Financial Integration through Production Networks*

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Abstract

This paper studies how interconnections between different plants in India propagate credit shocks through the production network. 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 this increase in bank debt almost one for one to their customer plants in the form of short-term trade credit. This allows the directly exposed plants to finance an increase in their employment and sales through increased trade credit. This liquidity spillover also improves sales, employment, and productivity at the customer plants. Our results underscore the credit multiplier effects of production networks and the importance of financial integration among firms with limited banking services.

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The presence of interconnections between different firms and sectors can function as a potential propagation mechanism for idiosyncratic shocks throughout the economy (Acemoglu et al., 2012). For example, there is widespread agreement in the literature that improved direct access to banking services can relax financing constraints and increase productivity among firms. But the effects of better access to banking services might impact a firm's production network more broadly. Many firms have long-lived economic relationships with both their input or upstream suppliers as well as their corporate or downstream customers, and trade or vendor credit is an important feature of these relationships. Firms often provide trade or vendor credit to downstream customers, or themselves depend on such short-term financing from their input providers within the production network (Amberg et al., 2021; Biais and Gollier, 1997; Brennan et al., 1988; Costello, 2020; Cuñat, 2006; Giannetti et al., 2021; Petersen and Rajan, 1997). Thus, firms that benefit directly from improved access to bank liquidity could in theory relieve financing constraints and improve financial management within their production network—extending accounts receivables to their downstream customers or reducing accounts payable owned to their input suppliers. As the theoretical literature observes, this possible redistribution of bank liquidity could in turn generate spillovers and economic gains in excess of the usual direct estimates of improved bank credit access found in the empirical literature.

To be sure, the extent of any liquidity redistribution and spillovers depend critically on the available rents within the production network. Intuitively, a firm that benefits from improved access to bank liquidity might be more willing to extend trade credit to a downstream customer if the firm's inputs are a regular and critical factor in the downstream customer's production process. This would reduce the risk of lending because the firm could always threaten to withhold future input supplies in order to enforce repayment; such lending would allow the firm to preserve rents from a long-lived relationship. Even if such liquidity redistribution features in a production network, empirically detecting these effects are difficult. Improved access to banking services can simultaneously affect many firms in a production network, making it hard to identify whether any

changes in trade credit emanate from a particular firm's access to bank credit or reflect a more general shift in bank credit supply or broader economic conditions.

We make progress on these questions using a change in Indian banking regulation that affected the supply of banking services within very narrow geographic areas across the country. We combine this regulatory-induced variation with new plant-level data that identify the input-out matrix or production network for each plant. The research design thus uses the plausibly exogenous variation in the supply of banking services within a locality over time to identify the impact of this banking shock both on the directly exposed plant, as well as on plants outside the locality but exposed indirectly to the banking shock via the production network. An attractive feature of this difference-in-difference research design is that we can test for the exogeneity of the banking shock using the micro-level data along with a suite of fixed effects that absorb alternative explanations.

In the first step in the analysis, we show that direct exposure to the spatial banking shock significantly affects both real and financial outcomes at the plant-level. Notably, in the years after a plant becomes 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. Overall, these results are consistent with the broad swath evidence suggesting that banking deregulation and the expansion of local credit can have economically large effects on real outcomes among exposed businesses (Jayaratne and Strahan, 1996).

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 exposed banks decline by about 9.6 percentage points (pp). To wit, 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 percent at exposed plants. When we scale bank debt by assets for smaller firms, the resulting leverage measure increases by 2 percentage points.

Correspondingly, plants exposed to the regulatory banking shock also redistribute liquidity through their production network, increasing accounts receivable or short-term financing to other firms in the production network. In particular, overall accounts receivables increase by about 10.6 percent. This 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 an equivalent expansion in trade credit. Further, the increase in bank debt is almost entirely transmitted to downstream firms, suggesting a significant multiplier effect.

We next make use of the input-output relationships for each plant to understand how the presence of interconnections between different firms and sectors propagate the local banking shock throughout the economy. The basic finding suggests that customer plants receive 8 percent more trade credit for plants that obtain 100% of their inputs from suppliers benefiting from bank branch expansion. We must clearly distinguish between the direct increase in credit supply of branch expansion from the trade credit channel. To this end, we conduct a cross-sectional test by comparing downstream plants that do not directly benefit from expansion in their districts with customer plants that benefited from branch expansion. That is, these downstream plants are located in districts ineligible for the branching expansion, and no direct access to increase bank financing. Indeed, we find that plants in districts where population in tier-3 centers is in the lowest quartile (about 5 pp.) draw 17.5% more of their financing from trade credit if their suppliers are all in treated districts.

Given that trade credit is relatively 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). If a product is 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). In keeping with this theoretical intuition, we find that when a product is available from a small set of suppliers, and a plant is obtaining 100% of its inputs from a treated district, then post branching expansion, such a plant increases its trade credit by 23 pp. as a fraction of total debt. Ultimately, downstream plants benefiting from credit spillover also experience improved sales and hire more employees.

