Trade Shocks and Credit Reallocation

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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.

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1 Introduction

The effect of trade liberalization on welfare and economic activity depends crucially on the ease with which factors of production move across firms, sectors, and regions, according to the changing patterns of comparative advantage. Significant evidence shows a slow adjustment of labor markets to trade shocks, which is associated with frictions in labor mobility due to geographical barriers or sector-specific skills. This paper contributes to this debate by empirically identifying a financial friction that arises endogenously in the aftermath of a trade shock, and hinders the reallocation of credit across firms and sectors.

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 the period (Figure 1b). Crucial to our analysis, non-performing loans (NPLs) almost doubled among these firms competing with imports from China, from €3.4 to €6 billion. This increase was large enough to erode banks' capital, which was €56 billions for the whole banking system on the onset of the shock. As a result, banks most exposed to these highly-hit sectors cut their supply of credit both to firms negatively affected by import competitions from China, and to those in sectors expected to benefit from the liberalization episode. This cut in the supply of credit restrained employment growth and investment of firms in otherwise expanding sectors. The direct magnitude of this lending-channel effect, abstracting from the general equilibrium response, led to 1.3 percentage points (pp) lower employment growth between 2002 and 2007.

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 measure bank exposure to the China shock by looking at the share of loans to firms across sectors that are heterogeneously hit by the 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.

We analyze the patterns of credit supply before and after China's entry into the WTO, across banks with different degrees of exposure. 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, changes in the firm's demand of credit due to the China trade shock itself. We find that one standard deviation of bank exposure implies 7.4% lower credit and 0.5 pp higher interest rate after 2002, relative to other banks lending to the same firm. Importantly, banks cut credit by a similar proportion both to firms subject to competition from China and to firms in sectors less affected by the shock. They also reduce credit supply to potential winners of the liberalization episode, that is, firms in sectors where Italy has a comparative advantage, top productivity firms, and even those that are more likely to benefit from cheaper inputs from China (downstream industries).

We find evidence of limited substitution across sources of funding; overall bank-firm relationships proved to be sticky. We arrive to this conclusion by comparing the total credit of firms that, prior to 2001, borrowed from the most exposed banks, relative to firms in the same 4-digit sector borrowing from less constrained sources; their total credit declined. Firms borrowing from a bank with a 10 pp higher exposure then faced a roughly 5% reduction in employment (as well as investments and revenues). Importantly, credit constraints not only amplified the shock to firms already hit by import competition from China, but also limited the real outcomes of firms in expanding sectors, in manufacturing and services. Without accounting for general equilibrium effects, the bank-lending channel explains 80,000 job losses in sectors already hit hard by competition from China; that is, almost one fourth of the overall jobs losses in these sectors. This channel also accounted for 30,000 missing jobs in the rest of the manufacturing sectors and 58,000 missing jobs in services.

Banks in our sample are specialized in economic activities along the lines described by Paravisini et al. (2017). Banks' balance sheets are therefore affected when their sectors of expertise suffer a negative shock. In our case, a one-standard-deviation higher bank exposure to the trade shock is associated with a 0.3 pp increase in the NPLs' share relative to banks' assets. This effect is sizable given that the NPLs ratio for the median bank in those years is 1.4%. Importantly, we do not observe any reaction to deposits or external capital injection. This lack of reaction coincides with the predictions of classical banking models such as 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 further support for this conclusion, we find that for equally exposed banks with more capital on the onset of the shock (above 14% tier-1 capital ratio), the increase of NPLs was decoupled from banks' lending capacity. These banks did not constrain their lending, relative to less exposed banks, and they reshuffled their portfolio toward expanding sectors (services or manufacturing less hit by competition from China). These banks, however, only account for less than 5% of total corporate credit.

We also explore the geographical dimension of the bank lending channel. 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 that our results apply across provinces, including those with lower exposure to the shock. This finding suggests that the endogeneous 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. While, 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 several 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.[1] Evidence on capital reallocation after trade shocks is limited, even though, as argued by Dix-Carneiro (2014), 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 look at the reallo-

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

cation 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.

Our paper is also related to the literature on the financial and real implications of shocks to banks.[2] 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 demand shocks spread into the general economy.

Finally, the paper is related to studies that look at how banks transmit liquidity shocks across geographical markets.[3] It also is similar in spirit to that of Giroud and Mueller (2019), where firms' internal networks propagate shocks across counties. Our results refer to transmission of the shock –in our case, a trade liberalization shock– across sectors of economic activities. We therefore add evidence on the banking sector's broader role in structural economic adjustment after trade liberalization.

The rest of the paper is structured as follows. Section 2 describes the data; section 3 explains the empirical strategy; section 4 reports the baseline results on the intensive and extensive margins of credit; section 5 estimates the effects on total credit and the real effects on output, investment and employment; section 6 focuses on the mechanism behind our findings; section 7 discusses alternative mechanisms and the robustness of our results; section 8 concludes.

[2]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).

[3]See, among others, Allen and Gale (2000), Kaminsky and Reinhart (2000), Gilje et al. (2016), Cortés and Strahan (2017), Byun et al. (2021), Bustos et al. (2020).

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.[4] 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.[5] 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).

Table 1 shows the summary statistics of banks and firms characteristics in our sample. The unit of observation in our empirical analysis is at the bank-firm annual level. The

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

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

dataset includes, on average, 504 banks and about 170,000 firms, of which 70,000 are in manufacturing.[6] 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, the fact that firms borrow from multiple banks is an essential feature of our identification strategy.

2.2 Defining firm and bank exposure to the China shock

To implement our empirical approach, we first need to identify firms' direct exposure to the increase in import competition from China. We follow closely Autor et al. (2013) in their empirical strategy and compute the following sector-level (4-digit) measure of exposure to the China shock[7]:

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

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 versus 1994-2001 average).[8] The denominator corresponds to the employment level in the same sector in 1991.[9] 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 by sector, with its median cutoff. Manufacturing sectors above and below the median

[6] 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).

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

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

[9] 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.

account for an equal share of total credit and employment.

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[10]:

$$Exposure_{-ib}^{IT} = \frac{\sum_{i' \neq i} C_{i'b} China_{i's}^{IT}}{\sum_{i' \neq i} C_{i'b}} \tag{2}$$

where C_{ib} is the outstanding credit of bank b to a manufacturing firm i, and, abusing notation, $China_{is}^{IT}$ 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.[11] 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.[12]

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

In Table 2, we follow the approach of Imbens and Wooldridge (2008) and show the balance of "high-exposed" and "low-exposed" banks by looking at the normalized difference of bank and borrower characteristics over the period 1998-2000. As a rule of

[10]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.

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

[12]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.

thumb, Imbens and Wooldridge (2008) argue a normalized difference of covariates above 0.25 standard deviations is substantial. In our case, all variables are within this tolerance threshold, although the average size (total assets) of more exposed banks is larger. Our empirical strategy, explained next, accounts for this heterogeneity. Reassuringly, the borrower characteristics across the two groups show a high degree of overlap.

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, measurement 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" ($China_s^{OC}$)[13]:

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

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

[13] The countries in the baseline regression are 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.

China, it has little effect on imports to the US from China:

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

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

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 that banks' exposure to import competition negatively affected credit supply to these potentially expanding sectors.

