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Abstract

This paper provides evidence that banks cut lending to US borrowers as a consequence of a trade shock. This adverse reaction is stronger for banks with higher ex-ante lending to US industries hit by the trade shock. Importantly, I document large heterogeneity in banks' reaction depending on their sectoral specialisation. Banks shield industries in which they are specialised in and at the same time reduce the availability of credit to industries they are not specialised in. The latter is driven by low-capital banks and lending to firms that are themselves hit by the trade shock. Banks' adjustments have adverse real effects.

Keywords: trade liberalisation, credit supply, sector specialisation, real effects

JEL classification: F14, F65, G21

1 Introduction

A large literature has emerged analysing the effects of trade liberalization on welfare and economic activity.[1] While classical theories of international trade outline that free trade creates winners and losers, the gains to winners are thought to offset any losses occurring to those adversely affected by changes in trade flows. Considering financial frictions, such as banks' funding constraints, when accounting the gains from trade might however alter prevailing considerations about the gains from trade.

This paper enriches the scarce evidence on the role of financial frictions in the reallocation of credit in the aftermath of a trade shock by identifying how banks adjust lending to US firms in response to a trade shock. Moreover, I investigate whether banks curtail lending differentially depending on their sectoral specialization. Such analysis adds to the literature on bank specialization by analysing its role in the reallocation of credit in a new country and context, in the case of a trade shock hitting US borrowers. Lastly, examining the interaction between sectoral specialization and bank as well as firm characteristics provides novel evidence on what drives the reaction of specialized and non-specialized banks respectively.

I exploit the rise of China to economic power and the induced changes in global trade patterns as a trade shock - an approach well-established in the literature (see, among others, Autor and Hanson 2013; Autor et al. 2014; Acemoglu et al. 2016; Autor et al. 2016; Bloom et al. 2016; Hombert and Matray 2018; Helm 2019). On this basis, I firstly analyse the effect of banks' exposure to the China shock on the patterns of credit supply to US firms. Given the sectoral specialization of banks' loan portfolios, banks are considered to be indirectly affected by trade liberalization (Paravisini et al. 2020; Federico et al. 2019; Giometti and Pietrosanti 2019). Following the estimation strategy by Federico et al. (2019), I identify how much US industries are affected by the increase in Chinese imports and construct banks' exposure to this trade shock by considering banks' share of loans to each industry weighted by the sector's change in imports from China. Given their financial constraints, banks might have to cut credit in order to compensate losses or liquidity shortfalls resulting from the negative consequences of trade shock for firms (Paravisini 2008; Chava and Purnanandam 2011; De Haas and Van Horen 2012; Adrian et al. 2013).

Secondly, I examine banks' differential response to the shock depending on whether the borrower is part of an industry that the bank is specialized in. Banks might adjust credit heterogeneously depending on how important the industry of the borrower is for the bank. Banks might shield or even extend credit to sectors they are specialized in

[1] Examples from this literature are Ben-David (1993), Pavcnik (2002), Amiti and Konings (2007), Chiquiar (2008), Edmonds et al. (2010), Topalova (2010), McCaig (2011), Autor and Hanson (2013), Acemoglu et al. (2016), Bloom et al. (2016), and Hombert and Matray (2018).

when they have to curtail lending. This rests on the argument that the more banks lend to an industry, the more it can acquire industry-specific information (Jahn et al. 2013; Giometti and Pietrosanti 2019; De Jonghe et al. 2020). Hence, they can develop an information advantage in industries they become specialized in which they are incentivized to protect in the case of a shock to their funding. The traditional view on this matter, in turn, rests on the benefits associated with bank diversification (Diamond 1984; Boyd and Prescott 1986; Rossi et al. 2009; Tabak et al. 2011; Shim 2019). Classical banking theory as well as recent empirical evidence suggests that the more diversified a bank's portfolio, the more likely it is to grant loans (Jimenez et al. 2012; Doerr and Schaz 2019). Thirdly, I shed light on the interaction of portfolio specialization and bank as well as firm characteristics by analysing banks' reaction separately for specialized and non-specialized banks.

I rely on data of syndicated loans extended by lender characteristics as well as trade flow data. For identification, I use a difference-in-difference set-up that allows to illustrate the effect of banks' exposure to the trade shock on their credit supply to firms after the trade shock. Since US product demand shocks may be related to the change in imports from China, used to construct banks' exposure, and bank lending, the identification strategy is enriched by an instrumental variable approach (Autor and Hanson 2013; Autor et al. 2014; Acemoglu et al. 2016). The sample period ranges from 1991 until 2007 with 2001 being the year in which the China shock started to unfold.[2]

The results show larger declines in outstanding credit for banks with higher ex-ante exposure to the trade shock. Furthermore, I identify that there indeed exists a differential effect how banks adjust their credit supply in response to a trade shock depending on whether the borrower is part of an industry the lender is specialized in. Specialized banks shield their borrowers while non-specialized banks reduce credit supply more with increasing exposure. Moreover, I illustrate that the reaction of non-specialized banks is driven by low capital banks and by lending to exposed firms. Lastly, I show how banks' adjustments in credit supply in response to the trade shock transmit to the real economy. Firms that borrow more from banks with larger exposure experience a larger reduction in performance. I find some indication that this negative effect is less severe for firms that are borrowing more from specialized banks.

This paper contributes to several strands of the literature. Firstly, it adds to the many papers that investigate how the economy responds to trade shocks. Many studies allow for labour market frictions and provide evidence on the short- and medium-term adjustment costs for workers and firms arising in response to large shifts in trade patterns (see, among others, Topalova 2010; Cosar 2013; Kovak 2013; Autor and Hanson

[2]The China shock is considered to have emerged when China entered the WTO in 2001 (see, for instance, Autor and Hanson 2013; Autor et al. 2014; Autor et al. 2016).

2013; Autor et al. 2014; Dix-Carneiro 2014; Autor et al. 2016; Acemoglu et al. 2016; Dix-Carneiro and Kovak 2017). Among the most prominent ones is the paper by Autor and Hanson (2013) who analyse the effects of rising import competition from China on US local labor markets. They find that rising exposure to China decreases employment and wages. Studies that consider financial frictions in this context are rather limited. Notable exceptions are the papers by Antras and Caballero (2009), who illustrate the adjustment of cross-border capital flows in response to trade liberalization, Antràs and Caballero (2010), who outline the effects of trade liberalization on welfare in financially underdeveloped countries, or Lanteri et al. (2019), who show the reallocation of machines in Peruvian manufacturing industries in response to the rise of China. Closest to this project is the paper by Federico et al. (2019) who analyse how banks adjust their credit supply to Italian firms in response to a trade shock. They find that banks exposed to the China shock decrease lending compared to non-exposed banks. I show that their findings apply also to US borrowers.

This work is also related to studies that consider the effect of shocks to banks on their lending decisions (Khwaja and Mian 2008; Ivashina and Scharfstein 2010; Cetorelli and Goldberg 2011; De Haas and Van Horen 2012). Since the global financial crisis several studies have furthermore identified that banks do transmit shocks heterogeneously to their borrowers depending on bank or firm characteristics. Giannetti and Laeven (2012a) as well as Giannetti and Laeven (2012b) illustrate a geographical dimension in the reallocation of credit and identify how banks adjust their credit supply to domestic relative to foreign borrowers in response to a shock at home. More recently, Paravisini et al. (2020) assess the reallocation of credit according to sectoral specialization. They construct a measure of lenders' specialization in export markets and find that exports to markets, the bank specializes in, are disproportionally affected by credit supply shocks. De Jonghe et al. (2020) address banks' specialization from a different angle. They highlight the role of specialization in banks' credit allocation in the context of the interbank market freeze after the failure of Lehmann Brothers. They find that banks reallocate credit to sectors they are specialized in. I find similar results. Specialized banks shield US borrowers while non-specialized banks react with a reduction of credit to the trade shock.

