Trade Shocks and Credit Reallocation

Stefano Federico*, Fadi Hassan†, Veronica Rappoport‡

December 2023

Abstract

This paper identifies a credit-supply contraction that arises endogenously after trade liberalization. Banks with loan portfolios concentrated in sectors exposed to competition from China face an increase in non-performing loans after China's entry into the World Trade Organization. As a result, they reduce the supply of credit to firms, irrespective of the firm's sector of operation. This cut in credit translates into lower employment, investment, and output. Through this mechanism, the financial channel amplifies the shock to firms already hit by import competition from China and passes it on to firms in sectors expected to expand upon trade liberalization.

*Bank of Italy

†Bank of Italy, CEP, and CEPR

‡London School of Economics, CEP, and CEPR

We thank Rodrigo Adao, Pol Antras, David Atkin, David Autor, Francesco Caselli, Gabriel Chodorow-Reich, Federico Cingano, Stefania Garetto, Nicola Gennaioli, Tarek Hassan, Elhanan Helpman, Killian Huber, Asim Khwaja, Matteo Maggiori, Atif Mian, Claudio Michelacci, Eduardo Morales, Holger Mueller, Melina Paopoutsi, Matteo Piazza, Thomas Philippon, Kadee Russ, Fabiano Schivardi, Andrei Shleifer, Amir Sufi, and Jeremy Stein for very insightful comments and discussions. We thank also seminar participants at Harvard, MIT, Boston College, Duke, NYU-Stern, LSE, EIEF, Barcelona Summer Forum, NBER ITI, Berkeley-PIIE Trade&Macro Forum, and HEC Finance Spring Conference. The opinions expressed and arguments employed herein are those of the authors and do not reflect the official views of the Bank of Italy.

1 Introduction

Trade liberalization has heterogeneous effects across economic sectors and, correspondingly, across regions or factors of production according to their exposure to affected economic activities.[1] In this paper, we show commercial banks are also exposed to trade shocks, based on the concentration of their loan portfolios in distinct activities. As a result, a liberalization episode triggers a lending-channel response. Firms related to more exposed banks suffer credit tightening, with consequences on employment and investment that go beyond the direct effect of the rise in import competition.

The originating trade shock in our analysis is the entry of China into the World Trade Organization (WTO). In Italy, the share of imports from China more than doubled between 2002 and 2007 (Figure 1a); sectors most exposed to import competition from China suffered a 12% decline in employment during that period, while the other sectors remained unaffected (Figure 1b). At the same time, non-performing loans (NPLs) almost doubled among firms competing with imports from China, from €3.4 billion to €6 billion. This increase was large enough to erode banks' capital, which was €56 billion for the whole banking system at the onset of the shock. As a result, banks more exposed to these highly-hit sectors cut their supply of credit to firms negatively affected by import competition from China and to firms in non-competing sectors. In this way, banks amplified the effect of the liberalization shock to highly-hit sectors and transmitted the negative effect toward sectors expected to expand.

Our analysis starts by measuring, for each sector of economic activity, the rise in imports per worker from China, along the lines of Autor et al. (2013). We then compute bank exposure to the China shock by looking at the share of loans to firms across sectors that are heterogeneously hit by the trade shock. To do so, we rely on the credit registry data for Italy and match it to the universe of banks and incorporated firms between 1998 and 2007.

Banks in our sample are specialized in economic activities along the lines described

[1] See, among others, Topalova (2010), Menezes-Filho and Muendler (2011), Autor et al. (2013), Kovak (2013), Dix-Carneiro (2014), Autor et al. (2014), Acemoglu et al. (2016), Hakobyan and McLaren (2016), Dix-Carneiro and Kovak (2017), Utar (2018).

by Paravisini et al. (2023). Banks' balance sheets are therefore affected when their main sectors of lending suffer a negative shock. We find a one-standard-deviation higher bank exposure to the trade shock is associated with a 0.3-percentage-point (pp) increase in the NPL share relative to banks' assets. This effect is sizable given that the NPL ratio for the median bank in those years is 1.4%. Importantly, we do not observe any reaction in deposits or external capital injections. This lack of reaction coincides with the predictions of classical banking models as in Froot et al. (1993), Holmstrom and Tirole (1997), Froot and Stein (1998), and Deyoung et al. (2015). In such frameworks, banks' losses cannot be immediately restored, due to costs in raising external capital, and they lead to a contraction in credit supply, as we observe in our setting.

We analyze the patterns of credit supply before and after China's entry into the WTO, across banks with different degrees of exposure to negatively affected sectors. To establish the causal effect of bank exposure on credit supply, we use the Khwaja and Mian (2008) within-firm estimator. The firm-time fixed effects absorb any firm-wide innovation that equally affects credit by all related banks, for example, firm-wide changes in credit demand due to the China trade shock itself. We find that one standard deviation of bank exposure implies 7.4% lower credit supply and a 0.5 pp higher interest rate after 2002, relative to other banks lending to the same firm. This effect diminishes with the ex-ante level of bank capitalization, which we interpret as a (inverse) measure of tightness of their lending capacity. Linearly extrapolating this heterogeneous effect, our results suggest that the increase in NPLs triggered by the China trade shock is decoupled from their lending capacity for banks with a tier-1 capital ratio above 14%. These banks, however, only account for less than 5% of total corporate credit.

Bank specialization in lending is not complete, which results in spillovers between borrowers operating in different industries. We find more exposed banks cut credit by a similar proportion both to firms subject to competition from China and to firms in sectors not directly affected by the trade shock. They also reduce credit supply to potential winners of the liberalization episode, that is, firms in sectors where Italy has a comparative advantage, highly productive firms, and even those that are more likely to benefit from cheaper inputs from China (downstream industries).

We follow the effect of this newly identified financial channel on firms' outcomes. First, we compare total credit of firms that, prior to 2001, borrowed from exposed banks, with total credit of firms in the same 4-digit sector borrowing from less constrained sources. A firm with 10% higher exposure to this liberalization-triggered financial channel had 6% lower credit. In line with previous literature, we therefore conclude, firms cannot easily substitute across sources of funding in the aftermath of a credit-supply shock.

Second, we estimate how this credit shock affected firms' real outcomes. On average, 10% higher exposure to the financial channel resulted in about 4%-6% lower employment, investment, and revenue growth, relative to other firms in the same sector borrowing from less exposed banks, with a substantially higher impact among firms in manufacturing sectors that overlap with the rise in imports from China: for these firms, a 10% higher exposure resulted in 10% lower employment growth, and, for investment and revenue growth, these figures increase to 11% and 12% respectively.

To account for both, the sensitivity of firms in different sectors to the credit shock and their dependence on exposed banks, we follow Chodorow-Reich (2014) and compute a *Partial Equilibrium Aggregation*. Without accounting for general-equilibrium responses, we measure the direct impact of the lending channel on employment. In sectors already hit by import competition, the growth rate of employment between 2002 and 2007 could have been 2.9 pp higher if the bank lending channel were not binding, namely, 80,000 job losses, almost one fourth of the overall jobs losses in these sectors. Exposed banks also transmitted the shock to services and manufacturing sectors not competing with imports from China. In those sectors, employment growth, which was positive in the aftermath of the trade shock, would have been 1.3 pp higher absent credit restrictions.

We also explore the geographical dimension of the bank lending channel.[2] Using information on the location and size of firms, we estimate the geographical concentration of sectors most hit by the increase in imports. We find our results apply across provinces, including those with lower exposure to the shock. This finding suggests the endogenous

[2]This is related to the literature on geographical transmission of liquidity shocks. See, among others, Allen and Gale (2000), Kaminsky and Reinhart (2000), Gilje et al. (2016), Cortés and Strahan (2017), Byun et al. (2021), and Bustos et al. (2020). Giroud and Mueller (2019) study how firms' internal networks propagate shocks across counties.

credit contraction by exposed banks, triggered by the increase in imports from China, propagated nationally, affecting firms beyond any potential local general-equilibrium effect on labor or non-tradables markets. Although, due to mobility frictions, labor market effects tend to be localized (see, e.g., Autor et al. 2013 and Hakobyan and McLaren 2016), the bank credit-channel is nationally diffused because banks operate in multiple regions.

This paper contributes to different strands of the literature. First, it is linked to the core question of how the economy adjusts to trade shocks. This literature has largely focused on the (slow) reallocation of workers across sectors.[3] Evidence on capital reallocation after trade shocks is limited, even though, as Dix-Carneiro (2014) argues, quantifying the mobility of capital and its interaction with labor-mobility frictions is essential to understanding the full transitional dynamics of the economy after a trade shock. Notable exceptions are Antràs and Caballero (2009), who focus on the effects of a trade shock on international capital flows across countries, Lanteri et al. (2019), who examine the reallocation of machines and physical capital in Peru in the aftermath of China's entry into the WTO, and Mayordomo and Rachedi (2019), who look at the effect of the China shock on Spanish banks.

Finally, our paper is also related to the literature on the financial and real implications of shocks to banks.[4] In this literature, the identification strategy largely relies on shocks that directly affect the financial sector. Instead, the shock to banks in our analysis comes from the performance of firms in the real sector. This finding allows us to learn not only about the consequences of the trade shock under study, but also about how real shocks spread into the general economy.

The rest of the paper is structured as follows. Section 2 describes the data; section 3 analyzes the effect of the liberalization shock on banks' credit supply; section 4 estimates the effect of these credit restrictions on firms' output, investment, and employment; section 5 focuses on the mechanism behind our findings; section 6 discusses alternative mecha-

[3]See, among others, Menezes-Filho and Muendler (2011), Autor et al. (2014), Acemoglu et al. (2016), Dix-Carneiro (2014), and Utar (2018); or across regions in Aghion et al. (2008), Topalova (2010), Autor et al. (2013), Kovak (2013), Hakobyan and McLaren (2016), and Dix-Carneiro and Kovak (2017).

[4]See, among others, Rosengren and Peek (2000), Gan (2007), Khwaja and Mian (2008), Paravisini (2008), Amiti and Weinstein (2011), Schnabl (2012), Chodorow-Reich (2014), Paravisini et al. (2015), Baskaya and Kalemli-Ozcan (2016), Cingano et al. (2016), Huber (2018), Amiti and Weinstein (2018), Jiménez et al. (2020), Martín et al. (2021).

nisms and the robustness of our results. Finally, section 7 concludes.

2 Data and Measurement

2.1 Data sources

Our analysis is based on a matched bank-firm dataset containing loans for a large sample of Italian companies. We obtain the final dataset by combining four sources: credit registry, banks' balance-sheet data, firms' balance-sheet data, and world bilateral imports by product.

The first source is the Italian Credit Register administered by the Bank of Italy, which contains a monthly panel of the outstanding debt of every borrower (firms or individuals) with loans above €75,000 with each bank operating in Italy. We focus on corporate borrowers and build an annual bank-firm panel, where loans are measured as the outstanding credit (committed credit lines and fixed-term loans) granted at the end of a given year.

Banks' balance-sheet data are from the Bank of Italy Supervisory reports, which provide detailed data on banks' assets and liabilities. Firms' balance-sheet data (including variables such as revenues, investment, employment, and wage bill) are taken from the CERVED database, which covers the universe of incorporated firms in Italy.[5] We match the bank-firm loan data to banks' and firms' balance-sheet data, using unique bank and firm identifiers, respectively.

Finally, we use data from the UN Comtrade Database on imports from China at the 6-digit Harmonized System (HS) product level for Italy and other advanced economies.[6] We convert the product classification to the more aggregate NACE 4-digit, using concordance tables provided by Eurostat. This information is needed to identify the exposure of firms and banks (via their loan portfolio) to the China shock (see subsection 2.2).

[5]Incorporated firms from CERVED account for 70% of value added in manufacturing and services from national accounts, and the trend follows the national one closely.

[6]We take the countries in the original paper of Autor et al. (2013): US, Australia, Denmark, Finland, France, Germany, Japan, New Zealand, Switzerland, and Spain. We focus on the extra-European countries for our baseline instrument.

Table 1 shows the summary statistics of bank and firm characteristics in our sample. The unit of observation in our empirical analysis is at the bank-firm annual level. The dataset includes, on average, 504 banks and about 170,000 firms, of which 70,000 are in manufacturing.[7] Italian firms usually borrow from multiple banks, even small firms (Detragiache et al., 2000). About 68% of firms in our sample borrow from two or more banks (75% in manufacturing), and these firms account for 90% of total credit and 84% of employment. The average number of banking relationships for firms with multiple lenders is 4.5. As we discuss in the following sections, we use the fact that firms borrow from multiple banks in our identification strategy.

2.2 Defining firm and bank exposure to the China shock

For our empirical strategy, we first need to identify firms' direct exposure to the increase in import competition from China. We closely follow Autor et al. (2013) in their empirical strategy and compute the following sector-level (4-digit) measure of exposure to the China shock[8]:

$$China_s^{IT} = \frac{\Delta M_s^{IT-CH}}{L_{s,1991}^{IT}}. \tag{1}$$

The numerator is the difference in Italy's imports from China in a given 4-digit NACE sector s between the years before and after China's entry to WTO (2002-2007 average vs. 1994-2001 average).[9] The denominator corresponds to the employment level in the same sector in 1991.[10] According to this measure, the five sectors with the highest exposure to the China shock are "Coke oven products," "Watches and clocks," "Television and radio receivers," "Games and toys," and "Other organic basic chemicals." The least exposed sectors are instead "Aircraft and spacecraft," "Carpets and rugs," "Beer", "Sugar," and "Distilled alcoholic beverages." Figure 2a shows the distribution of exposure to China

[7] We consolidate all bank-level variables and firm-bank credit at the banking group level and, as it is standard in the literature, we account for mergers and acquisitions by taking the 2007 groups' structure and build it back to 1998 (i.e., if bank 1 and bank 2 merged in 2003, they are treated as one bank since 1998).

[8] We exclude the oil and energy sectors, which are more volatile and subject to global fluctuations. If we include those sectors, all results hold.

[9] The results are robust to using the difference in imports between 1994 and 2007.

[10] We take the year 1991 because it is the one with census data. The alternative census year would be 2001, but employment figures are less likely exogenous to the increase in imports from China.

by sector, with its median cutoff. Manufacturing sectors above and below the median account for an equal share of total credit and employment in year 1991.

This sectoral measure of exposure is then applied to firms according to their reported main economic activity. Then, for each bank b (and firm i), we measure its exposure to the China shock as the weighted average of its borrowers' exposure (where the weights are given by the borrowers' share of loans in the bank's portfolio), leaving out firm i:[11]

$$Exposure^{IT}_{-ib} = \frac{\sum\limits_{i' \neq i} C_{i'b} China^{IT}_{i's}}{\sum\limits_{i' \neq i} C_{i'b}} \tag{2}$$

where C_{ib} is the outstanding credit of bank b to a manufacturing firm i, and, abusing notation, $China^{IT}_{is}$ corresponds to the measure of exposure defined in (1) for the main sector of activity of firm i.

