ISSN 1833-4474

Trade Credit and Sectoral Comovement during the Great Recession*

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Version: November, 2020

Keywords: C67, E23, E32, E44, E51, F40, G30

JEL Classification: Sectoral Comovement, Production Network, Trade Credit, Financial Friction

* This paper is a modified version of Gang Zhang's Job Market Paper 2018 titled "Sectoral Comovement During the Great Recession." We thank Eric van Wincoop and Eric Young, for enormous support. We also thank Zach Bethune, Huixin Bi, Brent Bundick, Taeyoung Doh, Huberto Ennis, Leland Farmer, Andrew Foerster, Ana Fostel, Pete Klenow, Jae Won Lee, Wei Li, Toshihiko Mukoyama, Dan Murphy, Jose Mustredel- Rio, Jun Nie, Sophie Osotimehin, Latchezar Popov, Alessandro Rebucci, Ariell Reshef, Pierre Sarte, Nicholas Sly, Lee Smith, YijiangWang, KieranWalsh, Chenggang Xu, Leslie Young,Willem van Zandweghe, Tao Zha for helpful discussion and comments. Zhang gratefully acknowledges financial support from the Bankard Fund for Political Economy.

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Trade Credit and Sectoral Comovement during the Great Recession*

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November 13, 2020

Abstract

We show that, unlike any other recession after World War II, sectoral output comovement significantly increased during the Great Recession. On the other hand, trade credit supply, as measured by the ratio of account receivables to the total value of outputs, collapsed during the Great Recession. We show that sectoral comovement was larger for sectors connected through trade credit. We then develop a multisector model with occasionally binding credit constraints and endogenous supply of trade credit to explain these facts. The model shows that equilibrium trade credit reflects both the intermediate supplier's and client's bank lending conditions, and thus has asymmetric effects on sectoral outputs. When banking shocks are idiosyncratic, trade credit serves as a mitigation mechanism as firms are able to substitute bank loans for trade credit. However, when banking shocks are strongly correlated, trade credit amplifies the negative financial shock and generates the sharp increase in sectoral comovement observed during the Great Recession. We show that production network models with reduced form wedges are unable to generate this pattern, and that a model with endogenous trade credit amplifies the Great Recession in 18%.

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1 Introduction

At the business cycle frequency, output of different sectors strongly comove. Two common explanations are aggregate shocks and sectoral shocks propagated and amplified through input-output linkages (e.g., see Long and Plosser (1983), Horvath (1998), Acemoglu et al. (2012), Hornstein and Praschnik (1997), Shea (2002), and Foerster et al. (2011)). In this paper, we claim that trade credit—deferred payments for intermediate inputs—is an important endogenous channel that increases sectoral comovement, as measured by the pairwise correlation of output growth between two sectors, during the Great Recession, even after controlling for input-output linkages and the aggregate banking shock.

We first show, using quarterly data for 44 sectors, that the distribution of pairwise correlations between sectoral output growth shifted significantly to the right during the recession and reverted to the pre–recession level in 2010.[1] Moreover, the rise in sectoral comovement is not a common feature for US recessions. With a subset of the quarterly data, we find that the distributions barely shifted in the 1990 or 2001 recessions. Using the annual data, we confirm the significant shift during the Great Recession, but we do not observe a similar shift during any other recession after World War II. Notably, the distribution shifted only slightly in the 1980 recession, even though it is comparable to the Great Recession in terms of the GDP drop.[2]

Second, the intensity of trade credit provision (reception), defined as the ratio of account receivables (payables) to sales (operation cost plus the change in inventory), collapsed during the Great Recession (10% decline) but not for the other recessions. We then show that during the Great Recession, sectoral comovement increased more (0.19 on average) in pairs of sectors that experienced a decline in trade credit larger than the cross sectoral median. This result remains the same after controlling for the trading flows in intermediate inputs, the bank lending shocks proposed by Chodorow-Reich (2014), and the sectoral characteristics. These facts together imply that trade credit has asymmetric effects and can largely amplify severe financial crisis.

To uncover the mechanism and reconcile these three facts, we develop a multisector model with an endogenous trade credit structure. In the model, firms are connected with

[1] In a contemporaneous work, Li and Martin (2017) document a similar fact. Our approach differs from theirs in two ways. First, we calculate the correlation over eight quarters, while they use annual data from 2007 to 2009. They find higher correlations on average. Second, we incorporate detailed manufacturing sectors, while they only use durable and nondurable manufacturing sectors.

[2] Using EuropStat, we also find that during the Great Recession, major European countries, including Germany, France, and the United Kingdom, experienced a rise in sectoral comovement as in the United States. Moreover, during the European debt crisis era, sectoral comovement in Spain, Italy, and Greece significantly increased, while Germany, France, and the United Kingdom did not experience the similar phenomenon. See Appendix C for more details.

each other via trading in intermediate inputs as well as financially through the trade credit chain. Similar to Bigio and La'O (2017), firms need to finance the advance payments for wages and part of intermediates through competitive banks, which require firms' shareholders to pledge a fraction of their outputs as collateral. This borrowing limit may place financial constraints on firms. To determine trade credit provision, all firms take their clients' responses in account and balance between the sales and loss of default.

In this model, sectoral productivity shocks can only be transmitted to the downstream, whereas bank lending shocks can be propagated to both the upstream and downstream sectors. In particular, due to the Cobb–Douglas form of preference and technology, a negative productivity shock to a sector can be transmitted to upstream sectors as the price of the upstream goods increases. The higher price reduces their clients' demand for intermediates, which further reduces their clients' outputs. Furthermore, a bank lending shock to one sector with a binding financial constraint can make it reduce the trade credit provision to its clients and demand more from its suppliers. Moreover, as in Kiyotaki and Moore (1997), adjusting trade credit has asymmetric effects on outputs in other sectors, contingent on the financial conditions of the suppliers and the clients. For example, if the client has sufficient amount of bank loan, it can use bank loan to replace trade credit. This leaves the client's output intact. Otherwise, the client become more financially constrained, which further distorts its production. In this case, the bank lending shock is transmitted to its clients. Analogously, the suppliers' responses also depends on their own financial conditions.

We calibrate the model to the US economy to examine the role of trade credit in propagating and amplifying shocks. First, we, both theoretically and empirically, show that merely the input-output linkage cannot account for the significant increase in pairwise correlations. Then, we use simulation and consider the case with the endogenous trade credit structure. The result shows that the density of pairwise correlations barely shifts during a recession, which, following the NBER, is defined as the real GDP declining by more than 1.5% for at least three consecutive periods. Even in a recession with GDP that drops 20% more than in the Great Recession, we still cannot observe the significant shift. After restricting to the recessions in which the financial constraints of firms in more than 75% sectors are binding for more than one period, we find the distribution on average shifts significantly during such recessions. Moreover, the pairwise correlations in the two-way trading group increase more on average than the ones in the one-way group. Also, the median intensity of trade credit declines by 8.1% during the recession, and such a decline in trade credit increases the pairwise correlations during the recession. In a counterfactual analysis, we fix the trade credit to the pre–recession level and find that the pairwise correlations decrease and the GDP drops by 2.3% on average instead of

2.8% in the case with the endogenous trade credit. This finding implies that trade credit amplifies shocks by 18%.

Trade credit is widely used in the United States. In 2016, the median ratios of accounts receivables and account payables relative to total assets are 6.6% and 6.0%, respectively, for big corporations with assets more than $250 million, while the ratios are 23.2% and 11.8%, respectively, for small firms with assets under $250 million.[3] Moreover, trade credit is the most important source for short–term finance. Account payables among big corporations in the United States are 8 times as much as a short–term bank loan, 11 times other short–term loans, and 25 times commercial paper; meanwhile, in small firms, account payables are 3 times as much as a short–term bank loan and 15 times other short-term loans. As emphasized in the statement made by Chrysler's CEO in the congressional testimony, no rescue fund 'would put sever pressure in having to pay CBD or cash upfront, and turn the whole financial equation up–side down'.

Our finding accords with the empirical literature that explains that transmission of bad financial shocks through the trade credit chain depends on the financial status of both the supplier and client. On the one hand, firms with high liquid assets or access to bank credit increase their provisions of trade credit, especially when their clients find themselves hard to borrow (e.g., see Garcia-Appendini and Montoriol-Garriga (2013) and Love et al. (2007)). On the other hand, the delinquency or default on trade credit deteriorates suppliers' financial status, which may further lead them to delinquency or default on their own trade credit. Boissay and Gropp (2013) find that firms in France are more likely to default on their trade credit if they are facing default from their clients. Jacobson and von Schedvin (2016) document that in Sweden, annual bankruptcy risks for suppliers increase by 53% if some of their clients file bankruptcy.

This paper contributes to the literature on production network models with endogenous trade credit in Reisher (2020), Altinoglu (2017), Shao (2019), and Luo (2020). The contributions of this paper to aforementioned papers are twofold. First, we develop a model of occasionally binding sectoral constraints that generate an asymmetric effect of trade credit on sectoral comovement, during severe financial crisis. Second, we provide empirical and quantitative evidence that, unlike any other post-war recession in the U.S, the large increase in sectoral comovement in the Great Recession was largely due to the endogenous response of trade credit to the aggregate financial shock.[4]

The remainder of the paper is organized as follows. Section 2 discusses the stylized facts. Section 3 describes the model and analyzes the equilibrium. Section 4 concludes.

[3] Our calculation from the QFR.

[4] This paper also contributes to the literature of production network and distortions in Bigio and La'O (2017), Baqaee and Farhi (2019), Miranda-Pinto and Young (2020). Unlike these papers, our model displays endogenous wedges that depend on financial conditions and trade credit provision.

2 Two Stylized Facts

In this section, we begin by describing how to construct the measurement of sectoral comovement. Then, we provide two stylized facts about the sectoral comovement during the Great Recession. First, sectors significantly comoved during the Great Recession. Second, the level of sectoral comovement is negatively correlated with the change in trade credit, even after controlling for input-output linkages.

2.1 The Measure of Sectoral Comovement

The correlation of real GDP growth between two countries is widely used to study the business cycle comovement across countries; for example, see Frankel and Rose (1998) and Clark and van Wincoop (2001). Here, a similar measure, the pairwise correlation of output growth between two sectors, is applied to study the inter–sector comovement. First, we combine sectoral sales from the Quarterly Financial Report (QFR) with real gross industrial output, provided by the Bureau of Economic Analysis (BEA).[5] In total, the sample contains 44 sectors, covering all private sectors in the United States except Finance, Insurance, and Real Estate (FIRE).[6] Note that sales from the QFR are in the nominal term. To make it consistent with the real gross output provided by BEA, we deflate all series by the industrial price indexes in 2009 dollars and adjust for seasonality using the X—12—ARIMA seasonal adjustment program. Then we take the quarter–to–quarter growth rates of sectoral outputs and calculate the correlation of output growth between any pair of sectors as

$$\mathbf{corr}\left(\Delta y_i, \Delta y_j\right) = \frac{\sum_{t\in\mathcal{T}} \left(\Delta y_{it} - \mathbf{avg}\left(\Delta y_i\right)\right)\left(\Delta y_{jt} - \mathbf{avg}\left(\Delta y_j\right)\right)}{\left(\#\mathcal{T} - 1\right)\mathbf{se}\left(\Delta y_i\right)\ \mathbf{se}\left(\Delta y_j\right)}, \tag{1}$$

where subscripts i and j stand for two sectors, $\mathcal{T}$ is the time window of calculation, Δy_{it} is the quarter-to-quarter growth rate of output for sector i at time t, and **avg** and **se** are respectively the sample mean and standard error of output growth rates over the time window $\mathcal{T}$. Throughout the analysis in the paper, we use eight consecutive quarters for the time window $\mathcal{T}$ unless otherwise stated. Note that given a certain time window, the correlation of pair (i, j) is the same as that of the pair (j, i), and hence, only one of them will be counted in our analysis.

[5]To test the consistence across two data sources, we compare the evolution of output growth rates for non-durable manufacture, durable manufacture, and wholesales sectors from two data sources respectively. The correlations between two sources are respectively 0.85, 0.7, and 0.76 from 2010Q1 to 2016Q4.

[6]Please refer to Table 8 in Appendix A.1 for the full list of sectors and their main characteristics.

2.2 Stylized Fact I

First, we examine the sectoral comovement during the Great Recession. Following Kahle and Stulz (2013), we choose 2007Q3–2009Q2 to cover the recession.[7] To compare, we also calculate the pairwise correlations before and after the recession, with 2005Q3–2007Q2 and 2009Q3–2011Q2 being chosen to respectively represent the periods before and after the recession. Figure 1 displays the kernel densities of 946 pairwise correlations for the three periods.[8] Before the recession, the density is hump-shaped with mean and median around 0.08, as shown in Table 1, and a near zero skewness suggests that it is almost symmetrical. During the recession, the density shifted significantly toward the right. The mean increases by 0.3, implying that the outputs of many sectors dropped together at that time. Moreover, the median rises even more, suggesting that a greater proportion of pairs move together than not. The density returned to the pre-crisis level soon after the recession. To test whether the densities before and after the recession are statistically different from the density during the recession, the Kolmogorov-Smirnov (KS) test is performed.[9] At the 0.1% significance level, the KS test rejects the null hypothesis that the density before (after) the recession is the same as the one during the recession. However, the standard deviation of the kernel density during the recession stays in line with its pre-crisis value. This result suggests that variation of sectoral comovement still exists. In Sections B and 2.3, we conduct several decompositions, based on the characteristics of sectors or pairs of sectors, and find that the trading in intermediates and the change in trade credit between two sectors are correlated with such high sectoral comovement during the Great Recession.

Is the high sectoral comovement a common feature for the US recessions? The answer is no. Because quarterly output data provided by BEA only start at 2005Q1 while all series from the QFR begin at 1987Q4, we use two methods to compare pairwise correlations during the Great Recession with those during other recessions. First, we focus only on manufacturing, wholesale, and retail sectors from the QFR. The sample covers two other recessions, specifically, the 1990 and 2001 recessions. In this case, the number of sectors drops to 20.[10] We adopt the same approach to calculate the pairwise correla-

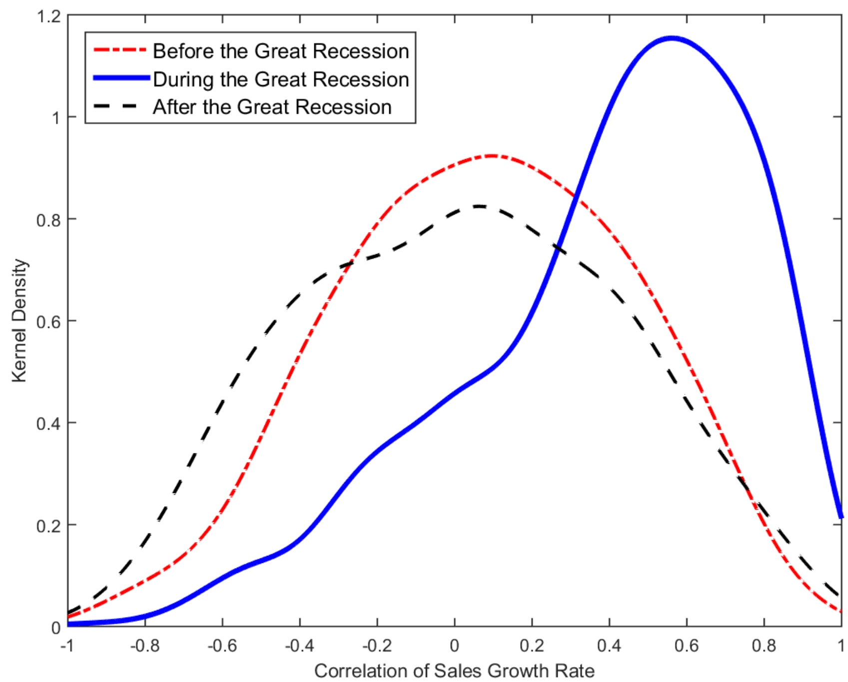
[7] We alter the coverage and length of time windows. All results here are robust.

[8] We also calculate the weighted kernel density using the gross output share as weights. The shift is slightly more apparent.

[9] KS statistics are calculated as $D_{t\tau} = \sqrt{\frac{N_X}{2}} \max_{x\in X} |F_t(x) - F_\tau(x)|$, where t and τ stand for two different periods, N_X is the number of points associated with the kernel density, and $F_t(x)$ is the cumulative density function associated with period t. The critical values of KS statistics at 0.1%, 1%, and 5% significance level are respectively 0.0616, 0.0515 and 0.0430 in this case.

[10] Since 2000Q4, the QFR adds disaggregate information for some sectors. For example, *Electrical and Electronic Equipment* is separately reported as three individual sectors since 2000Q4, namely *Computer and Peripheral Equipment*, *Communications Equipment*, and *All Other Electronic Products*. We use the crosswalk between SIC and NAICS to aggregate the sectors after to the ones before 2000Q4. In this case, the classifi-

Figure 1
Kernel Density for Pairwise Correlations during the Great Recession.



Note: The sectoral sales from the QFR are combined with the industrial gross output value by BEA. 2005Q3–2007Q2, 2007Q3–2009Q2, and 2009Q3–2011Q2, are chosen to represent before, during, and after the Great Recession, respectively. Equation (1) is used to calculate the pairwise correlation. The kernel density is applied to show the smoothed distribution of correlations for 946 pairs in each period. The dashed red, solid blue, and dotted black lines represent the densities before, during, and after the Great Recession, respectively.

