Trade Shocks and Bank Lending: Evidence from Antidumping Investigations of Chinese Firms

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Abstract

Using credit registry data from China, this paper examines the implications of antidumping trade shocks on exporting country's bank loan market. We find that a one-standard-deviation trade shock leads to a 7.2% increase in the likelihood of default in relative terms. Banks respond to the shock by raising the requirements of collateral or guarantee, shortening loan maturity, while leaving interest rates unchanged. Moreover, banks cut the supply of credit by 1.5% to affected borrowers. Firms that maintain bank-firm relationships are able to shield themselves from this particular demand shock to some extent. Lastly, we find some evidence in support of a spillover of trade shocks to unaffected sectors via banks. Our results suggest that trade shocks affect the allocation of credit via the banking sector.

Keywords: Antidumping, Bank Lending, China, Spillover
JEL: F10, F13, G21, G28

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1. Introduction

One central question in trade is how trade would affect the allocation of resources. While existing studies have provided plenty of evidence that import competition has reshaped the labor market (e.g., Autor et al., 2013), much less is known regarding how trade shocks would be transmitted to the capital market.[1] Moreover, existing studies mostly focus on the impact on domestic manufacturers of import competition from large exporters (e.g., China). Less effort is spent on the implications of trade policy, which has been used more and more intensively as part of the rise of trade protectionism and anti-globalization during the last decade. According to the data from Global Trade Alert displayed in Figure A1 in the Appendix, while trade has become more liberalized in general, the amount of trade restriction policies has increased by a substantially larger scale over the past decade. How trade restriction policies, such as antidumping (AD), would distort the credit allocation remains a significant question under this background. In this paper, we use the credit register data in China to investigate how antidumping measures on China's exports would affect the bank-lending.

China provides the best laboratory to study this question. On the one hand, as an emerging economy, China has benefitted from a series of trade liberalization policies since its reform and opening-up, especially during the post-WTO-accession period.[2] However, the recent China-U.S. trade war has made the wave of trade protectionism to the climax, posing great challenges to the overall economy and the particularly credit market. Studying how antidumping, the most frequently used temporary trade barrier, would affect China's bank-lending is therefore of high relevance given its importance to international trade.

On the other, unlike OECD countries, which heavily rely on direct finance, China features a foremost reliance on indirect finance, with bank lending being the most prominent part. For instance, the fraction of total financing from the banking sector is

[1] Federico, Hassan, and Rappoport (2019) is an exception. They find that after China enter into WTO, Italian firms face the import competition of Chinese products. Controlling for the credit demand, those banks who are more exposed to China shock cut their lending more due to banks' balance-sheet effect. Besides, Lanteri and Medina (2020) used detailed data of Peruvian manufacturing firms' investment dynamics and found that substantial frictions slowed down the capital reallocation.

[2] As shown by Brandt et al. (2013), entering WTO significantly boosts China's economic growth. China has become the largest exporter, and also the first target of trade protectionism measures in the world.

as big as 67% in 2016. Studying trade policy's impact on bank-lending would help us understand more about firms' response to trade policy.

To investigate the impact of antidumping on bank lending, we combine several datasets. We first retrieve the basic characteristics of antidumping investigations against China (e.g., initiation date, preliminary decisions and dates, final decisions and dates, target products) from the Global Antidumping Database. We combine antidumping cases with the exports value at the HS6 product-destination-year level during 2007-2015 for Jiangsu Province of China where the borrowers in our bank loan data are located. The third dataset is the loan data that includes the universe of bank loans borrowed by firms located in six representative prefectures in Jiangsu Province from January 2008 to June 2016. It provides the information of borrower's ID, ownership, amount of the loan, loan type, interest, maturing, whether they are secured or not etc.

Although the coverage is only one province of China, there are several advantages of this loan level data. First, the data is directly obtained from China Banking and Insurance Regulatory Commission, which guarantees the accuracy and reliability. Second, it includes the universal loans within the area. Due to the geographic restrictions of banking operation, this multiple bank loan data would allow us to track the firms' borrowing behavior across banks. Moreover, it covers loans borrowed by both large and small enterprises, with the latter often being neglected in previous studies. Third, Jiangsu Province is one of the most vibrant areas in China in terms of both exports and banking. In 2015, the export value of Jiangsu took up 14.9% of China's total exports. Seventeen years in a row, Jiangsu ranks the second in export value among all the provinces in China. The export value of these six prefectures in our dataset accounts for 71.3% of Jiangsu's total export value.

We construct a continuous product-level proxy for antidumping shocks by weighting each confirmed antidumping case with the corresponding exporting volume to the country that initiated the investigation. We first investigate how antidumping would affect the credit quality of borrowers. We find that loans extended to firms in the AD target industry are significantly more likely to become non-performing. In terms of economic magnitude, one-standard-deviation increase in trade shocks translates into an increase of default likelihood as large as 0.15 percentage points, equivalent to a 7.2% increase when evaluated at the mean. The other measure is loans' solvency status. We find that AD shock is associated with worse solvency status of loans. Meanwhile, banks recognize the deterioration of the credit quality of these borrowers, as revealed by the significantly lower internal loan ratings issued by banks when lending to AD-exposed borrowers. This finding suggests that the internal loan ratings issued by Chinese banks are informative about the credit quality of borrowers.

On the loan contract level, we find that banks require significantly more collateral/guarantee and shorten the maturity in response to the AD shock. Interestingly, the interest rate is insensitive to variations in AD shocks. This is perhaps due to the fact that Chinese banks are constrained by regulated lending rates during the bulk of our sample period. A consequence of this regulatory constraint is that banks rely more on non-pricing terms to factor in the default risk of borrowers.

We then investigate the impact of AD shock on the provision of credit. Overall, if a firm is more exposed to antidumping by one standard deviation, the total amount of loans the firm obtains from the bank tends to decline by 1.5%, which is equivalent to 11.5 million CNY when evaluated at the mean of the bank loan amount outstanding. Alternatively, we also construct an indicator of non-refinance at the bank-firm level. Banks in China keep long term relationship with firms by issuing new loans to refinance maturing loans which usually have a short maturity (e.g., around 11 months). Failing to roll-over maturing debt could severely disturb firms' on-going projects which are usually long-term. We find that AD shock significantly increases the likelihood of refinancing failure.

Next, we investigate whether the above adjustments are heterogeneous with respect to various firm and bank characteristics. First, we document that the existing bank-firm relationship could help firms when they are under antidumping. If a certain firm had borrowed from a certain bank within the past two years, we categorize this firm as a relationship borrower of its bank. In terms of both loan contract terms and the amount of loans, we find that firms with pre-existing relationship are better off compared with those without. This finding indicates that bank relationship is beneficial when firms face adverse shock (e.g., antidumping) in China.

Moreover, this adverse shock would also be transmitted from AD target firms to those not directly target ones (Federico, Hassan, and Rappoport, 2019). The main mechanism is through the deterioration of banks' balance sheet as a result of defaulting exporters that are exposed to antidumping. We construct a bank-level AD shock based on loans in banks' loan portfolio that are allocated to AD industries. Using firm-year fixed effects to isolate the loan supply side shock (Khwaja and Mian, 2008), we find that unaffected firms tend to obtain a smaller amount from more-exposed banks. This provides the evidence of trade shocks' spillover to unaffected sectors via banks.

Another interesting aspect our paper has explored is that whether Chinese banks are forward looking or backward looking. There are many steps of AD investigation, which usually last about 12 months. The three key stages are the initiation of the case, preliminary decision, and final decision. Since the loan data includes specific date of when the loan was issued, we are able to use the disaggregate loan data to check banks' timing to respond to AD by redefining AD shock with the initiation date. We find that the adjustment mainly happens after the final decision. Chinese banks are slow in responding to the trade shock, suggesting that they are "backward looking" instead of "forward looking". Brooks and Dovis (2020) modeled two types of financial constraints, the forward and backward looking ones, and their influences on the gains of trade liberalization. Our finding provides empirical evidence that backward looking debt limit is a more relevant case in China.

Although much evidence indicates that access to external finance would substantially affect firms' participation into exports, the link between trade policy and credit market is unclear. To our best knowledge, we are one of the first few papers which study how trade policy shocks would affect bank loans. In particular, our paper is the first to study how trade protectionism measures would affect the bank-lending relationship.

2. Literature Review

Our paper contributes to several strands of literature, including the relationship between trade and finance, the impact of antidumping, and bank-firm relationship in China's financial market.

The first strand of literature is the study on the relationship between trade and finance. For the direction on how finance affects trade, vast literature finds that access to external financial resource would boost exports. Studies at the country and country-sector levels indicates better financial development could facilitate exports (Beck 2002; Beck, 2003; Manova, 2013). At the firm level, prior studies indicate that firms that are less financially constrained are more likely to become exporters (Berman and Héricourt, 2010; Greenaway et al.; 2007; Muûls, 2015; Minetti and Zhu, 2011). Meanwhile, when we focus on the share exports in the total sales, Feenstra et al. (2014) show that the higher percentage of exports the more financially constrained the firm is. The impact of financial constraint on firm level exports also helps explain the trade collapse in financial crisis during 2008-2009 (Chor and Manova,2012; Paravisini, Rappoport, Schnabl and Wolfenzon, 2014).

In particular, focusing on the direct impact of banking on exports in China, Chen, Poncet, and Xiong (2020) finds that the development of city commercial banks makes China's domestic private firms export more. Moreover, at the loan level data, Ru (2021) uses the loan data from China's National Development Bank, which is China's largest policy bank, and find that the bank's lending to the upstream industries make the downstream export firms export more and export at lower prices.

Although various evidences indicate the access to financial resource would shape firms' export decisions in both extensive and intensive margins, the reverse direction on how trade would affect firm's finance is much less investigated. In corporate finance area, using the exogenous import tariff as the instrument variable for the market competition, Valta (2012) finds that the spread is 9.6% higher for firms in more competitive industries than those in the less competitive industries among the publicly traded U.S. firms 1992-2007. Moreover, Xu (2012) finds that when U.S. firms facing greater import competition, which is proxied by foreign exchange rate and import tariff, they would change their capital structure by issuing more equities and repaying debts. Since in China, issuing equities is not an option for most firms, we focus on the bank loans features including default, spread, maturity, and collateral requirement etc. Moreover, our sample is not limited to publicly listed firms, which allows us to study the bank-firm loan relationship for both big and small firms.

The mostly related paper is Federico, Hassan, and Rappoport (2019). Their innovative work to study how trade shock drives the reallocation of credit with the matched firm-bank loan data of Italy. They investigate how China shock, i.e. Italian firms facing greater import competition from China, would affect Italian bank-firm relationship. They find that sectors most affected by import competition from China would experience a decline in bank credit. There is also transmission of the shock from affected sector to unaffected sectors through the bank balance sheet effect. The aggregate implication is large.

Our paper is different from Federico, Hassan, and Rappoport (2019) from several perspectives. First, they focus on the trade shocks that originate from import competition and how such shocks affect the importing country. We look at the question from China as the exporting country. Our paper looks at the trade shocks of foreign trade protection policy on exporters' behavior. To our best knowledge, our paper is the first one to study this question from trade protection policy and bank-firm loan angle. Second, banking is more important in China than that in OECD countries. Third, we also investigate the heterogeneity adjustments among different bank-firm relationships. Besides the common bank-firm relationship in terms of previous lending history, China has the special background of preferential lending to state-owned firms due to the long history of state-owned economy. The big four banks are all state-owned banks. There are also thriving joint equity banks and city/rural commercial banks in China.