The results are robust to alternative definitions of firm and bank exposure to the shock.[12] To attenuate endogeneity issues and possible portfolio adjustments by banks in anticipation of China's entrance into the WTO, we measure banks' exposure, averaging the shares over the years 1998-1999. We prefer to average our measure of bank exposure over multiple years rather than a single year (e.g., 1998), so we avoid some bias that may arise from a year-specific shock at the beginning of the period.[13]

Figure 2b shows the distribution of this measure across banks. Banks in the top quartile of the distribution account for more than 80% of total credit. Whereas the overall credit to firms in sectors with above-median exposure to competition from China amounted to €184 billion at the onset of the shock (14% of GDP).

A standard concern is that Italy's imports from China might capture not only a pure "China supply" effect, but also shocks to Italian demand for imports. In addition, mea-

[11]To avoid endogeneity with the dependent variable, this measure is constructed leaving out firm i. In our sample, credit to firm i is typically too small to affect the aggregate bank exposure: the median firm accounts for 0.001% of bank credit. As a robustness check, in the Appendix, we also present the results when leaving out also the firm's entire sector.

[12]As a robustness check, in the Appendix, we measure bank exposure relative to bank total assets.

[13]We start from 1998 because it is the first year with data on banks' balance sheet in our sample. Our results are robust to including the year 2000 to compute banks' portfolio shares; results available upon request.

surement issues might exist, because this measure does not account for Italian exports being affected by China supply factors (e.g., Italian exports to Germany that are now substituted by Chinese exports to Germany). Following Autor et al. (2013), we instrument the trade shock using the variation in imports from China to a set of advanced economies outside Europe (ΔM_s^{OC}). Specifically, we compute an industry-level measure of exposure to the China shock based on imports from China to a group of "other countries" ($China_s^{OC}$)[14]:

$$China_s^{OC} = \frac{\Delta M_s^{OC-CH}}{L_{s,1991}^{IT}}. \tag{3}$$

This instrumental approach aims to recover supply-side determinants of imports from China, rather than Italian local factors. The motivation for this instrument is that high-income economies are similarly exposed to growth in imports from China that is driven by Chinese supply shocks. However, the instrument relies on two key underlying assumptions: (i) Industry demand shocks should be uncorrelated across countries and (ii) demand shocks from Italy do not trigger increasing returns to scale in Chinese manufacturing and do not induce them to export more to other high-income countries.

We then compute a measure of bank exposure that is exogenous to demand developments in Italy or Europe ($Exposure_{-ib}^{OC}$) and can therefore be used as an instrument in our estimation strategy. Moreover, this measure is also exogenous to Italian banks' supply of credit. In fact, although, in principle, bank credit in Italy can affect Italian imports from China, it has little effect on imports to the US from China:

$$Exposure_{-ib}^{OC} = \frac{\sum_{i' \neq i} C_{i'b}\, China_{i's}^{OC}}{\sum_{i' \neq i} C_{i'b}}. \tag{4}$$

Our measure of bank exposure focuses on the negative impact of China's entry into the WTO on firms in sectors *directly* hit by import competition. As a robustness check, we compute a measure of bank exposure that also considers the sectors that are *indirectly*

[14] The countries in the baseline regression are the US, Australia, Japan, and New Zealand (the extra-European countries in Autor et al. (2013)). Results (shown in the appendix) are robust to the inclusion of European countries, as well as to using only Australia, Japan, and New Zealand or the US separately.

hit through input-output linkages, namely, the sectors that sell inputs to the directly hit sectors.

Although the aggregate evolution of exports does not present a clear break around the time of China's entry into the WTO (Figure 1a), some sectors and firms may have benefited from the liberalization episode. We exploit this heterogeneity in the next section to show banks' exposure to import competition negatively affected credit supply to these potentially expanding sectors.

3 Trade Shock and Bank's Credit Supply

In this section, we investigate the evolution of credit supply by banks that were relatively more exposed to the trade shock. We establish that banks suffering from this shock ended up restricting their supply of credit. We then analyze how these banks adjusted credit across sectors heterogeneously exposed to import competition from China.

3.1 Methodology

Figure 3a compares the trends in aggregate lending to Italian companies between high-exposed banks (red dashed line) and low-exposed banks (blue continuous line). We select a threshold of banks' exposure so that each of the two groups accounts for half of the outstanding credit, and we use the non-leave-out version of equation (2). The two time series for aggregate credit are indexed to 100 at the end of 2001. Although lending growth was initially very similar across the two groups of banks, since 2002, the two trends start diverging: lending by banks that were more exposed to the China shock grew significantly less than lending by less exposed banks. This diverging pattern can be the result of both supply and demand factors, because firms subject to competition from China may shrink and demand less credit, driving the aggregate pattern of more exposed banks. Therefore, Figure 3b further disaggregates lending by the two groups of banks according to borrowers characteristics. In particular, we distinguish between firms operating in manufacturing sectors above the median of exposure to import competition from China (High-Hit) and firms in manufacturing sectors of exposure below the median (Low-Hit) and in Services. In this way, we can compare the lending patterns across banks with firms with a similar evolution of credit demand. The figure shows lending of highly exposed banks grew more slowly than lending of low-exposed banks for both groups of firms.

To formally establish the causal effect of bank exposure on credit supply, we use the Khwaja and Mian (2008) within-firm estimator. The results are driven by multi-bank firms, for which we can compare changes in credit across banks, for the same firm. As mentioned earlier, firms that borrow from multiple banks account for the bulk of total credit. For each bank-firm-year observation, our baseline specification is

$$\ln C_{ibt} = \beta_1 \, Exposure^{IT}_{-i,b} \times Post_t + \beta_2 \, Spec_{ibt} \times Post_t + \boldsymbol{X_b'}\boldsymbol{\delta} \times Post_t + \alpha_{it} + \gamma_{ib} + \epsilon_{ibt}. \quad (5)$$

The dependent variable is the log of outstanding credit, C_{ibt}, granted by bank b to firm i at the end of year t. Our variable of interest is $Exposure^{IT}_{-i,b}$, the ex-ante exposure of banks to borrowers competing with imports from China, instrumented with $Exposure^{OC}_{-i,b}$, defined using the imports from China into other non-European developed countries (equation (4)). The interaction dummy $Post_t$ is equal to 1 for the years after China's entry into the WTO (2002-2007), and 0 for the earlier years (1998-2001).

$\boldsymbol{X_b}$ is a vector of control variables (1998-1999 averages) of key bank attributes, interacted with a post-period dummy: the log-assets as a proxy of bank size; the share of NPLs, which captures bank performance and management; bank core liabilities, which control for the funding structure of the bank; and the capital ratio, which controls for the degree of bank leverage. We include a set of firm-bank fixed effects (γ_{ib}) that control for potential non-random matching between firms and banks and all time-invariant factors that may affect the loan level for any bank-firm pair. Finally, we add firm-year fixed-effects (α_{it}) that capture any shock that hits firm credit in year t across all related banks, including the changes in import competition from China. Given that our source of variation is at the bank level and the original China shock is defined at the sectoral level, we cluster the standard errors at the bank-sector level.[15] In the baseline specification, the observations

[15] As a robustness check, in the Appendix, we report shift-share instrumental variable coefficients, where standard errors are obtained from equivalent industry-level regressions (as in Borusyak et al., 2021). We

are unweighted.[16]

Our empirical strategy identifies credit-supply shocks under the assumption that within-firm changes in credit demand across banks are uncorrelated with the banks' exposure to the China shock. This assumption would be violated, for example, if firms reduce credit demand disproportionately for banks specialized in sectors competing with China. To account for that possibility, we add a specialization dummy (interacted with $Post_t$) as in Paravisini et al. (2023) that takes the value of 1 if a bank is specialized in the sector of the firm.[17]

Our identification strategy is based on the exogeneity of the industry-level increases in Chinese exports, conditional on the above-mentioned set of controls (i.e., the *shifts* in the *shift-share* instrument). Following Borusyak et al. (2021), we test this assumption by regressing selected pre-shock bank balance-sheet and borrower characteristics on the (non-leave-out version of the) shift-share instrument. The results are reported in Figure 4. We find no statistically significant relationships, with just a few exceptions: exposed banks are relatively larger (total assets is therefore included in the vector $\boldsymbol{X_b}$) and have a larger share of credit to firms, but with fewer NPLs and provisions before the shock. Reassuringly, the borrower characteristics are not significantly correlated with the instrument.[18]

3.2 Banks' credit supply

Table 2 reports the OLS (column 1) and 2SLS (column 2) results.[19] The coefficient of interest on bank exposure is statistically and quantitatively significant: a bank with a one-standard-deviation-higher exposure reduces credit supply by 7.4% after China's entrance

also present the results of a specification in which the definition of bank exposure does not include the firm's sector of operation.

[16]To address concerns of auto-correlation (see Bertrand et al., 2004), we show in the Appendix the estimation of equation (5) in first difference, taking the average of the pre- and post- period for the variables of interest. As a robustness, in the Appendix, we also show a specification with observations weighted by firms' employment.

[17]A bank is considered specialized in one sector if its share of loans in that sector is above the sum of the 75th percentile threshold and 1.5 the interquartile range across banks for a given sector-year.

[18]Figure A.4 reports the results of balancing tests on additional bank characteristics.

[19]In the Appendix, we show the results with different sets of controls and fixed effects.

into the WTO relative to other banks lending to the same firm. The comparison between the coefficient on OLS and that on 2SLS suggests demand factors explain little of the overall change in Italian imports from China, or at least its effect on bank credit. We show in the Appendix that the OLS bias is consistent with supply-driven factors explaining most of the volatility of Italian imports from China across sectors (weighted by banks' loans).

Columns (3) and (4) present the same specification using a different dependent variable: the interest rate bank b charges firm i in year t.[20] Only a subset of banks are required to report these data (130 banks, which account for 70% of total credit), resulting in a lower number of observations. Consistent with the results on credit amount (columns 1 and 2), we find banks more exposed to the China shock increased the interest rate relative to less exposed banks, for the same firm. A bank with a one-standard-deviation-higher exposure increased the price of credit by 0.5 pp after China entrance into the WTO, out of an average interest rate of 7% across firms in the post-2002 period.

Next, we exploit the panel structure of the data and estimate our coefficient of interest by year. This dynamic difference-in-differences (diff-in-diffs) estimator is plotted in Figure 5 for the full sample (panel a), for firms in low-hit sectors and services and for firms in high-hit sectors (panels b and c, respectively). We verify that credit supply by banks heterogeneous in their level of exposure did not show different pre-trends prior to the trade-liberalization episode. If anything, for high-hit sectors, 2001 represented a break in an upward trend (although not statistically different from zero). The decline in credit supply started after China's entrance into the WTO and plateaued around 2005. Unfortunately, we cannot test for the long-term effects of exposure on credit, because the global financial crisis hit banks in 2008.

3.3 Heterogeneous effects across firms

The China shock analyzed here is both a sectoral and, given its magnitude, macroeconomic shock. As predicted by a classic Heckscher-Ohlin or Ricardian framework, absent frictions in the reallocation of factors of production, firms not directly hit by the trade

[20] The interest rate is computed as the overall interests and fees payments from firm i to bank b (across all credit lines) relative to the overall amount of outstanding credit.

shock are expected to expand upon the liberalization episode. By analyzing the heterogeneous effect of bank credit supply across firms that are expected to expand and those most negatively hit expected to contract, we learn about whether exposed banks rebalanced their supply of credit away from sectors most hit by the trade shock.

To this end, we expand equation (5) with an interaction indicator dummy D_g for firms belonging to different economic sectors: high-hit and low-hit manufacturing (defined relative to the median exposure to competition from China in equation 1) and Services[21,22]:

$$\ln C_{ibt} = \sum_g \beta_g\, D_g \times\, Exposure^{IT}_{-i,b} \times Post_t + \beta_2\, Spec_{ibt} \times Post_t + \boldsymbol{X_b'\delta} \times Post_t + \alpha_{it} + \gamma_{ib} + \epsilon_{ibt}. \tag{6}$$

The results are reported in Table 3. We find the effect of bank exposure on the supply of credit is negative across the different types of firms. The point-estimates are not statistically different. We also divide firms by the quartile of their sectoral exposure to import-competition (rather than using a median cut-off) and find the coefficients are not statistically different across quartiles.[23]

Overall, we find exposed banks reduced the supply of credit by a similar magnitude across different groups of firms. More exposed banks did not prioritize expanding sectors when allocating their funds; rather, they also transmitted the negative effect of the lending channel to such sectors. This result is robust to alternative definitions of potential winners from the China shock, such as firms in *Low-Hit* sectors where Italy has a comparative advantage to export or firms that are highly productive (see section 6.1).

3.4 Effect on the number of bank-firm relationships

Our baseline specification in equation (5) estimates the effect of bank exposure to the trade shock on the *intensive* margin of credit, using bank-firm credit relations that exist before and after China's entrance into the WTO. In other words, this specification captures

[21] Services include wholesale and retails trade, transportation and storage, accommodation and food service activities, information and communication, and professional, scientific, and technical services. All service sectors are considered not directly affected by import competition from China.

[22] The results hold also if we define *Low-Hit* firms as those in the bottom quartile of exposure among manufacturing sectors.

[23] See Table A.7 in the Appendix.

the supply-driven rebalancing of the firm's credit across those banks that were already lending to the firm before 2001. But the contraction in credit supply may also trigger less-exposed banks to substitute for more-exposed banks.

We explore the *extensive* margin of credit, that is, the impact of bank exposure on the probability of closing or opening lending relationships. We run the following specification looking at the firm-bank relationships in the *Pre* and *Post* periods (1998-2001 vs. 2002-2007):

$$Exit_{ib\tau}\ (Entry_{ib\tau}) = \beta_1\ Exposure^{IT}_{(-i),b} \times Post_\tau + \beta_2\ Spec_{ib\tau} \times Post_\tau + \boldsymbol{X_b'}\boldsymbol{\delta} \times Post_\tau + \alpha_{i\tau} + \gamma_b + \epsilon_{ib\tau}. \tag{7}$$

In this two-period panel, τ refers to the years pre- and post-2002.

The specification on $Exit$ is run over the set of firms that have a credit relation with bank b in period τ. The dependent variable takes the value of 1 if the credit relation ends during the corresponding period (i.e., $C_{ib,t} > 0$ for at least one year in (1998, 2000) and $C_{ib,2001} = 0$ when $\tau = Pre$, and $C_{ib,t} > 0$ for at least one year in (2002, 2006) and $C_{ib,2007} = 0$ when $\tau = Post$), and 0 otherwise.

The specification on $Entry$ is run over all the potential firm-bank combinations, that is, taking all the banks in the province where the firm operates.[24] $Entry_{ib\tau}$ is equal to 1 if the relationship was created during the period τ (i.e., $C_{ib,98} = 0$ and $C_{ib,01} > 0$ when $\tau = Pre$, and $C_{ib,02} = 0$ and $C_{ib,07} > 0$ when $\tau = Post$), and 0 otherwise. Because this regression refers to new bank-credit relationships, the measure of exposure $Exposure^{IT}_b$ is not firm-specific. By definition, this measure is not using information on firm i.

