Trade-induced Credit Shocks and the Size of Productive Firms*

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Abstract

Import competition can affect domestic firms beyond directly exposed industries by weakening banks' lending capacity and tightening credit supply. I study whether such spillovers through the banking sector limit the expansion of productive firms. Using data from India between 1998 and 2007, I construct an industry-level measure of trade-induced credit shocks. I find that these shocks reduce sales more for high-productivity firms, with particularly pronounced effects among small and young firms. The findings highlight the importance of accounting for the financial transmission of import shocks and the potential vulnerability of productive firms to credit supply disruptions.

JEL codes: D22, F14, G21, L25

Keywords: Import Competition, Productive Firms, Credit Shocks, Spillovers

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1 Introduction

The share of economic activity directed toward more productive firms is important for raising aggregate productivity (Restuccia and Rogerson, 2017). A large trade literature has studied how opening to trade induces the expansion of high-productivity firms in directly trade-exposed industries (Melitz, 2003; Melitz and Redding, 2014). Import shocks, however, can also affect firms indirectly through their spillovers to the banking sector. Facing increased non-performing loans among firms hard-hit by import competition, banks contract their credit supply to all firms, including those not directly exposed to the shocks (Federico et al., 2025). Whether this financial transmission of import competition shapes the expansion of productive firms remains an open question.

I answer this question by examining whether such trade-induced credit shocks affect sales differently for low- and high-productivity firms, using firm-level data from India over 1998-2007. I begin by documenting two stylized facts. First, the market share of high-productivity manufacturing firms in India did not increase over the sample period, despite a substantial increase in import competition from China that might have been expected to favor their expansion based on the trade theory (Melitz, 2003). Second, the market share of high-productivity firms is significantly lower in industries with higher external financial dependence, suggesting that financial factors may play a role in explaining the absence of reallocation. Motivated by the facts and recent evidence that import competition negatively affects the banking sector (Federico et al., 2025), I study whether import competition indirectly constrains the expansion of productive firms through the banking channel.

To answer this question, I construct an industry-level measure of trade-induced credit shocks based on the exposure of other industries to Chinese import competition, weighted by each industry's initial share of total bank loans, following Federico et al. (2025). I estimate the heterogeneous effect of these trade-induced credit shocks on firm sales by interacting them with firms' initial productivity, controlling for firm and industry-year fixed

effects, and accounting for the direct effect of the firm's own industry import competition, interacted with productivity. To address potential endogeneity in Chinese imports into India, I follow Autor et al. (2013) and instrument Chinese imports into India with Chinese imports into other similar countries.

The results show that trade-induced credit shocks reduce sales significantly more for high-productivity firms than for low-productivity firms. That is, a one-standard-deviation increase in the trade-induced credit shocks leads to an additional 6-percentage-point decline in sales for a firm at the seventy-fifth percentile of the productivity distribution relative to a firm at the twenty-fifth percentile.

A natural concern is that the trade-induced credit shock measure may capture other non-financial channels through which import competition in other industries spills over to a given industry, most notably input-output linkages. I show that the estimated heterogeneous effect is robust to controlling for industries' exposure to upstream and downstream import competition. I further show that the results are not driven by import competition originating outside China, by differential sales trends across firms of different productivity, or by labor market frictions, and that they survive a battery of additional robustness checks.

To explain the empirical result, I present a stylized model with heterogeneous firms facing financial constraints and a representative bank that allocates its limited capital as loans to these firms. Firms differ in productivity and finance their working capital using both internal funds and bank loans. The bank faces a trade-off when allocating loans. More productive firms have higher expected future earnings, which reduce the costs of lending to them, but they may have less seizable collateral, which increases these costs. The model shows that whether a reduction in bank capital reduces the sales of high-productivity firms more depends on the relative responsiveness of bank loan supply and firms' ability to raise internal funds to productivity.

The model therefore yields two testable predictions. First, the heterogeneous effect

should be more pronounced among firms whose internal funds are likely to increase less with productivity. Second, it should be more pronounced among firms for which bank loan supply is likely to increase more strongly with productivity. I first test the prediction concerning internal funds. I show that high-productivity firms in India tend to be smaller and younger, and that the elasticity of profits, my proxy for internal funds, with respect to productivity, is lower for small and young firms. Consistent with the model's prediction, the estimated heterogeneous effect of trade-induced credit shocks on sales is more pronounced among these firms.

I then examine the prediction concerning bank loan supply. Since pure bank loan supply is unobservable, I use industry output risk to capture differences across industries in banks' responsiveness of loan supply to firm productivity. When future earnings are more predictable, banks may have greater confidence in using firms' productivity to assess their growth potential and therefore adjust loan supply more strongly in response to productivity. Consistent with the model's prediction, I show that the heterogeneous effect is stronger among firms in industries with lower output volatility.

My study contributes to three strands of literature. First, a large literature studies the direct effects of trade liberalization on manufacturing firms, both theoretically (Melitz, 2003; Melitz and Ottaviano, 2008) and empirically (Pavcnik, 2002; Bernard et al., 2006; Trefler, 2004; Harrison et al., 2013; Brandt et al., 2017; Ding et al., 2016), as well as its effects on the banking sector and credit supply (Federico et al., 2025; Chakraborty and Ritadhi, 2022). I contribute to this literature by showing that the transmission of import competition through the banking sector can constrain the expansion of high-productivity firms even in the absence of any direct exposure to trade. This indirect channel can therefore weaken productivity-enhancing reallocation following direct trade exposure, with implications for the aggregate productivity gains from trade.

Second, I contribute to the literature on the spillovers of import competition. Existing studies document that import competition can propagate across firms and industries

through input-output linkages (Pierce and Schott, 2016; Acemoglu et al., 2016; Aghion et al., 2024), or through local labor market (Helm, 2020). I complement this literature by identifying an indirect channel of transmission operating through the banking sector. Accounting for this financial transmission is important because the manufacturing and financial sectors are closely interdependent, and studying import competition shocks in the manufacturing sector in isolation from the financial sector can miss important channels through which these shocks propagate through the economy.

Lastly, my study also relates to the literature on the role of financial frictions in trade (Manova, 2013; Chaney, 2016; Kohn et al., 2016; Brooks and Dovis, 2020; Leibovici, 2021). This stream of literature studies how financial frictions affect firms' ability to export and the aggregate gains from trade. I contribute by examining the reverse direction of impact, in which trade can shape the financial environment and, in turn, indirectly affect manufacturing firms. This reverse channel matters because it shows that although predetermined financial frictions can affect trade, financial frictions themselves can be the outcome of trade, which can feed back to manufacturing firms. This feedback loop can have important implications for the aggregate gains from trade.

Overall, my findings highlight the importance of looking beyond the direct effects of import competition to their transmission through the financial sector. They also suggest that particular attention should be paid to small, young, high-productivity firms, whose growth may be especially vulnerable to financial disruptions.

The remainder of the paper proceeds as follows. Section 2 introduces the data and documents the motivating facts. Section 3 describes the empirical strategy. Section 4 presents the baseline results and addresses threats to identification. Section 5 uses a stylized model to provide potential mechanisms and test them empirically. Section 6 concludes.

2 Data and Stylized Facts

2.1 Data

I rely on firm-level data from the Centre for Monitoring the Indian Economy (CMIE) PROWESS database and industry-level data from various sources, including the Annual Survey of Industries (ASI) in India, the World Integrated Trade Solution (WITS) database, and United Nations Industrial Development Organization (UNIDO) INDSTAT database.

First, I use firm-level data from the PROWESS database.[1] This database covers both large and small firms, as well as publicly listed and unlisted firms in India. Financial information for large and listed firms is collected from annual income statements and balance sheets, while data for smaller firms are obtained through periodic surveys conducted by CMIE (Chakraborty et al., 2024). These firms account for approximately 60 to 70 percent of economic activity in the organized industrial sector (Goldberg et al., 2010). This broad coverage makes the dataset well suited for studying the impacts of trade shocks across high- and low-productivity firms. To estimate firm productivity, I use data on sales of goods, salaries, raw material expenses, and net fixed assets. Sales of goods, salaries, and raw material expenses are deflated using wholesale price indices with 1993 as the base year, while net fixed assets are deflated using the machinery wholesale price index.

Second, the industry-level outstanding loan data are from the 1998-1999 ASI, conducted by the Central Statistical Office of the Government of India. The ASI is the primary source of industrial statistics in India. The key variable drawn from the ASI is outstanding loans. I aggregate plant-level outstanding loans to the four-digit National Industrial Classification (NIC) industry level to measure the initial allocation of bank credit across industries.[2] This information is subsequently used to measure how import competition

[1] PROWESS database has been widely used in the literature studying firms in India. For instance, Topalova and Khandelwal (2011); Goldberg et al. (2010); De Loecker et al. (2016).

[2] Sampling weights provided by the ASI are applied when aggregating the data to the industry level. The industry classification in the 1998-1999 ASI follows NIC 1998. I map this classification to the 4-digit NIC 2008 system to ensure consistency with the industry classification used in the PROWESS firm-level data. Throughout the subsequent analysis, all industry-level variables are constructed at the 4-digit NIC

shocks in manufacturing industries spill over across industries through the banking channel. Details on the construction of the trade-induced credit shock measure are provided in Section 3.2.

Finally, all trade data used in the analysis are obtained from the WITS database. To construct the import competition measure, I complement the trade data with domestic production data from the UNIDO INDSTAT database. Both trade and production data are in thousands of US dollars and are at the industry level, classified according to the International Standard Industrial Classification (ISIC) Revision 3.1, which I map to the 4-digit NIC 2008 classification.

As described in more detail in Appendix C, after data cleaning and merging the firm-level and industry-level data, I obtain a final working sample with 24,447 firm-year observations for more than 4,400 firms in 76 four-digit NIC industries over the period 1998-2007.[3]

2.2 Stylized Facts

Stylized fact 1: The market share of high-productivity firms did not increase in India between 1998 and 2007

Figure 1 plots the market shares of firms across low-, medium-, and high-productivity groups. I estimate firm total factor productivity (TFP) using the method of Ackerberg et al. (2015) and classify firms into low-, medium-, and high-productivity groups based on terciles of initial productivity within their four-digit industry.[4] I then calculate the market share of each productivity group within each four-digit industry and aggregate across industries using each industry's share of total sales as weights.

Figure 1 shows that the market share of each productivity group remains relatively

2008 level.

[3]Note that the years in my empirical analysis refer to financial years, which typically end on March 31 in India. Thus, 1998 refers to the financial year starting on 1 April, 1998 and ending on March 31, 1999.

[4]"Initial" refers to the first period in which a firm appears in the working sample.

stable over the sample period. Low- and medium-productivity firms together account for more than 60% of aggregate sales in India, and there is no substantial increase in the market share of high-productivity firms.

This pattern is notable because India's exposure to import competition, particularly from China, increased markedly over the sample period, as shown in Figure A1 of the appendix. Standard trade models suggest that opening to trade reallocates market share toward more productive firms, thereby raising aggregate productivity (Melitz, 2003; Melitz and Ottaviano, 2008). The absence of such reallocation raises the question of whether factors beyond product-market competition may have constrained the expansion of productive firms.

