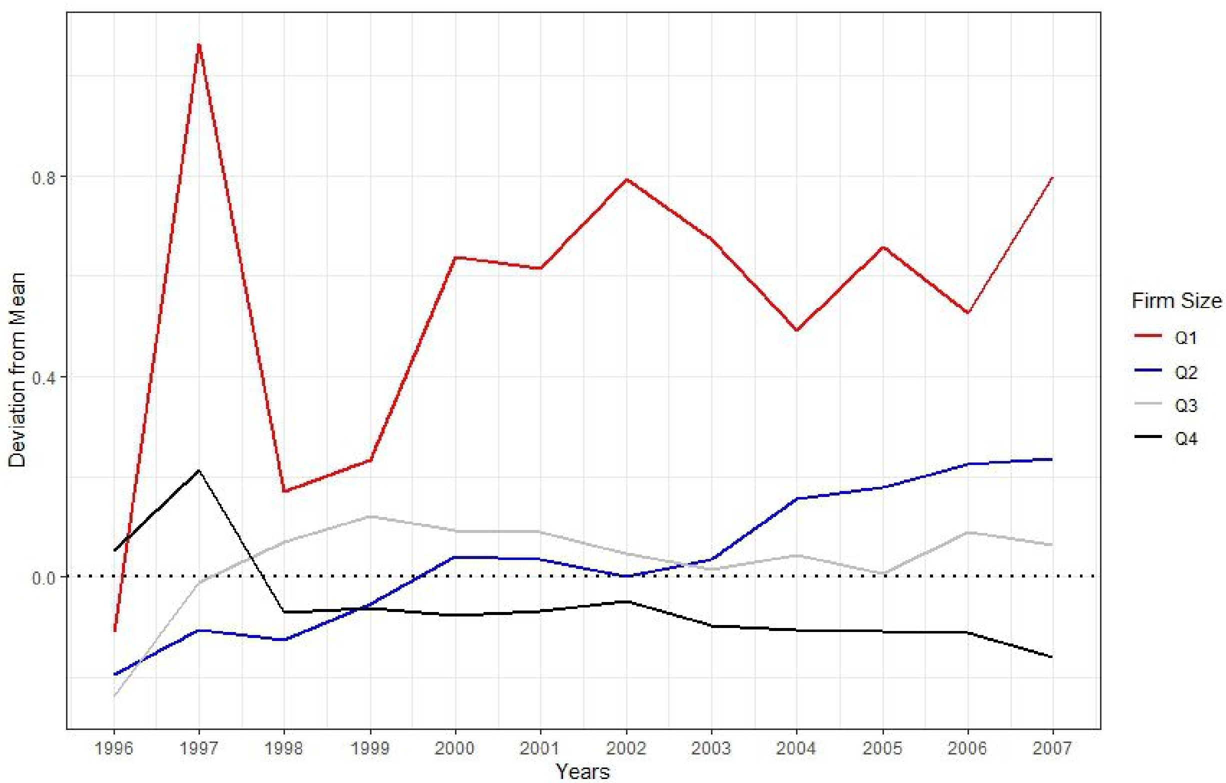

Figure 10: Median Deviation from weighted Industry-year geometric mean of $\log(1+\tau_{Ksi})$ for each year from 1996 to 2007.