The specification accounts for whether the bank is specialized in the sector in which the firm operates, for bank fixed effects, for the bank's pre-characteristics interacted with the period dummy, and for firm-period fixed effects. Standard errors are clustered at the bank-sector level. The coefficient of interest β_1 captures the marginal effect of a bank's exposure to the trade shock on the probability that bank b ends (starts) a credit relation with firm i. High elasticity of both exit and entry margins may suggest the replacement of more exposed banks with less constrained ones.

[24] From a regulatory point of view, a province is the relevant administrative unit to determine market concentration in lending.

We find that, as expected, more exposed banks are more likely to terminate credit relationships after 2002. In column (1) of Table 4, we show a one-standard-deviation increase in bank exposure is associated with a 4 pp increase in the probability of exit, out of an unconditional entry probability of 17.5%. The results are not significantly different for firms in high-hit and low-hit manufacturing sectors and Services (column 2).

Contrary to our priors, exposed banks *are not* less likely to start new credit relationships after China's entry into the WTO (columns 3 and 4). The baseline probability of entry over the universe of potential banks is very low (1.0%). The effect of exposure on entry is positive, but its magnitude is not economically large: a one-standard-deviation increase in bank exposure is associated with a 0.025 pp increase in the probability of entry.

Overall, more exposed banks reduced their number of credit relationships after 2002.[25] However, we do not find less exposed banks significantly increased their number of new clients (relative to other banks).

4 Transmission and Amplification of the Trade Shock

The previous section shows a significant negative effect of bank exposure to the China shock on its supply of credit. However, this result may not necessarily imply a negative effect on firms' overall credit availability. Firms could be rebalancing their sources of funding toward less exposed banks, ending up with no overall change in the firm-level amount of credit or real outcomes. Moreover, for banks' lending constraints to end up affecting firms' real outcomes, one needs to show that, first, overall firm availability of credit is reduced, relative to less affected firms, and second, that firms' real output is sensitive to changes in credit availability. This section addresses these goals.

[25]This finding is consistent with evidence from data on loan applications in Table A.8 in the Appendix. We find firms more exposed to the bank lending channel increase their number of applications to less exposed banks and decrease it to the more exposed ones, but we do not observe a change in the overall number of applications.

4.1 Lending channel and firm-level outcomes

To assess the overall impact of bank exposure to the China shock on the firm's availability of credit, we first compute, for each firm, the average exposure of related banks, weighted by its pre-2001 share of credit across banks:

$$Firm\ Level\ Exposure_i = \sum_b Exposure^{IT}_{-i,b}\ \frac{Credit_{ib}}{Total\ Credit_i}, \tag{8}$$

where $Exposure^{IT}_{-i,b}$ is the bank exposure to the shock (leaving out firm-i), defined in (2).

Using this firm-level exposure as the main independent variable, we run the following regression at the firm-year level:

$$\ln Y_{it} = \beta_1\ Firm\ Level\ Exposure_i \times Post_t + \boldsymbol{X_i'\delta} \times Post_t + \gamma_i + \delta_{st} + \epsilon_{ist}, \tag{9}$$

where Y_{it} refers to the firm-level dependent variable of firm i in year t, which is regressed on the interaction between firm-level exposure and the post-2001 dummy, firm fixed effects γ_i, and sector-time fixed effects δ_{st}. $Exposure^{IT}_{-ib}$ is instrumented, as usual, using $Exposure^{OC}_{-ib}$ in equation (4). $\boldsymbol{X_i}$ is a vector of pre-shock lender characteristics (weighted by the firm's share of credit) parallel to $\boldsymbol{X_b}$ in equation (5).[26]

We start by analyzing the overall supply of credit to the firm (i.e., $Y_{it} = C_{it}$). We interpret the coefficient β_1 in equation (9) as the effect in overall firm-level credit supply, under the assumption that, conditional on sector-time fixed effects and on the average characteristics of firms' lenders, firm-level demand for credit is uncorrelated with the exposure of its related banks to the shock. Column (1) in Table 5 shows an increase in firm-level exposure is associated with less firm-level credit.[27] The negative coefficient on firm-level exposure is confirmed. A 10% increase in firm-level exposure results in around 6% reduction in the supply of credit. Column (2) shows the 2SLS results of equation (9) for different groups of firms: high-hit and low-hit manufacturing sectors, and Services. A

[26] In Appendix A.12, we show the results of specification (9) that includes, as an additional control, the firm-time fixed effects ($\hat{\alpha_{it}}$) estimated in equation (5), as in Cingano et al. (2016), Bofondi et al. (2017), and Alfaro et al. (2021).

[27] Table A.14 reports the results of an alternative specification, based on a first difference between pre and post periods.

10% increase in firm-level exposure results in a 5% and 7% reduction of credit for firms in Services and *Low-Hit* manufacturing, respectively. The effect increases to 9% for firms in sectors most directly hit by import competition from China.

Next, we analyze how firms' share of exposed credit affects real outcomes.[28] Columns (3) to (8) report the marginal effects on employment, investment, and revenues, controlling for firm and sector-time fixed effects.[29] These results reflect the combination of firms' availability of credit and the elasticity of the corresponding real outcome to funding. Columns (3), (5) and (7) show the estimates for the full sample for firms. For the average firm, we find a 10% higher dependence on exposed banks is associated with a 4%-6% drop in their real outcomes, relative to other firms in the same sector. Columns (4), (6) and (8) show the heterogeneous effect across firms differently hit by import competition. Among firms in manufacturing sectors directly competing with Chinese imports (high-hit group), these effects are significantly larger: the impact on employment growth is 10%, and, for investment and revenue growth, these figures increase to 11% and 12%, respectively.[30]

4.2 Economic relevance

According to the results above, the sensitivity of real outcomes to credit restrictions by exposed banks is substantially higher for manufacturing firms in high-hit sectors. Moreover, by definition, firms in high-hit sectors are, on average, more dependent on those banks. They were therefore more likely to suffer from credit rationing. To account for these two factors, we follow Chodorow-Reich (2014) and compute what they call *partial-equilibrium aggregation*. Without accounting for general-equilibrium responses, this measure adds the direct impact of the lending channel on real outcomes, taking into account the joint distribution of firms' exposure to the financial shock and their sensitivity to credit. The full

[28]Results are robust to using a first-difference specification. See Table A.14 in the Appendix.

[29]Sector-time fixed effects absorb the direct effect of import competition from China on firms' real outcomes. A caveat is that these controls are based on firms' main sector of activity; therefore, they might not be complete for firms whose activities span multiple sectors that were differentially affected by the China shock.

[30]Table A.10 in the Appendix confirms the negative effects on employment, investment, and revenues also for low-hit firms that are highly productive and for those in sectors with a comparative advantage or that are downstream to the China shock and could benefit from cheaper inputs.

detail of the computations is in Appendix A.2.

Our results in Table 5 are estimated including sector-time fixed effects and a vector of pre-shock lending characteristics. They therefore compare the change in credit supply by firms differently exposed to the lending channel (i.e., the slope), but do not inform on its level (i.e., the intercept). Given this limitation, to perform this aggregation exercise, we assume firms in the bottom 10% of the distribution of exposure are unconstrained in their access to credit (at a constant interest rate).[31] Then, for each firm, we compute the difference in employment (credit) if it had a level of exposure equal to the "unconstrained" threshold. As an example, consider a firm in the 75th-percentile of the exposure distribution. We take the difference in firm-level exposure with respect to a firm in the 10th-percentile and multiply it by the coefficient -0.0295 estimated in Table 5, getting a relative employment differential of -0.95%. We apply the same logic to the entire distribution of firms (using the regression coefficients by group) and weight each firm according to its share of employment (resp. credit). In doing so, we are adding the direct effect of the lending channel, without allowing for general-equilibrium effects.

Table 6 shows the results of this aggregation exercise for employment (columns 1 and 2) by group of firms. We find the growth rate of employment for high-hit firms after China's entrance into the WTO could have been 2.9% higher if the bank lending channel were not binding. Given that employment in high-hit sectors declined by 335,000 workers in those years, the amplification effect of the lending channel is around 80,000 missing workers, almost one fourth of the overall job losses in these sectors. For low-hit manufacturing sectors, the effect was -1.4% on growth, which translates into about 32,000 forgone jobs (in those years 112,000 jobs were created in those sectors). Finally, for services, we find a negative effect of -1.3%, which implies this sector employed 60,000 fewer workers than it could have otherwise (employment in services grew by 865,000 units).[32] Columns (3) and (4) show the results for credit. Notice our quantification exercise is based on a counterfactual scenario without the financial shock. This scenario is not meant to capture

[31] Figure A.3 in the Appendix shows the share of credit and employment by deciles of firms' exposure. Firms in the bottom decile of the distribution account for 6% of total credit and employment, whereas firms in the top quartile of the distribution account for 42% of total employment and 40% of credit.

[32] The rise of employment in services is in line with the structural trend shown in Figure 1b, and it occurs in a period when the labor force increased by almost 1 million.

a counterfactual without the China shock. It captures the effect of the China shock absent the endogenous contraction in credit supply. In other words, it isolates the role of the lending-channel: how banks amplified the original shock to firms already hit by import competition and how they transmitted it to expanding sectors.

5 The Underlying Mechanism: Banks' NPLs

In this section, we investigate the mechanism that links the trade shock that firms face with the patterns of credit allocation by related banks.

We start by looking at the evolution of the value of NPLs for firms in high-hit and low-hit sectors , and Services (Figure 6). After having a similar declining trend up to 2001, they start to diverge. The stock of NPLs of high-hit firms starts to increase after 2001 and almost doubles by the end of our period of analysis, moving from €3.4 billion to €6 billion between 2002 and 2007 (equivalent to an increase from 10% to 20% of the share of non-financial corporations' NPLs). This increase was large relative to banks' capital, which was €56 billion for the whole system at the onset of the shock. The increase of NPLs of low-hit firms is lower; starting from €3.4 billion, it spikes in 2003 coincidentally with the GDP slowdown of Italy and falls subsequently to €4.2 billion, whereas NPLs of firms in services remain stable after 2001.

More formally, we estimate the following linear probability model at the bank-firm-period level:

$$NPL_{ib\tau} = \alpha_{ib} + \alpha_{b\tau} + \beta\, China_{is}^{IT} \times Post_{\tau} + \epsilon_{ib\tau}, \tag{10}$$

where $NPL_{ib\tau}$ is a dummy equal to 1 if the firm-bank loan is non-performing and the independent variable $China_{is}^{IT}$ corresponds to the exposure of firm i's sector to imports from China, as defined in (1), instrumented with (3). The specification includes a full set of firm-bank fixed effects and bank-period fixed effects. These controls are meant to capture time-invariant characteristics of the firm and bank, and also the potential reversed effect of bank-wide changes in credit supply on the performance of related firms. The results in Table 7 confirm import competition from China increased the probability of the firm defaulting: a one-standard-deviation increase in the former is associated with a rise in the latter by almost 1 pp, whereas the unconditional probability of default is 4%.

Next, we exploit detailed information on banks' balance sheet. To more formally test the link between bank exposure, NPLs, and lending capacity, we run the following specification:

$$Y_{bt} = \beta_1 \; Exposure_b^{IT} \times Post_t + \boldsymbol{X_b'\delta} \times Post_t + \gamma_b + \alpha_t + \epsilon_{bt}. \tag{11}$$

$Exposure_b^{IT}$ is the non-leave-out version of our measure of bank exposure as defined in equation (2), which as usual is instrumented with equation (4). We also control for a vector of bank pre-2000 characteristics interacted with a dummy for the years after China's entrance into the WTO, bank fixed effects, and time dummies. We cluster the standard errors at the bank level. The dependent variable Y_{bt} corresponds to the components of the bank's balance sheet. In particular, column (1) in Table 8 shows the results with $Y_{bt} = NPLs\ Ratio_{bt}$, the share of NPLs on total assets in banks' balance sheets. We confirm the evidence from Figure 6: a one-standard-deviation-higher bank exposure to the trade shock is associated with a 0.3 pp increase in the NPL ratio after China's entrance into the WTO. This effect is sizable given that the NPL ratio for the median bank in those years is 1.4% (the mean is 1.9%).

We find evidence that more exposed banks suffer from an erosion of their Tier 1 capital, namely, core capital relative to risk-weighted assets (column 2), which is consistent with the increase in NPLs. We also observe an increase in bank provisions (column 3), which suggests more exposed banks set aside additional funds to cover for potential losses on loans.[33]

We also explore whether more exposed banks suffer from funding issues such as (i) a reduction in deposits (column 4) because affected firms and households in depressed regions could have suffered from a fall in liquidity; (ii) a decrease in interbank lending (column 5); and (iii) higher funding costs (column 6). However, we do not find any significant difference along these dimensions. Finally, we do not find an effect on overall bank profitability (column 7).

[33]The dynamic diff-in-diffs in the Appendix shows no increase in provisions before China's entrance into the WTO, suggesting banks did not anticipate the shock.

Our results show NPLs increased for firms in sectors directly hit by import competition from China. Banks with a larger share of their loan portfolios in those affected sectors could not offset these losses with external capital, and thus reduced their commercial lending. This finding is consistent with the predictions of classical banking models such as Froot et al. (1993), Holmstrom and Tirole (1997), and Froot and Stein (1998). Note this transmission mechanism is not symmetric for positive or negative real shocks. The corporate debt contract may become non-performing when the firm goes through bad times, but its return does not follow a positive non-expected performance. This mechanism is different from the one at play in Bustos et al. (2020), who found deposits respond to firms' positive productivity shocks.

As further support for this conclusion, we compare credit supply by banks with heterogeneous capital ratios at the onset of the trade shock. Table 9 reports the results of our baseline specification in equation (5) interacted with the Tier 1 capital ratio before the shock (taking the 1998-99 average). This effect of the bank's balance-sheet shock on credit supply diminishes with the ex-ante level of bank capitalization, which we interpret as a (inverse) measure of tightness of their lending capacity. This effect is statistically and economically significant for firms in low-hit sectors and Services, but not for high-hit firms, suggesting less constrained banks, equally affected by the trade shock, tilted the composition of their portfolio away from high-hit firms. Extrapolating the estimated coefficients, the predicted effect of the trade shock on credit supply to firms in low-hit sectors and in Services is zero for banks with capital ratios above 14% (they accounted approximately for 5% of total credit prior to the shock). This result is consistent with banks' motive for holding buffer capital in Repullo and Suarez (2013): it enables exposed banks to respond to lending opportunities in expanding sectors, despite the increase in NPLs. Needless to say, because holding capital buffers is itself an endogenous decision of the bank, banks that chose to have extra capital could be those that are better at identifying lending opportunities; both factors would be confounded in the heterogeneous effect of banks' exposure on credit supply.

6 Robustness and Additional Results

In this section, we address several potential alternative mechanisms and identification challenges. Specifically, we analyze the heterogenous effects of bank exposure across alternative definitions of potential winners and explore the robustness of our results by expanding the definition of "exposed" sectors and banks to account for input-output linkages. We also study the geographical dimension of the lending channel.

