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Credit chain and sectoral comovement: A multi-region investigation

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CREDIT CHAIN AND SECTORAL COMOVEMENT

A MULTI-REGION INVESTIGATION

Hsiao-Hui Lee, S. Alex Yang, Yuxuan Zhang, and Kijin Kim

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Hsiao-Hui Lee, S. Alex Yang, Yuxuan Zhang,
and Kijin Kim

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ABSTRACT

This paper empirically examines how sectoral comovements are correlated with trade credit usage in a multi-region setting. Extending the models in Shea (2002) and Raddatz (2010), we develop a framework that captures the impact of trade credit usage on comovement between sectors within an economy and across economies separately. Using the Multi-Regional Input-Output Table developed by the Asian Development Bank, we assemble a dataset consisting of 14 manufacturing industries for 53 economies. We provide empirical evidence that trade credit linkage is an influential channel for both the domestic and cross-border shocks to propagate and create a more profound impact on industries around the globe. We find that the impact of domestic credit chains on sectoral comovement is twice as strong as that of the international ones. We further examine the time trend of this relationship and find that, from 2000 to 2018, the positive relationship between the intensity of trade credit usage and sectoral correlation decreases. We posit that this could be due to more diversified global trade pattern changes during these two decades.

Keywords: trade credit, credit chain, sectoral comovement, input-output table, systemic risk

JEL codes: E32, G29, G32

I. INTRODUCTION

As the volume of global trade nearly quadrupled over the last 2 decades, the global supply chain became increasingly interconnected. This interconnection has allowed companies to lower costs, but it also results in comovement across different sectors and regions. Consequently, a shock originating in one sector or geographic region can cascade into different sectors across the globe.

During the 2011 monsoon, for example, flood water inundated industrial estates in Thailand, hosting considerable global production capacity in a few sectors, causing hundreds of deaths and tremendous economic damage amid disruptions in manufacturing. As Thailand produced about a quarter of total hard drives in the world at that time, the floods caused a global hard drive shortage, pushing up prices and undermining profitability of downstream sectors. Such shocks can also propagate far beyond Thailand: Japanese companies such as Canon, Honda, and Toyota all produce a large share of products and/or components in Thailand, and the flooding hit these companies' profits and worker incomes in Japan.

An extreme weather event is only one type of shock demonstrating the interconnectedness of global supply chains. The global financial crisis in 2008 and the COVID-19 pandemic have likewise highlighted that sectors and regions are closely linked by the flow of physical goods.

Different sectors and regions also experience comovements due to financial flows between them. One of the most important financial linkages between companies within supply chains is trade credit. As credit extended by sellers to buyers in supply chains, trade credit is one of the most important sources of external financing globally (Rajan and Zingales 1995). It amounted to \$5.4 trillion in 2019 in the United States (US), for example, with growth outpacing that of GDP (Federal Reserve Board 2019). As such, it is a financial instrument with macroeconomic significance.

Trade credit also creates credit chains across firms in different sectors of the economy (Kiyotaki and Moore 1998). That is, different sectors in the economy are not only linked through business transactions (sellers and buyers of products and services), but also financially by providing and receiving trade credit from each other. An important implication of such credit chains is that trade credit could serve as an additional channel that links different sectors. Naturally, this would suggest that the intensity of trade credit usage positively influences sectoral correlation. Put differently, if sector A (buyer) receives a lot of trade credit from sector B (supplier), then a shock in sector A could translate into a larger shock in sector B relative to those sector pairs with less trade credit in between.

The above hypothesis was first confirmed empirically by Raddatz (2010) by combining the standard input-output matrix from the US Bureau of Labor Statistics and firm financial data from Worldscope and Compustat. However, data limitations left a few questions unanswered in the paper. First, without a multi-region input and output matrix, Raddatz (2010) exclusively studies transactions within each economy and it is thus unclear whether such credit chains act differently for domestic and international trade. Second, Raddatz (2010) focuses on a single time period in the early 2000s, yet the development of the global supply chain in the last two decades begs the question whether the dynamics between credit chain and sectoral comovement have changed over time. Finally, as an increasingly important powerhouse of the global economy, do Asian economies exhibit any special patterns?

To answer the above questions, this paper first extends the model in Shea (2002) and Raddatz (2010) to decompose the impact of trade credit usage on sectoral comovement by domestic and cross-border trade. Specifically, our model allows that the shock propagation via domestic credit chains has a different rate from that via cross-border chains. This allows us to empirically examine whether within- and cross-economy credit chains have different impact on sectoral comovement.

We then construct a new dataset to identify these two effects. Specifically, we triangulate the financial data from Compustat and Worldscope, the input-output table from the Multi-Region Input-Output (MRIO) Database developed by the Asian Development Bank (ADB), the growth rate of real value added using the Industrial Statistics database (INDSTAT) developed by the United Nations Industrial Development Organization (UNIDO), and the consumer price index (CPI) from the World Bank. With these, we construct a data set that consists of 14 industries from 53 economies.

Our empirical results suggest that the use of trade credit indeed positively correlates with sectoral comovement. The intensity of this correlation via the domestic credit chain is twice as strong as that via the cross-border credit chain, and the results are robust to training and the change of time windows in computing sectoral correlations.

Further, we examine how the correlation between trade credit usage and sectoral comovement evolves over time by using different MRIO data at 2000, 2007, 2013, and 2018. We find that both the positive relation between trade-credit usage intensity and correlations decreases. We posit that this could be due to more dissected supply chain structures that enable industries to diversify production as well as trade credit linkage intensity from domestic-based to foreign-based. By ruling out several plausible explanations, we provide robust empirical support for our hypothesis.

The paper contributes to two strands of research: trade credit and sectoral comovement, the former providing a rich and long literature, theoretical and empirical. The literature focuses on explaining the existence of trade credit, that is, why buyers borrow money from sellers in the presence of specialized financial institutions. Nadiri (1969) highlighted that trade credit is used as an effective marketing tool. Subsequent research have identified various reasons why trade credit is adopted, such as suppliers having easier access to financing (Schwartz 1974), price discrimination (Brennan, Miksimovic, and Zechner 1988), quality assurance (Long, Malitz, and Ravid 1993; Babich and Tang 2012), alleviating moral hazard (Burkart and Ellingsen 2004), facilitating relationship specific investment (Cuñat 2007), demand risk-sharing (Kouvelis and Zhao 2012; Yang and Birge 2018), and softening competition (Peura, Yang, and Lai 2017).

Relative to the theoretical literature, the empirical literature of trade credit is relatively new, largely due to data limitations. Earlier research in this field focuses on validating theories of trade credit and identifying determinants of trade credit, such as Petersen and Rajan (1997), Ng, Smith, and Smith (1999), and Giannetti, Burkart, and Ellingsen (2011). In a developing economy setting, McMillan and Woodruff (1999) document that trade credit is closely related to relationship building. Fisman and Love (2003) find that trade credit access could facilitate industry growth. Boissay and Gropp (2013) and Jacobson and Von Schedvin (2015) quantify how trade credit default cascades along the supply chain. Lee, Zhou, and Wang (2018) and Chod, Lyandres, and Yang (2019) examine the interaction between trade credit usage and the horizontal relationship between firms. Most recently, several studies focus on identifying the causal relationship between trade credit and operational and financial performance. Barrot (2016) shows that limiting trade credit provision improves the financial strength of upstream firms; Breza and Liberman (2017) and Chen, Jain, and Yang (2020), on the other hand, find that restricting trade credit provision reduces transaction volume between different firms and undermines downstream firms' investment and revenues.

Meanwhile, sectoral comovement is an important topic in macroeconomics. Macroeconomic models in general are concerned with business cycles, both correlated movements in economy-wide output over time and comovement between sectors (Lucas 1995). Long Jr and Plosser (1983) develop a multi-sector economy to capture shocks moving along input-output linkages. The model is extended by Shea (2002). Lilien (1982) points out that labor movement could be another source of linkage between sectoral comovement. Cooper and Haltiwanger (1990) develop a dynamic model to capture the sectoral comovement with inventory and offer empirical evidence to support their theory.

Combining the above two streams of work, the study of Kiyotaki and Moore (1998) is the first to formalize the idea of the credit chain, that is, different sectors are linked financially; this model was extended by Cardoso-Lecourtois (2004) and Boissay (2006). These studies highlight that, through trade credit, sectoral shocks can move both from upstream to downstream, and the other way around. Finally, Raddatz (2010) provides empirical evidence that the usage of trade credit does have a material impact on sectoral comovement.

Our paper extends Raddatz (2010) in three aspects: first, to distinguish domestic and international trade. Second and relatedly, using the Multi-Regional Input-Output Table developed by ADB, we empirically quantify the impact of trade credit on sectoral comovement for domestic and international transactions separately, revealing that such impact is stronger within an economy than in cross-border trade. Finally, unlike Raddatz (2010), which documents results from one year due to data limitation, we conduct the empirical analysis over nearly two decades. This longitude analysis shows the aforementioned impact changes over time, implying important trend in global supply chain.

II. THE MODEL

This section extends the model in Raddatz (2010) that examines the intra-economy sectoral comovement to analyze the sectoral comovement, not only within but also across economies. To do so, we consider an economy comprised of J sectors (indexed by subscripts i and j) and N economies (indexed by superscripts n and m). Following the notation in Raddatz (2010), we represent sectoral output fluctuations for sectors 1 to J at economies 1 to N in the following reduced form:

$$y = By + \lambda \quad (1)$$

In the above equation, λ is also a $(JN) \times 1$ vector that consists of elements λ_i^m for $i = 1, \dots, J$ and $m = 1, \dots, N$, where λ_i^m represents the sectoral shocks for sector i at economy m . B is a $(JN) \times (JN)$ matrix with elements b_{ij}^{mn} representing the share of total demand faced by sector i in economy m (the supplier) directly attributable to sector j in economy n (the customer). Combined, y is a $(JN) \times 1$ vector with elements y_i^m for $i = 1, \dots, J$ and $m = 1, \dots, N$, where y_i^m represents the sectoral output fluctuations for sector i at economy m .