The closest paper is Costello (2020). The author shows that adverse bank liquidity shocks spillover through the trade credit channel to downstream firms. We focus on the *benefits* of the trade credit channel as a transmission mechanism of liquidity from areas with more banks to areas with less banks. Thus, production networks are exporting liquidity to areas that need it. In this manner, production networks play a similar role to bank branch networks that also export liquidity from boom areas to non-boom areas (Gilje et al., 2016), thus financial integrating the economy.

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).

Overall, we find evidence in favor of bank liquidity spillovers and economic gains in production networks that are in excess of the direct estimates of improved bank credit access already documented in the literature.

1 Institutional Background and Data

This section first describes our plant-level production and financing data along with our data on Indian banks and the country's districts. We then provide some institutional background on the branching rule that we exploit for identification. The section ends with a comparison of the "treated" districts and plants with the remaining districts and plants.

1.1 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.[1]

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 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

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

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.

1.2 The "1:1" Branching Rule and Identification Strategy

Our paper uses plausibly exogenous variation in a district's exposure to new bank branches to understand the effects of banking services on firm productivity. The variation in branching 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 particularly 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.[2] 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.[3] 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.[4]

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

[2]See Branch Authorization Policy - Opening of branches in unbanked rural centers at `https://www.rbi.org.in/scripts/NotificationUser.aspx?Id=6613`.

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

[4]The 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 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.

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, the 2011 rule provides a plausibly exogenous source of branch entry at the district level that can help us identify the effects of competition on PSB lending.

To wit, the plausibly exogeneity of the 2011 rule stems from the fact that it was designed to foster financial inclusion among the historically underbanked population, and was not motivated by a desire to support credit supply to plants; also it was not intended to shape competition between private banks and government owned banks—the rule applied equally to both types of banks operating in the country. Additionally, the rule was aimed at the city-level, and not targeted at any of the 365 districts in our sample or the 301 districts with tier 3 cities: Banks were free to open branches in any of these districts with tier 3 cities—henceforth "tier 3 districts" (Figure 2).[5] However, several factors can still bias inference.

The period after 2011 was an unusually active period of bank regulation in India, and our identification strategy can possibly conflate the 2011 "1:1" rule with some of these post-2011 regulations that might also affect branching and market structure at the district-level. Notably, the RBI introduced new licensing guidelines in 2013 to encourage the entry of new private banks. Moreover, under the 2013 licensing rule, these new banks had to open 25 percent of their branches in tier 5 or tier 6 cities. The RBI also allowed new "small banks" to enter certain areas, beginning in 2014 in order to improve credit access for micro-enterprises and rural areas. And beginning in 2016, India moved to a continuous bank authorization policy rather than the previous one characterized by infrequent changes in private bank entry.[6]

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

[6]For a survey of these regulatory changes, see `https://rbidocs.rbi.org.in/rdocs/PublicationReport/Pdfs/IWG988615AAEB4A42729542102111DCA5FC.PDF`

The practical implications of these additional regulations on our research design might be limited however. By 2020 only two banks entered under the 2013 licensing guidelines, and the small banks that emerged under the 2014 regulations are mostly "unit" banks with little branching presence. These small banks also do not provide financial services to the larger firms that dominate our sample, and do not compete directly with the larger universal banks that have big branching networks. To help isolate the variation in the 2011 rule, we condition on our suite of bank-by-year, firm or district-by-year fixed effects. We also exclude the two banks that were licensed under the 2013 regulations and the small banks that emerged under the 2014 rule.

A potentially greater threat to identification is that although the regulations did not target any particular district, banks were still free to select the tier 3 cities in which to open branches. Thus, banks wishing to expand their branching networks could still strategically open their "excess branches" to meet the 1:1 rule in tier 3 districts based on the existing pattern of incumbent bank lending to local firms or other relevant unobserved factors. For example, districts in which plants are expanding and in need of bank finance, or those where incumbent banks have strong relationships with certain subset of firms, and the demand for finance is unmet among the other firms, could all be targets for entry after the 2011 regulation. This form of endogenous entry would then make it hard to tell apart the effects of entry from any pre-existing trend in local banking relationships. A more general formulation of this concern is that unobserved differences across tier 3 and other districts that simultaneously shape entry and lending relationships of incumbent firms can yield biased estimates.