Additionally, we report in the Appendix an extensive set of robustness checks with alternative measures of banks' and firms' exposure and with different econometric specifications. We show our main results are unchanged when: (i) using a different set of countries to define the instrument of imports from China; (ii) measuring bank exposure leaving out credit to the sector where the firm operates; (iii) measuring bank exposure relative to banks' total assets rather than banks' corporate loans; (iv) leaving out the main sectors in which Italy exports to China; (v) including alternative sets of controls and fixed effects; (vi) estimating a weighted least-squares specification with observations weighted by firm size; (vii) estimating a first-difference transformation of the baseline specification; (viii) allowing for alternative clustering of the standard errors; (ix) looking at the heterogeneous effects across groups of firms using a quartile division rather than a median cutoff for high-hit and low-hit sectors, as well as for productivity and comparative advantage.[34]

6.1 Additional dimensions of firms' heterogeneity

We expand the analysis in subsection 3.3 by contemplating additional dimensions of firms' heterogeneity. Within low-hit manufacturing sectors, we also explore different ways that some firms may have benefited from China's entry into the WTO: first, those firms in sectors in which Italy has a comparative advantage,[35] second, the most produc-

[34] We also explored heterogeneous effects by firm size and the Rajan-Zingales measure of financial dependence (available upon request). The effects do not vary with these dimensions of heterogeneity.

[35] Using COMTRADE data, we compute a standard Balassa index of revealed comparative advantage for each manufacturing 3-digit sector for 1994-1998. World exports correspond to the sum of exports from 89 countries (i.e., countries for which Comtrade data are available in each year of the reference period).

tive firms in sectors not directly competing with imports from China.[36] Figure A.1 in the Appendix shows the relative performance of these groups of firms in terms of exports or employment. We find that indeed the aggregate trend of these potential winners performs better after China entrance in the WTO relative to the other firms in the economy. Table A.9 in the Appendix shows the effect of the bank exposure on credit supply, estimated using the within-firm specification in equation (6). The results are not significantly different from our baseline estimates. Along the same lines, Table A.10 shows the heterogeneous performance of these groups of firms in terms of employment, investment and revenues, using the firm-level specification in equation (9). The results confirm the ones presented in subsection 4.1.

6.2 Taking into account input-output linkages

Our baseline identification of sectors affected by competition from China in equations (1) and (3) considers only the direct exposure of a given industry to imports from China, and therefore ignores the effects to downstream and upstream sectors. Table A.9 (column 3) in the Appendix shows the heterogeneous effect of the trade shock on credit supply in equation (6) for firms in downstream *Low-Hit* sectors. Banks more exposed to the shock also reduce lending to these firms, which are presumably benefited from cheaper inputs from China, relative to less exposed banks lending to the same firm. The corresponding effect on firm-level employment, investment and revenues are shown in Table A.10 in the Appendix.[37]

We also modify our measure of sectoral exposure to the liberalization shock by incorporating the indirect effect, through input-output linkages, on the demand for inputs used by sectors directly competing with China. Following Acemoglu et al. (2016), we calculate for each industry j the weighted average change in Chinese imports across all

[36] We compute total factor productivity at the firm level (TFPR) following Levinsohn and Petrin (2003) and Wooldridge (2009). We take the firm average and the sector-weighted average TFPR for the period 1998-1999, and we define high- versus low-productivity firms according to whether they are above or below their sectoral average.

[37] We compute a weighted average of downstream exposure to high-hit sectors, using the input-output table for Italy, which is available only at the 2 digit level, and select sectors above the median value; i.e., our group of interest is given by firms in low-hit sectors with a share of input from high-hit firms above the median.

industries that purchase from industry j. The weights are the shares of industry j's total sales that are used as inputs in each industry according to the 1995 input-output table, which predates China's entry into the WTO. One limitation is that for Italy, this information is available at the 2-digit industry only. Therefore, we assume that for a given 4-digit industry, its input and output shares are proportional to the corresponding shares of its 2-digit industry. We then compute the sum of our baseline measure of bank exposure and of the measure that takes into account the upstream effects on the borrowing industries.[38] Columns (7) and (8) of Table A.2 in the Appendix confirm the baseline results.

6.3 The geographical dimension of the bank lending channel

In this subsection, we investigate the geographical dimension of bank lending. Some economic activities may be geographically clustered. Then, the China shock may disproportionately affect some regions and their local labor market or non-tradable sector. We therefore analyze whether bank lending differs across regions.

Using information on the location and size of firms, we compute the employment-weighted average of its sectors' exposure to the China shock as defined in equation (3).[39] We look at our results across provinces with different sectoral compositions.[40] Table 10 reports the baseline results from equations (5) and (6), dividing our sample between firms located in provinces above and below the median share of employment in high-hit sectors. The effect of bank exposure on credit supply is negative and significant in all cases. More exposed banks reduced their share of credit, for the same firms, in all provinces in which they operate. The effect of bank exposure is only slightly larger in provinces with above-median concentration in exposed sectors. In other words, more constrained banks reduced their share of credit, especially in already depressed provinces, but they do so also in areas less affected by the shock and for firms with low exposure to import competition.

[38] The correlation between the baseline measure of bank exposure and the new one is 0.96.

[39] Italy has 108 provinces, which are administrative units of the intermediate level between a municipality and a region, comparable to US counties. The average bank typically operates across 15 provinces.

[40] In the Appendix, we also show how the results change with other dimensions of regional heterogeneity: innovation, education, and industrial diversification.

In the Appendix Table A.13, we show our conclusions in subsection 4.1 are robust to absorbing sector-province-time fixed effects. Overall, we conclude the lending-channel analyzed here operates beyond other potential mechanisms arising from local general-equilibrium effects.

7 Concluding Remarks

This study shows that, in the aftermath of a trade-liberalization episode, banks can amplify the shock to firms hit by import competition from China and propagate it to firms in sectors expected to expand upon liberalization. Focusing on China's entry into the WTO, we find banks with a portfolio of loans concentrated in sectors exposed to competition from China decrease their lending relative to less exposed banks. As import competition from China leads to higher NPLs among competing firms, the balance sheet of exposed banks suffers losses that lead to an erosion of their core capital. Consequently, these banks reduce their credit supply to all their related firms, irrespective of their industry of operation. Firms borrowing from exposed banks cannot perfectly substitute constrained sources of funding; their overall availability of credit is therefore reduced. We also find this financial tightening, which endogenously arises in the aftermath of the liberalization episode, has significant effects on employment, investment, and overall revenues.

References

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H. and Price, B. (2016), 'Import competition and the great us employment sag of the 2000s', *Journal of Labor Economics* **34**(S1), 141–198.

Adão, R., Kolesár, M. and Morales, E. (2019), 'Shift-Share Designs: Theory and Inference*', *The Quarterly Journal of Economics* **134**(4), 1949–2010.

Aghion, P., Burgess, R., Redding, S. J. and Zilibotti, F. (2008), 'The unequal effects of liberalization: Evidence from dismantling the license raj in india', *American Economic Review* **98**(4), 1397–1412.

Alfaro, L., García-Santana, M. and Moral-Benito, E. (2021), 'On the direct and indirect real effects of credit supply shocks', *Journal of Financial Economics* **139**(3), 895–921.

Allen, F. and Gale, D. (2000), 'Financial contagion', *Journal of Political Economy* **108**(1), 1–33.

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

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

Antràs, P. and Caballero, R. (2009), 'Trade and capital flows: A financial frictions perspective', *Journal of Political Economy* **117**(4), 701–744.

Autor, D. H., Dorn, D. and Hanson, G. H. (2013), 'The China syndrome: local labor market effects of import competition in the United States', *American Economic Review* **103**(6), 2121–68.

Autor, D. H., Dorn, D., Hanson, G. H. and Song, J. (2014), 'Trade adjustment: Worker-level evidence', *The Quarterly Journal of Economics* **129**(4), 1799–1860.

Baskaya, Y. S. and Kalemli-Ozcan, S. (2016), Sovereign risk and bank lending: Evidence from 1999 turkish earthquake, Working Paper 22335, National Bureau of Economic Research.

Bertrand, M., Duflo, E. and Mullainathan, S. (2004), 'How much should we trust differences-in-differences estimates?', *Quarterly Journal of Economics* **119**(1), 249–275.

Bofondi, M., Carpinelli, L. and Sette, E. (2017), 'Credit supply during a sovereign debt crisis', *Journal of the European Economic Association* **16**(3), 696–729.

Borusyak, K., Hull, P. and Jaravel, X. (2021), 'Quasi-Experimental Shift-Share Research Designs', *The Review of Economic Studies* **89**(1), 181–213.

Bustos, P., Garber, G. and Ponticelli, J. (2020), 'Capital Accumulation and Structural Transformation', *The Quarterly Journal of Economics* **135**(2), 1037–1094.

Byun, S., Lee, S. and Lee, S. H. (2021), Community banks and the mitigation of the china shock.

Chodorow-Reich, G. (2014), 'The employment effects of credit market disruptions: Firm-level evidence from the 2008-9 financial crisis', *The Quarterly Journal of Economics* **129**(1), 1–59.

Cingano, F. and Hassan, F. (2019), Foreign capital flows and productivity misallocation.

Cingano, F., Manaresi, F. and Sette, E. (2016), 'Does credit crunch investment down? new evidence on the real effects of the bank-lending channel', *Review of Financial Studies* **29**(10), 2737–2773.

Cortés, R. K. and Strahan, P. E. (2017), 'Tracing out capital flows: How financially integrated banks respond to natural disasters', *Journal of Financial Economics* **125**(1), 182 – 199.

Detragiache, E., Garella, P. and Guiso, L. (2000), 'Multiple versus single banking relationships: Theory and evidence', *Journal of Finance* **55**(3), 1133–1161.

Deyoung, R., Gron, A., Torna, G. and Winton, A. (2015), 'Risk overhang and loan portfolio decisions: Small business loan supply before and during the financial crisis', *Journal of Finance* **70**(6), 2451–2488.

Dix-Carneiro, R. (2014), 'Trade liberalization and labor market dynamics', *Econometrica* **82**(3), 825–885.

Dix-Carneiro, R. and Kovak, B. K. (2017), 'Trade liberalization and regional dynamics', *American Economic Review* **107**(10), 2908–46.

Froot, K. A., Scharfstein, D. S. and Stein, J. C. (1993), 'Risk management: Coordinating corporate investment and financing policies', *Journal of Finance* **48**(5), 1629–1658.

Froot, K. and Stein, J. C. (1998), 'Risk management, capital budgeting, and capital structure policy for financial institutions: an integrated approach', *Journal of Financial Economics* **47**, 55–82.

Gan, J. (2007), 'The Real Effects of Asset Market Bubbles: Loan- and Firm-Level Evidence of a Lending Channel', *Review of Financial Studies* **20**(6), 1941–1973.

Gilje, E. P., Loutskina, E. and Strahan, P. E. (2016), 'Exporting liquidity: Branch banking and financial integration', *The Journal of Finance* **71**(3), 1159–1184.

Giroud, X. and Mueller, H. M. (2019), 'Firms' internal networks and local economic shocks', *American Economic Review* **109**(10), 3617–49.

Hakobyan, S. and McLaren, J. (2016), 'Looking for Local Labor Market Effects of NAFTA', *The Review of Economics and Statistics* **98**(4), 728–741.

Holmstrom, B. and Tirole, J. (1997), 'Financial intermediation, loanable funds, and the real sector', *The Quarterly Journal of Economics* **112**(3), 663–691.

Huber, K. (2018), 'Disentangling the effects of a banking crisis: Evidence from german firms and counties', *American Economic Review* **108**(3), 868–898.

Jiménez, G., Mian, A., Peydró, J. L. and Saurina, J. (2020), 'The real effects of the bank lending channel', *Journal of Monetary Economics* **115**(C), 162–179.

Kaminsky, G. and Reinhart, C. (2000), 'On crises, contagion, and confusion', *Journal of International Economics* **51**(1), 145–168.

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

Kovak, B. K. (2013), 'Regional effects of trade reform: What is the correct measure of liberalization?', *American Economic Review* **103**(5), 1960–1976.

Lanteri, A., Medina, P. and Tan, E. (2019), Capital-reallocation frictions and trade shocks.

Levinsohn, J. and Petrin, A. (2003), 'Estimating production functions using inputs to control for unobservables', *Review of Economic Studies* **70**(2), 317–341.

Martín, A., Moral-Benito, E. and Schmitz, T. (2021), 'The Financial Transmission of Housing Booms: Evidence from Spain', *American Economic Review* **111**(3), 1013–1053.

Mayordomo, S. and Rachedi, O. (2019), 'The China syndrome affects banks: the credit supply channel of foreign import competition', *Banco de Espana WP* **1908**.

Menezes-Filho, N. A. and Muendler, M.-A. (2011), Labor reallocation in response to trade reform, NBER Working Papers 17372, National Bureau of Economic Research, Inc.

Paravisini, D. (2008), 'Local bank financial constraints and firm access to external finance', *Journal of Finance* **63**(5), 2161–2193.

Paravisini, D., Rappoport, V. and Schnabl, P. (2023), 'Specialization in Bank Lending: Evidence from Exporting Firms', *The Journal of Finance* **78**(4), 2049–2085.

Paravisini, D., Rappoport, V., Schnabl, P. and Wolfenzon, D. (2015), 'Dissecting the effect of credit supply on trade: Evidence from matched credit-export data', *Review of Economic Studies* **82**(1), 333–359.

Repullo, R. and Suarez, J. (2013), 'The Procyclical Effects of Bank Capital Regulation', *The Review of Financial Studies* **26**(2), 452–490.

Rosengren, E. S. and Peek, J. (2000), 'Collateral Damage: Effects of the Japanese Bank Crisis on Real Activity in the United States', *American Economic Review* **90**(1), 30–45.

Schnabl, P. (2012), 'The international transmission of bank liquidity shocks: Evidence from an emerging market', *The Journal of Finance* **67**(3), 897–932.

Topalova, P. (2010), 'Factor immobility and regional impacts of trade liberalization: Evidence on poverty from india', *American Economic Journal: Applied Economics* **2**(4), 1–41.

Utar, H. (2018), 'Workers beneath the floodgates: Low-wage import competition and workers' adjustment', *The Review of Economics and Statistics* **100**(4), 631–647.

Wooldridge, J. M. (2009), 'On estimating firm-level production functions using proxy variables to control for unobservables', *Economics Letters* **104**(3), 112–114.