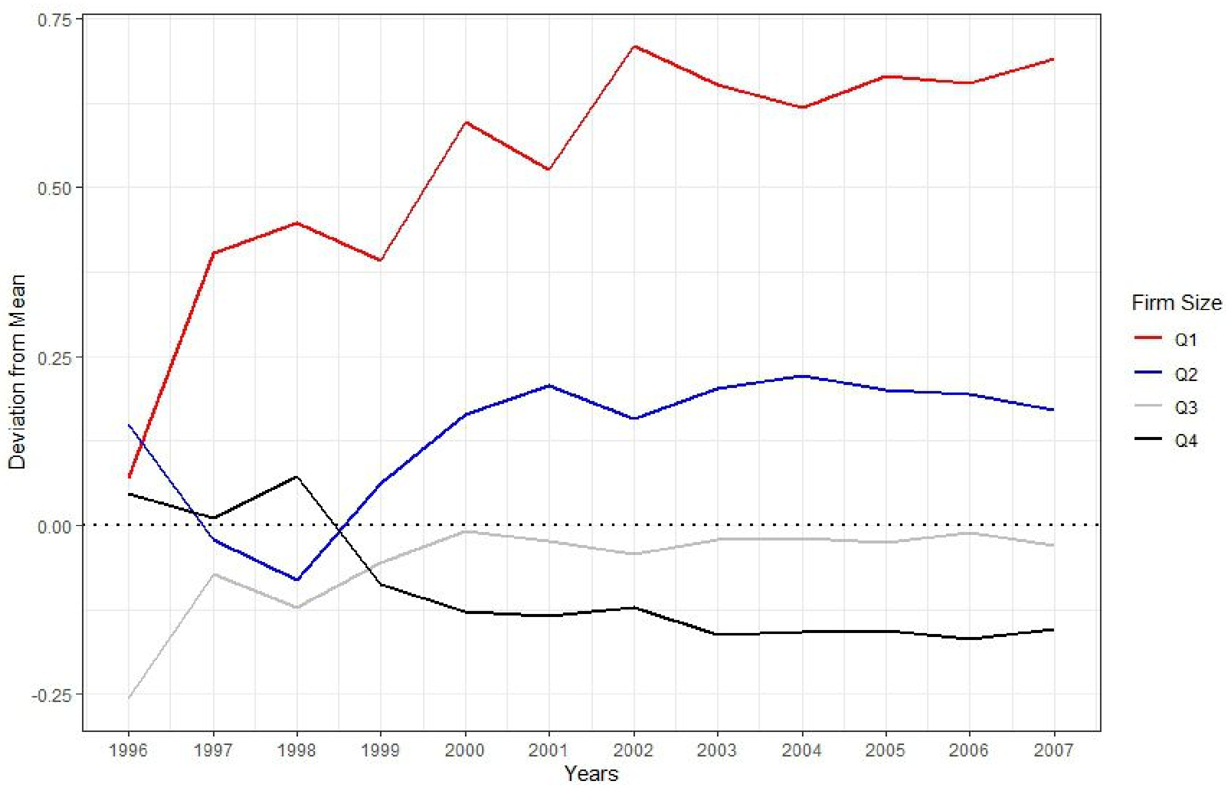

Figure 11: Mean Deviation from weighted Industry-year geometric mean of log(1-τ_{Ysi}) for each year from 1996 to 2007.

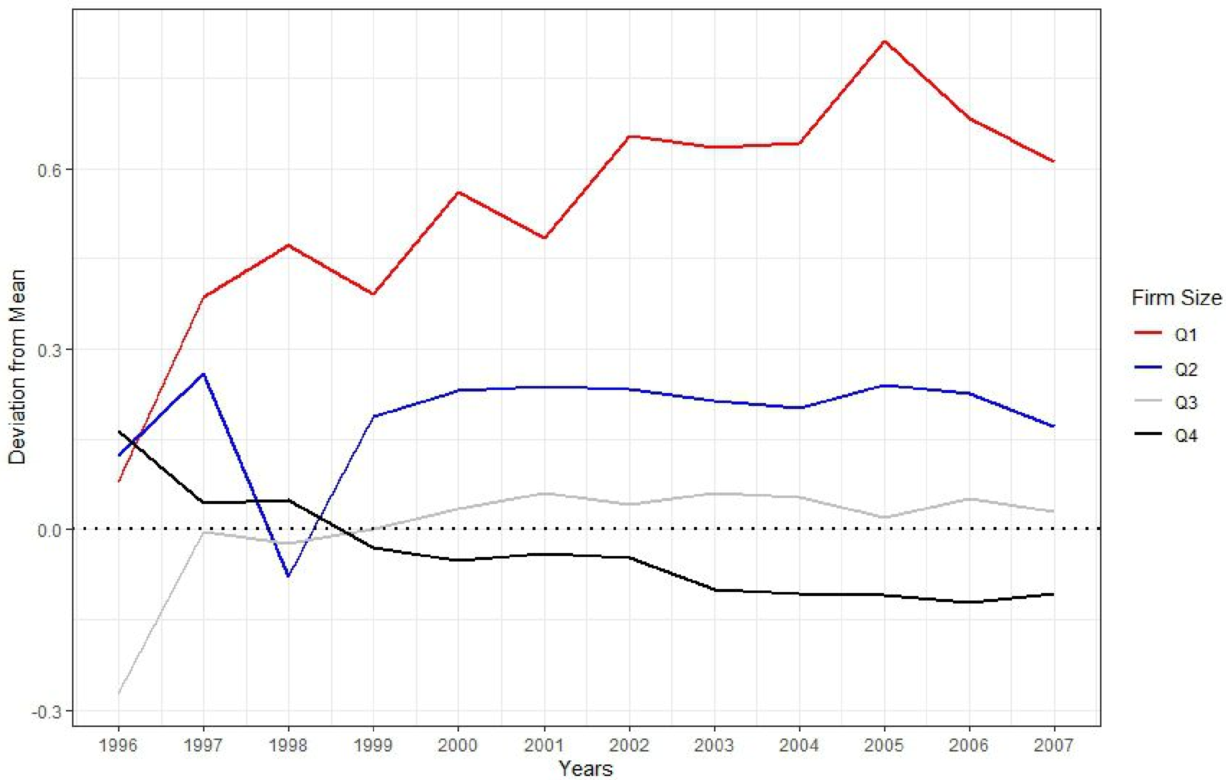

Figure 12: Median Deviation from weighted Industry-year geometric mean of log(1-τ_{Ysi}) for each year from 1996 to 2007.