The second strand of related literature is how antidumping would affect firms' behaviors. The most direct impact is antidumping investigations' impact on trade flows. The first and most natural change is trade destruction, which refers to the phenomenon that the corresponding exports of the target economy to the investigation economy would decrease after to anti-dumping. (Lu, Tao, and Zhang, 2013; Felbermayr and Sandkamp, 2020). Trade deflection refers to the phenomenon that the target country's corresponding exports to the third country would increase. (Bown and Crowley, 2007;

Chandra, 2016). The last trade flow change is the trade circumvention, Liu and Shi (2019) finds that that after antidumping the target country's exporters would export the products to a third economy, obtain the certificates of origins there, and then export to the investigation initiation country. Moreover, antidumping will affect exports through increasing uncertainty (Crowley, Meng, and Song, 2018).

Antidumping would also directly change other dimensions of exports, such as prices markup (Konings and Vandenbussche, 2004), product-scopes (Lu, Tao, and Zhang, 2019), productivity of firms in the domestic market (Konings and Vandenbussche, 2008; Pierce, 2011), the productivity of exporters (Chandra and Long, 2013; Wang, Lin, and Li, 2021), and stock prices (Hua et al., 2020). In a nutshell, all the evidence above focuses on firms' response to antidumping shocks. We provide a new angle to look at how banks adjust to antidumping shock. Firms' response to trade policy can be arisen from the endogenous financial constraint change.

The third strand related literature is the bank-firm relationship. In corporate finance literature, there are studies on how existing bank-firm relationship would affect bank's lending when firms are in the financial distress. The findings are mixed. Boot (2000) find that previous bank-firm relationship would help because banks care about long-term relationship with firms. Meanwhile, Li, Lu and Srinivasan (2019) find the opposite that previous bank-firm relationship would hurt when firms are in financial distress because they know more information about the firms. This dimension has not been explored in the setting of China. Our paper provides the first evidence of existing bank-firm relationship's influence through the angel of antidumping. We find that banks will offer better loan contracts to those firms which borrowed from them in the past two years.

As an emerging economy, China also has complicated and unique bank-firm relationship due to the state-owned economy. It leads to the financial market frictions, which would affect exports. For example, the preferential lending for state-owned enterprises (SOEs hereafter) or politically connected firms in general is significant problem. SOEs and more politically connected firms can get access to external finance more easily and at a lower cost. Brandt and Li (2003) finds that the trade credit cost is higher for private owned enterprises than that for state owned enterprises. Ding, Fan, and Lin (2018) find that firms with political connection export more in contract and financial dependent industries. Compared with these two papers, our paper provides a new angle to investigate the frictions in China's banking industry.

3. Institutional details and data

3.1 Antidumping investigations on Chinese exporters

China provides the ideal setting to study this question. Since its accession into WTO in 2001, China's export volume had skyrocketed, making it the largest exporter in the world for many years. Meanwhile, China is also the top target of antidumping investigations. According to Panel (a) of Figure A2 in the Appendix, the number of antidumping investigations is more than 50 cases each year since 2006 and reached the peak in 2008. Except that from 2010 to 2012, due to the hit of financial crisis and great trade collapse, the number of antidumping cases significantly dropped. The frequency of antidumping against China climbed back to a high level since 2013.

Antidumping investigations would hurt Chinese exporters greatly for a long time. According to Table A2, there are 771 antidumping investigations initiated between 2000 and 2015, among which 702 cases have reached the decision. Moreover, 581 cases out of the 702 cases have been adjudicated as "confirmed", which would lead to material antidumping tariff. Because of the high proportion of "confirmative" cases, the initiation of antidumping investigation sends a very bad signal. Instead of waiting for the final decision, banks and firms may respond at the initiation of investigation.

According to Panel (b) of Figure A2 in the Appendix, the top three economies that launch antidumping investigations against China are India, U.S., European Union. The temporary tariff rates associated with antidumping are usually much higher than normal tariff levels, sometimes the rate is almost prohibitive for trade. Among all the cases initiated between 2000 and 2015, the mean and the median antidumping tariff rates are 99.2% and 47.2%, respectively. In contrary, the average trade weighted imported tariff of U.S. is only 2%. Meanwhile, once the antidumping cases have been confirmed, they usually last at least for five years until the first sunset review. For some certain cases, it would continue for another five years. Therefore, antidumping duties tend to cause serious damage to firms' export and overall revenues. Among all the cases which have already been terminated, the average and median durations of antidumping are 66.8 and 60 months, respectively. The maximum duration is 159 months.

According to Panel (c) of Figure A2 in the Appendix, the top ten industries that have been investigated include: Iron and steel articles (73), inorganic chemicals(29), Iron and Steel (72), organic Chemicals(28), plastics and articles thereof (39)， Nuclear reactors, boilers, machinery and mechanical appliances; parts thereof (84), glass and glassware (70), Rubber and articles thereof (40), Paper and paperboard; articles of paper pulp, of paper or paperboard (48).

All that being said, antidumping represents a significant demand shock for affected exporting firms. Overall, the antidumping cases would generate a huge impact on Chinese exporting firms, especially on firms located in Jiangsu Province that rely more on exporting than firms in other parts of China. These antidumping demand shocks would be transmitted to the bank-firm relations, which would further affect firms' performance. It also provides us a window to investigate the bank-firm relationship across various ownership.

3.2 The Economy and Exports of Jiangsu Province

Although we don't have the national level bank-firm loan data, the corresponding data of Jiangsu Province provides a good representative to study this question. In 2016, the total GDP of Jiangsu is 7608.6 billion RMB, which was 10.23% of China's total and ranked the second place among all the provinces. The total GDP of the six prefectures in our sample was 3751.8 billion RMB, which was 49.31% of Jiangsu.

First, Jiangsu's economic and export sizes are large. Jiangsu Province is a major player in Chinese economy, especially in trade. The GDP and export value of Jiangsu Province rank No. 2 in China in our data period, which is just next to Guangdong Province. 17 years in a row, Jiangsu ranks the second in export value among all the provinces. In 2015, the export value of Jiangsu took up 14.9% of China's total exports. In 2015, among all Jiangsu's exports, the machinery exports take 47.9%. (HS2=85, Electrical machinery and equipment and parts thereof, 25.92%; sound recorders and reproducers; television image and sound recorders and reproducers, parts and accessories of such articles; HS2=84, it is called Nuclear reactors, boilers, machinery and mechanical appliances; parts thereof in the HS system, 21.98%).

Within Jiangsu, there exist significant heterogeneity with respect to economic development. In terms of trade volume, the 13 prefectures in Jiangsu Province could be ranked as: Soochow, Wuxi, Nanjing, Nantong, Changzhou, Yangzhou, Zhenjiang, Taizhou, Xuzhou, Yancheng, Lianyungang, Huaian, Suqian. Jiangsu's exports are concentrated in the southern part, especially in Soochow. According to Figure 1, in 2015, Soochow's export value is 53.7% of Jiangsu's total value, followed by Wuxi (11.3%), Nanjing (9.0%), Nantong (7.1%), Changzhou (6.7%). The rest cities took up 12.2% of the total export value. Moreover, at the city level, Soochow is the fourth biggest export city in China, next to Shanghai, Shenzhen and Beijing.

3.3 Banking in China

There are several different levels of banks in China. The first level are the national level state-owned banks. The most import ones are the big four major state-owned banks including Bank of China (BOC), Agriculture Bank of China (ABC), Industrial and Commercial Bank of China (ICBC), China Construction Bank (CCB). They conduct business at national levels. The big four state-owned banks have different specialties and concentration in various industries in history. As the financial development, the segmentation of their businesses has become blurred. For a long time, Bank of China is the dominant bank to control China's foreign exchange, international settlement for trade and non-trade, oversea remittance etc. Agriculture Bank of China was the first state-owned bank established in PRC. It has the largest number of branches and the largest geographic coverage in China. China Construction Bank focuses on the loans for infrastructure. Part of it policy related functions have been replaced by China Development Bank, which is a major policy bank. Besides the big four, there two more national level state-owned banks. China Communication Bank was China's first joint equity bank with the state-owned share dominant. China Postal Savings Bank of China.

The second level of banks are the joint equity commercial banks which operate at the national level. There include China Citic Bank, Shanghai Pudong Development, China Merchants Bank, Huaxia, China Everbright Bank, China Industrial Bank, China Minsheng Bank, China Guangfa Bank, Hengfeng Bank, China Zheshang Bank, Pingan Bank, China Bohai Bank

The third level of banks are the regionally operated city and rural commercial banks in Jiangsu. The city and rural commercial banks grow fast in China, especially in Jiangsu Province. There are 4 city commercial banks including Bank of Jiangsu, Bank of Nanjing, Bank of Suzhou, Jiangsu Changjiang Bank. There are 62 rural commercial banks.

3.4 Data

3.4.1 Antidumping investigations

The antidumping investigation data is obtained from Global Antidumping Data base. Antidumping investigations usually take 1 to 2 years to reach a conclusion. There are three key steps in the process, initiation of the case, preliminary decision, and final decision. During each stage of the case, whenever it is possible to be judged as negative, the investigation would stop and no actions would be imposed on the target products. Whenever it has been judged as confirmative, the antidumping duties would last for five years until the sunset review. The global antidumping duties also provide the data of covered HS product codes. Some cases target on very specific products at the HS 10-digit level, while other cases target on more generalized products at the HS 6-digit level or more aggregated levels. The HS 6-digit code is the most disaggregated level of the HS system that is internationally comparable.[3]

We convert HS2007 as well as HS2012 codes to HS2002 using the concordance table from UN Trade Statistics. Using the linking table from Brandt et al. (2017) that translates HS2002 product codes to CIC2003 industry codes, we obtain the industries that are covered by each case. As banks in our sample code industries using the

[3] In GAD data, in an antidumping case, the ad valorem tax is on country-product. Although there is heterogeneity of antidumping tariff rates across firms, the only affect a very limited number of firms.

CIC2011 version, we then convert CIC2003 to CIC2011. We are able to identify 3,422 antidumping cases with valid GB/T 4-digit industry codes between 2007 and 2015. Keeping cases for which the final decision is affirmative leaves us with 1,997 cases. We further drop 78 cases that have been terminated before reaching the final decisions. A firm is considered to be subject to antidumping duties if it is within the five years after the date on which the final decision is confirmative. For cases that were revoked, we use the period between the final decision date and the revoke date. There are in total 247 such cases.

As the importance of countries that launched antidumping investigations differs with respect to their contribution to the exporting volume, we weight each successful case using Jiangsu Province's exporting volume to the investigating country. To mitigate endogeneity concerns, we use exporting volume as of the last year as the weight of each successful antidumping investigation. Specifically, our main proxy for the exposure to anti-dumping duties is calculated as follows.

$$ADI_{s,t} = \sum_k d_{s,k,t} * (m_{s,k,t}/M_{s,t}) \tag{1}$$

The variable $d_{s,k,t}$ is a dummy indicating whether the CIC2011 four-digit industry s is under anti-dumping investigation from country k at month t. $m_{s,k,t}$ represents the total volume of goods exported to country k by firms in industry s during the last calendar year, and $M_{s,t}$ represents the total volume of exports to the whole world by firms in industry s during the last calendar year. By weighted each antidumping case by the importance of the country that initiates it, we can differentiate between cases that results in material impacts on the exporting firms and those that only have marginal impacts.