Table 1: Summary statistics

	Unit	Mean	S.D.	p25	p50	p75
Bank characteristics (n=504)						
Total Assets	€Millions	4,701	36,002	109	229	535
Liquid Assets	% Assets	30.5	14.1	21.8	27.9	37.9
Non-performing Loans	% Assets	2.6	2.6	1.1	1.9	3.3
Credit to Firms	% Assets	37.6	13.1	28.8	39.3	47.3
Profits	% Assets	1	0.5	0.7	1	1.2
Tier 1 capital	% R.W. Assets	10	4.4	7.0	9.1	11.8
Core Funding	% Liabilities	52.5	17.7	44.4	51.9	64.4
Operating provinces	Number	15	22	4	7	14
Bank Exposure to China	Weighted average of borrowers' exposure	0.89	0.76	0.34	0.76	1.21
Firm characteristics (n=170,265; manufacturing: 70.339; services: 99,926)						
Bank Credit	€Millions	2.3	16.6	0.32	0.70	1.7
Revenues	€Thousands	4,929	5,962	1,076	2,363	5,925
Fixed Assets	€Thousands	984	1,548	97	322	1,045
Gross Operating Margin	% Revenues	8.0	6.8	3.8	6.1	9.8
Credit Score	Units	5.0	1.9	4.0	5.0	7.0

Note: The table reports averages for 1998-2007. Bank balance-sheet data are from the Supervisory Reports-Bank of Italy. Credit data are from the Italian Credit Register. Firm balance-sheet data are from CERVED. Liquid assets include cash, interbank deposits, and bond holdings. Core funding refers to deposits. Firms' credit score is computed by CERVED based on past defaults and firms' balance-sheet information.

Table 2: Baseline results

Dep. Variable:	$\ln C_{ibt}$		i_{ibt}	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
$Exposure^{IT}_{-i,b} \times Post_t$	-0.068***	-0.074***	0.0059***	0.0052***
	(0.0046)	(0.0062)	(0.0004)	(0.0006)
		First stage		
$Exposure^{OC}_{-i,b} \times Post_t$		0.79***		1.01***
		(0.01)		(0.02)
AR-Wald test, F		131.78		79.82
Bank controls	✓	✓	✓	✓
Firm-time F.E.	✓	✓	✓	✓
Firm-bank F.E.	✓	✓	✓	✓
Observations	3499092	3499092	2291698	2291698
$Adj.R^2$	0.832	0.832	0.632	0.632

Note: The table reports the results of specification (5). In columns (1) and (2), the dependent variable is the log of outstanding credit between bank b and firm i in year t. In columns (3) and (4), it is log of interests and fees relative to outstanding credit, for bank b and firm i in year t. $Exposure^{IT}_{-i,b}$, defined in equation (2), is instrumented with equation (4). Bank controls include bank characteristics pre-2000 interacted with a post-2001 dummy. These are log-assets, share of NPLs, core-funding ratio, the capital ratio, and a firm-bank dummy that captures whether a firm operates in a sector of bank specialization. Standard errors are clustered at the bank-sector level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 3: Baseline results: Heterogeneous effects

Dependent Variable	$\ln C_{ibt}$	
	OLS	2SLS
	(1)	(2)
$Exposure^{IT}_{-i,b} \times Post_t \times Manuf\ HighHit_i$	-0.063***	-0.068***
	(0.0088)	(0.0131)
$Exposure^{IT}_{-i,b} \times Post_t \times Manuf\ LowHit_i$	-0.070***	-0.079***
	(0.0074)	(0.0102)
$Exposure^{IT}_{-i,b} \times Post_t \times Services_i$	-0.069***	-0.072***
	(0.0062)	(0.0084)
Bank controls	✓	✓
Firm-time F.E.	✓	✓
Firm-bank F.E.	✓	✓
Observations	3499092	3499092
Adj. R^2	0.832	0.832

Note: The table reports the 2SLS results of specification (6). $Exposure^{IT}_{-i,b}$ defined in equation (2) is instrumented with equation (4). High-hit and low-hit firms are manufacturing sectors above and below median exposure defined in equation (1). Standard errors are double clustered at the bank-sector level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 4: Firms entry and exit (2SLS)

Dependent:	$Exit_{ib\tau}(\times 100)$		$Entry_{ib\tau}(\times 100)$	
	(1)	(2)	(3)	(4)
$Exposure^{IT}_{(-i),b} \times Post_\tau$	3.96***		0.025***	
	(0.600)		(0.006)	
$Exposure^{IT}_{(-i),b} \times Post_\tau \times ManufHighHit_i$		3.18***		0.088***
		(0.954)		(0.011)
$Exposure^{IT}_{(-i),b} \times Post_\tau \times ManufLowHit_i$		3.66***		0.020*
		(0.851)		(0.010)
$Exposure^{IT}_{(-i),b} \times Post_\tau \times Services_i$		4.58***		0.007
		(0.730)		(0.007)
Bank controls	✓	✓	✓	✓
Firm-period F.E.	✓	✓	✓	✓
Bank F.E.	✓	✓	✓	✓
Observations	582,549	582,549	35,053,469	35,053,469
Adj. R^2	0.239	0.239	0.088	0.088

Note: The table reports the results of the extensive margin specification in equation (7). The dependent variable is a dummy that takes the value of 1 if firm i ends (exit) or starts (entry) a credit relation with bank b in period τ ($\tau = 1998 - 2001, 2002 - 2007$). Results are expressed in percentage points. Baseline unconditional probability for $Exit$ is 17.5% and for $Entry$ is 1.0%. $Exposure^{IT}_{(-i),b}$ is instrumented with (4), leaving firm i out in the case of exit. High-hit (low-hit) firms are manufacturing sectors with above (below) median exposure defined in equation (1). Bank controls include bank characteristics pre-2000 interacted with a post-2001 dummy. These are log-assets, share of NPLs, core-funding ratio, the capital ratio, and a firm-bank dummy that captures if a firm operates in a sector of bank specialization. Standard errors are clustered at the bank-sector level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 5: Effect on firms' outcomes (2SLS)

	$\ln C_{it}$		$\ln Emp_{it}$		$\ln Inv_{it}$		$\ln Rev_{it}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$FirmExp_i \times Post_t$	-0.0622***		-0.0475***		-0.0651***		-0.0668***	
	(0.0160)		(0.0136)		(0.0187)		(0.0140)	
$FirmExp_i \times Post_t \times HighHit_i$		-0.0850***		-0.0979***		-0.113***		-0.117***
		(0.0212)		(0.0179)		(0.0240)		(0.0188)
$FirmExp_i \times Post_t \times LowHit_i$		-0.0705***		-0.0564***		-0.0561**		-0.0514***
		(0.0189)		(0.0157)		(0.0221)		(0.0172)
$FirmExp_i \times Post_t \times Services_i$		-0.0485***		-0.0254*		-0.0486**		-0.0530***
		(0.0171)		(0.0146)		(0.0201)		(0.0146)
Firm F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Sector-time F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Bank controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	793968	793968	793968	793968	793968	793968	793968	793968
Adj. R^2	0.896	0.896	0.919	0.919	0.919	0.919	0.914	0.914

Note: The table reports the coefficients of the specification in equation (9). The dependent variable is the log of total outstanding credit of firm i in year t in columns (1)-(2), log of employment in columns (3)-(4), log of investment in columns (5)-(6) and log of revenues in columns (7)-(8). $FirmExp_i$ is defined in equation (8). Bank controls is vector of weighted average lender characteristics pre-2000 (log-assets, share of NPLs, core-funding ratio, and the capital ratio). Standard errors are clustered at the sector-main-bank level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 6: Aggregate effects of the bank-lending channel

	Employment		Credit	
	Growth (1)	Abs. variation (2)	Growth (3)	Abs. variation (bn.) (4)
High-Hit Manuf.	-2.9%	-79,350	-2.6%	-1.0
Low-Hit Manuf.	-1.4%	-31,800	-1.8%	-2.0
Services	-1.3%	-60,151	-1.7%	-3.0

Note: The table reports the results of the partial-equilibrium aggregation exercise discussed in subsection 4.2 and in Appendix A.2.

Table 7: Firm exposure and NPL

Dep. Var: $NPL_{ib\tau}$	OLS (1)	2SLS (2)
$China_{is}^{IT} \times Post_{\tau}$	0.00625***	0.00904***
	(0.00158)	(0.00242)
Firm-bank F.E.	✓	✓
Bank-period F.E.	✓	✓
Observations	671376	671376
Adjusted R-squared	0.560	0.560

Note: Results on specification (10). Explanatory variable $China_{is}^{IT}$ defined in equation (1), instrumented with (3). Standard errors double clustered at the firm and bank level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 8: Bank exposure and balance-sheet effects (2SLS)

	NPL (1)	Tier 1 (2)	Loan provisions (3)	Deposits (4)	Interbank (5)	Funding cost (6)	ROA (7)
$Exposure_b^{IT} \times Post_t$	0.003*** (0.0007)	-0.002*** (0.0006)	0.001** (0.0005)	0.000 (0.0018)	0.001 (0.003)	0.000 (0.0001)	0.000 (0.0001)
Bank Controls	✓	✓	✓	✓	✓	✓	✓
Bank F.E.	✓	✓	✓	✓	✓	✓	✓
Time F.E.	✓	✓	✓	✓	✓	✓	✓
Observations	4890	4890	4890	4890	4890	4890	4890
$Adj.R^2$	0.714	0.851	0.821	0.943	0.827	0.844	0.583

Note: The table reports the results of specification (11) with the following dependent variables: NPL ratio, tier 1 capital (capital relative to risk-weighted assets), provisions on firms' loans that are not NPL relative to assets, deposits, net interbank borrowing, funding cost, and return on assets. Variables are expressed as a share of bank overall liabilities if not otherwise specified. $Exposure_b^{IT}$ is defined in equation (2) instrumented with (4). All regressions include bank controls interacted with a post-2001 dummy (i.e., pre-2000 log-assets, core-funding ratio, NPL and the capital ratios). In each regression, we exclude the control that overlaps with the dependent variable. Standard errors are clustered at the bank level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 9: Baseline results: Interaction with tier1

Dep. Variable: $\ln C_{ibt}$	Full sample (1)	Manuf. Low-Hit	Manuf. High-Hit (2)	Services
$Exposure_{-i,b}^{IT} \times Post_t$	-0.112*** (0.0146)	-0.138*** (0.0249)	-0.0516** (0.0203)	-0.127*** (0.0170)
$Exposure_{-i,b}^{IT} \times Tier1_b \times Post_t$	0.474*** (0.152)	0.758*** (0.223)	-0.256 (0.242)	0.727*** (0.182)
$Tier1_b \times Post_t$	0.701*** (0.127)		0.763*** (0.128)	
Bank Controls	✓		✓	
Firm-Bank F.E.	✓		✓	
Firm-Time F.E.	✓		✓	
Observations	3497635		3497635	
$Adj.R^2$	0.832		0.832	

Note: The table reports results of specification (5) in column (1); and those of specification (6) in column (2). Relative to the baseline specification, we add an interaction term $Tier1_b$ (i.e., the ratio of core capital to risk-weighted assets for 1998-1999). $Exposure_{-i,b}^{IT}$ is instrumented with (4). All regressions include the rest of the corresponding interaction terms, bank controls interacted with a post-2001 dummy (i.e., pre-2000 log-assets, share of NPLs, core-funding ratio, the capital ratio, and firm-bank specialization dummies). Standard errors are clustered at the bank-sector level. ***significant at the 1% level, **5% level and *10% level.

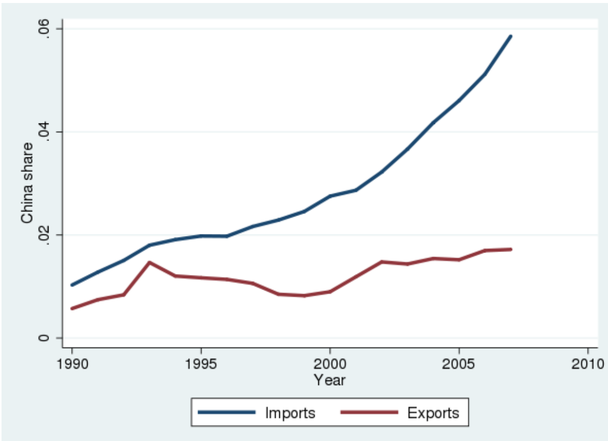
Table 10: Geographical effects by province exposure (2SLS)

Dependent variable: $\ln C_{ibt}$	*High exposed provinces* (1)	(2)	*Low exposed provinces* (3)	(4)
$Exposure^{IT}_{-i,b} \times Post_t$	-0.0827***		-0.0585***	
	(0.00786)		(0.00934)	
$Exposure^{IT}_{-i,b} \times Post_t \times Manuf.\ HighHit_i$		-0.0775***		-0.0480***
		(0.0166)		(0.0186)
$Exposure^{IT}_{-i,b} \times Post_t \times Manuf.\ LowHit_i$		-0.0784***		-0.0825***
		(0.0138)		(0.0144)
$Exposure^{IT}_{-i,b} \times Post_t \times Services_i$		-0.0881***		-0.0471***
		(0.0107)		(0.0127)
Bank controls	✓	✓	✓	✓
Firm-Time F.E.	✓	✓	✓	✓
Firm-Bank F.E.	✓	✓	✓	✓
Observations	2118046	2118046	1378456	1378456
$Adj.R^2$	0.835	0.835	0.828	0.828

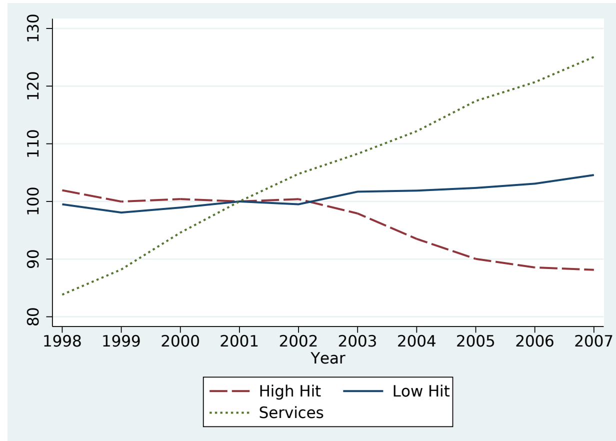
Note: The table reports results of specification (5) in columns (1) and (3) and specification (6) in columns (2) and (4). We group firms according to the exposure of their province to the China shock. High (low) exposed provinces correspond to those with a share of employment in high-hit sectors above (below) the median. The dependent variable is the log of outstanding credit between bank b and firm i in year t, $\ln C_{ibt}$. The variable $Exposure^{IT}_{-i,b}$ is instrumented with (4). Other bank controls include bank characteristics pre-2000 interacted with a post-2001 dummy. These are log-assets, share of NPLs, core-funding ratio, the capital ratio, and a firm-bank dummy that captures whether a firm operates in a sector of bank specialization. Standard errors are clustered at the bank-sector level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Figure 1: The China shock: aggregate patterns of trade and employment

(a) Import and Export Shares, from and to China



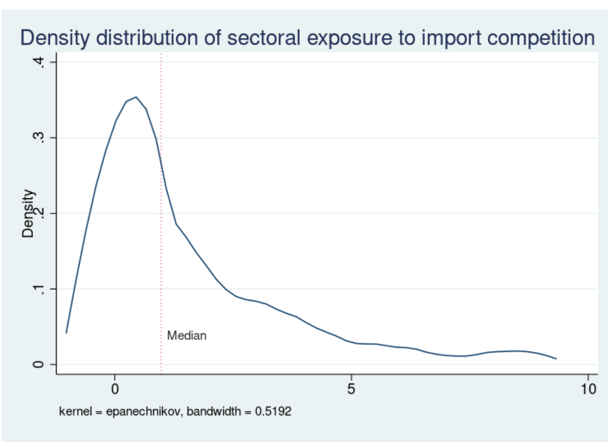
(b) Employment by Exposure



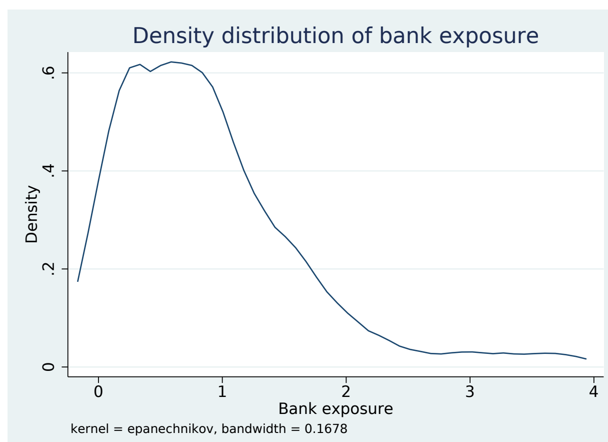
Note: Panel (a) shows the evolution of the share of exports and imports of Italy to and from China relative to total Italian exports and imports (COMTRADE data). Panel (b) shows the evolution of employment in services and in manufacturing sectors with high- vs. low-exposure to import competition from China (2001=100). We compute sectoral exposure to China following the approach by Autor et al. (2013) and then define high- and low-hit sectors as the ones above and below the median.