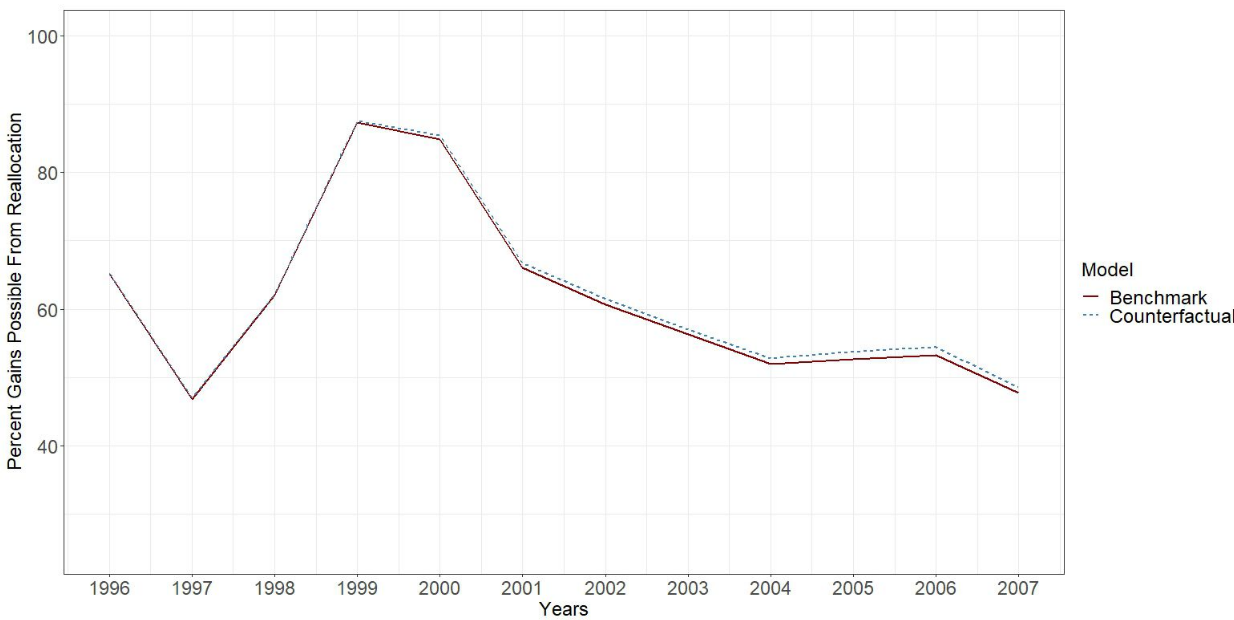

Figure 13: Percentage Gains Possible from Equalizing TFPR within Industries (2-Digit) Code.

Table 1: Summary Statistics: District level (3 digit zip code)

	Preexisting private/foreign banks	No preexisting private/foreign banks	
		New Private Banks	No Private Banks
# of Firms	5277	265	391
# of Districts	165	74	99
% of Q1 Firms	631	23	29
% of Q2 Firms	1177	51	99
% of Q3 Firms	1355	80	113
% of Q4 Firms	1627	111	150
Bank Loans	4.11	4.43	4.05
Assets (in Million INR)	375.8	549.15	342.3

Notes: The cut-off year is 2000 for this table. Results are qualitatively similar for all years between 1998 and 2002. Bank loans are in logarithm terms and firm assets are in Million INR.