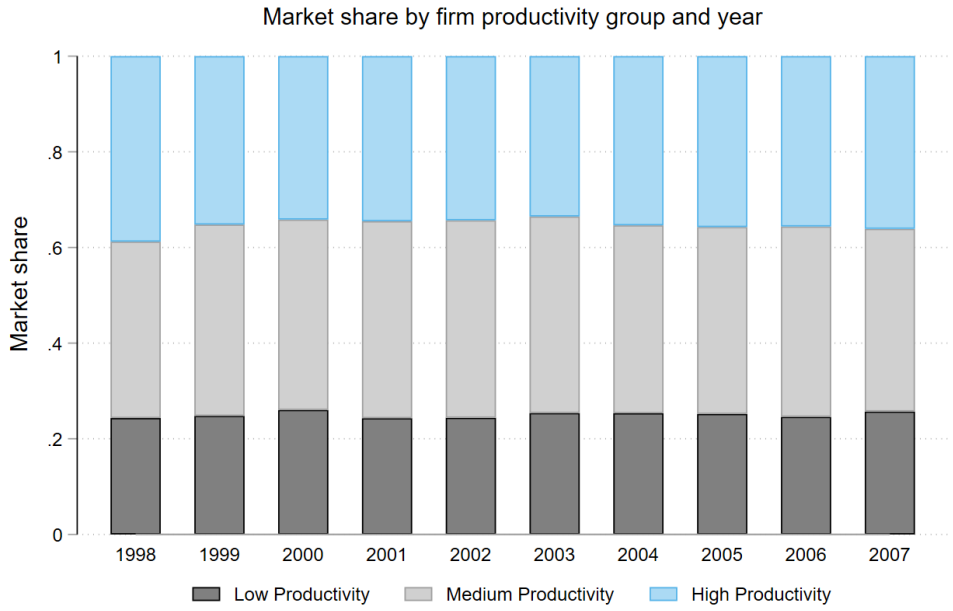


Figure 1: Market share by firm productivity group and year

Notes: Firm productivity is estimated using the Ackerberg et al. (2015) method. Within each four-digit industry, firms are classified into low-, medium-, and high-productivity groups based on terciles of initial productivity. For each year, the market share of each productivity group is calculated within each four-digit industry and then aggregated across industries using each industry's share of total sales as weights.

Stylized fact 2: The market share of high-productivity firms is lower in industries with higher external financial dependence

One potential factor is finance. To provide suggestive evidence on this possibility, I compare the market shares of high-productivity firms across industries with different degrees of external financial dependence. I measure industry-level external financial dependence using the index developed by Rajan and Zingales (1998) and classify industries as having high or low external financial dependence according to whether their index is above or below the median across all industries.

Figure 2 plots the average market share of high-productivity firms separately for the two groups of industries. The market share of high-productivity firms is lower in industries with higher external financial dependence, and the difference is statistically significant. This pattern suggests that financial conditions may be relevant for the ability of productive firms to expand.

These two stylized facts point to a potential role for financial conditions in shaping the reallocation of market share across firms. When financial conditions tighten, firms that depend more on external financing may face greater difficulty expanding. Recent literature shows that import competition can spill over to the banking sector by increasing non-performing loans among firms directly exposed to import shocks and weakening the balance sheets of their lenders, thereby reducing the supply of bank credit (Federico et al., 2025; Chakraborty and Ritadhi, 2022). Motivated by these facts and findings in the literature, I formally study whether import competition indirectly affects the expansion of productive firms through the banking channel in the remainder of the paper.

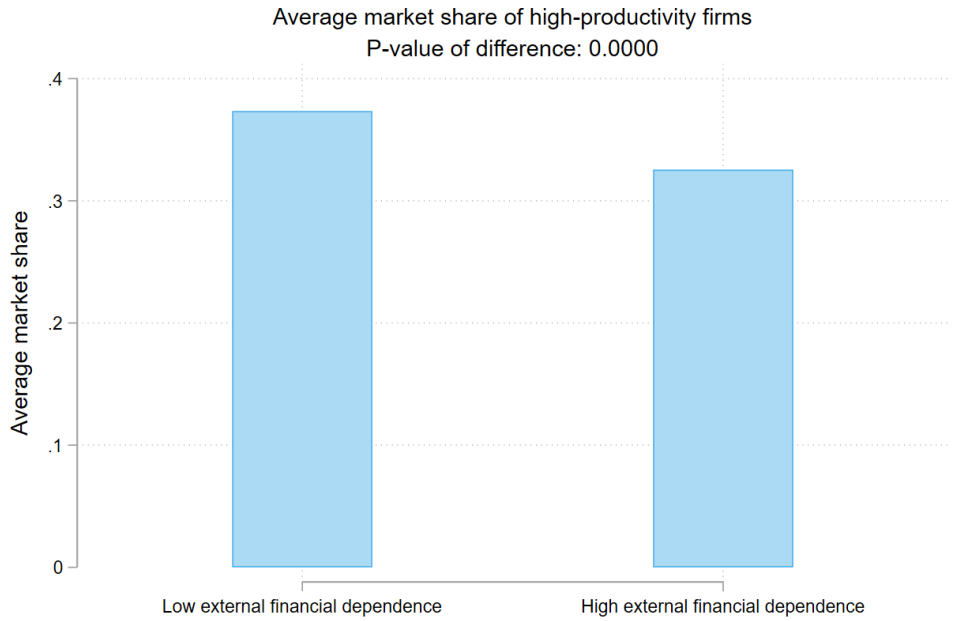


Figure 2: Average market share of high-productivity firms by industry external financial dependence

Notes: Firm productivity is estimated using the Ackerberg et al. (2015) method. Within each four-digit industry, firms are classified into low-, medium-, and high-productivity groups based on terciles of initial productivity. The market share of each productivity group is calculated within each four-digit industry and then aggregated across industries using each industry's share of total sales as weights. The figure reports the average aggregate market share over the sample period separately for industries with low and high external financial dependence. Industry-level external financial dependence is measured using Rajan and Zingales (1998) index, with industries classified as having low and high external financial dependence based on the median of the index across all industries.

3 Empirical Strategy

3.1 Empirical Specification

To examine the heterogeneous impact of trade-induced credit shocks on firm sales across firms with different levels of productivity, I estimate the following specification:

$$\ln Sales_{ijt} = \beta_1 lnTFP_i^{ini} \times TCS_{-jt} + \beta_2 lnTFP_i^{ini} \times IMPComp_{jt} + \alpha_{jt} + \mu_i + \epsilon_{ijt}, \quad (1)$$

where $\ln Sales_{ijt}$ is the logarithm of sales of firm i in industry j at time t. TCS_{-jt} measures trade-induced credit shocks, the measurement of which will be described in Section 3.2, and $lnTFP_i^{ini}$ is firm i's initial productivity. Firm productivity is calculated by esti-

mating production functions separately for each two-digit industry in the sample using the method of Ackerberg et al. (2015).[5] The production function estimation results are reported in Table A1 of the appendix. The coefficient of interest is β_1, which captures the heterogeneous effect of trade-induced credit shocks on firm sales across firms with different levels of productivity. A negative β_1 implies that trade-induced credit shocks affect sales more adversely for high-productivity firms than for low-productivity firms, resulting in a larger percentage decrease in sales. For ease of interpretation, I standardize TCS_{-jt} to have mean zero and unit standard deviation.

To account for any direct effects of import competition, I include the interaction between import competition in the firm's own industry and its initial productivity as a control variable. The measure of import competition, $IMPComp_{jt}$, will be described in Section 3.2. This control also captures other within-industry channels through which import competition may generate heterogeneous effects. $IMPComp_{jt}$ is also standardized to have mean zero and unit standard deviation. Finally, μ_i is firm fixed effects that control for time-invariant firm characteristics, and α_{jt} is four-digit industry-year fixed effects, which absorb level effects of import competition and trade-induced credit shocks, and all other industry-specific shocks. Standard errors are clustered at the 4-digit industry level to allow for arbitrary error correlations within industries over time.[6] The summary statistics of the main variables used in the regression analysis are reported in Table A2 of the appendix.

3.2 Measurement of Key Variables

Before constructing the trade-induced credit shock measure, I first measure each industry's direct exposure to import competition from China. Following Autor et al. (2013) and

[5] As a robustness check, I use Levinsohn and Petrin (2003) method to estimate firm productivity; the results remain the same.

[6] As a robustness check, I cluster standard errors at the 4-digit industry-year level; the results remain the same.

Acemoglu et al. (2016), the industry-level measure of Chinese import competition in India is defined as:

$$IMPComp_{jt} = \frac{M_{jt}}{Y_{j,98} + M_{j,98} - E_{j,98}}, \tag{2}$$

where M_{jt} is the total imports of Chinese goods in industry j at time t and $Y_{j,98} + M_{j,98} - E_{j,98}$ is the initial domestic absorption (measured as total domestic production, $Y_{j,98}$, plus industry imports, $M_{j,98}$, minus industry exports, $E_{j,98}$). Figure A1 of the appendix illustrates the evolution of the average Chinese import competition during the sample period. Following 2001, India experienced significant increases in import competition from China.

Based on this measure of import competition, I closely follow Federico et al. (2025) and construct an industry-level measure of trade-induced credit shocks (TCS) as the weighted average of exposure to Chinese import competition across industries, where the weights are given by industries' shares of total loans, leaving out industry j.[7] Specifically,

$$TCS_{-jt} = \frac{\sum_{j' \neq j} C_{j'} IMPComp_{j't}}{\sum_{j' \neq j} C_{j'}}, \tag{3}$$

where $C_{j'}$ is the outstanding loans in 1998 in manufacturing industry j'. $IMPComp_{j't}$ corresponds to the measure of import competition defined in equation (2). Excluding industry j when constructing the measure serves two purposes. First, it mitigates concerns about endogeneity with the dependent variable. Second, it allows the index to capture spillover effects from import competition in other industries. Figure A2 of the appendix illustrates the evolution of the average trade-induced credit shocks during the sample period, which closely mirrors the evolution of import competition.

This index has two complementary interpretations. From the manufacturing sector's perspective, TCS_{-jt} captures the extent to which industry j is exposed to import compe-

[7] Table A3 of the appendix presents summary statistics for the initial loan share. The table shows substantial variation in initial loan shares across industries, with a mean of 0.0133, a median of 0.0036, and a standard deviation of 0.0278.

tition shocks in other industries through the banking channel. That is, it measures how import competition shocks in other industries spill over to industry j through the banking sector.[8] From the banking sector's perspective, TCS_{-jt} reflects banks' exposure to import competition shocks faced by all other manufacturing industries except industry j.

Both interpretations rest on the same underlying mechanism: manufacturing industries rely on common financial intermediaries. When other industries face increased import competition, rising non-performing loans reduce the bank capital available for lending. Banks respond by tightening credit supply to all industries. As a result, an industry is exposed to import competition in other industries through the banking channel.