Figure 2: Distribution of sector- and bank-level measure of exposure

(a) Import competition by sector



(b) Bank exposure

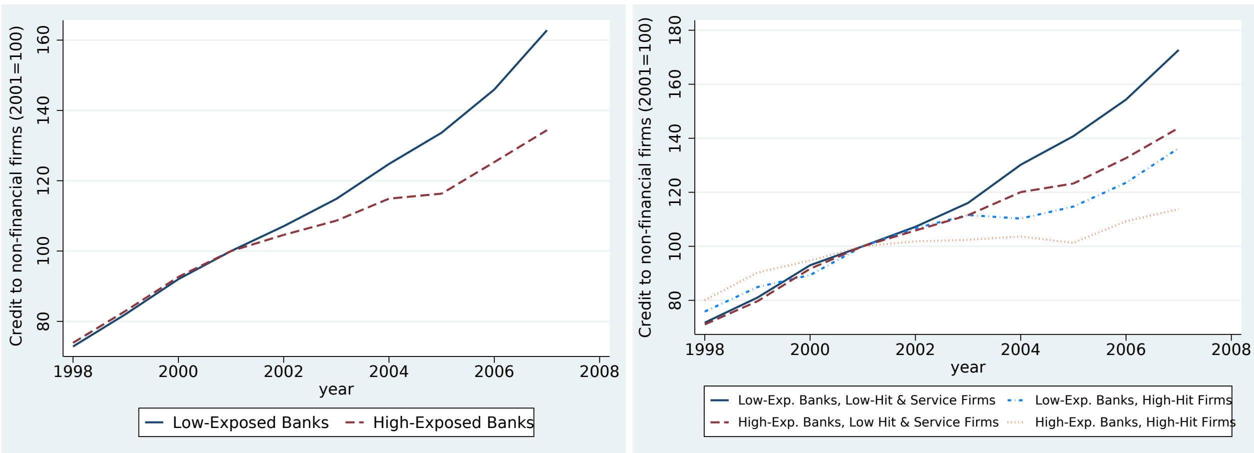


Note: Panel (a) shows the distribution of exposure to China at the sectoral level as defined in (1); panel (b) shows the distribution of bank exposure to China as defined in equation (2) (without leaving out firm i from credit weights).

Figure 3: Aggregate credit, by bank exposure

(a) Total

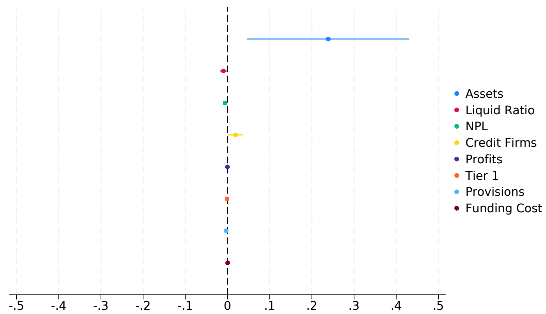
(b) Groups of Firms



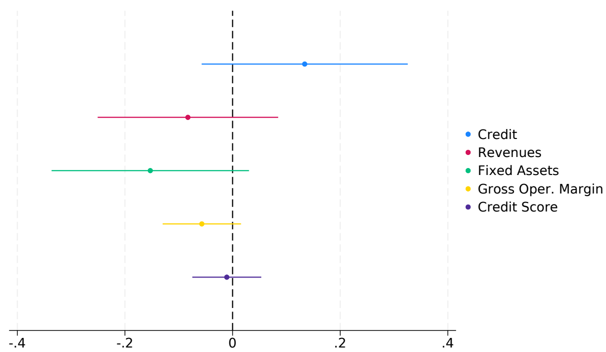
Note: The figure reports the evolution of the total outstanding credit by bank exposure. We divide the sample of banks between high- and low-exposed according to (2), such that both groups account for about half of total credit. In panel (b) firms are defined to be high-hit or low-hit according to whether they are in a sector subject to China competition above or below the median as defined in equation (1).

Figure 4: Balancing test on banks and borrowers characteristics

(a) Bank characteristics



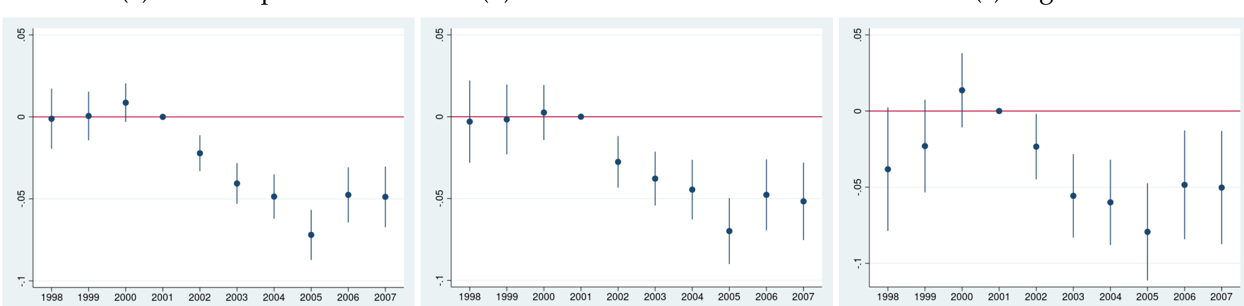
(b) Borrower characteristics



Note: The figure reports the results of regressions of bank and average borrower characteristics on the (non-leave out version of) the shift-share instrument. Following Borusyak et al. (2021), the regressions are implemented at the shock level, in order to obtain exposure-robust standard errors.

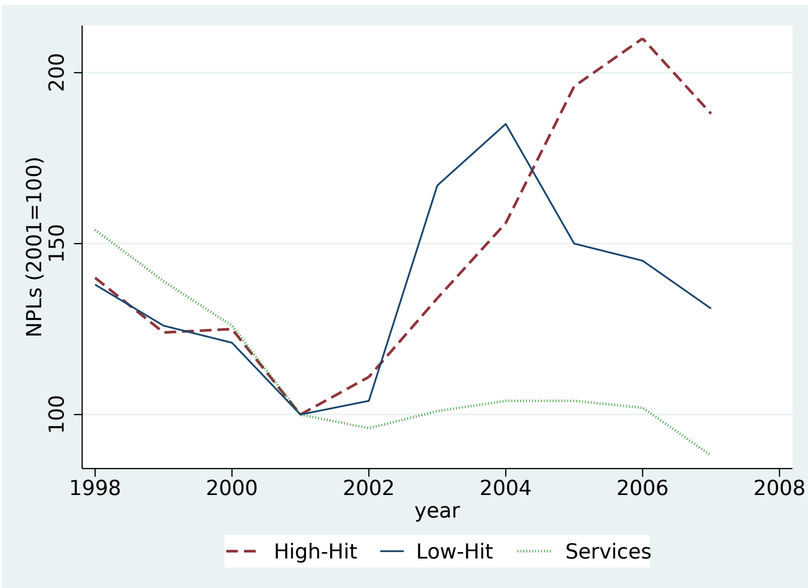
Figure 5: Dynamic Diff-in-Diffs (95% CI)

(a) Full Sample (b) Low-Hit and Services (c) High-Hit



Note: The figure reports the coefficients, with 95% confidence interval, of the variable $Exposure^{IT}_{-i,b}$, instrumented with the variable $Exposure^{OC}_{-i,b}$, coming from the dynamic diff-in-diffs version of specification (5) in panel (a) and from specification (6) in panels (b) and (c).

Figure 6: The underlying mechanism: The role of NPLs



Note: The figure reports the evolution of the total amount of NPLs by group of firms. The value of NPLs is normalized to 100 in 2001.

Appendix

Table A.1 replicates the baseline specifications in (5) and (6) with the instrumental variable defined using only imports from the US, or only from Australia, New Zealand, and Japan.

Table A.2 replicates the baseline specifications in (5) and (6) with (1) the Bank Exposure measure defined leaving out the sector of operation of the corresponding firm $Exposure^{IT}_{-ib} = Exposure^{IT}_{-sb}$, (2) bank exposure using assets (rather than total credit) in the denominator of definition (2), (3) leaving out the 15 main 4-digit sectors in which Italy exports to China (those 15 sectors account for more than half of Italian exports to China in the 1998-2007 average), and (4) a measure of bank exposure that accounts for input-output linkages as described in section 6.2.

Table A.3 replicates the baseline specifications in (5) and (6) with alternative sets of controls and fixed effects.

Table A.4 replicates the baseline specifications in (5) and (6) with observations weighted by the log-employment of firms.

Table A.5 estimates a first-difference transformation of the baseline specifications in (5) and (6), where the dependent variable is the change in the log of outstanding credit between bank b and firm i between the average of 1998-2001 and that of 2002-2007.

Table A.6 reports shift-share IV coefficients that are obtained from a weighted IV regression at the industry level, as in Borusyak et al. (2021). Standard errors allow for clustering at four-digit-sector level and are valid in the framework of Adão et al. (2019).

Table A.7 shows the results of our baseline specification in (6), including interactions with quartile dummies in terms of firm exposure, TFP, and comparative advantage.

Table A.8 shows the results of a regression of loan applications on firm-level exposure as defined in equation (8).

Tables A.9 and A.10 replicate specifications (6) and (9) adding additional dimensions of firm heterogeneity.

Table A.11 shows the results of our baseline specification in (6), splitting the sample of provinces above or below the median in terms of (i) the number of patents registered at the European Patent Office per 100,000 persons (i.e., innovation), (ii) the share of adults with at least a high school degree (i.e., skill), and (iii) industrial diversification defined according to a Herfindahl-Hirschman index.

Table A.12 replicates the specification (9) including the firm-time FE estimated in specification (5).

Table A.13 replicates specification in (9) including province-sector-time FE, rather than sector-time FE.

Table A.14 estimates a first-difference transmission of the specification in (9), where the dependent variable is the change in a given firm outcome between the average of 1998-2001 and that of 2002-2007.

Figure A.1 compares the patterns of exports and employment across groups of firms that are potential winners and losers from the China shock.

Figure A.2 shows the results of the dynamic difference-in-differences estimator of the specification in (11).

Figure A.3 shows the credit and employment shares by deciles of firm-exposure.

Subsection A.1 analyzes the OLS bias of the baseline estimation.

Subsection A.2 shows the computations and assumptions behind the figures in subsection 4.2 (economic relevance).

Table A.1: Robustness: Variations in the instrumental variable

Dep Var: $\ln C_{ibt}$	US		ANJ	
	(1)	(2)	(3)	(4)
$Exposure^{IT}_{-i,b} \times Post_t \times \ldots$	-0.0727***		-0.0759***	
	(0.00628)		(0.00634)	
$...ManufHighHit_i$		-0.0704***		-0.0625***
		(0.0132)		(0.0138)
$...ManufLowHit_i$		-0.0768***		-0.0870***
		(0.0103)		(0.0108)
$...Services_i$		-0.0714***		-0.0766***
		(0.00841)		(0.00852)
Bank controls	✓	✓	✓	✓
Firm-time F.E.	✓	✓	✓	✓
Firm-bank F.E.	✓	✓	✓	✓
Observations	3499092	3499092	3499092	3499092
Adjusted R-squared	0.832	0.832	0.832	0.832

Note: 2SLS baseline specifications (5) and (6). In columns (1) and (2), the instrument $Exposure^{OC}_{-sb}$ defined in (4) uses US imports in the corresponding sector. In columns (3) and (4), it uses Australia, New Zealand, and Japan. Bank controls include bank characteristics pre-2000 interacted with a post-2001 dummy, these are log-assets, share of NPLs, core-funding ratio, the capital ratio, and bank specialization. All regressions include firm-year fixed effects and firm-bank dummies. Standard errors are clustered at the bank-sector level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.2: Robustness: Variations in bank exposure measure

Dep. Variable: $\ln C_{ibt}$	Firm-Sector Out		Bank Assets		Export-Sector Out		Upstream Links	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Exposure^{IT}_{-ib} \times Post_t$	-0.0781***		-0.0436***		-0.0764***		-0.0748***	
	(0.00616)		(0.00845)		(0.00633)		(0.00607)	
... $\times$ $Man\ HighHit_i$		-0.0742***		-0.0420**		-0.0882***		-0.642***
		(0.0134)		(0.0178)		(0.0138)		(0.0129)
... $\times$ $Man\ LowHit_i$		-0.0825***		-0.0715***		-0.0778***		-0.0824***
		(0.00963)		(0.0144)		(0.0100)		(0.0099)
... $\times$ $Services_i$		-0.0774***		-0.0316***		-0.0700***		-0.0762***
		(0.00788)		(0.0107)		(0.00825)		(0.00809)
Bank controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm-time F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Firm-bank F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3473687	3473687	3499092	3499092	3252970	3252970	3499092	3499092
Adjusted R-squared	0.832	0.832	0.832	0.832	0.835	0.835	0.832	0.832