Table 2: Banking Competition and Access to Credit (Intensive Margin): District Level Analysis

	Intensive Margin										
	Aggregate							Size Heterogeneity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$bankbr_{dt-1}$	-1.053^{***}	-0.836^{**}	-0.743^{*}	-0.810^{*}	-0.815^{*}	-1.142^{**}	-0.686^{*}				
	(0.332)	(0.433)	(0.453)	(0.435)	(0.438)	(0.491)	(0.435)				
$bankbr_{dt-1} \times Quartile_1$								-1.591^{**}	-1.517^{**}	-1.634^{***}	-1.381^{**}
								(0.669)	(0.661)	(0.624)	(0.644)
$bankbr_{dt-1} \times Quartile_2$								0.122	0.180	0.138	0.200
								(0.532)	(0.562)	(0.405)	(0.531)
$bankbr_{dt-1} \times Quartile_3$								-0.476	-0.434	-0.374	-0.429
								(0.564)	(0.600)	(0.433)	(0.562)
$bankbr_{dt-1} \times Quartile_4$								-0.977	-0.918	-0.878	-0.921
								(0.723)	(0.775)	(0.594)	(0.735)
Firm Controls$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.87	0.88	0.90	0.90	0.90	0.90	0.88	0.90	0.90	0.90	0.90
N	1,376	1,351	1,239	1,239	1,239	1,239	1,351	1,239	1,239	1,239	1,239
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$bankbr_{dt-1}$ X $Assets_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
State FE X Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE (5-digit) X Year Trend	Yes	No	No	No	No	No	No	No	No	No	No
Industry FE (2-digit) X Year FE	No	Yes	No	No	No	No	No	No	No	No	No
Industry FE (3-digit) X Year FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Bankbr_{it}^{pf}$ X Industry FE (3-digit)	No	No	No	Yes	No	No	No	No	No	Yes	No
$Bankbr_{it}^{pf}$ X Year FE	No	No	No	No	Yes	No	No	No	Yes	No	No
$Bankbr_{it}^{pf}$ X Firm FE	No	No	No	No	No	Yes	No	Yes	Yes	Yes	Yes
$Bankbr_{it}^{pf}$ X State FE	No	No	No	No	No	No	Yes	No	No	No	Yes

Notes: Columns (1) – (11) use logarithm of total loans received by a firm as the dependent variable.

Table 3: Banking Competition and Access to Credit (Extensive Margin): District Level Analysis

	Extensive Margin										
	Aggregate							Size Heterogeneity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$bankbr_{it-1}$	0.062 (0.088)	0.052 (0.087)	0.002 (0.083)	−0.034 (0.091)	0.035 (0.087)	0.062 (0.110)	0.041 (0.088)				
$bankbr_{it-1} \times Quartile_1$								−0.208 (0.215)	−0.239 (0.207)	−0.227 (0.209)	−0.216 (0.207)
$bankbr_{it-1} \times Quartile_2$								0.196 (0.193)	0.199 (0.192)	0.180 (0.192)	0.191 (0.193)
$bankbr_{it-1} \times Quartile_3$								0.150 (0.209)	0.151 (0.207)	0.179 (0.214)	0.144 (0.211)
$bankbr_{it-1} \times Quartile_4$								0.139 (0.227)	0.146 (0.226)	0.192 (0.227)	0.139 (0.230)
Firm Controls$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.62	0.68	0.73	0.74	0.68	0.68	0.68	0.73	0.73	0.74	0.73
N	1,491	1,466	1,354	1,354	1,466	1,466	1,466	1,354	1,354	1,354	1,354
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Bankbr_{it}^{pf}$ X $Assets_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
State FE X Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE (5-digit) X Year Trend	Yes	No	No	No	No	No	No	No	No	No	No
Industry FE (2-digit) X Year FE	No	Yes	No	No	No	No	No	No	No	No	No
Industry FE (3-digit) X Year FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Bankbr_{it}^{pf}$ X Industry FE (3-digit)	No	No	No	Yes	No	No	No	No	No	Yes	No
$Bankbr_{it}^{pf}$ X Year FE	No	No	No	No	Yes	No	No	No	Yes	No	No
$Bankbr_{it}^{pf}$ X Firm FE	No	No	No	No	No	Yes	No	Yes	Yes	Yes	Yes
$Bankbr_{it}^{pf}$ X State FE	No	No	No	No	No	No	Yes	No	No	No	Yes

Notes: Columns (1) – (11) use whether a firm received a new loan or not as the dependent variable. bankbr$_{it}$ takes a value 1 when a new domestic private and/or foreign bank opens a branch in district j for any year ≥2000. We use $bankbr_{it-1}$ as a proxy for $bankbr_{it}$ 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, age squared, and size (assets) of a firm. Assets is used at $(t-1)$ period and corrected for inflation. Standard errors in parentheses are clustered at the district level. Intercepts are not reported. * ,**, *** denotes 10%, 5% and 1% level of significance, respectively.