3.4.2 Bank loans

We obtain bank loans from a credit registry maintained by the Jiangsu branch of CBIRC (Chinese Bank and Insurance Regulatory Commission). It covers the universe of bank loans issued to firms located in Jiangsu Province, which is among the most developed and open areas in China. Considering that the credit registry data is constructed for regulatory purposes, the quality of data is very reliable (Gao, Townsend and Yang 2019). The original sample contains close to 2 million loans issued between 2008 and 2016 to all non-financial firms located in six representative prefectures among the eleven prefectures in Jiangsu Provincial. The data also covers all types of banks that are currently active in China, including rural commercial banks, city commercial banks, joint-equity banks and state-owned banks. In particular, around half of the loans in our sample are funded by rural and city commercial banks, due to the prosperous local banking system in Jiangsu. Compared with loan data from one single bank that is used in several prior studies, the credit registry data enables us to study how heterogeneity across banks (e.g., NPL rate) could transfer the trade shock to unaffected sectors via the lending channel. Since one firm could borrow from several banks, the multi-bank data could give us the full picture of bank-firm relationship after trade shocks. It also enables us to study how the total credit supply from the banking sector responds to external demand shock.

The data contains basic loan contract terms, including the principal amount, maturity, interest rate, whether the loan is secured, the loan type, the name of the lender, and the internal credit rating of loans issued by banks. Besides, we are also able to track the solvency status of the loan. By regulation, Chinese banks have to evaluate the solvency status of loans in their portfolio on a routine basis and give a particular loan each of the five labels, i.e., pass, special-mention, substandard, doubtful and loss. According to regulation rules in China, loans that receive either the “doubtful” or “loss” label are categorized as non-performing loans. Unfortunately, for confidentiality reasons, we are not able to access the borrower identify, although each borrower in our data is identified by a unique ID and the code is unified across banks. Regarding borrower characteristics, our data contains the city of domicile, the firm age, the size category, the nature of firm ownership as well as the industry to which the firm belongs.[4]

[4] Firms in China are categorized as micro-, small-, medium- and large-sized enterprises, based on the number of employees and annual sales.

We start from 2,091,454 loans borrowed by firms located in our sample prefectures between 2008 and 2016. Several filters are applied to the original sample. We first drop loans for which important contractual terms or borrower characteristics are missing, including initiation date, maturity date, principal amount, whether it is a secured loan, interest rate, firm age and ownership. Loans with irregular contractual terms (e.g., maturity dates precede initiation dates, negative loan amount, zero interest rates) are dropped. We also exclude loans extended by non-bank institutions, such as financial companies and village credit cooperatives. We are left with 1,752,426 loans. As antidumping intensity is defined on GB/T 4-digit industry level, firms for which the industry is defined on 1-digit, 2-digit or 3-digit levels are also dropped. Note that the last filter results in a substantial loss of observations (1,251,854 observations dropped). The final sample includes 500,572 loans.[5]

As we calculate the intensity of antidumping duties on the 4-digit GB/T industry level, treated loans are those that are borrowed by firms operating in GB/T 4-digit industries with non-zero antidumping duties. Other loans are defined as control loans. In our main analysis, we follow Lu et al. (2013) and sharpen the identification strategy by comparing loans in the same GB/T 2-digit industries as treated loans with loans of firms subject to antidumping duties. Specifically, in each month, we only keep those GB/T 2-digit industries with non-zero issuance of control loans and treated loans. After applying this filter, we are left with 251,368 loans.

3.5 Summary statistics

Table 1 presents the summary statistics of main variables used in this paper. Firms in Panel A are from GBT 2-digit industries which contain at least one sub-industry under antidumping investigation and at least one sub-industry that is not subject to such investigation. Panel B shows the summary statistics for the full sample. Since the summary statistics are quite similar between these two panels, we focus on Panel A.

[5] Focusing on firms with four-digit industry codes could lead to sample selection bias, as firms whose industries are coded on a more aggregated level are likely to operate in several industries and thus are bigger in size. In Appendix Table 1, we provide the distribution of firm size and bank types across different industry aggregation levels. The distribution of both firm size and bank types are very similar across different levels of industry codes, suggesting that there is not much selection bias when using firms with four-digit industry codes.

The mean of antidumping intensity is 0.151, meaning that for an average firm, the industry to which it belongs has 15% of its exporting volume under antidumping penalty. Note that there is substantial dispersion with regard to the intensity of antidumping across industries. The median firm in our sample is not subject to any antidumping penalty, while the firm on the 75% percentile has 14% of its exporting volume under antidumping duties.

[Insert Table 1 about here]

As the majority of borrowers in our sample are SMEs, the loan amount is fairly small, with the average loan amount less than 5 million RMB (around $0.7 million) and the median is merely 2 million RMB (about $0.3 million). Considering the loan amount has a large skewness to the right, we take the natural log. Bank loans in China feature extremely short maturity, with the average loan in our sample having a maturity of less than 10 months and the median only 11 months. Only 7% of sample firms can receive bank credit that matures in two years.[6] Banks issue short-term loans to roll over maturing loans.

The average loan has a solvency status close to "Pass". The likelihood of loan default is around 2% in both the restricted sample and the full sample.[7] The default likelihood is close to what is provided in a recent paper by Ai et al. (2020) that uses a sample covering loans issued by big banks across the whole country of China. Loans on average receive a rating between AA and A. The average raw interest rate is above 7% annually. China liberalized both the lending and deposit rate in the fourth quarter of 2015. Prior to that, both the lending rate and the deposit rate offered by Chinese banks are heavily regulated. The central bank of China (PBOC) would issue policy rates that correspond to various maturities. As the second measure for the cost of debt, we follow Yu et al. (2019) and scale the difference between the raw interest rate and the maturity-matched policy rate by the policy rate. In other words, the scaled version of

[6] The maturity of bank loans in China is significantly shorter than that in the US (Valta 2012; Santos and Winton 2019) as well as in the international loan market (Giannetti and Yafeh 2015; Beyhaghi et al. 2020) in which the median loan usually matures in 4 or 5 years.

[7] In the baseline regression, we use the lowest status as the solvency status for each loan. In Appendix Table 3, we use the status at the end of the loan for a robustness check. The results are similar.

interest rate (*spread*) captures the relative spread over the policy rate. The average interest rate is 27% percent higher than the corresponding policy rate. More than 90% of loans in China are either secured by collateral or guaranteed for repayment. The proportion of secured loans in our sample is substantially larger than that reported in existing studies for which the sample covers relatively bigger borrowers (e.g., Yu et al. 2019; Ai et al. 2020).[8] This is perhaps due to banks' stringent risk management policies when lending to SMEs which dominate our sample.

The average firm age is 9.5 years. More than 80% of loans are issued by banks with which the firm has a lending relationship. Here relationship is a dummy that equals one if the firm has at least one loan with the bank during the last two years. Considering the extremely short loan maturity in China, we use a two-year window to define lending relationship, which is much shorter than what is usually used in the US setting.[9]

4. Empirical Results

In this section, we first lay out the empirical specification that allows us to quantify the impact of antidumping duties on various outcomes (e.g., default risk, loan contract terms, and loan supply). We then present the baseline results as well as the heterogeneity of the effect.

4.1 The empirical specification

When evaluating the impact of trade shocks on bank lending, we conduct analysis on both the single loan level and the firm level. While firm-level analysis allows us to gauge the impact of trade shocks on loan supply, loan-level analysis has the advantage of zooming in loan contractual terms conditional on receiving the credit. We first run fixed-effect regressions on the loan contract level which are specified as follows.

$$Y_{i,j,l,b,t} = \alpha_j + \gamma_t + c_{j,t} + m_{b,t} + \beta ADI_{l,t} + \Gamma X_{i,j,t} + \varepsilon_{i,j,l,b,t} \quad (2)$$

In Equation (2), i denotes a specific loan. j stands for the firm which obtains the

[8] If we restrict the borrowers to big firms, the percentage of secured loans is slightly higher than 75%.

[9] Prior research, such as Bharath et al. (2009), typically define bank relationship using lending records that trace back to five or ten years.

loan. l is the industry which firm j belongs to. t stands for the specific year-month the loan was issued. $Y_{i,j,l,t}$ denotes outcome variables defined at the single loan level, including default risk, internal loan ratings and loan contract terms. As our key regressor ($ADI_{l,t}$) is defined on the industry-month level, the time dummies (γ_t) are defined on the calendar year-month level. $X_{i,j,t}$ represents the set of control variables that are defined on either the loan level or the borrower level. Following Lu et al. (2013), we control for firm fixed effects that are denoted by α_j. To account for the impact of city-level economic conditions as well as loan supply side factors, we also control for city-month ($c_{j,t}$) and bank-month ($m_{b,t}$) fixed effects, respectively. Standard errors are clustered on the 4-digit GB/T industry level.

Next, we examine how the exposure to trade shocks affects the credit supply by banks. We estimate the following equation.

$$AMTOTD_{j,l,b,t} = \alpha_j + \gamma_t + c_{j,t} + m_{b,t} + \pi ADIAN_{l,t} + \Gamma X_{j,t} + \varepsilon_{j,l,b,t} \qquad (3)$$

The outcome variable ($AMTOTD_{j,l,t}$) is defined as the total amount of loans outstanding between firm i that operates in industry l and bank b at the end of year t. As the total loan amount outstanding is calculated at the end of each year, the key regressor, $ADIAN_{l,t}$, is also calculated on a yearly frequency. Specifically, it is defined as average of monthly *ADI* across the whole year. The baseline specification controls for firm (α_j), year (γ_t), city-year ($c_{j,t}$) as well as bank-year ($m_{b,t}$) fixed effects. Standard errors are clustered on the 4-digit GB/T industry level.

4.2 Loan default risk and loan quality

Firstly, we explore how trade shocks have altered the credit risk of domestic firms. Specifically, we utilize the five-scale loan solvency status that are provided by banks, including pass, special-mention, substandard, doubtful and loss. Consistent with the definition used by the Chinese regulators, *NPL* is a dummy that equals one if the loan ever receives a label of “doubtful” or “loss”. Note that estimating nonlinear models (e.g., panel logit or probit models) with a large number of individual fixed effects tends to aggravate the incidental parameters problem (Lancaster 2000; Greene 2008).

Therefore, we rely on linear models to predict loan default events. For the ease of interpretation, we multiply the estimated coefficients by 100 in NPL regressions.

In Column (1) of Table 2 Panel A, we control for firm and calendar month fixed effects. We also control for loan type fixed effects, as loans with different purposes have distinct default risk. In terms of firm characteristics, we control for firm age.[10] The coefficient estimate of *ADI* indicates that the default likelihood increases by 0.17% ($0.6174 * 0.28 \approx 0.1728$) for each one-standard-deviation increase in antidumping duties. When evaluated at the mean of default likelihood of sample loans, this effect represents an 8% decline in relative terms, suggesting that the effect of antidumping on default risk is economically meaningful.