Note: 2SLS baseline specifications (5) and (6). In columns (1) and (2), the independent variable is defined leaving out firm-i's sector of operation. In columns (3) and (4), it is defined using bank's total assets as denominator. The corresponding changes are also in the instrument $Exposure^{OC}_{-sb}$ defined in equation (4). In columns (5) and (6), the estimation excludes the main export sectors towards China. In columns (7) and (8) the definition of bank exposure considers not only the direct exposure of a given industry to imports from China, but also the effects on upstream sectors. Bank controls include bank characteristics pre-2000 interacted with a post-2001 dummy, namely, log-assets, share of NPLs, core-funding ratio, the capital ratio, and bank specialization. All regressions include firm-year fixed effects and firm-bank dummies. Standard errors are clustered at the bank-sector level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.3: Baseline with alternative sets of fixed effects

Dep. Variable: $\ln C_{ibt}$	(1)	(2)	(3)	(4)
	Panel 1: Average effects			
$Exposure^{IT}_{-ib} \times Post_t$	-0.0359***	-0.0591***	-0.0561***	-0.0735***
	(0.00527)	(0.00658)	(0.00601)	(0.00620)
	Panel 2: Heterogeneous effects			
$Exposure^{IT}_{-ib} \times Post_t$				
... $\times ManufHighHit_i$	-0.0478***	-0.0724***	-0.0728***	-0.0683***
	(0.00740)	(0.00871)	(0.00853)	(0.0131)
... $\times ManufLowHit_i$	-0.0353***	-0.0524***	-0.0631***	-0.0795***
	(0.00679)	(0.00760)	(0.00752)	(0.0102)
... $\times Services_i$	-0.0296***	-0.0550***	-0.0398***	-0.0728***
	(0.00628)	(0.00711)	(0.00710)	(0.00836)
Firm F.E.	YES	YES		
Bank F.E.	YES	YES		
Time F.E.	YES	YES	YES	
Bank controls		YES	YES	YES
Firm-bank F.E.			YES	YES
Firm-time F.E.				YES
Observations	3499092	3499092	3499092	3499092
Adjusted R-squared	0.644	0.644	0.821	0.832

Note: 2SLS specifications (5) (Panel 1) and (6) (Panel 2) with alternative sets of controls. Column (4) shows the baseline results, with the complete sets of controls. Standard errors are double clustered at the bank-sector level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.4: Baseline with weighted least squares

Dep. Variable: $\ln C_{ibt}$	Obs. weighted by firm size	
	(1)	(2)
$Exposure^{IT}_{-i,b} \times Post_t \times \ldots$	-0.0882***	
	(0.00852)	
$\ldots ManufHighHit_i$		-0.0854***
		(0.0162)
$\ldots ManufLowHit_i$		-0.0881***
		(0.0134)
$\ldots Services_i$		-0.0902***
		(0.0122)
Bank controls	✓	✓
Firm-time F.E.	✓	✓
Firm-bank F.E.	✓	✓
Observations	3499092	3499092
Adjusted R-squared	0.840	0.840

Note: 2SLS specifications (5) and (6) with observations weighted by the log-employment of firms. Bank controls include bank characteristics pre-2000 interacted with a post-2001 dummy, namely, log-assets, share of NPLs, core-funding ratio, the capital ratio, and bank specialization. All regressions include firm-year fixed effects and firm-bank dummies. Standard errors are clustered at the bank-sector level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.5: Baseline with first differences

Dep. Variable: $\Delta \ln C_{ib}$	First difference (1)	(2)
$Exposure^{IT}_{-i,b} \times \ldots$	-0.0652***	
	(0.00702)	
$\ldots ManufHighHit_i$		-0.0594***
		(0.0139)
$\ldots ManufLowHit_i$		-0.0837***
		(0.0128)
$\ldots Services_i$		-0.0573***
		(0.0095)
Bank controls	✓	✓
Firm F.E.	✓	✓
Observations	330874	330874
Adjusted R-squared	0.197	0.197

Note: 2SLS of a first-difference transformation of specifications (5) and (6). The dependent variable is the change in the log of outstanding credit between bank b and firm i between the average of 1998-2001 and that of 2002-2007. Standard errors are clustered at the bank-sector level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.6: Baseline with shift-share clustering

Dep Var: $\ln C_{ibt}$	Full sample (1)	High-Hit (2)	Low-Hit (3)	Services (4)
$Exposure_b^{IT} \times Post_t$	-0.0740***	-0.0768***	-0.0767***	-0.0593***
	(0.0181)	(0.0256)	(0.0254)	(0.0160)
Observations	5220	5220	5220	5220
Adjusted R-squared	0.836	0.836	0.836	0.836

Note: Shift-share 2SLS coefficients from equivalent industry-level regressions (as in Borusyak et al., 2021). Standard errors allow for clustering at the 4-digit-sector level, and are valid in the framework of Adão et al. (2019). Differently from baseline estimates, bank exposure is computed without leaving out firm i from credit weights. Outcome and treatment residuals are obtained from specifications that include bank characteristics pre-2000 interacted with a post-2001 dummy (log-assets, share of NPLs, core-funding ratio, capital ratio, and specialization), firm-year fixed effects, and firm-bank dummies. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.7: Baseline with heterogeneous effects: Quartiles

Dep. Variable: $\ln C_{ibt}$	$Exposure^{IT}_{-i,b} \times Post_t \times \ldots$		
	$\times Hit_q$	$\times LowHit\ TFP_q$	$\times LowHit\ CompAdv_q$
	(1)	(2)	(3)
$Q1$	-0.0837***	-0.104***	-0.110***
	(0.0143)	(0.0215)	(0.0356)
$Q2$	-0.0761***	-0.0877***	-0.128***
	(0.0149)	(0.0208)	(0.0293)
$Q3$	-0.0617***	-0.120***	-0.0555***
	(0.0174)	(0.0232)	(0.0182)
$Q4$	-0.0790***	-0.0656***	-0.104***
	(0.0196)	(0.0235)	(0.0209)
Bank controls	✓	✓	✓
Firm-time F.E.	✓	✓	✓
Firm-bank F.E.	✓	✓	✓
Observations	3499092	1315718	1720591
Adjusted R-squared	0.832	0.831	0.836

Note: 2SLS specifications (6) with interactions with quartile dummies in terms of firm exposure as defined in equation 1 (column 1), as well as TFP and comparative advantage within low-hit sectors (columns 2 and 3). Bank controls include bank characteristics pre-2000 interacted with a post-2001 dummy, namely, log-assets, share of NPLs, core-funding ratio, capital ratio, and bank specialization. All regressions include firm-year fixed effects and firm-bank dummies. Standard errors are clustered at the bank-sector level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.8: Loan applications

Dep. Variable: $\ln Applications_{i\tau}$	Applications to all banks (1)	Applications to less exposed banks (2)	Applications to more exposed banks (3)
$FirmLevelExposure_i \times Post_\tau$	-0.00907	0.109***	-0.0300**
	(0.0118)	(0.0175)	(0.0129)
Firm F.E.	✓	✓	✓
Period F.E.	✓	✓	✓
Observations	276988	88972	250594
Adj. R^2	0.419	0.289	0.377

Note: Loan applications come from the so-called "*richiesta di prima informazione*," which is an enquiry that a bank makes to the Bank of Italy to obtain information on the credit position of potential borrowers. These enquiries can be made by a bank only after it receives a formal application and if the applicant is a new client (not currently borrowing from the bank). Hence, it can be used a proxy for loan applications. An important caveat is that we cannot account for applications that are rejected without going through the "*richiesta di prima informazione*" or rejections resulting from preliminary discussions between firms and banks (i.e., without a formal application being made). With these caveats in mind, the table shows the results of the following 2SLS regression: $\ln Applications_{i\tau} = \beta_1\ Firm\ Level\ Exposure_i \times Post_\tau + \gamma_i + \delta_\tau + \epsilon_{i\tau}$, where we use our usual instrument. Firm-level exposure is defined in equation (8), and γ_i and δ_τ are firm and period fixed effects, respectively. We run this regression for the full sample of firms and banks (column 1) and then splitting loan applications between low- and high-exposed banks (column 2 and 3). Note the sum of observations in column (2) and (3) is higher than the observations in column (1) because firms can apply to banks in both groups. Standard errors are clustered at the firm level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.9: Baseline: Additional dimensions of heterogeneity

Dependent Variable:		$\ln C_{ibt}$	
	(1)	(2)	(3)
$Exposure^{IT}_{-i,b} \times Post_t \times \ldots$			
... $\times$ $CompAdv\ LowHit_i$	-0.0783***		
	(0.0140)		
... $\times$ $CompAdv\ HighHit_i$	-0.0784***		
	(0.0144)		
... $\times$ $NonCompAdv_i$	-0.0961***		
	(0.0174)		
... $\times$ $HighProd\ LowHit_i$		-0.0866***	
		(0.0178)	
... $\times$ $HighProd\ HighHit_i$		-0.0667***	
		(0.0211)	
... $\times$ $LowProd_i$		-0.0847***	
		(0.00937)	
... $\times$ $Downstream\ LowHit_i$			-0.0870***
			(0.0304)
... $\times$ $NonDownstream\ LowHit_i$			-0.0892***
			(0.0114)
... $\times$ $HighHit_i$			-0.073***
			(0.0114)
Bank controls	✓	✓	✓
Firm-time F.E.	✓	✓	✓
Firm-bank F.E.	✓	✓	✓
Observations	1754920	1907568	1923473
Adj. R^2	0.831	0.829	0.830

Note: The table reports the results of specification (6). $Exposure^{IT}_{-i,b}$ defined in equation (1) is instrumented with (3). The estimation is based on manufacturing low-hit sectors with export comparative advantages, high-productivity, and downstream relative to the high-hit sectors. Standard errors are clustered at the bank-sector level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.10: Firm-level outcomes: Additional dimensions of heterogeneity

Dependent Variable	$\ln Empl_{it}$ (1)	$\ln Inv_{it}$ (2)	$\ln Rev_{it}$ (3)
Independent Variable: $FirmLevelExposure_i \times Post_t$			
a. Comparative Adv. Low-Hit	-0.0566***	-0.0515**	-0.0512***
	(0.0167)	(0.0238)	(0.0183)
b. High productivity Low-Hit	-0.119***	-0.141***	-0.153***
	(0.0130)	(0.0180)	(0.0150)
c. Downstream Low-Hit	-0.0725***	-0.0517**	-0.0586***
	(0.0182)	(0.0253)	(0.0212)
Firm F.E.	✓	✓	✓
Sector-time F.E.	✓	✓	✓
Bank Controls	✓	✓	✓

Note: The table reports the results of specification (9). The explanatory variable $FirmLevelExposure_i$, defined in equation (8), instrumented using $Exposure^{OC}_{(-i),b}$. The dependent variable is (log of) employment in column (1), investment in (2), revenues in (3). The estimation is based on low-hit manufacturing sectors with export comparative advantages (row a), high-productivity (row b), and downstream relative to the high-hit sectors. Standard errors are clustered at the sector-main-bank level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.11: Baseline: Geographical heterogeneity

Dependent variable:	$\ln C_{ibt}$	
	coeff	std
Characteristic of firm's province		
a) Innovation (patents per person)		
High innovation	-0.0903***	(0.00816)
Low innovation	-0.0605***	(0.00891)
b) Education (share adults with high-school)		
High skilled	-0.0843***	(0.00799)
Low skilled	-0.0638***	(0.00889)
c) Industrial diversification (HHI)		
High diversification	-0.0824***	(0.00809)
Low diversification	-0.0674***	(0.00951)

Note: Baseline specification (5), splitting the sample of provinces above or below the median in terms of (i) the number of patents registered at the European Patent Office per 100,000 persons, (ii) the share of adults with at least a high-school degree, and (iii) industrial diversification defined according to a Herfindahl-Hirschman index. The source for each of these variables is Italy's National Statistical Institute. Bank controls include bank characteristics pre-2001 interacted with a post-2001 dummy, namely, log-assets, share of NPLs, core-funding ratio, capital ratio, and bank-firm specialization. All regressions include firm-year fixed effects and firm-bank dummies. Standard errors are clustered at the sector-bank level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.12: Robustness: Effect on firms' outcomes (2SLS)

	$\ln C_{it}$		$\ln Emp_{it}$		$\ln Inv_{it}$		$\ln Rev_{it}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$FirmExp_i \times Post_t$	-0.0559***		-0.0460***		-0.0629***		-0.0649***	
	(0.0108)		(0.0131)		(0.0180)		(0.0133)	
$FirmExp_i \times Post_t \times HighHit_i$		-0.0683***		-0.0937***		-0.108***		-0.112***
		(0.0141)		(0.0172)		(0.0231)		(0.0179)
$FirmExp_i \times Post_t \times LowHit_i$		-0.0589***		-0.0535***		-0.0526**		-0.0479**
		(0.0126)		(0.0151)		(0.0211)		(0.0163)
$FirmExp_i \times Post_t \times Services_i$		-0.0481***		-0.0257*		-0.0484**		-0.0533***
		(0.0114)		(0.0141)		(0.0195)		(0.0139)
Firm F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Sector-time F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm-time F.E. from (5)	✓	✓	✓	✓	✓	✓	✓	✓
Observations	793968	793968	793968	793968	793968	793968	793968	793968
Adj. R^2	0.953	0.953	0.923	0.923	0.922	0.922	0.919	0.919

Note: The table reports the coefficients of the specification in equation (9). The dependent variable is the log of total outstanding credit of firm i in year t in columns (1)-(2), log of employment in (3)-(4), log of investment in (5)-(6) and log of revenues in (7)-(8). $FirmExp_i$ is defined in equation (8), instrumented using $Exposure^{OC}_{(-i),b}$. In addition to firm FE, sector-time FE, and a vector of weighted average lender characteristics pre-2000 (log-assets, share of NPLs, core-funding ratio, and the capital ratio), this specification also includes the firm-time FE estimated in equation 5. Standard errors are clustered at the sector-main-bank level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.13: Robustness: Real effects on firms (2SLS)

Dependent Variable	$\ln Empl_{it}$ (1)	$\ln Inv_{it}$ (2)	$\ln Rev_{it}$ (3)
Independent Variable	$FirmLevelExposure_i \times Post_t$		
a. Full sample	-0.0489***	-0.0706***	-0.0679***
	(0.0177)	(0.0260)	(0.0184)
b. High-Hit manuf.	-0.0930***	-0.107***	-0.101***
	(0.0213)	(0.0287)	(0.0218)
c. Low-Hit manuf.	-0.0623***	-0.0658**	-0.0610***
	(0.0188)	(0.0277)	(0.0199)
d. Services	-0.0306*	-0.0628**	-0.0592***
	(0.0184)	(0.0275)	(0.0189)
e. Comp. Adv. Low-Hit	-0.0468***	-0.0321	-0.0379**
	(0.0187)	(0.0271)	(0.0193)
f. High Prod. Low-Hit	-0.120***	-0.118***	-0.121***
	(0.0133)	(0.0187)	(0.0138)
g. Downstream Low-Hit	-0.0760***	-0.0598**	-0.0630***
	(0.0215)	(0.0305)	(0.0228)
Firm F.E.	✓	✓	✓
Sector-province-time F.E.	✓	✓	✓
Bank Controls	✓	✓	✓