To build trade credit into the model, we denote $P_{ij}^{mn} \in [0, 1]$ as the fraction of direct demand b_{ij}^{mn} supplied by trade credit. Thus, we have:

$$b_{ij}^{mn} = P_{ij}^{mn} b_{ij}^{mn} + (1 - P_{ij}^{mn}) b_{ij}^{mn}. \quad (2)$$

If trade credit has an additional effect on the transmission of shocks (let the impact coefficient be α_{ij}^{mn}), the coefficient of direct linkages would be $b_{ij}^{mn}(1 + \alpha_{ij}^{mn}P_{ij}^{mn})$, in which we have a maximum of $(JN)^2$ different α_{ij}^{mn} .

To ensure that the model is tractable and that it can fit with data for estimation, we make the following two assumptions.

Assumption 1. P_{ij}^{mn} is constant across suppliers. That is, $\forall i$ and $m, P_{ij}^{mn} = P_j^n$.

Assumption 2. $\alpha_{ij}^{nn} = \alpha_{ij}^{mm} := \alpha^D$ and $\alpha_{ij}^{mn} = \alpha_{ij}^{nm} := \alpha^F$ for $n \neq m$.

Assumption 1 is similar to Raddatz (2010). Here, we assume that P_{ij}^{mn} is constant across suppliers regardless of which sector they are selling to and which economy the customers are located in. This assumption allows us to allocate trade credit received by a customer to be proportionally allocated to all its suppliers, as a firm only reports the aggregated trade credit (account payables) it receives from all suppliers. With this assumption, $\forall i, \forall m, P_{ij}^{mn} = P_j^n$. After (A1), we have reduced P_{ij}^{mn} (and therefore α_{ij}^{mn}) to JN .

Assumption 2 states that we only distinguish between domestic (D) and cross-border (F) trade credit. With Assumption 2, we can separate the effects of domestic and cross-border trade credit, that is,

$$B = B^D + B^F, \quad (3)$$

where B^D captures domestic trade and B^F captures cross-border trade. Let P be a diagonal matrix with elements P_j^n , we then can rewrite equation (2) as:

$$B(I + \alpha P) = B^D(I + \alpha^D P) + B^F(I + \alpha^F P). \quad (4)$$

Define $JN \times JN$ matrix $A(\alpha, B, P)$ as

$$A = [I - B(I + \alpha P)]^{-1} \quad (5)$$

$$= [I - B^D(I + \alpha^D P) - B^F(I + \alpha^F P)]^{-1} \quad (6)$$

We can then write y as

$$y = B(I + \alpha P)y + \lambda = A(\alpha, B, P)\lambda, \quad (7)$$

Taking a linear approximation to A around $\alpha^D = 0$ and $\alpha^F = 0$, we obtain:

$$A \approx D + \alpha^D \Gamma^D + \alpha^F \Gamma^F, \quad (8)$$

where

$$D = (I - B)^{-1} \quad (9)$$

$$\Gamma^D = D(B^D P)D, \quad (10)$$

$$\Gamma^F = D(B^F P)D, \quad (11)$$

If we assume that economy-sector shocks λ_j^n are independent and identically distributed, the correlation between sector i in economy m and sector k in economy o is:

$$\rho_{ik}^{mo} = \frac{\sum_n \sum_j a_{ij}^{mn} a_{kj}^{on}}{\left(\sum_n \sum_j (a_{ij}^{mn})^2 \sum_n \sum_j (a_{kj}^{on})^2 \right)^{1/2}}, \quad (12)$$

in which a_{ij}^{mn} is the $((m, i), (n, j))$ element of the matrix A . Taking a first-order approximation, equation (12) can be re-written as:

$$\begin{aligned} \rho_{ik}^{mo} \approx & \frac{\sum_n \sum_j d_{ij}^{mn} d_{kj}^{on}}{\left(\sum_n \sum_j (d_{ij}^{mn})^2 \sum_n \sum_j (d_{kj}^{on})^2 \right)^{1/2}} + \alpha^D \sum_n \sum_j \frac{d_{ij}^{mn} d_{kj}^{on} (\tilde{c}_{ij}^{Dmn} + \tilde{c}_{kj}^{Don})}{\left(\sum_r \sum_l (d_{il}^{mr})^2 \sum_r \sum_l (d_{kl}^{or})^2 \right)^{1/2}} \\ & + \alpha^F \sum_n \sum_j \frac{d_{ij}^{mn} d_{kj}^{on} (\tilde{c}_{ij}^{Fmn} + \tilde{c}_{kj}^{Fon})}{\left(\sum_r \sum_l (d_{il}^{mr})^2 \sum_r \sum_l (d_{kl}^{or})^2 \right)^{1/2}}, \end{aligned} \quad (13)$$

where

$$\tilde{c}_{ij}^{Dmn} = \frac{\Gamma_{ij}^{Dmn}}{d_{ij}^{mn}} - \frac{\sum_r \sum_l d_{il}^{mr} \Gamma_{il}^{Dmr}}{\sum_r \sum_l (d_{il}^{mr})^2}, \quad \text{and} \quad (14)$$

$$\tilde{c}_{ij}^{Fmn} = \frac{\Gamma_{ij}^{Fmn}}{d_{ij}^{mn}} - \frac{\sum_r \sum_l d_{il}^{mr} \Gamma_{il}^{Fmr}}{\sum_r \sum_l (d_{il}^{mr})^2}, \quad (15)$$

which measures the use of trade credit along the chain linking (m, i) and (n, j) , relative to the chains linking (m, i) and all other sectors and economies, and Γ_{ij}^{Fmn} (Γ_{ij}^{Dmn}) is the $((m, i), (n, j))$ element of the matrix Γ^F (Γ^D).

The three terms in equation (13) follow a similar form as those shown in equation (6) in Raddatz (2010): the first term in equation (13) represents the input-output linkage between two industries in two economies (which can be the same economy), whereas the second and third terms represent the credit chain linkage within the same economy and across two different economies, respectively. The main difference is that, in our model, both the denominator and the numerator have been expanded to include not only the sectors within an economy but also sectors across different economies.

Next, let C_{ik}^{Dmo} (C_{ik}^{Fmo}) denote the weighted average of the relative use of trade credit across all economy-sector pair (n, j) linking pairs (m, i) and (o, k) , in which the weights are determined by the product of the direct and indirect links between the three pairs. Formally,

$$C_{ik}^{Dmo} = \sum_n \sum_j \frac{d_{ij}^{mn} d_{kj}^{on} (\tilde{c}_{ij}^{Dmn} + \tilde{c}_{kj}^{Don})}{\left(\sum_r \sum_l (d_{il}^{mr})^2 \sum_r \sum_l (d_{kl}^{or})^2 \right)^{1/2}} \quad (16)$$

$$C_{ik}^{Fmo} = \sum_n \sum_j \frac{d_{ij}^{mn} d_{kj}^{on} (\tilde{c}_{ij}^{Fmn} + \tilde{c}_{kj}^{Fon})}{\left(\sum_r \sum_l (d_{il}^{mr})^2 \sum_r \sum_l (d_{kl}^{or})^2 \right)^{1/2}} \quad (17)$$

Intuitively, if the use of trade credit along the chain linking (n, j) and other state pairs is higher than average and is important, then shocks to this (n, j) pair increases the correlation between pairs (m, i) and (o, k) .

Finally, equation (13) also motivates us to test whether $\alpha^D = 0$ or $\alpha^F = 0$ based on the following:

$$\rho_{ik}^{mo} = \theta + \eta G_{ik}^{mo} + \alpha^D C_{ik}^{Dmo} + \alpha^F C_{ik}^{Fmo} + \gamma W_{ik}^{mo} + \epsilon_{ik}^{mo}, \quad (18)$$

in which θ represents various fixed effects,¹ G_{ik}^{mo} is the physical linkage between (m, i) and (o, k) , which is computed as the first term in equation (13), C_{ik}^{Dmo} and C_{ik}^{Fmo} captures trade credit usage, and W_{ik}^{mo} represents other determinants of sectoral correlation.

III. DATA AND VARIABLE CONSTRUCTIONS

To test equation (18), we need three major data inputs:

- (i) the use of trade credit P ;
- (ii) the input-output linkages B and D ;
- (iii) the sectoral correlations ρ .

We use data from Compustat and Worldscope for constructing trade credit usage P . To construct B and D , we use the Multi-Region Input-Output (MRIO) Database developed by ADB. This database collects the input-output data for 35 industries and 62 economies. The Online Appendix Table A1 lists the economies used in the analysis:² although the MRIO table lists 62 economies, Worldscope does not collect financial data from 7 of these (marked in * in Table A1), and so after dropping these, we are left with 55. As shown later, we drop two more economies, Cambodia and Mongolia, due to the low number of firms reported in Worldscope, resulting in the final dataset with 53 economies. Finally, to construct sectoral correlation ρ , we use INDSTAT at the 2-digit level of ISIC Revision 3 by UNIDO and the CPI from World Bank.

As our unit of analysis is at the industry level, and due to data availability, we follow the industry classification of the MRIO database and only include manufacturing industries in our analysis.

Next, we introduce the data used, our constructions of these three sets of variables, and brief summaries of each set.

¹ In Section 4, we consider various combinations of economy and sector fixed effects to capture the fixed determinants of the correlation between these combinations.

² The online appendix tables can be accessed at <https://www.adb.org/publications/credit-chain-sectoral-comovement>.