3 Empirical Strategy

For our identification strategy, we exploit the ex-ante heterogeneity across banks in terms of their exposure to the China shock, as defined in equation (2). The goal of our empirical strategy is to identify the impact of bank exposure on the supply of credit to firms and the implication this impact has on resource reallocation. 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).[14] 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. However, 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.

[14] We select a threshold of banks' exposure so that each of the two groups accounts for half of the outstanding credit.

Therefore, Figure 3b further disaggregates lending by the two groups of banks according to borrowers characteristics. In particular, we distinguish between firms operating in sectors above the median of exposure to import competition from China (*high-hit*) and firms in sectors of exposure below the median (*low-hit* firms) 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 that lending of highly exposed banks grew more slowly than that of low-exposed banks for both groups of firms. Although these aggregate patterns provide suggestive evidence of differences in credit allocation between banks, the results might be driven by compositional effects, demand shocks, and other multiple factors. Our empirical strategy will allow proper identification of such effects.

3.1 Baseline specification: The intensive margin of credit

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 across all related banks. The results are therefore 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

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

The dependent variable is the log of outstanding credit, C_{ibt}, granted by bank b to firm i at the end of year t. The variable $Exposure^{IT}_{-i,b}$ measures the ex-ante exposure of banks to borrowers competing with imports from China (measured using Italian imports from China) and it is interacted with the dummy $Post_t$ equal to 1 for the years after China's entry into 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.

This specification identifies credit-supply shocks under the assumption that changes in firms' credit demand resulting from the China shock are absorbed by the firm-time fixed effects. Put simply, the approach assumes firms' change in their demand of credit across banks is not systematically correlated with banks' exposure to the China shock. This assumption would be violated, for example, if banks were specialized in certain activities. Then, a negative sectoral shock may induce firms to reduce credit demand disproportionately for banks specialized in that sector. To account for that possibility, we add a specialization dummy (interacted with $Post_t$) as in Paravisini et al. (2017), that takes the value of 1 if a bank is specialized in the sector of the firm. In the Appendix, we also present the results of a specification in which the definition of bank exposure does not include the firm's sector of operation.[15]

The explanatory variable $Exposure^{IT}_{-i,b}$ imperfectly measures the China shock, because it is also determined by Italian demand factors. We therefore instrument the China supply-driven increase in imports with $Exposure^{OC}_{-i,b}$, defined using the imports from China into other non-European developed countries (equation (4)).

Given that our source of variation is at the bank level and the original China shock is defined at the sectoral level, we double cluster the standard errors at the bank and sector level.[16] In the baseline specification, the observations are unweighted.[17]

[15]Following Paravisini et al. (2017) a bank is considered to be specialized in one sector if its share of loans in that sector is above the sum of 75th percentile threshold and 1.5 the interquartile range across banks for a given sector-year.

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

[17]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.

3.2 Heterogeneous effects

The China shock analyzed here is both a sectoral and, given its magnitude, a 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 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 the mechanism through which the lending-channel affects the process of credit reallocation.

We investigate whether exposed banks rebalance their supply of credit away from sectors most hit by import competition from China, which would relax their lending constraint towards expanding sectors. To this end, we expand equation (5) with an interaction dummy D_g equal to 1 for firms belonging to the corresponding group, and 0 otherwise:

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

The groups include firms in sectors most negatively affected by competition from China, and those in sectors that were less affected or even benefited from the trade-liberalization shock. In the first group, we consider firms in manufacturing sectors with an above-median measure of exposure, as defined in (1). We denote those firms *High-Hit* and compare them with firms in *Low-Hit* sectors and services (Figure 1b shows their relative performance in terms of employment).

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; according to classic trade models (e.g., Ricardo-Viner), these sectors are expected to expand upon trade liberalization.[18] Along the same lines, according to models of trade with firms heterogeneity, such as Melitz (2003), we should expect more productive firms to expand and absorb more resources, especially in sectors

[18] 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).

not directly competing with imports from China.[19] And finally, we consider firms in downstream sectors, relative to the High-Hit ones, that now can benefit from cheaper inputs.[20] 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.

3.3 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 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 firms to change their sources of funding, which is the subject of this subsection.

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):

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

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

[19] 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.

[20] 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 median.

$C_{ib,2001} = 0$ for $\tau = Pre$, and $C_{ib,t} > 0$ for at least one year in (2002, 2006) and $C_{ib,2007} = 0$ for $\tau = Post$), 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. $Entry_{ib\tau}$ is equal to 1 if the relationship was created during the period τ (i.e, $C_{ib,98} = 0$ and $C_{ib,01} > 0$ for $\tau = Pre$, and $C_{ib,02} = 0$ and $C_{ib,07} > 0$ for $\tau = Post$), and 0 otherwise. Because this regression refers to new bank-credit relationships, the measure of exposure $Exposure_b^{IT}$ is not firm-specific. By definition, this measure is not using information on firm i.

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. The specification accounts for whether the bank is specialized in the sector in which the firm operates, for the bank's pre-characteristics, and for firm-period fixed effects. Standard errors are double-clustered at the bank and sector level. We run this specification also distinguishing the effects for firms in sectors that are high-hit, low-hit, and services.

The effect of bank exposure on the credit-extensive margin informs us of potential substitutability between sources of bank lending. High elasticity of both exit and entry margins may suggest the replacement of more exposed banks with less constrained ones. Moreover, in section 5, we estimate the effect of firms' borrowing from exposed banks on their total available credit, which accounts for both the intensive and extensive margin.

4 Baseline Results

4.1 Intensive margin of credit

Table 3 reports the results of OLS (column 1) and 2SLS (column 2) estimates of our baseline specification in equation (5). Firm-time fixed effects, firm-bank fixed effects, bank specialization dummy and bank controls, interacted with the $Post_t$ dummy, are always included.[21] The coefficient of interest on bank exposure is negative and statistically significant in both specifications. This finding suggests banks that are more exposed to

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

the China shock reduce lending compared to non-exposed banks after China's entry into WTO. The effect is quantitatively significant: a bank with a one-standard-deviation-higher exposure reduces credit supply by 7.4% after China's entrance 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 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 charged by bank b to firm i in year t.[22] 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 that 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 increases the price of credit by 0.5% after China entrance in 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-difference estimator is plotted in Figure 4 for the full sample, for firms in high-hit sectors and for firms in low-hit sectors and services. 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 plateaus around 2005. Unfortunately, we cannot test for the long-term effects of exposure on credit, because the global financial crisis hit banks in 2008.

[22] 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.

4.2 Heterogeneous effect of the credit-supply shock

In this subsection, we estimate how bank exposure affects credit supply across different groups of firms, differently affected by the liberalization episode. We analyze the heterogeneous effect on credit, using the specification in equation (6). Column 1 of Table 4 shows how more exposed banks cut credit to firms in sectors above (*HighHit*) and below (*LowHit*) the median exposure to competition from China (defined in equation (1)), in manufacturing or services.[23,24] 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. More exposed banks cut credit supply proportionately in the three groups of firms. We also divide firms by the quartile of their sectoral exposure to import-competition (rather than using a median cut-off) and we find the coefficients are not statistically different across quartiles.[25]

We confirm the effect of bank exposure on credit supply across other dimensions of firm heterogeneity that could also lead to reallocation of resources after the China shock. First, in column 2, we distinguish between firms in sectors where Italy has a comparative advantage in exporting. Among the sectors with comparative advantage, we identify those subject to competition from China above (*High-Hit*) and below (*Low-Hit*) the median. The coefficients are not statistically different for the three groups of manufacturing firms.