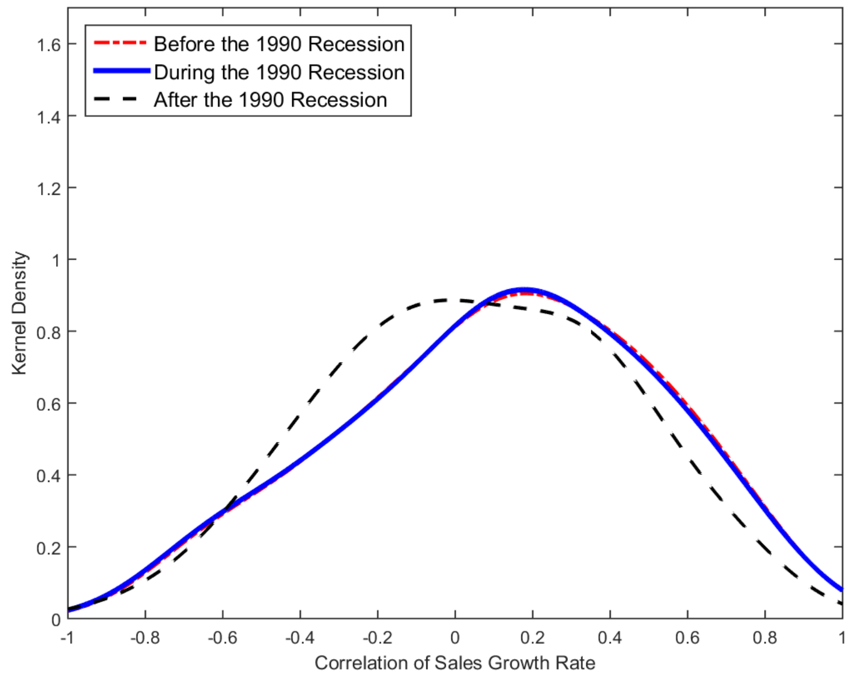
tions.[11] Figure 2 (3) shows the kernel densities of pairwise correlations before, during, and after the 1990 (2001) recession. Unlike the Great Recession, no rise in sectoral comovement is observed in the 1990 or 2001 recessions. Mean and median are unchanged during the 1990 recession and even decrease during the 2001 recession. For both recessions, the KS test cannot reject the null hypothesis that the kernel densities before and during the recession are the same at the 5% significance level. Moreover, the KS test rejects the null hypothesis, at the 0.1% significance level, that the kernel density during the 1990 (2001) recession is akin to the one during the Great Recession.

Second, the BEA provides the real gross outputs of 55 sectors since World War II, but at an annual frequency. We select a sample covering all private sectors except FIRE, and

cation is consistent when we calculate the kernel densities throughout the 2001 recession.

[11] 1989Q1–1990Q4, 1990Q1–1991Q4 and 1992Q1–1993Q4 are chosen to represent the before, during and the after the 1990 recession. 1998Q4–2000Q3, 2000Q4–2002Q3, and 2002Q4–2004Q3 are chosen for the 2001 recession.

Figure 2
Kernel Density for Pairwise Correlations during the 1990 Recession

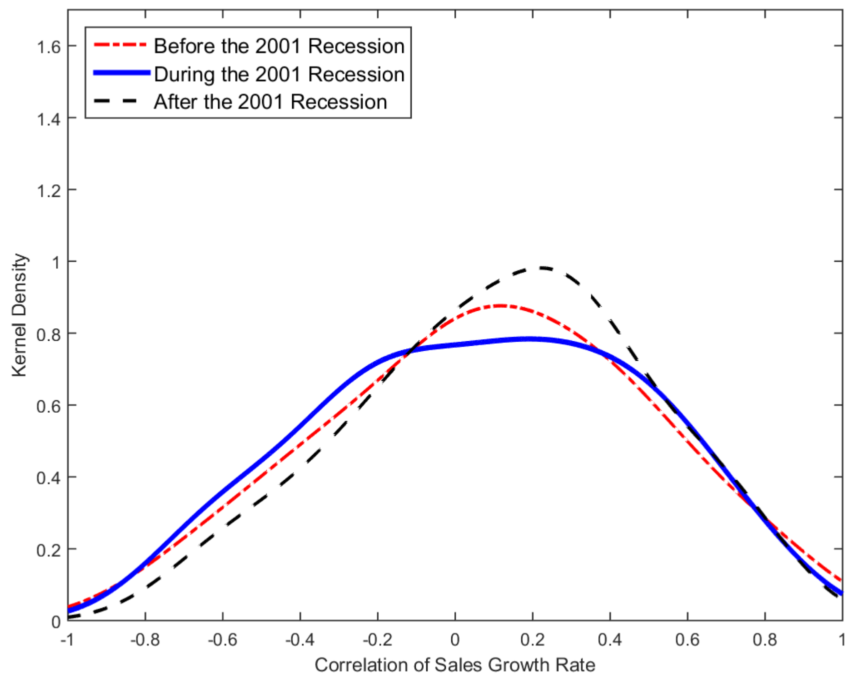


Note: Output data are from the QFR. The pairwise correlations are calculated as in Equation (1). 1989Q1–1990Q4, 1990Q1–1991Q4, and 1992Q1–1993Q4 are chosen to represent before, during. and after the 1990 recession, respectively. The dashed red, solid blue, and dotted black lines represent the densities before, during, and after the 1990 recession, respectively.

six recessions are studied, namely, the 1960, 1970, 1975, 1980, 1990, and Great Recessions. We use the Equation (1) to calculate the pairwise correlations over eight years, starting two years before each recession. Moreover, to compare the pairwise correlations during recessions, we also calculate the ones after the 1980 recession and before the Great Recession.[12] Figure 4 displays the kernel densities for all recessions and the controlling periods. Three observations can be made from this figure. First, the pairwise correlations calculated from the annual data are, in general, higher than the ones using the quarterly data. This result may be because some quarterly fluctuations can be averaged out in the annual data. Second, the density during the Great Recession still shifted significantly toward the right, compared with the one before. This observation is consistent with the one shown in Figure 1. Third, no significant shift is observed during other recessions. For example, the 1980 recession is the only one that is relatively comparable to the Great

[12]The period starting points are respectively 1957, 1967,1972,1978,1988,and 2005 for the 1960, 1970, 1975, 1980, and 2008 recessions, and 1983 for the post–1980 and 2000 for pre–2008 recession.

Figure 3
Kernel Density for Pairwise Correlations during the 2001 Recession



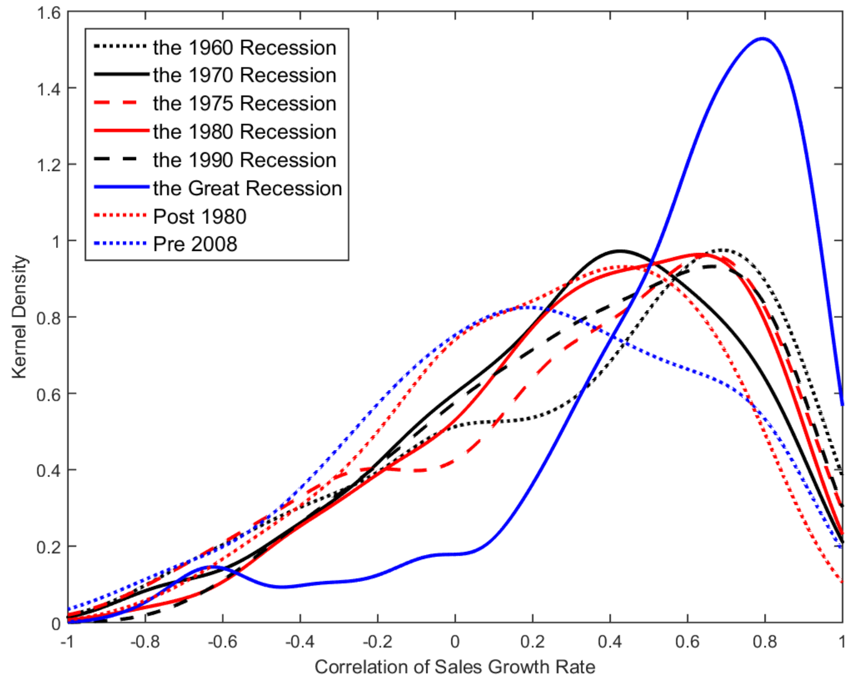
Note: Output data are from the QFR. The pairwise correlations are calculated as in Equation (1). 1998Q4–2000Q3, 2000Q4–2002Q3, and 2002Q4–2004Q3 are chosen to represent before, during, and after the 2001 recession. The dashed red, solid blue, and dotted black lines represent the densities before, during, and after the 2001 recession, respectively.

Recession in terms of GDP drop.[13] Surprisingly, the density during the 1980 recession shifted toward the right only slightly, if at all, compared to the density after the recession.

In Appendix C, we study European countries' sectoral comovement during the Great Recession and the European Debt Crisis. We find that all major countries in Europe, including Germany, France, the United Kingdom, Italy, Spain, and Portugal, experienced similar sectoral comovement as in the United States. This finding provides additional evidence to business cycle synchronization across countries during the 2008 Great Recession as documented in Bacchetta and van Wincoop (2016). Moreover, during the European Debt Crisis, Spain, Italy, and Greece all experienced the high sectoral comovement. However, Germany, France, and the United Kingdom did not have a similar increase in sectoral comovement over the same period. This finding suggests that the financial crisis differs from other recessions and has a significant implication on the sectoral comovement.

[13]According to FRED economic data, in 1982, the U.S. GDP dropped 1.9% with the deepest drop at 6.5% in 1982Q1, whereas GDP contracted 2.7% in 2008 with the largest contraction at 8.2% in 2008Q4.

Figure 4
Kernel Density for Pairwise Correlations across Recessions



Note: Gross output values in annual frequency are provided by the BEA. The pairwise correlations are calculated as in Equation (1). The period starting points are respectively 1967, 1972, 1978, 1988, and 2005 for the 1970, 1975, 1980, 1990, and 2008 recessions, while 1983 for the post–1980 and 2000 for pre–2008 recession.

2.3 Stylized Fact II

In this subsection, we examine how the change in trade credit during the Great Recession is correlated with the sectoral comovement. First, we introduce trade credit and its importance as a vehicle of firms' short-term finance. Second, we show that two sectors that experienced a decline in trade credit during the Great Recession are more correlated on average than two that did not. Third, we show that the increase in correlation remains the same, conditional on the change of intermediate trade flows, the bank lending shocks, and other sectoral characteristics.

2.3.1 The Usage of Trade Credit during the Great Recession

In addition to trading in intermediate inputs, firms simultaneously provide trade credit to their clients and receive the same from their suppliers in the form of deferred payments for goods or services output. Suppliers' claims against clients are recorded as account receivables in suppliers' balance sheets, while liabilities of clients to suppliers are recorded as clients' account payables. Trade credit is ubiquitous in and beyond the US markets.

In 2016, the median ratios of account receivables and account payables relative to total assets are 6.6% and 6.0%, respectively, for big corporations with assets more than $250 million, while the ratios are 23.2% and 11.8%, respectively, for small firms with assets under $250 million.[14] Worldscope, the worldwide surveys conducted by the World Bank, find that firms typically finance about 20% of their working capital with trade credit, and firms in 60% countries use trade credit more than bank credit for short–term financing. Moreover, trade credit is the most important source of short–term finance. In the United States, account payables among big corporations are 8 times as much as a short–term bank loan, 11 times other short–term loans, and 25 times commercial paper, while in small firms, they are 3 times as much as a short-term bank loan and 15 times other short–term loans.

To examine the evolution of trade credit usage, we use the US public firms' data from COMPUSTAT to calculate the intensity of trade credit provision and reception. We take the ratio of account receivables to total value of sales as the intensity of trade credit provision and the ratio of account payables to the sum of total operational costs and change in the inventory as the intensity of trade credit reception.[15] We then adjust for seasonality of two series for each firm and take the median value across firms in each quarter. Figure 5 displays the evolution of two ratios from 1980Q3 to 2016Q3. Both ratios fluctuate modestly over time, even throughout the 1990 and 2001 recession. In the 1980 recession, they increased moderately. During the Great Recession, they went up at the beginning and plummeted by roughly 10% starting in 2008Q3. This pattern indicates that in addition to output, more firms then either requested more downpayment for new intermediate orders or wrote off the existing trade credit. Love et al. (2007) study trade credit usage both in Mexico during the 1994 peso devaluation and in five East Asian countries during the 1997 Asian flu. They also find that the trade credit provision slightly increased at the beginning of the crisis and dropped largely afterward.

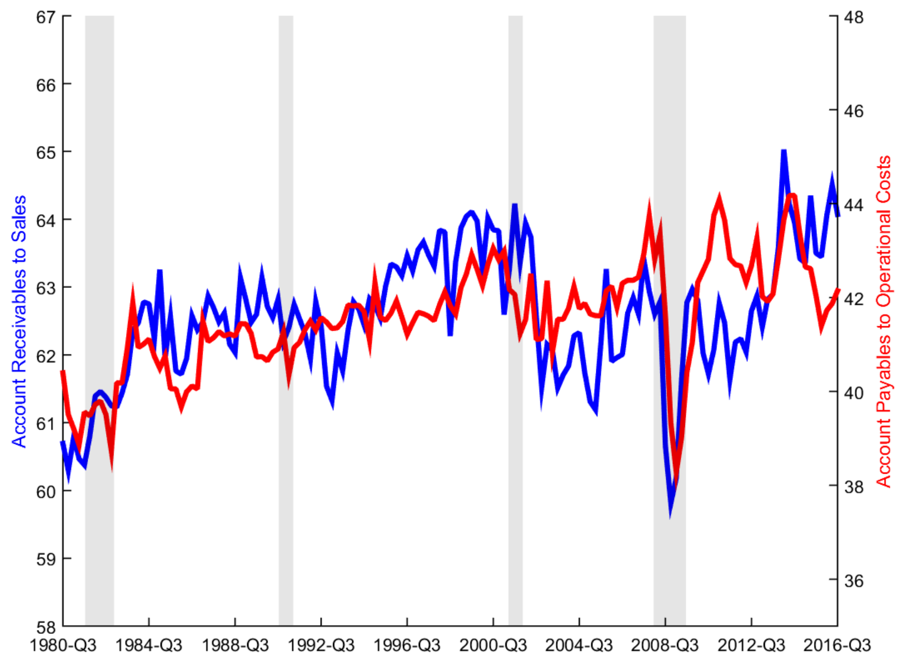
2.3.2 Sectoral Comovement vs the Change in Trade Credit Usage

From here on, we restrict our analysis to manufacturing, wholesale, and retail sectors from the QFR because of data limitation. For each sector, we calculate the quarterly intensities of trade credit provision and reception as in Section 2.3.1 and then adjust for seasonality. For each series, we take the median value over 2005Q3–2007Q2 and over 2008Q3–2009Q2 to respectively represent the intensities of trade credit provision (reception) before and during the recession. Then, we calculate the percentage change over two periods to measure the change in trade credit provision (reception) relative to the

[14]Author's calculation from the QFR.

[15]We select nonfinancial firms, following Kahle and Stulz (2013). See Appendix A.2 for details.

Figure 5
Evolution of Intensities of Trade Credit Provision and Reception



Note: We use the US public firms' data from Compustat to calculate the ratio of account receivables to output as the intensity of trade credit provision and the ratio of account payables to the sum of total operation costs and change in the inventory as the intensity of trade credit reception. Seasonality of both series is adjusted for each firm. The blue and red lines respectively represent the median value of trade credit provision and reception across firms in each period.

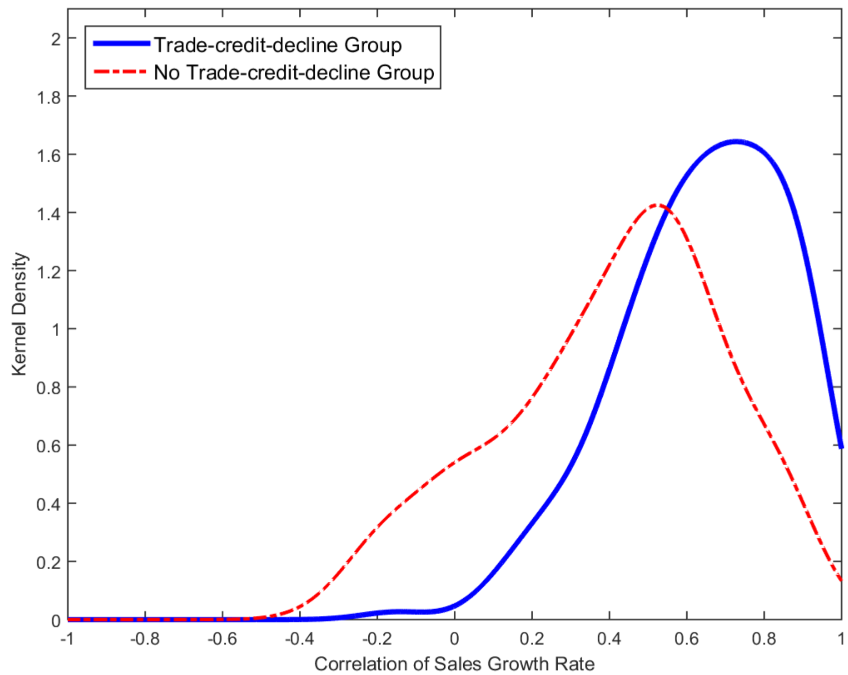
value of sales (operational cost). Note that these measures only estimate the change of gross trade credit provision to all clients of a firm or reception from its suppliers. Therefore, a pair is considered as experiencing trade credit decline during the Great Recession if both the intensity of the upstream sector's trade credit provision and the intensity of the downstream sector's trade credit reception declined by more than the median value.[16] Otherwise, the pair is categorized into the control group. Define

$$\mathbf{D}^{tc} = \mathbf{1}\left(\Delta\frac{AR_i}{S_i} < \Delta^m\frac{AR}{S} \;\; and \;\; \Delta\frac{AP_j}{OC_j} < \Delta^m\frac{AP}{OC}\right), \tag{2}$$

where $\Delta\frac{AR}{S}$ is the percentage change in account receivables relative to output, $\Delta\frac{AP}{OC}$ is the percentage change in account payables relative to the sum of operational costs and change in the inventories, and $\Delta^m\frac{AR}{S}$ and $\Delta^m\frac{AP}{OC}$ are respectively the median values of

[16] 6.3% and 6% are respectively the median drops of the intensity of trade credit provision and reception across sectors.

Figure 6
Kernel Density of Pairwise Correlations, by the Indicator of Decline in Trade Credit



Note: A pair is considered as experiencing trade credit decline during the Great Recession if both the intensity of the upstream sector's trade credit provision declined by more than 6.3% and the intensity of the downstream sector's trade credit reception declined by more than 6%. Otherwise, the pair is categorized into the control group. The blue solid and red dashed lines respectively represent the densities of group experiencing the decline in trade credit and the counterpart.

$\Delta\frac{AR}{S}$ and $\Delta\frac{AP}{OC}$. Figure 6 exhibits the kernel densities of the pairwise correlations during the Great Recession for two groups. The figure shows the relevance of the change in trade credit usage with the sectoral comovement. Specifically, two sectors that experienced a decline in trade credit have an average correlation that is 0.21 higher than two that did not, as Table 2 shows. The similarity of two densities is rejected by the KS test at the 0.1% significance level. In Appendix E, we show that the kernel densities of two groups are more or less the same before and after the Great Recession.