Table 4: Summary Statistics: Loans – New Private and/or Foreign Banking Relationships

	All Firms			Add Private/Foreign			No Private/Foreign		
Firm Size	Mean	Median	N	Mean	Median	N	Mean	Median	N
Q1	1.30	1.30	418	1.05	0.55	56	1.33	1.39	362
Q2	2.65	2.86	841	2.43	2.90	137	2.68	2.86	704
Q3	3.74	3.97	948	3.77	4.19	205	3.74	3.95	743
Q4	5.08	5.27	874	5.52	5.80	370	4.92	5.13	504
All Sizes	3.76	3.92	3084	4.44	4.85	768	3.63	3.80	2316

Notes: Add Private/Foreign includes firms with no private/foreign banking relationship in the year it first appears in the sample, but adds on at least one such banking relationship in the following years. *No Private/Foreign* includes all firms without any private/foreign banking relationship in the sample. *All Firms* includes all the firms in this sample.

Table 5: Summary Statistics: Loans – New Public Banking Relationships

	All Firms			Add Public Banks			Not Add Public Banks		
Firm Size	Mean	Median	N	Mean	Median	N	Mean	Median	N
Q1	1.30	1.30	418	0.78	0.26	24	1.33	1.38	394
Q2	2.65	2.86	841	2.68	3.13	80	2.65	2.86	761
Q3	3.74	3.97	948	4.19	4.42	160	3.70	3.93	788
Q4	5.08	5.27	874	5.84	5.83	354	4.84	5.09	520
All Sizes	3.76	3.92	3084	5.03	5.30	618	3.57	3.75	2466

Notes: Add Public Banks includes firms who increased their public banking relationships from in the year it first appears in the sample. *Not Add Public Banks* includes all firms do not increase or decrease their public banking relationships. *All Firms* includes all the firms in our sample.

Table 6: Banking Competition and Access to Credit (Intensive Margin): Firm Level Analysis

	Loans (Intensive Margin)							
	Aggregate					Size Heterogeneity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$pfswitch_{it>2000}$	-0.201 (0.312)	-0.248 (0.314)	-0.145 (0.316)	-0.219 (0.319)	-0.106 (0.303)			
$pfswitch_{it>2000} \times Quartile_1$						-0.617^{**} (0.323)	-0.629^{**} (0.319)	-0.603^{*} (0.316)
$pfswitch_{it>2000} \times Quartile_2$						-0.215 (0.212)	-0.210 (0.211)	-0.151 (0.210)
$pfswitch_{it>2000} \times Quartile_3$						0.002 (0.171)	-0.010 (0.172)	0.038 (0.177)
$pfswitch_{it>2000} \times Quartile_4$						0.205^{*} (0.116)	0.173^{*} (0.105)	0.162^{*} (0.095)
Firm Controls$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.82	0.83	0.84	0.84	0.84	0.80	0.80	0.80
N	9,088	9,049	9,049	9,049	9,049	9,094	9,094	9,094
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$pfswitch_{it>2000}$ X $Assets_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	No	No	No
State FE X Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digit) X Year FE	Yes	No	No	No	No	No	No	No
Industry FE (3-digit) X Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$pfswitch_{it>2000}$ X Year FE	No	No	Yes	No	No	Yes	No	No
$pfswitch_{it>2000}$ X Industry FE (3-digit)	No	No	No	Yes	No	No	Yes	No
$pfswitch_{it>2000}$ X State FE	No	No	No	No	Yes	No	No	Yes

Notes: Columns (1) – (8) use natural logarithm of total loans of a firm as the dependent variable. *pfswitch*$_{it}$ takes a value 1 when a firm i adds a new domestic private or foreign bank to its banking relationships in year t after it appears in our sample with no such relationships. *pfswitch*$_{it}$ is 0 in years when no such relationships exist. We use $pfswitch_{it-1}$ as a proxy for $pfswitch_{it}$ 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 number of relationships a firm has with public-sector banks, age, age squared, size (assets) of a firm. Assets is used at $(t-1)$ period and corrected for inflation. Standard errors in parentheses are clustered at the firm level. Intercepts are not reported. Coefficients of Public$_{it-1}$ are not reported.* ,**, *** denotes 10%, 5% and 1% level of significance, respectively.