3.3 Identification

A standard concern is that Indian imports from China may capture not only exogenous Chinese supply shocks and reduced trade costs, but also domestic shocks to Indian industries that affect import demand. Following Autor et al. (2013), Acemoglu et al. (2016), and Chakraborty et al. (2024), I address this concern by using Chinese imports into Brazil, Indonesia, Malaysia, and Mexico (BIMM) to instrument Chinese imports into India. Specifically, the instrumental variable for Chinese import competition in India is defined as:

$$IMPComp_{jt}^{IV} = \frac{M_{jt}^{BIMM}}{Y_{j,98} + M_{j,98} - E_{j,98}}, \tag{4}$$

where M_{jt}^{BIMM} is the total imports of Chinese goods in industry j at time t by Brazil, Indonesia, Malaysia, and Mexico. The motivation for this instrument is that these developing economies have similar levels of development to India, and are similarly exposed to growth in imports from China driven by Chinese supply shocks. Therefore, Chinese imports into these economies should be highly correlated with Chinese imports into In-

[8] To mitigate the concern that TCS may capture other non-financial spillover channels, I account for input-output linkages, which is a commonly acknowledged spillover channel in the literature, in Section 4.2.

dia. This is confirmed by the first-stage results of the IV estimation, which I will describe in the result section.[9]

The validity of this instrument also relies on the key assumption that Chinese imports into BIMM countries affect firm sales in India only through the channel of Chinese imports into India. The exclusion restriction may be violated if the import demand is correlated across countries. For instance, if a shock in Brazil that increases its demand for Chinese goods also increases (decreases) its demand for Indian goods, then increased (decreased) Indian exports to Brazil may affect Indian firms' sales. I examine this concern by regressing Indian exports to BIMM countries on Chinese exports to BIMM countries and find that the coefficient is not statistically significant, mitigating concerns about correlated import demand.[10]

Accordingly, the instrumental variable for trade-induced credit shocks is :

$$TCS^{IV}_{-jt} = \frac{\sum_{j' \neq j} C_{j'} IMPComp^{IV}_{j't}}{\sum_{j' \neq j} C_{j'}}. \tag{5}$$

The construction of the instrumental variable for TCS is analogous to the shift-share IV methodology (Borusyak et al., 2025; Goldsmith-Pinkham et al., 2020). The endogeneity concern surrounding the "shift", which captures import competition, is addressed by instrumenting Chinese imports into India with Chinese imports into other similar countries. A separate concern relates to the potential endogeneity of the "share", measured as the industry-level loan share. Industries with higher initial loan shares may systematically differ along other dimensions that also influence their responses to import competition shocks. Although using predetermined loan allocations helps mitigate simultaneity con-

[9] As a robustness check, I instrument for Chinese imports into India by Chinese imports into other Latin American countries; the results remain the same.

[10] Specifically, I estimate the following specification:

$$\ln Y^{BIMM}_{jt} = \gamma \ln M^{BIMM}_{jt} + \mu_j + \alpha_t + \epsilon_{jt},$$

where Y^{BIMM}_{jt} is Indian exports to BIMM countries in industry j and year t. M^{BIMM}_{jt} is Chinese exports to BIMM countries in the same industry and year. μ_j and α_t are industry and year fixed effects. ϵ_{jt} is an error term. See Table A4 of the appendix for the result.

cerns, it does not fully rule out correlations with other industry characteristics. As a result, observed spillovers of import competition shocks or other industry-level shocks may operate through non-financial channels rather than purely through the financial channel.

To address this concern, I conduct a series of balance tests. Specifically, I regress a set of industry characteristics measured at their 1998 levels on the initial loan share in 1998. These characteristics include capital intensity, skill intensity, average wages, and imported input intensity. As shown in Table A5 of the appendix, the initial loan share is uncorrelated with all industry characteristics.

4 Results

4.1 Baseline Results

The baseline results from estimating equation (1) are reported in Table 1. The dependent variable in all columns is the natural logarithm of firm sales. Column (1) estimates the heterogeneous effect of trade-induced credit shocks on firm sales, focusing on the indirect impact of import competition through the banking channel. The coefficient of the interaction between initial firm productivity and the measure of trade-induced credit shocks is negative and statistically significant. In column (2), I additionally control for the interaction between import competition in the firm's own industry and its initial productivity to account for the direct effects of import competition. The coefficient of the interaction between firm productivity and trade-induced credit shocks remains stable in magnitude and significance. I discuss the magnitude of the heterogeneous effect after introducing IV results below.

As discussed in Section 3.2, Indian imports from China may capture not only exogenous Chinese supply shocks and reduced trade costs, but also domestic shocks to Indian industries that affect import demand. To isolate exogenous variation in Chinese import competition, and consequently, in trade-induced credit shocks, I follow Autor et al.

Table 1: Baseline OLS and IV results

	(1)	(2)	(3)	(4)
Dependent variable	$\ln Sales_{ijt}$			
Estimation method	OLS		IV	
$lnTFP_i^{ini} \times TCS_{-jt}$	-0.068***	-0.069***	-0.076***	-0.069***
	(0.010)	(0.010)	(0.012)	(0.017)
$lnTFP_i^{ini} \times IMPComp_{jt}$		0.003		-0.019
		(0.007)		(0.029)
Observations	24,447	24,447	24,447	24,447
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes

Notes: The dependent variable in all columns is firm sales in logarithm. TCS is the measure of trade-induced credit shocks, as defined in equation (3). $lnTFP^{ini}$ is firm's initial productivity, estimated using Ackerberg et al. (2015) method. $IMPComp$ is the measure of import competition, as defined in equation (2). Both TCS and $IMPComp$ have been standardized to have mean zero and standard deviation one. All regressions include firm and four-digit industry-year fixed effects. Robust standard errors clustered at the four-digit industry level are reported in parentheses. *, **, and *** indicate significance at the 10, 5, and 1% levels, respectively.

(2013), Acemoglu et al. (2016), and Chakraborty et al. (2024) and use Chinese imports into Brazil, Indonesia, Malaysia, and Mexico (BIMM) to instrument Chinese imports into India. Columns (3) and (4) of Table 1 report the instrumental variables estimates. Both the coefficients of the interaction between firm productivity and trade-induced credit shocks remain negative and statistically significant. The first-stage results, reported in Table A6 of the appendix, show that the instruments are statistically and significantly correlated with the endogenous variables. The corresponding F-statistics are well above the conventional threshold, indicating that the instruments are strong.

To gauge the magnitude of the heterogeneous impact, consider firms at different points in the productivity distribution. Using the estimates in column (4) of Table 1, a one-standard-deviation increase in trade-induced credit shocks leads to a 6 percentage point larger decrease in sales for a high-productivity firm at the seventy-fifth percentile than for

a low-productivity firm at the twenty-fifth percentile.[11]

The direct import competition effects are not statistically significant in any specification and are unstable in sign. This imprecision is consistent with the inconclusive evidence in the literature on the impacts of import competition. Some studies find that rising import exposure intensifies competitive pressure, leading to declines in sales, employment, and innovation (Aghion et al., 2024; Autor et al., 2020; Pierce and Schott, 2016; Bernard et al., 2006), while others document positive escape-competition effects (Bloom et al., 2016) or no significant impact (Iacovone et al., 2011). Given that this study focuses on the indirect effects of import competition, I pay attention to the impact of trade-induced credit shocks, while controlling for the direct impact of import competition in all subsequent analyses.

4.2 Threats to Identification

Non-financial spillover channel

A major concern is that TCS may capture non-financial spillover channels of import competition in other industries. For instance, a widely studied spillover channel in the literature operates through sectoral input-output linkages (Acemoglu et al., 2016; Pierce and Schott, 2016). On the input side, when upstream industries face increased import competition, downstream industries may experience a contraction in domestic input supply, potentially offset by greater access to foreign inputs. On the output side, when downstream industries are negatively affected by import competition, their reduced demand can spill over and adversely affect upstream industries. Both channels might generate heterogeneous effects because firms with different levels of productivity may differ in their degree of integration into input-output chains. To account for these input-output

[11] For a firm at the twenty-fifth percentile of productivity, $\ln TFP$ is 0.87, while for a firm at the seventy-fifth percentile, $\ln TFP$ is 1.74. The difference between the two is therefore $1.74 - 0.87 = 0.87$. Given the estimated interaction coefficient is 0.04, the difference in the estimated impact on sales between firms at the seventy-fifth and twenty-fifth percentiles of productivity is $0.87 \times 0.069 = 0.06$, or approximately 6 percentage points.

linkages, I construct measures of each industry's exposure to upstream and downstream import competition.[12]

Table 2: Controlling for input-output linkages

	(1)	(2)	(3)	(4)
Dependent variable	$\ln Sales_{ijt}$			
$lnTFP_i^{ini} \times TCS_{-jt}$	-0.069***	-0.077***	-0.068***	-0.075***
	(0.017)	(0.029)	(0.016)	(0.026)
$lnTFP_i^{ini} \times IMPComp_{jt}$	-0.019	-0.037	-0.013	-0.029
	(0.029)	(0.039)	(0.032)	(0.042)
$lnTFP_i^{ini} \times IMPComp_{jt}^{up}$		0.477		0.407
		(0.849)		(0.811)
$lnTFP_i^{ini} \times IMPComp_{jt}^{down}$			-0.032	-0.032
			(0.049)	(0.053)
Observations	24,447	24,447	24,447	24,447
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Method	IV	IV	IV	IV

Notes: The dependent variable in all columns is firm sales in logarithm. TCS is the measure of trade-induced credit shocks, as defined in equation (3). $lnTFP^{ini}$ is firm's initial productivity, estimated using Ackerberg et al. (2015) method. $IMPComp$ is the measure of import competition, as defined in equation (2). Both TCS and $IMPComp$ have been standardized to have mean zero and standard deviation one. $IMPComp^{up}$ is the measure of exposure to upstream import competition, as defined in equation (6). $IMPComp^{down}$ is the measure of exposure to downstream import competition, as defined in equation (7). All regressions include firm and four-digit industry-year fixed effects. Robust standard errors clustered at the four-digit industry level are reported in parentheses. *, **, and *** indicate significance at the 10, 5, and 1% levels, respectively.

Both upstream and downstream exposure measures are instrumented in the same

[12]Specifically, industry j's exposure to upstream import competition is defined as,

$$IMPComp_{jt}^{up} = \sum_{j' \neq j} \omega_{j'j}^{up} IMPComp_{j't}, \tag{6}$$

where $\omega_{j'j}^{up}$ is the share of inputs sourced from upstream industry j' to industry j's total output. Similarly, industry j's exposure to downstream industry j''s import competition is given by

$$IMPComp_{jt}^{down} = \sum_{j' \neq j} \omega_{j'j}^{down} IMPComp_{j't}, \tag{7}$$

where $\omega_{j'j}^{down}$ is the share of industry j's output purchased by industry j'. These weights are calculated using India's 1993 input-output table.

manner as the main import competition variable. I then augment the baseline specification in equation (1) by including these exposure measures and their interactions with initial firm productivity. The results are reported in Table 2. Column (1) reproduces the baseline results for reference. Columns (2) and (3) separately control for upstream and downstream spillover channels, while column (4) includes both simultaneously. Across all specifications, the coefficient on the interaction between firm productivity and trade-induced credit shocks remains robust in magnitude and significance. This result suggests that the financial channel remains an important source of the observed spillover effects even after accounting for input-output linkages.

