

Financial Integration through Production Networks*

INDRANEEL CHAKRABORTY
APOORVA JAVADEKAR

SAKETH CHITYALA
RODNEY RAMCHARAN

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Abstract

This paper studies how interconnected plants distribute additional liquidity from banks through the supply chain. Using a spatially segmented bank branch expansion rule in India, we find that direct exposure to additional bank credit allows plants to hold less precautionary cash and increase bank debt. Directly exposed plants pass through liquidity to customer plants as short-term trade credit. This liquidity spillover improves sales, employment, and productivity at customer plants. Structural estimation yields an average credit multiplier of 1.48. Our results underscore the credit multiplier effects of production networks and the importance of financial integration among firms with limited banking services.

Keywords: Trade Credit, Supply Chains, Liquidity Allocation.

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There is widespread evidence that improved access to bank credit allows plants to expand production.¹ Much less is known however about how plants might distribute this bank liquidity through the supply chain. Some theories predict that firms which benefit directly from more bank liquidity could redistribute this liquidity through their production network using trade credit, helping to finance additional sales at more liquidity constrained plants and increasing overall output in excess of the usual direct estimates found in the empirical literature.² However, the direction of trade credit can depend on the relative bargaining power of firms in the supply chain. This can result in trade credit paradoxically flowing from firms with limited access to bank credit to the less constrained firms (Murfin and Njoroge, 2014; Giannetti et al., 2021). Relative price changes is another propagating mechanism through which firms might distribute liquidity shocks (Acemoglu et al., 2012). For example, a positive credit shock that relaxes financing constraints and increases output at a particular firm can change relative prices, affecting production decisions throughout the production network.

Clearly, the transmission of financial shocks onto the real economy is a central question. However, because plants in a network are similar and subject to common shocks, it is difficult to identify credibly whether and how plants might distribute bank liquidity through the supply chain. We make progress by using a change in Indian banking regulation that affected the supply of banking

¹See for example the literature emanating from Jayaratne and Strahan (1996), such as Black and Strahan (2002); Bertrand et al. (2007); Bai et al. (2018); Gissler et al. (2020). Our paper is also related to the literature on bank financing expansion in developing countries and its effects. Burgess and Pande (2005) use a branching expansion from 1969–1990 to study the impact of rural credit expansion on households at the more aggregated state-level. Using policy experiments from the 1980-1990 period, Cole (2009) shows that Indian credit nationalization lowered the cost of credit and worsened the quality of intermediation. Gormley et al. (2018) show that banks resolve bankruptcies more quickly when competition increases. Beyond developing countries, influential studies using deregulation waves in industrialized countries find that improved credit access engenders more efficient lending (Jayaratne and Strahan, 1996; Black and Strahan, 2002; Bertrand et al., 2007; Bai et al., 2018; Gissler et al., 2020).

²See for example Brennan et al. (1988); Biais and Gollier (1997); Cuñat (2006) and the discussion in Petersen and Rajan (1997). The evidence in Amberg et al. (2021); Costello (2020) show respectively how trade credit can provide liquidity insurance, and the importance of trade credit in transmitting banking sector shocks; Giannetti et al. (2021) elucidate the competitive effects of trade credit.

services within very narrow geographic areas. We combine this regulatory-induced variation in bank credit with new plant-level data that identify the input-output matrix or production network for each plant. This research design thus uses the plausibly exogenous variation in the change in the supply of banking services within a segmented geography to identify the impact of this banking shock both on directly exposed plants, as well as on plants outside the area of bank credit expansion but exposed indirectly to the banking shock via the production network.

The first step in the analysis shows that direct exposure to the spatial banking shock significantly affects both real and financial outcomes at directly exposed plants. Notably, in the years after a plant becomes directly exposed to the increase in banking services within its district, plant-level productivity increases by about 3.8 percent relative to the period before exposure, as well as relative to other non-exposed plants. Exposed plants also significantly expand employment, as well as investment; the former by about 4.2 percent and the latter by 7.5 percent. And consistent with this increase in the use of inputs, plant-level sales increase by 10.8 percent on average in the years after exposure to the positive spatial shock, while overall plant size expands by 6.3 percent. We also find evidence that relaxing financing constraints via this banking expansion also increases wages and benefits among workers at exposed plants. The results in this first step are consistent with the broad swath of evidence emanating from Jayaratne and Strahan (1996) which suggests that the expansion of bank credit can have economically large effects on real outcomes among exposed businesses.

We extend this literature, showing that improved access to banking services also affects financial management among plants directly exposed to the banking shock. Exposed plants decrease sharply their precautionary cash holdings and the ratio of cash to assets drops by 0.7 percentage points on average in the five years after the shock. When measured relative to short-term liabilities due to other plants in the production network—accounts payables—cash holdings at directly

exposed plants decline by about 9.6 percentage points. To wit, directly exposed plants, given their easier access to bank credit, appear to reduce their dependence on cash for short-term liquidity management. In keeping with this shift in liabilities management, we find a corresponding increase in bank debt. Outstanding bank debt increases by about 6.6 percentage points at exposed plants.

The second step in the analysis examines whether plants directly exposed to the local banking shock redistribute liquidity through their production network—an increase in accounts receivables—or use their improved financial position to hold-up more constrained plants in the network and extract rents—an increase in accounts payables among directly exposed banks. The aggregate evidence supports the liquidity redistribution hypothesis. Plants more directly exposed to the banking expansion increase accounts receivables or short-term financing to other firms in the production network. In particular, overall accounts receivables increase by about 10.6 percent after a plant becomes directly exposed to the local banking shock. The elasticity with respect to the banking shock is similar to the sales elasticity, suggesting that plants with greater access to bank credit help fund their sales expansion by a proportional expansion in trade credit.

In the third step, we use more detailed data on input-output relationships for each plant to understand how supply linkages propagate the granular banking shocks throughout the economy. We find that downstream customers receive significantly more trade credit when their upstream suppliers become exposed to an increase in bank credit supply. Specifically, the average downstream customer-plant receives about 8 percent more trade credit when its suppliers all become exposed to the banking shock. We take advantage of the spatial segmentation of the shock to exclude alternative interpretations. These cross-sectional tests compare downstream plants that do not directly benefit from the expansion in banking services in their district—those located in districts ineligible for the branching expansion and experience no change in their direct access bank financing—with

plants that also benefited from branch expansion.

We find that downstream plants in ineligible districts draw 17.5% more of their financing from trade credit if their upstream suppliers are all in treated districts. This redistribution of liquidity from exposed upstream suppliers is also larger when these upstream suppliers themselves have less growth opportunities, so that the shadow cost of liquidity redistribution is low. Moreover, controlling for relative price changes does not alter these results, suggesting that the trade credit channel is salient. Interestingly, there is no reverse upstream effect. If downstream plants become exposed to the banking shock, there is no evidence that they increase their use of trade credit from their upstream suppliers. Instead, downstream plants that become exposed to a banking shock substitute away from trade credit towards bank debt in order to finance operations.

Given that trade credit is relatively more expensive than longer-term bank loans, we explore the conditions under which suppliers are better positioned to provide credit than banks (Biais and Gollier, 1997). The logic of these tests exploit asset specificity and the ease of contract enforcement: If a product is available from a small set of suppliers, then those suppliers can better enforce repayment, increasing the potential for trade financing (Cuñat, 2006; Dass et al., 2014). In keeping with this theoretical intuition, we find that when a product is available from a small set of suppliers, and a plant obtains 100% of its inputs from a treated district, then post branching expansion, such a plant increases its trade credit by 23 percentage points as a fraction of total debt.

Finally, we construct a parsimonious model to estimate the trade credit multiplier in India in our sample period. Taking the model to the data, we obtain estimates for trade credit multipliers by sector in India in this period. The significant variation of estimated trade credit multipliers points to relative financial constraints across industries.

To our knowledge, this is the first paper to provide direct evidence on how a clearly identified local financial sector shock propagates through the national supply chain in an emerging market.

Emerging market economies are usually characterized by high levels of establishment-level financing constraints, and these results highlight the importance of trade credit in redistributing liquidity within supply networks. Conversely, this evidence shows that relaxing bank financing constraints even in limited areas can induce potentially sizeable aggregate changes in output and employment via this trade credit channel. In this way, these results can help inform the refinement of theories that emphasize the importance of production networks in shaping aggregate fluctuations.

Our work is related to several literatures. Using large firms in the US, Costello (2020) shows how disruptions in bank lending during the 2009 financial crisis affected firms through the trade credit channel. Alfaro et al. (2021) tackles a similar question using econometrically identified banking shocks in Spain; in this case, the authors find that both price and trade credit are important adjustment margins, though the effects on employment are counter-cyclical. Although not focused on the supply chain linkages, perhaps the closest paper to ours is Restrepo et al. (2019), which show both that trade credit and cash can substitute for adverse shocks to bank liquidity in Colombia, and that this substitution can have real consequences. The large effects in our paper reflect in part the effects of a persistent credit supply increase within an emerging market economy with financial frictions, allowing liquidity redistribution through trade credit spillovers to have substantial real effects on employment and productivity. Similarly, the idea that liquidity can be exported is similar to the evidence in Gilje et al. (2016) which focuses on banking networks.

Our paper is also related to the literature on bank financing expansion in developing countries and its effects. Burgess and Pande (2005) use a branching expansion from 1969–1990 to study the impact of rural credit expansion on households at the more aggregated state-level. Using policy experiments from the 1980–1990 period, Cole (2009) shows that Indian credit nationalization lowered the cost of credit and worsened the quality of intermediation. Gormley et al. (2018) show that banks resolve bankruptcies more quickly when competition increases.