2.3.3 Controlling for input-output linkages and banking shock

The positive correlation between the decline in the intensity of credit trade and the rise in sectoral comovement can be driven by a change in the intermediate trading flows between two sectors or their external borrowing conditions. In particular, outputs in many sectors collapsed during the Great Recession. Such a collapse may sharply reduce demands for their intermediate inputs and further cause outputs of their upstream sector to contract as well. Thus two sectors would move together. Meanwhile, if the intensity of trade credit usage between two sectors responds convexly to the change in trading of intermediates, a drop in the latter can cause the former to shrink more. In this case, both the decline in the intensity of trade credit and the rise in sectoral comovement are caused by the collapse in intermediate trading. Moreover, the literature has documented the credit crunch from banks during the Great Recession; for example, see Ivashina and Scharfsteinb (2010), Brunnermeier (2009), and Shleifer and Vishny (2010). This bank lending shock can generate contractions across various types of firms' activities, including cutting off production and limiting trade credit issuance. In this case, the positive correlation between the decline in credit trade and the increase in sectoral comovement can be caused by the bank lending shocks.

In this subsection, we conduct mean difference tests to study whether the positive correlation observed in Section 2.3.2 still exists, even conditional on intermediate trading flows and bank lending during the Great Recession. Because no comprehensive dataset is available to measure the change in intermediate trading flows between two sectors, we define

$$\Delta TF_{ij} = \gamma_{ij}\, Output\_Share_j\, \Delta y_j, \tag{3}$$

where γ_{ij} is element (i,j) of the inverse Leontief matrix, $Output\_Share_j$ is the output share of sector j over the total economy in 2007, and Δy_j is the percentage change in sector j's output from 2007 to 2008. γ_{ij} incorporates both direct and indirect trading in intermediate inputs from sector i to j.[17] Output shares are used to make the change in output directly comparable across sectors. Thus ΔTF_{ij} measures the percentage change in sector i's output, corresponding to the change in sector j's output through direct and indirect intermediate trading between the two sectors.

For bank lending shock, we adopt the measure proposed by Chodorow-Reich (2014) to assess the difficulty of borrowing from the syndicated loan market during the Great Recession relative to its pre–recession level.[18] First, define $L_{b,-f}$ as the quantity of loans made by bank b to all borrowers except firm f during the Great Recession relative to its pre–recession level as

$$L_{b,-f} = \frac{2\sum_{k\neq f,l}\alpha_{b,k,l,crisis}}{\sum_{k\neq f,l}\alpha_{b,k,l,before}}, \tag{4}$$

where $\alpha_{b,k,l,t}$ is the share of the syndicated loan l from bank b to firm k over period t.[19]

[17]We also consider only including the direct linkage using input–output matrix. All results here are robust.

[18]Note that borrowers in the syndicated loan market can be unlisted or unrated firms. This wide coverage can be helpful in understanding the external borrowing condition, compared to the case in which listed firms are the sole focus

[19]Roughly a third of all loans have shares available among lenders. For the rest, we follow Chodorow-Reich (2014) and Ivashina and Scharfsteinb (2010). First, according to the number of arranger and follower

The 'before' period covers October 2005 through June 2007 except from July to September 2006, while the period of October 2008 through June 2009 are used for 'crisis'. $L_{b,-f}$ measures the difficulty of borrowing from a bank b, in terms of extensive margin, exogenously to a firm f.[20] We define the measure of difficulty of borrowing for each firm as

$$BL\_Shock_f = \sum_{b \in \mathcal{S}_f} \alpha_{b,f,last,before} L_{b,-f},$$

where $\mathcal{S}_f$ is the set of banks lending to firm f and $\alpha_{b,f,last,before}$ is the lending share of the last loan before the Great Recession. Notably, BL_Shock_f is the weighted average of the difficulty of borrowing in the syndicated loan market across all lenders. Last, we take the median value across firms for each sector as the sectoral bank lending shock, denoted as BL_Shock_i.[21]

Next, we divide all pairs into four categories, based on the values of change in their intermediate trading and the bank lending shocks. In particular, a pair is categorized into the group experiencing a large decline in trading flows if trading in intermediate inputs between them is smaller than the median across all pairs. Also, a pair is considered as experiencing severe difficulty in borrowing from banks if both sectors receive a bank lending shock larger than the median.[22] Then, we define

$$\mathbf{D}_{ij}^{tf} = \mathbf{1}\Big(\Delta TF_{ij} < \Delta^m TF\Big), \tag{5}$$

$$\mathbf{D}_{ij}^{bl} = \mathbf{1}\Big(BL\_Shock_i \leq BL\_Shock^m \text{ and } BL\_Shock_j \leq BL\_Shock^m\Big), \tag{6}$$

where $\Delta^m TF$ stands for the median value of ΔTF across all pairs and BL_Shock^m is the median of BL_Shock across all sectors.

lenders, we make them into 16 groups based on population. Then we use the available shares to calculate the average share of arranger and lender in each group and assign the share to each lender accordingly.

[20]We also use the size of loans relative to firms' output instead of the indicator of borrowing. The results here are robust. However, many loans are in the form of the credit line, and the information about withdrawing is not available. Thus using the relative size of loan may underestimate the difficulty of borrowing condition for firms during the Great Recession.

[21]We also use 25 and 75 percentile values. We only find robust results using 25 percentile values.

[22]The median value of TF_{ij} is -8.55×10^{-6}. The median of BL_Shock is 0.55.

Table 3
Increase in Pairwise Correlations

	$\mathbf{D}^{tc}=1$		$\mathbf{D}^{tc}=0$		Diff	
	Obs	Mean of Δ**corr**	Obs	Mean of Δ**corr**	Mean	t-stat
$\mathbf{D}^{tf}=1$ and $\mathbf{D}^{bl}=1$	47	0.66	66	0.43	0.23	3.09
$\mathbf{D}^{tf}=0$ and $\mathbf{D}^{bl}=1$	24	0.56	87	0.32	0.24	2.23
$\mathbf{D}^{tf}=1$ and $\mathbf{D}^{bl}=0$	45	0.56	80	0.51	0.06	0.75
$\mathbf{D}^{tf}=0$ and $\mathbf{D}^{bl}=0$	26	0.53	100	0.29	0.24	2.54

Notes: All kernel densities f are calculated on unit interval $[-1,1]$ with bandwidth 0.001. *p-value* for the KS statistics is reported in the parentheses. The critical values of KS statistics at 0.1%, 1%, and 5% significance level are respectively 0.0616, 0.0515 and 0.0430 in this case.

Within each category, we perform the mean difference test and examine whether two sectors experiencing the trade credit collapse during the Great Recession still have a higher correlation on average. Table 3 reports the statistics from the tests. Several observations can be drawn. First, the pairwise correlation in the trade–credit–decline group increases more than among their counterparts across all categories. Even for the pairs in which both sectors do not significantly contract the intermediate trading or have difficulty borrowing from the banks, their pairwise correlations increase significantly during the recession if the trade credit between them collapse. Surprisingly, the difference of the increase in the fourth category is almost as large as that in the first category, given that only a fifth of them experience collapse in trade credit in the fourth category. Second, the increases are statistically significant except in the third category. Third, the trading in intermediate inputs and the bank lending condition are indeed relevant to the pairwise correlations. Two sectors that experience a large decline in intermediate trading or had severe trouble borrowing from the banks have a higher average correlation than two that do not. Also, they are more likely to experience a decline in trade credit. Moreover, in Appendix 2.4, we conduct a regression to examine how much the increase in pairwise correlations is associated with the indicator of trade–credit–decline. The results show that experiencing the decline in trade credit during Great Recession is associated with an increase of 0.19 in pairwise correlation on average, and the results are robust even after controlling for various of sectoral characteristics. Furthermore, in the online Appendix, we show that the average correlations during the Great Recession are, in terms of statistics, significantly higher for two sectors that experience the decline in trade credit, and the results are robust across four categories. Also, we find that the average correlation between two trade–credit groups is not, in terms of statistics, significantly different before or after the Great Recession across four categories.

2.4 Regression about the Importance of Trade Credit

In this section, we study the relevance of the change in trade credit with the rise in sectoral comovement through a linear regression as

$$\Delta\mathbf{corr}_{ij} = \alpha_0 + \alpha_1\mathbf{D}^{tc} + \alpha_2\mathbf{D}^{tf} + \alpha_3\mathbf{D}^{bl} + \alpha_4\mathbf{D}^{tc}\times\mathbf{D}^{tf} + \alpha_5\mathbf{D}^{tc}\times\mathbf{D}^{bl} + \beta_1'\Delta X_i + \beta_2'\Delta X_j\epsilon_{ij}, \quad (7)$$

where $\mathbf{D}^{tc}$, $\mathbf{D}^{tf}$, and $\mathbf{D}^{bl}$ are respectively defined in Equation 2, 5, and 6, and X contains sectoral characteristics such as the share of intermediate inputs share over the total output value, extensive margin of sectoral connectedness, intensive margin of sectoral connectedness, and output share for final usage. Both OLS and Tobit regression are applied. Table 4 shows the results. The coefficient of trade credit group is statistically significant and the results are robust even after controlling sectoral characteristics.

Table 4
Results for the Regression 7

	(1)	(2)	(3)	(4)	(5)
$\mathbf{D}^{tc}$	.182***	.27**	.183***	.263**	.272**
	(.0424)	(.0921)	(.0458)	(.0908)	(.092)
$\mathbf{D}^{tf}$	.138***	.181***	.0366	.0833	.079
	(.0416)	(.0508)	(.0488)	(.0558)	(.0553)
$\mathbf{D}^{bl}$	.0228	.0107	-.0983	−.135+	−.13+
	(.0401)	(.0503)	(.0693)	(.0748)	(.0741)
$\mathbf{D}^{tc} \times \mathbf{D}^{tf}$		−.184+		-.218*	-.211*
		(.109)		(.111)	(.111)
$\mathbf{D}^{tc} \times \mathbf{D}^{bl}$		.00416		.0492	.0529
		(.132)		(.135)	(.141)
Obs	475	475	475	475	475
Method	OLS	OLS	OLS	OLS	Tobit
Sectoral Char	No	No	Yes	Yes	Yes
R^2	.0686	.0749	.135	.145	

Notes: $\mathbf{D}^{tc}$, $\mathbf{D}^{tf}$, and $\mathbf{D}^{bl}$ are respectively defined in Equation 2, 5, and 6, and X contains sectoral characteristics such as the share of intermediate inputs share over the total output value, extensive margin of sectoral connectedness, intensive margin of sectoral connectedness, and output share for final usage. Standard errors in parentheses. "+", "*", "**", and "***" respectively stand for *p–value* smaller than 10%, 5%, 1%, and 0.1%.

In this section, we have shown that trade credit was an important driver of the increased sectoral comovement observed during the Great Recession. This fact holds strong even after controlling for sectors intermediate input linkages and the aggregate banking credit affecting all sectors. In the next section, we develop a model to explain how endogenous trade credit is able to amplify large negative financial shocks and match the observed facts we document.

3 Model

In this section, we develop a multisector model to uncover the mechanism of the rise in sectoral comovement during the Great Recession. First, we describe the environment of the multisector model incorporating an endogenous trade credit structure and discuss its solution. Then, we discuss the limitation of the model without the financial constraint to generate sectoral comovement. Next, we simulate the model with 15 sectors and show that this model can replicate the three stylized facts observed in Section 2. Last, we conduct a counterfactual analysis to highlight the role of trade credit in amplifying shocks during the financial recession.

3.1 Environment

3.1.1 Firms

Suppose that the economy has N sectors, each of which has a continuum of firms on the interval $[0,1]$. Each firm hires labor and purchases intermediate inputs from other firms to produce consumption goods for household and intermediate inputs for other firms. Assume that each firm purchases (provides) intermediates from (to) at most one firm in each sector. Refer to firms providing (receiving) intermediates as suppliers (clients). Sectors are interconnected with each other via this vertical production network. Suppose that the production of firm $k \in [0,1]$ in sector i takes Cobb-Douglas form:

$$y_i(k) = z_i \xi_i(k) \prod_{j=1}^{N} m_{ji}^{\omega_{ji}} l_i^{\alpha_i}, \tag{8}$$

where z_i and $\xi_i(k)$ are respectively the sector and firm–level productivities, m_{ji} is the intermediate inputs delivered from firms in sector j, ω_{ji} is the share of expenditure on intermediate inputs from sector j over the gross value of output, l_i is the employed labor, and α_i is the labor share.[23] Note that $\omega_{ji} = 0$ means that firms in sector i do not purchase intermediate inputs from any firms in sector j. Suppose the firm–specific productivity ξ_i is Bernoulli distributed:

$$\xi_i = \begin{cases} \xi_i^h & with \quad prob\ 1-\kappa \\ \xi_i^l & with \quad prob\ \kappa. \end{cases}$$

Without the loss of generality, assume $(1-\kappa)\xi_i^h + \kappa\xi_i^l = 1\ \forall i$. Let y_i be the sectoral output, which is aggregated across all firms in sector i as $y_i = \int_0^1 y_i(k)\mathbf{d}k$. Also, by law of large

[23]One can think that in this mode, firms use capital as well. Just the capital is always set to 1.

number, y_i can be interpreted as the expected output as $y_i = \mathbf{E}_i[y_i(k)]$, where $\mathbf{E}_i[\cdot]$ is the expectation operator of the firm–specific productivity for firms in sector i. Moreover, we assume that for any sector i, the sectoral productivity follows an $AR(1)$ process as

$$\log \mathbf{z}_{i,t+1} = \rho_i \log \mathbf{z}_{it} + \epsilon_{i,t+1}, \tag{9}$$

where the vector of $\{\epsilon_{it}\}$, $\epsilon_t = [\epsilon_{1t}, \ldots, \epsilon_{Nt}]'$, is serially independent, following a joint normal distribution $\mathcal{N}\Big(\mathbf{0}, \Sigma\Big)$. Here, Σ is a symmetric and positive definite matrix.

Each period is split into two stages. At the first stage, only sectoral productivities are realized, and hence firms are still uncertain about their productions because of the unknown firm-level productivities. Nevertheless, they need to order intermediate inputs and employ workers in order to produce later. In this case, they make the decision based on the expectation of the firm-specific productivities. Also, due to the uncertainty, firms' ability to make payments for labor and intermediate inputs is at risk. Therefore, workers and suppliers demand to be paid in advance. We assume that workers have strong bargaining power over firms and they are consequently compensated upfront at the full amount. The payments for intermediate inputs are divided into two parts: cash before delivery (CBD) and trade credit. The former is due to the first stage, while the latter is deferred until the next stage when their clients realize their revenue. The division is endogenously decided by suppliers. Suppose that no profits can be stored over periods. To fulfill the upfront payment for workers and suppliers, firms firstly exhaust the CBD received from their clients and then borrow from banks if there is a shortage. Therefore, the amount of borrowing for firms in sector i is:

$$b_i = \max\Big\{ \underbrace{wl_i}_{wage} + \underbrace{\sum_{j=1}^{N}\Big(1-d_{ji}\Big)p_j m_{ji}}_{CBD\ to\ be\ paid} - \underbrace{\sum_{j=1}^{N}\Big(1-d_{ij}\Big)p_i m_{ij}, 0}_{CBD\ received}\Big\}, \tag{10}$$

where w is the wage, p_j is the price of intermediate inputs from sector j, and d is the proportion of trade credit over the total intermediate payment. For example, the total payment for intermediate inputs delivered from firms in sector j to firms in sector i, $p_j m_{ji}$, is divided into two parts: $(1-d_{ji})p_j m_{ji}$ as CBD and $d_{ji}p_j m_{ji}$ as trade credit.

At the second stage, firms realize their specific productivities. All goods are produced and delivered. As discussed later, due to the agreement between shareholders and banks, bank loans is guaranteed to be repaid. However, because trade credit is not collateralized nor endorsed by shareholders, clients can choose to default on trade credit if they do not have enough revenue. If suppliers find out that their clients default on trade credit when they generate enough revenue to pay back, suppliers will punish them by not providing intermediate inputs such that clients will not be able to produce in the future. To ensure the truth telling, at the end of each period, both suppliers and clients verify information provided by counterparts. Also, this verification process is costly when the intensity of trade credit in equilibrium deviates away from the neutral level, $\bar{d}$, which is the intensity without any shocks. Assume that the cost is $\varphi_i(d_{ji} - \bar{d}_j)^2 p_j$ per unit of intermediate inputs.[24] Here φ is the parameter governing the size of such verification cost. Moreover, we assume that suppliers bear this cost. Assumption 1 lays out the conditions that $\left\{\xi_i^l\right\}$ should satisfy.

Assumption 1 *Assume that for each i, ξ_i^l is sufficiently low such that firms with low productivities are not able to pay back trade credit and ξ_i^l is sufficiently high such that they can produce enough to produce enough for their clients.*

The first part of Assumption 1 rule out the meaningless case that even firms with low productivities can generate enough revenue to repay trade credit. The second part ensures that these firms still can produce enough and deliver intermediate inputs as ordered. In this case, all firms make the same revenue from the intermediate–input market, while firms with high productivities sell more in the consumption–good market. Note that firms have a probability κ to draw such low productivity. By the law of large numbers, κ fraction of them in each sector choose to default.

3.1.2 Banks

Suppose many competitive banks exogenously exist in the economy and they have deep pockets and offer loans to firms. Also, suppose they are risk–averse. Because some firms will have low productivities and thus may not generate enough revenue, banks concern about the firms' ability to repay so that they are reluctant to lend. To ensure banks, firms' shareholders make an agreement with banks and promise to take over the debt responsibilities when firms cannot. To enforce such agreement, banks ask shareholders to pledge some fraction of the expected revenue from the consumption-good market as collateral. This is because by the time when banks lend to firms, banks cannot tell which firms will have low productivities so that they ask for the access to liquidate outputs in the consumption-good market. Also, banks do not take trade credit as collateral because of its potential default risk. Denote the proportion of revenue that can be pledged as collateral is e_i for firms in sector i. Loans from banks are in the form of credit line that gives firms permissions to access loans up to a limit, namely $e_i p_i c_i$. In other words, firms

[24] Luo (2020) uses an asymmetric cost function (only upward adjustments are costly). We instead assume a symmetric verification cost function to clearly emphasize that the asymmetric effect of trade credit in our model does not depend on an asymmetric verification cost function.

in sector i are subject to the financial constraint as

$$b_i \leq e_i p_i c_i \quad with \quad e_i = \bar{e}_i \epsilon_i^e, \tag{11}$$

where ϵ_i^e follows a log-normal distribution $\log \mathcal{N}\left(0, \sigma_i^e\right)$.

Note that two sources of credit, namely bank and trade credit, coexist in our model. They differ in two ways. First, trade credit is just the deferral of payments, and at least some firms need bank credit to pay their workers and CBD. Thus, trade credit is the vehicle for redistributing bank loans. Second, bank loans are collateralized by income of shareholders, and thus they will always be repaid. However, trade credit is determined by suppliers. It is not secured, and clients default if they cannot generate enough revenue.