IV exclusion restriction

My instrument for Chinese imports into India is Chinese imports into Brazil, Indonesia, Malaysia, and Mexico (BIMM). The IV exclusion restriction requires that Chinese imports into BIMM countries affect firm sales in India only through the channel of Chinese imports into India. Although I have addressed one concern that import demand may be correlated across countries by showing that Chinese exports to BIMM countries are not significantly correlated with Indian exports to BIMM countries, there may be other confounding factors correlated with Chinese imports into BIMM countries that affect firm sales in India. For instance, industry-specific technology or policy shocks in India may affect industries in BIMM countries because of their economic connections or institutional and technological similarities, consequently affecting BIMM countries' import demand from China. I address this concern by using Chinese imports into Latin American countries or European countries as alternate instruments for Chinese imports into India.[13] The results remain robust, as shown in columns (1) and (2) of Table 3.[14]

Another concern is that import competition from China may be correlated with im-

[13] I consider Chinese imports into Argentina, Brazil, Costa Rica, Chile, Colombia, Mexico, Paraguay, Peru, Uruguay and Venezuela.

[14] In Table A4 of the appendix, I show that there is no statistically significant correlation between Chinese exports to LAM countries and Indian exports to LAM countries, and no statistically significant correlation between Chinese exports to EU countries and Indian exports to EU.

port competition from other countries, which may also affect firm sales in India. This may also be the case with Chinese import competition in Latin American countries or European countries, making my IVs invalid. To address this concern, I control for import competition from all other countries apart from China by including its interaction with initial firm productivity.[15] The result in column (3) of Table 3 remains robust.

Table 3: Address threats to IV exclusion restriction and control for differential trends

Dependent variable	(1)	(2)	(3)	(4)	(5)
	$\ln Sales_{ijt}$				
	IV-LAM	IV-EU	IMPComp Others	Labor Market	Differential Trends
$lnTFP_i^{ini} \times TCS_{-jt}$	-0.072***	-0.077***	-0.072***	-0.068***	-0.083***
	(0.014)	(0.016)	(0.016)	(0.017)	(0.019)
$lnTFP_i^{ini} \times IMPComp_{jt}$	-0.004	0.015	-0.030	-0.020	-0.017
	(0.018)	(0.030)	(0.042)	(0.030)	(0.028)
Observations	24,447	24,447	24,447	24,447	24,447
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Method	IV	IV	IV	IV	IV

Notes: The dependent variable in all columns is firm sales in logarithm. TCS is the measure of trade-induced credit shocks, as defined in equation (3). $lnTFP^{ini}$ is firm's initial productivity, estimated using Ackerberg et al. (2015) method. $IMPComp$ is the measure of import competition, as defined in equation (2). In columns (1) and (2), I use Chinese exports to Latin American countries and European countries as alternate instruments for Chinese imports into India, respectively. In column (3), I control for import competition from all other countries and its interaction with firm productivity. In column (4), I control for the measure of labor market frictions and its interaction with firm productivity. I use the within-industry dispersion of firms' marginal revenue product of labor (MRPL) as a broad measure of labor market frictions. In column (5), I control for initial-productivity-bin-by-year trends. All regressions include firm and four-digit industry-year fixed effects. Robust standard errors clustered at the four-digit industry level are reported in parentheses. *, **, and *** indicate significance at the 10, 5, and 1% levels, respectively.

A final confounding factor I consider is labor market frictions, which may have heterogeneous effects on firm sales. While it is less likely that labor market frictions facing an industry in India are correlated with Chinese imports into BIMM countries, given their important role in affecting firm sales, I control for the measure of labor market fric-

[15]The measure of import competition from all other countries follows the same measurement of Chinese import competition, as defined in equation (2).

tions and its interaction with initial firm productivity in the baseline specification. I use the within-industry dispersion of firms' marginal revenue product of labor (MRPL) as a broad measure of labor market frictions.[16] The justification for using the standard deviation of MRPL as a proxy for labor market frictions facing an industry is as follows: in a frictionless labor market, labor should be reallocated across firms until MRPLs are equalized; hence, greater MRPL dispersion indicates greater labor misallocation and may reflect various frictions that impede worker reallocation.[17] As shown in column (4) of Table 3, the results remain unchanged after accounting for the potential role of labor market frictions in driving the heterogeneity.

Differential trends

One concern is that high-productivity firms may experience different sales trends from low-productivity firms even in the absence of trade-induced credit shocks. For instance, high-productivity firms may exhibit systematically stronger sales growth over time for reasons unrelated to credit conditions. If such a trend exists and is omitted from the baseline specification, it would bias the estimate of β_1 toward zero, because TCS itself trends upward over the sample period as Chinese import competition intensifies. Given that the estimated β_1 is already negative, this suggests that the baseline estimate is, if anything, a conservative estimate of the true heterogeneous effect, making omitted differential trends a less concerning threat, although I still address it formally below.

To examine this concern, I control for initial-productivity-bin-by-year trends. I divide firms into four bins based on initial productivity and include interactions between bin

[16]Following Bau and Matray (2023), under the revenue Cobb-Douglas production function, firm i's MRPL in industry j is $MRPL_{it} = \frac{\partial Revenue_{it}}{\partial L_{it}} = \alpha_j^L \frac{Revenue_{it}}{L_{it}}$, where $Revenue_{it}$ is firm sales, L_{it} is total salaries, and α_j^L is the output elasticity of labor, estimated from production function estimation. Then, industry-level labor misallocation is measured as the standard deviation of firm $MRPL$ within the industry.

[17]One concern of using time-varying labor market misallocation is that labor market misallocation may itself be the outcome of trade-induced credit shocks. But the barely changed coefficients of β_1 after controlling for the measure of labor market frictions and its interaction with firm productivity mitigate the concern.

indicators and a linear year trend.[18] This absorbs differential sales trends driven by initial productivity. As shown in column (5) of Table 3, the estimated β_1 becomes slightly larger in magnitude under this specification, consistent with the direction of bias discussed above.

Pre-trends

Lastly, I exploit the panel structure of the data to conduct an event-study analysis and test for pre-trends. Specifically, I examine whether, prior to the import competition shocks stemming from China's entry into the WTO in 2001, firms with different levels of initial productivity were already experiencing systematically different sales trends across industries with varying exposure to trade-induced credit shocks. To do so, I classify an industry as having high trade-induced credit shocks if its change in TCS between 1998 and 2007 is above the median across all industries. I then interact initial firm productivity with this high-shock indicator and a full set of year indicators, using 2001 as the reference year.[19] Figure A3 of the appendix presents the results. I find no evidence of pre-trends: the coefficients of interest before 2001 are statistically insignificant.

4.3 Robustness Checks

In Table A7 of the appendix, I conduct a battery of robustness checks on my baseline results. In column (1), I re-estimate TFP using the method of Levinsohn and Petrin (2003).

[18] I do not instead control for a continuous initial productivity interacted with a year trend because TCS is itself close to a time-series variable; a continuous productivity-by-year trend control would therefore absorb much of the identifying variation in $lnTFP^{ini} \times TCS$, leaving little variation to estimate β_1 precisely. Using coarser productivity bins interacted with a year trend is a less demanding specification that still accounts for the bulk of any productivity-driven trend while preserving identifying variation.

[19] Specifically, I estimate the following specification:

$$\begin{aligned} \ln Sale_{ijt} = &\sum_{t \neq 2001} \beta_{1t} lnTFP_i^{ini} \times TCS_High_j \times \mathbf{1}[Year = t] + \sum_{t \neq 2001} \beta_{2t} lnTFP_i^{ini} \times \mathbf{1}[Year = t] \\ &+ \beta_3 lnTFP_i^{ini} \times IMPComp_{jt} \times + \alpha_{jt} + \mu_i + \epsilon_{ijt}, \end{aligned} \tag{8}$$

where TCS_High_j equals to one if industry j's change in TCS between 1998 and 2007 is above the median across all industries, and zero otherwise.

In column (2), I use an alternative measure of import competition, in which Chinese imports are normalized by initial employment for each industry.[20] In column (3), I estimate a first-difference version of the baseline specification. In column (4), one-year lagged TCS and $IMPComp$ are used in the regression. In column (5), I use market share as outcome. In column (6), I control for a set of firm characteristics by interacting each characteristic with TCS. Lastly, in column (7), I cluster standard errors at the industry-year level. In all cases, the interaction coefficient of interest remains robust.[21]

5 Mechanisms

The preceding empirical analysis provides robust evidence that high-productivity firms are more adversely affected by trade-induced credit shocks in India. To explain this finding, I develop a stylized model of an economy with heterogeneous firms facing financial constraints and a representative bank that allocates its limited capital as loans to these firms. The model highlights two channels that can generate the heterogeneity observed in the empirical results: the bank loan supply channel and the firm internal funds channel.

I first present the bank's problem, showing how it allocates its limited capital across firms. I then turn to the firm's problem, showing how firms finance production and how their sales respond to a reduction in bank capital. After presenting the model, I use the data to examine the two channels separately.

[20] Industry-level employment data are from the UNIDO INDSTAT database.

[21] One exception is that the interaction coefficient of interest becomes statistically insignificant when I re-estimate TFP using Levinsohn and Petrin (2003) method, but the magnitude remains similar to the baseline result.

5.1 Model

5.1.1 Banks

A representative bank in an economy faces a mass of borrowers (firms), who are characterized by productivity z and asset tangibility t. t represents the fraction of a firm's total assets that can be used as collateral. In the Indian data, I observe a negative correlation between productivity and tangibility.[22] Thus, I make the following assumption:

Assumption 1. *Asset tangibility is decreasing in productivity,* $t_z = \frac{\partial t}{\partial z} < 0$.

I develop the model in partial equilibrium with an exogenous interest rate, r, that is homogeneous across borrowers. This assumption is made for simplicity, since the heterogeneity in lending costs that I allow for and describe in the next subsection is on its own sufficient to generate heterogeneous loan allocation. It also implies that I am studying the short-term impact of bank capital shocks, over a horizon in which the interest rate does not respond.[23] Therefore, the revenue from lending B_i to borrower i is rB_i.

Lending cost and capital constraint

In its lending activities, the bank incurs screening costs before loan origination and monitoring costs afterward. Following Kopecky and VanHoose (2006) and the standard convex-cost assumption used in the literature, I model the bank's lending costs as a quadratic function of loan size, $f(B_i, a_i) = \frac{1}{2}a(t_i, z_i)B_i^2$, where $a(t_i, z_i)$ is a positive, borrower-specific lending cost coefficient. Banks expend effort on screening and monitoring by collecting information to learn about the quality of the borrower and its investment project. This effort is lower when the bank bears less risk of the project failing, whether because of higher seizable collateral (Manove et al., 2001; Mattesini, 1990) or higher expected future

[22] See column (1) of Table A8 of the appendix for the results. Additionally, Figure A4a of the appendix shows that high-productivity firms tend to have less physical assets, which also indicates that high-productivity firms have lower tangibility.