1 Institutional Background and Data

Common shocks to the production network can contaminate inference, and the research design uses the variation in a plant’s exposure to banking services, as induced by a change in India’s banking regulations, to identify the impact of a credit shock on a plant and its overall production network. This subsection provides narrative and statistical evidence suggesting that a particular plant’s exposure to the banking shock is conditionally exogenous within the baseline empirical framework.

1.1 The “1:1” Branching Rule and Identification Strategy

The variation in a plant’s exposure to banking services comes from Indian branching regulations introduced in 2011 (Figure 1). New regulations sought to significantly increase bank entry across the nation and expand credit access to underserved areas in particular. We focus on a salient dimension of this regulatory push: The Reserve Bank of India (RBI)’s—India’s banking regulator—July 15th, 2011 circular aimed at increasing branching in underserved areas.³ The July 2011 administrative circular required that henceforth the number of branches that a bank opens in bigger cities must be less than the number of branches opened in smaller cities. The RBI classifies Indian cities based on their decadal census population using 6 categories or tiers: Tier 1 cities have a population above 100,000; tier 2 cities have 99,999– 50,000 people; and tier 3 cities have 49,999–20,000 people.⁴ The administrative rule required that the number of branches opened in tier 1 or tier 2 cities cannot exceed the number opened in tier 3 or higher cities.⁵

³See Branch Authorization Policy - Opening of branches in unbanked rural centers at <https://www.rbi.org.in/scripts/NotificationUser.aspx?Id=6613>.

⁴Tier 4: 19,999–10,000; tier 5: 9,999–5,000 and tier 6: less than 5,000 people.

⁵The precise language is “Authorisation is given by the Reserve Bank for opening branches in Tier 1 and Tier 2 centres which would generally not exceed the total number of branches proposed to be opened in Tier 3 to Tier 6 centres as well as in North Eastern States and Sikkim. While issuing such authorisation, Reserve Bank would factor

Put differently, banks had to follow an “at least 1:1 rule” in their branch location decisions after 2011. This means that a bank planning to open 10 branches in tier 1 or 2 cities as part of its regular operations would now also have to open at least 10 branches in tier 3 or higher cities anywhere else in the country. Cities are administratively located in districts. And an implication of the 2011 “at least 1:1 rule” is that districts with tier 3 cities gain more new branches after 2011 relative to districts without a tier 3 city. By creating incidental variation in the number of branches opened in districts with tier 3 cities, henceforth “tier 3 districts”, the 2011 rule provides a plausibly exogenous source of branch entry at the district level.⁶

Before discussing potential threats to identification, let us gauge whether the “at least 1:1” rule affected the pattern of bank branching trends and could reasonably be viewed as a positive banking shock in tier 3 districts. To this end, we estimate Eq. 1:

$$branches_{it} = \alpha_i + \delta_t + \sum_t \beta_t \cdot \mathbb{1}(t) \cdot \mathbb{1}(\text{Has Tier 3})_i + v_{it} \quad (1)$$

where $branches_{it}$ is the number of branches in district i in year t ; α_i and δ_t are district and year fixed effects; the variable of interest is $\mathbb{1}(\text{Has Tier 3})_i$ indicator variable, which equals 1 if a district has at least one tier 3 city and 0 otherwise. The coefficients $\beta_t \cdot \mathbb{1}(t)$ allow the impact of the tier 3 indicator variable on the number of branches in a district to vary by year. These series of coefficients thus help to identify both whether the 2011 regulation induced banks to increase branching networks in tier 3 districts and whether any increase in lending post-2011 is part of pre-existing branching trends.

We estimate Eq. 1 from 2009–2020. Panel B of Figure 1 plots the annual estimates of β .

in whether at least one third of the total number of branches proposed to be opened in Tier 3 to Tier 6 centres are in underbanked districts of underbanked States as also upon regulatory and supervisory comfort and critical assessment of bank’s performance in financial inclusion, priority sector lending and customer service, etc.”

⁶Summary statistics of plants, conditional on whether a plant is in a tier 3 district, are presented in Table 1 and discussed shortly.

These annual estimates show that the 2011 “at least 1:1” branching rule significantly increased the number of branches in districts with tier 3 cities. This effect is economically large, and persists for about 5 years after the rule before gradually tapering off. One year after the rule, eligible districts gain about 2.8 branches more than otherwise, and this “excess entry” peaks at about 6 branches in 2014. A total of about 20 new branches open in the treated districts in the 5 years after the rule. Central to our identification strategy is the fact that there are no pre-trends in new branch entry: The 2011 rule appears not to be an attempt to either “ratify” existing positive entry trends, nor to reverse declining entry in tier 3 districts.

The fact the branching rule increased the supply of banking services in tier 3 eligible districts after the rule, and the absence of any differences in branching between tier 3 and non-tier 3 districts before 2011 is a necessary condition for our research design. But a determined skeptic can still argue that the insignificant pre-trends reflect the pre-2011 regulatory environment, and the fact that banks could not easily expand physical branching in this period. But once the 2011 “at least 1:1” regulation was passed, banks selectively choose to open branches in the most economically active tier 3 districts; the tier 3 districts for example where plants are already expanding and in need of external finance. This endogenous selection of branching entry into tier 3 districts based on pre-2011 trends in economic activity could then still bias inference.

To address this concern, we identify each plant’s district, and estimate a difference-in-differences specification similar to Eq. 1. The dependent variable is the log employment in the calendar year at a plant. We include plant fixed effects, along with industry-by-year fixed effects, and cluster standard errors at the district level. The plant level data are available from 2008–2015 and the annual estimates of β are in Figure 2. We find no evidence that plant-level employment trends differed between tier 3 and non-tier 3 districts in the period before 2011. But foreshadowing the results in Section 2, there is striking evidence that the level of employment increased significantly among

plants exposed to the branching expansion—those located in a tier 3 district after 2011—relative to otherwise. In sum, while the 2011 branching regulation increased branching in tier 3 districts after 2011, there is no evidence that this branching expansion reflected pre-trends in either branching or economic activity.

Finally, a concern is that only government owned banks, which provide a sizeable portion of credit in India, took advantage of the rule change. This may mean that banks may have non-economic mandates from the government that shape banks' entry decisions, possibly leading to selective entry and biased estimates. To gauge whether the entry decisions of public sector banks were more swayed by the at "at least 1:1 rule", we re-estimate the basic difference-in-difference equation, but separately for public and private banks. As can be seen in Table 2, using either measures both private banks and government owned banks take advantage of the rule change and open more branches.

The evidence is clear that the policy change induced a significant increase in bank branches after 2011 in tier 3 districts relative to otherwise, and likely constitutes an exogenous increase in banking services for plants located in tier 3 districts. Yet tier 3 districts—those eligible for the expansion—might be different than other districts, and this unobserved heterogeneity can still contaminate inference. To assess this risk, Table 1 presents the ex-ante characteristics of treatment and control groups. Panel A compares the district-level characteristics across districts with tier 3 population centers (treated group) and those without tier 3 centers (control). Treated districts have larger mean population (2.3 million compared to 1.3 million) and larger areas (156 square kilometer compared to 61 sq km). The treated districts, with higher population, also have more plants (49 compared to 23). At the same time, treated districts have lower cumulative population growth rate during 2001–2011. This may indicate, if anything, a slower pace of economic growth or urbanization in the treated districts before the policy period. The treated and control districts

are comparable in terms of rainfall—a key measure of agricultural productivity in India—and population density.

Panel B studies the plant-level characteristics conditional on location. First, plants in treated and control districts are comparable before the rule change in terms of annual sales, total assets, fixed assets, number of workers, and efficiency measured by Total Factor Revenue Productivity (TFP). We compute TFP for each plant following Hsieh and Klenow (2009).⁷ Treated plants are younger by a few years compared to plants in districts without tier 3 population centers. Panel B shows that there are some important differences in terms of financial structure across treated and control plants. Treated plants use slightly more leverage (debt scaled by assets ratio of 35% vs. 32.4%), and provide less trade credit (receivables/sales ratio of 27.2% compared to 32.5%) ex-ante. Treated plants also hold more precautionary cash before the rule change.

Therefore, to address any remaining concern from these pre-existing differences across districts, the baseline empirical specification uses a difference-in-difference research design with a suite of fixed effects that allow for differential trends. Concretely, we define exposure to the branching expansion regulation as whether a plant is located in a district that has at least one tier 3 city—a tier 3 district in 2011. For these exposed plants, the difference-in-difference design then compares plant level outcomes y_{it} after 2011 relative to before, as well as compared to plants not located in tier 3 districts.

$$y_{it} = \alpha_{st} + \delta_i + \delta_{i\ Pre\ t} + \beta \cdot [\mathbb{1}(Post) \times \mathbb{1}(Has\ Tier\ 3)_i] + \varepsilon_{it}, \quad (2)$$

We include a set of fixed effects to isolate the effect of the rule change on plant outcomes. We use industry \times year fixed effects (α_{st}) to absorb any industry-specific shocks in a particular year.

⁷To this end, we obtain labor and capital shares for various U.S. industries from the Bureau of Economic Analysis (BEA) and map these shares to the Indian industries (identified using NIC2 scheme).

We include plant fixed effects (δ_i) to absorb time-invariant plant-specific heterogeneity. We also include a host of “ex-ante plant characteristics \times post” fixed effects in our baseline ($\delta_{i\text{Pre }t}$). In particular, we include plant size (2011) quartile \times post, and plant age (2011) quartile \times post fixed effects to allow for differential trends in the post period for the smaller or younger plants. These fixed effects can help absorb any pre-trends based ex-ante plant and district characteristics. In addition, we conduct analyses using propensity score matching based on district-level economic and demographic factors. We describe the main results in the next section, but first provide a brief overview of the data.