Output is produced under conditions of perfect competition. At the first stage, before firm-specific productivities are realized, all firms in the same sectorare *ex ante* the same so that they make the same decisions. In this case, taking the prices for output and inputs and the intensities of trade credit issued by all suppliers as given, firms hire labor, order intermediate inputs, and determine the intensity of trade credit providing to their clients to maximize the expected profits:

$$\max_{m_{ji}, l_i, d_{ij}} \; p_i z_i \prod_{j=1}^{N} m_{ji}^{\omega_{ji}} l_i^{\alpha_i} - \sum_{j=1}^{N} \kappa d_{ij} p_i m_{ij} - w l_i - \sum_{j=1}^{N} \left(1 - \kappa d_{ji}\right) p_j m_{ji} - \varphi_i \sum_{j=1}^{N} (d_{ij} - \bar{d}_i)^2 p_i m_{ij} \tag{12}$$

$$s.t. \qquad w l_i + \sum_{j=1}^{N} \left(1 - d_{ji}\right) p_j m_{ji} \leq e_i p_i c_i + \sum_{j=1}^{N} \left(1 - d_{ij}\right) p_i m_{ij},$$

where the first two terms stands are the expected revenue, the fourth term is the expected cost of purchasing intermediate inputs, and the constraint is a result of combination of Equation (10) with (11). Here, the loss or gain of default on trade credit is taken into account. This problem can be broken into two steps. In the first step, the firm chooses the amount of labor l_i and intermediate inputs $\left\{m_{ji}\right\}_j$ to use, given the wage w, prices of the intermediate inputs $\left\{p_j\right\}_j$, and the intensities of trade credit received from their suppliers $\left\{d_{ji}\right\}_j$. Suppose that μ_i is the Lagrange multiplier for the financial constraint of firms in sector i. The solution to the first step is presented in the following lemma.

Lemma 1 *Given a vector of prices $\left\{\left\{p_j\right\}_j, w\right\}$ and the intensities of trade credit receptions from other sectors $\left\{d_{ji}\right\}_j$, the optimal conditions of firms in sector i satisfy the following conditions:*

$$w l_i = \alpha_i \theta_i^l p_i y_i, \;\; with \;\; \theta_i^l = \frac{1}{1 + \mu_i}, \tag{13}$$

$$p_j m_{ji} = \omega_{ji} \theta_{ji}^m p_i y_i, \;\; with \;\; \theta_{ji}^m = \frac{1}{1 - \kappa d_{ji} + (1 - d_{ji}) \mu_i}. \tag{14}$$

Proof: see Appendix F.

Lemma 1 implies the expenditure on labor and intermediate inputs are respectively proportional to the total value of expected output. This is a classical result of Cobb-Douglas technology. Moreover, if the financial constraints are not binding, the proportions are equal to labor and intermediate inputs shares, i.e. α and ω. If firms are financially constrained, distortions on labor and intermediate input are induced and consequently they cannot reach their profit-maximizing production.

Moreover, the *wedge* θ_{ji}^m is increasing in d_{ji}. It implies that the more trade credit suppliers in sector j provide, the more intermediates from sector j are purchased from sector i. In the second step, when firms determine trade credit supply, they take this fact into account. Given the gross value of output for their clients in sector j, i.e. $p_j y_j$, firms in sector i choose the intensity of trade credit to solve

$$\begin{aligned} &\max_{d_{ij}} \ \left(1-\kappa d_{ij}-\varphi_i(d_{ij}-\bar{d}_i)^2\right)p_i m_{ij} \\ s.t. \qquad & p_i m_{ij} = \frac{\omega_{ij}}{1-\kappa d_{ij}+(1-d_{ij})\mu_j} p_j y_j, \\ & wl_i + \sum_{j=1}^{N}\left(1-d_{ji}\right)p_j m_{ji} \le e_i p_i c_i + \sum_{j=1}^{N}\left(1-d_{ij}\right)p_i m_{ij}. \end{aligned}$$

Issuing more trade credit has a trade–off: increasing the sales of intermediate inputs while enhancing the loss in the case of default. Lemma 2 describes the solution to the problem.

Lemma 2 *Assume that $\kappa+\bar{d}_i<1$, for $\forall i$. Given the price of good i and the gross value of output for their clients in sector j, the optimal condition to determine the intensity of trade credit is*

$$d_{ij} = \frac{1+\mu_j}{\kappa+\mu_j} - \sqrt{\left(\frac{1+\mu_j}{\kappa+\mu_j}-\bar{d}_i\right)^2 + \frac{(1-\kappa)(\mu_i-\mu_j)}{\varphi_i(\kappa+\mu_j)}}. \qquad (15)$$

Proof: see Appendix F.

Lemma 2 implies that the intensity of trade credit is only adjusted to the financial conditions of both supplier and client. Proposition 1 describes how it is adjusted.

Proposition 1 *Given the Lagrange multipliers for both the supplier i's and client j's financial constraints, μ_i and μ_j respectively, we have*

- *if $\mu_i=\mu_j$, $d_{ij}=\bar{d}_i$;*
- *if $\mu_i>\mu_j$, $d_{ij}<\bar{d}_i$;*

- *if* $\mu_i < \mu_j$, $d_{ij} > \bar{d}_i$.

Moreover, if $\kappa + \varphi_i\left(1 - \bar{d}_i\right)^2 < 1$ *for* $\forall i$, *then we have*

$$\frac{\partial d_{ij}}{\partial \mu_i} < 0, \quad and \quad \frac{\partial d_{ij}}{\partial \mu_j} > 0.$$

Proof: see Appendix F.

The first part of Proposition 1 suggests that the intensity of trade credit is determined by the relative financial conditions of both suppliers and clients. If suppliers have relatively worse financial conditions, i.e. μ_i is larger than μ_j, then less trade credit is extended, compared to the natural level. Similarly, if clients have relatively worse financial conditions, then the suppliers extend more trade credit than the natural level. The second part of Proposition 1 implies that the intensity of trade credit is decreasing as the suppliers' financial conditions deteriorate, while increasing as the clients become more financially constrained. These two mechanisms are crucial in shaping the asymmetric effects of trade credit. In mild financial crisis, if key intermediate input suppliers are relatively less constrained, they internalize the benefit of relaxing other sectors constraints via providing more trade credit. However, in severe financial crisis, the deterioration of several sectors' financial constraints leads to cascade effects and the collapse of trade credit.

Proposition 2 *Assume that* $\kappa < 2\varphi_i\left(1 - \bar{d}_i\right)$ *for* $\forall i$. *The distortions on labor and intermediate inputs satisfy*

$$\frac{\partial \theta_i^l}{\partial \mu_i} < 0, \; \frac{\partial \theta_{ji}^m}{\partial \mu_j} < 0, \; and \; \frac{\partial \theta_{ji}^m}{\partial \mu_i} \begin{cases} < 0 & if \;\; \mu_i < \frac{2\varphi_j\left(1-\kappa\bar{d}_j\right)\left(1-\bar{d}_j\right)+(1-\kappa)(\mu_j-\kappa)}{1-\kappa-\varphi_j\left(1-\bar{d}_j\right)^2} \\ \geq 0 & otherwise \end{cases}$$

Proof: see Appendix F.

Proposition 2 implies that as the financial constraint becomes binding, labor and intermediate inputs will be distorted. Moreover, if one supplier becomes financially constrained, the incentive for the supplier to extend trade credit reduces so that the clients will spend smaller proportion of their cost on goods provided by this supplier.

3.1.3 Households and Market Clearing Conditions

Suppose a representative household exists in the economy with utility $\mathbf{U}(c, l) = \log c - \eta l$, where c is the consumption bundle, l is hours worked, and the parameter η governs the disutility from working. The total expenditure must be weakly less than the household's labor income plus net profits and transfer from firms. Given the prices and wage, the household's objective is to choose a consumption bundle and labor to maximize her utility subject to her budget constraint as

$$\max_{c_t, l_t} \mathbf{E}_0 \left[\sum_{t=0}^{\infty} \beta^t \Big(\log c_t - \eta l_t \Big) \right] \tag{16}$$

$$s.t. \qquad p_t c_t \leq w_t l_t + \pi_t + T_t,$$

where p is the price index, π is the total profit generated by all firms, and T is the total verification costs paid by firms. The first order conditions yield

$$\eta c = \frac{w}{p}. \tag{17}$$

Moreover, the consumption bundle is defined as the composition of goods from all sectors as

$$c = \prod_{i=1}^{N} \left(\frac{c_i}{\nu_i} \right)^{\nu_i}, \tag{18}$$

and the price index is defined as

$$p = \left(\prod_{i=1}^{N} p_i \right)^{\nu_i}, \tag{19}$$

where ν_i is the share of the household's expenditure on sector i's goods and $\sum_{i=1}^{N} \nu_i = 1$. Moreover, a household's demand for goods in any sector i is given as

$$c_i = \nu_i \frac{p}{p_i} c. \tag{20}$$

All products in any sector are served for two purposes: intermediate inputs and consumption goods. Thus output in any sector should be equal to the summation of consumption by household and intermediate inputs shipping to every sectors; that is, for any sector $i \in \Big\{1, \ldots, N\Big\}$,

$$y_i = c_i + \sum_{j=1}^{N} m_{ij}. \tag{21}$$

Finally, labor supply is equal to labor demand across firms in all sectors as

$$l = \sum_{i=1}^{N} l_i. \tag{22}$$

3.1.4 Definition of Equilibrium

Now we define the competitive equilibrium in our model as

Definition 1 *A **competitive equilibrium** is defined as commodity prices $\left\{p_i\right\}_i$ and wage w, sectoral output $\left\{y_i\right\}_i$, consumption goods $\left\{c_i\right\}_i$, intermediate inputs $\left\{m_{ji}\right\}_{j,i}$, labor allocations $\left\{l_i\right\}_i$, and the intensities of trade credit provision $\left\{d_{ji}\right\}_{j,i}$, such that*

1. *Given a vector of prices $\left\{\left\{p_j\right\}_j, w\right\}$ and the intensities of trade credit receptions from other sectors $\left\{d_{ji}\right\}_j$, firms in any sector i choose intermediate inputs $\left\{m_{ji}\right\}_{j,i}$, labor l_i, and the intensities of trade credit provision $\left\{d_{ij}\right\}_j$ to maximize the expected profit as in (12);*
2. *Given $\left\{p_i\right\}_i$ and w, the representative household chooses consumption goods $\left\{c_i\right\}_i$ and labor l to maximizes her utility as in (16);*
3. *Prices clear commodity markets in (21);*
4. *Aggregate price index, normalized to 1, clears the labor market (22).*

3.2 Analysis of Equilibrium

Before analyzing the model, we need to show the existence of ξ_i^l for $\forall\ i$ such that the Assumption 1 is satisfied. Proposition 3 describe a sufficient condition for the existence.

Proposition 3 *Under some appropriate assumption of parameters, for each sector i, there exists $\underline{\xi}_i^l$ and $\bar{\xi}_i^l$ such that for $\xi_i^l \in [\underline{\xi}_i^l, \bar{\xi}_i^l]$, Assumption 1 is satisfied.*
Proof: see Appendix F.

To prove the Proposition 3, we solve the model under Assumption 1, find the lower and upper bound of ξ_i^l for each i as $\underline{\xi}_i^l$ and $\bar{\xi}_i^l$ respectively, and verify the equilibrium. Therefore, $\xi_i^l \in [\underline{\xi}_i^l, \bar{\xi}_i^l]$ is just a sufficient but not necessary condition.

Then, we examine the pairwise correlations implied by the model. First, define

$$\Omega = \begin{bmatrix} \omega_{11} & \dots & \omega_{1N} \\ \vdots & \ddots & \vdots \\ \omega_{N1} & \dots & \omega_{NN} \end{bmatrix}, \Theta_m = \begin{bmatrix} \theta_{11}^m & \dots & \theta_{1N}^m \\ \vdots & \ddots & \vdots \\ \theta_{N1}^m & \dots & \theta_{NN}^m \end{bmatrix}, \mathbf{M}_\omega = \begin{bmatrix} \omega_{11} & & & \dots & \omega_{1N} & & \\ & \ddots & & \dots & & \ddots & \\ & & \omega_{N1} & \dots & & & \omega_{NN} \end{bmatrix},$$

$$\mathbf{D}_\alpha = \begin{bmatrix} \alpha_1 & & \\ & \ddots & \\ & & \alpha_N \end{bmatrix}, \text{ and } \mathbf{D}_\pi = \begin{bmatrix} 1-\alpha_1-\sum_{j=1}^N \omega_{j1} & & \\ & \ddots & \\ & & 1-\alpha_N-\sum_{j=1}^N \omega_{jN} \end{bmatrix}$$

Also, define $\tilde{\nu} = (\mathbf{I} - \Omega' \diamond \Theta_m')^{-1}\nu$, where $\diamond$ is the Hadamard (entrywise) product and $\nu = [\nu_1, \dots, \nu_N]'$. Note that each element of $\tilde{\nu}$ corresponds the total value of sectoral outputs with the aggregate consumption, i.e.

$$p_i y_i = \tilde{\nu}_i c, \ \ for\ \forall\ i \tag{23}$$

Let $\Delta \log y_t = [\Delta \log y_{1t}, \ldots, \Delta \log y_{Nt}]'$, $\Delta \log \theta_t^m = \left[\Delta \log \theta_{11,t}^m, \ldots, \Delta \log \theta_{1N,t}^m, \ldots, \log \theta_{N1,t}^m, \ldots, \log \theta_{NN,t}^m\right]'$, $\Delta \log z_t = [\Delta \log z_{1t}, \ldots, \Delta \log z_{Nt}]'$, and $\Delta \log \theta_t^l = \left[\Delta \log \theta_{1t}^l, \ldots, \Delta \log \theta_{Nt}^l\right]'$. Moreover, Lemma 2 implies that the value of vectors $\log \theta_t^m$ and $\log \theta_t^l$ only rely on these binding financial constraints, which further depend on the exogeneously bank lending shocks, e_i. Proposition 4 describes a solution for the vector of sectoral output growth.

Proposition 4 *Given the distortions on inputs, $\log \theta_t^m$ and $\log \theta_t^l$, the vector of sectoral output growth rates is*

$$\Delta \log y_t = (\boldsymbol{I} - \Omega')^{-1} \Big(\underbrace{\Delta \log z_t}_{\%\,\Delta \text{ in productivities}} + \underbrace{\mathbf{M}_\omega \Delta \log \theta_t^m + \mathbf{D}_\alpha \Delta \log \theta_t^l + (\boldsymbol{I} - \Omega' - \mathbf{D}_\pi) \Delta \log \tilde{v}_t}_{\text{Distortions caused by the Financial Friction}} \Big), \quad (24)$$

Proof: see Appendix F.

Proposition 4 illustrates two sources that can affect the growth rates of sectoral outputs. The first one is sectoral productivity shocks. Second, distortions induced by the binding financial constraints also affect the sectoral outputs. If one sector receives a negative bank lending shock, which further causes the financial constraint binding, then the production will be distorted by this binding constraint.

Moreover, Proposition 4 highlights two transmission channels. The first one is the input-output linkage, which has been emphasized by the recent literature, such as Foerster et al. (2011), Gabaix (2011), Acemoglu et al. (2012), and Bigio and La'O (2017). With the Leontief inverse matrix, a negative productivity or bank lending shock to one sector can influence outputs of others through both direct and indirect linkages in intermediate inputs. Here, the 'direct' linkage describe the case where two sectors have trading relationship in intermediate inputs, whereas two sectors are 'indirectly' linked if they have trading relationship with a third sector, as either supplier or client or both. Also, two sectors can be both directly and indirectly connected. Note that, due to the Cobb-Douglas form of preference and technology, the shock can only be transmitted to the downstream sector through this channel. This is because the prices of goods in the upstream respond to the shock and perfectly offset the effects of the shock on its production. Relaxing the unitary elasticity of substitution, like Atalay (2017), Carvalho et al. (Accepted), and Miranda-Pinto and Young (2020), can generate the upstream transmission. We stick to the unitary assumption to keep the solution analytically tractable.

Furthermore, in addition to input–output linkage, the trade credit chain can propagate the negative bank lending shocks to other sectors. For example, firm A, B, and C from three different sectors and firm A provides intermediate inputs to B, which further supplies to C. Suppose that firm B receives a negative financial shock and become it financially constrained. Proposition 1 suggests that firm B will contract its provision of trade credit to firm C and instead ask for more CBD. Whether this adjustment in trade credit affect firm C's output depends on the firm C's financial condition. If firm C has sufficient amount of bank loans, it can use them to replace trade credit and fulfill the increased requirement for CBD. In this case, firm C's output will not be affected. However, if firm C is also financially constrained or on the edge of being financially constrained, such adjustment makes it more financially tightened or become so. In this case, the firm C's outputs will be also distorted by such a binding constraint. Moreover, this channel can transmit the financial shock to upstream as well. Proposition 1 also suggests that firm A will extend more trade credit. Lower requirement for CBD alleviates the firm B's financial constraints and further helps it to partially restore output. As in Kiyotaki and Moore (1997), if firm A has a deep pocket, firm A's output will not be affected. However, if firm A is also financial constrained, then such adjustment will make firm A more constrained, which further distorts firm A's output.

Here, the trade credit chain is the key to explain the asymmetric pattern of sectoral comovement observed in data. Over the normal economic recession, the financial conditions for many firms are relatively sound. Trade partners can adjust the issuance of trade credit to help out troubled firms. In this case, the trade credit chain is a cushion for bank lending shocks. It is less likely to observe a large scale of sectoral comovement. However, during the financial crisis, many firms experience trouble of borrowing from banks. In this case, the trade credit chain plays as a conduit by spreading the borrowing trouble to others, given the fact that it is the most important short-term finance source. Many firms' outputs are affected and it is very likely to have an economy-wide contraction, i.e. high sectoral comovement.

3.3 Calibration

We calibrate the model with 15 two-digit industries in the U.S. economy.[25] These cover all private industries except FIRE. Table 5 describes parameters to be calibrated.[26] In particular, we use the IO table to calculate the share of intermediate inputs delivered from sector i to j over the gross value of sector j output as ω_{ij}.