A. The Use of Trade Credit (Matrix P)

The intensity of trade credit usage is defined as the ratio of the average accounts payable at the end of years t and $t-1$ to the cost of goods sold in year t . Similar to Raddatz (2010), we make the following assumption, due to the data availability issue:

Assumption 3. The ratio of an industry's use of trade credit to the average use in an economy (P_j^n / P^n) is assumed constant across economies, so the elements of P in a given economy can be expressed as the product of this ratio, P_j , and the economy's use of trade credit P^n . Formally,

$$P_j^n = P_j \times P^n. \quad (19)$$

This assumption enables us to leverage the extensive data coverage for US firms without sacrificing economies with much less data coverage. We construct P_j based on the Compustat database using US data, and P^n based on the Worldscope database. We detail our procedures as follows. First, we extract public firms' accounts payable and cost of goods sold from two databases, Compustat and Worldscope, in which the former is used for US publicly listed firms, and the latter for non-US firms. We resort to the Compustat database for the industry-level financial data aggregation in the US. We collect data from 1990 to 2019, and then map these publicly listed firms using their four-digit Standard Industry Classification (SIC) code to the 35 industries used in MRIO. To clean the data, we remove observations outside the US (e.g., American Depositary Receipts (ADR) and Global Depositary Receipts (GDR)), with missing or negative cost of goods sold, and belonging to Industry 28 (the financial intermediation industry) for it performs financial transactions differently from other industries. For observations with missing accounts payable (about 0.6% out of total observations), we treat them as zero. After the above data cleaning procedure, this data set presents 17,110 unique US firms, with 173,663 firm-year observations. In Table A2 (see the Online Appendix), we list the number of firms and the number of firms with more than 5 years of data for each US industry.³

Next, we resort to Worldscope for financial information for the non-US firms in 54 economies. Similar to Compustat, we collect data from 1990 to 2019, and then map these firms using their four-digit SIC. After data cleaning,⁴ we have 69,250 unique manufacturing and service firms from 32 industries across 55 economies from 1990 to 2019,⁵ with a total of 808,288 observations. Table A3 gives the number of firms and the number of firms with more than 5 years of data for each of the 55 economies in Worldscope. We note that, in this dataset, data coverage is limited among developing economies. We also analyze the data coverage at the economy-industry level. Table A4 presents the result summary and indicates the low data coverage of Cambodia and Mongolia. Out of the 32 industries, Table A4 suggests that only 26 economies report more than 5 firms (each with at least 5 years of data) in more than 20 industries.⁶

With these raw data, we next present the computation steps to obtain the use of trade credit (the matrix P). For a given firm and year, the use of trade credit corresponds to the average of the

³ Industry 1 (agriculture, hunting, forestry and fishing) and Industry 35 (private households with employed persons) do not have enough data for computation. After dropping these two industries, we have 32 industries, including both manufacturing and service; for comparison, Raddatz (2010) analyzed 28 manufacturing industries for 43 economies.

⁴ We remove observations with missing economy, industry, or cost of goods sold, and then treat missing accounts payable as zero. To be consistent, we remove observations in industry 1, 28, and 35.

⁵ Raddatz (2010) uses Worldscope 2006, which contains 10,500 manufacturing firms in 58 economies.

⁶ In Raddatz (2010), 21 economies report more than 5 firms in more than 10 industries without the requirement that each firm has at least 5 years of data.

accounts payable at the end of years $t-1$ and t divided by the total cost of goods sold in year t , and we denote it as p_t^i .

$$p_t^i = \frac{\text{Accounts payable}_{t-1}^i + \text{Accounts payable}_t^i}{2 \times \text{Cost of Goods Sold}_t^i}. \quad (20)$$

Thus, the first step is to construct the firm-level representative measure of payables by taking the median of p_t^i across time for each firm reporting data to the Worldscope database. Only firms with more than 5 years of (annual) data from 1990 to 2019 are kept in the sample to reduce the impact of cyclical fluctuation.

Next, within economy n (except the US), the median of the representative ratios of those firms located in n is used as a economy-level representative value of payables financing (P^n). For industry level trade credit usage P_j , by using data from Compustat, we construct representative ratios for each industry j in the US (P_j^{US}) by taking the median ratio across US firms within the industry. Based on Assumption 3, we then can have: $P_j = P_j^{US}/P^{US}$, and $P_j^n = P_j \times P^n$.

In Table A5, we present the use of trade credit (columns with payables financing) and the use of bank credit (columns with short-term debt to payables) for economies listed in Worldscope.⁷ Table A6 presents these two for the manufacturing industries in the US. We report these summary statistics for 2000, 2007, 2013, and 2018, due to the data availability from 2000 to 2018 as well as a preparation for the time trend analyses later.

B. Input-Output Linkages (B and D)

Similar to the World Input-Output Database and the input-output (IO) table developed by the US Bureau of Economic Analysis, the ADB includes more Asian economies to respond to the increasing needs to expand coverage of the World Input-Output Database in its MRIO project. In this paper, we use the 2018 MRIO table as the benchmark in our analysis, and will use other years' MRIO tables for our exploration of the time changes of sectoral comovements.

The benefit of using the MRIO tables comes from the coverage of trade information. Raddatz (2010) uses the 1992 Input-Output (or USE and MAKE) tables provided by the US Bureau of Economic Analysis. As only one economy's IO table is used, Raddatz (2010) assumes that the IO linkages across industries are technologically determined, and therefore, linkage measures obtained in an economy with good available information, such as the US, can be extrapolated to the rest of the economies in the sample. In our paper, the MRIO tables not only provide intra-economy trade volumes but also inter-economy trade volumes, which enable us to study beyond the industry-level comovement within an economy, but also those across different economies.

Another advantage of the MRIO table is that, instead of using USE and MAKE tables, the structure of the MRIO table directly records the trade flows. Hence, we can compute matrix B directly from the MRIO data without making additional assumptions. Finally, we consider 53 economies (the 55 economies that overlapped with the Worldscope database less Cambodia and Mongolia, which have insufficient data coverage) and 14 manufacturing sectors, because the UNIDO INDSTAT database only provides information for manufacturing industries. The 14 sectors are denoted as sectors 3 to 16.

⁷ To construct the variables with short-term debt to payables, we follow the same procedure described above but replace accounts payable by short-term debts.

To obtain both B and D , we follow Shea (2002). Specifically, we start by computing D . According to Miller and Blair (2009), the technical input coefficient matrix, β , is defined as:

$$\beta_{ij}^{mn} = \frac{\text{Value of input } (m,i) \text{ bought by } (n,j) \text{ producers}}{\text{Total value of } (n,j) \text{ production}}. \quad (21)$$

Based on the multi-sectoral general equilibrium model developed by Shea (2002), we can estimate the fluctuations in industry i (denoted as q_i) as follows:

$$q_i = K_i + \sum_{k=1}^N \text{COST}_{ik} s_k + \sum_{k=1}^N \text{DEM}_{ik} d_k, \quad (22)$$

which suggests that fluctuations in industry i (q_i) depend on technology shock s_k and taste (demand) shock d_k . COST_{ik} is the ultimate dollar requirement of good k per dollar sold of good i , after incorporating both direct and indirect linkages. DEM_{ik} is the steady state share of demand for i ultimately embodied in final purchases of k , which is the D matrix in Raddatz (2010) and our targeted matrix. Technology shocks propagate downstream, so they affect only sectors that use k as an input, but not upstream sectors that supply inputs to k . Conversely, taste shocks propagate upstream.⁸ Computation for COST and DEM according to Eq. (A.11) and (A.12) in Shea (2002) is as follows:

$$\text{COST} = [(I - \beta)^{-1}]^T, \quad (23)$$

where β is a matrix whose $((m, i), (n, j))$ element is the share of economy m industry i 's cost directly attributable to economy n industry j (computed according to Eq. (21)), and

$$\text{DEM}_{ik} = \frac{\text{COST}_{ki} f_k}{\sum_{z=1}^N \text{COST}_{zi} f_z}, \quad (24)$$

where f_k is industry k 's final demand defined as the sum of purchases from consumption, government, and nonmanufacturing industries.⁹

As a result, to compute D and B , we start by computing technical input coefficient matrix β using equation (21), and then compute the COST matrix using equation (23).¹⁰ Next, we compute final demand f_k by summing over final consumption in the MRIO table and finally compute matrix D based on Eq. (24). With D , we compute matrix $B = I - D^{-1}$, and decompose B into B^D for domestic flows and B^F for cross-economy flows: $B = B^D + B^F$.

With the matrices P , B , and D , we can finally compute the credit linkages, C_{ik}^{Dmo} and C_{ik}^{Fmo} , and then present our model specifications. Recall that Raddatz (2010) defines $\Gamma = D(BP)D$. We then start by computing $\Gamma^D = D(B^D P)D$, $\Gamma^F = D(B^F P)D$, and $\Gamma = D(BP)D$, using the three matrices obtained from previous sections, and we have $\Gamma = \Gamma^D + \Gamma^F$. Then using equation (13), we compute C_{ik}^{Dmo} (stored in matrix C^D), C_{ik}^{Fmo} (stored in matrix C^F) and C_{ik}^{mo} (stored in matrix C^W). In Tables A7 and A8,

⁸ As the use of trade credit affects upstream shock propagation, so in equation (1) of Raddatz (2010), it only contains matrix D .

⁹ In the MRIO table, the "final uses" item contains five elements: (i) final consumption expenditure by households, (ii) final consumption expenditure by non-profit organizations serving households, (iii) final consumption expenditure by government, (iv) gross fixed capital formation, and (v) changes in inventories and valuables. We currently use the first three elements to approximate for final demand.

¹⁰ In this step, we remove the five economies-sectors that have almost zero-column sums in COST or D . Originally, the number of economies-sector should be 53×14 , which is 742. After moving these five-economies sectors, our final matrix size is 737×737 .

we report the top-20 economy-industry pairs with the strongest domestic and cross-border trade credit linkage, respectively.

C. Sectoral Correlations (ρ)

Finally, we illustrate how we construct the correlation of the growth rates of real value added across all industries in multiple economies. We use the UNIDO INDSTAT database¹¹ as the source for nominal value added from 1963 to 2018 and World Bank's CPI data from 1960 to 2019 (which sets base year 2010 = 100) for 54 economies (except Taipei,China).¹² For Taipei,China, we obtain CPI from 1981 to 2019 from its official statistics website.¹³

The UNIDO INDSTAT data include 174 economies (full coverage for the 55 economies in Table A3) and comprise 23 manufacturing sectors (based on 2-digit level of ISIC industry classification). As a result, our unit of analysis will be on the manufacturing industries. We choose CPI as our deflator when computing sectoral correlation, whereas Raddatz (2010) used producer price index. We use the CPI data from World Bank as it is the only deflator with historical data across economies and sufficiently good data coverage. After data cleaning,¹⁴ we construct real value added equals nominal value added divided by CPI/100.