[23] Interest rates are regulated by the Reserve Bank of India, so banks do not have full authority to set them as they might otherwise wish.

profitability and growth.[24] I therefore make the following assumption about the lending cost coefficient:

Assumption 2. *The lending cost coefficient $a(t_i, z_i)$ is directly decreasing in productivity ($\frac{\partial a}{\partial z} < 0$), while indirectly increasing in productivity through asset tangibility ($\frac{\partial a}{\partial t}\frac{\partial t}{\partial z} > 0$).*

In addition to lending costs, the bank is subject to a capital constraint, whereby total lending cannot exceed available bank capital,

$$\sum_i B_i \leq K, \tag{9}$$

where K denotes available bank capital and is exogenous from the bank's perspective. When the bank is hit by a negative shock that raises its non-performing assets, the total capital available for lending decreases.

Loan allocation

The bank selects the allocation of loans across borrowers to maximize profit net of lending costs, subject to the capital constraint. Solving the bank's maximization problem gives the optimal loan supply to each borrower as follows:[25]

$$B_i = \frac{K}{A}\frac{1}{a(t_i, z_i)}, \tag{10}$$

where $A = \sum_i \frac{1}{a(t_i,z_i)}$ is an aggregate variable that, assuming there is a large number of firms in the economy, does not depend on any single firm's tangibility or productivity.

Equation (10) implies that loan supply increases with available bank capital, while its relationship with borrower productivity is ambiguous: higher-productivity borrowers tend to be allocated fewer loans because of higher lending costs arising from lower tangibility, but more loans because of lower lending costs arising directly from higher

[24]The heterogeneity in $a(t_i, z_i)$ also reflects two lending rules prevalent in the literature and in practice: the collateral-based lending rule and the earning-based lending rule (Lian and Ma, 2020). In collateral-based lending, firms with higher value of collateral assets face a higher lending limit. In earning-based lending, firms with higher future earnings from continuing operations face a higher lending limit.

[25]The full derivation of the bank's profit maximization problem is provided in Appendix B.1.

productivity.

Although the relationship between borrower productivity and loan supply is ambiguous in theory, I impose the following assumption based on Indian data:[26]

Assumption 3. *Bank loan supply is increasing in borrower productivity,* $B_z = \frac{\partial B}{\partial z} > 0$.

This assumption also reflects official lending policies in India that recommend a projected-turnover-based lending rule for working capital financing (Banerjee et al., 2004), under which more productive firms have higher lending limits.

5.1.2 Firms

Production and financial constraint

Firms produce output y using labor l as the only input, with a constant-returns-to-scale production technology, $y = zl$. Monopolistically competitive firms face downward-sloping demand curves, $y = p^{-\sigma}$, where p is the price of the product and $\sigma > 1$ is the elasticity of substitution between any two products.[27] Thus, firm sales are given by $s = py = (zl)^{\frac{\sigma-1}{\sigma}}$.

Before production takes place and revenues are realized, firms must pay working capital, which is the wage bill, wl, in advance. They finance this working capital requirement using internal funds and bank borrowing. Formally, the financial constraint facing the firm is

$$wl \leq I(z) + B(K, z), \tag{11}$$

where $B(K, z)$ denotes the bank loan supplied to the firm, determined in the bank's problem according to equation (10), and $I(z)$ denotes internal funds, such as retained earnings.[28] I make the following assumption about the internal funds:

[26] Columns (2) and (3) of Table A8 of the appendix show an overall positive correlation between firm productivity and the loans it receives.

[27] Following Gopinath et al. (2017), this demand function is used in a partial equilibrium model in which the demand shifter and the sectoral price index are normalized to 1.

[28] More generally, $I(z)$ can represent any other sources of financing, such as funds raised through equity markets.

Assumption 4. *Internal funds are increasing in productivity,* $I_z = \frac{\partial I}{\partial z} > 0$.

Following Banerjee and Duflo (2014), I assume that the working capital constraint above always binds throughout the rest of the analysis. Thus, the firm's problem is to maximize profit net of borrowing costs, subject to the working capital constraint. Solving the constrained optimization problem gives the optimal sales as follows:[29]

$$s^* = \left(z \frac{I(z) + B(K, z)}{w} \right)^{\alpha}, \tag{12}$$

where $\alpha = \frac{\sigma - 1}{\sigma} \in (0, 1)$. Equation (12) shows that any shock to bank capital K affects firm sales only through loan supply $B(K, z)$.

5.1.3 The heterogeneous impact of bank capital reduction on firm sales

The objective of the model is to study the heterogeneous impact of bank capital reduction on firm sales. I use the following cross-partial derivative to characterize the heterogeneity:

$$\frac{\partial^2 \ln s^*}{\partial K \, \partial z} = \Gamma \left(\frac{B_z}{B} - \frac{I_z}{I} \right), \tag{13}$$

where $\Gamma = \alpha \frac{BI}{K(I+B)^2}$.[30] The cross-partial derivative is positive when $\frac{B_z}{B} > \frac{I_z}{I}$. In words, high-productivity firms' sales are more sensitive to changes in bank capital when the bank's loan supply grows faster than the firm's internal funds as productivity increases.

The intuition for the result is as follows. Heterogeneity arises from the relative responsiveness of the bank's willingness to lend and the firm's ability to raise internal funds to productivity. When bank loan supply grows faster than firms' ability to raise internal funds as productivity increases, high-productivity firms become more dependent on bank loan supply. They are therefore more adversely affected by reductions in bank capital. The opposite holds when internal funds rise faster than bank lending.

[29] The full derivation of the firm's profit maximization problem is provided in Appendix B.2.
[30] The derivation is provided in Appendix B.3.

Although I cannot directly test whether bank loan supply increases faster than firms' internal funds as productivity rises, because pure bank loan supply is unobservable, the model yields two testable predictions. First, the heterogeneous effect should be more pronounced among firms whose internal funds are likely to increase less with productivity. Second, the heterogeneous effect should be more pronounced among firms for which bank loan supply is likely to increase more strongly with productivity. I test these two predictions separately in the following subsections.

5.2 Test of internal funds channel

To examine the internal funds channel, I focus on firm size and age, which provide economically meaningful sources of heterogeneity in firms' ability to generate internal funds. I first show that high-productivity firms in India tend to be smaller and younger, and that the elasticity of internal funds to productivity is lower among smaller and younger firms. I then test the model's prediction that the heterogeneous effect of trade-induced credit shocks on firm sales should consequently be more pronounced among these firms.

5.2.1 Firm Size

Figure A4a of the appendix shows that high-productivity firms in India tend to be smaller in terms of physical assets. This pattern motivates examining whether the relationship between productivity and internal funds differs by firm size. Since direct measures of firms' internal funds are unavailable, I use after-tax profits as a principal source of internally generated funds. I then divide firms into three size groups based on terciles of initial physical assets and estimate the following specification:

$$\ln Profits_{ijt} = \rho_1 lnTFP_{it-1} + \sum_{k=2,3} \rho_k lnTFP_{it-1} \times Size_Bin_k + \alpha_{jt} + \mu_i + \epsilon_{ijt}, \qquad (14)$$

where $\ln Profits_{ijt}$ denotes the firm's after-tax profits in natural logarithm. I use one-year lagged productivity and control for firm and industry-year fixed effects in the regression. The coefficient ρ_1 captures the elasticity of profits to productivity for firms in the smallest size group, while ρ_k measures the difference in this elasticity between size group k and the smallest group.

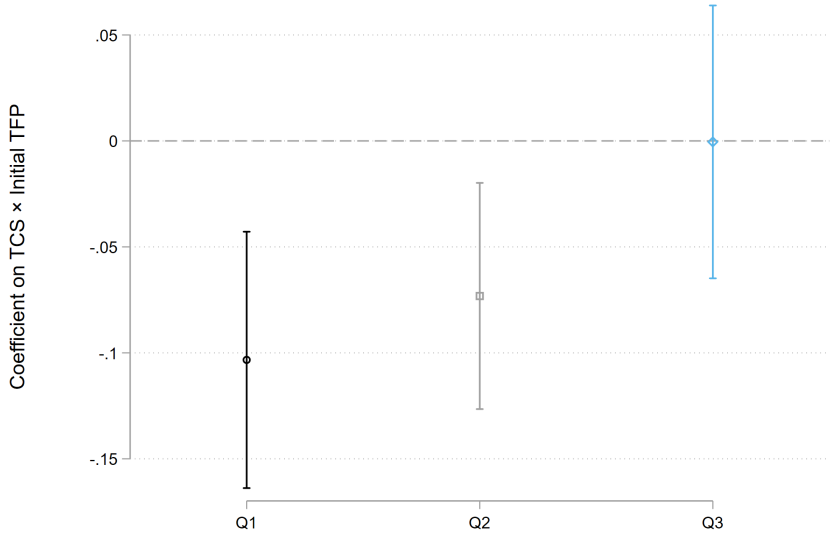
The results in column (1) of Table A9 of the appendix show that the elasticity of profits to productivity is lower for small firms in the first size group than for large firms, and it is statistically and significantly smaller than the largest firms in the third size group.

This observation yields a testable prediction of the model. If the internal funds channel is valid, the heterogeneous effect of TCS should be stronger among smaller firms, where internal funds increase less with productivity. I therefore re-estimate the baseline specification separately for each group. The results, reported in Figure 3a, show that the interaction coefficient of interest is most negative among firms in the smallest size group and is statistically insignificant among firms in the largest size group, consistent with the model's prediction.

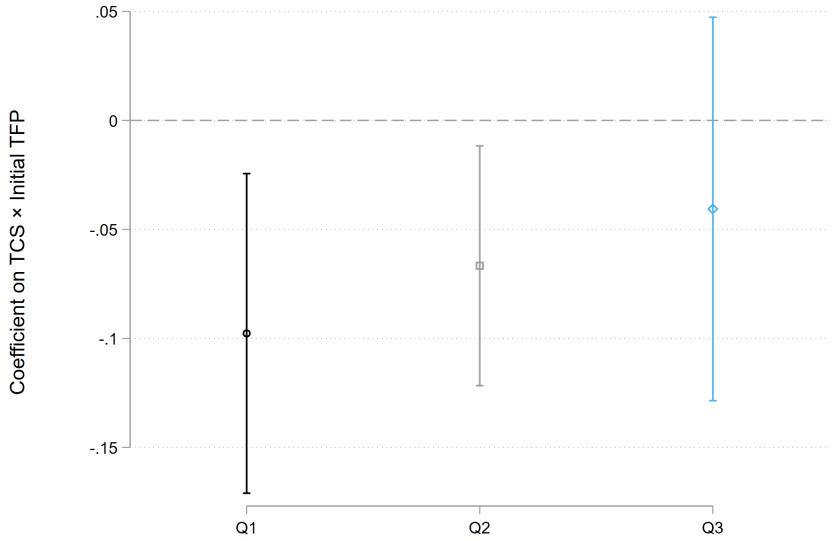
5.2.2 Firm Age

Firm age provides a second dimension along which to examine the model's mechanism. Figure A4b of the appendix shows that high-productivity firms in India tend to be younger. In addition, I also examine whether the relationship between productivity and internal funds differs by firm age. As in the size analysis, the specification in equation (14) is estimated across firm-age groups. Column (2) of Table A9 of the appendix shows that the point estimate of the productivity-profit elasticity is lower for younger firms, although the difference across age groups is not statistically significant. Thus, the evidence on the relationship between productivity and internal funds by firm age is suggestive rather than conclusive.