Our model displays a trade credit matrix with a typical element d_{ij} (Equation 15) and a sectoral wedge matrix with a typical element θ_{ij}^{m} (Equation 14). We treat the trade credit matrix as unobserved and calibrate the model implied non-binding constraint equilibrium to match the observed pre-recession (2007) median value of trade credit across public firms in each sector. At this baseline calibration, Equation 15 dictates that all entries of the trade credit matrix equal $\left\{\bar{d}_i\right\}_i$, the neutral trade credit intensity. During

[25]We use 15 industries instead of 44 as in Section 2 because this choice allows us to identify a sufficient number of 'financial' recessions with a reasonable number of simulations in Section 3.5.

[26]Refer to Appendix G for details.

a recession, when sectoral constraints bind, our model displays a non-symmetric trade credit matrix.[27]

The verification cost $\left\{\varphi_i\right\}_i$ is set to match the variance of trade credit provision from 2000 through 2007. In equilibrium, all firms with the low firm-specific productivities choose to default on their trade credit. Thus, κ is set to 0.06, which is the default rate of trade credit in Sweden as documented in Jacobson and von Schedvin (2016).

Then, the bank lending shocks for each sector are independent, following the log normal distribution $\log\mathcal{N}\left(0,(\sigma_i^e)^2\right)$. σ_i^e is estimated as the standard deviation of the bank lending index, proposed by Chodorow-Reich (2014), between 2002 and 2007. Suppose $\bar{e}_i^0$ is the bank lending condition where the financial constraint of firms in sector i are just binding. Then we set $\bar{e}_i$ such that the financial constraints are binding with one-third chance, fixing all intensities of trade credit are equal to the ones in the neutral state.

Next, we estimate the autocorrelation coefficients $\left\{\rho_i\right\}_i$ and the covariance σ_{ij}^z. In doing so, we first take the sectoral output growth rates from 2010Q1 to 2016Q4 in data, because the data before the Great Recession is too short to estimate. We start with the neutral state, and back up all series of the sectoral productivities using the sectoral output growth, assuming that no financial constraints are binding. Then, we use MLE to estimate Equation (9) for $\left\{\rho_i\right\}_i$ and σ_{ij}^z.

3.4 Limitation of Canonical Multi–sector Business Cycle Model

Before our analysis on the model with the endogenous trade credit structure, we test whether the canonical multi–sector business cycle model without the endogenous trade credit structure can generate the two stylized facts documented in Section 2. To do so, we set all e_i sufficiently high such that all financial constraints are not binding. In this case, trade credit will always be equal to the natural levels. Now, the solution is same as in the canonical model. Proposition 5 describes the correlations of output growth between two sectors implied by this model.

Proposition 5 *Suppose e_i is sufficiently large for all sectors i such that no financial constraints are binding. Given any sequence of realizations $\Delta\log\mathbf{z}$, the correlation of output growth rates between sector i and j is*

$$\mathbf{corr}\left(\Delta\log y_i,\Delta\log y_j\right)=\sqrt{\frac{\delta_j\widetilde{\mathbf{M}}_{ij}\delta_i'}{\delta_i\widetilde{\mathbf{M}}_{ij}\delta_j'}},\tag{25}$$

[27] Altinoglu (2017) follows a different approach by assuming that the trade credit matrix is observed. The author proxies the trade credit matrix using COMPUSTAT data on trade credit flows. A key assumption that facilitates the mapping between the model and the data is that, in his model, constraints are always binding.

where δ_i is the ith row of the Leontief inverse matrix $(\mathbf{I}-\Omega')^{-1}$, $\widetilde{\mathbf{M}}_{ij} = \mathbf{M}_z\delta_i'\delta_j\mathbf{M}_z$, and $\mathbf{M}_z = \frac{1}{T-1}\sum_t \Delta\log z_t \Delta\log z_t'$.

Proof: see Appendix F

Proposition 5 suggests that the output growth rate in any sector is a linear combination of percentage changes in sectoral productivities. The vector δ_i is the influence vector in Acemoglu et al. (2012), in which each element measures how much the sectoral output growth responds to a percentage change in each sector's productivity through direct and indirect linkages. No matter how much sectoral productivities are realized, the influence vectors stay the same. Moreover, the pairwise correlation only depends on how much their influence vectors differ. If one sector has the influence vector similar with the other's, outputs of both sectors evolve analogously and the pairwise correlation is high.

To examine how much the influence vectors differ across sectors, we apply the calibration in Section 3.3 and use two measurements, namely the Euclidean norm and the angular separation, to examine the difference.[28] The former measures the absolute distance between two vectors, while the latter calculates the cosine angle between them in the vector space, regardless of the length of vectors. The larger the Euclidean norm or the smaller the angular separation, the more two vectors differ. Table 6 shows the statistics for two distance measurements. The means of Euclidean norm and angular separation are 1.58 and 0.14, respectively. These means with all other statistics show that the influence vectors are statistically different from each other and some of them are nearly orthogonal. The existence of significantly different influence vectors implies that the pairwise correlations are slightly positive on average, and this implication is consistent with our observations in data, where the pairwise correlations are about 0.15 on average before and after the Great Recession.

Then, we test Equation 25 by conduct the following regression:

$$\mathbf{Corr}_{ij} = \beta_0 + \beta_1 D_{ij}^{AS} + \gamma_i \mathbf{D}_i + \gamma_j \mathbf{D}_j + \epsilon_{ij}, \tag{26}$$

where $\mathbf{Corr}_{ij}$ is the pairwise correlation of sectoral output growth rates between sector i and j, D_{ij}^{AS} is the angular separation of two influence vectors, and $\mathbf{D}_i$ is a dummy variable for sector i, controlling for sectoral fixed effects. Here, two values for pairwise correlation are used: namely the one before the Great Recession and the change during the

[28] The Euclidean distance and angular separation of weighted vectors between sector i and j are respectively

$$D^{EU} = \sqrt{\sum_{l=1}^{N}(\delta_{il}-\delta_{jl})^2}, \quad and \quad D^{AS} = \frac{\left|\sum_{l=1}^{N}\delta_{il}\delta_{jl}\right|}{\sqrt{\sum_{l=1}^{N}\delta_{il}^2}\sqrt{\sum_{l=1}^{N}\delta_{jl}^2}}$$

Great Recession. As shown in Table 7, the coefficient of the angular separation measurement is positive and statistically significant for the pairwise correlation before the Great Recession. This result demonstrates the empirical relevance of the model without the endogenous trade credit structure, but the relevance only restrict to the data before the Great Recession. The coefficient for the change in the pairwise correlation is still positive but not statistically significant, indicating that only input-output linkage is not sufficient to deliver the significantly increase in sectoral comovement. To test the validity of the measurement, we also calculate the angular separations of row or column vectors of IO matrix, where $sup_i = [\omega_{i1}, \ldots, \omega_{iN}]$ and $cln_i = [\omega_{1i}, \ldots, \omega_{Ni}]$. These two distances measure how similar two sectors are as suppliers or clients. Unlike the one in the main regression, these two only count for direct linkage. The coefficients are positive but not statistically significant. It implies that the indirect linkage plays an important role in explaining the synergy among sectors before the Great Recession.

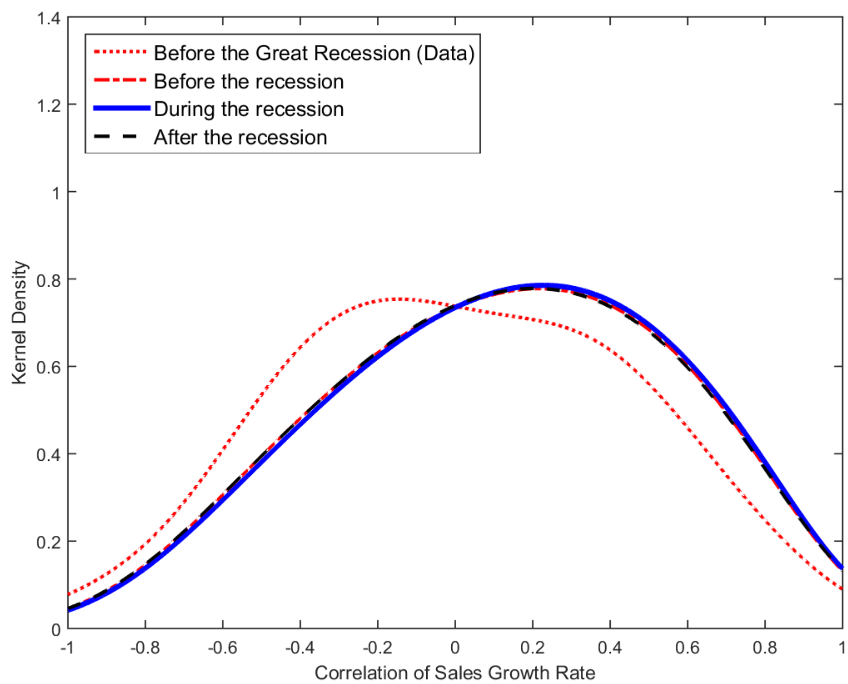
3.5 Simulation on the Model with Endogenous Trade Credit

In this section, we apply the calibration in Section 3.3 and conduct 10 million simulations of the model with the endogenous trade credit structure. Then we compare the kernel densities of pairwise correlations under different scenarios, and find that three stylized facts can be qualitatively replicated when the medium size of sectors receive negative bank lending shocks.

We define the real GDP in our model as the consumption bundle c in Equation (18). The volatility of the GDP growth across all simulated periods is 2.95%, which is comparable to the volatility of the US GDP growth rate in the last 20 years.[29] Following the classification of recession used by the National Bureau of Economic Research, we define some periods in a recession if the real GDP drops more than 1.5% for more than two consecutive periods. We also exclude two recessions if the latter starts within eight periods after the former ends. In this case, 67541 recessions are identified, covering 2.2% of total simulated periods. For each recession, we choose two periods before the recession as the starting point, calculate the pairwise correlations over eight periods since the starting point, and then take the kernel density. To compare, we also choose eight periods before and after the recession and repeat the same exercise. Figure 7 displays the average kernel density before, during, and after all recessions, compared to the one before the Great Recession with data. A few observations are noted. First, the kernel density generated by the model has slightly larger mean but smaller standard deviation than the corresponding statistics in data. It may be because the data used to estimate is from 2010 to 2016. Second, three kernel densities generated by data almost overlap one another, and no rise

[29]All growth rates are measured at the compound annual rate.

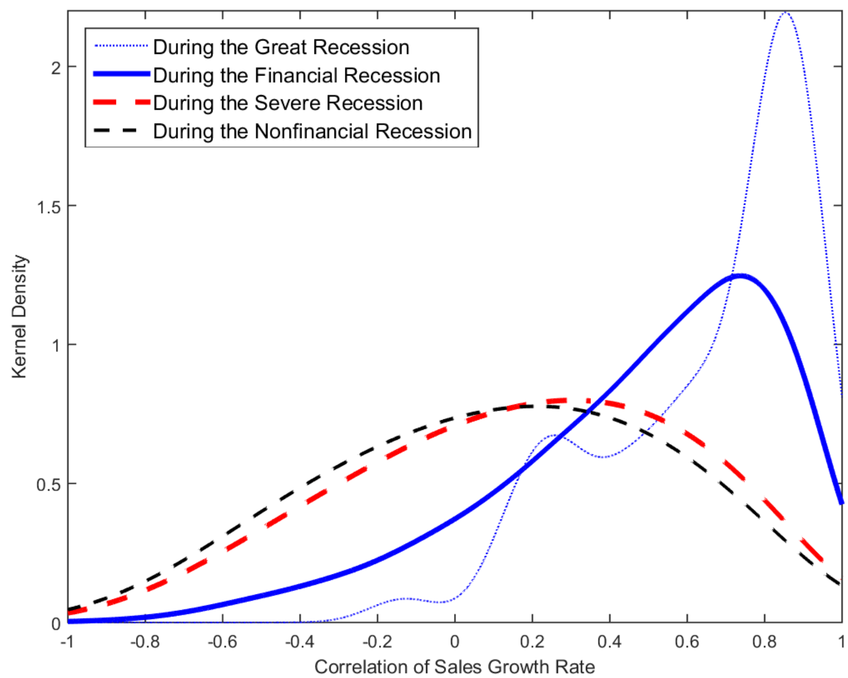
Note: A recession is identified if the real GDP drops more than 1.5% for more than two consecutive periods.



in sectoral comovement is observed during the recession.

Next, we restrict our analysis to two different types of scenarios. First, we define a recession as a 'severe' recessions if the average and the minimal GDP respectively drop more than 3.25% and 10.44%. Given the fact that the US GDP declined 2.8% in 2008 with the largest drop of 8.7% in 2008Q4, this criteria is aggressive because both counts in our definition are 20% more than ones during the Great Recession. In total, 2370 recessions are left, covering 0.08% of the simulated periods. The average drop in GDP during the 'severe' recession is 3.8%, compared to the average decline of 1.9% across all recessions. Second, we define a recession as a 'financial' recession if the financial constraints in more than three quarters of sectors are binding for at least two periods during the recession. Here, 365 episodes are categorized as financial recessions, covering 0.01% of the simulated periods. GDP during the 'financial' recession drops by 2.8% on average. Figure 8 displays the average kernel densities for different types of scenarios, namely 'non–financial', 'severe', and 'financial' recessions, compared to the one during the Great Recession with data. As shown in Figure 8, only the density during the 'financial' recession significantly shifts toward the right, as shown in the one with data. Moreover, the average of pairwise correlations during the financial recession in the model is 0.56, given that the average in data is 0.81. However, the density during the 'severe' moderately shifts to the right. This is consistent with evidence we find during the 1980 recession, which is also considered a 'severe' recession as the real GDP dropped by 1.9% in 1980, with the largest drop of 6.5% in 1982Q1.

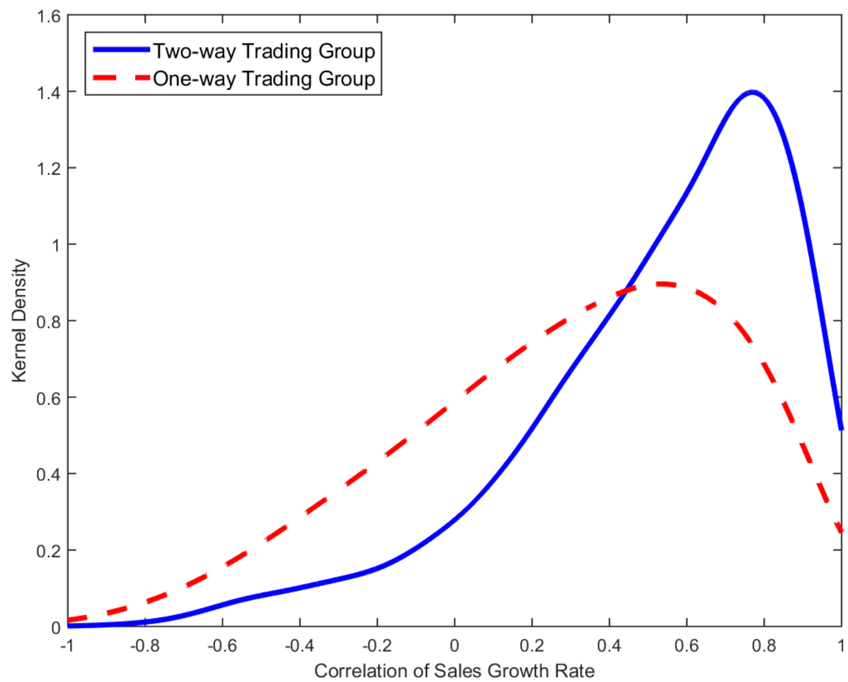
Note: A recessions is categorized as a 'severe' recession if the average and the minimal GDP respectively drop more than 3.25% and 10.44% during the recession. A recession is categorized as a 'financial' recession if the financial constraints in more than three quarters of sectors are binding for at least two periods during the recession.



Here, a few caveats should be noted. First, the pairwise correlations with 15 sectors is higher on average than ones with 44 sectors in Section 2. This is because the former one averages out the different dynamics of some sub–sectors under the same classification. Second, the binding financial constraint can be caused either by a negatively financial shock or by the adjustment in trade credit. In the 'financial' recession, on average, 60% of sectors with binding constraint receive negatively financial shocks. The rest become financial constrained because of the endogenous trade credit structure. Third, only 36 episodes are classified as both 'severe' recessions and 'financial' recessions.

Then, we perform the decomposition based on the extensive margin of sectoral interconnectedness, as in Section B. Note that the IO matrix with 15 two-digit sectors is denser than the one used in the empirical analysis. We then set the element of the IO matrix equal to 0 if the intermediate share of total inputs is less than 0.5% instead of 0.1% using in Section B. In this case, we have 85 pairs in the two-way trading group and

Figure 9
Kernel Density, by Extent of Interconnectedness



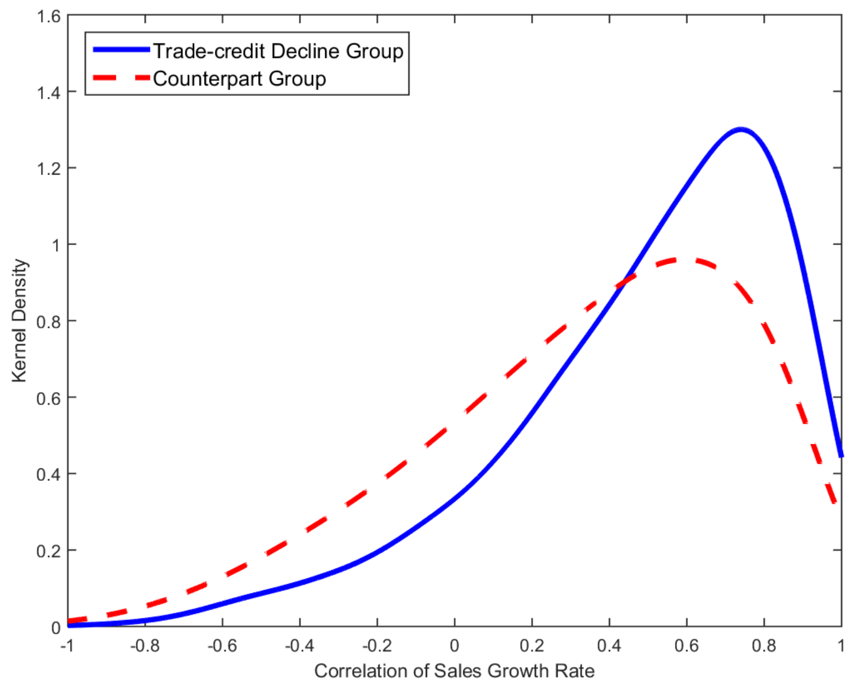
20 pairs in the one-way trading group. Figure 9 displays the average kernel density for two groups. As in stylized fact II, the average correlation in the two-way trading group is higher on average than the average in the one-way trading group.