However, because we use data matched to the bank and firm, bank-by-year, firm or district-by-year fixed effects can non-parametrically absorb most of these unobserved differences across districts. Still, to gauge whether the pattern of branching post "at least 1:1" reflect pre-existing branching trends, we estimate Equation (1):

$$branches_{it} = \alpha_i + \delta_t + \beta \cdot tier\ 3_i \times year + \nu_{it} \tag{1}$$

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 the $tier\ 3_i$ indicator variable, which equals 1 if a district has at least one tier 3 city and 0 otherwise. The sequences of coefficients $\beta \times year$ allows 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 Equation (1) from 2009–2020. Panel B of Figure 1 plots the annual estimates of β. 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 3.3 branches more than otherwise, and this "excess entry" peaks at about 6 branches in 2014. 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 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 may not be sufficient. 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 Equation (1). The dependent variable is the log employment in the calendar year at a plant. We include plant fixed effects, along with sector-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 3. 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 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 from their entry decisions. Hence, we estimate the following equation to capture the average effect of the rule on number of bank branches:

$$branches_{it} = \alpha_i + \delta_t + \beta \cdot tier\ 3_i \times post_t + \nu_{it}, \tag{2}$$

where the time period is 2008–2015, with indicator variable *post* as 1 for years 2011–2015. We report the results in Table 2. We measure bank entry as the number of new branches opened by a bank in Columns (1)–(3) in response to the rule change. In the next three columns, we measure bank entry as new branches opened by a bank scaled by existing branches. As can be seen, using either measures both private banks and government owned banks take advantage of the rule change and open more branches.

1.3 Comparison of Treatment and Control Groups

Table 1 present 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 area (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 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 and population density.

Regarding credit access, treated and control districts have similar number of banks per district (74.92 compared to 75.76) as per 2001 census. The RBI data on the number of branches in the district note that in 2011, treated districts have 181 branches on average compared to 145 for control districts. However, the difference is statistically insignificant. Banks branches in a district grew by 19.96% in the pre-Period (2008–2011) for treated district compared to 17.89% for control districts; the unconditional difference in growth rates is weakly significant at 10% level. Given the differences above, our empirical approach takes multiple steps to address ex-ante heterogeneity between treated and control districts.

Next, 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. Again, given the differences in plant characteristics, we absorb ex-ante plant size$\times$time and plant age$\times$time fixed effects in all our analyses.

[7]To 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).

2 Direct Impact of Branching Expansion

This sections presents evidence showing that when supply of bank finance increases, i.e., there is a positive credit shock, firm outcomes improve. Further, firms propagate the credit supply shock forward through the production network.

2.1 Real Effects

This subsection examines the direct impact of exposure to the branching expansion regulation on plant-level outcomes.

As shown in Equation 3 below, the basic research design defines 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.

$$y_{it} = \alpha_{st} + \beta_y \times [\mathbb{1}(Post) \times \mathbb{1}(\text{Has Tier 3})] + \delta_{i-Pre,t} + \varepsilon_{it}, \tag{3}$$

We include a set fixed effects to isolate the effect of rule change on plant outcomes. We use industry$\times$year fixed effects (α_{st}) to absorb any industry-specific shocks in a particular year. We include plant fixed effects to absorb time-invariant plant-specific heterogeneity. We also include host of "ex-ante plant characteristics $\times$ post" fixed effects in our baseline ($\delta_{i-Pre,t}$). 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 are important as the summary table indicates that treated plants are economically bigger (though not statistically) and are younger.

Parallel-trends assumption: Before we tabulate the effects, we provide some figures to address identification concerns with our research design. Using log sales as the dependent variable,

Panel A of Figure 3 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 banks are about 6.3 percent relative to otherwise. Improved access to bank capital can help plants increase investment, and using the same specification as before, Panel C of Figure 3 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 Equation 3 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.[8]

Moreover, these effects are economically large and statistically significant even after clustering the errors at the treatment level.

Potential confounding effects of the financial crisis: The absence of pre-trends shown in Figure 3 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.

Pre-period district characteristics: The summary statistics document that treated districts are more populous, larger area and more number of 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.

Placebo test: 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

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

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

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.

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 4 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.

Matched sample: Table 4 further attempts to address concerns that the differences between treated and control districts lead to the estimated effects. 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.

We next investigate labor market outcomes at the plant level. Table 5 reports the effect of bank entry on labor market outcomes. Columns (1) and (2) report the effect of the rule change and corresponding branch expansion on 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%. The additional financing and investment leads to 6% higher output per worker. 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.

2.2 Financial Outcomes

The analyses above demonstrate that bank branch expansion has improved firm real outcomes. However, firms may be performing better because presence of banks improves economic conditions in general, and not through credit supply to firms. Hence, it is important to establish that plants in these locations take financial decisions that suggests direct improvement in their access to credit supply.

We start with Column (1) in Table 6 that shows that plants in districts benefiting from bank branch expansion need to hold less cash as a fraction of assets. The reduction in working capital requirements points towards the possibility of ready access to credit if need be. Yet, if the plants are taking more medium or long term debt financing, then the 0.7 pp. reduction in cash holdings may be due to increase in assets rather than reduction in cash.

Hence, in Column (2), we scale cash holdings by total current liabilities, and find a 9.6 pp relative reduction in cash holdings. The estimate suggests that plants need to hold less cash and therefore less working capital in presence of improved access to credit from banks if need be. The additional credit is not all prospective, 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. How does these plants utilize the additional bank debt? Column 4 shows that treated plants extend 10.6pp more trade credit indicating that at least part of the improved credit supply transmits to the customers of the treated plants through the production network.