The reallocation channel of a trade shock might work not only across sectors but also within sectors, with the more productive firms absorbing the resources of the less productive ones (as in Melitz, 2003). To analyze the role of bank credit supply in this process, we divide our sample of manufacturing firms according to their productivity, relative to their sector, before China's entrance into the WTO. Column 3 of Table 4 shows the effect of the shock on credit supply was not different for high-productivity firms.

Finally, we analyze the heterogeneous effect of bank exposure on credit supply for

[23]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 as not directly affected by import competition from China.

[24]The results hold also if we define *LowHit* firms as those in the bottom quartile of exposure among manufacturing sectors.

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

firms in downstream sectors (column 4) and find a negative effect also for firms that are in low-hit sectors and could potentially benefit from cheaper inputs from China.

Overall, we find bank exposure to the China shock triggered a reduction in their credit supply, relative to less exposed banks, across the different groups of firms. More exposed banks did not prioritize expanding sectors when allocating their constrained lending funds. Section 5 looks at whether (and how much) this effect hinders the reallocation of resources across sectors, which is crucial to the welfare effect of a trade-liberalization episode.

4.3 Extensive margin

We find that, as expected, more exposed banks are more likely to terminate credit relationships after 2002. In columns 1 and 2 of Table 5, 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%, with little difference across sectors.

Contrary to our priors, exposed banks *are not* less likely to start new credit relationships after China's entry into the WTO. In columns 3 and 4, we consider the probability of entry, over all banks operating in the firm's province. 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 an increase in the probability of entry of 0.025 pp.

Overall, more exposed banks reduced their number of credit relationships after 2002. In that sense, the China shock resulted in some reshuffling in firms' sources of funding, away from most exposed banks.[26] As we show in the next section, this reshuffling did not offset the overall contraction in credit experienced by firms connected to exposed banks.

[26] This is consistent with evidence from data on loan applications in Table A.8 in the Appendix. We find that 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.

5 Firm-level Credit and Real Outcomes

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 towards less exposed banks, ending up with no overall change in the firm-level amount of credit or real outcomes. For banks' lending constraints to end up affecting firms' real outcomes, one needs that, first, overall firm availability of credit is reduced, relative to comparable less affected firms, and second, that firms' real output is sensitive to changes in credit availability.

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 firm-i out), defined in (2).

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

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

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 (8).

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 changes in the firm-level demand for credit are accounted for by the sector-time fixed effect. Moreover, following Cingano et al. (2016), Bofondi et al. (2017), and Alfaro et al. (2021) we also include, as an additional control, the firm-time fixed effects ($\hat{\alpha_{it}}$) estimated in equation (5), which capture changes in the firm-level amount of credit demand that are common across all the firm's lenders. Columns 1 and 2 in Table 6 present the results with and without the inclusion of this firm-time fixed effect. The results are not statistically different. A 10% increase in firm-level exposure results in a reduction in the supply of credit of around 4%.

Columns 3 to 8 in Table 6 show the 2SLS results of equation (9) for different groups of firms. In columns 3 to 5, we report the effect interacted with three group dummies, firms in high-hit and low-hit manufacturing sectors, and services. In columns 6 to 8, we focus on low-hit firms expected to expand after the liberalization episode: firms in sectors for which Italy has a comparative advantage, most productive firms, and firms that are downstream relative to the high-hit ones. We conclude that firms could not freely substitute their sources of funding when their related banks cut credit supply. As a result, their overall availability of credit was reduced after 2001, compared with other firms in the same sector (although to a lesser extent for services and downstream firms).

Next, we analyze how firms' share of exposed credit affects real outcomes. Table 7 reports the marginal effects on employment (column 1), investment (column 2), and revenues (column 3), controlling for firm and sector-time fixed effects. These results reflect the combination of firms' availability of credit and the elasticity of the corresponding real outcome to funding. Row a shows 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 4.9%-5.9% drop in their real outcomes, relative to other firms in the same sector. The coefficients are negative and significant for all groups of firms, but substantial heterogeneity exists across them.

Highly productive firms in *Low-Hit* sectors were the most affected by the cut in credit by their related banks. A 10% larger dependence on exposed banks implied an 8% drop in the availability of credit relative to other firms in the same sector (column 7 in Table 6) and resulted in a 10% reduction in employment, 15% in investment, and 16% in revenues, relative to other firms in the same sectors (row f in Table 7).

Overall, our findings suggest banks' exposure to the trade shock ended up affecting the availability of credit of their related firms and therefore their level of employment, investment, and overall activities, irrespective of their economic sector. This way, constrained banks amplified the downturn of firms already hit by China's entry into the WTO. Moreover, the trade shock was transmitted, through this lending-channel, to firms not directly competing against imports from China, or to even those expected to expand upon the liberalization episode.

5.1 Economic relevance

The results shown above are based on estimations that absorb general equilibrium effects. They therefore face the usual caveats when we try to interpret them in macroeconomic terms. To grasp an idea of their economic relevance, we present in this subsection the direct magnitude of the lending-channel effect, without accounting for the general equilibrium response, along the lines in Chodorow-Reich (2014). The full detail of the computations is in Appendix A.2.

As a first step, we assume firms in the bottom 10% of the distribution of exposure are unconstrained in their access to credit (at a constant interest rate).[27] 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 -0.0489 estimated in Table 7, getting a relative employment differential of -1.36%. 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 8 shows the results of this aggregation exercise for employment (columns 1 and 2) by group of firms. We find that the growth rate of employment for High-Hit firms after China's entrance in 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 work-

[27] 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.

ers 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 translated into about 30,000 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 that this sector employed 58,000 less workers than it could have otherwise (employment in services grew by 865,000 units).[28] Columns 3 and 4 shows the results for credit. Notice that our aggregation 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.

6 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. First, we look at the evolution of the value of NPLs for firms in sectors *High-Hit*, *Low-Hit*, and services (Figure 5). 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 to €6 billion between 2002 and 2007 (equivalent to a rise from 10% to 20% of the share of non-financial corporations' NPLs). This increase was large relative to banks' capital, which was €56 billions for the whole system on 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-year level:

$$NPL_{ibt} = \alpha_{ib} + \alpha_{bt} + \beta\, China^{IT}_{is} \times Post_t + \epsilon_{ibt}, \tag{10}$$

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

where NPL_{ibt} is a dummy equal to 1 if the firm-bank loan is non-performing and the independent variable $China^{IT}_{is}$ corresponds to the exposure of firm i's sector to imports from China, as defined in (3), instrumented with (4). The specification includes a full set of firm-bank fixed effects and bank-time 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 9 confirm import competition from China increased the probability of the firm defaulting: a one standard deviation increase in the former is associated to 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 test more formally the link between bank exposure, NPLs, and lending capacity, we run the following specification:

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

The variable $Exposure^{IT}_b$ is 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 entrance in 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 10 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 5: a one-standard-deviation-higher bank exposure to the trade shock is associated with a 0.3 pp increase in the NPLs' ratio after China's entrance into the WTO. This effect is sizable given that the NPLs 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 – 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.[29]

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); (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).