Given the suggestive evidence that internal funds grow less with productivity for



(a) Small vs. Large



(b) Young vs. Old

Figure 3: Heterogeneous effects of trade-induced credit shocks by firm size and age

Notes: Panel (a) shows the estimated coefficients of the interaction between firm productivity and trade-induced credit shocks for different size groups. Firms are divided into three groups based on the tercile of firm size in terms of initial physical assets. Panel (b) shows the estimated coefficients of the interaction between firm productivity and trade-induced credit shocks for different age groups. Firms are divided into three groups based on the tercile of firm age.

younger firms, the heterogeneous effect of TCS should be stronger among younger firms if the internal funds channel is valid. I therefore re-estimate the baseline specification separately for each age group. The results, reported in Figure 3b, show that the interac-

tion coefficient of interest is more negative and statistically significant for younger firms, while it is statistically insignificant among the oldest firms. Again, the results are consistent with the model's prediction.

5.3 Test of bank loan supply channel

To examine the bank loan supply channel, I use industry-level characteristics that may be correlated with the responsiveness of bank loan supply to productivity across industries, since I do not observe firm-level bank loan supply. In particular, I focus on industry output risk. In industries where future earnings are more predictable, banks may have greater confidence in using firms' productivity to assess their growth potential and therefore adjust loan supply more strongly in response to productivity. In contrast, greater uncertainty about future earnings may make banks more cautious and reduce their reliance on productivity when making lending decisions. Thus, the growth rate of bank loan supply to productivity would be lower in industries with greater output risk. If the bank loan supply channel is valid, the heterogeneous effect of trade-induced credit shocks should be stronger in industries with lower output risk.

I measure industry output risk using the volatility of industry sales growth following Sundaram (2019). I construct this measure using industry-level data from UNIDO for the pre-China-shock period 1998-2001. Specifically, I first estimate

$$G_{jt} = \alpha_j + \mu_t + \theta_{jt}, \tag{15}$$

where G_{jt} denotes the growth rate of sales in industry j at time t, α_j and μ_t are industry and year fixed effects, and θ_{jt} is an idiosyncratic error term. I define industry output volatility as the standard deviation of predicted residuals over the period 1998-2001. This measure captures deviations of industry sales growth after accounting for industry- and common year-specific shocks to sales growth.

I then test whether the heterogeneous effect of trade-induced credit shocks on firm sales is more pronounced among firms in industries with lower output volatility. I divide industries into three groups based on the tercile of this volatility measure and re-estimate the baseline specification separately for each group. The results, reported in Figure 4, show that the interaction coefficient of interest is most negative among firms in industries with the lowest output volatility and becomes statistically insignificant among firms in industries with the highest output volatility. This pattern is consistent with the model's prediction that the heterogeneous effect of trade-induced credit shocks is stronger when bank loan supply is more responsive to firm productivity, providing supporting evidence for the model's mechanism.

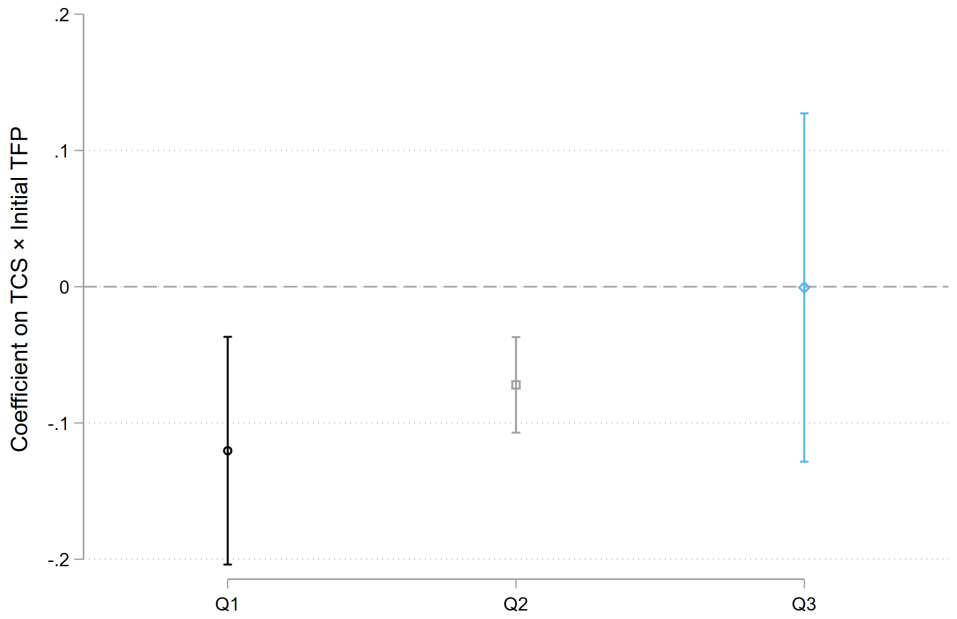


Figure 4: Heterogeneous effects of trade-induced credit shocks by industry output volatility

Notes: The figure shows the estimated coefficients of the interaction between firm productivity and trade-induced credit shocks for different industry-volatility groups. Industries are divided into three groups based on the tercile of industry output volatility measure.

6 Conclusion

In this paper, I examine whether import competition shocks transmitted indirectly through the banking sector affect firm sales differently across the productivity distribution. Using firm-level data from India between 1998 and 2007, I document that the market share of high-productivity firms did not expand over the sample period and show that financial factors may explain the pattern.

Empirically, I construct an industry-level measure of trade-induced credit shocks based on Chinese import competition in other industries, weighted by the initial distribution of bank loans across industries. I use Chinese imports into other similar countries as an instrument for Chinese imports into India. The results show that trade-induced credit shocks reduce sales disproportionately more for high-productivity firms. This result is robust to accounting for input-output spillovers, import competition from other countries, differential trends, labor market frictions, and other robustness checks.

To interpret this finding, I develop a simple model in which a capital-constrained bank lends to heterogeneous firms that need internal funds and external borrowing to finance their production. The model shows that a reduction in bank capital disproportionately harms the sales of high-productivity firms when bank loan supply increases with productivity more rapidly than firms' internal funds do. Consistent with the model's mechanisms, I show that the heterogeneous effect of trade-induced credit shocks is stronger among smaller and younger firms, whose internal funds rise less with productivity, and among firms in industries with lower output volatility, where bank loan supply may be more responsive to productivity.

The findings highlight an important but potentially overlooked dimension of trade. The consequences of import competition depend not only on its direct effects on firms but also on its transmission through the financial sector. This indirect channel can constrain the expansion of high-productivity firms, particularly those that are small and young. Understanding the consequences of import competition shocks therefore requires atten-

tion to both the financial sector through which these shocks propagate and the types of firms that are most vulnerable to this transmission.

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A Additional Tables and Figures

A.1 Tables

Table A1: Production function estimates by two-digit industries

Industry	Obs.	Labor	Capital	Returns to Scale
Food products and beverages	3,755	0.643	0.322	0.965
Textiles, apparel	4,212	0.569	0.393	0.962
Paper and paper products	1,263	0.598	0.448	1.046
Chemicals	5,898	0.760	0.319	1.079
Rubber and plastic	2,100	0.731	0.334	1.064
Nonmetallic mineral products	1,202	0.673	0.462	1.135
Basic metals	3,964	0.521	0.376	0.897
Fabricated metal products	1,100	0.687	0.293	0.980
Machinery and equipment	2,043	0.799	0.251	1.050
Electrical machinery and communication	2,714	0.725	0.315	1.040
Motor vehicles, trailers	1,841	0.721	0.391	1.112
Average		0.669	0.348	1.017

Notes: This table reports the output elasticities of labor and capital for each two-digit industry in the sample. These elasticities are estimated from revenue production functions using the method of Ackerberg et al. (2015).

Table A2: Summary statistics

	Obs.	Mean	SD	Min	Max
$\ln Sales$	24,447	5.795	1.616	0.336	9.854
$lnTFP^{ini}$	24,447	1.269	0.909	-5.656	5.570
TCS	24,447	0.000	1.000	-0.919	2.399
$IMPComp$	24,447	0.000	1.000	-0.421	24.089

Note: This table reports the number of observations, mean, standard deviation, minimum, and maximum of key variables used in the regression. $\ln Sales$ is firm sales in logarithm. $lnTFP^{ini}$ is firm's initial productivity, estimated using Ackerberg et al. (2015) method. TCS is the measure of trade-induced credit shocks, as defined in equation (3). $IMPComp$ is the measure of import competition, as defined in equation (2). Both TCS and $IMPComp$ have been standardized to have mean zero and standard deviation one.

Table A3: Summary statistics of loan share in 1998

Variable	Obs.	Mean	Median	SD	Min	Max
Loan Share	76	0.0133	0.0036	0.0278	0.000006	0.1836

Notes: Loan Share is defined as the ratio of outstanding loans to total outstanding loans at the four-digit NIC industry level in 1998. The data are obtained from the ASI for the year 1998-99.

Table A4: Testing for correlated import demand effects

	(1)	(2)	(3)
Dependent variable	$\ln Y^{BIMM}$	$\ln Y^{LAM}$	$\ln Y^{EU}$
ln(Chinese Exports to BIMM)	0.021		
	(0.095)		
ln(Chinese Exports to LAM)		0.237	
		(0.166)	
ln(Chinese Exports to EU)			-0.004
			(0.114)
Observations	741	741	741
4-digit Industry-Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Notes: The unit of observation in each column is a 4-digit NIC industry and year. The dependent variable in column (1) is the natural logarithm of Indian exports to Brazil, Indonesia, Malaysia, and Mexico (BIMM). In column (2), the dependent variable is the natural logarithm of Indian exports to Latin American countries, including Argentina, Brazil, Costa Rica, Chile, Colombia, Mexico, Paraguay, Peru, Uruguay and Venezuela (LAM). In column (3), the dependent variable is the natural logarithm of Indian exports to EU countries. All regressions include four-digit industry and year fixed effects. Robust standard errors in parentheses are clustered at the four-digit industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A5: Balance tests of industry characteristics

Dependent variable:	(1)	(2)	(3)	(4)
	Capital Intensity	Skill Intensity	LnWage	Imported Input Share
LS_j^{ini}	-0.075	-0.769	0.807	-0.196
	(0.369)	(0.481)	(1.872)	(0.258)
Observations	75	76	76	75
R-squared	0.002	0.079	0.011	0.015

Notes: The independent variable, LS_j^{ini}, is the initial loan share, measured as the ratio of outstanding loans in industry j to total outstanding loans. The dependent variables are capital intensity in column (1), measured as one minus the ratio of the wage bill to value added; skill intensity in column (2), measured as the ratio of non-production workers to total employment; average wage in log in column (3); and the share of imported materials in total materials in column (4). All industry characteristics are measured at their 1998 levels using ASI data. In all specifications, observations are weighted by 1998 industry employment. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10, 5, and 1% levels, respectively.