[Insert Table 2 about here]

City-level economic shocks could affect the default likelihood of local firms. Meanwhile, it is well known that industries tend to agglomerate in certain cities, which might be related to the incidence of antidumping investigations. We therefore control for city-month fixed effects in Column (2). The coefficient of ADI barely changes after controlling for city-month fixed effects, indicating that city-level economic shocks are not driving the results. Lastly, considering that lender-level shocks (e.g., capital adequacy and risk management policy) could also determine the delinquency status of loans, we control for bank-month fixed effects that capture time-varying bank characteristics. The coefficient of ADI is marginally significant, with the magnitude becoming slightly smaller. In terms of economic magnitude, a one-standard-deviation shock in *ADI* translates into an increase of default likelihood as large as 0.15%, equivalent to a 7% increase when evaluated at the mean.

Using the dichotomy of performing versus non-performing loans makes it easier to interpret our findings. However, the NPL measure ignores the nuance of firms' credit profile which is likely to be continuous. We therefore switch to a continuous variable (*Status*) that captures the continuum of loan quality. Specifically, the variable *Status*

[10] As we cannot access the accounting numbers, most of firm characteristics (e.g., ownership) in our sample are time-invariant. Such variables will be absorbed by firm fixed effects.

takes the value from 1 to 5, with 5 representing loans that ever receive the label of "pass" and 1 representing loans that ever receive the "loss" label. Note that in order to capture the changes in firms' credit profile, we trace the solvency status of each loan from its issuance to maturity, and use the worst solvency status.[11]

Panel B of Table 2 reports the results of loan solvency status regressions that adopt the same specification as Panel A. The coefficients of *ADI* are negative and statistically significant in all columns, indicating a significant decline in the credit quality of borrowers that are subject to antidumping penalty. The magnitude of coefficients ranges from 0.023 in Column (3) to 0.026 in Column (1). In terms of economic magnitude, one-standard-deviation increase in *ADI* translates into a 0.58%-0.66% decline in credit quality when evaluated at the mean, which is much smaller in magnitude Compared with the economic impact documented in Panel A.[12]

4.3 Internal loan rating

We next check whether banks *ex ante* recognize the deterioration of loan quality using internal loan ratings given by banks when making the lending decision. Internal loan ratings contain relevant information regarding the credit quality of borrowers, especially following reforms that delegated authority to loan officers after China's entry into WTO (Qian et al. 2015). As loans in our sample are issued during the post-reform period, we expect that banks' internal loan ratings should incorporate firms' exposure to antidumping duties.[13]

[Insert Table 3 about here]

Banks in China do not adopt a uniform system to rate loans internally, making the coding of internal loan ratings very difficult. We put all rating symbols into six levels,

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[11] As robustness, we use the solvency status at the maturity date and find very similar results. Coefficient estimates are shown in Table A3.

[12] A one-standard-deviation increase in ADI (0.28) leads to a decline in loan solvency status by 0.0064 (0.28*0.023=0.0064) according to Column (4) and by 0.0076 (0.28*0.026=0.0073) according to Column (1). Considering the sample mean of loan solvency status is 1.107, they represent a 0.58% and 0.66% decline, respectively.

[13] In untabulated analysis, we find that internal loan ratings at issuance have significant predictive power of post-issuance loan default in our sample. One potential issue is that our sample period overlaps with the stimulus program which could lead to rating inflation. However, according to a recent study by Yuan et al. (2020), the rating criteria was not altered even during this period, indicating no structural change in the internal loan rating criteria.

i.e., AAA, AA, A, B, C, below-C. We then assign numeric values to these six levels of rating, with 6 indicating loans that are AAA-rated and 1 representing ratings below C. We rerun the regressions in Table 2 and replace the dependent variables with the numerical value of internal loan ratings (*Rating*). As shown in Table 3, the coefficient estimates of ADI are significantly positive in all columns, indicating that banks tend to give lower ratings to firms subject to antidumping duties. In terms of the economic magnitude, a one-standard-deviation increase in *ADI* translates into a 0.017-0.026 notch decline in ratings, equivalent to a 0.6%-1% decline in relative terms.[14]

4.4 Loan contract terms

In this subsection, we examine the impact of trade shocks on three key loan contract terms, i.e., interest rate, maturity and security. Prior to interest rate liberalization (Liu, Wang and Xu 2021; Wang, Wang, Wang and Zhou 2020), bank loans in China are priced using PBoC policy rate as the benchmark. In other words, lending rates are typically expressed in relative spreads over maturity-matched policy rate. We thus measure the cost of loans as the relative spread that is calculated as the difference between the raw interest rate and the maturity-matched policy rate, divided by the corresponding policy rate.[15] Results are shown in Panel A of Table 4. No matter which specification we choose, the coefficient estimates of ADI are never significant, meaning that the cost of loans does not respond to trade shocks.

[Insert Table 4 about here]

Panel B presents the results of regressions that examine the impact on loan maturity (in months). No matter which model specification is used, ADI is always significantly negatively related to loan maturity. This implies that banks tend to provide loans with shorter maturity to firms under antidumping penalties. Although the maturity of China's loans is already short in general, being exposed to antidumping duties leads to even

[14] Interestingly, the economic magnitude is very close to that in Table 2 Panel B which evaluates the impact of ADI on the solvency status of loans, indicating that banks' internal loan rating is informative of the future evolution of loan quality.

[15] Simply using the raw interest rate generates very similar findings.

shorter loan maturity. In terms of economic significance, (have to check the definition of the dependent variable. In particular, it is in the natural log or the initial value.)

Bank lending in China features a prevalent usage of collateral and guarantee. As shown in Table 1, nine out of every ten loans are secured by either collateral or guarantee. Given that lending on a secured basis provides effective risk management for banks, it is meaningful to examine how trade shocks affect the usage of these two devices in lending. Panel C of Table 4 presents the results. Note that we multiply the estimated coefficients by one hundred for the ease of interpretation. The coefficients of *ADI* are statistically significant at 5% level in all columns, suggesting that being subject to trade shocks and the associated increase in default risk leads to a higher likelihood of pledging collateral or using a guarantor. In terms of economic significance, the likelihood of issuing a secured loan is 0.25%-0.42% higher following one standard deviation increase in *ADI*, representing a 0.27%-0.39% increase in relative terms.

4.5 Loan amount

Perhaps a more important question to ask is the implications of trade shock on the amount of debt financing. As our data includes the universe of bank lending for firms located in sample prefecture, we can gauge the impact of antidumping investigations on credit supply. We calculate the total principal amount of loans outstanding for each firm-bank pair at the end of each year. Firms exit the sample as soon as the last loan they borrow matures. For firms that stop borrowing from one bank while still have loans with other banks, we code the amount to zero for this particular firm-bank pair.[16] Our sample consists of 110,345 firm-bank-year observations. The average annual total amount outstanding loan at firm-bank level in our sample is around 3.4 million RMB (around 0.5 million USD). To be consistent with the time frequency of the loan amount variable, we take the average of monthly *ADI* across the whole year and generate a new AD intensity variable (*ADIAN*) that is defined on the yearly level.

[Insert Table 5 about here]

[16] Using only non-zero outstanding loan amount leads to a slight decline in sample size. Our results are both qualitatively and quantitatively similar if we use this sample instead.

We estimate Equation (3) and present the results in Table 5. According to Column (1), firms under AD penalty face a significant contraction in bank lending. The coefficient of *ADIAN* implies that loan amount tends to decline by 1.5% following a one-standard-deviation trade shock. Column (2) controls for city-year fixed effects to absorb time-varying city-level economic shock. The coefficient magnitude of *ADIAN* becomes larger. Results are quite similar when we further take into account the supply side of loans by controlling for bank-month fixed effects in Column (3).

According to Table 1, the mean (median) loan maturity is only about nine (eleven) months. Having to borrow short-term loans exposes Chinese firms to substantial rollover risk. As an alternative test of the effect of antidumping on loan supply, we investigate firms' ability to roll over maturing debt depends on antidumping intensity. We define successful refinancing as follows. For each maturing loan, if there is at least one loan issued during the three months following the maturity month, the firm is considered to have successfully refinanced its maturing debt. We construct a dummy variable (*nonrefin*) that monitors the refinancing status of firms every month. It takes the value of one if the firm *fails* to refinance its maturing debt each month, and zero otherwise. Table A3 presents the results of regressions in which the dummy *nonrefin* is the dependent variable. The coefficient estimate of ADI is significantly positive in all specifications, suggesting that being subject to antidumping significantly increases the likelihood that the firm is unable to rollover its debt. According to Column (3), a one-standard-deviation increase in ADI is associated with a 0.2% increase in the likelihood of failing to refinance existing debt while the unconditional likelihood is 14.7%.

Overall, we find that banks tend to cut the supply of credit once the firm is subject to antidumping. While banks are unlikely to stop rolling over loan completely, they tend to cut the lending amount substantially.

4.6 Discussion on industry-level antidumping exposure

Antidumping represents a well-defined shock to firm exports that varies across industries and months. Although firms with different trade partners would suffer differently within the same industry, it represents an adverse shock for the overall industry. For example, a firm A that exports a large share of its sales to U.S. tends to suffer significantly when U.S. initiates anti-dumping investigations on Chinese products which firm A exports. The demand shock is definitely of a smaller magnitude for another firm B who produces the same product and whose major trade partner is EU. However, the antidumping investigation by U.S. still limits firm B's potential to sell its products in the U.S.

Antidumping investigations usually target on the whole product category or industry, although the firm-specific punishment imposed might vary. Firms could adjust their customer base through routing their sales from the initiating country to other trade partners or targeting the domestic market. However, this could not fully compensate the negative shocks of antidumping investigations, as it is costly to adjust the trade flows. Within the industry that is subject to antidumping investigation, there are three groups of firms: the first group of firms directly export to the initiating country; the second group of firms are those which export to other countries than the initiating country; the third group only targets the domestic market. Due to the uncertainty raised by AD investigations and the associated increased competition, both the second and the third groups of firms would get hurt by the trade policy shock.

Although we could not directly distinguish exporters from non-exporters in our data, our argument is as follows. If we cannot find such negative impact, it does not necessarily indicate that there is no such effect. Instead, the reason could be that we cannot identify the affected firms precisely. However, based on our investigations, we do find the negative impact of the loan contract terms and amounts to these firms that are more exposed to the antidumping shocks. It indicates our finding provides a lower bound of the true impact of antidumping on the most directly target firms (i.e., the first group in the discussion above). In other words, the negative impact on these exporters should be even larger.

5. Additional Analysis

In this section, we present the results of several additional analysis. First, we show our results are robust to several empirical concerns. We next investigate the heterogeneity among different stages of antidumping investigations. Lastly, we extend the main analysis by checking whether the effect of antidumping spillover to unaffected sectors via the banking sector.

5.1 Heterogeneity of the effect

In this subsection, we investigate how the effect of trade shocks on loan contract terms as well as total loan amount varies across firms or banks with different characteristics. First, we explore the role of existing bank-firm relationship in banks' lending decisions when borrowers suffer from antidumping investigation. Having an existing bank-firm relationship is a double-edged sword when firms are in hard times. On the one hand, banks may become helping hands for firms because they care about the long-term relationship with firms (Boot 2000). On the other hand, banks may be very alert with firms' negative shocks since they know these firms well. Contrary to what is suggested by traditional literature on the benefits of relationship lending, a recent paper by Li, Lu and Srinivasan (2019) shows that relationship banks do not seem to offer more favorable terms to firms that are in distress. Having said that, the prior relationship between existing bank-firm relationship and loans is ambiguous.