More generally, this paper contributes to the literature on the interaction of trade and finance by highlighting the impact of large changes in trade flows on banks' lending decisions. Papers in this area have typically dealt with the importance of finance for trade such as Amiti and Weinstein (2011), who examine the effect of bank health on firms' export growth, or Niepmann and Schmidt-Eisenlohr (2017), who outline how a credit supply shock impacts trade patterns.

2 Empirical strategy

The aim of this study is to identify how banks adjust their credit supply in response to a trade shock. I follow an identification strategy similar to Federico et al. (2019) who rely on a difference-in-difference set-up. The respective setting compares the availability of credit provided by banks after the shock depending on their ex-ante exposure to the trade shock. For each bank-firm-quarter observation, I estimate the following equation:

$$\begin{aligned} \ln(\text{Credit})_{b,f,j,t} = \beta_1 \text{Exposure}_b^{US} \times \text{Post}_t \\ + \gamma \text{X'}_{b,t} + \zeta_{b,f} + \zeta_{j,t} + \varepsilon_{b,f,j,t}. \end{aligned} \tag{1}$$

The dependent variable is the log of outstanding credit by bank b to firm f operating in industry j in quarter t. $Exposure_b^{US}$ measures the pre-shock exposure of bank b to the trade shock. Post_t divides the sample period into a pre- and post-shock period. The cut-off point is the year 2001 as China's export growth accelerated afterwards. Hence, the pre-shock period dates from 1991 to 2000 and the post-shock period from 2001 until 2007. The vector $\text{X'}_{b,t}$ contains bank-specific control variables such as size (log of total assets), return on assets, the ratio of non-performing loans to total assets and a measure for banks' funding structure (short-term debt to total assets). $\zeta_{b,f}$ are bank-firm fixed effects which capture firm and bank heterogeneity as well as all time-invariant factors that influence loan-level outcomes for each bank-firm pair such as e.g. relationship or distance.

I slightly modify the set-up by Federico et al. (2019) to accommodate single bank-firm relationships and use industry-time fixed effects instead of firm-time fixed effects in order to capture credit demand. The underlying assumption is that firms within a certain industry change their loan demand in the same way. $\varepsilon_{b,f,j,t}$ is the idiosyncratic error term. The interaction term $Exposure_b^{US} \times Post_t$ therefore identifies the effect of the shock on credit supply. A negative and statistically significant β_1 would indicate that with increasing exposure to the trade shock banks' supply of credit declines by more after the shock compared to before the shock.

To alleviate potential endogeneity concerns that result from how $Exposure_b^{US}$ is constructed, I enrich the difference-in-difference set-up with an instrumental variable approach in the fashion of Autor and Hanson (2013). In the construction of $Exposure_b^{US}$ trade flows between the United States and China are used as weights for the degree of exposure to the China shock of each industry a bank is lending to. This implies that product demand shocks originating within the United States could correlate both with $Exposure_b^{US}$ via the trade flows and simultaneously with bank lending.[3] Since

[3] I defer further discussion on how the exposure measure is constructed and the logic of the instrument to Section 3.

$Exposure_b^{US}$ enters Equation (1) interacted with $Post_t$, the system of structural equations is non-linear in its endogenous variable. Therefore, I proceed by retrieving the fitted values of the instrument and interact them with $Post_t$. The product is then used as the instrument in the 2SLS procedure (Wooldridge 2010). First stage results illustrate the relevance of the instrument. I obtain positive and statistically significant coefficients of 1.020 (Column (1) in Table 2). The F statistic is approximately 252 indicating that the instrument is a strong predictor for bank exposure.

In a second step, I investigate whether banks adjust their credit supply differentially after the trade shock depending on their sectoral specialization. Despite this being the underlying rational of banks' heterogeneity in terms of exposure to the trade shock, De Jonghe et al. (2020) have shown that banks' sectoral specialization also matters for how banks adjust their credit supply in response to a financial shock. To investigate if and how banks' response varies in the context of a trade shock, I extend Equation (1) by interacting $Exposure_b^{US} \times Post_t$ with the binary variable $Specialized_{b,j}$ indicating whether the bank is specialized in the industry of the respective borrower. Hence, β_3 in Equation (2) identifies the differential effect of bank exposure on credit supply depending on banks sectoral specialization.

$$\begin{aligned}\ln(\text{Credit})_{b,f,j,t} = {} & \beta_1 \text{Exposure}_b^{US} \times \text{Post}_t \\ & + \ \beta_2 \text{Post}_t \times \text{Specialized}_{b,j} \\ & + \ \beta_3 \text{Exposure}_b^{US} \times \text{Post}_t \times \text{Specialized}_{b,j} \\ & + \ \gamma \text{X'}_{b,t} + \zeta_{b,f} + \zeta_{j,t} + \varepsilon_{b,f,j,t}\end{aligned} \tag{2}$$

The single terms $Exposure_b^{US}$ and $Post_t$ in Equation (1) as well as $Specialized_{b,j}$ and the interaction between $Exposure_b^{US}$ and $Specialized_{b,j}$ in Equation (2) are absorbed by the fixed effects.

3 Data

3.1 Data and data generation process

The primary data source for the main analysis is the Thomson Reuters' LPC DealScan database encompassing detailed loan-level information covering the syndicated loan market. I begin with all facilities issued in the period from 1991 until 2007. Given the focus of this work, I sample only banks that are lead arrangers.[4] I follow Bharath et al. (2011) on how to determine the lead bank(s) in the syndicate. Loan proportions

[4]Various studies proceed in a similar manner and focus only on lead arrangers. See, for instance, Chodorow-Reich (2014), Acharya et al. (2018), and Schwert (2018).

are allocated to lead arrangers according to the breakdown provided by DealScan if available or equally allocated among all participants in the syndicate (De Haas and Van Horen 2013). I use these proportions to construct a stock variable that captures the availability of credit at each point in time between each bank-firm combination. Each loan enters banks' loan books until it matures. Thereby, I only draw from non-zero loan outcomes just as Doerr and Schaz (2019). I aggregate all outstanding loan shares for each bank-firm pair in quarter t. Hence, the level of observation in this study is bank-firm-quarter. Banks can be of any origin but I keep only loans syndicated in the United States. I exclude loans extended to non-US firms and to the financial, real estate or public sector.

Bank-level information are retrieved from Compustat. Since Compustat and DealScan do not share a common identifier, I use the linking table made available by Michael Schwert (2018) that links loan information to lender characteristics at the holding company level. I exclude all observations with negative values in total assets or total debt from banks' balance sheets. This results in a sample of 68 banks and 252,748 bank-firm observations.