Next, we measure the strength of this transmission channel. To compare the effect of additional bank debt to a firm on the amount of trade credit extended by the firm, we note that bank debt scaled by assets for the median firm is at 30.28 pp. At the same time, accounts receivable scaled by assets is at 19.23 pp. for the median firm. Given the estimated coefficients in columns (3) and (4), the median plant extends unit credit for each Indian Rupee that it borrows as a result of credit

expansion due the branching rule.[9]

Larger plants should be more able to overcome location specific financing frictions. Hence, if local financing options are important, smaller plants should benefit more if banks open in the vicinity. Column (5) expands on the previous column to include an indicator for firms in the lowest quartile of the asset distribution. These firms increase their bank debt by more than twice compared to the average plant. Even after scaling debt by assets, in Column (6), we note an increase of 2 pp. in leverage for smaller plants after the rule change.

What are the use of the additional financing? Capital expenditure is a use, and we have seen evidence of that in Table 3. Another use of newly obtained funds is reducing reliance on relatively more expensive sources of financing, such as trade credit. Column (7) shows that on average, there is more trade credit to go around in districts with more branches. We will investigate this trade credit expansion in the next section to understand spillover effects. At the same time, smaller plants, presumably face relatively stricter credit conditions of trade credit than the larger plants. The estimated coefficient of the triple interaction in Column (7) shows that these plants are reducing their use of trade credit. By comparing the coefficients of triple interactions in columns (6) and (7), we note that for the smaller plants, the increase in bank credit scaled by assets is almost equal in magnitude to the reduction of trade credit.

In Column (8), we scale the outcome variable of accounts payable by debt, where debt is the sum of accounts payable and bank debt. The estimates suggest that the average accounts payable as a proportion of external financing increases by 1.2 pp. At the same time for smaller plants in areas with branch expansion due to rule change, we see an about four times faster reduction of trade credit usage and greater utilization of bank debt.

The results provide two inferences. With higher credit supply, there is higher trade credit overall. At the same time, when bank financing becomes directly available, as is the case for

[9]Ratio of trade credit growth to bank debt growth = (Median plant's amount of trade credit $\times$ trade credit growth) / (Median plant's amount of bank debt $\times$ bank debt growth) = $(0.1923 \times 0.1056)/(0.3027 \times 0.0664) \approx 1$.

smaller plants, there is substitution away from the relatively more expensive trade towards bank financing.

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 cost of financing through trade credit may be high, the benefits of trade credit spillover may yet exist if plants face credit rationing (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. 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 inputs, 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:

$$\text{Input Exposure to Treatment}_{pt} = \sum_{i \in I_{pt}} f_{it} \times \left(\frac{c_{ipt}}{\sum\limits_{i \in I_{pt}} c_i} \right). \tag{4}$$

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, i.e., whether payables are increasing faster. This test will help us understand the relative ease of access of accounts payable compared to bank debt. 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 more available to downstream plants.

How do we distinguish the direct increase in credit supply of branch expansion from the trade credit channel? One way 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 direct 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 estimates 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.

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 Equation 4, 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 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 is true even when we scale the payables by assets in Column 2 or by total debt in column 3 indicating that these plants obtain more trade credit relative the expansion in the scale or the debt of the firm. This result confirms our intuition presented earlier 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.

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 higher fraction of inputs from treated districts expand sales more. Sales increase by 2.32% more for plants that purchase a one standard deviation 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 1.39%. Ultimately, downstream plants increase their productivity, as shown in

[10]Specifically, 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 value)

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 districts. We observe improved real outcomes for the plants with treated suppliers but which are not directly treated, clearly evidencing the importance of the trade credit spillover channel. Results are similar if we only utilize districts with no tier-3 population centers.

4 Conclusion

Our paper investigates the effects of exogenous banking entry into local markets on the plants real and financial outcomes. Novel to the literature, we show that improved bank credit access mitigates the precautionary liquidity concerns for the plant as evidenced by reduced cash holdings of the treated plants. Additionally, we document how smaller plants shift away from the expensive trade credit and utilize more bank debt after the banking entry. We contribute to the growing literature on the trade credit. First we document that improved bank credit results in increased supply of trade credit in general. Specifically, we document spillover of improved banking credit through trade credit channel to the downstream customers. In particular, our results show that even if plants do not have direct credit access, supply chain networks can provide credit access to downstream firms. Firms with improved credit access in India are utilizing additional bank debt to extend trade credit to their suppliers. The extension of trade credit matches almost 1:1 with the amount of additional bank debt taken by the supplying plant. The ratio of credit extension to bank debt suggests a significant credit multiplier effect.

The result of credit transmission is twofold. First, 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. Thus, production networks can play an important role in financial integration of firms with limited banking services.