Table 7: Banking Competition and Access to Credit (Extensive Margin): Firm Level Analysis

	Loans (Extensive Margin)							
	Aggregate					Size Heterogeneity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$pfswitch_{it-1}$	-0.065 (0.072)	-0.067 (0.075)	-0.032 (0.073)	-0.056 (0.070)	-0.019 (0.073)			
$switch_{it-1} \times Quartile_1$						-0.134 (0.124)	-0.159 (0.120)	-0.121 (0.122)
$pfswitch_{it-1} \times Quartile_2$						-0.080^{*} (0.045)	-0.076^{+} (0.049)	-0.068 (0.050)
$pfswitch_{it-1} \times Quartile_3$						0.043 (0.030)	0.037 (0.029)	0.055^{*} (0.030)
$pfswitch_{it-1} \times Quartile_4$						0.018 (0.019)	0.013 (0.017)	0.006 (0.017)
Firm Controls$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.57	0.58	0.59	0.59	0.59	0.57	0.57	0.57
N	9,088	9,049	9,049	9,049	9,049	9,094	9,094	9,094
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$pfswitch_{it-1}$ X $Assets_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	No	No	No
State FE X Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digit) X Year FE	Yes	No	No	No	No	No	No	No
Industry FE (3-digit) X Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Switch_{it}^{pf}$ X Year FE	No	No	Yes	No	No	Yes	No	No
$pfswitch_{it-1}$ X Industry FE (3-digit)	No	No	No	Yes	No	No	Yes	No
$pfswitch_{it-1}$ X State FE	No	No	No	No	Yes	No	No	Yes

Notes: Columns (1) – (8) use as dependent variable an indicator that takes value 1 if firm i gets a loan in year t, and 0 otherwise. $pfswitch_{it-1}$ takes a value 1 when a firm i adds a new domestic private or foreign bank to its banking relationships in year t after it appears in our sample with no such relationships. $pfswitch_{it}$ is 0 in years when no such relationships exist. We use $pfswitch_{it-1}$ as a proxy for $pfswitch_{it}$ 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 number of relationships a firm has with public-sector banks, age, age squared, size (assets) of a firm. Assets is used at $(t-1)$ period and corrected for inflation. Standard errors in parentheses are clustered at the firm level. Coefficients of Public$_{it-1}$ are not reported. Intercepts are not reported. * ,**, *** denotes 10%, 5% and 1% level of significance, respectively.

Table 8: Banking Competition and Access to Credit: Test for Selection Effects

	Loans							
	Intensive Margin				Extensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Pre-Public_{it-1}$	-0.011 (0.078)	0.012 (0.072)			0.006 (0.018)	0.015 (0.017)		
$Pre-Public_{it-1} \times Quartile_1$			0.898^{**} (0.432)	0.854^{*} (0.435)			0.302^{***} (0.102)	0.304^{***} (0.099)
$Pre-Public_{it-1} \times Quartile_2$			-0.046 (0.212)	-0.036 (0.208)			-0.034 (0.042)	0.032 (0.045)
$Pre-Public_{it-1} \times Quartile_3$			-0.278 (0.206)	-0.195 (0.201)			-0.071 (0.054)	-0.063 (0.045)
$Pre-Public_{it-1} \times Quartile_4$			0.071 (0.138)	0.083 (0.133)			0.007 (0.026)	0.015 (0.026)
Firm Controls$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.84	0.84	0.81	0.82	0.59	0.59	0.58	0.59
N	9,049	9,049	9,055	9,055	9,049	9,049	9,055	9,055
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$PrePublic_{it-1}$ X $Assets_{i,t-1}$	Yes	Yes	No	No	Yes	Yes	No	No
State FE X Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE (3-digit) X Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Pre-Public_{it-1}$ X Year FE	Yes	No	Yes	No	Yes	No	Yes	No
$Pre-Public_{it-1}$ X Industry FE (3-digit)	No	Yes	No	Yes	No	No	No	No

Notes: Columns (1) – (4) use intensive margin of loans or logarithm of total amount of loans as the dependent variable, whereas columns (5) – (8) use extensive margin of loans or an indicator variable which takes value 1 if a firm received a new loan or not as the dependent variable. $Pre-Public_{it}$ takes the value 1 if firm i in year t had a pre-existing relationship with a public-sector bank or experience an increase in the number of public banking relationships. We use lagged value of $Pre-Public_{it}$ for reasons explained in the main text. Quartiles $Qr_{i=1,2,3,4}$ are defined according to the total assets of a firm. 'Firm Controls' include number of relationships a firm has with public-sector banks, age, age squared, size (assets) of a firm. Assets is used at $(t-1)$ period and corrected for inflation. Standard errors in parentheses are clustered at the firm level. Intercepts are not reported. * ,**, *** denotes 10%, 5% and 1% level of significance, respectively.