1.2 Data Sources

Our main source of data is the Annual Survey of Industries (ASI) database, which provides plant-level financial and productivity variables starting from the year 1990. The ASI database provides information about plants including production numbers, input cost, output prices, employment levels, wages of workers, and assets and liabilities at the plant-level. One concern is that the ASI data provides plant location details only if the plant starts prior to the year 2011. Fortunately, as we utilize the ASI data in the context of the RBI policy changes that occurred in June 2011, and because we exclude the first year of data for all plants, we know the location for each plant that gets included in the analysis. In addition to excluding the first year of data for a plant, we also exclude any plants with assets less than INR 0.5 million. Further, we consider only manufacturing plants with 2-Digit National Industry Classification (NIC) Codes between 1–33.⁸

Next, we use data from the Reserve Bank of India’s (RBI) Basic Statistical Returns (BSR). The returns provide aggregate annual banking deposits and credit data at the district-level starting

⁸The ASI data has also been used by previous researchers including Hsieh and Klenow (2009); Martin et al. (2017) and recently Bau and Matray (2020).

from the year 2010. The returns also divide the deposits and credit data by the type of banks - namely public sector and private banks. We also obtain annual data since 2005 on newly opened branches within each district, divided by the type of bank. The RBI policy changes that we utilize, applies differently to various tiers of population centers. To understand the potential effect of RBI policy changes on a district, we use Indian census data from the year 2001 to identify population center tiers present in a district, consistent with the RBI circular. One district can and usually have multiple tiers.

2 Direct Impact of Branching Expansion

This section investigates the direct benefits of bank branching expansion to plants. We investigate a set of outcomes including plant-level productivity and employment.

2.1 Plant Outcomes

This section presents the results from estimating Eq. 2 with the full suite of fixed effects. Before we tabulate the effects of exposure to the banking shock, we first provide some figures to assess the plausibility of the research design. Using log sales as the dependent variable, Panel A of Figure 2 assesses the parallel trends assumption—a necessary condition to interpret causally the difference-in-difference estimates. This figure plots the coefficient on the tier 3 district indicator interacted with year indicator variables that span our sample period (2009–2015)—the omitted base year is 2008. Before 2011, there is no significant difference in plant sales among those located in tier 3 districts versus those in non-tier 3 districts. However, after 2011, log sales across the two types of plants diverge. The point estimates suggest that on average exposed plants experience a 10.8% increase in sales relative to period before 2011, as well as relative to plants not located in tier 3

districts.

Panel B focuses on plant size, defined as the log of plant assets. A similar pattern emerges. The evolution of plant sizes across districts were statistically identical in the period before 2011, but then diverged after the law, so that on average, exposed plants are about 6.3 percent larger relative to otherwise. Improved access to bank capital can help plants increase investment, and using the same specification as before, Panel C of Figure 2 plots the evolution of fixed capital investment. After a plant becomes exposed to the banking expansion, investment on average increases by 7.5 percent relative to otherwise; and as before, there are no trend differences in the evolution of this variable in the pre-2011 period. Finally, panel D examines employment. A similar pattern emerges. Employment at exposed banks increase by about 4.2 percent relative to otherwise, suggesting that improved access to credit allowed plants to expand production significantly.

Panel A of Table 3 reports the estimates of Eq. 2 as baseline results. The point estimate in Column (1) suggests that on average, treated plants experience a 10.8% increase in sales. Column (2) shows that plants expand their asset base by 6.3%. Fixed assets increase by 7.5% suggesting that plants invest more in productive assets when bank branches increase in their districts (Column 3). Along with capital expenditure, plants also hire more employees, as noted in Column (4). Finally, benefiting plants experience 3.8% higher productivity post rule change.⁹ Moreover, these effects are economically large and statistically significant even after clustering the errors at the treatment level.

⁹Following Hsieh and Klenow (2009), Total Factor Productivity (TFP) is computed as follows for plant p :

$$TFP_{pt} = \frac{Sales_{pt}}{K_{pt-1}^{1-\alpha_{sp}} (Wages_{pt-1})^{\alpha_{sp}}}$$

where sales, capital (K), and total wages are all nominal variables measured in Indian Rupees. α is the labor share of the output for the sector s of plant p . We borrow the industry specific labor shares as of 2011 from the U.S. Bureau of Labor Statistics and map the 14 industries identified by Bureau of Labor Statistics (BLS) to 33 industry codes in ASI data.

The absence of pre-trends shown in Figure 2 suggests that these results likely reflect the causal impact of the branching expansion. However, the sample period overlaps with the 2008–2009 financial crisis, and these results might reflect the heterogeneity in the effects of this shock across the Indian economy. To be sure, the baseline specification includes plant fixed effects, as well as industry-by-year fixed effects to absorb aggregate shocks to specific industries, and allow for separate post-2011 trends for plants of varying sizes and age. But as a further robustness check, Panel B of Table 3 restricts the sample only to the most economically active districts—those are the districts with an above median number of plants—and thus most exposed to any long-term effects of the financial crisis. The basic results remain.

The summary statistics document that treated districts are more populous, larger area and have more plants relative to the control districts in 2011. Hence, Panel C includes district population quartile times year fixed effects to allow for heterogeneity in the experience of prevalent aggregate economic conditions by size of district. The basic results, again, remain.

To further gauge whether these results are an artifact of unobserved variation in the cross-section of districts, we run a placebo test where we randomize plant exposure. The approach randomly assigns districts to tier 3 based on the mean tier 3 districts in 2011. We repeat this random assignment experiment 1,000 times. Each time, with the randomly assigned indicator of exposure with a mean that matches the 2011 mean number of tier 3 districts, we estimate the baseline regression coefficients. For these regressions, we use the logarithm of sales and workers, and cash scaled by assets as dependent variables. Figure 3 plots the distribution of estimated treatment coefficients along with the t-statistics. The mean coefficient and t-statistic is zero, suggesting that the observed effects of the banking expansion on plant-level outcomes are unlikely to occur by chance.

Table 4 further attempts to address concerns that the differences between treated and control

districts might bias these estimates. To this end, as the number of districts with non-tier 3 population centers is relatively smaller, we match such districts with districts that have tier 3 population centers. Panel B shows the characteristics on which we conduct a nearest neighbor match, with replacement of treated districts. The set of districts have similar population, expenditure, area, and plants per capita. Panel A finds that the results remain similar when we conduct a regression analysis on plants in this subset of districts.

2.2 Labor Market and Financial Outcomes

Improved access to bank credit can affect labor market outcomes, as well as financial management decisions, and we next study these adjustment margins. Our first set of tests focus on the labor market (Table 5). Easier access to credit that enable plants to increase output can also increase the demand for both unskilled and skilled or managerial labor. Columns (1) and (2) thus report the effect of the rule change and corresponding branch expansion on the number of self-reported managers and workers at a plant. We note that while the number of managers may have increased, the number of workers increases by 3.9%. Despite the increase in the number of workers, the evidence suggests that this relaxation in financing constraints is also associated with improved labor productivity, as output per worker is about 6% higher among treated plants relative to otherwise. Although India has a potentially large pool of surplus labor in some areas, this increase in the demand for labor is also associated with higher wages. Column (4) reports that employees share the benefits of higher productivity, and receive 3.5% higher wages. Columns (5) and (6) show that the gains in wages are potentially present for managers, but are statistically significant for workers.

Consistent with the evidence in the broader literature, we have shown that an expansion in banking services can significantly increase plant-level output and labor productivity. But improved access to banking services can also affect financial management at exposed plants, as plants might

adjust their precautionary holdings of cash when access to bank credit improves. Also, plants can transmit bank liquidity through their supply network using trade credit, leading to large spillover effects in output and employment throughout the supply chain. Before tackling these spillover effects, we first document the direct financial management effects.

We start with column (1) in Table 6 that shows that plants in districts benefiting from bank branch expansion hold 0.7 pp less cash as a fraction of assets. This is consistent with the fact that improved access to bank liquidity via credit lines and loans can reduce the need for plants to self-insure through cash holdings. Of course, this result might be mechanically driven by the increase in plant assets, and column (2) uses total financial liabilities as the denominator. The ratio of cash holdings to liabilities also declines; this ratio declines by about 9.6 percentage points after exposure relative to otherwise. Consistent with the idea that the banking expansion shock relaxed financing constraints, column (3) reports that plants utilize 6.6% more credit (logarithm of bank debt) in areas that benefit from bank branch expansion due to the 1:1 rule.

Moreover, there is evidence that plants exposed to the banking shock may have redistributed bank liquidity through the supply chain to increase output. Column (4) shows that treated plants extended 10.6 percentage points more trade credit—accounts receivables. Thus, liquidity redistribution through the supply chain is significant.

If upstream suppliers have less growth opportunities, then the shadow cost of liquidity redistribution is low. Hence, in such a case, we should expect a larger redistribution of liquidity from upstream suppliers who benefit from bank liquidity. Column (5) shows this to be the case. The estimated coefficient of the triple interaction points out that less profitable firms that benefit from branch expansion due to the 1:1 rule extend relatively more trade credit.

3 Spillover Effects

The previous section shows that branching expansion in districts directly helps plants that exist in those locations. It also shows that benefiting plants pass on the credit to their customers. In this section, we investigate how the credit spillover benefits downstream firms.

3.1 Credit spillover through the production network

While the cost of financing through trade credit may be high, the redistribution of trade credit through the supply chain can be important for plants that are credit rationed (Nocke and Thanassoulis, 2014). To estimate the effect of spillover on downstream plants, we need to estimate the exposure of each plant to branch expansion through its suppliers. We do not directly observe bilateral lending relationships, but our data provide us with a list of inputs i that a plant p utilizes along with the input costs c_i . Thus, we can estimate the importance of each input to the firm's production. In addition, for each input i , we calculate the fraction f_i in the aggregate that is produced in treated districts of India. The sum of treatment fractions of inputs weighted by their relative importance for the plant provides us with a measure of exposure of each plant to branching expansion:

$$\text{Input Exposure to Treatment}_{pt} = \sum_{i \in I_{pt}} f_{it} \times \left(\frac{c_{ipt}}{\sum_{i \in I_{pt}} c_{it}} \right). \quad (3)$$

where I_{pt} denotes the set of all the inputs plant p uses at time t . We calculate the exposure of each plant the year before branching expansion in 2011.