Next, we illustrate the steps to construct the sectoral comovement across economies and across years. First, we compute the growth rate for the real value added g_{it}^m , which is the growth rate of industry i in economy m between years $t - 1$ and t . Then, we compute the average \bar{g}_i^m across times, which is taking an average of g_{it}^m for all t . Finally, the correlation across economies and years is computed as:

$$\rho_{ij}^{mn} = \frac{\left(\sum_{t=1}^T (g_{it}^m - \bar{g}_i^m)(g_{jt}^n - \bar{g}_j^n) \right) (T_{ij}^{mn})^{-1}}{\left(\sum_{t=1}^T \left(\frac{T_{it}^{m-1}}{T_i^m} \right) \frac{(g_{it}^m - \bar{g}_i^m)^2}{T_i^{m-1}} \sum_{t=1}^T \left(\frac{T_{jt}^{n-1}}{T_j^n} \right) \frac{(g_{jt}^n - \bar{g}_j^n)^2}{T_j^{n-1}} \right)} = \frac{\left(\sum_{t=1}^T (g_{it}^m - \bar{g}_i^m)(g_{jt}^n - \bar{g}_j^n) \right) (T_{ij}^{mn})^{-1}}{\sqrt{\frac{T_i^{m-1}}{T_i^m} SD(g_{it}^m)} \sqrt{\frac{T_j^{n-1}}{T_j^n} SD(g_{jt}^n)}}, \quad (25)$$

in which T_{ij}^{mn} is the number of observations with data for sector i economy m and sector j economy n and T_i^m is the number of observations for sector i economy m .¹⁵

Computing correlation based on equation (25) from 1990 to 2018, we have further cleaned the data.¹⁶ See Table 1, in which we report the summary statistics for overall correlations, domestic

¹¹ We use the 2020 edition of INDSTAT2 ISIC Revision 3.

¹² World Bank. Data. <https://data.worldbank.org/indicator/FP.CPI.TOTL> (accessed 30 July 2021).

¹³ National Statistics. <http://statdb.dgbas.gov.tw/pxweb/dialog/statfile1L.asp> (accessed 30 July 2021).

¹⁴ We remove observations with missing nominal value added, and we map the 23 manufacturing sectors (based on the 2-digit level of ISIC industry classification) from UNIDO to 14 manufacturing sectors from MRIO and aggregate values for these 14 sectors, and we merge the CPI data based on economy \times year while removing observations with missing or zero CPI.

¹⁵ Raddatz (2010) (footnote 15 on page 991) specifies that “[w]ith N sectors and T observations (per sector), there are $N(N-1)/2$ correlation coefficients to be estimated from NT observations. The order condition therefore requires that $T > (N-1)/2$ for a full rank matrix. With 28 sectors, this requires 14 observations at a minimum. I allowed for one more than that.”

¹⁶ We drop missing correlations, correlations with higher than 1 or smaller than -1; these cases are likely to occur when T_{ijmn} is small. At the end, there are 416,469 economy-sectors left.

(i.e., within-economy) correlations, and the cross-border (i.e., cross-economy) correlations for all the data. We note that the domestic correlation is higher than the ones from Raddatz (2010), likely because of a higher level of aggregation in our setting. To further justify the need to differentiate domestic from cross-border correlations for our economy-industry setup, we also report the domestic and cross-border correlations using 20 years of prior data from the year specified in Table 2.

One potential concern with the baseline measure is the use of a common deflator: in the presence of significant heterogeneity in the evolution of prices across industries, the correlations computed with a common deflator may be driven by the correlation of relative inflation rates instead of the correlation of real output growth. This concern can be addressed by using the correlation of the growth rates of the index of industrial production, also reported in UNIDO. Results obtained using this measure are not affected by the relative price problem, but results obtained using real value added are preferable because the production index data are of lower quality and smaller coverage than the value-added data. Nevertheless, this choice does not affect the results.

Table 1: Summary Statistics for Sectoral Correlation

	Mean	SD	Min	p(25)	p(50)	p(75)	Max
Overall correlation	0.16	0.28	-1.00	-0.01	0.16	0.34	1
Domestic correlation	0.50	0.36	-0.99	0.24	0.54	0.80	1
Cross-border correlation	0.16	0.27	-1.00	-0.02	0.15	0.33	1

SD = standard deviation, Min = minimum value, p(25) = 25th percentile, p(50) = 50th percentile, p(75) = 75th percentile, Max = maximum value.

Source: Authors' estimates.

Table 2: Domestic and Cross-Border Correlations by Economy, Previous 20 Years

Economy	Domestic Average Correlation				Cross-Border Average Correlation			
	2000	2007	2013	2018	2000	2007	2013	2018
Australia	0.76	0.60	0.55	0.49	0.11	0.18	0.17	0.24
Austria	0.59	0.51	0.55	0.58	0.23	0.19	0.24	0.30
Belgium	0.46	0.51	0.31	0.40	0.20	0.23	0.18	0.23
Bulgaria	0.63	0.47	0.22	0.24
Brazil	0.70	0.72	0.72	0.78	-0.07	0.14	0.15	0.25
Canada	0.52	0.35	0.37	0.42	0.12	0.09	0.15	0.19
Switzerland	0.56	0.53	0.37	0.30	0.14	0.22	0.17	0.16
PRC	0.82	0.70	0.77	0.81	-0.13	0.07	0.19	0.21
Cyprus	0.50	0.52	0.20	0.20
Germany	0.71	0.65	0.59	0.60	0.10	0.23	0.25	0.27
Denmark	0.63	0.46	0.39	0.47	0.22	0.17	0.19	0.26
Spain	0.75	0.68	0.71	0.70	0.29	0.24	0.27	0.31
Estonia	0.57	0.56	0.27	0.29
Finland	0.64	0.57	0.47	0.43	0.22	0.21	0.21	0.28
France	0.78	0.67	0.58	0.57	0.27	0.23	0.24	0.30
United Kingdom	0.71	0.64	0.57	0.53	0.25	0.19	0.22	0.25
Greece	0.49	0.76	0.69	0.61	0.19	0.25	0.19	0.19
Croatia	0.47	0.43	0.18	0.23

continued on next page

Table 2 *continued*

Economy	Domestic Average Correlation				Cross-Border Average Correlation			
	2000	2007	2013	2018	2000	2007	2013	2018
Hungary	0.49	0.56	0.52	0.50	0.12	0.16	0.21	0.25
Indonesia	0.58	0.56	0.53	0.32	0.05	0.13	0.16	0.12
India	0.23	0.37	0.33	0.37	0.07	0.16	0.17	0.18
Ireland	0.53	0.35	0.24	0.22	0.19	0.13	0.13	0.16
Italy	0.72	0.64	0.69	0.71	0.25	0.21	0.25	0.35
Japan	0.85	0.77	0.56	0.52	0.22	0.13	0.16	0.13
Korea, Republic of	0.78	0.65	0.68	0.61	0.20	0.11	0.18	0.13
Lithuania	0.51	0.50	0.27	0.28
Luxembourg	0.45	0.32	0.29	0.33	0.21	0.19	0.18	0.23
Latvia	0.38	0.46	0.16	0.20
Mexico	0.57	0.52	0.61	0.50	-0.17	0.04	0.06	0.12
Malta	0.13	0.10	0.05	0.06
Netherlands	0.67	0.60	0.53	0.53	0.25	0.21	0.22	0.29
Norway	0.48	0.38	0.43	0.45	0.19	0.17	0.21	0.25
Poland	0.62	0.69	0.53	0.53	0.00	0.10	0.21	0.24
Portugal	0.58	0.45	0.43	0.44	0.20	0.15	0.19	0.24
Romania	0.74	0.65	0.18	0.17
Russian Federation	...	0.73	0.74	0.70	...	0.17	0.21	0.27
Slovakia	...	0.56	0.48	0.55	...	0.09	0.15	0.21
Slovenia	...	0.64	0.47	0.58	...	0.08	0.24	0.31
Sweden	0.64	0.60	0.50	0.51	0.23	0.23	0.25	0.29
Turkey	0.74	0.75	0.78	0.67	0.07	0.25	0.21	0.20
Taipei,China	0.69	0.41	0.42	0.38	0.17	0.10	0.14	0.14
United States	0.31	0.28	0.24	0.26	0.10	0.04	0.08	0.10
Bangladesh	0.09	0.05	0.03	-0.05
Malaysia	0.48	0.49	0.47	0.36	0.07	0.05	0.14	0.10
Philippines	0.42	0.44	0.32	0.26	0.15	0.10	0.06	0.04
Thailand	0.35	0.36	0.50	0.52	0.01	0.04	0.10	0.09
Viet Nam	0.45	0.46	-0.04	-0.02
Kazakhstan	0.46	0.67	0.15	0.15
Sri Lanka	0.38	0.55	0.49	0.48	-0.04	0.07	0.08	0.08
Pakistan	0.21	0.60	0.70	...	0.04	0.15	0.24	...
Fiji	0.27	0.30	0.09	0.16
Singapore	0.47	0.45	0.34	0.19	0.12	0.13	0.13	0.11
Hong Kong, China	0.36	0.14	0.15	0.12	0.13	0.02	-0.01	-0.01
Mean	0.57	0.54	0.49	0.47	0.13	0.15	0.17	0.19
Median	0.58	0.56	0.50	0.50	0.14	0.15	0.18	0.21
SD	0.16	0.14	0.16	0.17	0.11	0.07	0.07	0.09

SD = standard deviation, PRC = People's Republic of China, ... = data not available

Source: Authors' estimates.

IV. EMPIRICAL RESULTS

A. Base Results

With all variables constructed, our model specification is thus:

$$\rho_{ik}^{mo} = \theta + \eta G_{ik}^{mo} + \alpha^D C_{ik}^{Dmo} + \alpha^F C_{ik}^{Fmo} + \gamma W_{ik}^{mo} + \epsilon_{ik}^{mo}, \quad (26)$$

in which W_{ik}^{mo} includes other determinants of sectoral correlation, and G_{ik}^{mo} is the physical linkage between (m, i) and (m, i) , which is computed as the first term in Eq. (13). We consider two fixed effects combinations: (1) economy fixed effects for input and output economies separately, and industry fixed effects for input and output industries separately, and (2) economy-industry joint fixed effects for input and output economy-industry pairs. We cluster standard errors based on the fixed effects combinations.

We present our results in models 1 to 4 of Table 3. Models (1) and (2) consider only an aggregate credit linkage (i.e., we do not separate the within and across economy credit linkages) for the two fixed effects combinations, and (3) and (4) consider the domestic and cross-border credit linkages, separately. In this specification, we use the 2018 MRIO table in computing the input-output linkage, and we compute the sectoral correlation using the prior 20 years INDSTAT and CPI data.