Table A6: First-stage results

	(1)	(2)
Dependent variable	$lnTFP_i^{ini} \times TCS_{-jt}$	$lnTFP_i^{ini} \times IMPComp_{jt}$
$lnTFP_i^{ini} \times TCS_{-jt}^{IV}$	10.905***	2.723***
	(0.097)	(0.719)
$lnTFP_i^{ini} \times IMPComp_{jt}^{IV}$	0.064*	1.277
	(0.036)	(0.880)
Observations	24,447	24,447
Firm FE	Yes	Yes
Industry-Year FE	Yes	Yes
SW F-statistic	42.05	3.87

Notes: The dependent variables in columns (1) and (2) are the measure of trade-induced credit shocks and its interaction with firm initial productivity, respectively. The dependent variables in columns (3) and (4) are the measure of import competition and its interaction with firm initial productivity, respectively. All regressions include firm and four-digit industry-year fixed effects. Robust standard errors clustered at the four-digit industry level are reported in parentheses. *, **, and *** indicate significance at the 10, 5, and 1% levels, respectively.

Table A7: Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Alternate TFP	Alternate IMPComp	First Diff	One-year Lagged IDV	Market Share	Firm Characteristics	Cluster SE at Industry-Year
$lnTFP_i^{ini} \times TCS_{-jt}$	-0.067	-0.065***	-0.064***	-0.056***	-0.069***	-0.070***	-0.069***
	(0.042)	(0.015)	(0.011)	(0.021)	(0.017)	(0.016)	(0.013)
$lnTFP_i^{ini} \times IMPComp_{jt}$	-0.116	-0.022	0.003	-0.047	-0.019	-0.024	-0.019
	(0.096)	(0.029)	(0.009)	(0.043)	(0.029)	(0.029)	(0.024)
Observations	24,447	24,447	19,034	23,834	24,447	24,447	24,447
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Method	IV	IV	IV	IV	IV	IV	IV

Notes: The dependent variable is the logarithm of firm sales in columns (1), (2), (4), (6) and (7), is the first difference of log firm sales in column (3), and is the logarithm of market share in column (5). TCS is the measure of trade-induced credit shocks, as defined in equation (3). $lnTFP^{ini}$ is firm's initial productivity, estimated using the method of Ackerberg et al. (2015). $IMPComp$ is the measure of import competition, as defined in equation (2). Both TCS and $IMPComp$ have been standardized to have mean zero and standard deviation one. In column (1), I re-estimate TFP using the method of Levinsohn and Petrin (2003). In column (2), I use an alternative measure of import competition, in which Chinese imports are normalized by initial employment for each industry. In column (3), I estimate a first-difference version of the baseline specification. Column (4) uses one-year lagged independent variables. Column (5) uses the logarithm of market share as the outcome, which is measured as the ratio of firm sale to its four-digit industry sale. Column (6) controls for a set of firm characteristics by interacting each characteristic with TCS. Column (7) clusters standard errors at the industry-year level. All regressions include firm and four-digit industry-year fixed effects. Robust standard errors clustered at the four-digit industry level in columns (1) to (6) are reported in parentheses. *, **, and *** indicate significance at the 10, 5, and 1% levels, respectively.

Table A8: The relationship between productivity, tangibility, and borrowing inflows

	(1)	(2)	(3)
Dependent variable	Tangibility	$\ln(1 + \text{BorrowingInflow})$	$\text{asinh}(\text{BorrowingInflow})$
$\ln \text{TFP}_{it-1}$	-0.044***	0.101***	0.113***
	(0.005)	(0.038)	(0.041)
Observations	17,603	8,686	8,686
R^2	0.0161	0.0013	0.0014
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes

Notes: Firm-level data used in this table are sourced from the Centre for Monitoring the Indian Economy (CMIE) PROWESS database, covering the years 1998 to 2007. See Appendix C for details on data cleaning and working sample construction. TFP is estimated using Ackerberg et al. (2015) method. Tangibility is measured as the share of tangible assets (i.e., gross property, plant and equipment) to total assets. Borrowing inflow is cash inflow due to proceeds from total borrowings. Column (1) reports firm-level panel estimates of the relationship between productivity and tangibility with firm and year fixed effects, using one-year lagged TFP. Columns (2) and (3) report firm-level panel estimates of the relationship between productivity and borrowing inflows with firm and year fixed effects, using one-year lagged TFP. Robust standard errors are clustered at the firm level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A9: The relationship between productivity and internal funds across firm size and age groups

	(1)	(2)
Dependent variable	ln Profits	ln Profits
$lnTFP_{it-1}$	0.155***	0.179***
	(0.040)	(0.043)
$lnTFP_{it-1} \times Size_Bin_2$	0.048	
	(0.062)	
$lnTFP_{it-1} \times Size_Bin_3$	0.161**	
	(0.068)	
$lnTFP_{it-1} \times Age_Bin_2$		0.055
		(0.065)
$lnTFP_{it-1} \times Age_Bin_3$		0.056
		(0.065)
Observations	13,926	13,926
R^2	0.857	0.857
Firm FE	Yes	Yes
Industry-Year FE	Yes	Yes

Notes: The outcome variable in both columns is the logarithm of firm after-tax profits. TFP is estimated using Ackerberg et al. (2015) method. Firms are divided into three size groups based on terciles of initial physical assets and into three age groups based on terciles of firm age. $Size_Bin_2$ equals one for firms in the second size group and zero otherwise, while $Size_Bin_3$ equals one for firms in the third size group and zero otherwise. Similarly, Age_Bin_2 equals one for firms in the second age group and zero otherwise, while Age_Bin_3 equals one for firms in the third age group and zero otherwise. Robust standard errors are clustered at the firm level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

A.2 Figures

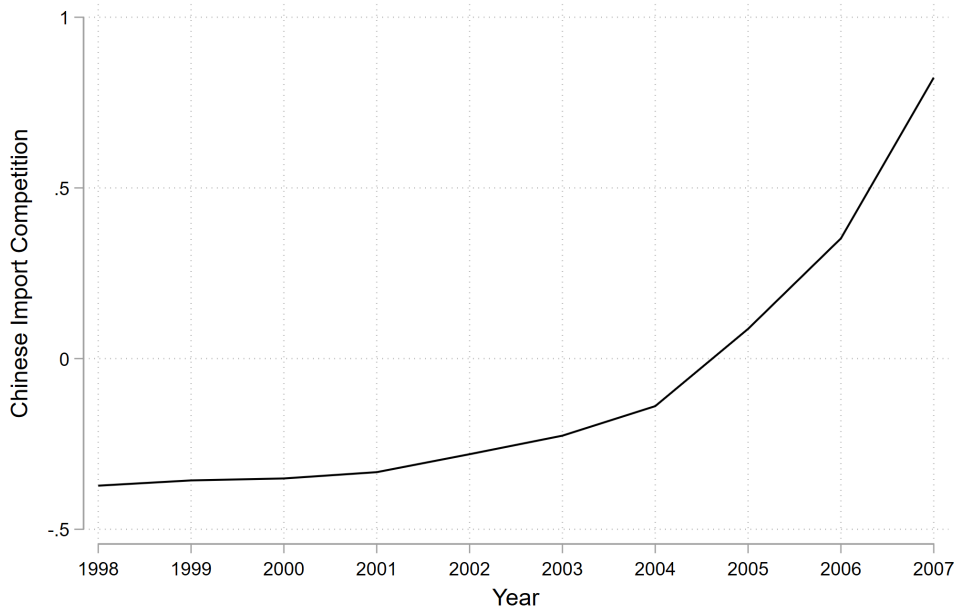


Figure A1: Trend in the Chinese import competition in India between 1998 and 2007

Notes: Import competition is measured as the ratio of Chinese imports to initial domestic absorption in India, as defined in equation (2). I first calculate import competition at the industry level and then plot the cross-industry average for each year over the sample period.

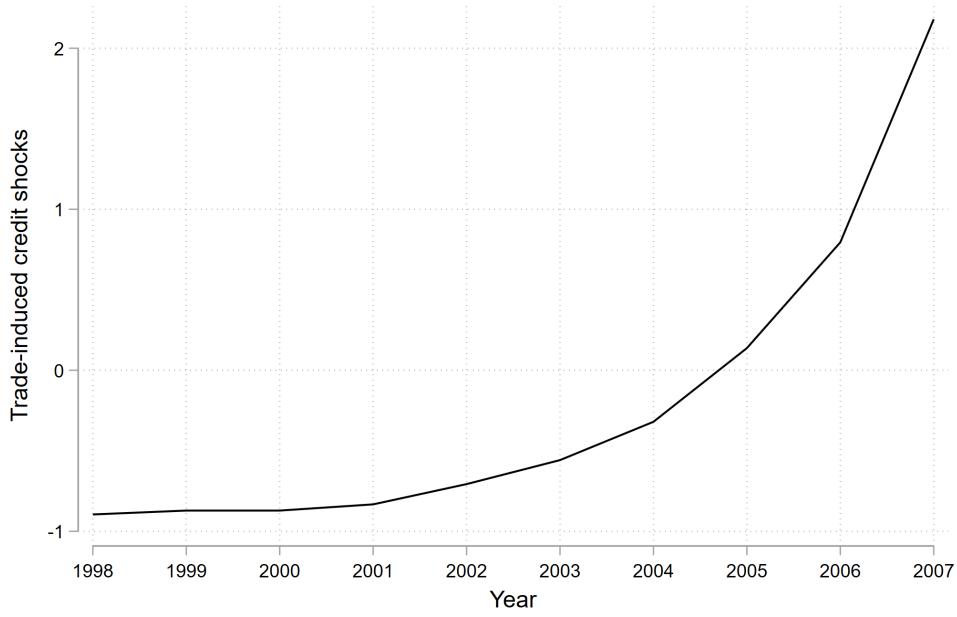


Figure A2: Trend in the trade-induced credit shocks in India between 1998 and 2007

Notes: Trade-induced credit shocks (TCS) are measured as the weighted average of exposure to Chinese import competition across industries, where the weights are given by each industry's share of total loans, as defined in equation (3). I first calculate TCS at the industry level and then plot the cross-industry average TCS for each year over the sample period.