Overall, 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 is consistent with the predictions of classical banking models such as Froot et al. (1993), Holmstrom and Tirole (1997), Froot and Stein (1998). Notice 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 confirm the following corollary. Banks with high tier 1 capital, relative to regulatory requirements, are less constrained in their lending capacity. Columns 2, 4 and 6 in Table 11 report the results of our baseline specification in (5) interacted with the tier 1 capital ratio before the shock (taking the 1998-99 average). We find a positive interaction term between the capital ratio and bank exposure; in other words, for a given level of exposure to the China shock, higher capitalized banks supply more credit than other banks for the same firm. This effect is statistically and economically significant for firms in low-hit sectors and services, but not for high-hit firms, suggesting banks with a higher capital buffer were tilting the composition of their portfolio away from high-hit firms. Our estimates imply firms in low-hit sectors and in services linked to banks in the top quintile of the distribution of tier 1 capital (about 14% capital ratio) did

[29]The dynamic diff-in-diff in the Appendix shows that there was no increase in provisions before the China entrance in the WTO, suggesting banks did not anticipate the shock.

not suffer from lower credit supply after China's entrance into the WTO. These banks, however, accounted for less than 5% of total credit before the shock, so their buffering effect on the economy was very limited.

7 Alternative mechanisms and robustness

In this section, we address several potential alternative mechanisms and identification challenges. Specifically, we analyze the geographical dimension of the lending channel. We also explore the robustness of our results by expanding the definition of "exposed" sectors and banks to account for input-output linkages, and address confounding factors that could undermine our identification strategy.

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 that 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 square 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 cut-off for High-Hit and Low-Hit, as well as for productivity and comparative advantage.[30]

7.1 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

[30] 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.

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).[31] We look at our results across provinces with different sectoral compositions.[32] Table 12 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 larger in provinces with above-median concentration in exposed sectors: -0.08 versus -0.05 for firms in directly hit sectors, and -0.09 versus -0.05 for firms in services. 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.

In the Appendix, we show our conclusions in section 5 referring to firm-level outcomes are maintained when absorbing sector-province-time fixed effects. The effects on employment, investment, and revenues are not systematically different when the firms in the control group are located in the same or a different province (within the same sector). Overall, we conclude the lending-channel analyzed here operates above and beyond other potential mechanisms arising from local general equilibrium effects.

7.2 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 upstream sectors (lower demand of inputs from hit customers). Following Acemoglu et al. (2016), we calculate for each industry j the weighted average change in Chinese imports across all industries that purchase from industry j. The weights are the shares of industry j's total sales that are used as inputs in each indus-

[31] 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.

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

try 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 modify our baseline measure of bank exposure by adding the upstream effects on the borrowing industries.[33] Columns 7 and 8 of Table A.2 in the Appendix confirm the baseline results.

7.3 Confounding shocks to the banking sector

Potential threats to our identification strategy might arise from other factors affecting banks post 2001, that could be correlated with their exposure to the China shock.[34]

Italian banks have experienced a boom in cross-border liabilities since late 2002. The foreign funding of banks increased from an average of slightly above €200 billion in the period of 1998-2002 (15% of GDP) to €900 billion in 2007 (56% of GDP). This increase in foreign funding was not unique to Italy, but was common to other European periphery countries such as Spain and Portugal, and it was part of a loose global financial cycle. Our concern is that banks more exposed to the China shock could be the ones that benefited less from these capital inflows, so our results are not driven by the exposure that a bank has to China, but by the boom of international capital flows that happens around that time. Following Cingano and Hassan (2019), we use the bank share of foreign liabilities in the 1998-2001 period as an instrument for its overall capital inflows in the 2002-2007 period. Column 1 of Table A.11 in the Appendix shows the result of our baseline specification adding the share of foreign liabilities pre-2001 as a control, and the results are confirmed.

Second, we explore the potential confounding factors related to the GDP slowdown in 2002-2003. We are concerned that the decrease in lending captures a heterogeneous exposure to the GDP slowdown across banks, rather than to the trade shock. To account for this effect, we use balance-sheet data to identify the sectors that experienced a decrease in

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

[34] We considered also the case of automation as an additional potential confounding factor that can hit firms and then propagate to banks in a similar way to our trade shock; we do not find evidence that this is the case. The results of this exercise are available upon request.

revenues in the 2002-2003 relative to 2000-2001 periods (i.e., the most pro-cyclical sectors). We then compute the share of loans to those sectors that banks have in their portfolio and regress it on exposure to the China shock. We add the average share of loans to the declining sectors in the years 1998-2000 (interacted with a post-dummy) as an additional control in the baseline estimation (column 2 in Table A.11) and the results do not change significantly.

Finally, we control for the increase in securitization in the early 2000 that affected bank liquidity and, potentially, their lending capacity. If banks exposed to China have different degrees of loan securization, our results could be biased: the effect of an increase in NPLs on the bank's credit supply would be lower if those NPLs were securitized. To account for this possibility, we compute the average share of securitized lending by banks in the years 1998-2000 and add it as a control (interacted with the post-dummy) in our baseline regression.[35] Column 3 of Table A.11 shows the effect of bank exposure is negative and significant, however the point estimate is slightly lower, suggesting banks with higher exposure to hit sectors may have held a larger share of securitazion. Overall, the baseline results are not significantly changed by these potentially confounding factors.

8 Concluding Remarks

This study shows that the decrease in banks' supply of credit in the aftermath of a trade shock is an important channel that can affect the welfare costs associated with trade-liberalization episodes. Focusing on China's entry into the WTO as an exogenous shock, we find that 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.

This phenomenon results in substantial spillovers between losers and winners from

[35] As a robustness check, we also take the share of securitized loans in 2001 as the degree of securitization in the 1998-2000 period was still relatively low.

trade liberalization, through the endogenous credit constraint of banks: exposed banks reduce credit supply not only to firms that are directly subject to competition from China, but also to firms that are not affected by China and should actually expand, including high-productivity firms and firms in sectors where Italy has a comparative advantage to export.

We find that firms are unable to perfectly substitute negatively affected banks with alternative sources of credit. Therefore, the aggregate credit of firms linked to exposed banks decreases relative to other firms. This effect has negative implications on the employment, investments, and revenues of firms, hindering the reallocation of resources towards potential winners from trade liberalization.

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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: Banks: Balancing tests

	Unit	*High Exposed* Mean	S.D.	*Low Exposed* Mean	S.D.	Normalized difference
Bank characteristics						
Total Assets	€Millions	6,140	24,289	2,720	28,720	0.12
Liquid Assets	% Assets	14.9	9.72	16.2	9.29	-0.14
Nonperforming Loans	% Assets	3.3	5.3	4.0	4.2	-0.14
Credit to Firms	% Assets	40.1	12.8	37.5	12.6	0.20
Profits	% Assets	1.20	0.6	1.28	0.6	-0.13
Tier 1 capital	% R.W. Assets	9.0	3.5	9.6	3.8	-0.15
Provisions	% Assets	2.7	2.1	3.3	3.0	-0.20
Funding cost	% Liabilities	2.7	0.6	2.6	0.4	0.14
Borrower characteristics						
Bank Credit	€Millions	0.61	3.6	0.64	3.3	-0.01
Revenues	€Thousands	7,072	7,081	6,094	6,600	0.14
Fixed Assets	€Thousands	1,393	1,874	1,201	1,731	0.10
Gross operating margin	% Revenues	8.2	6.5	8.2	6.6	0.00
Credit Score	Units	5.2	1.8	5.1	1.8	0.00

Note: The table reports averages for 1998-2000. High-Exposed and Low-Exposed banks are defined using a threshold exposure so that each of the two groups accounts for half of the outstanding credit. The last column shows the Normalized difference between the two groups. Following Imbens and Wooldridge (2008), an absolute value above 0.25 suggests an imbalance between the two groups.