To construct firms' exposure to the China shock, I retrieve trade data from the UN Comtrade database which provides bilateral trade flows at the 6-digit HS product level. I concord these trade flows to 4-digit SIC industries using a crosswalk provided by the World Bank. I aggregate the data to the 3-digit SIC level and undertake some additional adjustments in order to ensure compatibility with the other data sources as well as the matching of trade flows to firms such that no firm is immune to the trade shock by construction. Standard industry classifications allow merging trade flows with loan level information. Following Autor and Hanson (2013), the sample period covers the years 1991 until 2007. Just as in their work, availability of data not only for US-China trade but also for trade between China and other developed countries determines the start of the sample period. The sample ends in 2007 in order to avoid the inclusion of the global financial crisis.

For the subsequent analysis at the firm-level, I use firm characteristics from Compustat. To merge firm-level data with loan-level information, I rely on matching table provided by Michael Roberts, which builds on the work by Chava and Roberts (2008). Combining DealScan and Compustat reduces observations due to the limited availability of information in Compustat. Therefore, the firm-level analysis can only be conducted for a subsample. I drop firm-quarters with negative values in total debt or total assets. Moreover, firm quarters in which asset or sales growth is more than 100 percent are excluded to account for mergers and acquisitions. The sample then encompasses around 4,600 firms.

3.2 Variable construction

To implement the outlined empirical approach, I firstly need to construct a measure to capture US firms' exposure to the trade shock. I exploit cross-industry variation in US firms' exposure to China and construct measures of trade exposure per industry on the basis of bilateral trade data between the United States and China. In its construction, I follow Bloom et al. (2016) very closely and consider the change in imports from China to the United States normalized by total US imports at the 3-digit industry level:

$$\Delta\text{Import exposure}_j^{US} = \frac{\Delta\text{US Imports from China}_{j,1991-2000}}{\text{Total US imports}_{j,1991}} \tag{3}$$

As Federico et al. (2019), I use only the pre-shock period for the calculation of this measure. On this basis, I construct a continuous measure of banks' exposure to the China shock as the average share of loans a bank extends to a industry j in the pre-shock period to total loans weighted by the industry's import exposure:

$$\text{Exposure}_{b,j}^{US} = \frac{\text{Loans}_{b,j}}{\text{Loans}_b} \times \Delta\text{Import exposure}_j^{US} \tag{4}$$

For the estimation $Exposure_{b,j}^{US}$ is averaged across industries such that it varies only at the bank-level and thereby proxies a bank's overall exposure to the trade shock.

A key concern for the subsequent estimation is that trade flows may be related to unobserved US product demand shocks which, in turn, could correlate with bank lending. The instrumental variable approach applied to alleviate such concern isolates the supply component in the rise of import competition from China. I instrument $Exposure_b^{US}$ by $Exposure_b^{EO}$ in which the share of loans is weighted by an import exposure measure calculated on the basis of trade flows between eight other developed countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland) and China, $\Delta Import\ exposure_j^{EO}$. The underlying rational behind this is that high-income economies are assumed to be similarly affected by the rise in import competition from China. Moreover, this assumes that product demand shocks are uncorrelated across developed countries (Autor and Hanson 2013).

To measure banks' sectoral specialization, I rely on the approach by Paravisini et al. (2020) and consider bank b to be specialized in industry j if it's average share of loans over the pre-shock period is a right-tail outlier relative to the other banks' portfolio shares in industry j. More specifically, bank b is specialized in industry j ($Specialized_{b,j} = 1$) if its share of loans is larger than the sum of the 75th percentile and the 1.5 interquartile range of the distribution of banks' portfolio shares in industry j. This applies to 13 percent of all observations.

3.3 Descriptive statistics

Central for the validity of any difference-in-difference design is that treatment and control group would follow similar trends in absence of treatment. In order to assess whether this is the case and given the continuous nature of treatment, I report pre-shock averages of relevant variables for exposed and non-exposed banks. Banks are exposed (non-exposed) if their exposure to the trade shock is above (below) the median bank exposure[5]. Bank and firm characteristics are winsorized at the 99th percentile or at the one and 99th percentile. Following Imbens and Wooldridge (2009), I report normalized differences by treatment status (exposed and non-exposed banks) in Table 1. A normalized difference between ± 0.25 indicates that groups are not systematically different and linear regression methods are adequate.

Exposed and non-exposed banks exhibit similar trends before the trade shock as illustrated by average pre-shock percentage changes in Panel A in Table 1. Neither bank nor firm characteristics develop differentially in the pre-shock period. Not only trends but also levels are largely similar across treatment and control group which gives additional plausibility to the parallel trend assumption. Importantly, credit made available by exposed and non-exposed banks is sufficiently equal. This applies both to the constructed loan volume as well as to the facility volume itself. The only characteristics in which banks differ before the shock is their size. Exposed banks are a somewhat smaller than non-exposed banks. Reassuringly, any mechanism that has resulted in different sizes across the two groups has not impacted trends and I do control for banks' size in the regression equations. Overall, I find that trends and levels of relevant variables are similar across the two groups prior to the trade shock and thereby suggestive of parallel trends in the absence of treatment. This is also confirmed by running a placebo regression in which the shock hits in the middle of the pre-shock period. As required, this delivers an insignificant estimate (see Column (5) in Table A4 in the Appendix).

[Table 1 around here]

4 Results

Column (1) in Table 2 present 2SLS results from estimating Equation (1). Standard errors are clustered at the bank and industry level. Column (1) reports results without bank controls included in the estimation. The coefficient of interest β_1 is negative and statistically significant. This identifies that after the shock banks react to an increase in exposure with a larger reduction in outstanding credit. A bank with exposure at the

[5] The median bank exposure is 0.044.

75th percentile reduces credit by around 1.3 percentage points more after the shock compared to a bank with exposure at the 25th percentile. Column (2) introduces control variables, which does not change the results in terms of statistical significance and the direction of the effect but increase its magnitude slightly.

[Table 2 around here]

This confirms the results by Federico et al. (2019) and provides further evidence on the role of financial frictions in the adjustment processes in response to a trade shock. Banks are indirectly exposed to trade shocks via their sectorial composition of loans. This results in larger declines in credit supply for banks with higher exposure. This can impede factor reallocation in the economy and thereby lead to larger unrealized gains from trade. However, the results does not seem to be economically extensive. This might be explained by the research design as well as by the particularities of the syndicated loan market and the banks operating in it. First, the effect measures the response of the lead arranger only while I abstract from potential adjustments made by the other syndicate participants. Second, banks active in this market are large which generally have a lower sensitivity of lending to financial constraints (Paravisini 2008). Therefore, their reaction is expected to be less strong than the reaction by smaller banks. Third, while the volume of syndicated lending is substantial, neither does it cover all of commercial lending in the United States, nor does DealScan cover the entire syndicated loan market. Hence, I may systemically underestimate the overall reduction in lending. Nonetheless, the fact that I find evidence in this particular set-up is very encouraging that there indeed exist adverse effects of trade shocks on bank lending.