Using the measure above, Table 7 investigates the effect of branching expansion on plants that purchase from treated districts. We note in column (1) that customer plants experience an 8 pp. increase in accounts payable scaled by assets, suggesting that the treated plants are extending their

customers more credit. This additional credit also helps explain why the sales of the treated plants rise.

It is important to check whether accounts payable of customer plants are increasing in proportion to overall debt. If our results reflect latent factors that precipitate an overall increase in credit usage, then both trade credit and overall debt might increase in the same proportion. But if we have identified a trade credit shock via bank liquidity redistribution, then the relative importance of accounts payables in overall liabilities will increase. Column (2) scales accounts payable by total plant debt which includes bank debt and accounts payables. We find that accounts payable relative to total debt increases by 11 pp. for plants that obtain 100% of their inputs from suppliers benefiting from bank branch expansion. Thus, trade credit financing becomes relatively more important for downstream plants with upstream suppliers exposed to the banking expansion.

How do we distinguish further the direct increase in credit supply of branch expansion from the trade credit channel? Our test builds on the idea that plants tend to obtain most of their bank credit from nearby banks. Thus, one way to isolate the relative importance of trade credit is to investigate the effect of branch expansion on downstream plants that do not directly benefit from expansion in their districts. These plants will be more dependent on trade credit, as they have no increase in physical access to bank financing. Hence, in columns (3) and (4), we divide plants based on the fraction of district population that resides in the tier 3 towns. The argument is that plants in districts with less treatment to branching expansion should be the ones drawing more credit from their suppliers who directly benefit from new bank branches.

The triple interaction coefficient suggests that plants in districts where population in tier 3 centers is in the lowest quartile (about 5 pp.) draw 12% more trade credit as a fraction of assets (column 3). Column (4) shows that such plants obtain 17.5% more of their financing from trade credit compared to bank debt if their suppliers are all in treated districts. Column (5) checks

whether relative prices are an alternative mechanism through which upstream exposed plants redistribute liquidity. To do this, we calculate the change in the price of inputs for each plant compared to the previous year. The price coefficient is not significant while the trade credit interaction terms remain unchanged.

Trade credit is relatively expensive. Yet, research has identified conditions under which suppliers are better positioned to provide credit than banks (Biais and Gollier, 1997). Specifically, if a product is only available from a small set of suppliers, then suppliers can better enforce repayment, increasing the potential of trade financing (Cuñat, 2006; Dass et al., 2014). Following a similar process to that in Eq. 3, we calculate the Herfindahl-Hirschman Index (HHI) of each input used by a downstream firm. We then aggregate these input specific indices using the relative value of each input in the firm’s production. This approach gives us a measure of the supply competition in the input markets for a plant. Plants facing the smallest weighted value in their inputs are then marked as “Low Supplier Competition” plants.¹⁰

Table 8 documents the results for the competition channel. Column (1) shows that plants obtaining inputs from the treated supplier expand their trade payables or in other words get more trade credit if the supplier operates in a less competitive product market. This result holds even when we scale the payables by assets in column (2) or by total debt in column (3). This result is consistent with the theoretical idea that when the product is available from a small set of suppliers, then better enforcement of trade credit contracts allow suppliers to extend more trade credit downstream, once they get better access to bank credit in the post-2011 period.

¹⁰Specifically, we construct Input HHI for each plant p as

$$\text{Input HHI}_{pt} = \sum_{i \in I_{pt}} w_{ipt} \times HHI_{it}$$

where HHI_{it} for product i is the Herfindahl-Hirschman Index computed using producer’s all-India market share using the ASI data and w_{ipt} is the weight of the product i in plant p ’s inputs (by currency value).

3.2 Real outcomes at plants receiving trade credit

Additional trade credit to plants ultimately should lead to improvement in firm outcomes. Table 9 reports the effects of trade credit spillover on benefiting customer firms. Column (1) reports that after branching expansion, plants with a higher fraction of inputs from treated districts expand sales more. Sales increase by 2.34% more for plants that purchase a one standard deviation (3.28%) more inputs from treated districts. Employment also receives a boost. Column (2) reports that plants with one standard deviation more inputs from treated districts benefiting from branch expansion, expand employment by 1.40%. Ultimately, downstream plants increase their productivity, as shown in column (3).

The spillover channel, if it works, should also benefit plants in districts with less or no access to branching expansion. This is because as long as plants providing inputs benefit from more bank branches, higher trade credit and improved real effects should follow. Hence, columns (4)–(6) investigate districts that have the lowest quartile of population in tier 3 towns.

We observe improved real outcomes for the plants with treated suppliers even though the plants are not directly treated. Given the importance of physical distance in Indian banking relationships, these results point to the importance of the trade credit spillover channel. Results are similar if we only utilize districts with no tier 3 population centers.

4 Estimation of Credit Network Multiplier

A well established literature seeks to understand the impact on aggregate productivity of microeconomic shocks. The standard framework for this stream of literature is a multisector, general equilibrium, static model of intermediate good trade. Primary factors of production and demand are exogenously fixed. The benchmark is an economy at productive efficiency Diamond and Mir-

reels (1971). In an efficient economy however, small distortions in allocation have zero first order effects on TFP (Harberger, 1954). Two departures yield important insights. First, Baqaee and Farhi (2019) focus on inefficient economies and show that improvements in allocative efficiency, due to reallocation over time of market share to high-markup firms, accounts for about half of the aggregate TFP growth in U.S. between 1997–2015. Second, Bigio and La’O (2020) continue to focus on efficient economies but allow supply of labor to be endogenously determined. The authors show that while sectoral distortions generate no first-order loss in productive efficiency, they produce first-order effects on the labor wedge. The authors show that the U.S. input-output network amplifies micro distortions by a factor of 2 (labor wedge network multiplier).

The source of distortions in the above frameworks can be markups, taxes, financing frictions, etc. Researchers have used the Bigio and La’O (2020) framework and investigated the role of trade credit in amplifying microeconomic shocks. In particular, Altinoglu (2021) introduces trade credit with limited pledgeability of future cash flows into the framework of Bigio and La’O (2020), and shows that trade credit plays an important role in business cycle fluctuations. Alfaro et al. (2021) also utilize the framework of Bigio and La’O (2020) for efficient economies. The authors find that credit supply shocks have sizable direct and downstream propagation effects on employment, investment, and output, especially during the 2008–2009 crisis, but no significant impact on employment during the expansion.

In our paper, we investigate how additional capital from bank entry is shared across the production network through firms. Analogous to the household endogenous labor supply problem (Chari et al., 2007; Karabarbounis, 2014; Bigio and La’O, 2020), we consider firms’ endogenous credit supply to the downstream network. In comparison to the literature, and in keeping with our empirical results, we allow demand for a firms’ output to be endogenous to offered trade credit as well. As trade credit supply and demand do not have to equalize across India, an economy wide clearing

condition like the first welfare theorem is not appropriate. Hence, we utilize sector level profit maximization conditions for our exercise (as suggested by Baqaee and Farhi, 2019, for inefficient economies). Our approach utilizes plant level data to estimate the credit multiplier effect through the production network. We abstract away from other wedges in the economy. Thus, while we are also interested in understanding credit multiplier effect due to financial frictions, our paper does not investigate microfoundations of business cycles.

We have seen evidence that plants directly exposed to the banking sector expansion increase output and redistribute liquidity further down the supply chain. These latter plants in turn also increase output and sales, suggesting that improved access to banking sector credit can increase output both among directly exposed plants, as well as in the overall supply chain. Below, we construct a parsimonious model to estimate the credit multiplier in India in this period due to the trade credit channel. The model is static and features a representative firm for the final goods production sector within each industry. The firm rents capital K , and produces a good according to the following production function $y_s = A_s K^{\alpha_s}$, where s denotes industry, A_s is the total factor productivity and α_s denotes the output elasticity of capital specific to industry s . We abstract away from labor in this parsimonious model.

In this standard setup, we introduce a role of trade-credit in the model. Specifically, demand for the good produced by the firm is an increasing function of the trade-credit extended by the firm to its customers. The producer firm rents the trade-credit it offers, which adds to the cost of production. Producer firm's profit maximization problem is thus as follows:

$$\max_{c,y} p \cdot y - r(K + c), \tag{4}$$

where p is the product price, and where demand y is spurred by credit c offered by the firm in

question as follows:

$$y = a - b_p p + b_c c^\theta. \quad (5)$$

where b_p and b_c denote the sensitivity of demand to the price and the trade-credit extended. We assume a linear relation between price p and quantity above. The first order condition for c yields optimal credit c^* for a given level of capital K :

$$c^* = \left(\frac{b_c \theta}{r b_p} \cdot y \right)^{\frac{1}{1-\theta}}, \quad (6)$$

As we estimate below, optimal credit level turns out to be a concave function of quantity desired, which is intuitive. We take logarithms to obtain an equation that can be easily estimated: the relation between quantity y or capital K and credit supply c^* is given by:

$$\begin{aligned} \ln c^* &= \frac{1}{1-\theta} \ln y + \frac{1}{1-\theta} \ln \frac{\theta b_c}{r b_p} \\ &= \frac{\alpha}{1-\theta} \ln K + \frac{1}{1-\theta} \ln \frac{A \theta b_c}{r b_p} \end{aligned} \quad (7)$$

where we substituted the production function in the second line. The novelty of our data is that we observe the quantity of each of the product produced and sold by each plant as well as the per unit price. This allows us to estimate the first equation above and recover θ by regressing log of trade-credit extended on log of quantity sold.