Table 3: 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***	0.0048***	0.0053***
	(0.0046)	(0.0062)	(0.0004)	(0.0005)
		First stage		
$Exposure^{OC}_{-i,b} \times Post_t$		0.80***		1.01***
		(0.01)		(0.02)
AR-Wald test, F		131.78		145.81
Bank controls	✓	✓	✓	✓
Firm-time F.E.	✓	✓	✓	✓
Firm-bank F.E.	✓	✓	✓	✓
Observations	3499092	3499092	2492506	2492506
$Adj.R^2$	0.832	0.832	0.627	0.627

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 (2), is instrumented with (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 if a firm operates in a sector of bank specialization. Standard errors are double clustered at the bank and sector level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 4: Heterogeneous Effects (2SLS)

Dependent Variable: $\ln C_{ibt}$	(1)	(2)	(3)	(4)
$Exposure^{IT}_{-i,b} \times Post_t \times \ldots$				
... $\times$ $Manuf\ HighHit_i$	-0.0683***			
	(0.0131)			
... $\times$ $Manuf\ LowHit_i$	-0.0795***			
	(0.0102)			
... $\times$ $Services_i$	-0.0728***			
	(0.0083)			
... $\times$ $CompAdv\ LowHit_i$		-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)	
... $\times$ $LowProd_i$			-0.0845***	
			(0.00937)	
... $\times$ $Downstream\ LowHit_i$				-0.0954***
				(0.0119)
... $\times$ $NonDownstream\ LowHit_i$				-0.0701***
				(0.0231)
... $\times$ $HighHit_i$				-0.0683***
				(0.0131)
Bank controls	✓	✓	✓	✓
Firm-time F.E.	✓	✓	✓	✓
Firm-bank F.E.	✓	✓	✓	✓
Observations	3499092	1754920	1907568	1923473
Adj. R^2	0.832	0.831	0.829	0.830

Note: The table reports the 2SLS results of specification (6). $Exposure^{IT}_{-i,b}$ defined in (2) is instrumented with (4). *High-Hit* and *Low-Hit* firms are manufacturing sectors above and below median exposure defined in (1). In column 2, manufacturing firms are further grouped according to their comparative advantage (Balassa index above or below 1). In column 3, manufacturing firms with high (low) productivity are those with TFPR above (below) their sectoral average for the period 1998-1999. In column 4 Low-Hit firms are divided by their degree of downstreamness (below and above median) relative to High-Hit firms. 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 double clustered at the bank and sector level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 5: Firms entry and exit (2SLS)

Dependent:	$Exit_{ib\tau}(\times 100)$ (1)	(2)	$Entry_{ib\tau}(\times 100)$ (3)	(4)
$Exposure^{IT}_{(-i),b} \times Post_\tau$	3.96***		0.025***	
	(0.006)		(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 FE	✓	✓	✓	✓
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 (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 1.9%. $Exposure^{IT}_{(-i),b}$ 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 (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 double clustered at the bank and sector level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 6: Effects on firms' total credit (2SLS)

Dep Var: $\ln C_{it}$	Full-sample		Manuf Low-Hit	Manuf High-Hit	Services	Comparative Adv. Low-Hit	High Product. Low-Hit	Downstream Low-Hit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$FirmLevelExposure_i \times Post_t$	-0.0468***	-0.0370***	-0.0532***	-0.0756***	-0.0332***	-0.0490***	-0.0801***	-0.0379***
	(0.00945)	(0.0138)	(0.0120)	(0.0119)	(0.0105)	(0.0133)	(0.0134)	(0.0130)
Firm-time FE from (5)	✓		✓	✓	✓	✓	✓	✓
Bank controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm-F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Sector-time F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Observations	899397	899397		899397		458575	458575	458598
Adj. R^2	0.951	0.890		0.951		0.954	0.954	0.954

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, $\ln C_{it}$. $FirmLevelExposure_i$ is defined in (8), instrumented using (8). Columns 3-5 report the coefficients of the corresponding group estimated in the full sample of firms. Columns 6-8 report the coefficient of the corresponding group estimated in the sample of manufacturing firms. All regressions include firm fixed effects, sector-time dummies, and the firm-time fixed effects estimated in Equation 5 as a proxy of credit demand (except column 2), a 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 7: 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***	-0.0585***	-0.0589***
	(0.0091)	(0.0161)	(0.0127)
b. Low-Hit Manuf	-0.0532***	-0.0410***	-0.0391**
	(0.0113)	(0.0199)	(0.0186)
c. High-Hit Manuf	-0.0904***	-0.134***	-0.138***
	(0.0153)	(0.0223)	(0.0222)
d. Services	-0.0322***	-0.0387**	-0.0396***
	(0.0103)	(0.0187)	(0.0128)
e. Comparative Adv. Low-Hit	-0.0490***	-0.0581**	-0.0604***
	(0.0171)	(0.0231)	(0.023)
f. High productivity Low-Hit	-0.104***	-0.149***	-0.158***
	(0.0165)	(0.0225)	(0.0209)
g. Downstream Low-Hit	-0.0418**	-0.0388**	-0.0422*
	(0.017)	(0.018)	(0.0256)
Firm-F.E.	✓	✓	✓
Sector-time F.E.	✓	✓	✓

Note: The table reports the results of specification (9). The explanatory variable $FirmLevelExposure_i$, defined in (8), captures the weighted average of the exposure of banks a firm was borrowing from; it is instrumented using $Exposure^{OC}_{(-i),b}$ in (8). 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 manufacturing Low-Hit, High-Hit, and services (rows a, b, c), 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. 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 8: 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%	-79,804	-2.3%	-1.8
Low-Hit Manuf.	-1.4%	-29,841	-1.4%	-1.0
Services	-1.3%	-58,340	-1.3%	-1.6

Note: The table reports the results of the partial equilibrium aggregation exercise discussed in subsection 5.1 and in Appendix A.2.

Table 9: Firm exposure and NPL

Dep. Var: NPL_{ibt}	OLS (1)	2SLS (2)
$China_{is}^{IT} \times Post_t$	0.00625**	0.00904***
	(0.00158)	(0.00241)
Firm-bank FE	✓	✓
Bank-time FE	✓	✓
Observations	671376	671376
Adjusted R-squared	0.560	0.560

Note: Results on specification (10). Explanatory variable $China_{ist}^{IT}$ defined in (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 10: 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***	-0.002***	0.001**	0.000	0.001	0.000	0.000
	(0.0007)	(0.0006)	(0.0005)	(0.0018)	(0.003)	(0.0001)	(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: non performing loans 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 (2) instrumented with (4). All regressions include bank controls interacted with a post-2001 dummy (i.e., pre-2000 log-assets, core-funding ratio, non-performing loans and the capital ratio). 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 11: Baseline results: the interaction with Tier 1 capital (2SLS)