Although the average result does not seem to be economically extensive, it hides some large underlying heterogeneity which becomes apparent when considering differences across banks' sectoral specialization. Column (3) displays the results from estimating Equation (2) without variables. The finding illustrates large heterogeneity in terms of whether the bank is specialized in the industry of the borrower. Banks that are not specialized in the industry of the respective borrower respond to an increase in exposure with cutting back credit supply to a larger degree after the shock. More specifically, a bank with an exposure at the 75th percentile reduces credit supply by nearly 3 percentage points more after the shock than a bank with an exposure at the 25th percentile. In contrast, banks with different exposures do not adjust credit supply heterogeneously after the shock when the borrower is part of an industry that the bank is specialized in. Estimating Equation (2) with bank controls confirms the results (Column (4)). Hence, bank specialization does not only play an important role in determining banks exposure to a trade shock but also in the reallocation of credit after the shock. This confirms that the results by De Jonghe et al. (2020) apply also in the context of a trade shock hitting US borrowers. Moreover, it provides further evidence that banks protect industries in which they have built-up an information advantage and have invested resources in to do so (Jahn et al. 2013; Giometti and Pietrosanti 2019; De Jonghe et al. 2020).[6]

To shed more light on which bank or firm characteristics are driving these effects, I conduct some estimations on the subset of specialized and non-specialized banks separately. One important consideration in this context is the extent of banks' financial constraints that might limit their ability to protect industries in which they are specialized in or magnify the reaction towards industries in which the bank is not specialized in. With lower capital ratios implying higher financial constraints, previous literature has shown that reallocation effects were concentrated among financially more constrained banks (Paravisini 2008; Chakraborty et al. 2018). In addition, banks might not shield borrowers equally or cut lending equally across borrowers (Liberti and Sturgess 2018; Federico et al. 2019; De Jonghe et al. 2020). Particularly relevant in the present context is whether borrowers themselves are affected by the trade shock. Banks should in particular allocate credit away from industries which prospects are inherently uncertain due to the increased important competition from China and towards industries not subject to such competition. To uncover the interaction of bank specialization and these two dimensions I extend $Exposure^{US} \times Post$ either by a binary variable indicating whether a bank had an average Tier 1 capital ratio below or above the median before the shock, *Cap*, or a dummy that assumes a value of 1 if the borrower belongs to an industry that is directly exposed to the trade shock and zero otherwise, *Exposed*. The respective coefficients capture the additional reallocation of credit that is due to banks capital position or firms' direct exposure to the shock respectively.

Table 3 shows the results for the subsample of non-specialized banks in Column (1) and (2) and for specialized banks in Column (3) and (4).

[Table 3 around here]

Column (1) highlights that among the non-specialized banks it is in particular low capital banks that drive the reduction of credit while high capital banks do not react to an increase in their exposure. Moreover, it is of importance whether the borrower itself is exposed to the shock. Non-specialized banks with higher exposure react with a higher reduction in credit to exposed firms. However, the reaction towards a firm that is not-exposed does not differ between a bank with an exposure at the 25th and a bank with an exposure at the 75th percentile. Specialized bank shield their borrowers irrespective of the state of their capital position. Column (3) illustrates that the reaction

[6] In contrast to De Jonghe et al. (2020), robustness checks show that neither banks' market share nor firm characteristics play a role in the pass-through of the trade shock.

of low and high capital banks when facing higher exposure is not statistically different. Interestingly, it is also not of importance whether the firm is exposed itself to the shock (Column (4)). This illustrates the importance of these industries to the banks. Specialized banks protect their information advantage irrespective of their capitalization and firms' uncertain prospects due to higher import competition.

5 Robustness checks

For robustness, I reestimate Equation (1) as well as Equation (2) with modifications along several dimensions.

Alternative exposure measures I employ alternative definitions of banks' exposure in Equation (1) to show that results stay qualitatively unchanged when exposure is differently constructed. Table A2 in the Appendix displays the results: In Column (1), I weight banks' share of loans per industry by the change in imports over the full sample period instead of using only the pre-shock period; in Column (2), I use the average level of imports over the pre-shock period as a weight for banks' share of loans (Bernard et al. 2006; Bloom et al. 2016; Hombert and Matray 2018); in Column (3), I weight the loan share by the change in net imports instead of only by imports (Autor and Hanson 2013); in Column (4), I adapt Federico et al. (2019)'s way of proceeding and use the change between pre- and post-shock averages as a weight.

Alternative model specifications I illustrate that the results do not depend on the particular specification used. I show in Table A3 that results from Equation (1) are unchanged when clustering at the bank-firm (Column 1) or bank-2-digit-industry level (Column (2)). Moreover, Column (3) and (4) demonstrate that results are qualitatively unchanged when using firm-time fixed effects or, following Degryse et al. (2019), using industry-location-size-time fixed effect. This leads, however, to firms having only a single bank relationship or missing information on size and location dropping out of the sample.

Table A4 indicates that the results are additionally robust to: an alternative approach how the dependent variable is constructed (Column (1)). So far, I split each facility's volume according to the breakdown provided by DealScan or, if not available, follow the procedure in De Haas and Van Horen (2013) and assume that each syndicate member contributed the same amount to the facility. Now, I use the 'alternative rule' by De Haas and Van Horen (2013) and allocate half of each facility's volume to the lead arrangers and half to the other participants. Among each group, the facility volume is then distributed equally. Results remain qualitatively unchanged when estimating with OLS instead of 2SLS (Column (2))and when collapsing the time dimension to check for the presence of serial correlation (Column (3)) (Bertrand et al. 2004). To ensure that the results are not driven by time trends unrelated to the China shock, I furthermore run a time-placebo estimation in which I divide the pre-shock period into two equally long parts and assign the shock to the second half. I then rerun Estimation 1 for observations before and after the pseudo trade shock. Column (4) shows that there is no effect of exposure after the placebo shock on credit supply which confirms that I do not mistake the effect of the China shock with other trends.

Alternative definitions of specialization Table A5 shows the robustness of banks' response to the trade shock in terms of sectoral specialization as estimated in Equation (2) to alternative definitions of specialization. Firstly, I modify the binary indicator for sectoral specialization according to Paravisini et al. (2020) and define it alternatively by a share of credit larger than the 90th percentile of all banks' distribution. Column (2) in Table A5 reports the results of this modification. Secondly, I exchange the binary indicator with a continuous indicator, which is the share of credit by bank b to industry j to bank b's total loan volume. This corresponds to the measure used by De Jonghe et al. (2020). Column (3) shows that the results remain unchanged.

Alternative reallocation channels I illustrate that the reallocation effects according to banks' sectoral specialization are not picking up other types of banks' portfolio choices. Therefore, I include an additional interaction between $Exposure^{US} \times Post$ and other possible reallocation channels in Equation (2). I show that the results on sectoral specialization are independent of whether the bank has a low/high market share in the industry of the borrower before the shock (Column (3) in Table A5) and whether firms' profitability/ratio of total debt to total assets is below/above the median (Column (1) and (2) in Table A6). In contrast to De Jonghe et al. (2020), I do not find that banks adjust their credit supply differentially according to market share or firm characteristics. In this manner, I also test whether my findings are robust to portfolio choices in terms of geographical specialization. Therefore, I include region fixed effects (Column (3)) and add in Column (4) an interaction between $Exposure^{US} \times Post$ and an indicator whether the bank is specialized/not specialized in the region the borrower is located in.[7]

[7] To determine whether or not a bank has a high market share in an industry/ is specialized in the region of the borrower, I again apply the framework by Paravisini et al. (2020). Furthermore, note that Column (1) and (2) in Table A6 is estimated on a reduced sample as it requires the incorporation of firm characteristics which availability is limited due to the match between DealScan and Compustat.