To understand how the additional liquidity transmits through the production network, we differentiate the relation above. We obtain a relation between marginal trade credit and marginal capital investment:

$$dc = \frac{\alpha}{1-\theta} \frac{c}{K} dK \quad (8)$$

Thus, \$1 of marginal financing will be shared between additional capital dK and additional trade credit dc in the following proportion:

$$\begin{aligned} dK &= \frac{(1 - \theta)}{(1 - \theta) + \alpha \frac{c}{K}} \\ dc &= \frac{\alpha \frac{c}{K}}{(1 - \theta) + \alpha \frac{c}{K}} \end{aligned} \quad (9)$$

Under the assumption that the trade credit transmits down the supply chain, we obtain an expression for the trade credit multiplier, i.e., the amount of credit created in the production network for unit amount of credit provided by a bank:

$$\text{Credit Multiplier} = 1 + \frac{\alpha}{1 - \theta} \frac{c}{K} \quad (10)$$

To obtain a numerical estimate of the Credit Multiplier in Eq. 10, we estimate Eq. 7 in data using the relation between capital K and trade credit c . The estimated average value of the term $\frac{\alpha}{1 - \theta} = 0.67$, which is statistically significant at the 1% level. Figure 4 plots the estimated multipliers by industry. The significant variation of estimated trade credit multipliers points to relative financial constraints across industries.

Our simple yet useful estimation suggests that on average, an extra \$1 of bank credit generates a total of \$1.48 worth of credit in presence of the trade-credit channel. As a comparison, Bigio and La'O (2020) provide a back-of-the-envelope estimate of the labor wedge network multiplier in an efficient economy to be about 2. One policy implication of our finding is that bank expansion program is more effective if new banks provide additional credit to the firms with significant downstream production linkages so as to maximize the multiplier effect through the trade-credit channel.

5 Conclusion

We investigate how interconnections between different plants in India propagate additional credit supply through the production network. First, we show that direct exposure to the spatial banking shock significantly affects both real and financial outcomes at directly exposed plants. Second, we show that plants directly exposed to the local banking shock redistribute liquidity through their production network, increasing short-term financing to other firms in the production network. Third, we use the input-output relationships for each plant to understand how supply linkages propagate the granular banking shocks throughout the economy. Finally, we construct a parsimonious model to estimate the trade credit multiplier in India in our sample period.

In sum, these results suggest that rather than using their improved liquidity position to extract rents from their suppliers, plants exposed to banking shocks redistribute this liquidity through the supply chain. As a result, firms extending trade credit can increase their own sales as their customers are able to purchase on credit. Second, downstream firms are able to increase their own sales, employment, and productivity. Taken together, relaxing bank financing constraints even in limited areas can induce potentially sizeable aggregate changes in output and employment via this trade credit channel. In this way, these results can help inform the refinement of theories that emphasize the importance of production networks in shaping aggregate fluctuations.

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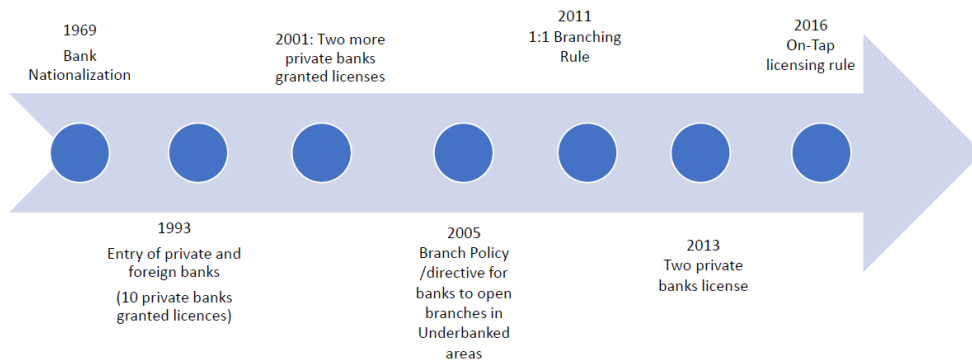
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Figure 1: Bank Entry due to RBI “1:1” policy

The top panel provides a timeline of policy actions taken by the Reserve Bank of India regarding bank entry. The lower panel reports the additional entry of banks in districts with tier 3 cities after the Reserve Bank of India adopted the 1:1 Branch Policy (See Equation 1 in the text).

(a) Timeline of policy actions



(b) Number of additional branches per district

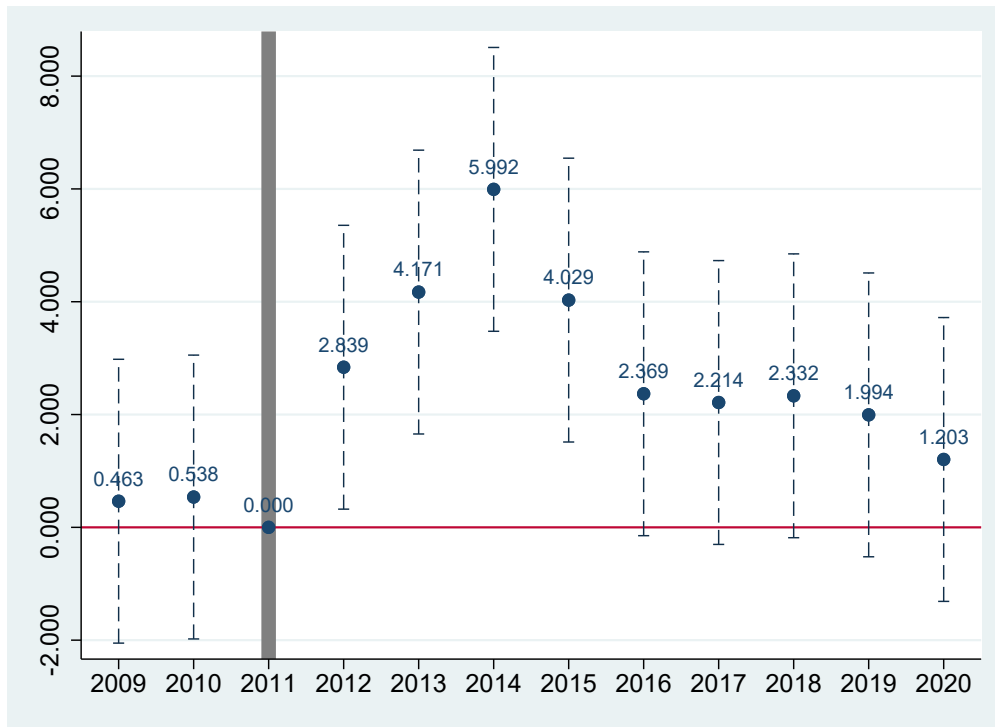
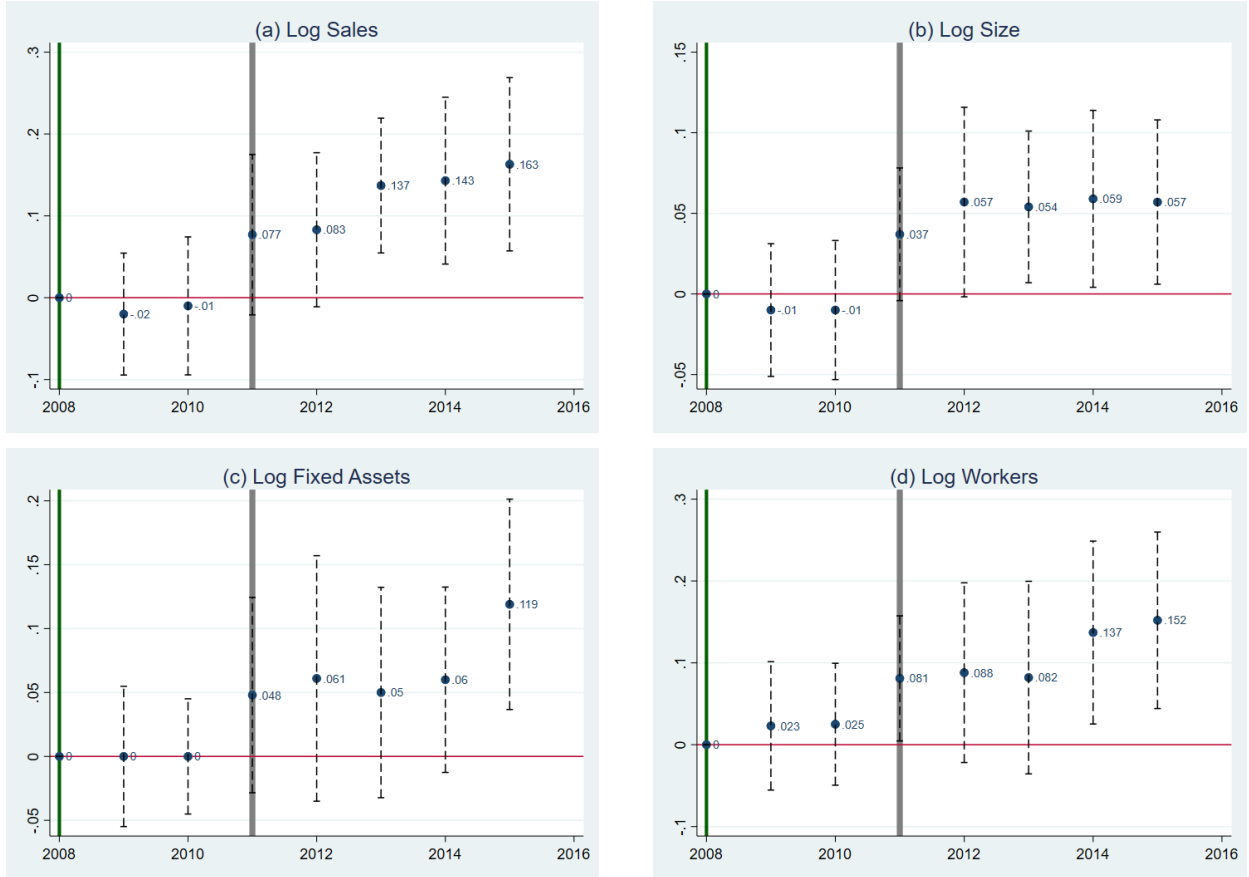