Table 3: Regression Table, 2018, Previous 20 Years

	(1) ρ_{ik}^{mo}	(2) ρ_{ik}^{mo}	(3) ρ_{ik}^{mo}	(4) ρ_{ik}^{mo}
G_{ik}^{mo}	0.781*** (0.0364)	0.784*** (0.0151)	0.759*** (0.0374)	0.736*** (0.0146)
C_{ik}^{mo}	3.271** (1.018)	3.342*** (0.461)		
C_{ik}^{Dmo}			6.050*** (1.138)	5.883*** (0.524)
C_{ik}^{Fmo}			2.990** (0.865)	2.880*** (0.456)
Constant	0.185*** (0.000561)	0.185*** (0.000796)	0.186*** (0.000412)	0.186*** (0.000824)
Economy m FE	yes	no	yes	no
Economy o FE	yes	no	yes	no
Industry i FE	yes	no	yes	no
Industry k FE	yes	no	yes	no
Economy-industry pair (m, i) FE	no	yes	no	yes
Economy-industry pair (o, k) FE	no	yes	no	yes
Observations	511,589	511,589	511,589	511,589
R^2	0.226	0.427	0.227	0.428
Within R^2	0.024	0.031	0.025	0.031

FE = fixed effects.

Notes: Standard errors in parentheses and are robust to heteroskedasticity. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Source: Authors' estimates.

Two observations are notable. First, we echo the results shown in Raddatz (2010); the significant and positive coefficient of C_{ik}^{mo} in (1) and (2) support the hypothesis that the intensity of the use of trade credit increases the correlation between the two industries linked by the credit chain.

Second, we find that after separating the credit linkage, C_{ik}^{mo} , to the domestic component (or within economy linkage), C_{ik}^{Dmo} , and the cross-border component (or cross-border linkage), C_{ik}^{Fmo} , the results remain similar in that the intensity of the use of trade credit still increases the correlation between the two industries, regardless of whether these two industries are in the same economy or different economies, as the coefficients of the two are positive and significant. Moreover, the comparison between the coefficients of C_{ik}^{Dmo} and C_{ik}^{Fmo} suggests that the domestic credit linkage has higher impact on the correlation between two industries within the same economy than that between two in two different economies.

B. Robustness

We note that one possible concern of the base specification is whether the results are robust to outliers. It could be possible that our results are driven by the strong correlations between a few strong economies and/or dominating industries. To address this concern, we follow two traditional approaches to reduce the effect of outliers: winsorization or trimming, the former is to set the extreme values of sectoral correlations (higher or lower than a certain threshold) to the value at the threshold, whereas the latter is to drop these extreme values from the sample.

We report the results of the above two robustness tests in Table A9. The first three columns are the results after winsorizing the sectoral correlation based on the top 1, 3, and 5 percentiles, and the last column shows the result after we trim the top 5% values. As we can observe from the coefficients of C_{ik}^{Dmo} and C_{ik}^{Fmo} , these two remain positive and significant, thereby, again, supporting our hypothesis that the intensity of the use of trade credit increases sectoral correlation. The magnitude of the two also suggests that the influence of domestic trade intensity is higher than that of cross-border one; although the extreme values indeed have impact on how much these trade intensity influences the correlation (as the gap between the two is slightly reduced), the impact is minor.

To further examine the outlier issues, we winsorize and trim our sample based on the respective percentile cutoffs based on the economy pairs instead of doing so for the entire sample and report the results in Table A10, and we again obtain qualitatively the same results.

C. Time Variation

In this section, we explore how the intensity of the use of trade credit influences sectoral correlation differently from 2000 to 2018. Specifically, we repeat the regression model in equation (26) but use the MRIO tables in year 2000, 2007, 2013, and 2018.¹⁷ In Table 4, we report our empirical results when the sectoral correlations are computed based on the prior 20 years of data.

¹⁷ Although the MRIO tables first started coverage in 2000, the next available table is conducted for 2007. Therefore, we pick the first two available tables in studying the time variation. The most updated table at the time of this study is conducted for 2018, and we find the middle year between 2007 and 2018 as another time span in our study, which is 2013.

Table 4: Regression Table (Time Window: Previous 20 Years)

	2000 ρ_{ik}^{mo}	2007 ρ_{ik}^{mo}	2013 ρ_{ik}^{mo}	2018 ρ_{ik}^{mo}
G_{ik}^{mo}	0.862*** (0.0184)	0.810*** (0.0122)	0.791*** (0.0126)	0.763*** (0.0146)
C_{ik}^{Dmo}	12.12*** (1.175)	11.54*** (0.859)	7.842*** (0.667)	5.883*** (0.524)
C_{ik}^{Fmo}	8.477*** (1.258)	5.015*** (0.899)	3.696*** (0.659)	2.880*** (0.456)
Constant	0.123*** (0.00146)	0.140*** (0.00136)	0.163*** (0.000884)	0.186*** (0.000824)
Economy-industry pair (m, i) FE	yes	yes	yes	yes
Economy-industry pair (o, k) FE	yes	yes	yes	yes
Observations	269,673	320,728	529,837	511,589
R^2	0.347	0.275	0.329	0.428
Within R^2	0.058	0.054	0.033	0.031

FE = fixed effects.

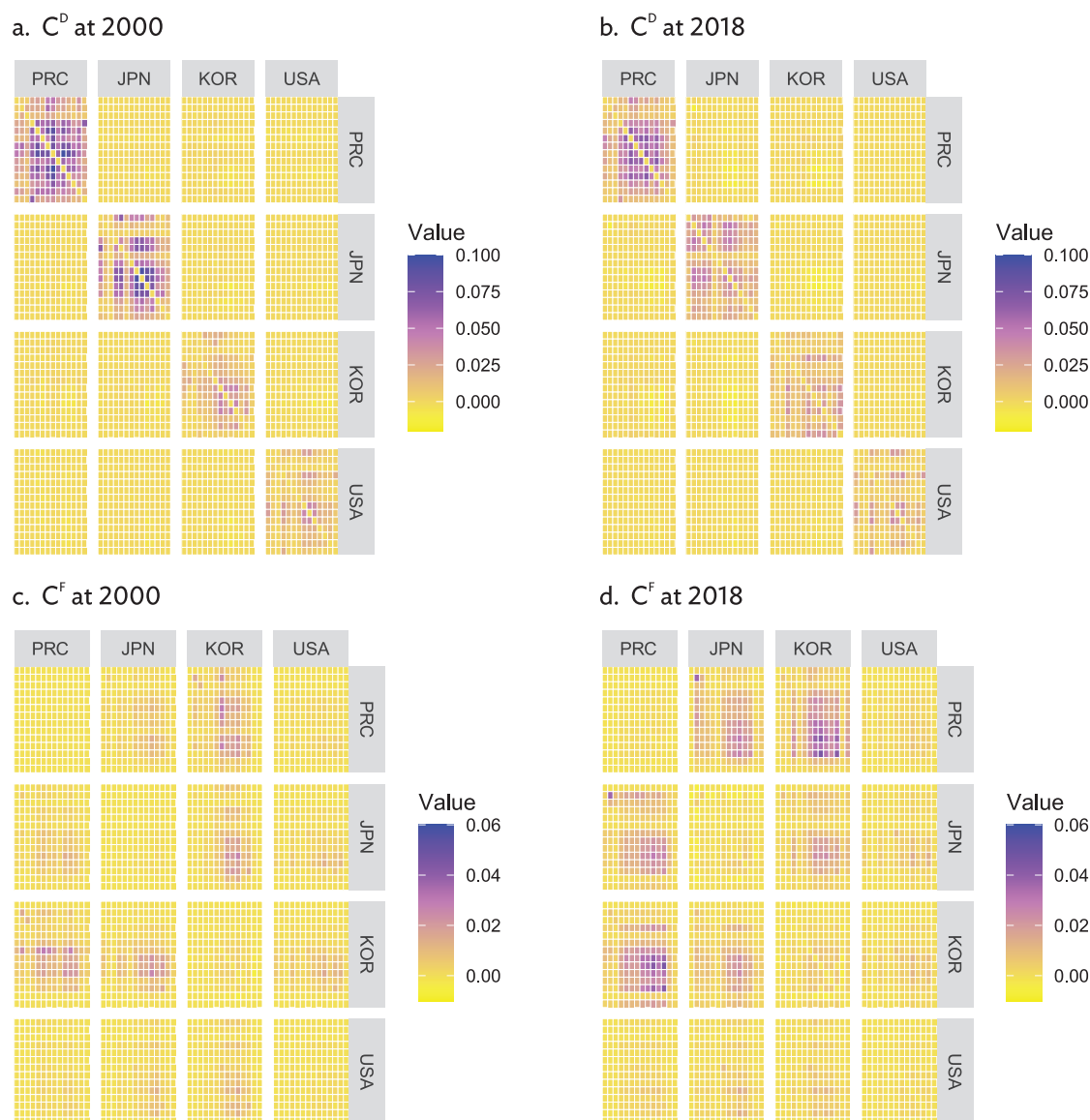
Notes: Standard errors in parentheses and are robust to heteroskedasticity. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Source: Authors' estimates.

We observe a decreasing trend of the positive relation between both the domestic and cross-border intensity of trade credit usage and correlations. First, while the coefficients of C_{ik}^{Dmo} and C_{ik}^{Fmo} remain significant and positive, the coefficient of C_{ik}^{Dmo} changes from 12.12, to 11.54, to 7.842, to 5.883 and the coefficient of C_{ik}^{Fmo} changes from 8.477, 5.015, 3.696, to 2.880 from 2000 to 2018. This decreasing trend suggests that the trade linkage intensity is gradually reducing its impact on sectoral correlations, regardless of the domestic or cross-border ones. We note that a similar pattern can be observed when we compute sectoral correlation based on the prior 10 years of data (see Table A11 for the results), except that using only 10 years of data, correlations tend to respond to a sudden change of pattern. Nonetheless, we still have a roughly decreasing trend, with a dip in 2013.