6 Real effects

I have shown that banks adjust credit supply when hit indirectly by a trade shock. The higher a bank's exposure to the shock, the more it reduces credit supply in response to the shock. Moreover, I illustrate that banks adjust their credit supply differentially depending on their sectoral specialization. In this section, I investigate how this translates to the real economy. To identify how banks' adjustments affect firm-level outcomes, I firstly need to construct a measures that captures firms' exposure to the bank lending channel of the trade shock (Federico et al. 2019). Therefore, I weight the average share of firm f's credit from bank b over the pre-shock period by bank b's exposure to the trade shock:

$$\text{Firm exposure}_{f,b}^{US} = \frac{\text{Loans}_{f,b}}{\text{Loans}_{f}} \times \text{Exposure}_{b}^{US} \tag{5}$$

To arrive at a firm-specific measure to be used in the estimations, denoted by *Firm exposure*$_f^{US}$, I average the product across banks. An exposure of zero indicates that firm f borrows only from non-exposed banks. For firms that were not active on the syndicated loan market before the shock, I assign an exposure of zero since these firms are, by construction, not exposed to the bank lending channel of the trade shock (see Gropp et al. (2019) for a similar proceeding).

I employ the measure in the following regression equation to estimate the transmission of the bank lending channel to real variables:

$$\begin{aligned} \text{Y}_{f,t} = {} & \beta_1 \text{Firm exposure}_{f}^{US} \times \text{Post}_t \\ & + \ \gamma \text{X'}_{f,t} + \zeta_f + \zeta_{j,t} + \varepsilon_{f,t}. \end{aligned} \tag{6}$$

As the dependent variable $Y_{f,t}$, I employ several measures of firm performance: sales growth, the ratio of tangible assets to total assets, return on equity and a profit margin.The first two constitute important determinants of firms' performance while the latter two are relative measures that capture firms' profitability relative to their equity and in relation to their business activity. The vector $X'_{f,t}$ contains time-varying firm controls such as size (log of total assets), leverage (the ratio of total debt to total assets), and a proxy for the amount of trade credit a firm receives (the ratio of accounts payable to the cost of goods sold as in Raddatz (2010)). As in the previous set-up, all variables are winsorized at the 99th or at the first and 99th percentile. ζ_f and $\zeta_{j,t}$ are firm and industry-time fixed effects which absorb the single terms *Firm exposure*$_f^{US}$ and *Post*$_t$. To isolate the causal effect of firms' exposure to the bank lending channel, I proceed as previously by instrumenting *Firm exposure*$_f^{US}$ with a measure in which *Exposure*$_b^{EO}$ is used as a weight for a firm's share of loans from a specific bank. Hence,

β_1 captures the extent to which the shock to banks is transmitted to the firm level via adjustments in bank lending.

Table 4 reports the results from estimating Equation (6) on the reduced sample for which firm-level information is available. Standard errors are clustered at the industry level. For all 4 outcome variables, it illustrates that firms with larger exposure to the bank lending channel experience a larger reduction in sales growth, have less tangible assets, lower return on equity as well as a lower profit margin. Hence, firm performance worsens more after the shock, the higher a firm's exposure to the bank lending channel of the trade shock.

[Table 4 around here]

In order to investigate whether the differential response according to sectoral specialization translates into heterogeneous developments at the firm level depending on firms' links to specialized banks, I construct a firm-specific measure that captures the importance of specialized banks in firms' overall bank relations. Therefore, I average $Specialized_{b,j}$ at the firm level. This provides me with an continuous indicator on the share of banks specialized in industry j connected to firm f, which is part of industry j. A measure of zero indicates that a firm is not connected to any specialized bank while a measure of 1 indicates that a firm is only connected to banks that are specialized in the industry of the borrower. I transform the continuous indicator into a binary variable, *High*, to simplify interpretation [8]. It assumes a value of 1 if the share of specialized banks is above the median and zero otherwise. I re-run Equation (6) with an interaction between *High* and $Firm\ exposure^{US} \times Post$. Table 5 displays the results.

[Table 5 around here]

The estimation results provide mixed evidence on whether the reallocation of credit according to banks' sectoral specialization has real effects. Sales growth and the ratio of tangible assets to total assets are affected differentially while this does not transmit to diverging developments of firms' return on equity or profit margin. This partially contrasts the findings by De Jonghe et al. (2020) who do not find reallocation effects in terms of sectoral specialization at the firm level.

7 Conclusion

I conduct a comprehensive assessment on banks' adjustment in terms of credit supply when they are hit indirectly by a trade shock via their loan portfolios. Given the sectoral

[8] The results still hold when the continuous indicator is used.

specialization of banks' loan portfolios, I construct a bank-specific exposure measure to the shock. I rely on detailed loan-level information combined with bank characteristics and trade flow data as well. I track all loans syndicated on the US secondary market on quarterly basis between 1991 and 2007.

Focusing on the accession of China to the WTO as the trade shock under study, I identify that banks with higher ex-ante exposure to the trade shock reduce credit supply to US borrowers more after the shock. This provides further evidence on the role of financial frictions when analysing the effects of trade liberalization on economic activity. Facing credit constraints themselves, banks adjust the availability of credit to their borrowers in response to a trade shock. This translates into adverse real effects after the shock in terms of firm performance.

Moreover, I uncover important heterogeneity in banks' reaction by considering banks' specialization. Banks shield borrowers that are part of an industry in which the bank is specialized. In contrast, banks, when lending to a borrower that is not part of an industry the bank is specialized in, increasingly reduce credit with higher exposure. This is driven by banks that are less capitalized before the shock as well as by lending to firms that are themselves exposed to the trade shock. Lastly, I find some evidence that banks' heterogeneous response in terms of sectoral specialization transmits to the real economy.

These findings provide valuable input for accounting the gains from trade. Considering financial frictions unveils banks' adverse reaction to trade liberalization restraining the reallocation of factors across firms. They also contribute to the debate on portfolio specialization versus diversification by shedding more light on the complex implications of portfolio specialization in a new context. On the one hand, the applied approach contemplates that the more specialized a bank is in industries directly exposed to the trade shock, the higher their exposure to the trade shock. On the other hand, banks try to protect the industries in which they are specialized by not reacting with larger reductions in the availability of credit to higher exposure.

Tables

Table 1: Parallel trends

	Exposed banks		*Non-exposed banks*		
	Mean	SD	Mean	SD	ND
Panel A: Percentage Changes					
Bank characteristics					
ΔTotal assets	11.541	23.584	19.173	31.016	-0.20
ΔEquity	1.844	13.154	2.331	10.803	-0.03
ΔNPL	-5.623	55.652	1.147	33.950	-0.10
ΔROA	2.195	119.154	-5.385	159.736	0.04
ΔShort-term funding	5.538	49.926	4.200	28.825	0.02
Firm characteristics					
ΔImport exposure	0.074	0.226	0.064	0.237	0.03
ΔTotal assets	11.662	21.540	12.482	23.591	-0.03
ΔROA	-32.550	193.147	-25.823	183.318	-0.03
ΔLeverage	63.047	203.459	60.866	224.074	0.01
ΔTobin's Q	1.614	10.797	1.198	11.592	0.03
ΔInvestment	37.101	84.093	32.423	91.303	0.04
Panel B: Levels					
Loan volume (mio)	1.104	5.321	1.588	2.891	-0.08
Facility volume (mio)	4.894	15.137	7.947	22.580	-0.11
Bank characteristics					
Size	7.171	1.000	8.103	0.545	-0.82
Equity	0.068	0.019	0.064	0.012	0.17
NPL	0.007	0.006	0.006	0.005	0.10
ROA	0.003	0.002	0.003	0.002	-0.04
Short-term funding	0.136	0.086	0.153	0.053	-0.16
Firm characteristics					
Size	1.817	1.339	2.149	1.434	-0.17
ROA	0.003	0.014	0.004	0.014	-0.02
Leverage	0.248	0.192	0.285	0.199	-0.13
Tobin's Q	1.214	0.767	1.321	0.766	-0.10
Investment	0.073	0.054	0.069	0.051	0.05

Note: This table reports statistics for relevant variables as their pre-shock average (1991-2000) dividing the sample between exposed and non-exposed banks. Exposed (non-exposed) banks have a share of loans to industries subject to competition from China above (below) the median over the pre-shock period. Panel A reports the variables in percentage changes and Panel B in levels. Firm characteristics are based on a reduced sample due to limited data availability. For detailed variable definitions see Table A1 in the Appendix.