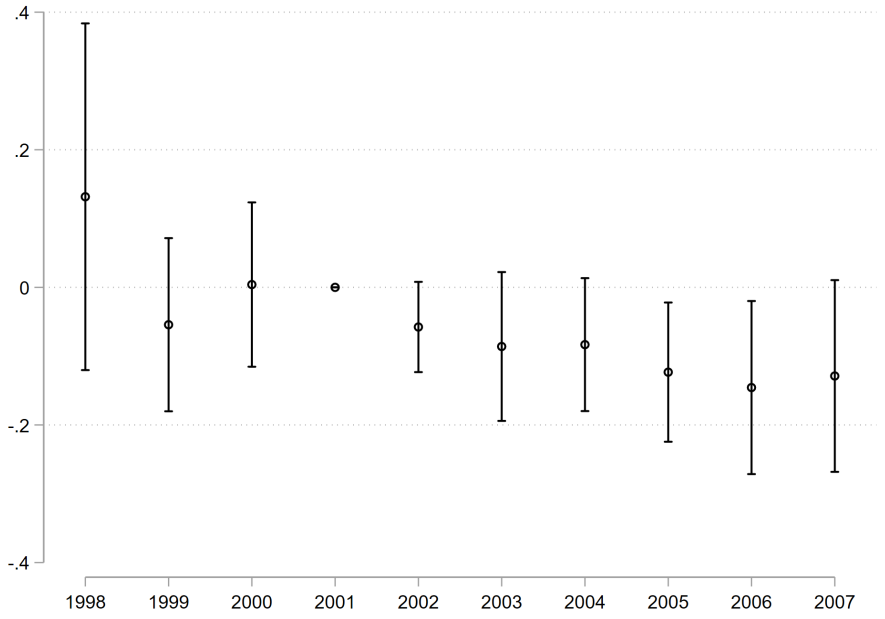
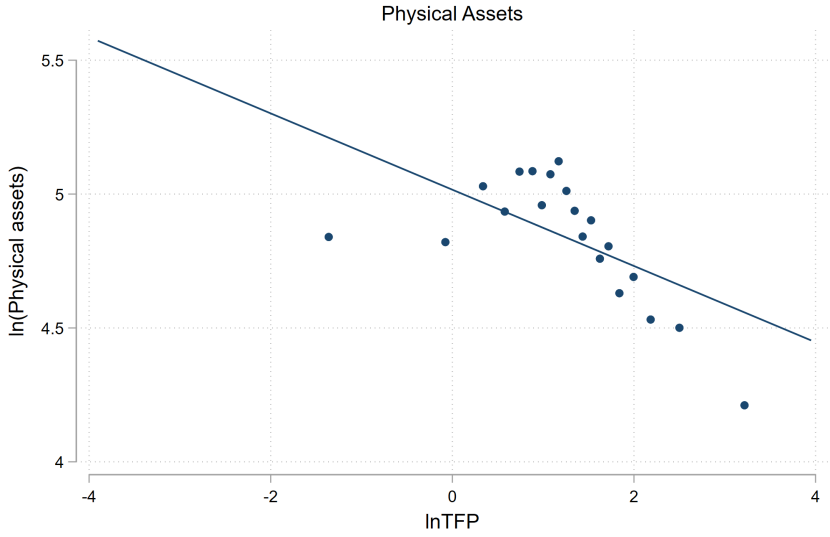
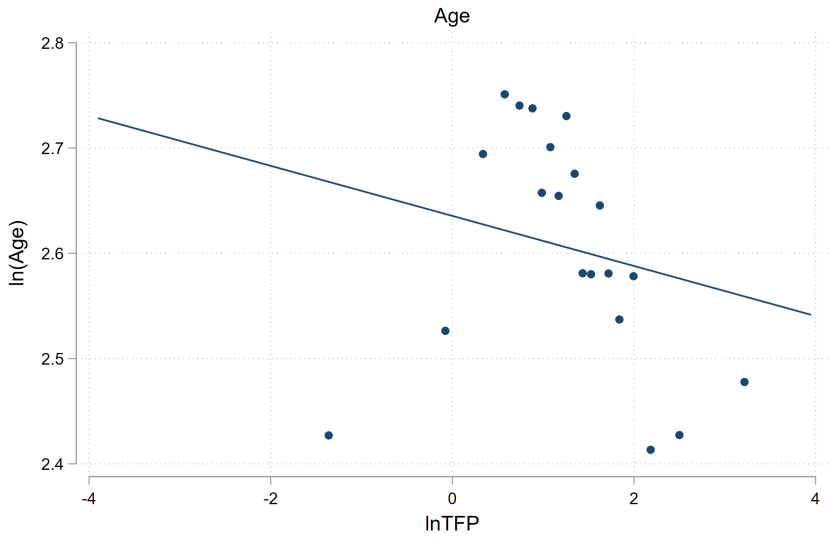


Figure A3: Event-study estimates of the heterogeneous impact of trade-induced credit shocks on firm sales

Notes: The figure reports the coefficients of the variable $lnTFP_i^{ini} \times TCS_High_j$ by year, with 95 percent confidence interval.



(a)



(b)

Figure A4: Binscatter plots of the relationship between firm productivity and physical assets and age.

Notes: Firm-level data used in this figure is sourced from the Centre for Monitoring the Indian Economy (CMIE) PROWESS database, covering years between 1998 and 2007. See Appendix C for details on data cleaning and working sample construction. Firms' initial-year observations are used in plotting. TFP is estimated using Ackerberg et al. (2015) method.

B Model Appendix

B.1 Solution to the bank's problem

The representative bank selects the allocation of loans across borrowers to maximize profit net of lending costs, subject to the capital constraint. The bank's optimization problem is

$$\begin{aligned} &\max_{B_i} \sum_i [rB_i - f(B_i, a_i)] \\ &s.t. \qquad \sum_i B_i \leq K. \end{aligned} \tag{B1}$$

The Lagrangian associated with the above problem is given by

$$\mathcal{L} = \sum_i [rB_i - f(B_i, a_i)] + \lambda \left(K - \sum_i B_i \right),$$

where λ denotes Lagrange multiplier.

The first-order conditions (FOCs) for the above problem with respect to B_i and λ are given by

$$a(t_i, z_i)B_i = r - \lambda,$$

and

$$\sum_i B_i = K.$$

Combining the FOCs gives the solution for λ and the optimal loan supply B_i as follows:

$$\lambda = r - \frac{K}{A},$$

where $A = \sum_i \frac{1}{a(t_i, z_i)}$. And,

$$B_i = \frac{K}{A}\frac{1}{a(t_i, z_i)}.$$

B.2 Solution to the firm's problem

Given the financial constraint, the firm's profit maximization problem is

$$\begin{aligned} \pi(K,z) &= \max_l (zl)^{\frac{\sigma-1}{\sigma}} - wl - rB(K,z) \\ s.t. \qquad & wl \leq I(z) + B(K,z). \end{aligned} \tag{B2}$$

The corresponding Lagrangian is

$$\mathcal{L} = (zl)^{\frac{\sigma-1}{\sigma}} - wl - rB(K,z) + \mu\left(I(z) + B(K,z) - wl\right),$$

where μ denotes Lagrange multiplier.

The FOC with respect to l gives

$$\alpha z^{\alpha} l^{\alpha-1} = (1+\mu)w,$$

$$l = \left(\frac{\alpha z^{\alpha}}{(1+\mu)w}\right)^{\frac{1}{1-\alpha}},$$

where $\alpha = \frac{\sigma-1}{\sigma} \in (0,1)$.

The FOC with respect to μ gives

$$wl = I(z) + B(K,z).$$

Substituting the optimal labor demand into the financial constraint gives

$$\mu = \alpha w^{-\alpha} z^{\alpha} (I(z) + B(K,z))^{\alpha-1} - 1.$$

Substituting μ into the FOC with respect to l gives the optimal labor demand as

$$l^* = \frac{I(z) + B(K, z)}{w}.$$

Thus, optimal sales are given by

$$s^* = (zl^*)^\alpha = \left(z \frac{I(z) + B(K, z)}{w} \right)^\alpha.$$

B.3 Derivation of the cross-partial derivative of firm sales

The logarithm of optimal sales is given by[31]

$$\ln s^* = \alpha \ln z + \alpha \ln(I(z) + B(K, z)) - \alpha \ln w.$$

The first derivative of $\ln s^*$ with respect to K is given by

$$\frac{\partial \ln s^*}{\partial K} = \alpha \frac{B_K}{I + B},$$

where $B_K = \frac{\partial B_i}{\partial K}$. To characterize heterogeneity in the impact of bank capital shocks on firm sales, differentiating $\frac{\partial \ln s^*}{\partial K}$ with respect to productivity z gives

$$\frac{\partial^2 \ln s^*}{\partial K \, \partial z} = \alpha \frac{B_{Kz}(I + B) - B_K(I_z + B_z)}{(I + B)^2}, \tag{B3}$$

where $B_{Kz} = \frac{\partial B_K}{\partial z}$. Based on loan supply equation (10),

$$B_K = \frac{\partial B_i}{\partial K} = \frac{1}{Aa(t_i, z_i)} = \frac{B}{K},$$

[31] Examining the impact on the logarithm of firm's optimal sales removes scale effects. Firms with higher productivity have higher sales in levels and therefore naturally experience larger absolute changes in sales for a given change in loan supply. Using the logarithm instead focuses on percentage changes in sales, which are more informative for understanding the heterogeneous effects of bank capital shocks and are also consistent with the outcome variable used in the empirical analysis.

$$B_{Kz} = \frac{\partial B_K}{\partial z} = \frac{B_z}{K}.$$

Plugging B_K and B_{Kz} from above equations into the cross-partial derivative (B3) gives

$$\begin{aligned} \frac{\partial^2 \ln s^*}{\partial K \, \partial z} &= \alpha \frac{\frac{B_z}{K}(I+B) - \frac{B}{K}(I_z + B_z)}{(I+B)^2} \\ &= \alpha \frac{B_z I - B I_z}{K(I+B)^2} \\ &= \alpha \frac{BI}{K(I+B)^2} \left(\frac{B_z}{B} - \frac{I_z}{I} \right). \end{aligned} \tag{B4}$$

C Data Cleaning and Sample Construction

C.1 Firm-level data

I construct firm-level sample from *Standalone Annual Financial Statements* dataset in the PROWESS database. I merge this dataset with the *Identity* dataset using a unique firm identifier to obtain firm's NIC codes. As all industry-level variables are constructed at four-digit NIC level, I drop firms with reported NIC codes less than four digits.

The year indicator in the database is reported in the YYYYMMDD format. For example, if a company's financial statements cover the period from 1 April 2004 to 31 March 2005, the recorded date is 20050331. Given that most Indian firms end their financial year on March 31, I retain only those firms whose reporting period ends on March 31 and spans a full 12 months to ensure consistency across firms and over time. I use data for the years 1998 to 2007.

I conduct cleaning for the main financial variables used in the estimation of firm productivity, including sales of goods, salaries, raw-material expenditure, and net fixed asset. I linearly interpolate observations that are missing or non-positive when valid positive observations are available in both the preceding and following year. Specifically, an observation is interpolated only when it lies exactly one year between two consecutive valid firm-year observations, with the interpolated value equal to the arithmetic mean of the two neighboring observations. Finally, I drop observations for which these variables remain missing or non-positive after interpolation. This procedure ensures that the final sample contains economically meaningful, positive values for the key variables used in the subsequent estimation and analysis.

C.2 Industry-level data

I obtain data on industry-level outstanding loans from the 1998-99 Annual Survey of Industries (ASI). I begin with the ASI *working capital and loans* module and retain ob-

servations corresponding to the closing value of outstanding loans. I then merge these observations with the ASI *identification* module using the establishment identifier to obtain the survey sampling weights and industry classification 1998 NIC system, which I convert to four-digit NIC 2008 system. This allows the 1998-99 loan measures to be consistently matched with the industry classification used in the analysis. I then aggregate establishment-level outstanding loans to the four-digit industry level using the ASI sampling weights.

Trade data from WITS and domestic production data from UNIDO are in thousands of US dollars and are at the industry level, classified according to ISIC Revision 3.1, which I map to the 4-digit NIC 2008 classification.

Merging industry-level data with firm-level data using four-digit NIC codes and year, I obtain the final working sample with 24,473 firm-year observations for more than 4,400 firms in 76 four-digit NIC industries over the period 1998-2007.