One plausible explanation is that the booming global trade credit linkages provide a risk diversification mechanism. We provide heatmaps of C_{ik}^{Dmo} and C_{ik}^{Fmo} for four economies: the People's Republic of China, Japan, the Republic of Korea, and the US at years 2000 and 2018 in Figure 1. By comparing Figures 1(a) and 1(b), we observe that the intensity of the domestic use of trade credit declined during these 18 years; the diagonal values are colored by the intensity of the use of trade credit, and a more purple color refers to a higher intensity. On the other hand, by comparing Figures 1(c) and 1(d), we observe that the intensity of the cross-border use of trade credit increases during these 18 years; the off-diagonal values are colored by the intensity of the use of trade credit, and a more purple color refers to a higher intensity. From 2000 to 2018, production processes have been dissected into smaller and smaller, yet more and more specialized steps, thereby enabling international trades that are searching for cheap and high quality production sites/suppliers. As a result, trade credit linkages naturally have been diversified among different industries and/or different economies. With a more diversified credit linkage, the impact of certain shocks occurring in an industry thus plays a less important role, regardless of whether this trade credit linkage happens domestically or abroad.

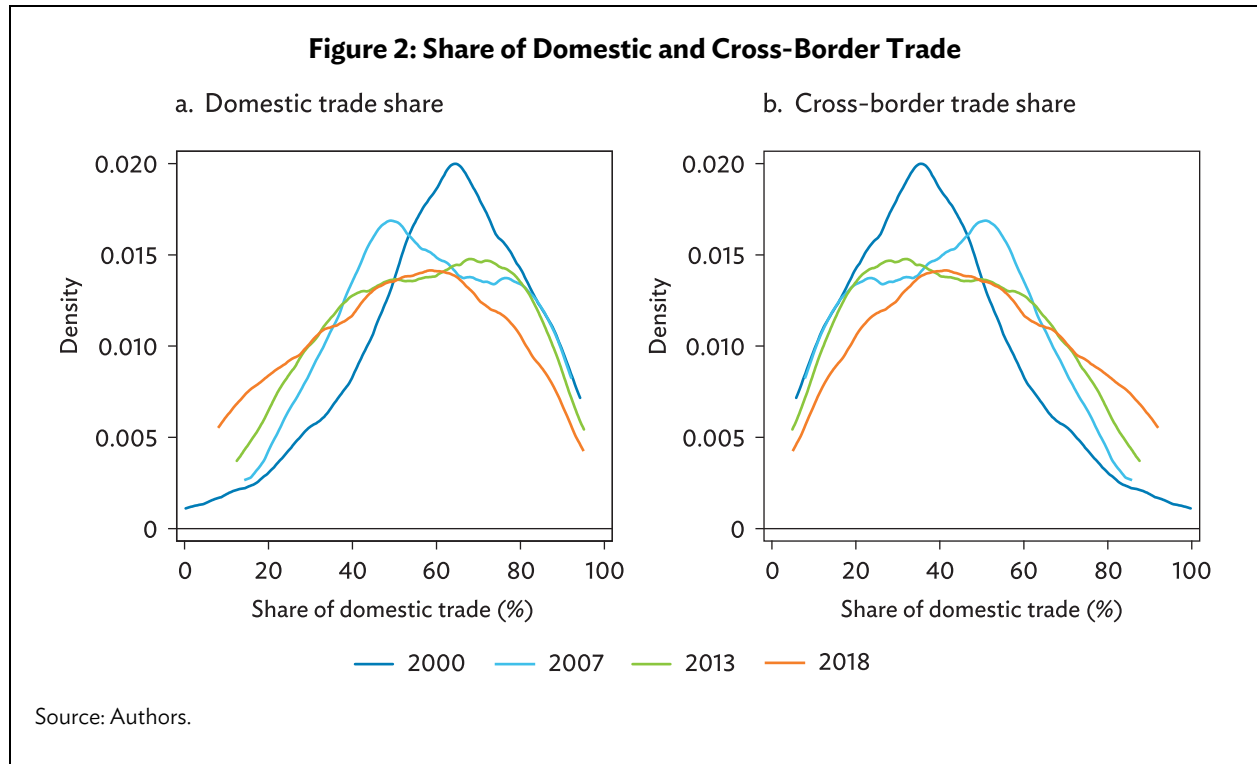
We further support our argument using the domestic and cross-border trade share changes. See Figure 2 for the two plots as well as Table 5 for the summary statistics for the domestic trade share.

Figure 1: Heatmaps: C^D and C^F at 2000 and 2018, Time Window, Previous 20 Years

JPN = Japan, KOR = Republic of Korea, PRC = People's Republic of China, USA = United States.

Source: Authors.

We find that in Figure 2(a), the domestic trade shares are shifting to the left when time increases, whereas in Figure 2(b), the cross-border trade shares are shifting to the right. A similar pattern can also be found in Table 5, in which the mean and the three percentiles are both decreasing throughout time. We note that although United Nations Conference on Trade and Development's World Investment Report (UNCTAD 2020) finds that the level of the globalization of production continued to increase until 2010, then stagnated after that, our results on the share distributions on domestic and cross-border trades are still in a state of change over time (at least, fine-tuning the distribution of trades), even after 2010. This comparison also highlights the contribution of our analysis; while global trading volume has reached a steady state, the distribution has not, leading to a still-changing magnitude of sectoral comovement.

**Table 5: Summary Statistics of Domestic Trade Share**

	2000	2007	2013	2018
Mean	61.7	58.4	56.8	51.8
SD	21.1	20.4	21.6	23.7
25th percentile	51.1	44.9	38.9	34.9
50th percentile	63.9	55.5	56.0	50.5
75th percentile	76.5	76.5	74.6	71.6

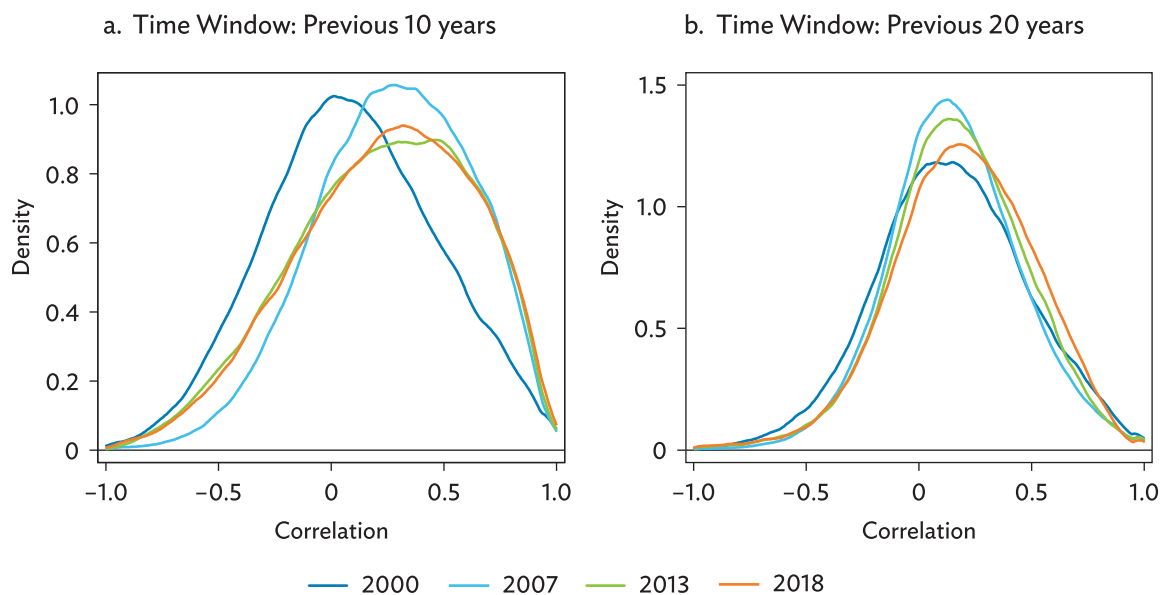
SD = standard deviation.

Source: Authors' estimates.

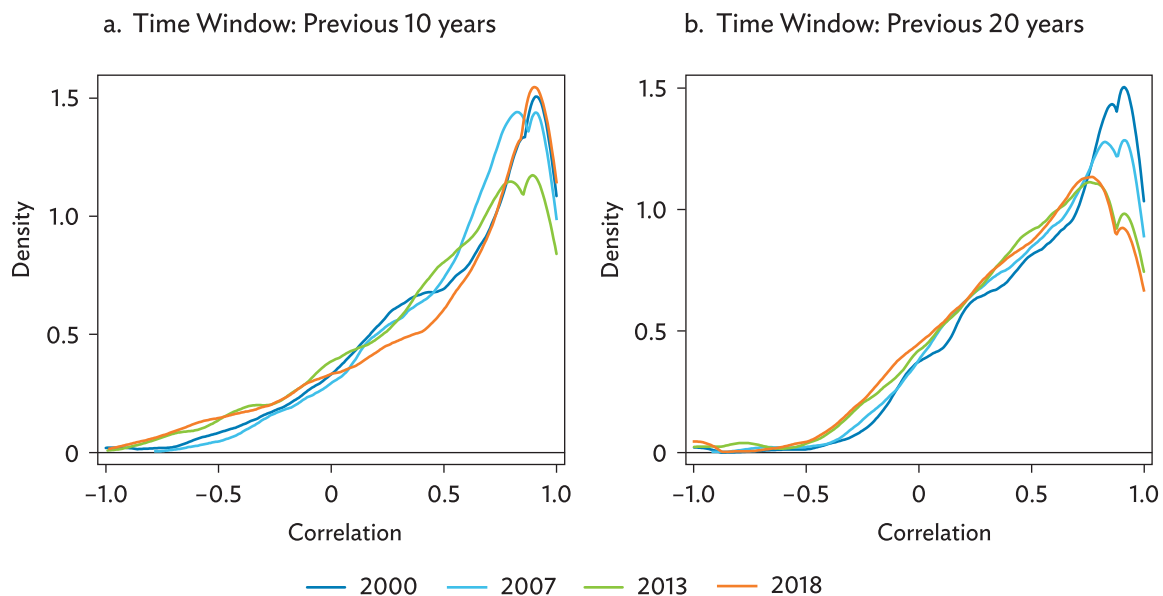
Another plausible explanation for the decreasing could be that global economies are gradually reducing their sectoral correlation by means of decoupling risks (e.g., better use of inventory management to buffer against uncertainties and shocks). To rule out this alternative, we plot overall correlations, the domestic correlations, and cross-border correlations in Figures 3–5, respectively, for a time window of the prior 10 years (a)¹⁸ and a time window of the prior 20 years (b). We also provide the summary statistics of these figures in Table 6.