Table 9: Mean and Median of log(1+τ_{Ksi}) scaled by log of industry average for years 1996, 2000 and 2007

	1996		2000		2007	
Firm Size	Mean	Median	Mean	Median	Mean	Median
Q1	0.15	-0.11	0.60	0.63	0.72	0.80
Q2	-0.05	-0.19	0.07	0.04	0.22	0.23
Q3	-0.19	-0.23	0.08	0.09	0.03	0.06
Q4	0.13	0.05	-0.15	-0.07	-0.23	-0.15
All Sizes	0.0	-0.13	0.0	0.02	0.0	0.02

Notes: TFPR distribution computed from the data is winsorized to exclude the top 1% and bottom 1%. Geometric mean of (1-τ_{Ksi}) is computed using the remaining data.

Table 10: Mean and Median of log(1-τ_{Ysi}) scaled by log of industry average for years 1996, 2000 and 2007

	1996		2000		2007	
Firm Size	Mean	Median	Mean	Median	Mean	Median
Q1	0.07	0.08	0.59	0.55	0.69	0.61
Q2	0.14	0.12	0.16	0.23	0.16	0.17
Q3	-0.19	-0.23	0.08	0.09	0.03	0.06
Q4	0.04	0.16	-0.00	0.03	-0.15	-0.10
All Sizes	0.0	0.0	0.0	0.04	0.01	0.0

Notes: TFPR distribution computed from the data is winsorized to exclude the top 1% and bottom 1%. Geometric mean of (1-τ_{Ysi}) is computed using the remaining data.

Table 11: Banking Competition and Misallocation

	Misallocation Capital Market					Misallocation Aggregate				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$pfswitch_{it-1}$	0.077 (0.127)	0.034 (0.127)	0.045 (0.127)			0.004 (0.131)	-0.021 (0.127)			
$pfswitch_{it-1} \times Quartile_1$				0.187*** (0.071)	0.176*** (0.069)			0.061 (0.182)	0.059 (0.192)	0.093*** (0.034)
$pfswitch_{it-1} \times Quartile_2$				0.106 (0.163)	0.115 (0.154)			0.060 (0.070)	0.041 (0.070)	0.053 (0.091)
$pfswitch_{it-1} \times Quartile_3$				0.090 (0.056)	0.082 (0.054)			-0.041 (0.051)	-0.055 (0.052)	0.020 (0.027)
$pfswitch_{it-1} \times Quartile_4$				-0.103*** (0.034)	-0.117*** (0.032)			0.001 (0.031)	0.004 (0.030)	-0.042** (0.018)
$(\frac{1-\tau^Y_{ij}}{1-\tau^Y_j})_{it}$										-0.775 (0.051)
Firm Controls$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.89	0.89	0.89	0.89	0.89	0.84	0.84	0.83	0.84	0.84
N	5,009	5,009	5,009	6,926	6,926	5,009	5,009	6,926	6,926	6,926
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$pfswitch_{it-1}$ X $Assets_{it-1}$	Yes	Yes	Yes	No	No	Yes	Yes	No	No	No
State FE X Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$pfswitch_{it-1}$ X Year FE	Yes	No	No	Yes	No	Yes	No	Yes	No	Yes
$pfswitch_{it-1}$ X Industry FE (3-digit)	No	Yes	No	No	No	No	No	No	No	No
$pfswitch_{it-1}$ X State FE	No	No	Yes	No	Yes	No	Yes	No	Yes	No

Notes: Columns (1) – (5) use misallocation measure related to capital market, $\log(\frac{1+\tau^K_{ij}}{1+\tau^K_j})$, whereas columns (6) – (9) uses the aggregate measure of misallocation, $\log(\frac{\text{TFPR}_{ij}}{\text{TFPR}_j})$ respectively, as the dependent variable. *pfswitch*$_{it}$ takes a value 1 when a firm i adds a new domestic private or foreign bank to its banking relationships in year t after it appears in our sample with no such relationships. *pfswitch*$_{it}$ is 0 in years when no such relationships exist. We use $pfswitch_{it-1}$ as a proxy for $pfswitch_{it}$ 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 number of relationships a firm has with public-sector banks, age, age squared, size (assets) of a firm. Assets is used at $(t-1)$ period and corrected for inflation. Standard errors in parentheses are clustered at the firm level. Coefficients of Public$_{it-1}$ are not reported. Intercepts are not reported. * ,**, *** denotes 10%, 5% and 1% level of significance, respectively.

Table 12: Factors Affecting Banks' Choice of Clients

	$pfswitch_i$		
	OLS	Logit	Probit
	(1)	(2)	(3)
$\log(\frac{1+\tau_{ij}^K}{1+\tau_j^K})$	0.008	0.057	0.032
	(0.007)	(0.055)	(0.031)
$Size_i$	0.083***	0.651***	0.363***
	(0.010)	(0.077)	(0.041)
R-Square	0.16	0.10	0.10
N	2,337	2,006	2,006
Industry FE	Yes	Yes	Yes

Notes: Columns (1) – (3) use $\log(\frac{1+\tau_{ij}^K}{1+\tau_j^K})$ as the main dependent variable. It measures the distortion arising out of the capital market. Size$_i$ is the size of firm i. Standard errors in parentheses are robust standard errors. Intercepts are not reported. *,**, *** denotes 10%, 5% and 1% level of significance, respectively.