Note: The table reports the results of specification (9). The explanatory variable $FirmLevelExposure_i$, defined in equation (8), captures the weighted average of the exposure of banks a firm was borrowing from; it is instrumented using $Exposure^{OC}_{(-i),b}$. The dependent variable is (log of) employment in column (1), investment in 2, revenues in 3. The estimation is based on the full sample of firms (row a), decomposition of the full sample in low-hit and high-hit manufacturing sectors, and services (rows b, c, d), and within manufacturing low-hit sectors, firms in sectors with export comparative advantages (row e), high-productivity (row f), and downstream relative to the high-hit sectors. All regressions include firm FE, sector-province-time FE, and a vector of weighted average lender characteristics pre-2000 (log-assets, share of NPLs, core-funding ratio, and capital ratio). Standard errors are clustered at the sector-main-bank level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

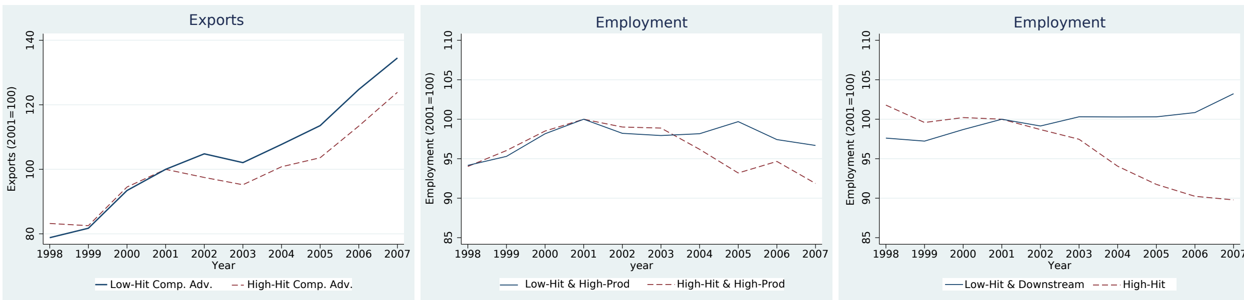
Table A.14: Effect on firms' outcomes (2SLS) - First differences

	$\ln C_{it}$		$\ln Emp_{it}$		$\ln Inv_{it}$		$\ln Rev_{it}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$FirmExp_i$	-0.0467***		-0.0377***		-0.0572***		-0.0549**	
	(0.0127)		(0.0125)		(0.0169)		(0.0126)	
$FirmExp_i \times HighHit_i$		-0.0590***		-0.0831***		-0.0951***		-0.0883***
		(0.0198)		(0.0207)		(0.0273)		(0.0216)
$FirmExp_i \times LowHit_i$		-0.0557***		-0.0602***		-0.0342***		-0.0388**
		(0.0183)		(0.0182)		(0.0245)		(0.0195)
$FirmExp_i \times Services_i$		-0.0339**		-0.0101		-0.0494**		-0.0466***
		(0.0158)		(0.0157)		(0.0212)		(0.0152)
Sector F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Bank controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	99382	99382	99382	99382	99382	99382	99382	99382
Adj. R^2	0.031	0.031	0.026	0.026	0.032	0.032	0.041	0.041

Note: The table reports the results of a first-difference transformation of specification (9). The dependent variable is the change in the log of total outstanding credit of firm i between the average of 1998-2001 and that of 2002-2007 in columns (1)-(2), log of employment in (3)-(4), log of investment in (5)-(6) and log of revenues in (7)-(8). $FirmExp_i$ is defined in equation(8), instrumented using $Exposure^{OC}_{(-i),b}$ in (8). All regressions include sector FE and a vector of weighted average lender characteristics pre-2000 (log-assets, share of NPLs, core-funding ratio, and capital ratio). Standard errors are clustered at the sector-main-bank level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Figure A.1: Exports and employment by groups of firms

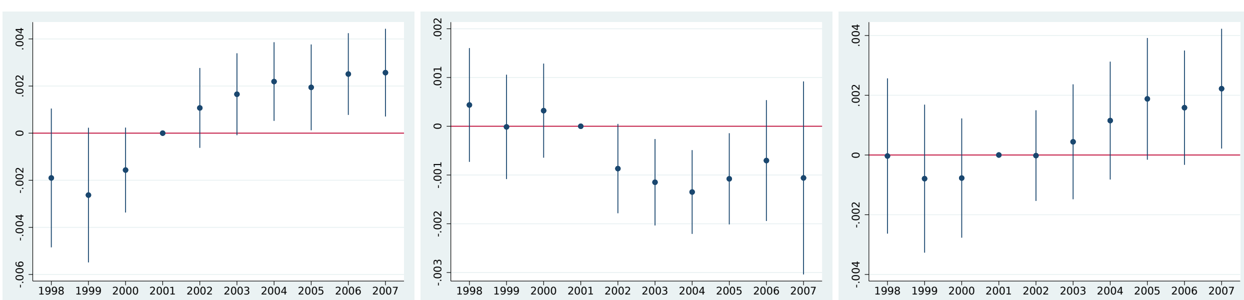
(a) Comparative advantage (b) Productivity (c) Downstream



Note: Panel (a) shows the evolution of exports for firms in sectors with comparative advantage before China's entrance into the WTO (defined through a Balassa index), distinguishing between those that are low- and high-hit sectors by import competition from China (2001=100). Panel (b) shows the evolution of employment for high-productivity firms distinguishing between those that are low- and high-hit sectors by import competition from China. Panel (c) shows the evolution of employment for low-hit firms in downstream sectors relative to high-hit firms.

Figure A.2: Dynamic diff-in-diffs (95% CI) on banks' balance sheet

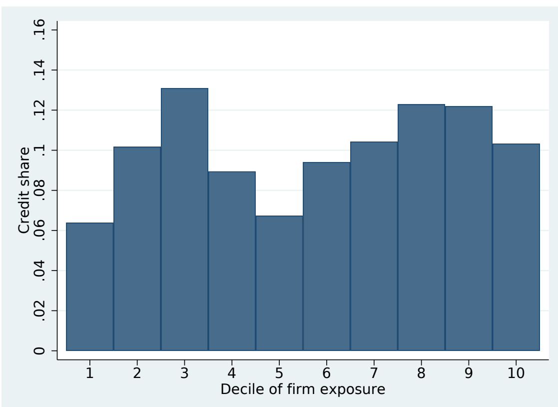
(a) NPLs (b) Tier 1 (c) Provisions



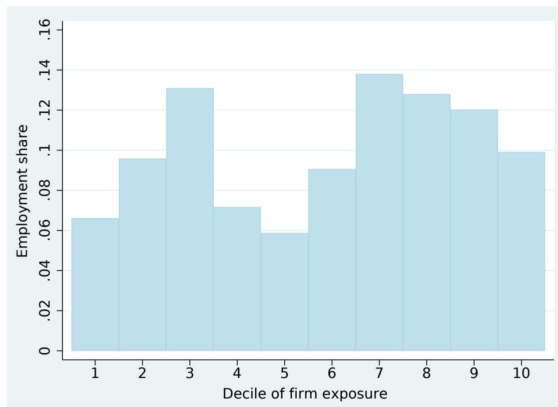
Note: The figure reports the coefficients, with 95% confidence interval of the variable $Exposure_b^{IT}$, instrumented with the variable $Exposure_{i,b}^{OC}$, coming from the dynamic diff-in-diffs regression of specification (11).

Figure A.3: Firm-level exposure, credit, and employment shares by decile

(a) Credit share

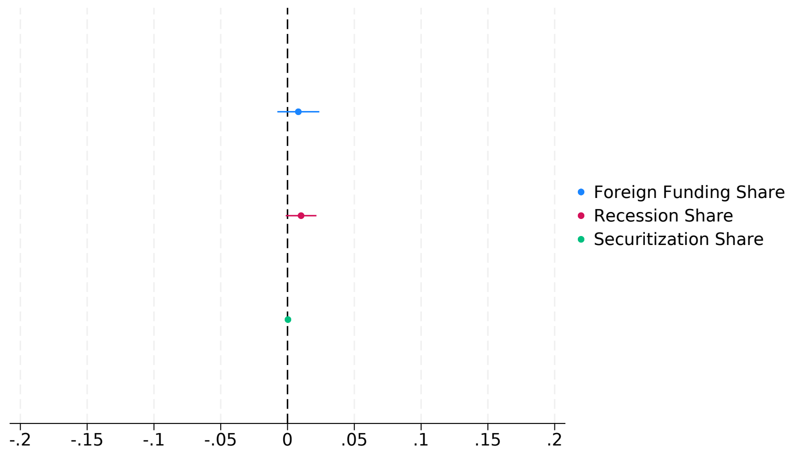


(b) Employment share



Note: This figure reports the credit and employment shares by deciles of firm exposure as defined in equation (8)

Figure A.4: Balancing test on additional bank characteristics



Note: This figure reports the results of regressions on the (non-leave-out version of the) shift-share instrument of bank shares related to three additional bank characteristics: (a) share of foreign liabilities in the 1998-2001 period as a measure of banks' exposure to capital inflows (following Cingano and Hassan (2019)); (b) share of loans to sectors that experienced a decrease in revenues in the 2002-2003 relative to 2000-2001 periods as a measure of pro-cyclicality of loan portfolio; (c) share of securitized lending by banks in the years 1998-2000. Following Borusyak et al. (2021), the regressions are implemented at the shock level to obtain exposure-robust standard errors.

A.1 OLS Bias

We are interested in the following model of supply-induced variation in bank credit:

$$\ln C_{ibt} = \alpha_{ib} + \alpha_{it} + \beta\, IM^S_{bt} + \epsilon_{bit},$$

where IM^S_{bt} corresponds to shocks to bank b derived from the increase of imports supply from China into Italy across sectors (weighted by bank-b's portfolio shares in each sector).

We do not observe IM^S_{bt}. Instead, we observe total change in imports from China into Italy, which is driven by supply and demand factors:

$$IM_{bt} = IM^D_{bt} + IM^S_{bt}$$

The OLS regression estimates β_{OLS} using IM_{bt} as the explanatory variable:

$$\ln C_{ibt} = \alpha_{ib} + \alpha_{it} + \beta_{OLS}\, IM_{bt} + \epsilon_{bit}.$$

The OLS estimate is therefore a weighted average of our coefficient of interest (i.e., the effect of the *supply-driven* rise in imports) and the effect of demand-driven factors:

$$\beta_{OLS} = \beta_{IV}\frac{\sigma^2_S}{\sigma^2_S + \sigma^2_D} + \beta_D\frac{\sigma^2_D}{\sigma^2_S + \sigma^2_D},$$

where the weights depend on σ^2_S and σ^2_D, which correspond to the volatility of the supply and demand factors in overall import volatility.

We use IM^{OC}_{bt} (i.e., bank exposure computed using imports from China by other countries) as an instrument for IM^S_{bt}. The instrument IM^{OC}_{bt} is itself given by supply and demand factors in other countries. Our assumption is that demand factors in other countries (e.g., Australia, Japan, New Zealand, and the US) are not correlated with demand factors in Italy. From Table 2 we get: $\beta_{OLS} = -0.068$ and $\beta_{IV} = -0.074$.

In the extreme case in which IM^{OC}_{bt} captures *all* supply-driven forces of Italian imports from China, the residual of the first stage in Table 2 would be driven by demand-side forces. We therefore use this residual to instrument for demand-driven changes in imports, IM^D_{bt}, in our baseline regression. Under this assumption, the estimated $\beta_D = -0.062$ captures the effect of bank exposure to cross-sectoral demand-driven changes in imports from China. In this case, the implied supply-driven volatility would account for around 50% of the total cross-sector volatility of imports from China into Italy (weighted by the bank's portfolio shares), which is similar to the estimates of Autor et al. (2013).

However, this estimate represents a lower-bound, because we do not expect our instrument to capture all supply-driven imports. So, in the other extreme case in which the increase in imports from China is (in expectation) supply driven, although not entirely captured by our instrument, the coefficient β_D would be zero. The difference between the OLS and IV estimates would then be given by the classic attenuation bias. In this upper-bound case, our instrument IM^{OC}_{bt} would be capturing around 90% of the total cross-sector volatility of imports from China into Italy (weighted by bank's portfolio shares).

Overall, we conclude our instrument is capturing at least half, and up to 90%, of the volatility of bank exposure to import from China. The volatility of bank exposure to import from China is therefore mostly driven by the irruption of China into world markets and not by Italian changes in demand for imports.

A.2 Aggregate Effects

In subsection 4.2, we present the additive effect of the lending channel on credit and employment. This is a *partial-equilibrium aggregation* similar to the one in Chodorow-Reich (2014). It relies on two main caveats.

First, all the results are relative to the firms in the bottom decile of the distribution of firm-level exposure as defined in (8). This procedure is equivalent to assuming these firms did not suffer changes in their access to credit in 2002-2007.

Second, we do not incorporate general-equilibrium effects; the results shown in subsection 4.2 correspond to the sum of the direct effects of the lending-channel on credit and employment across all firms above the 10-percentile. Intuitively, the computation here corresponds to the *shift* of the curve (demand shift in the case of employment, supply shift in the case of firm credit) and not the resulting equilibrium quantities.

We define the counterfactual growth rate g^Y of outcome Y ($\Delta \ln Y$) for firms in the bottom 10% of exposure distribution:

$$g^Y = \alpha^Y + \beta^Y E[Exposure_i | Exposure_i < Exposure_{P10}].$$

Let $\overline{X} \equiv E[Exposure_i | Exposure_i < Exposure_{P10}]$. Then, for all firms with $Exposure_i > Exposure_{P10}$, the effect of the lending channel, relative to this group of firms, is

$$\begin{aligned} \ln Y_{iPost} - \ln Y_{iPre} &= \alpha^Y + \beta^Y Exposure_i \\ &= g^Y + \beta^Y \ (Exposure_i - \overline{X}). \end{aligned}$$

Given our definition of *partial-equilibrium aggregate*, the percentage change in aggregate output $Y = \sum_i Y_i$ is the weighted sum of growth rates across all firms in the economy: $\Delta \ln Y = \sum_i \Delta \ln Y_i \omega_i^Y$, where ω_i^Y is firm-i's share of output Y. Then,

$$\Delta \ln Y = g^Y + \beta^Y \ \sum_i (Exposure_i - \overline{X}) \cdot \omega_i^Y.$$

We perform a change in variables. Let $\omega^Y(x)$ be the share of output Y by all firms i with $Exposure_i = x$ (the shares of credit and employment by firm exposure are shown in Figure A.3). Then,

$$\Delta \ln Y = g^Y + \beta^Y \ \sum_x (x - \overline{X}) \cdot \omega^Y(x).$$

The first term corresponds to the counterfactual growth rate if all firms grew at the rate of the benchmark firms. The second effect corresponds to the deviation implied by the lending-channel effect.

Notice our counterfactual is not meant to capture a scenario without the China shock.

It captures the effect of the China shock absent the endogenous contraction in credit supply. In other words, it isolates the role of the lending-channel: how banks amplified the original shock to firms already hit by import competition, and how they transmitted it to expanding sectors.