Last, we perform the decomposition based on whether two sectors experience the decline in trade credit during the 'financial' recessions. Unlike the measurement in Section 2.3, we can observe bilateral trade credit between two sectors. Then, to examine the role of trade credit in sectoral comovement, we define a pair as experiencing a large decline in trade credit if the percentage change of the trade credit provided by either sector declines more than the median value across all pairs of sectors. Note that the mean of the median value for all financial recessions is 8.1%, which is slightly higher than the 6.3% in the data. Figure 10 displays the average kernel density for two groups. As in stylized fact III, the average correlation in the trade–credit decline group is higher on average than the counterpart group.

3.6 Counterfactual Analysis

We test what happens to the pairwise correlations and aggregate economic outcome (GDP) if the intensity of trade credit during the financial crisis cannot be adjusted. We first

Figure 10
Kernel Density, by Extent of Interconnectedness

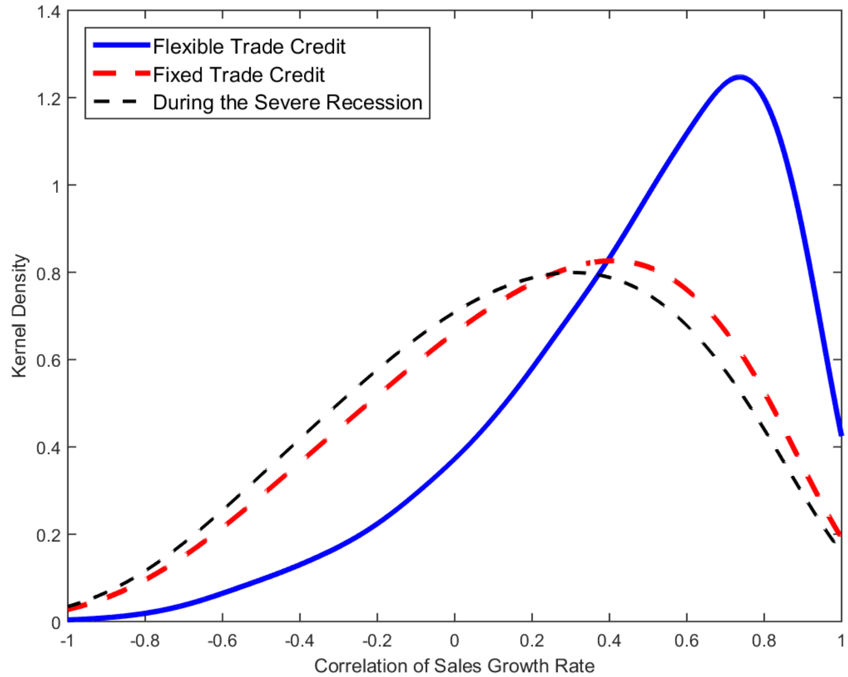


modify our model such that the trade credit during the financial recession is fixed to the level at one period before the recession starts. In this case, the model becomes isomorphic to the one in Bigio and La'O (2017). Using the same set of productivity and bank lending shocks, we recalculate the pairwise correlations and the kernel density. Figure 11 shows the comparison of the kernel densities with and without an endogenous trade credit structure. Without adjusting the trade credit, the shift in the density is modest in these recessions. Moreover, with a fixed trade credit, the average GDP drops by 2.3% on average across recessions. This outcome implies that the decline in trade credit during the financial recession amplifies shocks by about 18%.

4 Conclusion

In this paper, we document a large increase in sectoral comovement and a large decline in trade credit during the Great Recession. We construct a multisector model with input-output linkages, occasionally binding sectoral financial constraints, and endogenous trade credit provision and that show that i) trade credit can serve as a mitigation mechanism for negative sectoral shocks, but ii) it can serve as an important amplification mechanism for aggregate negative financial shocks, as the one observed during the Great

Note: We fix the trade credit during the financial recessions to the level at one period before the recession starts. Using the same set of productivities and bank lending shocks, we recalculate the pairwise correlations and the kernel density.



Recession. The model predicts a collapse in trade credit when an aggregate shock distorts external finance for most sectors. The collapse in trade credit leads to a sharp increase in sectoral comovement. We show that a model with endogenous trade credit amplifies the Great Recession by 18%.

Table 1
Pairwise Correlations of Output Growth Rates: Stylized Fact I

	Mean	Median	Std	Skewness	KS Statistics
the Great Recession					
Before the recession	0.08	0.09	0.38	-0.11	0.19 (0.00)
During the recession	0.38	0.46	0.38	-0.71	
After the recession	0.02	0.02	0.42	0.01	0.24 (0.00)
the 1990 recession					
Before the recession	0.11	0.14	0.41	-0.23	0.00 (1.00)
During the recession	0.11	0.14	0.41	-0.23	
After the recession	0.05	0.06	0.39	-0.06	0.04 (0.06)
the 2001 recession					
Before the recession	0.08	0.10	0.42	-0.12	0.03 (0.18)
During the recession	0.07	0.08	0.43	-0.10	
After the recession	0.12	0.14	0.39	-0.20	0.05 (0.01)
Comparison: across recessions					
the Great Recession vs the 1990 recession					0.19 (0.00)
the Great Recession vs the 2001 recession					0.23 (0.00)

Notes: All kernel densities f are calculated on unit interval [1,1] with bandwidth 0.001. The *p-value* for the KS statistics is reported in the parentheses. The critical values of KS statistics at 0.1%, 1%, and 5% significance levels are respectively 0.0616, 0.0515, and 0.0430 in this case.

Table 2
Pairwise Correlations of Output Growth Rates: Stylized Fact III

	Mean	Median	Std	Skewness	KS Statistics
Group experiencing trade credit decline					
Before the Great Recession	0.08	0.10	0.39	-0.21	0.43 (0.00)
During the Great Recession	0.61	0.67	0.22	-0.36	
After the Great Recession	0.12	0.14	0.43	-0.12	0.43 (0.00)
Group not experiencing trade credit decline					
Before the Great Recession	0.09	0.10	0.37	-0.06	0.43 (0.00)
During the Great Recession	0.40	0.44	0.30	-0.39	
After the Great Recession	0.08	0.11	0.38	-0.22	0.43 (0.00)
KS Test across groups during the Great Recession					
Decline vs No Decline					0.19 (0.00)

Notes: All kernel densities f are calculated on unit interval $[-1,1]$ with bandwidth 0.001. *p-value* for the KS statistics is reported in the parentheses. The critical values of KS statistics at 0.1%, 1%, and 5% significance level are respectively 0.0616, 0.0515 and 0.0430 in this case.

Table 5
Calibration

	Parameters	Source/Target	Value
N	number of sectors	2-digit industries in the US	15
α_i	labor share	sectoral labor share	Appendix G
ω_{ij}	intermediates share	the U.S. IO table (2007)	Appendix G
φ_i	TC adjustment cost	var of TC (2000–2007)	Appendix G
$\bar{d}_i$	TC in the neutral state	median TC (2007)	Appendix G
ρ_i	autocorrelation for sectoral productivities	estimated by author	Appendix G
σ_{ij}^z	covariance of ϵ_i^z and ϵ_j^z	estimated by author	Appendix G
$\bar{e}_i$	mean of bank lending condition	calculated from the neutral state	Appendix G
σ_i^e	var of bank lending shocks	Chodorow-Reich (2014)	Appendix G
κ	prob of low proudctivities	Jacobson and von Schedvin (2016)	0.06
η	disutility from working	standard	1.9

Table 6
Statistics: Distance Measure for Influence Vector δ_i

	Mean	Median	Std	Min	Max
Euclidean Norm	1.58	1.53	0.15	1.42	1.97
Angular Separation	0.14	0.11	0.10	0.01	0.46
	(82.0^o)	(83.7^o)		(88.3^o)	(62.7^o)

Table 7
Regression Results: Equation (26)

	$\mathbf{Corr}_{before}$				$\mathbf{Corr}_{crisis} - \mathbf{Corr}_{before}$	
$D^{AS}(\delta_i, \delta_j)$	1.11**	1.06*			.362	.658
	(.397)	(.541)			(.462)	(.691)
$D^{AS}(sup_i, sup_j)$			.193			
			(.172)			
$D^{AS}(cln_i, cln_j)$				.109		
				(.247)		
Sectoral FE	No	Yes	Yes	Yes	No	Yes
R^2	.0711	0.18	.0129	0.18	.00592	.751

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A Data

A.1 Quarterly Finance Report

The Quarterly Finance Report (QFR) includes all corporations engaged primarily in manufacturing with total assets of $250,000 and over, and all corporations engaged primarily in mining, wholesale trade, and retail trade industries with total assets of $50 million and over. The QFR sampling frame is developed from a file received annually from the IRS. Another random samples are selected for firms have less than $250,000 total assets. Each firm in the random sample is kept for eight successive quarters. The QFR separately reports representative income statement and balance sheet for big corporations, small business and industry total for 31 industries.

In our analysis, the industry total is used. All sales value in the QFR is in nominal term. We deflate all series by the U.S. GDP deflator with the 2009 dollar equal to 100 and adjust for seasonality using the X–12–ARIMA seasonal adjustment program. Last, we combine the sales from the QFR with gross output value provided by the Bureau of Economic Analysis (BEA). The sample consists of 44 non-FIRE private sectors. Table 8 reports the list of sectors and their main characteristics. 'Consumption' and 'input' are respectively the shares of products used as consumption goods and intermediate inputs. $\Delta\frac{AR}{S}$ and $\Delta\frac{AP}{OC}$ are defined in Section 2.3.2. BL_Shock is defined in Section 2.3.3.

A.2 Compustat

Following Kahle and Stulz (2013), we use Compustat Database and create our firm-level sample by filtering out

- Observations with negative totala ssets (atq), negative sales (saleq), negative cash and marketable securities,cash and marketable securities greater than total assets;
- Firms not incorporated in the US;
- All financial firms (firms with standard industrial classification(SIC) codes between 6000 and and 6999);
- Firms with market capitalization less than $50 million and with book value of assets is less than $10 million
- Firms with quarterly asset or sales growth greater than 100% at some point during sample period
- Observations which have cash and marketable securities greater than total assets;

Then we construct measurements for the intensity of trade credit provision and reception as

$$Intensity\ of\ Trade\ Credit\ Provision = \frac{Accounts\ Receivables\ (rectq)}{Total\ Sales\ (sales)};$$

$$Intensity\ of\ Trade\ Credit\ Reception = \frac{Accounts\ Payables(apq)}{Operational\ Costs\ (cogsq){+}\Delta Inventory\ (invtq)};$$

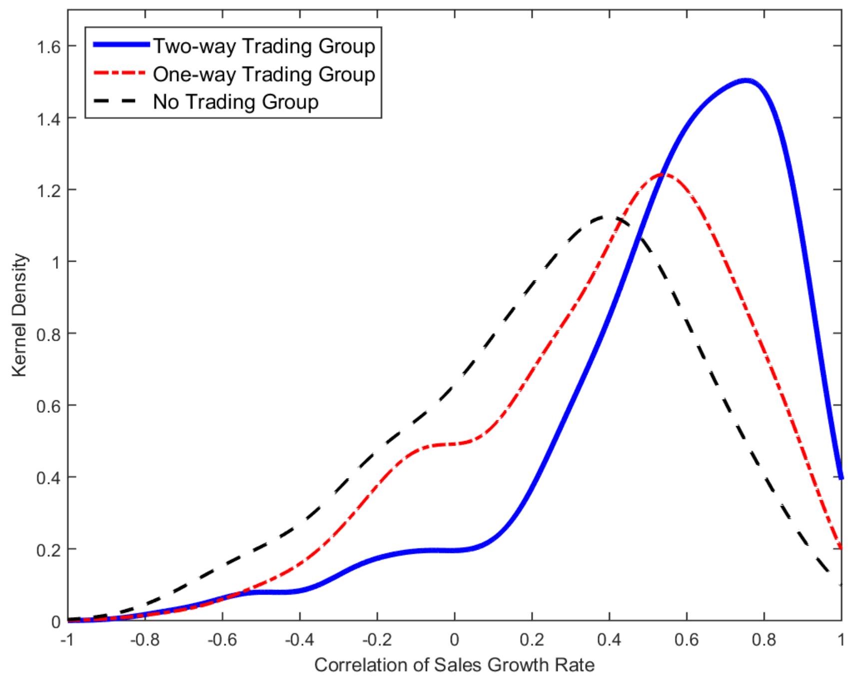
B Stylized Fact OLD2 role of intermediate-input linkages

Next, we examine the role of trading in intermediate inputs in the increase of the sectoral comovement during the Great Recession. To identify the intermediate trading relationship between two sectors, we aggregate the 2007 US Industry Input-Output (IO) table with 385 industries into one with 45 private sectors, including FIRE. We calculate the input-output matrix, each element of which is the share of intermediate inputs from the upstream to the downstream sector over the total intermediates used by the downstream one. If such a share is too low, namely 0.1%, we set it equal to 0.[30] Then all pairs are categorized into three groups, according to the extent of their interconnectedness. In particular, two sectors are classified into the two-way trading group if they are both intermediate provider and purchaser to each other, into the one-way trading group if only one sector purchases intermediate inputs from the other but not vice versa, and no trading group if no intermediate input is traded between them. Each group has 381, 410, and 155 pairs, respectively.

Figure 12 displays the comparison of kernel densities during the Great Recession across three groups. The extents of interconnectedness between two sectors are positively correlated with the sectoral comovement during the recession. In particular, the two-way trading group has 0.17 higher average correlation than the one-way group and 0.31 higher than the no trading group, as Table 9 shows. This outcome implies that the pairs with two-way interconnection mainly drive the sectoral comovement during the Great Recession, and it also indicates that a sector-specific shock can be transmitted via the production network. Also, medians follow the same order, and the difference is slightly larger across groups. High skewness in the two-way group suggests that many pairs in this group move at the same pace during the Great Recession. The KS statistics are 0.16 comparing the two-way with the one-way trading group, 0.23 comparing the two-way with the no trading group, and 0.09 comparing the one-way with no-trading group. All tests reject the null hypothesis that two densities are the same at the 0.1% significance level.

[30] We also try to relax such restraints and other restraints, namely 0.05% and 0.25%. All results here are robust.

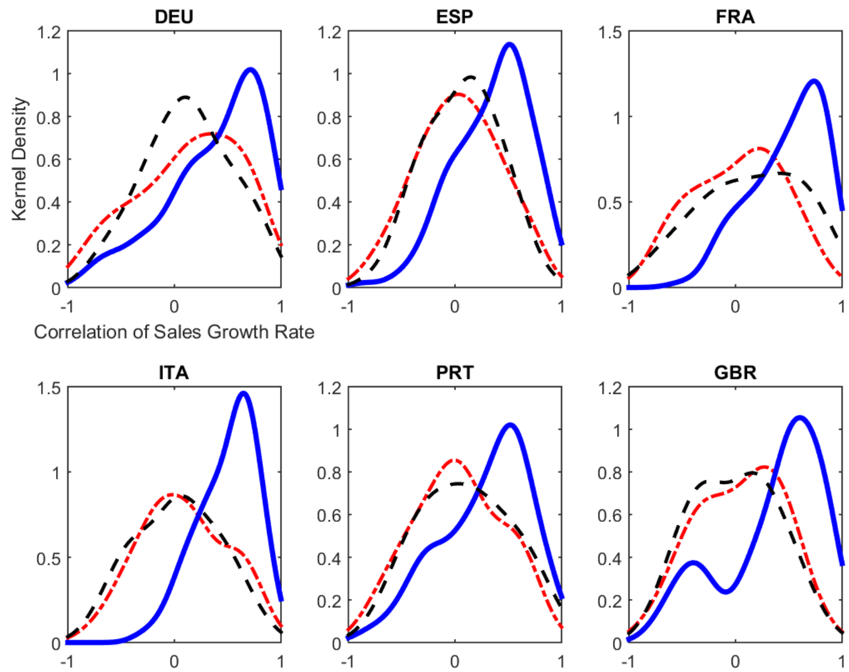
Note: Two-way trading group, in which two sectors are both intermediate inputs provider and purchaser to each other; one-way trading group, in which only one sector purchases intermediate inputs from the other but not vice versa; and no trading group, in which no intermediate input is traded between two sectors. There are respectively 381, 410, and 155 pairs in each group. Equation (1) is used to calculate the correlation of output growth rate. The solid blue, dashed red, and dotted black lines represent the densities for the two-way, one-way, and no-trade groups, respectively.



Fixing the same categorization before and after the Great Recession, we take pairwise correlations and calculate kernel densities for each group. The densities before and after the Great Recession, however, have very similar statistical moments across three groups, as shown in Table 9. Figures 16 and 17 in Appendix E display the kernel densities of three groups before and after the Great Recession, respectively, and overlap one another. Moreover, a mean difference test is conducted to determine whether the increase of pairwise correlations from the pre–crisis level differs across groups. The average increases in the pairwise correlations are 0.40, 0.27, and 0.13 for the two-way, one-way, and no trading groups, respectively. All mean differences are statistically significant at the 0.1% significance level. These findings suggest that the higher margin of interconnectedness also corresponds to a larger increase in sectoral comovement.

In Appendix D, we further categorize sectors based on whether the products from a sector are mainly used as consumption goods or intermediate inputs. The results are consistent with stylized fact II. The group in which sectors mainly provide their goods as intermediate inputs has a higher pairwise correlation on average during the Great Re-

Figure 13
Pairwise Correlations of Major European Countries during the Great Recession



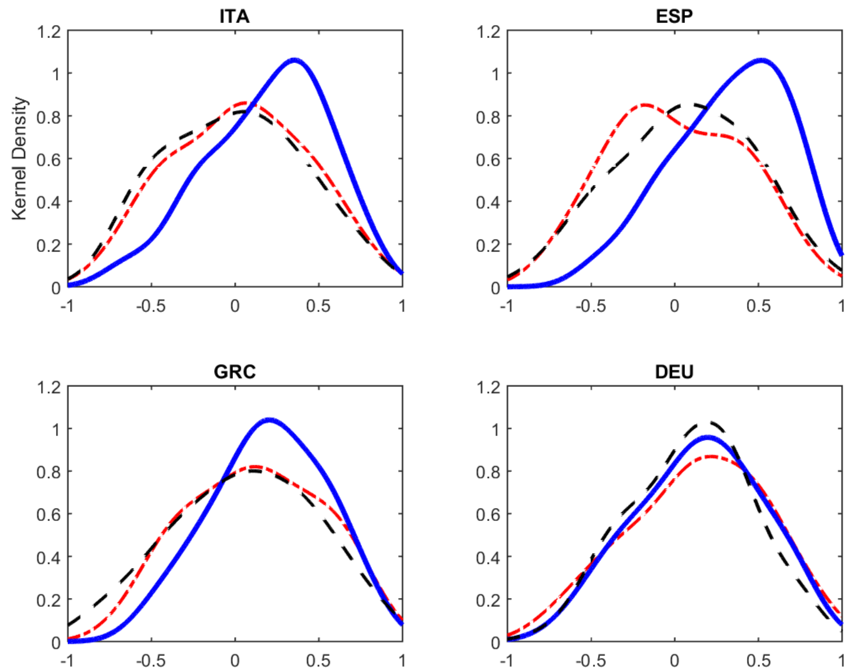
cession than the counterpart. This finding shows the relevance of input-output linkage among sectors with the sectoral comovement. Moreover, we compare the pairwise correlations of manufacturing with those of service sectors. The difference of two kernel densities is not statistically significant because some service sectors also serve as important intermediate providers.