[Insert Table 6 about here]

Since China's loan term is in general shorter than that in the U.S., we establish our relationship dummy based on whether the firm has borrowed money from a certain bank in the past two years. To test whether the effect of antidumping on loan terms and loan amount varies with lending relationship, we add the interaction term between ADI and the relationship dummy in our baseline regression. Panels A-D of Table 5 present the result of regressions in which the outcome variables are interest spread, maturity, the use of collateral and total loan amount, respectively. As shown in Column (1) of these four panels, lending relationship could mitigate part of the impact of antidumping on the requirement of collateral (Panel C) and the contraction of loan supply (Panel D). For instance, while firms under antidumping penalties have a significantly higher likelihood of borrowing secured debt, the increase in this likelihood is much smaller for those with bank relationship. In relative terms, lending relationship can mitigate more than 40% of the effect of ADI on secured debt. Firms with bank relationship face an equal decline in loan maturity in response to antidumping as those firms without bank relationship. Interestingly, relationship banks seem to provide cheaper loans to firms under antidumping, as shown in Panel A. These results imply that bank relationship does provide financial flexibility when borrowers suffer from trade shock.

SOEs have privileged access to financing in China (Bai, Liu, Yao 2021). It is possible that SOEs are insulated from external shocks with respect to access to bank financing. As indicated by coefficient estimates in Column (2) of Panels A-C, loan contract terms offered to SOEs and non-SOEs following antidumping duties do not seem to differ significantly. SOEs do not have access to more credit when they are subject to antidumping (Panel D). A caveat here is that our findings may not be generalized to other provinces in China, as our sample loans are issued in one of most developed provinces in China which are more likely to be market-driven and hence are less likely to have a biased distribution of credit in favor of SOEs.

Banks with dominant or significant government ownership are characterized by low efficiency (Berger et al. 2006). In particular, the lending of these banks typically is not guided by information (Yu et al. 2019). We categorize banks in our sample into three types, including rural/city commercial banks, state-owned banks (the big-5 banks as well as The Postal Savings Bank) and joint-equity banks. Results shown in Column (3) of Panels A-D support this prediction. Compared with other banks, joint-equity banks are more likely to cut the loan amount (Panel D), shorten the loan maturity (Panel B) and require collateral (Panel C). Interestingly, they lower the interest spread.

5.2 Robustness test

5.2.1 Controlling for industry-level shocks

First, we aim to address the concern that the impact we document is a result of unobserved industry-level shocks that affect both the antidumping investigation outcome and bank loan terms as well as default risk. These shocks can come from both the demand side and the supply side. One supply-side candidate is over-capacity.

Industries with over-capacity, due to increased domestic competition and ever declining profit margins, are more likely to dump their products in foreign markets and hence are more likely to be subject to antidumping investigations. Considering the relatively low profitability and growth prospect, banks are reluctant to extend credit to these industries. While fully eliminating this concern is almost impossible, we take advantage of one feature of antidumping investigations, i.e., usually not all products/sub-industries in one big industry are covered. By directly comparing affected products/sub-industries and those unaffected that belong to the same broad industry, we are able to control for unobservable shocks happening on the industry level and mitigate the bias of the estimated treatment effect. In our setting, as the treatment is defined on the GB/T 4-digit industry level, we are actually comparing one affected GB/T 4-digit industry with another GB/T 4-digit industry, which is under the same GB/T 2-digit industry but is not subject to antidumping duties.

[Insert Table 7 about here]

We implement this strategy by adding 2-digit-industry-month fixed effects in the baseline regression. The first three columns of Table 7 Panel A reports the results of industry-month fixed effect regressions. Similar to the baseline regression results, interest rate does not respond to the trade shock, as shown in Column (1). The coefficient estimate in Column (2) indicates that compared with unaffected firms in the same broad industry, affected firms tend to receive loans with a shorter maturity. The coefficient magnitude is slightly smaller than that in the baseline regression (Column (3) of Table 4 Panel B). We continue to observe an increase in security requirements. The coefficient magnitude of the secured loan regression is also smaller when compared with that in our baseline regression (Column (3) of Table 4 Panel C), suggesting that part of the baseline effect can be explained by industry-level time-varying credit risk. As shown in Column (4) of Panel A, there is a significant decline in loan amount in response to antidumping duties, after controlling for industry-time fixed effects.

5.2.2 Controlling for industry-level growth in bank lending

Antidumping investigations could follow the massive expansion of industry-level capacities that is usually associated with rapid growth bank lending. As a consequence, the observed changes in loan contract terms as well as credit supply could be a result of mean reversion. An alternative approach to control for the non-randomness of antidumping investigations is to control for the growth of bank lending in that industry. We compute the average growth rate of total bank lending at the GBT 4-digit level during the past two years and include this proxy in our baseline regressions. Panel B of Table 7 presents the results. The coefficient estimates of ADI are largely consistent with our baseline results, suggesting that our results are not driven by mean reversion of bank lending.

5.2.3 Full sample analysis

In our main analysis, we define the treated group as firms that belong to the same GB/T 2-digit industry as firms that are subject to antidumping duties, following Lu et al. (2013). While this approach facilitates the fair comparison between treated and control firms, it brings in concerns related to sample selection. In this subsection, we rerun our main analysis using the full sample that contains 500,572 loans. Results for loan contract terms are reported in Columns (1)-(3) of Panel C. Column (4) of Panel C shows the result of loan amount regressions using the full sample. Overall, results are similar to the baseline findings.

5.3 Different stages of investigations

The investigation period of antidumping usually lasts for 1 to 2 years. Among all the cases target China which have been initiated, around 80% of them will reach a confirmative final decision. In this subsection, we investigate the implications of different stages of AD investigations on bank lending. To capture the effect of preliminary decisions, we first focus on cases for which the preliminary decision is affirmative. We then consider the 5-year period following affirmative preliminary decisions as the event period. For revoked cases, we use the period between the date of preliminary decisions and the date of being revoked. Similar to the main measure, we weight each preliminary case by the share of exporting volume to the country that initiates the case. The variable *PD* therefore capture the intensity of antidumping cases that are preliminarily affirmative for each GB/T 4-digit industry.

[Insert Table 8 about here]

According to Table 8 Panel A, the default risk of firms under preliminary AD decisions is not significantly higher than those not subject to such decisions. Despite the absence of higher default risk, banks require more collateral when lending to firms that have received affirmative preliminary antidumping decisions. This finding highlights the importance of secured lending in Chinese banks' risk management. We do not observe a significant change in either interest rate or maturity.

5.4 Spillover Effect through the Banking Sector

In a recent paper, Federico, Hassan, and Rappoport (2019) use Italian credit registry data and find that banks whose loan portfolio tilts toward sectors that are more exposed to import competition from China have higher ratios of non-performing loans. More importantly, sectors that are not exposure to Chinese import competition experience a contraction in bank lending as a consequence of thinner bank capital, suggesting that trade shocks spillover to unaffected sectors via financial intermediaries. As shown in our main analysis, loans in sectors that are subject to antidumping duties experience a non-trivial increase in default risk. Due to the impairment of balance sheet, banks that are more exposed to these sectors are expected to become less capable of providing credit to firms.

To gauge banks' exposure to antidumping duties, we calculate the fraction of loan portfolio allocated to industries subject to antidumping penalties at the end of last year for a given bank (*ADEXP*). As we are interested in whether the trade shock spillovers to the unaffected sectors, we restrict the sample to borrowers that are not subject to antidumping duties. Following Khwaja and Mian (2008), we control for firm-year fixed effects to absorb time-varying firm-level demand shocks. Essentially, we are comparing the total loan amount, or the terms of loans offered to the same firm at the same year by banks that have different exposures to antidumping penalty. Note that observations in the sample is on the firm-bank-year level.

[Insert Table 9 about here]

Table 9 presents the results of total loan amount. When lending to the same firm at the same year, banks that are subject to more severe shocks to their loan portfolio as a result of antidumping investigations cut lending more. This finding implies that external trade shocks, by weakening banks' balance sheet, could lead to a contraction in credit supply to unaffected firms.

[Insert Table 10 about here]

We also examine whether affected banks adjust the contract terms of their loans using the sample of single loans. Table 10 presents the results of the spillover effect on loan contract terms. Results in Columns (1) and (4) indicate that firms have to pay extra costs of funds when borrowing from banks that are more exposed to trade shocks, given the same credit demand. However, neither loan maturity nor the collateral/guarantee requirements seem to be related to banks' exposure to antidumping investigations.

6. Conclusion

Using granular antidumping investigations defined on the industry level, this paper examines how trade shocks affect the domestic bank lending market. We find that firms in industries subject to more severe antidumping duties have much higher loan default frequencies, consistent with the usual expectation that trade shocks cause material damages to firm sales and cash flow. Banks adjust loan contractual terms in several ways: they raise the requirements of collateral and guarantee, and they shorten the maturity of new loans. However, we do not find a significant response of loan interest rate to antidumping investigations. We observe a significant contraction of credit supply to firms in affected industries. Such firms also find it more difficult to rollover existing debt. There is some heterogeneity in the effects of interest. In particular, firms with bank relationships are able to shield themselves from the adverse effects of antidumping in terms of both the access to credit and debt contractual terms. We find some evidence of the spillover of trade shocks to non-tradeable firms via the banking sector. When borrowing from banks that are more exposed to trade shocks, firms get smaller loans and have to pay higher interest rate.

It should be noted that although we argue that trade policy shocks are out of the control of domestic manufacturers and we include fixed effects defined on broad industry categories in our regressions, it is inevitable that our results could be contaminated by various endogeneity concerns (e.g., omitted variables). Future research should aim for identifying the purely causal impact of trade policy shocks by extracting the exogeneous portion of trade policy intensity.