Both the figures and the summary statistics reveal that comparing 2000 with 2018, while the overall correlation increases from 0.144 to 0.198, the domestic correlation decreases from 0.574 to 0.476 (use 20 years as our time window), whereas the cross-border correlation increases from 0.132 to 0.193.

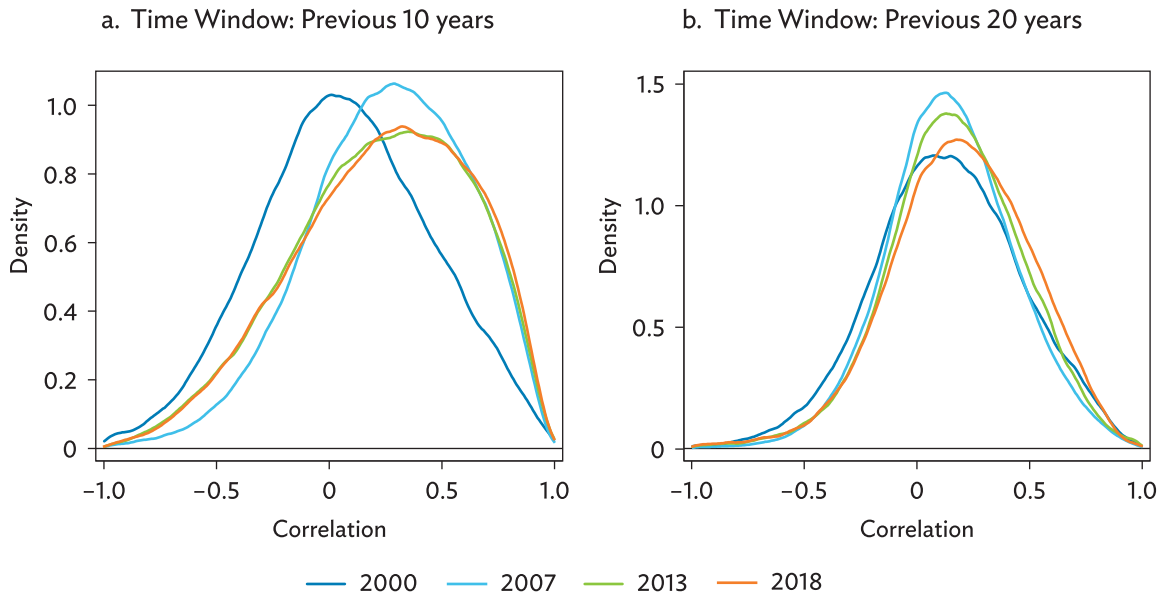
¹⁸ As we previously mentioned, we can see that by using a 20-year time window, the density of correlations tends to be more consistent throughout these 20 years, supporting our use of 20 years in our main specification and the reason the results in Table A11 tends to be volatile for the four time points.

Figure 3: Density of Overall Correlations

Source: Authors' estimates.

Figure 4: Density of Domestic Correlations

Source: Authors' estimates.

Figure 5: Density of Cross-Border Correlations

Source: Authors' estimates.

Table 6: Summary Statistics of Correlation

	Time Window: 10 Years				Time Window: 20 Years			
	2000	2007	2013	2018	2000	2007	2013	2018
Overall Correlation								
Mean	0.081	0.268	0.23	0.241	0.144	0.157	0.175	0.198
SD	0.388	0.354	0.392	0.395	0.334	0.291	0.304	0.316
Domestic Correlation								
Mean	0.521	0.565	0.462	0.515	0.574	0.547	0.491	0.476
SD	0.431	0.369	0.429	0.437	0.352	0.352	0.384	0.388
Cross-Border Correlation								
Mean	0.069	0.26	0.225	0.235	0.132	0.148	0.169	0.193
SD	0.379	0.35	0.39	0.392	0.326	0.283	0.299	0.312

SD = standard deviation.

Source: Authors' estimates.

The decline in domestic sector correlation of the US is also documented by Irvine and Schuh (2005), who compare US sector correlations during 1967–1983 and 1984–2001. The increasing trend of the cross-border correlation may be a result of many factors, such as that cross-border information barriers were lifted from 2000 to 2018. The number changes again, supporting our previous explanation about the diversification resulting from a more dissected value chain structure. Moreover, in our regression specification, we used the overall correlation as our dependent variable. Therefore, the increasing overall correlation helps rule out the explanation that the decreasing trend in the intensity of the use of trade credit increases correlation is a result of decreasing correlations.

Next, we examine another plausible explanation that the decreasing trend is a result of global trends of reducing need for payables financing. In this case, even though the intensity heatmaps show more diversified trade credit linkages, as the overall trend to relying less on payables financing, shocks are less likely to propagate via the channel of value chains. To reject this explanation, we provide summary statistics of the economy-level payables financing P^n (which is the median of the representative ratios of publicly listed firms in economy n) in Table 7. As suggested from the summary statistics, we find that economy-level payables financing is increasing, including the mean as well as the 25th and 75th percentiles, suggesting that firms are relying more on payables as one way of managing their cash flow, instead of reducing their reliance on payables.

Table 7: Summary Statistics of Economy-Level Payables Financing P^n

	Time Window: 10 Years				Time Window: 20 Years			
	2000	2007	2013	2018	2000	2007	2013	2018
Mean	0.131	0.145	0.148	0.163	0.122	0.139	0.144	0.154
SD	0.053	0.047	0.052	0.056	0.048	0.043	0.05	0.052
25 th	0.103	0.115	0.111	0.13	0.091	0.111	0.112	0.121
75 th	0.153	0.166	0.165	0.185	0.141	0.162	0.158	0.18
No. of economies	38	41	53	53	38	41	53	53

SD = standard deviation.

Source: Authors' estimates.

A related explanation is that, although the overall economy-level increases trade credit usage, such an increasing trend only exists within the same industry, because firms in the same industry have better understanding of their peers and hence, higher confidence and trust in trade credit. In this case, the sector-level trade credit rate, P_j then should decrease, and such a reduction of trade credit rates drives our result. We report the sector-level trade credit ratio in Table 8. Again, while some industries reduce their trade credit ratios, a good number of the sectors also rely more on trade credit, and even for the reducing ones, the difference is not high.

Table 8: Sector-Level Trade Credit Ratio P_j , Time Window: Previous 20 Years

Industry	2000	2007	2013	2018
3 (Food, beverages, and tobacco)	0.807	0.795	0.793	0.84
4 (Textiles and textile products)	0.797	0.747	0.752	0.728
5 (Leather, leather, and footwear)	0.656	0.715	0.729	0.704
6 (Wood, products of wood and cork)	0.647	0.627	0.584	0.601
7 (Paper, printing, and publishing)	0.902	0.838	0.803	0.786
8 (Coke, refined petroleum, and nuclear fuel)	0.991	0.896	0.709	0.647
9 (Chemicals and chemical products)	1.154	1.101	1.021	0.986
10 (Rubber and plastics)	0.928	0.887	0.849	0.855
11 (Other non-metallic mineral)	0.786	0.803	0.846	0.866
12 (Basic metals and fabricated metal)	0.86	0.854	0.842	0.815
13 (Machinery, nec)	1.156	1.129	1.152	1.144
14 (Electrical and optical equipment)	1.126	1.144	1.159	1.191
15 (Transport equipment)	0.874	0.875	0.910	0.996
16 (Manufacturing, NEC; recycling)	0.872	0.915	0.937	0.985

nec = not elsewhere classified.

Source: Authors' estimates.

Our final plausible explanation related to the trade credit ratio is that in our analysis for 2000 and 2018, we used different P matrices, and the decreasing result is due to the fundamental differences of this different timeline in approximating the use of trade credit. While the timeline is consistent in each of the regressions, we again perform another set of regression models based on the combination of MRIO table (either 2000 or 2018) and the growth rate of real value added (either between 1980 and 2000 or between 1998 and 2018) and the trade credit data (either from 1980 to 2000 or from 1998 to 2018). We make the first two consistent to reduce the number of combinations, and report the four combinations in Table 9. We then can compare the case MRIO(2018) with $P(2018)$ against MRIO(2000) with $P(2018)$ or MRIO(2018) with $P(2000)$ against MRIO(2000) with $P(2000)$. Although the magnitude slightly changes, the trend toward decreasing is consistent.

Table 9: Combination of MRIO Table and Trade Credit Across Times

	MRIO(2018) P(2018)	MRIO(2018) P(2000)	MRIO(2000) P(2000)	MRIO(2000) P(2018)
G_{ik}^{mo}	0.754*** (0.0150)	0.784*** (0.0169)	0.862*** (0.0184)	0.843*** (0.0154)
C_{ik}^{Dmo}	5.122*** (0.509)	4.858*** (0.625)	12.12*** (1.175)	10.89*** (0.922)
C_{ik}^{Fmo}	3.218*** (0.546)	2.798*** (0.696)	8.477*** (1.258)	6.700*** (1.045)
Constant	0.191*** (0.00118)	0.193*** (0.00118)	0.123*** (0.00146)	0.122*** (0.00163)
(m, i) FE	yes	yes	yes	yes
(o, k) FE	yes	yes	yes	yes
Observations	262,563	262,563	269,673	269,673
R^2	0.452	0.451	0.347	0.348
Within R^2	0.049	0.047	0.058	0.059

FE = fixed effects.

Notes: Standard errors in parentheses and are robust to heteroskedasticity. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Source: Authors' estimates.

D. Trade Credit Financing versus Bank Credit Financing

In this section, we compare trade credit and the bank financing, and examine how they influence sectoral comovement. To do that, we follow a similar procedure in Section 3 to construct the credit linkage variables (domestic and cross-border components) of bank credit financing by replacing accounts payable by short-term debt, and denote them as C_{ik}^{Dmo} (debt to COGS) and C_{ik}^{Fmo} (debt to COGS), respectively. Also to better explain the relative dependence of these two sources of financing, we construct the related variables using the debt to payables ratios, and annotate them with debt to payables. Finally, with the newly constructed variables, we repeat our analysis and show the results in Table 10.