Figure 2: Yearly Effects of Bank-Entry on Plant Outcomes

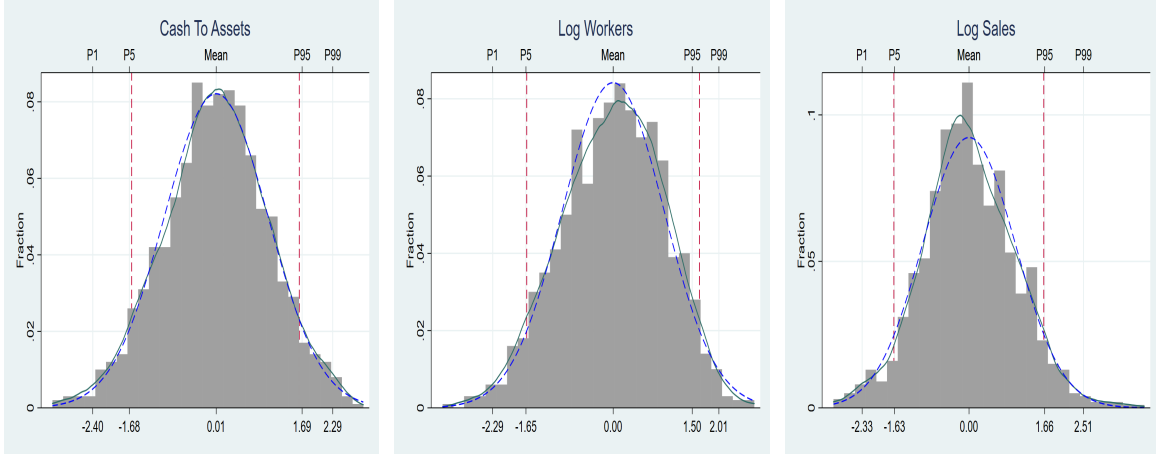


The figure plots the coefficient β_{yt} for $t \in \mathcal{T} = \{2008, \dots, 2015\}$ in the following regression:

$$y_{it} = \alpha_{st} + \delta_i + \delta_{i\text{Pre}t} + \sum_{t \in \mathcal{T}} \beta_{yt} \cdot \mathbb{1}(t) \cdot \mathbb{1}(\text{Has Tier 3})_i + \varepsilon_{it}$$

where y_{it} is the outcome for plant i in year t , $\mathbb{1}(t)$ indicates the dummy for the year t , $\mathbb{1}(\text{Has Tier 3})_i$ indicates the dummy for the districts having at least one tier 3 town, α_{st} are the industry \times year fixed effects, δ_i are the plant fixed effects, and $\delta_{i\text{Pre}t}$ are the pre-period or ex-ante plant size and age groups \times year fixed effects. The standard errors are clustered at the district level. The base year in the specification is 2008 depicted by the the green vertical line. The vertical gray line denotes the year of implementation of the law. We estimate our baseline difference-in-difference coefficient for four variables namely, Log of Sales, Log Size, Log Fixed Assets, Log Workers. The dashed lines around β_{yt} are 5% confidence intervals.

Figure 3: Distribution of t-statistics from Randomized Treatment Exercise



The figure plots the distribution of t-statistics obtained from the randomized treatment exercise over 1000 trials. In each trial, the treatment is randomized over possible districts, where the treatment probability is matched with the observed treatment probability in our sample. Then, for each trial $k = 1, 2, \dots, 1000$, we estimate our baseline difference-in-difference coefficient for three variables namely, Log of Total Workers, Log of Sales, and Cash/Assets ratio as follows:

$$y_{it}^k = \alpha_{st} + \delta_i + \delta_{i \text{ Pre } t} + \beta_{yk} \cdot \mathbb{1}(\text{Post}) \cdot \mathbb{1}(\text{Has Tier 3})_i + \varepsilon_{it}$$

where α_{st} are the industry \times time fixed effects, δ_i are plant fixed effects, and $\delta_{i \text{ Pre } t}$ are the pre-period or ex-ante plant size and age quartiles \times year fixed effects. The standard errors are clustered at the district level. The figure plots the histogram of 1000 t-statistics corresponding to β_{yk} , for each of the three y . The two red vertical lines highlight the 5th and the 95th percentile of the distribution. The bottom of X-axis report the 1, 5, 50, 95, and 99 percentiles of the distribution while top X-axis mark the corresponding percentiles for standard normal distribution. The figure also overlays the standard normal distribution (dashed blue line) and the kernel density estimation (green line). The following table reports the summary of β_y and $t(\beta_y)$ in the sample and in the randomized trial:

	Log Sales		Log Workers		Cash/Assets	
	β_y	$t(\beta_y)$	β_y	$t(\beta_y)$	β_y	$t(\beta_y)$
Mean	0.000	0.004	0.000	0.002	0.001	0.014
Median	0.000	-0.039	0.000	0.047	0.002	0.014
P5	-0.021	-1.626	-0.016	-1.655	-0.214	-1.684
P25	-0.008	-0.630	-0.007	-0.676	-0.080	-0.634
P75	0.009	0.672	0.007	0.707	0.089	0.720
P95	0.021	1.658	0.015	1.503	0.206	1.694
Reported Statistic in Sample	0.108***	4.981	0.042***	2.823	0.007***	2.366

Figure 4: Trade Credit Multiplier

Estimated trade credit multiplier by industry. Credit multiplier is the amount of credit created in the production network for unit amount of credit provided by a bank (Eq. 10). We focus on manufacturing plants with 2-Digit National Industry Classification (NIC) Codes between 1–33. The mean multiplier (red line) is 1.48.

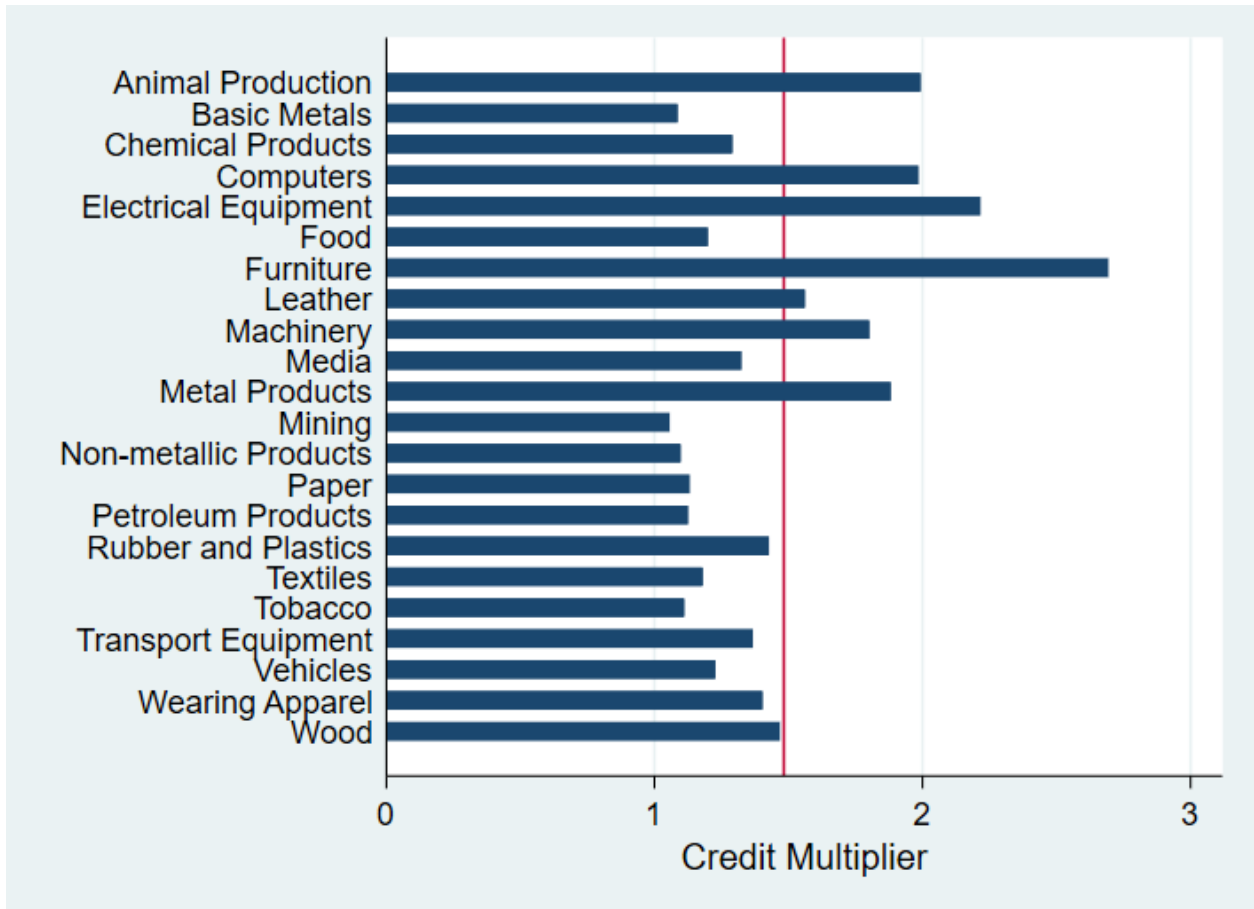


Table 1: Summary Statistics

This Table contains summary statistics for Treated and Control districts in the Pre-Policy period. Districts having Tier 3 towns are treated while those without even a single tier 3 town are classified as control districts. A plant is treated if it is located in the treated district. Otherwise it is a control plant. Panel A provides district-level characteristics while Panel B provides plant level characteristics. The standard errors are Newey-West robust standard errors and ***, **, * indicates significance at less than 1%, 5%, and 10% levels respectively.