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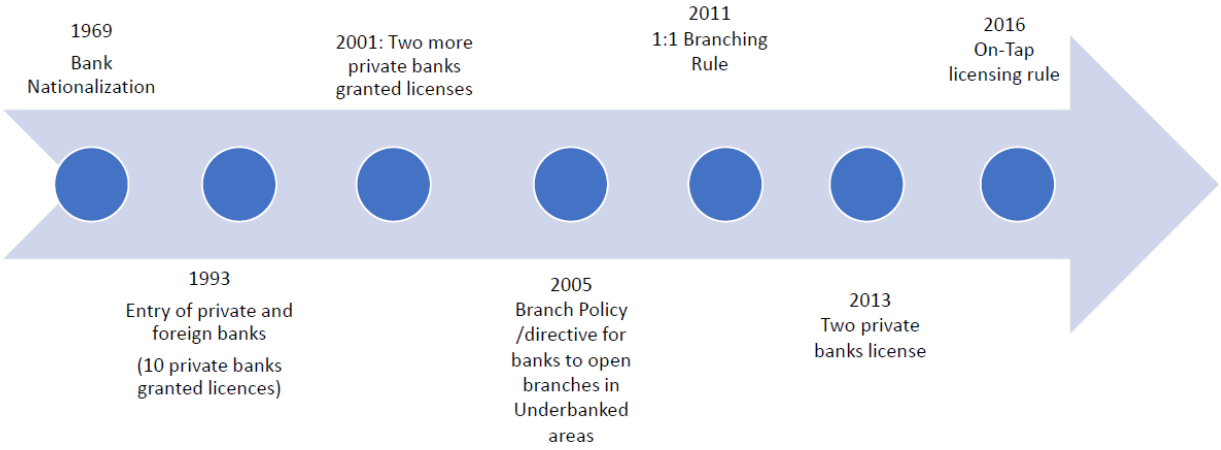
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Figure 1: Bank Entry due to RBI “1:1" policy

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

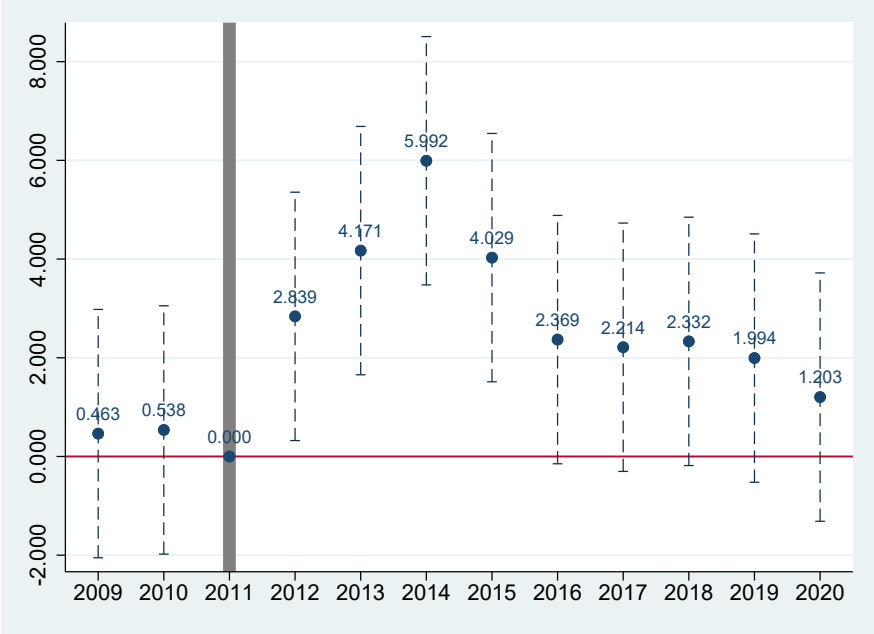


Figure 2: Tier-3 Districts for RBI “1:1" policy

The figure maps the districts with tier-3 centers. The census-driven population classification was used by the Reserve Bank of India for its policy. The “missing” districts are not present in the panel because they do not have significant production activity, as measured by the presence of a firm in the loan dataset provided by the Ministry of Corporate Affairs, Government of India.