Table 13: Banking Competition and Firm Performance

	Profits						Sales					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$pfswitch_{it-1}$	-0.601 (0.424)	-0.371 (0.430)	-0.492 (0.429)				0.026 (0.168)	0.026 (0.160)	-0.0002 (0.170)			
$pfswitch_{it-1} \times Quartile_1$				-1.121^{**} (0.512)	-1.107^{**} (0.534)	-1.219^{**} (0.535)				-0.242^{*} (0.125)	-0.248^{**} (0.120)	-0.257^{**} (0.123)
$pfswitch_{it-1} \times Quartile_2$				-0.531^{***} (0.196)	-0.458^{**} (0.200)	-0.482^{**} (0.200)				-0.220^{*} (0.113)	-0.260^{**} (0.111)	-0.245^{**} (0.118)
$pfswitch_{it-1} \times Quartile_3$				0.056 (0.291)	0.075 (0.277)	0.047 (0.274)				-0.091 (0.343)	-0.110 (0.289)	-0.105 (0.345)
$pfswitch_{it-1} \times Quartile_4$				0.227^{**} (0.112)	0.248^{**} (0.117)	0.246^{**} (0.115)				0.168^{**} (0.070)	0.224^{***} (0.068)	0.226^{***} (0.071)
Firm Controls$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.86	0.86	0.86	0.86	0.86	0.86	0.96	0.96	0.96	0.95	0.95	0.95
N	3,371	3,377	3,377	3,371	3,377	3,377	4,932	4,933	4,933	4,932	4,933	4,933
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$pfswitch_{it-1}$ X $Assets_{it-1}$	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	No	No	No
State FE*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE (3-digit)*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$pfswitch_{it-1}$ X Year FE	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No
$pfswitch_{it-1}$ X Industry FE (3-digit)	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No
$pfswitch_{it-1}$ X State FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

Notes: Columns (1) – (6) use logarithm of total profits after tax of a firm and, columns (7) – (12) use logarithm of total sales as the dependent variable respectively. *pfswitch*$_{it-1}$ takes a value 1 when a firm i adds a new domestic private or foreign bank to its banking relationships in year t after it appears in our sample with no such relationships. *pfswitch*$_{it-1}$ is 0 in years when no such relationships exist. We use $pfswitch_{it-1}$ as a proxy for $pfswitch_{it-1}$ 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 number of relationships a firm has with public-sector banks, age, age squared, size (assets) of a firm. Assets is used at $(t-1)$ period and corrected for inflation. Standard errors in parentheses are clustered at the firm level. Coefficients of Public$_{it-1}$ are not reported. Intercepts are not reported. * ,**, *** denotes 10%, 5% and 1% level of significance, respectively.

Table 14: Dispersion of the absolute value of log(TFPR) scaled by industry average for 1996, 2000 and 2007.

1996				1999				2007			
S.D.	75-25	90-10	N	S.D.	75-25	90-10	N	S.D.	75-25	90-10	N
0.64	0.71	1.64	259	0.83	0.9	1.95	451	0.69	0.75	1.57	2225

Notes: TFPR series for all firms in the sample is filtered to exclude the top 1% and bottom 1% of the distribution. The series is then logged and scaled by the logarithm of the geometric mean of TFPR of the industry and year where the firm observation belongs.

Table 15: Potential Gains from Misallocation by Equalizing TFPR within Industries(2-Digit NIC) from 1996 to 2007 (in percentages)

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Benchmark	65.1	46.8	62.0	87.2	84.8	66.1	60.7	56.3	51.9	52.7	53.2	47.7
Counterfactual	65.2	47.0	62.1	87.5	85.4	66.7	61.4	57.0	52.8	54.7	54.3	48.6
Difference	0.15	0.22	0.13	0.26	0.59	0.60	0.77	0.72	0.89	0.99	1.10	0.89

Notes: Potential Gains means the percentage gains in output possible by equalizing TFPR across firms within industries. *Benchmark* reports the potential gains observable from the data. *Counterfactual* reports the potential gains in output if the capital distortions did not change for the firms who added a domestic private/foreign bank in their banking portfolio, all other things remaining the same. *Difference* reports the direct output gain from domestic private/foreign banking relationships.

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