Dep. Variable: $\ln C_{ibt}$	Full sample		Manuf. Low-Hit		Manuf. High-Hit		Services	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Exposure_b^{IT} \times Post_t$	-0.0749***	-0.118***	-0.0792***	-0.131***	-0.0691***	-0.0890***	-0.0755***	-0.125***
	(0.00630)	(0.0144)	(0.00864)	(0.0178)	(0.0132)	(0.0195)	(0.00759)	(0.0152)
$Exposure_b^{IT} \times HighTier1_b \times Post_t$		0.517***		0.642***		0.0977		0.677***
		(0.150)		(0.203)		(0.203)		(0.167)
$HighTier1_b \times Post_t$		0.907***		0.950***		0.950***		0.950***
		(0.122)		(0.122)		(0.122)		(0.122)
Bank Controls	✓	✓	✓	✓	✓	✓	✓	✓
Bank F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Firm-Time F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3499092	3499092	3499092	3499092	3499092	3499092	3499092	3499092
$Adj.R^2$	0.836	0.836	0.836	0.836	0.836	0.836	0.836	0.836

Note: The table reports results of specification (5) in columns 1 and 2; and those of specification (6) in columns 3-8. Relative to the baseline specification, we add an interaction term $HighTier1_b$ in columns 2, 4, 6 and 8 (i.e., the ratio of core capital to risk-weighted assets for 1998-1999). $Exposure^{IT}_{-i,b}$ 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 double clustered at the bank and sector level. ***significant at the 1% level, **5% level and *10% level.

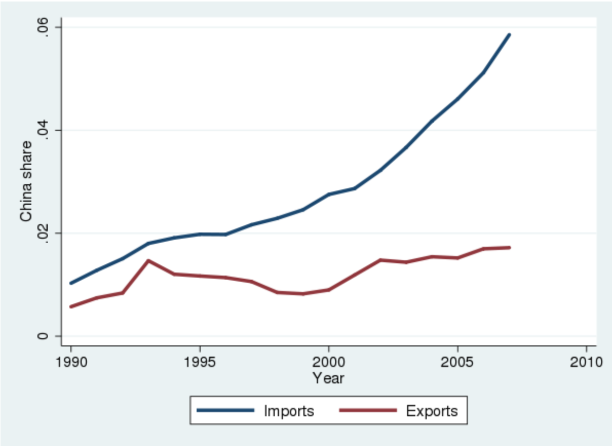
Table 12: Geographical effects by province exposure (2SLS)

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
Adjusted R-squared	0.835	0.835	0.828	0.828

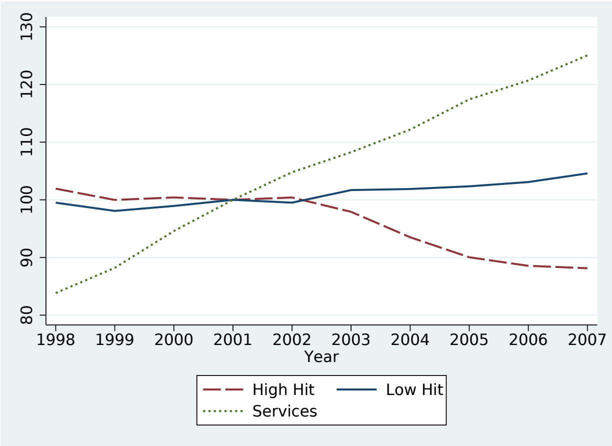
Note: The table reports results of specification (5) in columns 1 and 3 and specification (6) in columns 2 and 4. We group firms according to the exposure of their province to the China shock. High (Low) exposed provinces correspond to those with a share of employment in high-hit sectors above (below) 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 if a firm operates in a sector of bank specialization. Standard errors are double clustered at the bank and 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



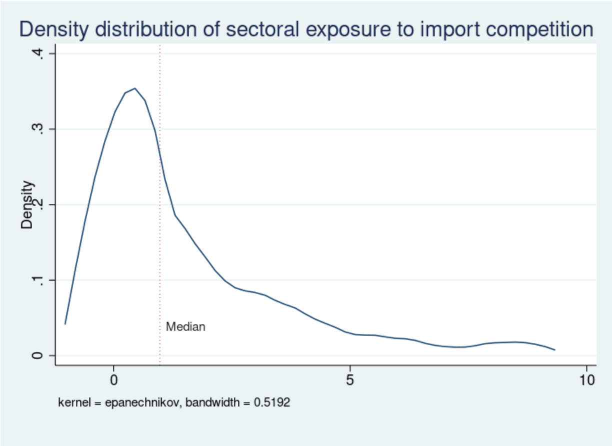
(b) Employment by Exposure



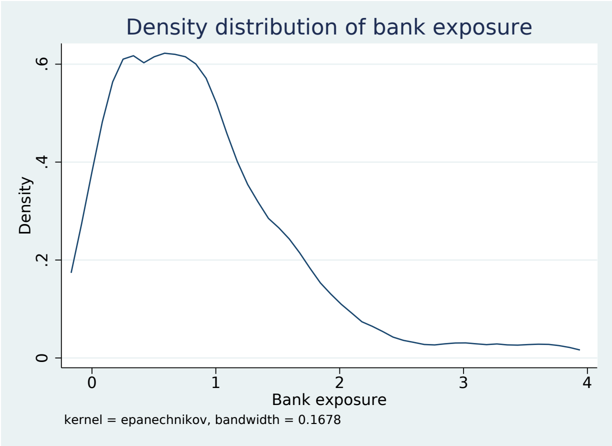
Note: Panel (a) shows the evolution of the share of exports and imports of Italy to and from China relative to total Italian exports and imports (COMTRADE data). Panel (b) shows the evolution of employment in services and in manufacturing sectors with high- vs. low-exposure to import competition from 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



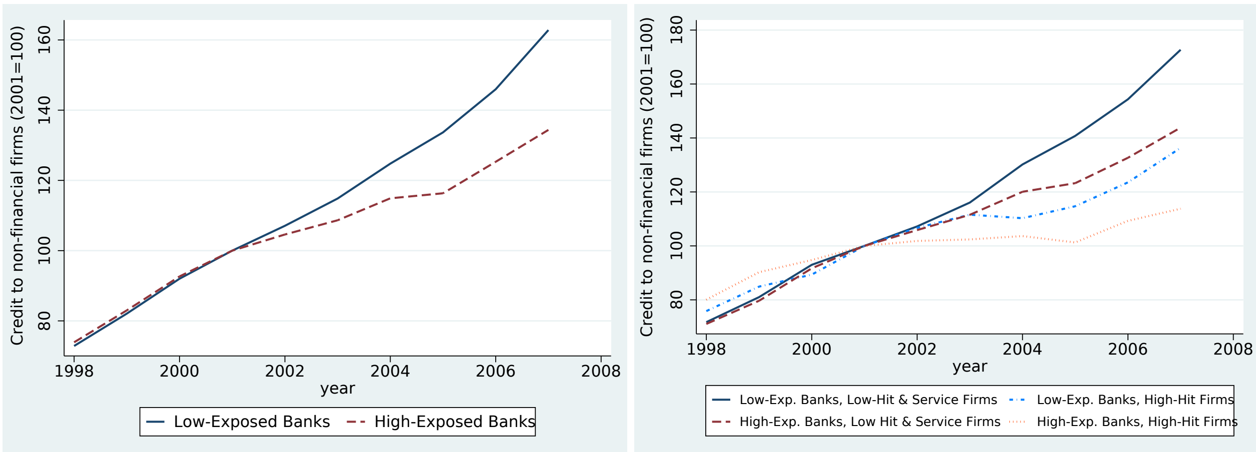
(b) Bank exposure



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 (2).