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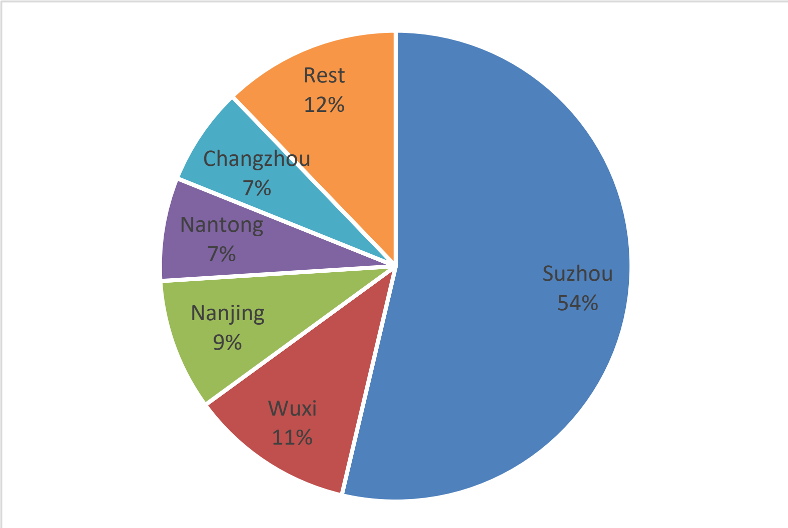
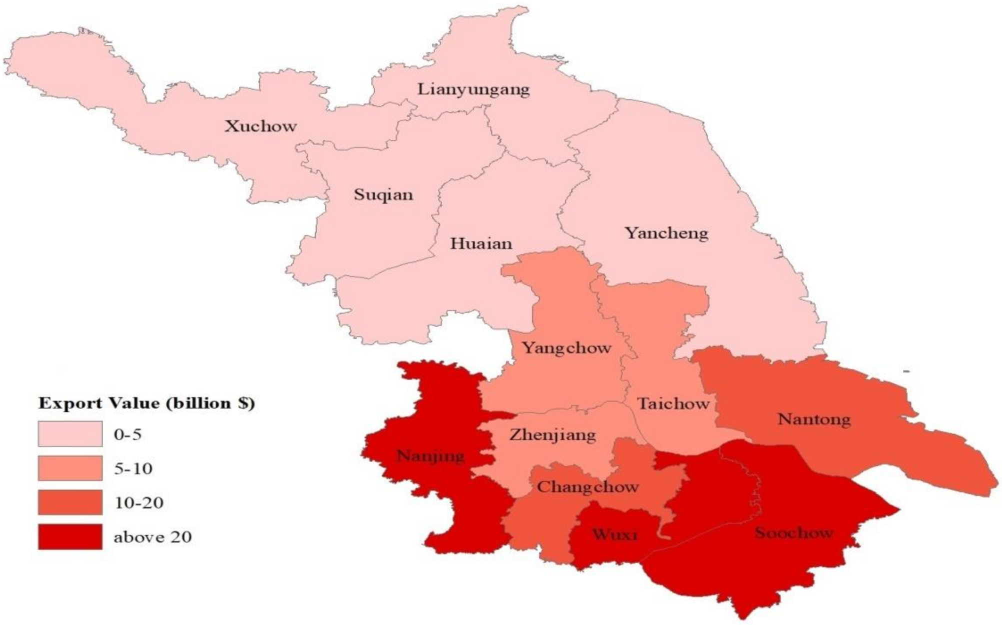


(a) The city level export percentage of Jiangsu Province in 2015



(b) City level export value of Jiangsu Province in 2015

Figure 1: City-level export of Jiangsu Province

Notes: Export volume is obtained from the China Customs Office. In Panel (a), the rest includes the prefecture of Yangzhou (2.5%), Zhenjiang (2.1%), Taizhou (1.9%), Xuzhou (1.5%), Yancheng (1.4%), Lianyungang (1.3%), Huaian (0.8%) and Suqian (0.6%).

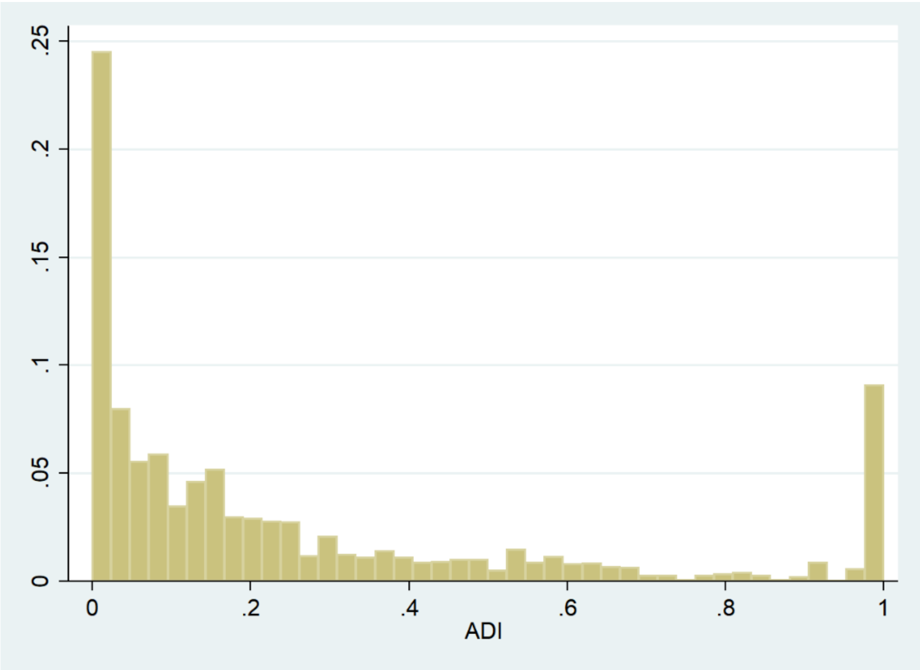


Figure 2: Industry-level Antidumping Intensity

This figure displays the distribution of antidumping intensity that is defined on GBT 4-digit industry level. Each antidumping case that is confirmative in the final stage is weighted by the fraction of the export volume to the launching importer country to total export volume of certain products of Jiangsu Province of China. The sample period is from 2006 to 2015.

Table 1: Summary Statistics

This table presents the summary statistics for main variables used in this paper. Firms in Panel A are from GBT 2-digit industries which contain at least one sub-industry under antidumping investigation and at least one sub-industry that is not subject to such investigation. Panel B shows the summary statistics for the full sample.

Panel A: Restricted sample

Statistics	N	Mean	P50	P25	P75	S.D.
ADI	251,368	0.151	0.000	0.000	0.144	0.280
Amount	251,368	4.748	2.000	1.000	5.000	83.380
Maturity	251,368	9.752	11.100	6.033	12.133	6.528
Status	251,368	1.107	1.000	1.000	1.000	0.418
NPL (Y/N)	251,368	0.021	0.000	0.000	0.000	0.144
Rating	86,820	2.660	3.000	2.000	3.000	1.012
Interest	251,368	7.286	7.080	6.000	8.100	2.126
Spread	251,368	0.266	0.200	0.050	0.398	0.332
Secured (Y/N)	251,368	0.917	1.000	1.000	1.000	0.276
Firm age	251,368	9.521	9.000	6.000	12.000	5.309
Relationship (Y/N)	251,368	0.823	1.000	1.000	1.000	0.381
SOE (Y/N)	251,368	0.001	0.000	0.000	0.000	0.034
SOB (Y/N)	251,368	0.336	0.000	0.000	1.000	0.472
JEB (Y/N)	251,368	0.084	0.000	0.000	0.000	0.278
ADEXP	238,895	0.040	0.000	0.000	0.085	0.065

Panel B: Full sample

Statistics	N	Mean	P50	P25	P75	S.D.
ADI	500,572	0.091	0.000	0.000	0.020	0.230
Amount	500,572	8.638	2.500	1.000	6.000	69.011
Maturity	500,572	12.745	11.667	6.067	12.133	16.274
Status	500,572	1.103	1.000	1.000	1.000	0.410
NPL (Y/N)	500,572	0.020	0.000	0.000	0.000	0.139
Rating	179,722	2.702	3.000	2.000	3.000	0.981
Interest	500,572	7.302	7.020	6.000	8.100	2.167
Spread	500,572	0.262	0.200	0.035	0.391	0.347
Secured (Y/N)	500,572	0.915	1.000	1.000	1.000	0.279
Firm age	500,572	9.107	8.000	5.000	12.000	5.556
Relationship (Y/N)	500,572	0.733	1.000	0.000	1.000	0.442
SOE (Y/N)	500,572	0.019	0.000	0.000	0.000	0.137
SOB (Y/N)	500,572	0.344	0.000	0.000	1.000	0.475
JEB (Y/N)	500,572	0.100	0.000	0.000	0.000	0.300
ADEXP	468,401	0.033	0.000	0.000	0.056	0.065

Table 2: Antidumping and Loan Default Risk

This table presents the results of regressions that examine the effect of antidumping on bank loan default risk. The sample includes banks loans issued by firms located in Jiangsu Province of China during the 2007-2016 period. *ADI* represents the intensity of antidumping penalties to which the borrower's GB/T 4-digit industry is subject. Banks in China are required to issue a label to each loan that represents the loan's solvency status, including pass, special-mention, substandard, doubtful and loss. The dependent variable in Panel A is a dummy that equals one for loans that receive a label of "doubtful" or "loss" as solvency status. The outcome variable in Panel B is a continuous variable that ranges from 1 to 5, with value of 5 representing "pass" loans and 1 representing "loss" loans. Calendar month represents the month in which the loan is issued. Robust standard errors are adjusted for clustering at the GBT 4-digit industry level. To ease interpretation, the estimated coefficients in Panel A has been multiplied by a factor of 100. Corresponding standard errors are shown below the estimates in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Antidumping and the likelihood of NPL

	(2)	(3)	(4)
Dependent variable	*NPL*	*NPL*	*NPL*
ADI	0.6174**	0.6064**	0.5430*
	(0.3096)	(0.3010)	(0.3090)
log(age)	3.0366***	2.9053***	2.5884***
	(0.6085)	(0.6284)	(0.6101)
Firm FE	Yes	Yes	Yes
Calendar month FE	Yes	Yes	Yes
Loan type FE	Yes	Yes	Yes
City-month FE	No	Yes	Yes
Bank-month FE	No	No	Yes
Observations	251,368	251,368	251,368
R-squared	0.328	0.330	0.350

Panel B: Antidumping and loan solvency status

	(2)	(3)	(4)
Dependent variable	*Status*	*Status*	*Status*
ADI	-0.0258**	-0.0240**	-0.0227**
	(0.0101)	(0.0096)	(0.0099)
log(age)	-0.1070***	-0.0967***	-0.0972***
	(0.0210)	(0.0219)	(0.0220)
Firm FE	Yes	Yes	Yes
Calendar month FE	Yes	Yes	Yes
Loan type FE	Yes	Yes	Yes
City-month FE	No	Yes	Yes
Bank-month FE	No	No	Yes
Observations	251,368	251,368	251,368
R-squared	0.400	0.402	0.424

Table 3: Antidumping and the Internal Credit Rating

This table presents the results of regressions of internal credit rating on antidumping intensity. The dependent variable (*Rating*) is defined as bank's internal rating of the borrower, taking the value of 1 to 5, with 1 representing the riskiest borrowers. Control variables include firm age, loan amount and maturity, all of which are in natural log. Robust standard errors are adjusted for clustering at the GB/T 4-digit industry level. Corresponding standard errors are shown below the estimates in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(2)	(3)	(4)
Dependent variable	*Rating*	*Rating*	*Rating*
ADI	-0.0909***	-0.0820***	-0.0597**
	(0.0301)	(0.0293)	(0.0244)
log(age)	0.1973***	0.2480***	0.1896***
	(0.0702)	(0.0742)	(0.0621)
Firm FE	Yes	Yes	Yes
Calendar month FE	Yes	Yes	Yes
Loan type FE	Yes	Yes	Yes
City-month FE	No	Yes	Yes
Bank-month FE	No	No	Yes
Observations	101,829	101,829	101,829
R-squared	0.510	0.515	0.749

Table 4: Antidumping and Bank Loan Contract Terms

This table presents the results of regressions that examine the effect of antidumping on bank loan contract terms. *Spread* is defined as the difference between the raw interest rate and maturity-matched official lending rate issued by PBoC, scaled by the official rate. *Secured* is a dummy variable that takes the value of one if the loan is neither secured by a collateral or guaranteed. To ease interpretation, the estimated coefficients in Panel C has been multiplied by a factor of 100. Robust standard errors are adjusted for clustering at the GBT 4-digit industry level. Corresponding standard errors are shown below the estimates in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Interest rate