C Sectoral Comovemeng in European Countries

EuroStat Database provides the information about production in industries for major European countries. We choose the same period as in Section 2.2 and calculate the pairwise correlations among sectors. Figure 13 displays the kernel densities of the pairwise correlations in Germany, Spain, France, Italy, Portugal, and UK. As in the U.S., these European countries have experience the similar increase in sectoral comovement.

Using the same dataset, we also examine the sectoral comovement during the European Debt Crisis. Figure 14 shows the kernel densities of the pairwise correlations for Spain, Italy, Greece and Germany with the crisis period starting at 2011Q3. We find the increase in sectoral comovement in Spain, Italy and Greece, but not in Germany, France

Figure 14
Pairwise Correlations of Major European Countries during the European Debt Crisis

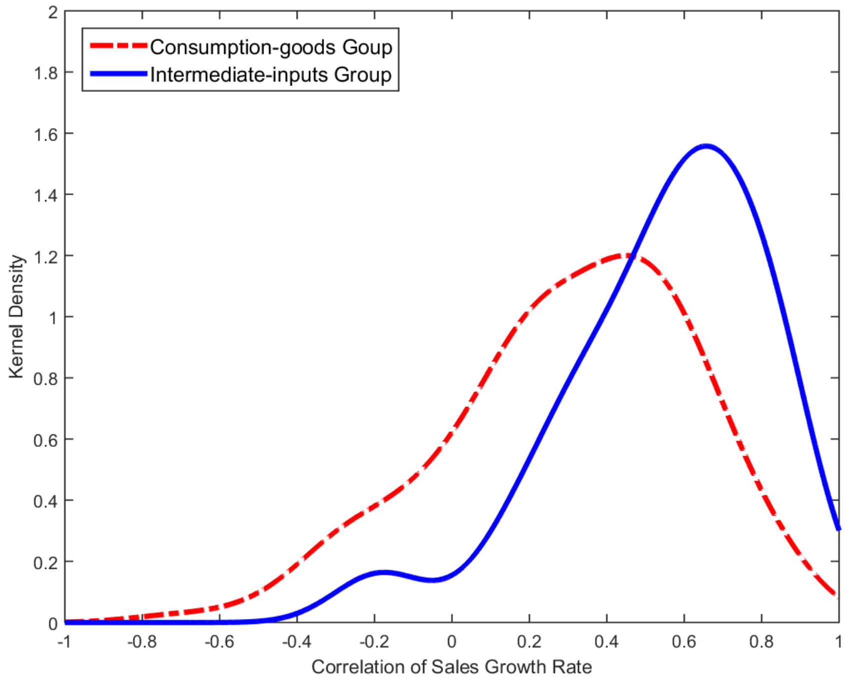


and the UK.

D Robustness Check for Other Decompositions

Mian and Sufi (2010) and Mian et al. (2013) document that the U.S. experienced a large decline across various types of consumption goods during the Great Recession. It indicates that sectors providing more of their products as consumption goods would be more likely to move together driven by such decline in consumption. To test this, we divide all sectors into two groups based on the share of their products used mainly as consumption goods or intermediate inputs in 2007. One sector is categorized in the consumption–goods group if the share of products used as consumption goods is more than the median value, namely 30%, across sectors. On the other hand, it is classified in the intermediate–inputs if the sector provide more than 60% of their goods as intermediate inputs, where 60% is the median value of such shares across sectors. Figure 15 shows the comparison for the kernel densities during the Great Recession across two groups, where the blue solid and red dashed lines represent the final goods and intermediate inputs group respectively. The figure suggests the opposite to our expectation.

Note: Consumption–goods group in which the share of products used as consumption goods is more than the median value across sectors; and Intermediate-inputs group in which the share of products used as consumption goods is less than the median value across sectors. Equation 1 is used to calculate the correlation of sales growth rate. The blue solid and red dashed lines represent the densities for the intermediate–inputs and consumption–goods group respectively.

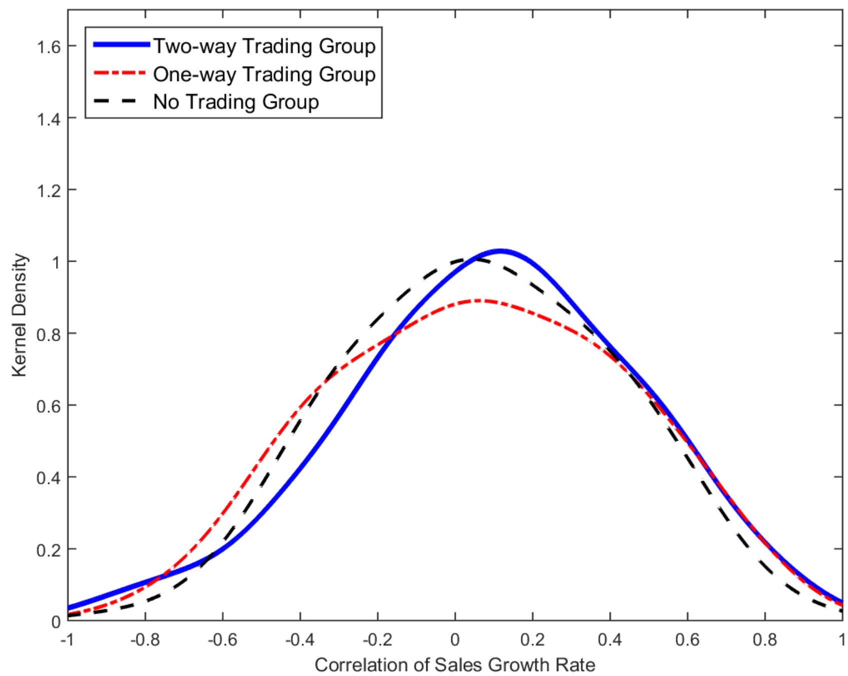


In particular, the intermediate–inputs group has higher correlation, by 0.17 on average and 0.23 on median. The KS statistics for comparing the densities across groups is 0.12, which is more than the critical value at the 0.1% significance level. It means that two kernel densities are statistically significantly different from each other. Moreover, in the online Appendix, we show that the kernel densities before (after) the recession for two groups are not statistically significantly different from each other. This finding confirms the stylized fact II in Sector B and demonstrate the relevance of input-output linkage among sectors with the rise in sectoral comovement.

E Comparison: Kernel Densities before (after) the Great Recession

Figure 16 and 17 respectively display the kernel densities of three types of interconnectedness before and after the Great Recession. Figure 18 and 19 show that the kernel densities of two trade-credit groups before and after the Great Recession.

Note: Two–way trading group where two sectors are both intermediate inputs provider and purchaser to each other; one–way trading group where only one sector purchases intermediate inputs from the other but not other way around; and no trading group where no intermediate input is traded between two sectors. There are respectively 381, 410, and 155 pairs in each group. Equation 1 is used to calculate the correlation of sales growth rate. The blue solid, red dashed, and black dotted lines represent the densities for the two–way, one–way and no–trade group respectively.



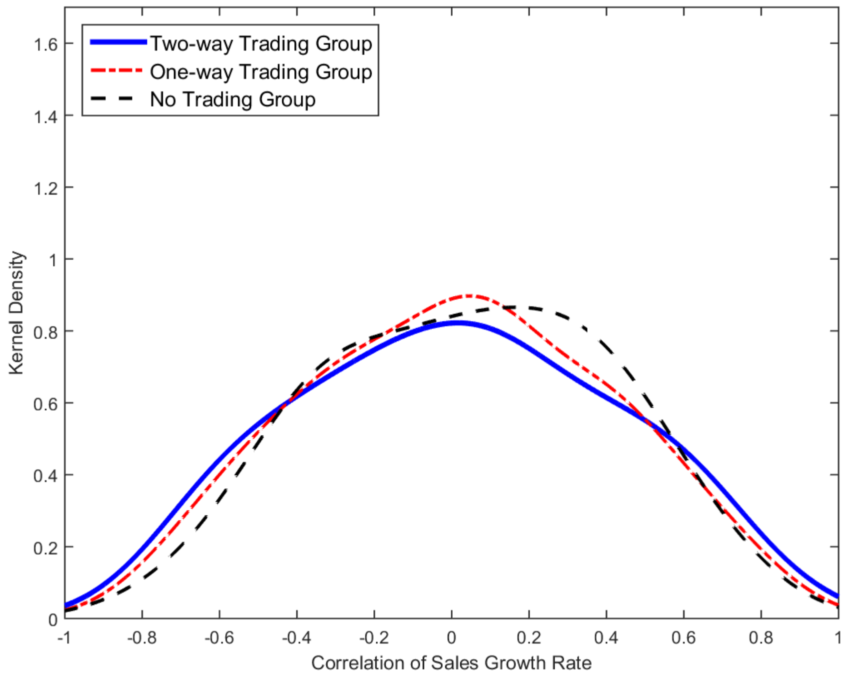
F Proof of Lemmas and Propositions

F.1 Proof of Lemma 1

Suppose μ_i is the Lagrange multiplier for the financial constraint of firms in sector i. Then the Lagrangian for firms' problem is

$$\mathcal{L} = p_i z_i \prod_{j=1}^{N} m_{ji}^{\omega_{ji}} l_i^{\alpha_i} - \sum_{j=1}^{N} \kappa d_{ij} p_i m_{ij} - w l_i - \sum_{j=1}^{N} \left(1-\kappa d_{ji}\right) p_j m_{ji} - \varphi_i \sum_{j=1}^{N} \left(d_{ij} - \bar{d}_i\right)^2 p_i m_{ij}$$
$$+\mu_i \left(e_i p_i c_i + \sum_{j=1}^{N} \left(1-d_{ij}\right) p_i m_{ij} - w l_i + \sum_{j=1}^{N} \left(1-d_{ji}\right) p_j m_{ji} \right) \quad (27)$$

Note: Two–way trading group where two sectors are both intermediate inputs provider and purchaser to each other; one–way trading group where only one sector purchases intermediate inputs from the other but not other way around; and no trading group where no intermediate input is traded between two sectors. There are respectively 381, 410, and 155 pairs in each group. Equation 1 is used to calculate the correlation of sales growth rate. The blue solid, red dashed, and black dotted lines represent the densities for the two–way, one–way and no–trade group respectively.



The first order conditions for l_i and m_{ji} are

$$(l_i) \qquad \alpha_i \frac{p_i y_i}{l_i} = (1+\mu_i) w \tag{28}$$

$$(m_{ji}) \qquad \omega_{ji} \frac{p_i y_i}{m_{ji}} = (1-\kappa d_{ji} + (1-d_{ji})\mu_i) p_j \tag{29}$$

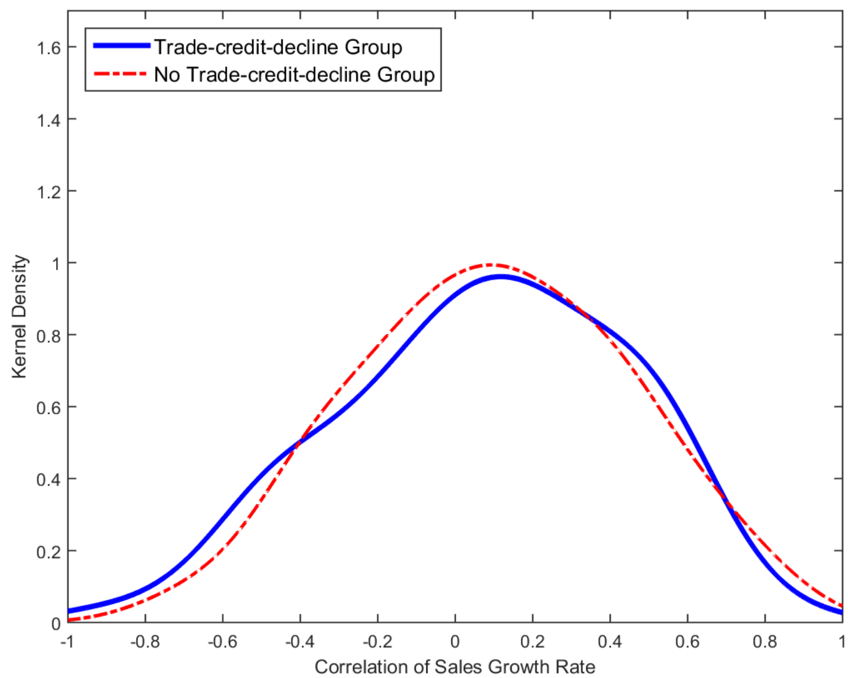
Let

$$\theta_i^l = \frac{1}{1+\mu_i} \tag{30}$$

$$\theta_{ji}^m = \frac{1}{1-\kappa d_{ji} + (1-d_{ji})\mu_i} \tag{31}$$

Then, combining Equation (30) with (28), we have Equation (13); and combining Equation (31) with (29), we have Equation (14).

Note: A pair is considered as experiencing trade credit decline during the Great Recession if both the intensity of the upstream sector's trade credit provision declined more than 6.3% and the intensity of the downstream sector's trade credit reception declined more than 6.0%. Otherwise, the pair is categorized into the control group. The blue solid and red dashed lines respectively represent the densities of group experiencing the decline in trade credit and the counterpart.



F.2 Proof of Lemma 2

The Lagrangian for firms' problem in the second step is

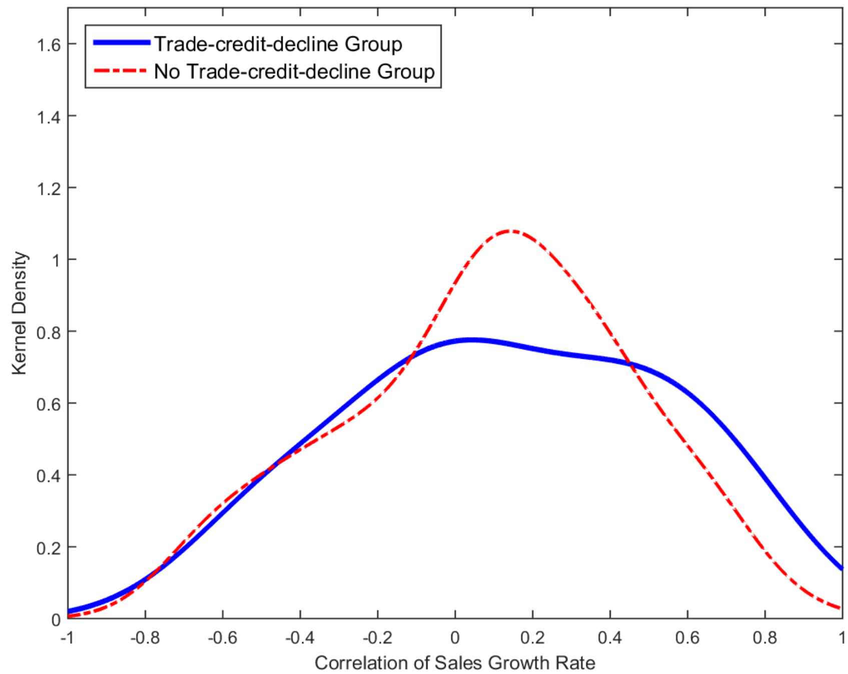
$$\begin{aligned}\mathcal{L}^d &= \left(1-\kappa d_{ij}-\varphi_i\left(d_{ij}-\bar{d}_i\right)^2+\left(1-d_{ij}\right)\mu_i\right)\omega_{ij}\theta^m_{ij}p_j y_j \\ &\approx \frac{1-\kappa d_{ij}-\varphi_i\left(d_{ij}-\bar{d}_i\right)^2+(1-d_{ij})\mu_i}{1-\kappa d_{ij}+(1-d_{ij})\mu_j}\end{aligned}$$

The first order conditions for d_{ij} is

$$\varphi_i(\kappa+\mu_j)\left(d_{ij}-\bar{d}_i\right)^2-2\varphi_i\left(1+\mu_j-\left(\kappa+\mu_j\right)\bar{d}_i\right)\left(d_{ij}-\bar{d}_i\right)=(1-\kappa)\left(\mu_i-\mu_j\right) \tag{32}$$

Solving Equation (32) for d_{ij}, we have Equation 15.

Note: A pair is considered as experiencing trade credit decline during the Great Recession if both the intensity of the upstream sector's trade credit provision declined more than 6.3% and the intensity of the downstream sector's trade credit reception declined more than 6.0%. Otherwise, the pair is categorized into the control group. The blue solid and red dashed lines respectively represent the densities of group experiencing the decline in trade credit and the counterpart.



F.3 Proof of Proposition 1

Rewriting Equation 32, we have

$$-\varphi_i\left(d_{ij}-\bar{d}_i\right)\left(2\left(1+\mu_j\right)-(\kappa+\mu_j)d_{ij}-\left(\kappa+\mu_j\right)\bar{d}_i\right)=(1-\kappa)\left(\mu_i-\mu_j\right) \tag{33}$$

Since $d_{ij} \leq 1$, $\bar{d}_i \leq 1$, and $\kappa < 1$, then $2\left(1+\mu_j\right)-(\kappa+\mu_j)d_{ij}-\left(\kappa+\mu_j\right)\bar{d}_i > 0$. If $\mu_i = \mu_j$, then the LHS of Equation (32) is equal to zero. This implies $d_{ij} = \bar{d}_i$. If $\mu_i > \mu_j$, then the LHS of Equation (32) is positive, which further implies $d_{ij} < \bar{d}_i$. If $\mu_i < \mu_j$, then the LHS of Equation (32) is negative, which further implies $d_{ij} > \bar{d}_i$.