Table 2: The effect of bank exposure on lending

	(1) IV	(2) IV	(3) IV	(4) IV
$\text{Exposure}^{US} \times \text{Post}$	-0.214*	-0.254*	-0.438**	-0.560***
	(0.119)	(0.145)	(0.168)	(0.188)
Post × Specialized			-0.141*	-0.165**
			(0.076)	(0.073)
$\text{Exposure}^{US} \times \text{Post} \times \text{Specialized}$			0.521***	0.658***
			(0.072)	(0.070)
$\text{Exposure}^{US} \times \text{Post}\big\|_{25\rightarrow 75}$	-0.013*	-0.016*		
	(0.071)	(0.008)		
$\text{Exposure}^{US} \times \text{Post}\big\|_{25\rightarrow 75}$ if Specialized=0			-0.027**	-0.034***
			(0.125)	(0.117)
$\text{Exposure}^{US} \times \text{Post}\big\|_{25\rightarrow 75}$ if Specialized=1			0.006	0.006
			(0.008)	(0.008)
	First Stage			
$\text{Exposure}^{EO} \times \text{Post}$	1.025***	1.021***	1.012***	1.006***
	(0.059)	(0.060)	(0.070)	(0.076)
$\text{Exposure}^{EO} \times \text{Post} \times \text{Specialized}$			1.059***	1.050***
			(0.051)	(0.050)
F statistic	297.74	291.925	137.022	130.490
Observations	252,748	252,748	252,748	252,748
Bank controls	No	Yes	No	Yes
Bank-Firm FE	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes
Number of banks	68	68	68	68
Number of firms	9,466	9,466	9,466	9,466
Clustering	Bank-Ind	Bank-Ind	Bank-Ind	Bank-Ind

Note: This table explores how banks adjust their credit supply following a trade shock, as specified in Equation (1) (Column (1) and (2)) and Equation (2) (Column (3) and (4)). The dependent variable is the log of outstanding credit at bank-firm-quarter level, $ln(Credit)_{b,f,j,t}$. $Exposure^{US}$ captures banks' exposure to the trade shock on the basis of banks' share of credit to exposed industries. It is instrumented by $Exposure^{EO}$. *Post* indicates the time period after China's entry into the WTO. The binary variable *Specialized* illustrates whether a firm operates in a sector in which the bank is specialized in. Bank controls include size, return on assets, ratio of non-performing assets, and short-term funding ratio. For detailed variable definitions see Table A1 in the Appendix. Each specification includes bank-firm as well as 2-digit industry-time fixed effects. Standard errors are clustered at bank and 3-digit industry level and reported in parentheses. The F statistic is the Kleibergen-Paap Wald rk F statistic for weak identification. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Subsample analysis in terms of banks' sectoral specialization

	(1)	(2)	(3)	(4)
	Non-specialized		Specialized	
$\text{Exposure}^{US} \times \text{Post}$	-1.032***	-0.248	-0.600	-0.069
	0.212)	(0.191)	(0.460)	(0.217)
Post × Cap	-0.070**		-0.259***	
	(0.031)		(0.092)	
$\text{Exposure}^{US} \times \text{Post} \times \text{Cap}$	0.926***		0.853*	
	(0.285)		(0.465)	
Post × Exposed		0.076**		0.095
		(0.034)		(0.233)
$\text{Exposure}^{US} \times \text{Post} \times \text{Exposed}$		-0.584**		0.308
		(0.034)		(0.233)
$\text{Exposure} \times \text{Post}\|_{25\rightarrow 75}$ if Cap=0	-0.063***		-0.037	
	(0.012)		(0.028)	
$\text{Exposure} \times \text{Post}\|_{25\rightarrow 75}$ if Cap=1	-0.006		-0.016	
	(0.012)		(0.010)	
$\text{Exposure} \times \text{Post}\|_{25\rightarrow 75}$ if Exposed=0		-0.015		-0.010
		(0.012)		(0.009)
$\text{Exposure} \times \text{Post}\|_{25\rightarrow 75}$ if Exposed=1		-0.051***		-0.015
		(0.014)		(0.015)
Observations	219,742	219,742	32,456	32,456
Bank controls	Yes	Yes	Yes	Yes
Bank-Firm FE	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes
Number of banks	64	64	65	65
Number of firms	8,238	8,238	2,170	2,170
Clustering	Bank-Ind	Bank-Ind	Bank-Ind	Bank-Ind

Note: This table explores how banks adjust their credit supply following a trade shock separately for specialized (Column (1) and (2)) and non-specialized banks (Column (3) and (4)). The dependent variable is the log of outstanding credit at bank-firm-quarter level, $\textit{ln(Credit)}_{b,f,j,t}$. $\textit{Exposure}^{US}$ captures banks' exposure to the trade shock on the basis of banks' share of credit to exposed industries. It is instrumented by $\textit{Exposure}^{EO}$. *Post* indicates the time period after China's entry into the WTO. *Cap* assumes a value of 1 (0) if a bank's capital ratio is above (below) the median. The binary variable *Exposed* illustrates whether the firm itself is affected by the trade shock. Bank controls include size, return on assets, ratio of non-performing assets, and short-term funding ratio. For detailed variable definitions see Table A1 in the Appendix. Each specification includes bank-firm as well as 2-digit industry-time fixed effects. Standard errors are clustered at bank and 3-digit industry level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: The effect of the bank lending channel on firm outcomes (2SLS)

	(1) Sales	(2) Tangibility	(3) ROE	(4) Profits
Firm Exposure^{US} × Post	-5.257*	0.029***	-0.034**	-1.696***
	(2.861)	(0.007)	(0.014)	(0.379)
Firm Exposure^{US} × Post$\Big\|_{25\to75}$	-0.260*	0.001***	-0.002**	-0.084***
	(0.141)	(0.000)	(0.001)	(0.019)
	First-stage			
Firm Exposure^{EO} × Post	0.999***	1.000***	1.000***	0.999***
	(0.014)	(0.014)	(0.013)	(0.013)
F statistic	5063.81	5064.56	5800.25	5611.76
Observations	150,492	150,266	161,656	161,853
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes
Number of firms	4,732	4,731	4,864	4,864
Clustering	Industry	Industry	Industry	Industry

Note: This table investigates the effect of the bank lending channel of the trade shock on firm-level outcomes. *Firm Exposure*^{US} captures firms' indirect exposure to the trade shock via borrowing from exposed banks. It is instrumented with *Firm Exposure*^{EO}. Firm controls include size, leverage, and trade credit. Each specification includes firm and 2-digit-industry-time fixed effects. Standard errors are clustered at the 3-digit industry level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: The differential effect of the bank lending channel on firm outcomes (2SLS)