	(2)	(3)	(4)
Dependent variable	*Spread*	*Spread*	*Spread*
ADI	-0.2196	-0.1458	-0.1822
	(0.4803)	(0.4315)	(0.2165)
log(age)	-4.0404***	-1.0389	-0.2095
	(1.2780)	(1.2692)	(0.9501)
Firm FE	Yes	Yes	Yes
Calendar month FE	Yes	Yes	Yes
Loan type FE	Yes	Yes	Yes
City-month FE	No	Yes	Yes
Bank-month FE	No	No	Yes
Observations	251,368	251,368	251,368
R-squared	0.523	0.534	0.648

Panel B: Loan maturity

Dependent variable	(2) *Maturity*	(3) *Maturity*	(4) *Maturity*
ADI	-0.1963**	-0.2137**	-0.1939**
	(0.0902)	(0.0899)	(0.0876)
log(age)	-1.0527***	-1.1535***	-1.3208***
	(0.2825)	(0.2969)	(0.2838)
	-0.1963**	-0.2137**	-0.1939**
Firm FE	Yes	Yes	Yes
Calendar month FE	Yes	Yes	Yes
Loan type FE	Yes	Yes	Yes
City-month FE	No	Yes	Yes
Bank-month FE	No	No	Yes
Observations	251,368	251,368	251,368
R-squared	0.534	0.536	0.557

Panel C: The use of collateral

Dependent variable	(2) *Secured*	(3) *Secured*	(4) *Secured*
ADI	1.2217**	1.4765***	0.8865***
	(0.5964)	(0.4407)	(0.3230)
log(age)	-2.9650**	-0.1182	1.0821
	(1.3086)	(1.0963)	(0.8766)
Firm FE	Yes	Yes	Yes
Calendar month FE	Yes	Yes	Yes
Loan type FE	Yes	Yes	Yes
City-month FE	No	Yes	Yes
Bank-month FE	No	No	Yes
Observations	251,368	251,368	251,368
R-squared	0.330	0.350	0.458

Table 5: Antidumping and the Loan Amount

This table presents the results of regressions that examine the effect of antidumping investigations on the total amount of loans obtained from banks. The dependent variable, *AMTOTD*, is defined as the total principal amount of loans outstanding at the end of each year for each firm-bank pair (in natural log). It takes the value of zero if the firm stops borrowing from the bank while maintaining banking relationship with other banks. *ADIAN* is the average antidumping intensity of the previous year. Robust standard errors are adjusted for clustering at the GBT 4-digit industry level. Corresponding standard errors are shown below the estimates in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Dependent variable	*AMTOTD*	*AMTOTD*	*AMTOTD*
ADIAN	-0.0286*	-0.0335**	-0.0319**
	(0.0147)	(0.0134)	(0.0140)
log(age)	0.2076***	0.1881***	0.1896***
	(0.0259)	(0.0257)	(0.0261)
Firm FE	Yes	Yes	Yes
Calendar month FE	Yes	Yes	Yes
City-month FE	No	Yes	Yes
Bank-month FE	No	No	Yes
Observations	110,345	110,345	110,338
R-squared	0.157	0.159	0.209

Table 6: Heterogeneity of the Effect of Antidumping on Loan Contract Terms

This table presents the results of regressions that examine how the effect of antidumping on loan contract terms differs among different types of borrowers and lenders. *Relationship* is a dummy that equals one if the firm has borrowed from the bank at least once during the last two years. The dummy *SOE* indicates state-owned enterprises. Banks are categorized into three types, including state-owned banks (*SOB*), joint-equity banks (*JEB*) as well as rural and city commercial banks. We control for firm, calendar month, loan-type, city-month and bank-month fixed effects in every specification in Panels A-C for which the sample includes individual bank loans. The sample used in Panel D includes firm-bank-year observations of the total loan amount outstanding for each bank-firm pair at the end of each year. Robust standard errors are adjusted for clustering at the GBT 4-digit industry level. Corresponding standard errors are shown below the estimates in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: The heterogeneous effect of ADI on interest rate

	(1)	(2)	(3)
Dependent variable	*Spread*	*Spread*	*Spread*
ADI	0.2973	-0.1827	-0.2848
	(0.2748)	(0.2165)	(0.2216)
ADI * Relationship	-0.5480***		
	(0.2031)		
Relationship	0.8409***		
	(0.2040)		
ADI * SOE		3.5023	
		(7.1881)	
ADI * SOB			0.7615*
			(0.4140)
ADI * JEB			-1.2919*
			(0.6885)
log(age)	-0.4860	-0.2107	-0.2164
	(0.9543)	(0.9501)	(0.9504)
Observations	251,368	251,368	251,368
R-squared	0.648	0.648	0.648

Panel B: The heterogeneous effect of ADI on loan maturity

Dependent variable	(1) *Maturity*	(2) *Maturity*	(3) *Maturity*
ADI	-0.1816*	-0.1937**	-0.1925**
	(0.0994)	(0.0876)	(0.0911)
ADI * Relationship	-0.0088		
	(0.0683)		
Relationship	-0.6221***		
	(0.0737)		
ADI * SOE		-0.9451	
		(1.5757)	
ADI * SOB			-0.0802
			(0.0884)
ADI * JEB			0.2413**
			(0.1100)
log(age)	-1.0768***	-1.3204***	-1.3198***
	(0.2850)	(0.2839)	(0.2837)
Observations	251,368	251,368	251,368
R-squared	0.558	0.557	0.557

Panel C: The heterogeneous effect of ADI on collateral

Dependent variable	(1) *Secured*	(2) *Secured*	(3) *Secured*
ADI	1.3755***	0.8858***	0.4861**
	(0.4169)	(0.3228)	(0.2294)
ADI * Relationship	-0.5611***		
	(0.2121)		
Relationship	1.1146***		
	(0.1952)		
ADI * SOE		5.0471	
		(5.7415)	
ADI * SOB			0.7817*
			(0.4616)
ADI * JEB			1.9584*
			(1.0468)
log(age)	0.6999	1.0804	1.0818
	(0.8846)	(0.8768)	(0.8746)
Observations	251,368	251,368	251,368
R-squared	0.458	0.458	0.458

Panel D: The heterogeneous effect of ADI on loan amount

Dependent variable	(1) *AMTOTD*	(2) *AMTOTD*	(3) *AMTOTD*
ADI	-0.0432**	-0.0189*	-0.0106
	(0.0188)	(0.0106)	(0.0093)
ADI * Relationship	0.0521*		
	(0.0308)		
Relationship	1.0785***		
	(0.0176)		
ADI * SOE		0.0762	
		(0.1046)	
ADI * SOB			-0.0415
			(0.0285)
ADI * JEB			-0.0475*
			(0.0287)
log(age)	-0.1502***	0.1890***	0.1893***
	(0.0234)	(0.0260)	(0.0260)
Observations	110,338	110,338	110,338
R-squared	0.436	0.209	0.209

Table 7: Robustness Test

This table presents the results of several robustness tests. We control for industry-month fixed effects in Panel A. Panel B controls for the average growth rate of total bank lending on the GBT 4-digit level during the past two years. In Panel C, we re-estimate the baseline model using the full sample. Unless otherwise specified, we control for firm, calendar month, city-month and bank-month fixed effects in every specification. As the sample in Panel A consists of single loans, we also control for loan type fixed effects. Robust standard errors are adjusted for clustering at the GBT 4-digit industry level. Corresponding standard errors are shown below the estimates in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Within-industry estimation

	(1)	(2)	(3)	(4)
Dependent var.	*Spread*	*Maturity*	*Secured*	*AMTOTD*
ADI	-0.0681	-0.1748*	0.8211**	-0.0187*
	(0.2827)	(0.0923)	(0.3678)	(0.0106)
log(age)	-0.4396	-1.2695***	1.2697	0.1891***
	(0.9243)	(0.2898)	(0.8845)	(0.0261)
Sample	Restr.	Restr.	Restr.	Restr.
Industry-month FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan-type FE	Yes	Yes	Yes	No
City-month FE	Yes	Yes	Yes	Yes
Bank-month FE	Yes	Yes	Yes	Yes
Observations	251,368	251,368	251,368	110,338
R-squared	0.649	0.558	0.459	0.209

Panel B: Controlling for lagged loan growth

	(1)	(2)	(3)	(4)
Dependent var.	*Spread*	*Maturity*	*Secured*	*AMTOTD*
ADI	-0.1814	-0.1948**	0.8890***	-0.0308**
	(0.2169)	(0.0881)	(0.3232)	(0.0138)
log(age)	-0.2658	-1.3309***	1.1021	0.1929***
	(0.9547)	(0.2851)	(0.8703)	(0.0260)
Loan growth	-0.0032***	-0.0010**	-0.0004	0.0016
	(0.0009)	(0.0004)	(0.0009)	(0.0023)
Sample	Restr.	Restr.	Restr.	Restr.
Industry-month FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan-type FE	Yes	Yes	Yes	No
City-month FE	Yes	Yes	Yes	Yes
Bank-month FE	Yes	Yes	Yes	Yes
Observations	251,063	251,063	251,063	110,155
R-squared	0.648	0.557	0.458	0.209

Panel C: Full sample analysis

	(1)	(2)	(3)	(4)
Dependent var.	*Spread*	*Maturity*	*Secured*	*AMTOTD*
ADI	-0.1536	-0.1276**	0.6226**	-0.0326*
	(0.2839)	(0.0602)	(0.3060)	(0.0168)
log(age)	-0.4305	-2.3296***	1.5054**	0.2939***
	(0.6864)	(0.8885)	(0.6413)	(0.0497)
Sample	All	All	All	All
Industry-month FE	No	No	No	No
Firm FE	Yes	Yes	Yes	Yes
Loan-type FE	Yes	Yes	Yes	No
City-month FE	Yes	Yes	Yes	Yes
Bank-month FE	Yes	Yes	Yes	Yes
Observations	251,368	251,368	251,368	216,991
R-squared	0.649	0.558	0.459	0.205

Table 8: The Effect of Different Stages of Antidumping Investigations

This table presents the results of regressions that examine the effect of different stages of antidumping investigations. We calculate an alternative measure of antidumping intensity (*PD*) using cases for which the preliminary decision is affirmative. Robust standard errors are adjusted for clustering at the GBT 4-digit industry level. Corresponding standard errors are shown below the estimates in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Dependent variable	*Spread*	*Maturity*	*Secured*
PD	-0.4031	-0.1587	0.8880***
	(0.3615)	(0.1158)	(0.3123)
log(age)	-0.2040	-1.3221***	1.0838
	(0.9496)	(0.2841)	(0.8761)
Firm FE	Yes	Yes	Yes
Calendar month FE	Yes	Yes	Yes
City-month FE	Yes	Yes	Yes
Bank-month FE	Yes	Yes	Yes
Observations	251,368	251,368	251,368
R-squared	0.648	0.557	0.458

Table 9: The Potential Spillover Effect on Loan Amount

This table presents the results of regressions that examine the potential spillover of loan defaults in the sector subject to antidumping duties to unaffected sectors. *ADEXP* is defined as the fraction of the entire loan portfolio that is allocated to industries subject to antidumping penalties at the end of last year for a given bank. *AMTOTD* is defined as the total principal of loans outstanding at the end of each year for each firm-bank pair (in natural log). The sample only includes borrowers not subject to antidumping duties. Every specification control for firm-year and loan-type fixed effects. Robust standard errors are adjusted for clustering at the bank level. Corresponding standard errors are shown below the estimates in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Dependent variable	*AMTOTD*	*AMTOTD*
ADEXP	-0.9744**	-0.7872**
	(0.3970)	(0.3747)
Industries	restricted	All
Firm-year FE	Yes	Yes
Observations	41,484	78,751
R-squared	0.489	0.647