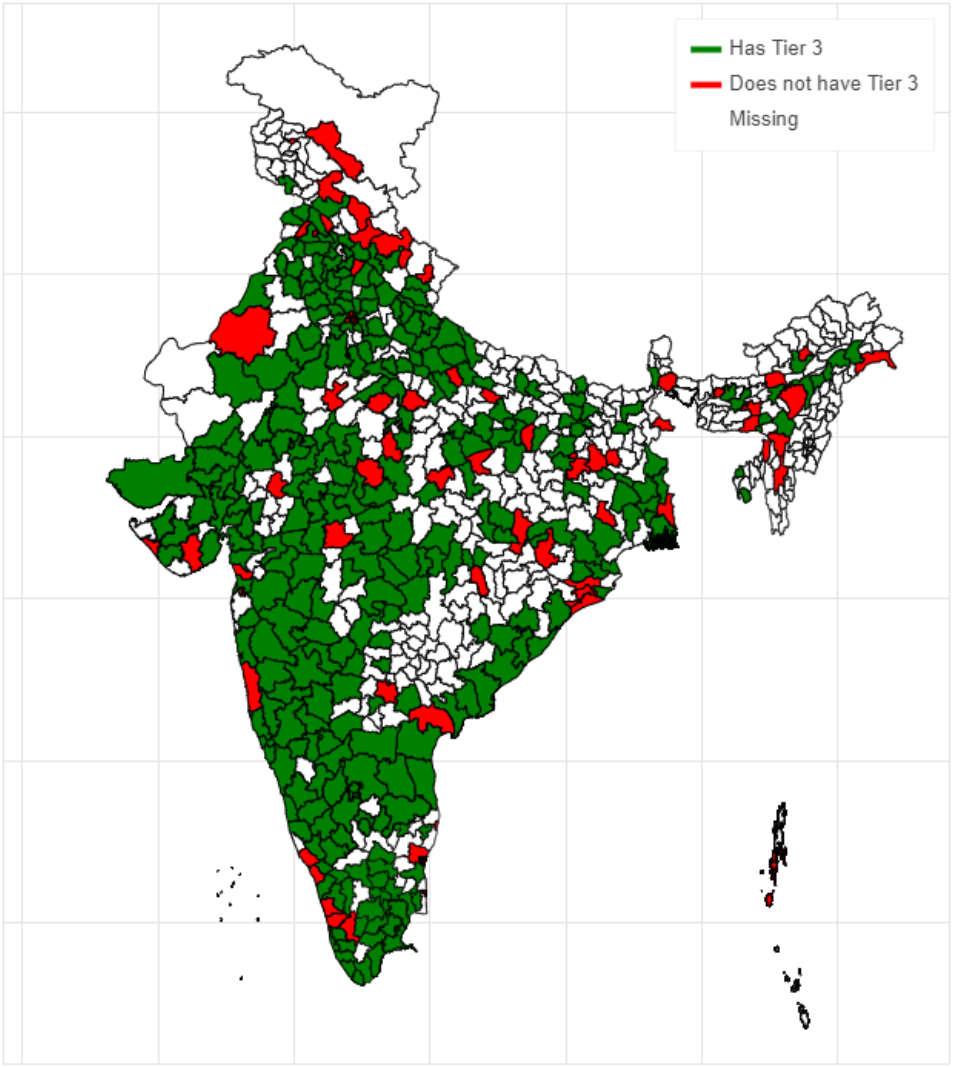
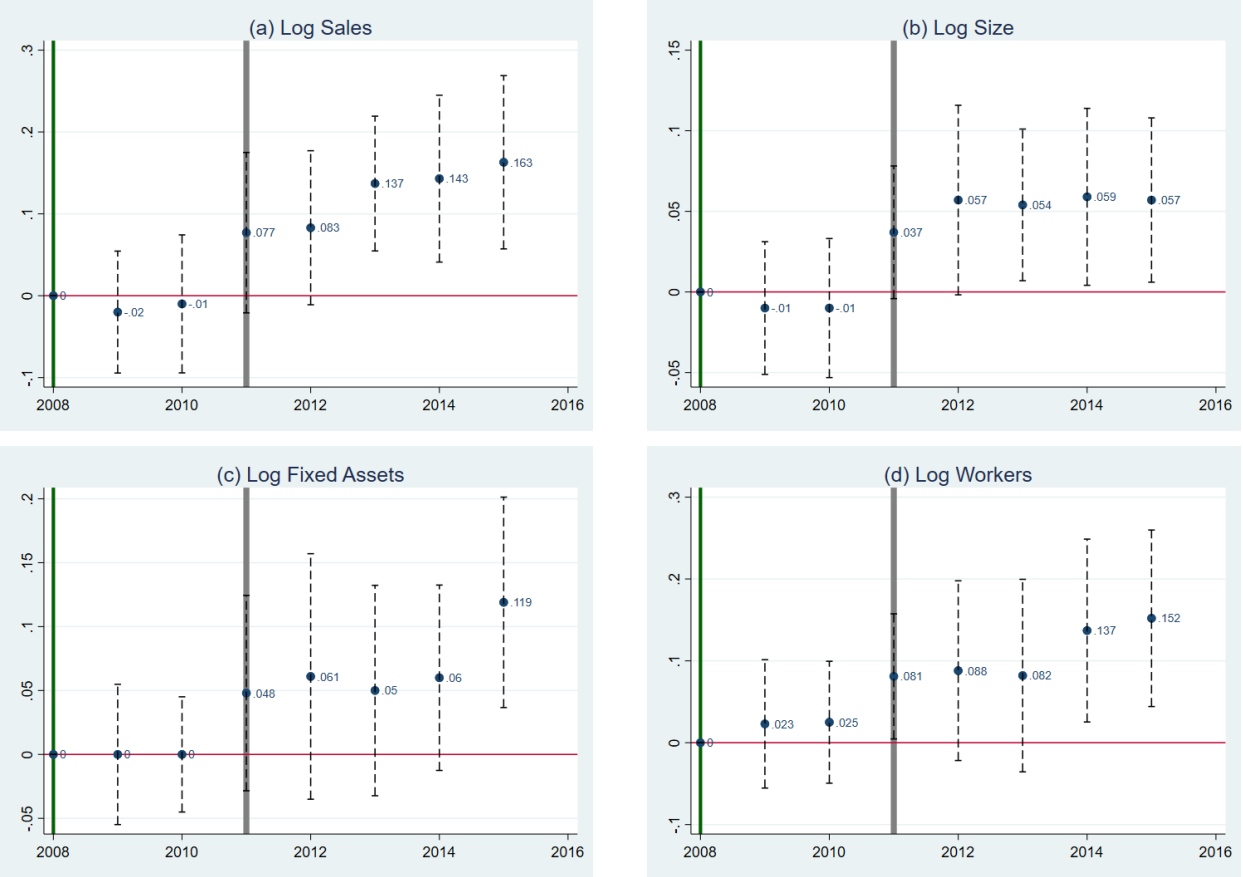