Table 10: Regression Table with Short-Term Debt, 2018, Previous 20 Years

	(1)	(2)	(3)	(4)	(5)
	ρ_{ik}^{mo}	ρ_{ik}^{mo}	ρ_{ik}^{mo}	ρ_{ik}^{mo}	ρ_{ik}^{mo}
G_{ik}^{mo}	0.785*** (0.0136)	0.851*** (0.0174)	0.787*** (0.0137)	0.871*** (0.0186)	0.784*** (0.0135)
C_{ik}^{Dmo} (payables to COGS)	5.681*** (0.709)		5.656*** (0.934)		5.235*** (0.777)
C_{ik}^{Fmo} (payables to COGS)	2.678*** (0.491)		3.447*** (0.697)		2.914*** (0.566)
C_{ik}^{Dmo} (debt to COGS)		-1.370*** (0.358)	-0.00124 (0.397)		
C_{ik}^{Fmo} (debt to COGS)		-0.386* (0.183)	0.465* (0.225)		
C_{ik}^{Dmo} (debt to payables)				-0.115** (0.0379)	-0.0365 (0.0292)
C_{ik}^{Fmo} (debt to payables)				-0.0126 (0.0155)	0.0231 (0.0141)
Constant	0.187*** (0.000813)	0.188*** (0.000650)	0.187*** (0.000791)	0.189*** (0.000513)	0.187*** (0.000787)
Economy-industry pair (m, i) FE	yes	yes	yes	yes	yes
Economy-industry pair (o, k) FE	yes	yes	yes	yes	yes
Observations	511,589	511,589	511,589	511,589	511,589
R^2	0.427	0.427	0.427	0.427	0.427
Within R^2	0.031	0.0295	0.0307	0.0293	0.0307

COGS = cost of goods sold, FE = fixed effects.

Notes: Standard errors in parentheses and are robust to heteroskedasticity. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

We compute G_{ik}^{mo} directly from the MRIO table, while Raddatz (2010) assumed that IO linkages in the US can be extrapolated to the rest of the economies, therefore, the effect of bank credit in our model might be different from that of the U.S.

Source: Authors' estimates.

Model 1 in Table 10 serves as a benchmark as it includes the standard constructs in equation (26). Model 2 replaces the main explanatory variables of credit linkage constructed using payables by those using short-term debt, whereas model 3 include both. Similarly, models 4 and 5 are the regression results with debt-to-payable related variables, without and with the controls of payables to COGS variables, respectively. We observe that without controlling for the payables financing, relying more on domestic bank credit (either considering the ratio to cost of goods sold or to payables) may seem to lead to a sizable reduction on sectoral correlations, whereas more on cross-border bank credit may have reduce sectoral correlation though the effect is much minor. However, after we control for the trade credit linkage variables, the effect of bank credit linkages disappears.

While the results above suggest that bank credit financing does not help mitigate shock propagation, we suspect that this result could be due to the geographic differences. To examine whether the bank credit linkages have differential impacts for economies in Asia where the economic activities are more export-oriented and the banking industry is less mature, we consider three dummy variables for the domestic and cross-border linkage for the bank credit linkage variables. For the domestic credit linkage, we differentiate whether this domestic link happens within an Asian economy

or not by considering an interaction term between C_{ik}^{Dmo} with a dummy variable, $Asia = 1$ if m and o are both in Asia, and $Asia = 0$, otherwise. For the cross-border linkage, we include two interactions terms, $C_{ik}^{Fmo} \times \text{Either from Asia}$ and $C_{ik}^{Fmo} \times \text{Both from Asia}$, in which the former refers to the case where m (exclusive) or o are in Asia, and the latter refers to the case where both m and o are in Asia. All C_{ik}^{Dmo} and C_{ik}^{Fmo} variable, if not noted, are based on the corresponding debt-related variables.

We report the results in Table 11. Models 1 to 3 refer to the result with the debt-to-COGS related variable without Asia related interaction terms, with Asia interaction terms, and finally with additional controls of payables-to-COGS related variables. Models 4 to 6 follow a similar order, except that we do so for debt-to-payables related variables. We observe two interesting results. First, when trading within Asia economies, regardless of domestic trades within an Asia economy or cross-border trades among Asia economies, relying more on bank credit than trade credit may help mitigate shock propagation, as the coefficients of $C_{ik}^{Dmo} \times Asia$ and $C_{ik}^{Fmo} \times \text{Both from Asia}$ in Models 5 and 6 are both negative and significant. Second, using more bank credit mitigates shock propagation for domestic trades in Asia, as the coefficients of $C_{ik}^{Dmo} \times Asia$ are negative and significant in models 2 and 3.

Table 11: Regression Table with Short-Term Debt and Asia Interactions, 2018, Previous 20 Years

	(1) ρ_{ik}^{mo}	(2) ρ_{ik}^{mo}	(3) ρ_{ik}^{mo}	(4) ρ_{ik}^{mo}	(5) ρ_{ik}^{mo}	(6) ρ_{ik}^{mo}
G_{ik}^{mo}	0.851*** (0.0174)	0.825*** (0.0164)	0.780*** (0.0131)	0.871*** (0.0186)	0.832*** (0.0176)	0.776*** (0.0129)
C_{ik}^{Dmo} (payables to COGS)			4.879*** (0.930)			4.391*** (0.794)
C_{ik}^{Fmo} (payables to COGS)			2.319** (0.722)			1.801** (0.616)
C_{ik}^{Dmo} (debt to COGS)	-1.370*** (0.358)	-0.769* (0.350)	0.322 (0.373)			
C_{ik}^{Fmo} (debt to COGS)	-0.386* (0.183)	-0.357 (0.215)	0.0581 (0.254)			
C_{ik}^{Dmo} (debt to payables)				-0.115** (0.0379)	-0.0564* (0.0270)	-0.000873 (0.0215)
C_{ik}^{Fmo} (debt to payables)				-0.0126 (0.0155)	-0.00503 (0.0175)	0.00605 (0.0182)
$C_{ik}^{Dmo} \times Asia$		-1.914*** (0.551)	-1.423** (0.531)		-0.290*** (0.0654)	-0.212*** (0.0637)
$C_{ik}^{Fmo} \times \text{Either from Asia}$		1.703** (0.568)	1.643** (0.558)		0.0359 (0.0493)	0.0292 (0.0476)
$C_{ik}^{Fmo} \times \text{Both from Asia}$		-1.844** (0.699)	-1.341 (0.733)		-0.508*** (0.0997)	-0.460*** (0.0991)
Constant	0.188*** (0.000650)	0.189*** (0.000526)	0.188*** (0.000761)	0.189*** (0.000513)	0.189*** (0.000429)	0.187*** (0.000778)
Economy-industry pair (m, i) FE	yes	yes	yes	yes	yes	yes
Economy-industry pair (o, k) FE	yes	yes	yes	yes	yes	yes

continued on next page

Table 11 *continued*

	(1)	(2)	(3)	(4)	(5)	(6)
	ρ_{ik}^{mo}	ρ_{ik}^{mo}	ρ_{ik}^{mo}	ρ_{ik}^{mo}	ρ_{ik}^{mo}	ρ_{ik}^{mo}
Observations	511,589	511,589	511,589	511,589	511,589	511,589
R^2	0.427	0.427	0.428	0.427	0.428	0.428
Within R^2	0.0295	0.0309	0.032	0.0293	0.0312	0.032

COGS = cost of goods sold, FE = fixed effects.

Notes: Standard errors in parentheses and are robust to heteroskedasticity. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Source: Authors' estimates.

V. POLICY IMPLICATIONS AND CONCLUSIONS

Trade credit is a widely used source of short-term external financing, and it connects buyers and sellers within a supply chain. In this paper, we develop a framework that captures the impact of the credit chain on domestic and international trade separately. Leveraging the ADB Multi-Regional Input-Output Table, we assemble a dataset including 14 manufacturing industries and 53 economies. We find that the use of trade credit indeed enhances sectoral comovement, and the intensity of this impact is twice as strong for within-economy transactions as for international ones. We further find that over the last two decades, this intensity in general declined. Our final comparison on the use of trade credit and bank credit offers insights around the geographic use of the two financing tools.

Our work offers the following policy implications. First, similar to Raddatz (2010), trade credit linkage is indeed an effective channel for shocks to propagation via value chains. Our work extends Raddatz (2010) to differentiate domestic and cross-border trades as two different channels for shock propagation, though the domestic channel has a stronger impact than the cross-border one. In this case, supply chain finance programs that allow upstream suppliers to receive cash before trade credit maturity could be a valuable instrument that helps decompose such correlation, and possibly lowers systemic risk.

Our results also imply that in the past two decades, the influence of these two channels on sectoral comovements both declined, possibly due to a higher level of risk diversification. Combining these results, governments can encourage diversifying cross-border trades among firms in the manufacturing industries. Second, our final comparison between the use of trade credit and bank credit also suggests the need for credit redistribution from financial institutions to the manufacturing sector in Asia to reduce the degree of shock propagation.

This research can be extended in different directions. First, no existing theory rationalizes the difference of credit chain impacts between domestic and international trade. Further development in this direction could be promising. Second, as in Raddatz (2010), our results are not based on causal identifications. When adopting exogenous shocks for identifications, one could potentially identify how different types of shocks (e.g., extreme weather, financial crisis, global pandemic) are propagated differently through both physical and credit channels. Further study using a specific shock on certain sector/geographic regions could be explored. Finally, due to data limitations, this work focuses mainly on financial variables, such as payables and bank credit. Should reliable data become available, we could examine the impact of other factors, such as inventory, on sectoral comovement.

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Credit Chain and Sectoral Comovement: A Multi-Region Investigation

Global supply chains become increasingly interconnected via financial linkages such as trade credit, thereby resulting in comovement across different sectors and regions. This paper empirically examines the impact of trade credit usage on comovement between sectors within each economy and across economies separately. It finds that trade credit linkage is an influential channel for both domestic and cross-border shocks to propagate and create a more profound impact on industries around the globe. It also shows that the impact of the domestic credit chains on sectoral comovement is twice as strong as that of the international ones.

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