Panel A: District Characteristics				
	Treated	Control	Diff	t-stat
	(1)	(2)	(3)	(4)
Population (2011)	2,354,469	1,361,452	993,017***	(6.760)
Area	156	61	95.170***	(4.907)
Population growth % (2001-11)	177.980	207.983	-30.003***	(-2.595)
Rain (Cm)	1,129	1,209	-80.219	(-0.948)
Density	4,555	4,372	183.311	(0.414)
Banks	74	75	-0.848	(-0.055)
Branches (2008)	150	122	27.596	(1.371)
Branches (2011)	181	145	35.938	(1.443)
Branches Growth % (2008-2011)	19.966	17.890	2.076*	(1.774)
Number of Plants	49.294	23.350	25.944***	(9.292)
Panel B: Plant Characteristics				
	Treated	Control	Diff	t-stat
	(1)	(2)	(3)	(4)
Real Characteristics				
Sales (Mn, INR)	1398.063	1315.481	82.582	(0.170)
Size (Mn, INR)	1112.857	772.949	339.908	(1.250)
TFPR (INR)	6.965	7.191	-0.227	(-1.284)
Fixed Assets (Mn, INR)	500.335	307.840	192.495	(1.271)
Workers	245.814	280.859	-35.045*	(-1.667)
Age (Years)	22.489	26.617	-4.128***	(-10.352)
Financial Characteristics				
Bank Debt (Mn INR)	352.564	220.939	131.625	(1.406)
Receivables/Sales, %	27.205	32.494	-5.289***	(-3.596)
Payables/Assets, %	20.453	20.602	-0.149	(-0.285)
Debt/Assets, %	35.015	32.383	2.632***	(2.897)
Cash/Assets, %	5.938	7.619	-1.681***	(-6.787)
Wages Per Worker (INR, Annual)	79,638	86,975	-7,336**	(-2.016)

Table 2: The Impact of the RBI’s “1:1” Branching Expansion on Bank Entry

The table presents the evidence on effectiveness of branch expansion policy enacted in 2011-12 by RBI. The policy introduced 1:1 rule requiring banks to open at least 1 branch in tiers 3 to 6 for each branch it plans to open in tiers 1 and 2. The estimates utilizes data between 2008-2015 and Post-Law dummy indicates year is between 2011 and 2015, including the years — the period after the law was passed. *Tier 3* indicator is 1 if a district has a tier 3 center. In columns 1-3, the dependent variable is the number of new branches opened during the year in the district by all banks, private banks, or government owned banks (public sector banks, i.e., PSBs), respectively. In columns 4-6, the dependent variable is the new branches in the district as a fraction of national new branches during the year, again computed for all banks, and separately for private and public banks. All specifications include year and district fixed effects and standard errors are clustered by district and are in parentheses.

	District New Branches			District Share of New Branches		
	All banks (1)	Private (2)	PSB (3)	All banks (4)	Private (5)	PSB (6)
$\mathbb{1}(\text{Has Tier 3}) \times \mathbb{1}(\text{Post})$	3.8921*** (0.8662)	1.1183*** (0.4248)	2.7241*** (0.6295)	0.0693** (0.0297)	0.1141** (0.0522)	0.0550** (0.0244)
Year FE	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y
Observations	3,208	3,208	3,200	3,208	3,208	3,200
Adjusted R^2	0.8644	0.7532	0.8196	0.8441	0.7622	0.8014

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Bank Entry and Real Plant Outcomes

This table conducts the difference-in-difference (DID) estimation of exogenous bank entry on the plant-level real outcomes. The branch expansion policy was enacted in 2011-12 by the RBI. The estimates utilize data from 2008 up to 2015 and Post indicator is 1 for years 2012–2015. Observations are at the plant-year level. Has Tier 3 dummy identifies the treated districts having at least one tier 3 town. All the specifications include plant, Industry \times Year, Pre-age \times Post, and Pre- Size \times Post fixed effects, where Pre-Age and Pre-Size indicates plant age and size in 2011. Panel A reports the result for the entire sample, while Panel B restricts the sample to the districts having above-median number of plants in 2011. Panel C reports results after including district population quartile times year fixed effects. Standard errors are clustered at district level and are in parentheses. ***, **, * indicates significance at less than 1%, 5%, and 10% respectively.

Panel A: Baseline Results					
	Log Sales (1)	Log Plant Size (2)	Log Investment (3)	Log Employment (4)	Log TFP (5)
$\mathbb{1}(\text{Has Tier 3}) \times \mathbb{1}(\text{Post})$	0.1081*** (0.0217)	0.0628*** (0.0166)	0.0745*** (0.0268)	0.0415*** (0.0147)	0.0376*** (0.0144)
Observations	157,420	172,700	172,814	172,644	157,467
Adjusted R^2	0.9287	0.9609	0.9328	0.9302	0.7239
Panel B: Larger districts					
	Log Sales (1)	Log Plant Size (2)	Log Investment (3)	Log Employment (4)	Log TFP (5)
$\mathbb{1}(\text{Has Tier 3}) \times \mathbb{1}(\text{Post})$	0.1233*** (0.0229)	0.0669*** (0.0182)	0.0837*** (0.0291)	0.0432*** (0.0164)	0.0468*** (0.0165)
Observations	145,742	160,115	160,220	160,100	145,751
Adjusted R^2	0.9276	0.9602	0.9307	0.9296	0.6971
Panel C: Population trends					
	Log Sales (1)	Log Plant Size (2)	Log Investment (3)	Log Employment (4)	Log TFP (5)
$\mathbb{1}(\text{Has Tier 3}) \times \mathbb{1}(\text{Post})$	0.1121*** (0.0216)	0.0533*** (0.0197)	0.0702** (0.0310)	0.0630*** (0.0155)	0.0332** (0.0163)
Observations	157,420	172,700	172,814	172,644	157,444
Adjusted R^2	0.9285	0.9608	0.9328	0.9298	0.6963
All Panels					
Plant FE	Y	Y	Y	Y	Y
Industry \times Year FE	Y	Y	Y	Y	Y
Pre-Size \times Post FE	Y	Y	Y	Y	Y
Pre-Age \times Post FE	Y	Y	Y	Y	Y
Panel C					
Population \times Post	Y	Y	Y	Y	Y

Table 4: Bank Entry and Real Plant Outcomes: Matching Estimation

This table conducts the difference-in-difference (DID) estimation of exogenous bank entry on the plant-level real outcomes using matching methods. The branch expansion policy was enacted in 2011-12 by the RBI. The estimates utilizes data from 2008 up to 2015 and Post indicator is 1 for years 2012–2015. Observations are at the plant-year level. Has Tier 3 dummy identifies the treated districts having at least one tier 3 town. All the specifications include plant, Industry \times Year, Pre-age \times Post, and Pre- Size \times Post fixed effects, where Pre-Age and Pre-Size indicates plant age and size in 2011. Panel A reports the results using nearest-neighbor matching method. Panel B reports the variables used to construct match between treated and control variables. Standard errors are clustered at district level and are in parentheses. ***, **, * indicates significance at less than 1%, 5%, and 10% respectively.

Panel A: Nearest-Neighbor Matching						
	Log Sales (1)	Log Plant Size (2)	Log Investment (3)	Log Employment (4)	Log TFP (5)	
$\mathbb{1}(\text{Has Tier 3}) \times \mathbb{1}(\text{Post})$	0.2541*** (0.0722)	0.1123*** (0.0367)	0.2403*** (0.0445)	0.0593* (0.0325)	0.1449** (0.0676)	
Observations	16,501	17,496	17,499	17,466	16,526	
Adjusted R^2	0.9248	0.9685	0.9432	0.9334	0.7218	
Plant FE	Y	Y	Y	Y	Y	
Industry \times Year FE	Y	Y	Y	Y	Y	
Pre-Size \times Post FE	Y	Y	Y	Y	Y	
Pre-Age \times Post FE	Y	Y	Y	Y	Y	
Panel B: Summary Statistics of covariates used for matching						
	Obs (1)	Mean (2)	Std. dev (3)	Min (4)	Max (5)	Diff. t-test (6)
Log Total district pop. (Treated)	55	11.9922	1.2551	9.9794	15.3947	
Log Total district pop. (Control)	66	11.9388	1.3814	9.4865	16.2986	0.5043
Log Per capita expense (Treated)	55	2.7804	2.7044	-2.6665	8.6631	
Log Per capita expense (Control)	66	3.1453	2.7957	-2.4398	9.3529	-0.6906
Log Area (Treated)	55	3.8462	0.9222	2.0541	6.1985	
Log Area (Control)	66	3.7879	0.9072	2.1389	6.4019	0.6983
Log Plant count per capita (Treated)	55	-9.8360	1.2497	-12.2225	-5.3609	
Log Plant count per capita (Control)	66	-9.7930	1.3179	-13.5075	-5.5161	-0.1597

Table 5: Bank Entry and Labor Market Outcomes

This table conducts the difference-in-difference (DID) estimation of exogenous bank entry on the plant-level labor outcomes. The branch expansion policy was enacted in 2011-12 by the RBI. The estimates utilize data from 2008 up to 2015 and Post indicator is 1 for years 2012–2015. Observations are at the plant-year level. Has Tier 3 dummy identifies the treated districts having at least one tier 3 town. All the specifications include plant, Industry \times Year, Pre-age \times Post, and Pre- Size \times Post fixed effects, where Pre-Age and Pre-Size indicates plant age and size in 2011. Standard errors are clustered at district level and are in parentheses. ***, **, * indicates significance at less than 1%, 5%, and 10% respectively.