Taking the first derivative of Equation (15), we have

$$\frac{\partial d_{ij}}{\partial \mu_i} = -\frac{1-\kappa}{2\varphi_i\left(1-\kappa d_{ij}+\left(1-d_{ij}\right)\mu_j\right)} < 0 \tag{34}$$

$$\frac{\partial d_{ij}}{\partial \mu_j} = \frac{1-\kappa-\varphi_i\left(d_{ij}-\bar{d}_i\right)\left(2-d_{ij}-\bar{d}_i\right)}{2\varphi_i\left(1-\kappa d_{ij}+\left(1-d_{ij}\right)\mu_j\right)} \tag{35}$$

Since $\left(d_{ij}-\bar{d}_i\right)\left(2-d_{ij}-\bar{d}_i\right) = -\left(1-d_{ij}\right)^2+\left(1-\bar{d}_i\right)^2 < \left(1-\bar{d}_i\right)^2$, then

$$\frac{\partial d_{ij}}{\partial \mu_j} > \frac{1-\kappa-\varphi_i\left(1-\bar{d}_i\right)^2}{2\varphi_i\left(1-\kappa d_{ij}+\left(1-d_{ij}\right)\mu_j\right)} > 0 \tag{36}$$

F.4 Proof of Proposition 2

It is trivial to show that $\frac{\partial \theta_i^l}{\partial \mu_i} < 0$. Then, combining Equation (31) with (15), we have

$$\theta_{ji}^m = \sqrt{\frac{1}{\left(1-\kappa\bar{d}_j+\left(1-\bar{d}_j\right)\mu_i\right)^2+\frac{1-\kappa}{\varphi_j}\left(\mu_j-\mu_i\right)(\kappa+\mu_i)}}$$

It is trivial to show that $\frac{\partial \theta_{ji}^m}{\partial \mu_j} < 0$. Let

$$\begin{aligned} g &= \left(1-\kappa\bar{d}_j+\left(1-\bar{d}_j\right)\mu_i\right)^2+\frac{1-\kappa}{\varphi_j}\left(\mu_j-\mu_i\right)(\kappa+\mu_i) \\ &\approx -\frac{1-\kappa-\varphi_j\left(1-\bar{d}_j\right)^2}{\varphi_j}\mu_i^2+\left(2\left(1-\kappa\bar{d}_j\right)\left(1-\bar{d}_j\right)+\frac{1-\kappa}{\varphi_i}\left(\mu_j-\kappa\right)\right)\mu_i \end{aligned}$$

Then we have $\frac{\partial g}{\partial \mu_i} > 0$ for $\mu_i < \frac{2\varphi_j\left(1-\kappa\bar{d}_j\right)\left(1-\bar{d}_j\right)+(1-\kappa)(\mu_j-\kappa)}{1-\kappa-\varphi_j\left(1-\bar{d}_j\right)^2}$ and $\frac{\partial g}{\partial \mu_i} \leq 0$, otherwise. The former implies $\frac{\partial \theta_{ji}^m}{\partial \mu_i} < 0$, whereas the latter suggests $\frac{\partial \theta_{ji}^m}{\partial \mu_i} \geq 0$. Moreover, the assumption, $\kappa < 2\varphi_i\left(1-\bar{d}_i\right)$, implies that $2\varphi_j\left(1-\kappa\bar{d}_j\right)\left(1-\bar{d}_j\right)+(1-\kappa)(\mu_j-\kappa) > 0$.

F.5 Proof of Proposition 3

First, we want to show that there exists $\bar{\xi}_i^l$ such that for all $xi_i^l < \bar{\xi}_i^l$,

$$\xi_i^l p_i y_i - w l_i - \sum_{j=1}^{N} p_j m_{ji} < 0 \tag{37}$$

In this case, we have the LHS of Equation (37) as

$$\begin{aligned}
\textbf{LHS} &= \left(\xi_i^l - \alpha_i \theta_i^l - \sum_{j=1}^{N} \omega_{ji} \theta_{ji}^m\right) p_i y_i \\
&\approx \xi_i^l - \alpha_i \theta_i^l - \sum_{j=1}^{N} \omega_{ji} \theta_{ji}^m \\
&= \xi_i^l - \frac{\alpha_i}{1+\mu_i} - \sum_{j=1}^{N} \frac{\omega_{ji}}{\sqrt{\left(1-\kappa \bar{d}_j + \left(1-\bar{d}_j\right)\mu_i\right)^2 + \frac{1-\kappa}{\varphi_j}\left(\mu_j - \mu_i\right)(\kappa + \mu_i)}}
\end{aligned}$$

Let $\bar{\xi}_i^l = \inf\left\{\frac{\alpha_i}{1+\mu_i} - \sum_{j=1}^{N} \frac{\omega_{ji}}{\sqrt{\left(1-\kappa \bar{d}_j + \left(1-\bar{d}_j\right)\mu_i\right)^2 + \frac{1-\kappa}{\varphi_j}\left(\mu_j - \mu_i\right)(\kappa + \mu_i)}}\right\}$. Then, Equation (37) holds for $\xi_i^l < \bar{\xi}_i^l$. Second, we want to show that there exists $\underline{\xi}_i^l$ such that for all $\xi_i^l > \underline{\xi}_i^l$,

$$\xi_i^l y_i > \sum_{j=1}^{N} m_{ij} \tag{38}$$

By the market clearing condition, Equation (38) becomes

$$\xi_i^l y_i > y_i - c_i$$

Given $y = (\mathbf{I} - \Omega' \circ \Theta_m')^{-1} \nu = \tilde{\nu} c$, Equation (38) becomes

$$\xi_i^l > 1 - \frac{\nu_i}{\tilde{\nu}_i}$$

Let $\underline{\xi}_i^l = \sup\left\{1 - \frac{\nu_i}{\tilde{\nu}_i}\right\}$. Then, Equation (38) holds for $\xi_i^l > \underline{\xi}_i^l$. Under some appropriate assumption for parameters, we have $\bar{\xi}_i^l > \underline{\xi}_i^l$.

F.6 Proof of Proposition 4

Combining Equation (13) with (14), we have

$$p_i y_i = \left(p_i z_i \left(\frac{\omega_{ji} \theta_{ji}^m}{p_j}\right)^{\omega_{ji}} \left(\frac{\alpha_i \theta_i^l}{w}\right)^{\alpha_i}\right)^{\frac{1}{1-\alpha_i - \sum_{j=1}^{N} \omega_{ji}}} \tag{39}$$

Taking logarithm of Equation (39) and stacking across all sectors, we have

$$\mathbf{D}_\pi (\log p_t + \log y_t) = \log z_t + (\mathbf{I} - \Omega') \log p_t + \mathbf{M}_\omega (\log \omega + \log \theta_t^m) + \mathbf{D}_\alpha \left(\log \alpha + \log \theta_t^l - \mathbf{1} \log w\right) \tag{40}$$

The optimal condition for the household's problem is

$$\eta c = w \tag{41}$$

Taking logarithm of Equation (23) and stacking across all sectors, we have

$$\log p_t + \log y_t = \log \tilde{\nu}_t + \mathbf{1} \log c \tag{42}$$

Replacing $\log p_t$ with Equation (42) and w with Equation (41), we have

$$\begin{aligned} \mathbf{D}_\pi (\log \tilde{\nu}_t + \mathbf{1} \log c) \;\; &= \;\; \log z_t + (\mathbf{I} - \Omega')(-\log y_t + \log \tilde{\nu}_t + \mathbf{1} \log c) \\ &\quad + \mathbf{M}_\omega (\log \omega + \log \theta_t^m) + \mathbf{D}_\alpha \left(\log \alpha + \log \theta_t^l - \mathbf{1} (\log c + \log \eta) \right) \end{aligned}$$

Let $\log \mathcal{C} = \mathbf{M}_\omega \log \omega + \mathbf{D}_\alpha \log \alpha - \mathbf{D}_\alpha \mathbf{1} \log \eta$. Then we have

$$\log y_t = (\mathbf{I} - \Omega')^{-1} \left(\log \mathcal{C} + \log z_t + \mathbf{M}_\omega \log \theta_t^m + \mathbf{D}_\alpha \log \theta_t^l + (\mathbf{I} - \Omega' - \mathbf{D}_\pi) \log \tilde{\nu}_t \right) \tag{43}$$

where $(\mathbf{D}_k + \mathbf{D}_\alpha)\mathbf{1} = (\mathbf{I} - \Omega')\mathbf{1}$. Taking the first difference of Equation (43) results Equation 24. Moreover, because $\nu' \log p_t = 0$ and $\nu' \mathbf{1} = 1$, then we have

$$\begin{aligned} \log c \;\; &= \;\; \nu' (\log y_t - \log \tilde{\nu}_t) \\ &= \;\; \nu' (\mathbf{I} - \Omega')^{-1} \left(\log \mathcal{C} + \log z_t + \mathbf{M}_\omega \log \theta_t^m + \mathbf{D}_\alpha \log \theta_t^l - \mathbf{D}_\pi \log \tilde{\nu}_t \right) \end{aligned} \tag{44}$$

F.7 Proof of Proposition 5

Let δ_i be the ith row of matrix $(\mathbf{I} - \Omega')^{-1}$. Then we have

$$\Delta \log y_{it} = \delta_i \Delta \log z_t \tag{45}$$

For $\forall\ i, j$, the sample covariance of output growth between sector i and j is

$$\begin{aligned} \mathbf{cov}\left(\Delta \log(y_i), \Delta \log(y_j) \right) \;\; &= \;\; \frac{1}{T-1} \sum_{t=1}^{T} \Delta \log y_{it} \Delta \log y_{jt} \\ &= \;\; \frac{1}{T-1} \sum_{t=1}^{T} \delta_i \Delta \log z_t \Delta \log z_t{}' \delta_j' \\ &= \;\; \delta_i \left(\frac{1}{T-1} \sum_{t=1}^{T} \Delta \log z_t \Delta \log z_t{}' \right) \delta_j' \end{aligned} \tag{46}$$

where the second equation is due to Equation (45). Let $\mathbf{M}_z = \frac{1}{T-1}\sum_{t=1}^{T} \Delta \log z_t \Delta \log z_t{}'$. Then the sample correlation between sector i and j

$$
\begin{aligned}
\mathbf{corr}\Big(\Delta \log(y_i), \Delta \log(y_j)\Big) &= \sqrt{\frac{\delta_i \mathbf{M}_z \delta_j' \delta_i \mathbf{M}_z \delta_j'}{\delta_i \mathbf{M}_z \delta_i' \delta_j \mathbf{M}_z \delta_j'}} \\
&= \sqrt{\frac{\mathbf{tr}\Big(\delta_i \mathbf{M}_z \delta_j' \delta_i \mathbf{M}_z \delta_j'\Big)}{\delta_i \mathbf{M}_z \delta_i' \delta_j \mathbf{M}_z \delta_j'}} \\
&= \sqrt{\frac{\mathbf{tr}\Big(\delta_j \mathbf{M}_z \delta_i' \delta_j \mathbf{M}_z \delta_i'\Big)}{\delta_i \mathbf{M}_z \delta_i' \delta_j \mathbf{M}_z \delta_j'}} \\
&= \sqrt{\frac{\delta_j \mathbf{M}_z \delta_i' \delta_j \mathbf{M}_z \delta_i'}{\delta_i \mathbf{M}_z \delta_i' \delta_j \mathbf{M}_z \delta_j'}}
\end{aligned}
$$

G Value of Parameters

Table 8
List of Sectors and Characteristics

Industry	Source	Consumption	Input	$\Delta\frac{AR}{S}$	$\Delta\frac{AP}{OC}$	BL_Shock
Agriculture, forestry, fishing, and hunting	BEA	17%	82%	NA	NA	0.70
Mining	BEA	0%	138%	NA	NA	0.64
Utilities	BEA	45%	55%	NA	NA	0.56
Construction	BEA	0%	15%	NA	NA	0.64
Food	QFR	56%	44%	-9%	-1%	0.60
Beverage and Tobacco Products	QFR	93%	16%	-20%	-46%	0.55
Textile Mills and Textile Product Mills	QFR	43%	79%	0%	-14%	0.54
Apparel and Leather Products	QFR	534%	50%	-6%	-1%	0.48
Wood Products	QFR	4%	106%	-1%	4%	0.65
Paper	QFR	13%	91%	1%	4%	0.57
Printing and Related Support Activities	QFR	3%	97%	-6%	-8%	0.42
Petroleum and Coal Products	QFR	37%	73%	-27%	-29%	0.51
All Other Chemicals	QFR	33%	65%	-9%	5%	0.54
Plastics and Rubber Products	QFR	13%	94%	-11%	0%	0.49
Nonmetallic Mineral Products	QFR	7%	106%	-5%	-3%	0.53
Foundries	QFR	1%	100%	-6%	2%	0.47
Fabricated Metal Products	QFR	4%	99%	-6%	-15%	0.54
Machinery	QFR	3%	42%	-13%	-3%	0.52
All Other Electronic Products	QFR	16%	57%	-10%	-10%	0.58
Electrical Equipment, Appliances, and Components	QFR	28%	78%	-7%	-1%	0.58
Furniture and Related Products	QFR	55%	39%	-4%	-6%	0.55
Miscellaneous Manufacturing	QFR	64%	46%	-5%	0%	0.53
Iron, Steel, and Ferroalloys	QFR	0%	120%	-11%	-27%	0.51
Computer and Peripheral Equipment	QFR	51%	59%	-1%	0%	0.57
Basic Chemicals, Resins, and Synthetics	QFR	0%	93%	-12%	-14%	0.53
Motor Vehicles and Parts	QFR	41%	48%	1%	-12%	0.48
Nonferrous Metals	QFR	0%	130%	-21%	-20%	0.47
Communications Equipment	QFR	10%	61%	-13%	-9%	0.58
Pharmaceuticals and Medicines	QFR	93%	45%	3%	24%	0.57
Aerospace Products and Parts	QFR	9%	33%	4%	3%	0.59
Wholesale Trade	QFR	32%	44%	-2%	-6%	0.52
Food and Beverage Stores	QFR	99%	1%	-22%	-7%	0.59
Clothing and General Merchandise Stores	QFR	96%	3%	-28%	-11%	0.55
All Other Retail Trade	QFR	82%	13%	-6%	-10%	0.60
Transportation and warehousing	BEA	26%	61%	NA	NA	0.58
Information	BEA	37%	45%	NA	NA	0.53
Professional and business services	BEA	7%	61%	NA	NA	0.57
Management of companies and enterprises	BEA	0%	100%	NA	NA	0.52
Administrative and waste management services	BEA	9%	91%	NA	NA	0.57
Educational services, health care, and social assistance	BEA	93%	6%	NA	NA	0.56
Health care and social assistance	BEA	99%	1%	NA	NA	0.43
Arts, entertainment, and recreation	BEA	74%	24%	NA	NA	0.62
Accommodation and food services	BEA	79%	21%	NA	NA	0.67
Other services, except government	BEA	73%	28%	NA	NA	0.53

Table 9
Pairwise Correlations of Output Growth Rates: Stylized Fact II

	Mean	Median	Std	Skewness	KS Statistics
Two–way Trading Group					
Before the Great Recession	0.10	0.12	0.39	-0.20	0.27 (0.00)
During the Great Recession	0.50	0.60	0.34	-1.21	
After the Great Recession	0.01	0.01	0.44	0.05	0.36 (0.00)
One–way Trading Group					
Before the Great Recession	0.06	0.07	0.40	-0.04	0.17 (0.00)
During the Great Recession	0.33	0.40	0.37	-0.53	
After the Great Recession	0.01	0.03	0.41	-0.01	0.19 (0.00)
No Trading Group					
Before the Great Recession	0.06	0.07	0.36	-0.06	0.11 (0.00)
During the Great Recession	0.19	0.24	0.39	-0.35	
After the Great Recession	0.04	0.06	0.43	-0.06	0.11 (0.00)
KS Test across Groups during the Great Recession					
Two–way vs One–way					0.16 (0.00)
Two–way vs No Trading					0.23 (0.00)
One–way vs No Trading					0.09 (0.00)

Notes: All kernel densities f are calculated on unit interval [1,1] with bandwidth 0.001. The *p-value* for the KS statistics is reported in the parentheses. The critical values of KS statistics at 0.1%, 1%, and 5% significance levels are respectively 0.0616, 0.0515, and 0.0430 in this case.

Table 10
Sales Growth Rate Correlation: Stylized Fact II

	Mean	Median	Std	Skewness	KS Statistics
Consumption–goods Group					
Before the Great Recession	0.07	0.09	0.42	-0.13	0.17 (0.00)
During the Great Recession	0.30	0.34	0.33	-0.49	
After the Great Recession	-0.01	0.01	0.41	-0.04	0.20 (0.00)
Intermediate–inputs Group					
Before the Great Recession	0.08	0.08	0.38	-0.08	0.17 (0.00)
During the Great Recession	0.47	0.57	0.36	-1.04	
After the Great Recession	0.05	0.07	0.42	-0.07	0.20 (0.00)
KS Test across Groups during the Great Recession					
Intermediate vs Consumption					0.12 (0.00)

Notes: All kernel densities f are calculated on unit interval $[-1,1]$ with bandwidth 0.001. *p-value* for the KS statistics is reported in the parentheses. The critical values of KS statistics at 0.1%, 1%, and 5% significance level are respectively 0.0616, 0.0515 and 0.0430 in this case.

Table 11
Value of Parameters

	Sectors	α	ν	φ	$\bar{d}$	ρ	σ^e	$\bar{e}$
1	Agriculture	0.12	0.01	0.02	0.43	0.75	0.01	0.13
2	Mining	0.13	0.00	0.02	0.89	0.81	0.03	0.15
3	Utilities & Construction	0.28	0.03	0.03	0.46	0.86	0.05	0.52
4	Durable goods	0.18	0.13	0.03	0.55	0.72	0.05	0.49
5	Nondurable goods	0.16	0.09	0.03	0.48	0.80	0.04	0.45
6	Wholesale	0.34	0.05	0.03	0.44	0.69	0.05	0.50
7	Retail	0.38	0.14	0.01	0.42	0.21	0.05	0.49
8	Transportation	0.30	0.03	0.03	0.30	0.73	0.05	0.57
9	Information	0.22	0.05	0.04	0.64	0.34	0.03	0.35
10	Professional services	0.42	0.02	0.02	0.65	0.70	0.01	0.88
11	Administrative services	0.48	0.01	0.03	0.37	0.30	0.03	0.79
12	Educational services	0.53	0.03	0.03	0.25	0.88	0.06	0.65
13	Health care	0.50	0.23	0.02	0.30	0.76	0.06	0.63
14	Recreation services	0.34	0.11	0.02	0.21	0.86	0.05	0.50
15	Other services	0.41	0.06	0.01	0.37	0.66	0.05	0.55