	(1) Sales	(2) Tangibility	(3) ROE	(4) Profits
Firm Exposure × Post	-18.825***	0.057***	-0.062	-1.892***
	(6.066)	(0.016)	(0.038)	(0.586)
Post × High	-1.385	-0.002	-0.004	0.239
	(1.051)	(0.004)	(0.006)	(0.333)
Firm Exposure × Post × High	7.879*	-0.022**	0.006	-0.262
	(4.519)	(0.010)	(0.029)	(0.573)
Firm Exposure × Post$\|_{25\rightarrow75}$	-0.931***	0.003***	-0.003	-0.094***
	(0.300)	(0.001)	(0.002)	(0.029)
Firm Exposure × Post × High$\|_{25\rightarrow75}$	-0.022	0.001***	-0.001	-0.096***
	(0.162)	0(0.000)	(0.001)	(0.029)
Observations	150,492	150,266	161,656	161,853
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes
Number of firms	4,732	4,731	4,864	4,864
Clustering	Industry	Industry	Industry	Industry

Note: This table investigates the differential effect of the bank lending channel of the trade shock on firm-level outcomes depending on the share of specialized banks in firms' credit portfolio. *Firm Exposure*^{US} captures firms' indirect exposure to the trade shock via borrowing from exposed banks. It is instrumented with *Firm Exposure*^{EO}. *High* assumes a value of 1 if firms borrow from a high share of specialized banks and zero otherwise. Firm controls include size, leverage, and trade credit. Each specification includes firm and 2-digit-industry-time fixed effects. Standard errors are clustered at the 3-digit industry level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Appendix

Table A1: Variable definitions

Variable name	Description
Bank characteristics	
Exposure	Banks' average pre-shock share of loans to industry j to total loans weighted by industry j import exposure
Specialized	A dummy variable indicating whether a bank is specialized in the industry of the respective borrower (*Specialized*=1) or not (*Specialized*=0)
High Share	A dummy variable indicating whether a bank has a high market share in the industry of the respective borrower (*High Share*=1) or not (*High Share*=0)
High Region	A dummy variable indicated whether a bank is specialized in the region of the respective borrower (*High Region*=1) or not (*High Region*=0)
Cap	A dummy variable indicated whether a bank has a pre-shock average *Tier 1 capital* ratio above (*Cap*=1) or below (*Cap*=0) the median
Size	Log of total assets
Short-term funding	Short-term debt to total assets
NPL	Non-performing assets to total assets
ROA	Net income to total assets
Equity	Common equity divided by total assets
Deposits	Deposits divided by total assets
Tier 1 capital	Equity capital plus minority interests less portion of perpetual preferred stock and goodwill as a percent of adjusted risk-weighted assets
Liquidity	Cash divided by total assets
Firm characteristics	
ΔImport exposure	Change in US imports from China over pre-shock period divided by beginning of period total US imports
Firm exposure	Firms' average share of credit from bank b over the pre-shock period weighted by bank b's exposure to the trade shock

Table A1: Variable definitions

Variable name	Description
Exposed	A dummy variable indicating whether a firm is part of an industry that has an Δ*Import exposure* above (*Exposed*=1) or below (*Exposed*=0) the median
Size	Log of total assets
ROA	Income before extraordinary items divided by total assets
Leverage	Total debt divided by total assets
Tobin's Q	Total assets minus book equity plus market capitalization divided by total assets
Investment	Capital expenditure divided by total assets
Sales	Quarter-on-quarter growth of sales in percent
Tangibility	Tangible assets to total assets
ROE	Net income minus preferred dividends divided by total assets
Profits	Total sales minus the costs of goods sold divided by total assets
High	A dummy variable indicating whether a firm is borrowing from a share of specialized above (*High*=1) or below (*High*=0) the median
High ROA	A dummmy variable indicating whether a firm has a pre-shock average *ROA* above (*High ROA*=1) or below (*High ROA*=0) the median
High Leverage	A dummmy variable indicating whether a firm has a pre-shock average *Leverage* above (*High Leverage*=1) or below (*High Leverage*=0) the median

Table A2: Robustness checks I (2SLS)

	(1) Full	(2) Level	(3) Net	(4) Frederico et al.
Exposure^{US} × Post	-0.058*	-0.458*	-0.671*	-0.115*
	(0.033)	(0.237)	(0.372)	(0.067)
Observations	252,748	252,748	252,748	252,748
Bank controls	Yes	Yes	Yes	Yes
Bank-Firm FE	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes
Number of banks	68	68	68	68
Number of firms	9,466	9,466	9,466	9,466
Clustering	Bank-Ind	Bank-Ind	Bank-Ind	Bank-Ind

Note: This table explores how banks adjust their credit supply following a trade shock, as specified in Equation (1). The dependent variable is the log of outstanding credit at bank-firm-quarter level, $ln(Credit)_{b,f,j,t}$. $Exposure^{US}$ captures banks' exposure to the trade shock on the basis of banks' share of credit to exposed industries. It is instrumented by $Exposure^{EO}$. *Post* indicates the time period after China's entry into the WTO. Bank controls include size, return on assets, ratio of non-performing assets, and short-term funding ratio. For detailed variable definitions see Table A1 in the Appendix. Each specification includes bank-firm as well as 2-digit industry-time fixed effects. Standard errors are clustered at bank and 3-digit industry level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Robustness checks II (2SLS)

	(1) Cluster1	(2) Cluster2	(3) Firm FE	(4) ILS FE
Exposure^{US} $\times$ Post	-0.254*	-0.254*	-0.429**	-0.231*
	(0.147)	(0.139)	(0.183)	(0.121)
Observations	252,748	252,748	72,542	76,709
Bank controls	Yes	Yes	Yes	Yes
Bank-Firm FE	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	No	No
Number of banks	68	68	67	66
Number of firms	9,466	9,466	2,234	2,596
Clustering	Bank-Firm	Bank 2-Ind	Bank-Ind	Bank-Ind

Note: This table explores how banks adjust their credit supply following a trade shock, as specified in Equation (1). The dependent variable is the log of outstanding credit at bank-firm-quarter level, *ln(Credit)*$_{b,f,j,t}$. *Exposure*^{US} captures banks' exposure to the trade shock on the basis of banks' share of credit to exposed industries. It is instrumented by *Exposure*^{EO}. *Post* indicates the time period after China's entry into the WTO. Bank controls include size, return on assets, ratio of non-performing assets, and short-term funding ratio. For detailed variable definitions see Table A1 in the Appendix. Column (1) and (2) include bank-firm as well as 2-digit industry-time fixed effects. Column (3) and (4) replace the 2-digit industry-time fixed effects with firm-time and industry-size-location-time fixed effects. The clustering scheme varies across the specifications as indicted at the bottom. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Robustness checks III

	(1) Allocation2	(2) OLS	(3) Collapsed	(4) Placebo
Exposure^{US} × Post	-0.259**	-0.166	-0.200**	-0.123
	(0.129)	(0.112)	(0.081)	(0.131)
Observations	252,748	252,748	9,830	102,165
Controls	Yes	Yes	Yes	Yes
Bank-Firm FE	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes
Number of banks	68	68	41	64
Number of firms	9,466	9,466	4,167	6,037
Clustering	Bank Ind	Bank Ind	Bank Ind	Bank Ind