	Log Managers (1)	Log Workers (2)	Output Per Worker (3)	Wages Per Employee (4)	Wages Per Manager (5)	Wages Per Worker (6)
$\mathbb{1}(\text{Has Tier 3}) \times \mathbb{1}(\text{Post})$	0.0313 (0.0249)	0.0391** (0.0162)	0.0602*** (0.0179)	0.0351*** (0.0099)	0.0286 (0.0277)	0.0317*** (0.0118)
Plant FE	Y	Y	Y	Y	Y	Y
Industry \times Year FE	Y	Y	Y	Y	Y	Y
Pre-Size \times Post FE	Y	Y	Y	Y	Y	Y
Pre-Age \times Post FE	Y	Y	Y	Y	Y	Y
Observations	158,932	171,807	143,352	172,539	158,434	171,731
Adjusted R^2	0.8635	0.9195	0.8149	0.8324	0.7583	0.7856

Table 6: Bank Entry and Financial Outcomes

This table conducts the difference-in-difference (DID) estimation of exogenous bank entry on the plant-level financial outcomes. The branch expansion policy was enacted in 2011-12 by the RBI. The estimates utilizes data from 2008 up to 2015 and Post indicator is 1 for years 2012–2015. Observations are at the plant-year level. Has Tier 3 dummy identifies the treated districts having at least one tier 3 town. Indicator *High Profitability* identifies plants in the top quartile of the profit distribution. Debt is computed as the sum of bank debt and accounts payables. All the specifications include plant, Industry \times Year, Pre-age \times Post, and Pre- Size \times Post fixed effects, where Pre-Age and Pre-Size indicates plant age and size in 2011. Standard errors are clustered at district level and are in parentheses. ***, **, * indicates significance at less than 1%, 5%, and 10% respectively.

	Cash / Assets (1)	Cash / Current Liabilities. (2)	Log Bank-Debt (3)	Log A/C Receivable (4)	A/C Receivable / Sales (5)
$\mathbb{1}(\text{Has Tier 3}) \times \mathbb{1}(\text{Post})$	-0.0071** (0.0030)	-0.0956** (0.0439)	0.0664** (0.0261)	0.1056*** (0.0244)	-0.0074 (0.0064)
$\mathbb{1}(\text{High Profitability})$					-0.0676*** (0.0152)
$\mathbb{1}(\text{Has Tier 3}) \times \mathbb{1}(\text{High Profitability})$					0.0348** (0.0158)
$\mathbb{1}(\text{Post}) \times \mathbb{1}(\text{High Profitability})$					0.0255*** (0.0082)
$\mathbb{1}(\text{Has Tier 3}) \times \mathbb{1}(\text{Post}) \times \mathbb{1}(\text{High Profitability})$					-0.0263*** (0.0092)
Plant FE	Y	Y	Y	Y	Y
Industry \times Year FE	Y	Y	Y	Y	Y
Pre-Size \times Post FE	Y	Y	Y	Y	Y
Pre-Age \times Post FE	Y	Y	Y	Y	Y
Observations	172,700	163,756	144,076	160,116	157,382
Adjusted R^2	0.4956	0.5562	0.8367	0.8457	0.5679

Table 7: Bank Entry and Spillover of Financial Outcomes

This table conducts the difference-in-difference (DID) estimation of the effect of the exogenous bank entry on the financial spillovers through the production network. The branch expansion policy was enacted in 2011-12 by the RBI. The estimates utilize data from 2008 up to 2015 and Post indicator is 1 for years 2012–2015. Input exposure to Treatment variable is as defined in equation 3 and captures the fraction of inputs (by value) supplied by the treated suppliers. For each district, we compute the fraction of the population residing in tier 3 towns for that district. “Low Plant Treatment Intensity” dummy takes value of 1 if plant’s district is in the bottom quartile of the distribution of that fraction. Debt includes bank-debt and accounts payables. Observations are at the plant-year level. All the specifications include plant, Industry \times Year, Pre-age \times Post, and Pre- Size \times Post fixed effects, where Pre-Age and Pre-Size indicates plant age and size in 2011. Standard errors are clustered at district level and are in parentheses. ***, **, * indicates significance at less than 1%, 5%, and 10% respectively.

	Payables/ Assets (1)	Payables/ Debt (2)	Payables/ Assets (3)	Payables/ Debt (4)	Payables/ Assets (5)	Payables/ Debt (6)
$\mathbb{1}(\text{Post}) \times$ Input Exposure to Treatment	0.0807** (0.0402)	0.1134** (0.0518)	0.0341 (0.0449)	0.0442 (0.0661)	-0.0158 (0.0515)	0.0008 (0.0767)
$\mathbb{1}(\text{Post}) \times$ $\mathbb{1}(\text{Low Plant Treatment Intensity})$			-0.0335*** (0.0126)	-0.0448*** (0.0163)	-0.0369*** (0.0124)	-0.0467** (0.0182)
$\mathbb{1}(\text{Post}) \times$ Input Exposure to Treatment \times $\mathbb{1}(\text{Low Plant Treatment Intensity})$			0.1199* (0.0623)	0.1749** (0.0777)	0.1413** (0.0611)	0.1867** (0.0879)
Change in input prices					0.0007 (0.0008)	-0.0001 (0.0012)
Industry \times Year FE	Y	Y	Y	Y	Y	Y
Pre-Size \times Post FE	Y	Y	Y	Y	Y	Y
Pre-Age \times Post FE	Y	Y	Y	Y	Y	Y
Observations	165,540	161,685	165,540	161,685	139,681	136,990
Adj. R-sq	0.5737	0.6385	0.5739	0.6386	0.5773	0.6454

Table 8: Bank Entry and Spillover of Financial Outcomes: Competition Channel

This table conducts the difference-in-difference (DID) estimation of the effect of the exogenous bank entry on the financial spillovers through the production network. The branch expansion policy was enacted in 2011-12 by the RBI. The estimates utilizes data from 2008 up to 2015 and Post indicator is 1 for years 2012–2015. Input exposure to Treatment variable is as defined in equation 3 and captures the fraction of inputs (by value) supplied by the treated suppliers. For each product code (i), we compute the Herfindahl index for the year 2011 using the production/output data by plants. Then for each of the plant (p), we compute the Input Herfindahl index as the Product Herfindahl index weighted by the weight of that product in plant’s total inputs (w_{ipt}). Low Supplier Competition dummy takes value of 1 if plant’s 2011 Input Herfindahl index is in the top quartile of the distribution.

$$\text{Input HHI}_{pt} = \sum_{i \in I_{pt}} w_{ipt} \times HHI_{it}$$

Debt includes bank-debt and accounts payables. Observations are at the plant-year level. All the specifications include plant, Industry \times Year, Pre-age \times Post, and Pre- Size \times Post fixed effects, where Pre-Age and Pre-Size indicates plant age and size in 2011. Standard errors are clustered at district level and are in parentheses. ***, **, * indicates significance at less than 1%, 5%, and 10% respectively.

	Log Payables (1)	Payables/ Assets (2)	Payables/ Debt (3)
$\mathbb{1}(\text{Post}) \times$ Input Exposure to Treatment	-0.1218 (0.3772)	0.0291 (0.0517)	0.0187 (0.0742)
$\mathbb{1}(\text{Post}) \times$ Low Supplier Competition	-0.2690** (0.1177)	-0.0196 (0.0151)	-0.0413* (0.0213)
$\mathbb{1}(\text{Post}) \times$ Input Exposure to Treatment \times Low Supplier Competition	1.3952** (0.5559)	0.1234* (0.0723)	0.2295** (0.1054)
Industry \times Year FE	Y	Y	Y
Pre-Size \times Post FE	Y	Y	Y
Pre-Age \times Post FE	Y	Y	Y
Observations	154,987	165,540	161,685
Adj R-sq	0.8478	0.5737	0.6385

Table 9: Bank Entry and Spillover of Real Outcomes

This table conducts the difference-in-difference (DID) estimation of the effect of the exogenous bank entry on the real spillovers through the production network. The branch expansion policy was enacted in 2011-12 by the RBI. The estimates utilizes data from 2008 up to 2015 and Post indicator is 1 for years 2012–2015. Input exposure to Treatment variable is as defined in equation 3 and captures the fraction of inputs (by value) supplied by the treated suppliers. For each district, we compute the fraction of the population residing in tier 3 towns for that district. “Low Plant Treatment Intensity” dummy takes value of 1 if plant’s district is in the bottom quartile of the distribution of that fraction. All the specifications include plant, Industry \times Year, Pre-age \times Post, and Pre- Size \times Post fixed effects, where Pre-Age and Pre-Size indicates plant age and size in 2011. Standard errors are clustered at district level and are in parentheses. ***, **, * indicates significance at less than 1%, 5%, and 10% respectively.

	Baseline			Low Plant Treatment Intensity		
	Log Sales (1)	Log Employment (2)	Log TFP (3)	Log Sales (4)	Log Employment (5)	Log TFP (6)
$\mathbb{1}(\text{Post}) \times$ Input Exposure to Treatment	0.7143*** (0.2116)	0.4257*** (0.1470)	0.4860*** (0.1352)	1.0703*** (0.3496)	0.5592*** (0.1929)	0.6088*** (0.2151)
Plant FE	Y	Y	Y	Y	Y	Y
Industry \times Year FE	Y	Y	Y	Y	Y	Y
Pre-Size \times Post FE	Y	Y	Y	Y	Y	Y
Pre-Age \times Post FE	Y	Y	Y	Y	Y	Y
Observations	157,721	165,407	157,738	51,050	54,578	51,074
Adjusted R^2	0.9289	0.9314	0.7225	0.9269	0.9364	0.7266