Figure 3: Aggregate credit, by bank exposure

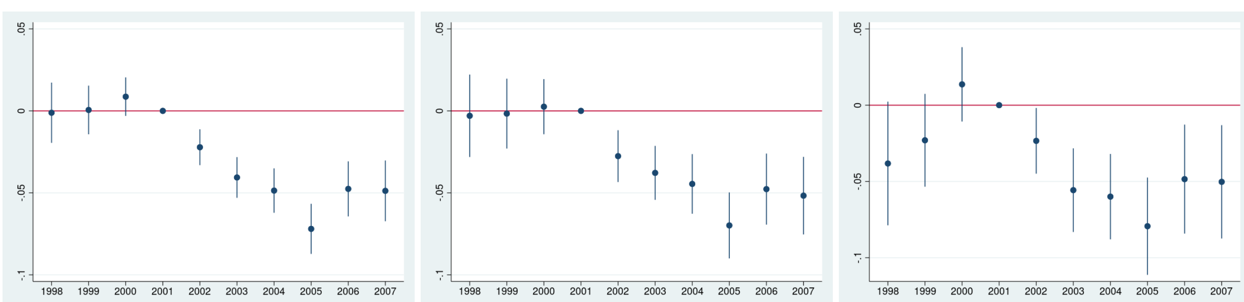
(a) Total (b) Groups of Firms



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 (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 median as defined in (1).

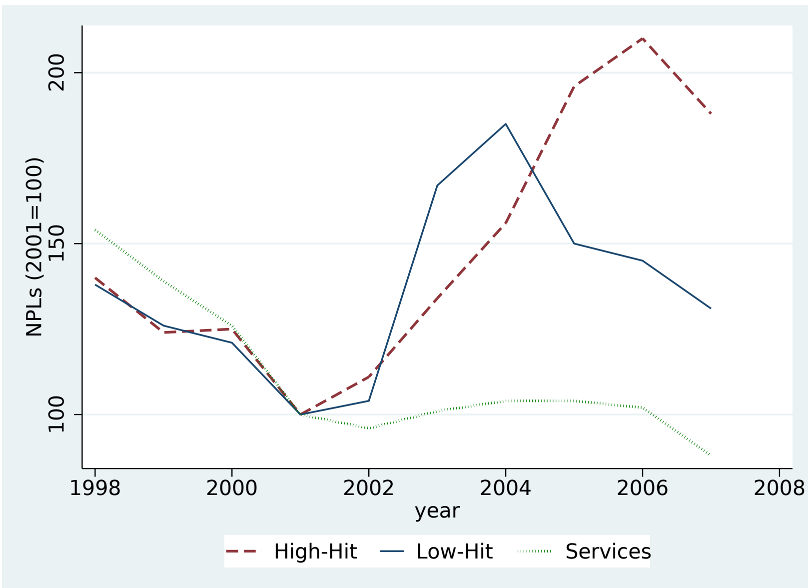
Figure 4: Dynamic Diff-in-Diff (95% CI)

(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-diff version of specification (5) in panel (a) and from specification (6) in panels (b) and (c).

Figure 5: 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 US, or only imports 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 fifteen 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 7.2.

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 the level of four-digit sector 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 (8).

Table A.9 shows the results of our baseline specification in (6), splitting the sample of provinces above or below median in terms: 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.10 replicates specification in (9) including province-sector-time FE, rather than sector-time FE.

Table A.11 shows the robustness of our results to possible confounding shocks to the banking sector discussed in Section 7.3.

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 difference estimator of 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 5.1 (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-firm specialization	✓	✓	✓	✓
Bank controls	✓	✓	✓	✓
Firm-time F.E.	✓	✓	✓	✓
Firm-bank F.E.	✓	✓	✓	✓
Observations	3499092	3499092	3499092	3499092
Adjusted R-squared	0.836	0.836	0.836	0.836

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, and the capital ratio. All regressions include firm-year fixed effects and firm-bank dummies. Standard errors are double clustered at the bank and 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**		-0.0881***		-0.642***
		(0.0134)		(0.0178)		(0.0139)		(0.0129)
... $\times$ $Man\ LowHit_i$		-0.0825***		-0.0715***		-0.0780***		-0.0824***
		(0.00963)		(0.0144)		(0.0100)		(0.0099)
... $\times$ $Services_i$		-0.0744***		-0.0316***		-0.0699***		-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 (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 to upstream sectors. 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 double clustered at the bank and 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: No heterogeneous effects			
$Exposure^{IT}_{-ib} \times Post_t$	-0.0359***	-0.0591***	-0.0560***	-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***	-0.0727***	-0.0683***
	(0.00740)	(0.00871)	(0.00853)	(0.0131)
... $\times ManufLowHit_i$	-0.0352***	-0.0522***	-0.0634***	-0.0795***
	(0.00679)	(0.00759)	(0.00752)	(0.0100)
... $\times Services_i$	-0.0297***	-0.0550***	-0.0396***	-0.0728***
	(0.00628)	(0.00711)	(0.00710)	(0.00831)
Firm FE	YES	YES		
Bank FE	YES	YES		
Time FE	YES	YES	YES	
Bank controls		YES	YES	YES
Firm-bank FE			YES	YES
Firm-time FE				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)	
$\ldots HighHit_i$		-0.0854***
		(0.0162)
$\ldots LowHit_i$		-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, 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 double clustered at the bank and 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)	
...$HighHit_i$		-0.0594***
		(0.0139)
...$LowHit_i$		-0.0837***
		(0.0128)
...$Services_i$		-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 (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 double clustered at the bank and sector. ***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)	HighHit (2)	LowHit (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 level of four-digit sector, and are valid in the framework of Adão et al. (2019). In contrast to the baseline estimates, bank exposure is computed without leaving out firm i from credit weights. Outcome and treatment residuals are obtained from specifications which include bank characteristics pre-2001 interacted with a post-2001 dummy (log-assets, share of NPLs, core-funding ratio, and the capital ratio), firm-year fixed effects, firm-bank dummies, and specialization. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.7: Baseline with heterogenous 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***	-0.0960***	-0.0757***
	(0.0143)	(0.00852)	(0.0283)
$Q2$	-0.0761***	-0.0845***	-0.111***
	(0.0149)	(0.0162)	(0.0214)
$Q3$	-0.0617***	-0.0782***	-0.0654**
	(0.0174)	(0.0134)	(0.0138)
$Q4$	-0.0790***	-0.0710***	-0.0884***
	(0.0196)	(0.0122)	(0.0141)
Bank controls	✓	✓	✓
Firm-time F.E.	✓	✓	✓
Firm-bank F.E.	✓	✓	✓
Observations	3499092	1754920	1907568
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 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, 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 double clustered at the bank and sector level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.8: Loan applications

Dep. Variable: $\ln Applications_{it}$	Applications to all banks (1)	Applications to less exposed banks (2)	Applications to more exposed banks (3)
$FirmLevelExposure_i \times Post_t$	-0.00907	0.109***	-0.0300**
	(0.0118)	(0.0175)	(0.0129)
Firm F.E.	✓	✓	✓
Time F.E.	✓	✓	✓
Observations	276988	88972	250594
Adjusted R-squared	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 of 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: $\ln Applications_{it} = \beta_1\ Firm\ Level\ Exposure_i \times Post_t + \gamma_i + \delta_t + \epsilon_{it}$, where we use our usual instrument. Firm level exposure is defined in (8), γ_i and δ_t are firm and year 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). Notice that 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 - Geographical heterogeneity