Note: This table explores how banks adjust their credit supply following a trade shock, as specified in Equation (1). The dependent variable is the log of outstanding credit at bank-firm-quarter level, $ln(Credit)_{b,f,j,t}$. $Exposure^{US}$ captures banks' exposure to the trade shock on the basis of banks' share of credit to exposed industries. It is instrumented by $Exposure^{EO}$, except in Column (2) which is estimated via OLS. *Post* indicates the time period after China's entry into the WTO, except in Column (4) in which a placebo shock is simulated to take place in the middle of the pre-shock period. Bank controls include size, return on assets, ratio of non-performing assets, and short-term funding ratio. For detailed variable definitions see Table A1 in the Appendix. Each specification includes bank-firm as well as 2-digit industry-time fixed effects. Standard errors are clustered at bank and 3-digit industry level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Robustness checks IV (2SLS)

	(1) OLS	(2) P 90	(3) Contin.	(4) High Share
$\text{Exposure}^{US} \times \text{Post}$	-0.427**	-0.540**	-0.427**	-0.558***
	(0.179)	(0.214)	(0.207)	(0.188)
Post × Specialized	-0.167**	-0.092**	-1.268**	-0.163**
	(0.069)	(0.042)	(0.479)	(0.070)
$\text{Exposure}^{US} \times \text{Post} \times \text{Specialized}$	0.573***	0.496***	3.005**	0.655***
	(0.189)	0.174)	(1.200)	(0.186)
Post × High Share				0.034
				(0.086)
$\text{Exposure}^{US} \times \text{Post} \times \text{High Share}$				-0.826
				(1.278)
Observations	252,748	252,748	252,748	252,748
Controls	Yes	Yes	Yes	Yes
Bank-Firm FE	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes
Number of banks	68	68	68	68
Number of firms	9,466	9,466	9,466	9,466
Clustering	Bank-Ind	Bank-Ind	Bank-Ind	Bank-Ind

Note: This table explores how banks adjust their credit supply following a trade shock, as specified in Equation (2). The dependent variable is the log of outstanding credit at bank-firm-quarter level, $ln(Credit)_{b,f,j,t}$. $Exposure^{US}$ captures banks' exposure to the trade shock on the basis of banks' share of credit to exposed industries. It is instrumented by $Exposure^{EO}$ except in Column (1) which is estimated with OLS. *Post* indicates the time period after China's entry into the WTO. The binary variable *Specialized* illustrates whether a firm operates in a sector in which the bank is specialized in. *High Share* takes on a value of 1 if a firm operates in a sector in which the bank has a high market share. Bank controls include size, return on assets, ratio of non-performing assets, and short-term funding ratio. For detailed variable definitions see Table A1 in the Appendix. Each specification includes bank-firm as well as 2-digit industry-time fixed effects. Standard errors are clustered at bank and 3-digit industry level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Robustness checks V (2SLS)

	(1) Firm Char. I	(2) Firm Char. II	(3) Region FE	(4) Reginal Spec.
$\text{Exposure}^{US} \times \text{Post}$	-0.759***	-0.583***	-0.653***	-0.731***
	(0.243)	(0.197)	(0.223)	(0.240)
Post × High	-0.224***	-0.192***	-0.197**	-0.152**
	(0.070)	(0.067)	(0.076)	(0.072)
$\text{Exposure}^{US} \times \text{Post} \times \text{Specialized}$	0.914***	0.839***	0.793***	0.596***
	(0.182)	(0.182)	(0.214)	(0.188)
Post × High ROA	0.076**			
	(0.030)			
$\text{Exposure}^{US} \times \text{Post} \times \text{High ROA}$	0.286			
	(0.237)			
Post × High Leverage		0.056		
		(0.034)		
$\text{Exposure}^{US} \times \text{Post} \times$ High Leverage		-0.680		
		(0.544)		
Post × High Region				-0.038
				(0.029)
$\text{Exposure}^{US} \times \text{Post} \times$ High Region				0.314
				(0.220)
Observations	151,657	151,385	205,451	252,748
Controls	Yes	Yes	Yes	Yes
Bank-Firm FE	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes
Number of banks	67	67	68	68
Number of firms	4,536	4,528	7,031	9,466
Clustering	Bank-Ind	Bank-Ind	Bank-Ind	Bank-Ind

Note: This table explores how banks adjust their credit supply following a trade shock, as specified in Equation (1) (Column (1) and (2)) and Equation (2) (Column (3) and (4)). The dependent variable is the log of outstanding credit at bank-firm-quarter level, $ln(Credit)_{b,f,j,t}$. $Exposure^{US}$ captures banks' exposure to the trade shock on the basis of banks' share of credit to exposed industries. It is instrumented by $Exposure^{EO}$. *Post* indicates the time period after China's entry into the WTO. The binary variable *Specialized* illustrates whether a firm operates in a sector in which the bank is specialized in. *High ROA* (*High Leverage*) assumes a value of 1 if a firm has a high return on assets (a high leverage ratio) and zero otherwise. *High Region* takes on a value of 1 if a firm operates in a in a region in which the bank is specialized in. Bank controls include size, return on assets, ratio of non-performing assets, and short-term funding ratio. For detailed variable definitions see Table A1 in the Appendix. Each specification includes bank-firm as well as 2-digit industry-time fixed effects. Column (3) addionally incorporates region fixed effect. Standard errors are clustered at bank and 3-digit industry level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

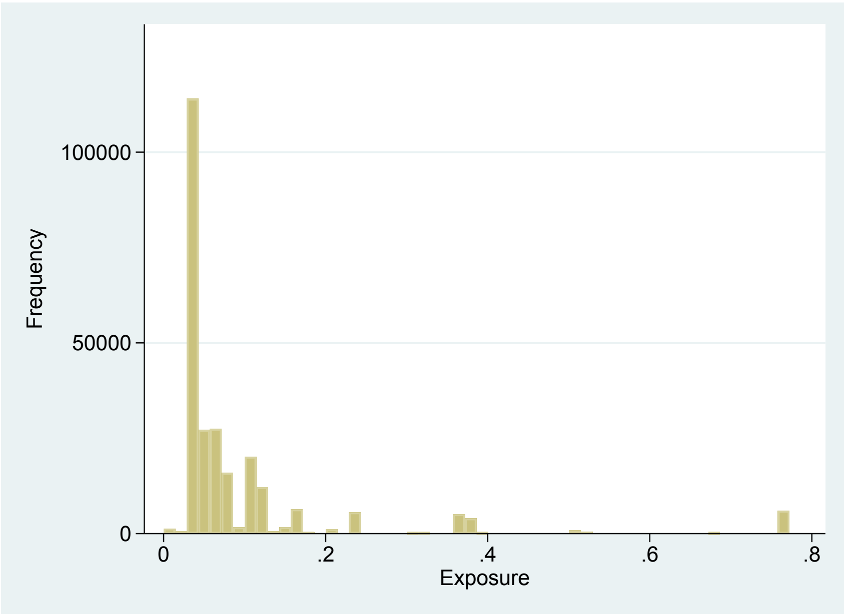

Figure A1: The distribution of banks' exposure to the trade shock

Notes: This figure shows the distribution of banks' ex-ante exposure to the trade shock, $Exposure^{US}$, in the estimation sample. It is constructed as in Equation (3) and averaged across industries for the estimations.

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