Figure 3: Yearly Effects of Bank-Entry on Real Outcomes

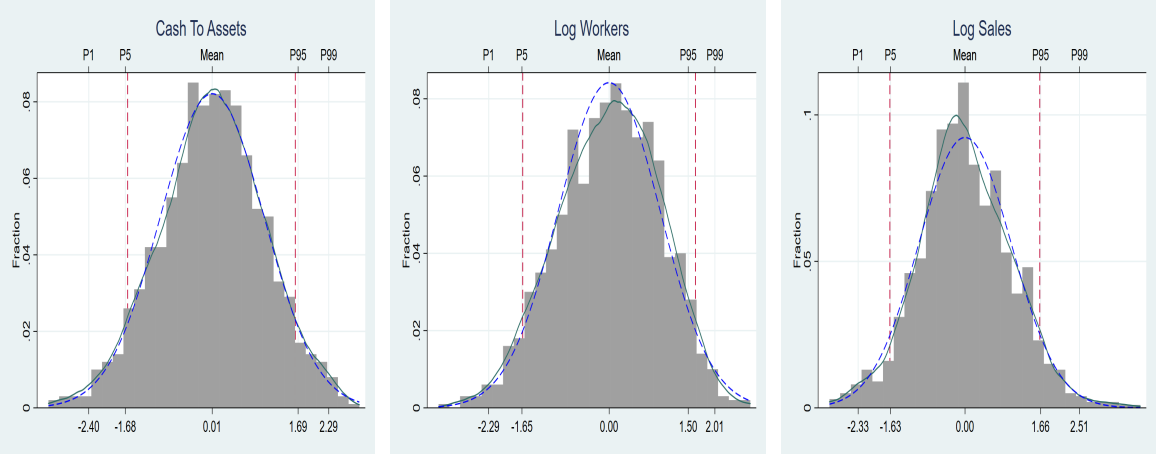


The figure plots the coefficient β_{yt} for $t \in \mathscr{T} = \{2008, ..., 2015\}$ in the following regression

$$y_{it} = \alpha_{st} + \sum_{t \in \mathscr{T}} \beta_{yt} \times \mathbb{1}(t) \times \mathbb{1}(\text{Has Tier 3}) + \delta_{i-Pre,t} + \varepsilon_{it}$$

where $\mathbb{1}(t)$ indicates the dummy for the year t, $\mathbb{1}(\text{Has Tier 3})$ indicates the dummy for the districts having at least one tier-3 town, α_{st} are the industry$\times$year fixed effects, and $\delta_{i-Pre,t}$ are the pre-period or ex-ante 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 4: 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 $k = 1, 2, ...1000$, 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:

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

where α_{st} are the industry$\times$ time fixed effects, and $\delta_{i-Pre,t}$ are the pre-period or ex-ante 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 5^{th} and the 95^{th} 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