Dependent variable:	$\ln C_{ibt}$ coeff	std
Characteristic of firm's province		
a) Innovation (patents per person)		
High innovation	-0.0928***	(0.00833)
Low innovation	-0.0604***	(0.00906)
b) Education (share adults with high-school)		
High skilled	-0.0850***	(0.00818)
Low skilled	-0.0658***	(0.00902)
c) Industrial diversification (HHI)		
High diversification	-0.0845***	(0.00826)
Low diversification	-0.0674***	(0.00961)

Note: Baseline specification (5), splitting the sample of provinces above or below median in terms: 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, these are log-assets, share of NPLs, core-funding ratio, and the capital ratio, and bank-firm specialization. All regressions include firm-year fixed effects and firm-bank dummies. 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.10: 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	-0.0350***	-0.0563***	-0.0471***
	(0.009)	(0.0131)	(0.0120)
b. Low-Hit manuf.	-0.0427***	-0.0421**	-0.0391**
	(0.0137)	(0.0196)	(0.0198)
c. High-Hit manuf.	-0.0693***	-0.108***	-0.104***
	(0.0184)	(0.0236)	(0.0243)
d. Services	-0.0258***	-0.049***	-0.0385***
	(0.00873)	(0.0143)	(0.0135)
e. Comp. Adv. Low-Hit	-0.0460**	-0.0547**	-0.0568**
	(0.0181)	(0.0235)	(0.0254)
f. High Prod. Low-Hit	-0.102***	-0.147***	-0.157***
	(0.0204)	(0.0274)	(0.0240)
g. Downstream Low-Hit	-0.0393**	-0.0380**	-0.0419*
	(0.0173)	(0.018)	(0.0252)
Firm-F.E.	✓	✓	✓
Sector-province-time F.E.	✓	✓	✓

Note: The table reports the results of specification (9). The explanatory variable $FirmLevelExposure_i$, defined in (8), captures the weighted average of the exposure of banks a firm was borrowing from; it is instrumented using $Exposure^{OC}_{(-i),b}$ in (8). 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 manufacturing Low-Hit, High-Hit, and services (rows a, b, c), 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 fixed effects, sector-province-time fixed effects. Standard errors are double clustered at the sector and bank level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

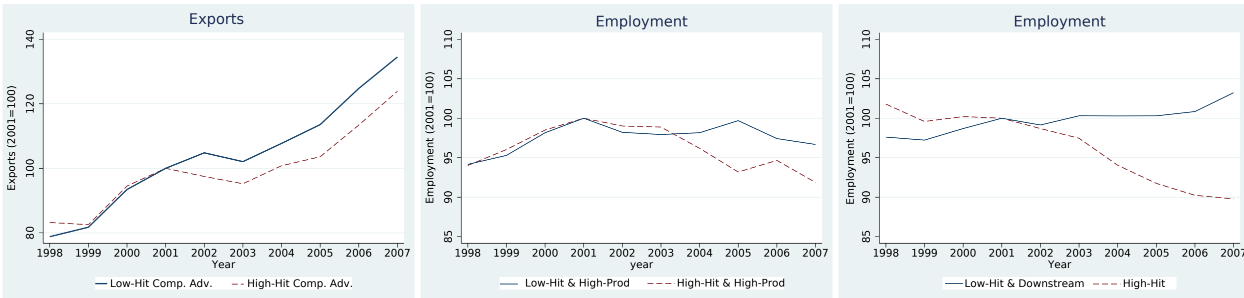
Table A.11: Robustness and Confounding Effects

Dependent : $\ln C_{ibt}$	Foreign funding (1)	Recession (2)	Securitization (3)	All (4)
$Exposure^{IT}_{-i,b} \times Post_t$	-0.0717***	-0.0685***	-0.0624***	-0.0523***
	(0.00623)	(0.00677)	(0.00623)	(0.00691)
$Foreign\ Funding\ Share_b \times Post_t$	0.183***			-0.0219
	(0.0487)			(0.0491)
$Recession\ Share_b \times Post_t$		-0.127***		-0.242***
		(0.0383)		(0.0386)
$Securitization\ Share_b \times Post_t$			-0.835***	-0.896***
			(0.0721)	(0.0759)
Bank controls	✓	✓	✓	✓
Firm-time F.E.	✓	✓	✓	✓
Firm-bank F.E.	✓	✓	✓	✓
Observations	3499092	3499092	3499092	3499092
$Adj.R^2$	0.832	0.832	0.833	0.833

Note: The table reports the coefficients of the baseline specifications in Equation (5), to which we add controls for potential confounding factors: i) the share of foreign liabilities on the onset of the shock as a proxy of exposure to the post-2002 boom of capital inflows (column 1); ii) the share of loans to sectors more exposed to the Recession of 2001-02 (column 2); iii) the share of securitized lending before 2001 (column 3). 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 dummy that captures if a firm operates in a sector of bank specialization. All regressions include firm-year fixed effects and firm-bank dummies. Standard errors are double clustered at the bank and sector 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 entrance in 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.

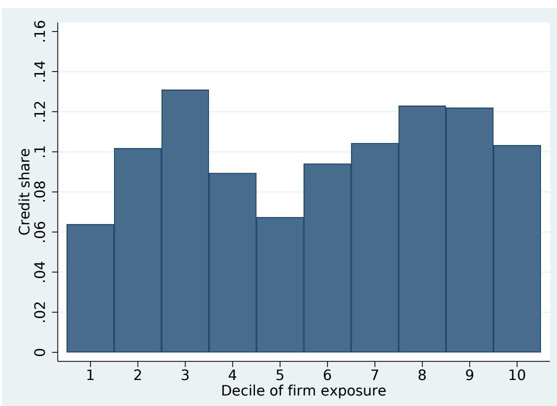
Figure A.2: Dynamic Diff-in-Diff (95% CI) on Banks' Balance Sheet

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

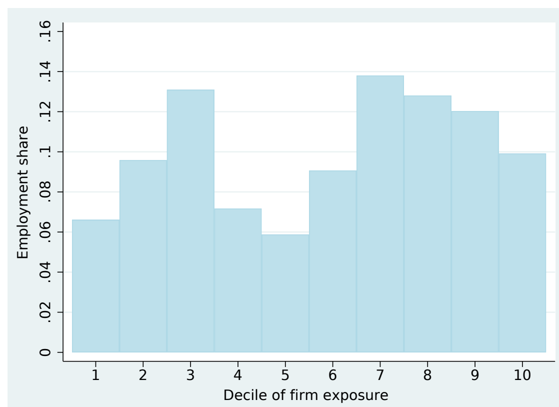
Note: The figure reports the coefficients, with 95% confidence interval of the variable $Exposure_b^{IT}$, instrumented with the variable $Exposure_{i,b}^{OC}$, coming from the dynamic diff-in-diff regression of specification (11).

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

(a) Credit share



(b) Employment share



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

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 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 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 *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 USA) are not correlated with demand factors in Italy. From Table 3 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 3 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 bank's portfolio shares), which is similar to the estimates of Autor et al. (2013).

However, this represents a lower-bound as we do not expect our instrument to capture all supply-driven imports. So, in the other extreme case in which the rise in imports from China are (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 that 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 5.1 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 is equivalent to assuming that 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 5.1 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:

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

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 that 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.