Table 10: The Potential Spillover Effect on Contract Terms

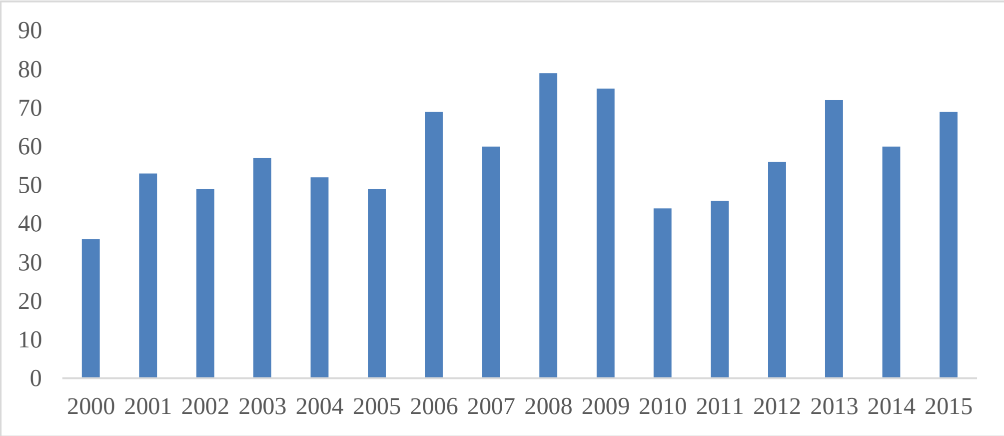
This table presents the results of regressions that examine the potential spillover of loan defaults in the sector subject to antidumping duties to unaffected sectors. *ADEXP* is defined as the weight of loan portfolio allocated to industries subject to antidumping penalties at the end of last year for a given bank. The sample only includes borrowers not subject to antidumping duties. Every specification control for firm-year and loan-type fixed effects. Robust standard errors are adjusted for clustering at the bank level. Corresponding standard errors are shown below the estimates in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Dependent variables	*Spread*	*Maturity*	*Secured*
ADEXP	1.3815***	2.9055	0.1963
	(0.1645)	(2.0244)	(0.1345)
Firm-year FE	Yes	Yes	Yes
Loan-type FE	Yes	Yes	Yes
Observations	238,895	238,895	238,895
R-squared	0.666	0.651	0.416

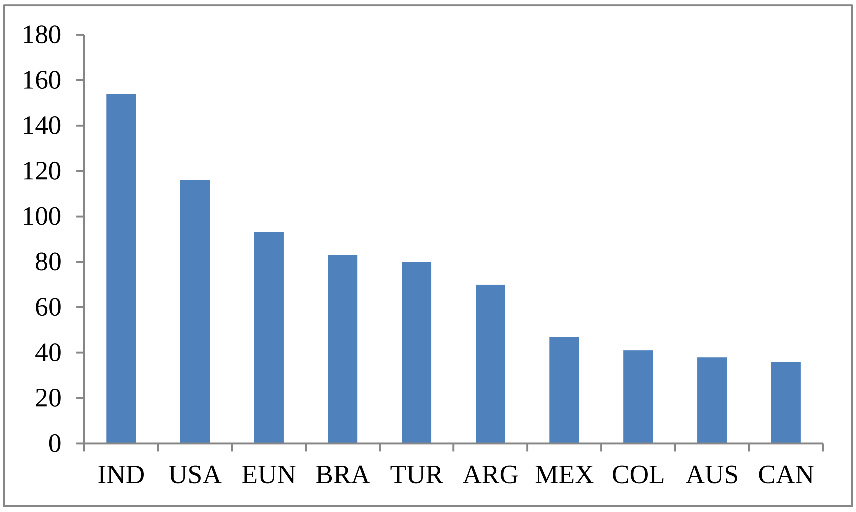
APPENDIX

Figure A1: Worldwide Trade Restriction Policies and Trade Liberalization Policies from 2009 to 2019

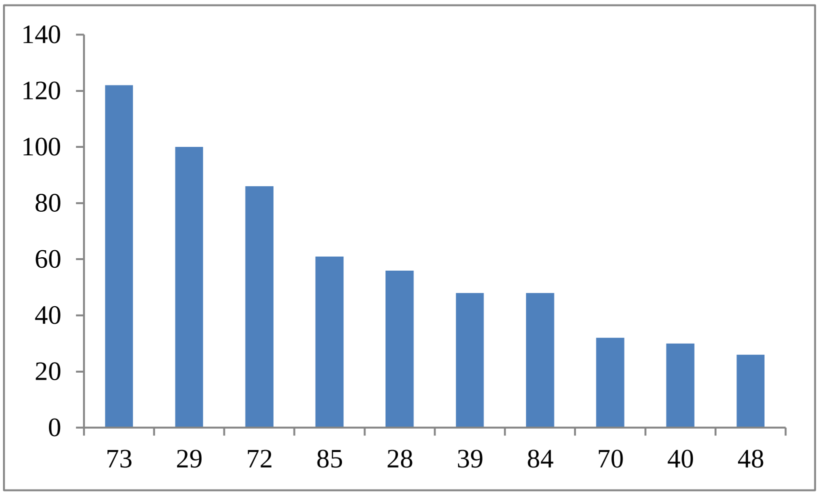
Source: Global Trade Alert



(a) The number of antidumping cases against China from 2000 to 2015



(b) Top 10 Economies mostly antidumping investigates China's exports



(c) Top 10 Chinese products (HS2 level) mostly antidumping investigated

Figure A2: Antidumping investigations against Chinese exporters

Source: Global Antidumping Database

Table A1 Aggregation levels of Industries across banks and firm sizes

This table presents the distribution of bank type (in Panel A) and firm size (in Panel B) across sample firms for which the GB/T industry affiliation is coded with different levels of coarseness.

Panel A: The distribution of bank type

Bank type	Rural commercial	City commercial	State-owned	Joint-equity
1-digit industry code	31.35%	14.28%	37.55%	16.82%
2-digit industry code	49.43%	8.51%	33.03%	9.02%
3-digit industry code	50.25%	11.91%	30.70%	7.14%
4-digit industry code	38.70%	16.82%	34.44%	10.04%

Panel B: The distribution of firm size

Bank type	Big	Medium	Small	Micro
1-digit industry code	2.43%	8.59%	85.44%	3.55%
2-digit industry code	3.47%	14.97%	79.55%	2.00%
3-digit industry code	4.53%	12.81%	81.60%	1.05%
4-digit industry code	3.90%	10.98%	83.14%	1.98%

Table A2 Antidumping investigations and confirmative cases on China from 2000 to 2015

This table presents the distribution of antidumping investigations and confirmed cases during the period from 2000 to 2015. We obtain relevant information of antidumping cases from the Global Antidumping Database.

Case Initiation Year	No. of Cases	No. of Confirmative Cases	Percentage of Confirmative
2000	25	20	80.0%
2001	44	40	90.9%
2002	37	34	91.9%
2003	35	27	77.1%
2004	36	30	83.3%
2005	33	24	72.7%
2006	48	36	75.0%
2007	40	36	90.0%
2008	48	41	85.4%
2009	74	67	90.5%
2010	46	33	71.7%
2011	46	39	84.8%
2012	57	48	84.2%
2013	73	57	78.1%
2014	60	49	81.7%
2015	69		

Table A3: Antidumping and Loan Solvency Status at Maturity

This table presents the results of regressions that examine the effect of antidumping on bank loan solvency status at maturity. The outcome variable is the solvency status of the loan at maturity, which is a continuous variable that ranges from 1 to 5, with value of 5 representing "pass" loans and 1 representing "loss" loans. Calendar month represents the month in which the loan is issued. Robust standard errors are adjusted for clustering at the GBT 4-digit industry level. Corresponding standard errors are shown below the estimates in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(2)	(3)	(4)
Dependent variable	*Status*	*Status*	*Status*
ADI	-0.0180**	-0.0160**	-0.0166**
	(0.0082)	(0.0077)	(0.0075)
log(age)	-0.0596***	-0.0476***	-0.0481***
	(0.0159)	(0.0160)	(0.0159)
Firm FE	Yes	Yes	Yes
Calendar month FE	Yes	Yes	Yes
Loan type FE	Yes	Yes	Yes
City-month FE	No	Yes	Yes
Bank-month FE	No	No	Yes
Observations	251,368	251,368	251,368
R-squared	0.433	0.436	0.453

Table A4: The effect of lagged antidumping duties on loan contract terms

This table shows the results of regressions of loan contract terms on lagged antidumping duties. We regress loan contract terms against weighted antidumping duties three (six) months prior to the loan issuance month in Panel A (Panel B). Robust standard errors are adjusted for clustering at the GBT 4-digit industry level. Corresponding standard errors are shown below the estimates in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: ADI lagged for three months

	(1)	(2)	(3)
Dependent variable	*Spread*	*Maturity*	*Secured*
ADI3	-0.1711	-0.0128*	0.8334***
	(0.2282)	(0.0070)	(0.2773)
log(age)	-0.2092	-0.0882***	1.0806
	(0.9500)	(0.0229)	(0.8762)
Firm FE	Yes	Yes	Yes
Calendar month FE	Yes	Yes	Yes
City-month FE	Yes	Yes	Yes
Bank-month FE	Yes	Yes	Yes
Observations	251,368	251,368	251,368
R-squared	0.648	0.400	0.458

Panel B: ADI lagged for six months

	(1)	(2)	(3)
Dependent variable	*Spread*	*Maturity*	*Secured*
ADI6	-0.2054	-0.0882***	1.0848
	(0.9496)	(0.0228)	(0.8760)
log(age)	-0.2547	-0.0135**	0.6144***
	(0.2049)	(0.0060)	(0.2364)
Firm FE	Yes	Yes	Yes
Calendar month FE	Yes	Yes	Yes
City-month FE	Yes	Yes	Yes
Bank-month FE	Yes	Yes	Yes
Observations	251,368	251,368	251,368
R-squared	0.648	0.400	0.458

Table A5: Antidumping and the failure to refinance maturing debt

This table shows the results of regressions that examine the impact of antidumping on the likelihood of successful debt refinancing. The dependent variable (*nonrefin*) is a dummy that equals one if the firm fails to refinance its maturing debt with new loans from banks each month, and zero otherwise. Robust standard errors are adjusted for clustering at the GBT 4-digit industry level. Corresponding standard errors are shown below the estimates in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(2)	(3)	(4)
Dependent variable	*nonrefin*	*nonrefin*	*nonrefin*
ADI	0.0054**	0.0078***	0.0066***
	(0.0021)	(0.0017)	(0.0019)
log(age)	0.0818***	0.0759***	0.0773***
	(0.0089)	(0.0085)	(0.0084)
Firm FE	Yes	Yes	Yes
Calendar month FE	Yes	Yes	Yes
City-month FE	No	Yes	Yes
Bank-month FE	No	Yes	Yes
Industry-month FE	No	No	Yes
Observations	885,421	885,421	885,421
R-squared	0.117	0.121	0.122