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 singles tier 3 towns 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 characters tics. 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	Private	PSB	All banks	Private	PSB
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Has Tier 3) $\times$ $\mathbb{1}$(Post)	3.8921***	1.1183***	2.7241***	0.0693**	0.1141**	0.0550**
	(0.8662)	(0.4248)	(0.6295)	(0.0297)	(0.0522)	(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 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× Year, Pre-age × *Post*, and Pre- Size × *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 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)
$\mathbb{1}$(Has Tier 3) × $\mathbb{1}$(Post)	0.1081***	0.0628***	0.0745***	0.0415***	0.0376***
	(0.0217)	(0.0166)	(0.0268)	(0.0147)	(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)
$\mathbb{1}$(Has Tier 3) × $\mathbb{1}$(Post)	0.1233***	0.0669***	0.0837***	0.0432***	0.0468***
	(0.0229)	(0.0182)	(0.0291)	(0.0164)	(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)
$\mathbb{1}$(Has Tier 3) × $\mathbb{1}$(Post)	0.1121***	0.0533***	0.0702**	0.0630***	0.0332**
	(0.0216)	(0.0197)	(0.0310)	(0.0155)	(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×Year FE	Y	Y	Y	Y	Y
Pre-Size×Post FE	Y	Y	Y	Y	Y
Pre-Age×Post FE	Y	Y	Y	Y	Y
Panel C					
Population × 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 mathching 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-neighbourhood 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-Neighbourhood Matching				
	Log Sales (1)	Log Plant Size (2)	Log Investment (3)	Log Employment (4)	Log TFP (5)
$\mathbb{1}$(Has Tier 3) $\times$ $\mathbb{1}$(Post)	0.2541***	0.1123***	0.2403***	0.0593*	0.1449**
	(0.0722)	(0.0367)	(0.0445)	(0.0325)	(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 real 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. All the specifications include plant, Industry× Year, Pre-age × *Post*, and Pre- Size × *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)
$\mathbb{1}$(Has Tier 3) × $\mathbb{1}$(Post)	0.0313	0.0391**	0.0602***	0.0351***	0.0286	0.0317***
	(0.0249)	(0.0162)	(0.0179)	(0.0099)	(0.0277)	(0.0118)
Plant FE	Y	Y	Y	Y	Y	Y
Industry×Year FE	Y	Y	Y	Y	Y	Y
Pre-Size×Post FE	Y	Y	Y	Y	Y	Y
Pre-Age×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 Small identifies plants in the bottom quartile of the pre-size 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	Cash / Current Liabilities.	Log Bank-Debt	Log A/C Receivable	Log Bank-Debt	Bank Debt / Assets	Payables / Assets	Payables / Debt
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Has Tier 3) $\times$ $\mathbb{1}$(Post)	-0.0071**	-0.0956**	0.0664**	0.1056***	0.0277	-0.0016	0.0108**	0.0120*
	(0.0030)	(0.0439)	(0.0261)	(0.0244)	(0.0321)	(0.0077)	(0.0044)	(0.0062)
$\mathbb{1}$(Post) $\times$ $\mathbb{1}$(*Small*)					-0.1449***	-0.0231***	0.0222**	0.0358***
					(0.0458)	(0.0089)	(0.0095)	(0.0103)
$\mathbb{1}$(Has Tier 3) $\times$ $\mathbb{1}$(Post)					0.1358***	0.0201**	-0.0226**	-0.0450***
$\times$ $\mathbb{1}$(*Small*)					(0.0431)	(0.0089)	(0.0089)	(0.0093)
Plant FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry$\times$Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-Size$\times$Post FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-Age$\times$Post FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	172,700	163,756	144,076	160,116	144,076	172,700	172,700	167,450
Adjusted R^2	0.4956	0.5562	0.8367	0.8457	0.8367	0.6145	0.5709	0.6338

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 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 4 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× Year, Pre-age × *Post*, and Pre- Size × *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)
𝟙(Post)×	0.0807**	0.1134**	0.0341	0.0442
Input Exposure to Treatment	(0.0402)	(0.0518)	(0.0449)	(0.0661)
𝟙(Post)×			-0.0335***	-0.0448***
𝟙(Low Plant Treatment Intensity)			(0.0126)	(0.0163)
𝟙(Post)×			0.1199*	0.1749**
Input Exposure to Treatment ×			(0.0623)	(0.0777)
𝟙(Low Plant Treatment Intensity)				
Industry×Year FE	Y	Y	Y	Y
Pre-Size×Post FE	Y	Y	Y	Y
Pre-Age×Post FE	Y	Y	Y	Y
Observations	165,540	161,685	165,540	161,685
Adj. R-sq	165,540	161,685	165,540	161,685

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 4 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)
$\mathbb{1}$(Post)$\times$	-0.1218	0.0291	0.0187
Input Exposure to Treatment	(0.3772)	(0.0517)	(0.0742)
$\mathbb{1}$(Post)$\times$	-0.2690**	-0.0196	-0.0413*
Low Supplier Competition	(0.1177)	(0.0151)	(0.0213)
$\mathbb{1}$(Post)$\times$	1.3952**	0.1234*	0.2295**
Input Exposure to Treatment$\times$	(0.5559)	(0.0723)	(0.1054)
Low Supplier Competition			
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 4 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	Log Employment	Log TFP	Log Sales	Log Employment	Log TFP
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Post)$\times$ Input Exposure to Treatment	0.7143***	0.4257***	0.4860***	1.0703***	0.5592***	0.6088***
	(0.2116)	(0.1470)	(0.1352)	(0.3496)	(0.1929)	(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