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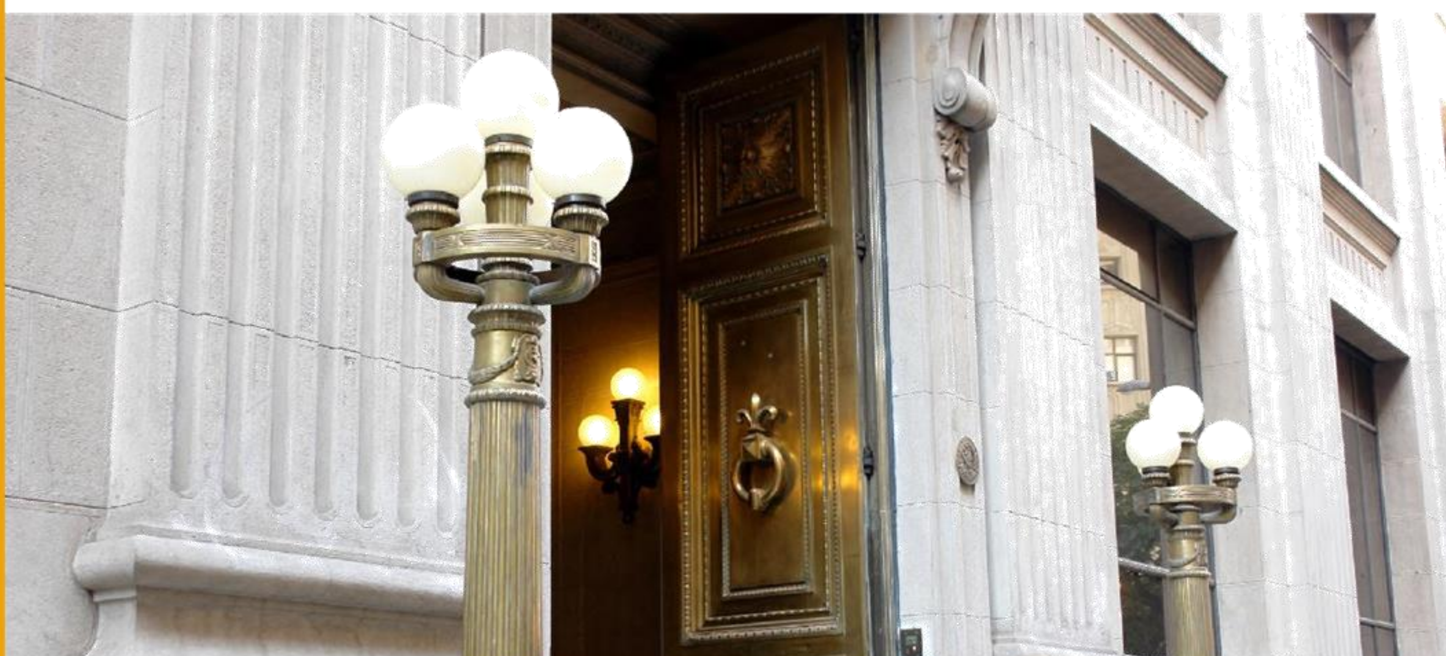

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Trade Credit and Sectoral Comovement during Recessions*

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Abstract

We show that sectoral comovement did not change for any post-war US recession, with the only exception of the Great Recession. Using sector-level and firm-level data, we argue that this large increase was driven mainly by the endogenous response of firm-to-firm credit (trade credit). We then develop a multisector model with input-output linkages, financial frictions, and endogenous supply of trade credit and show that the financial shocks after Lehman Brothers' collapse triggered a response of trade credit that can qualitatively and quantitatively account for the large shift in comovement. A model with fixed trade-credit, subject to the same productivity and financial shocks, generates no increase in comovement and implies a 20% smaller decline in GDP than in the endogenous case. In contrast, we show that trade credit in the other previous recessions acted as a cushion that mitigated negative sectoral spillovers.

Resumen

Mostramos que el comovimiento sectorial no cambió en ninguna recesión estadounidense de la posguerra, con la única excepción de la Gran Recesión. Utilizando datos a nivel de sector y a nivel de empresa, argumentamos que este gran aumento fue impulsado principalmente por la respuesta endógena de crédito de empresa a empresa (crédito de comercio). Luego desarrollamos un modelo multisectorial con redes productivas, fricciones financieras y oferta endógena de crédito de comercio y mostramos que los shocks financieros posteriores al colapso de Lehman Brothers desencadenaron una respuesta del crédito de comercio que puede explicar cualitativa y cuantitativamente el gran aumento en el comovimiento sectorial. Un modelo con crédito de comercio fijo, sujeto a la misma secuencia de choques productivos y financieros, no genera aumento en el comovimiento sectorial e implica una disminución del PIB 20% menor que en el caso de crédito de comercio endógeno. En contraste, mostramos que en las recesiones anteriores, el crédito de comercio actuó como un colchón que mitigó los efectos de choques sectoriales negativos.

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1 Introduction

At the business cycle frequency, the output of different sectors or firms comoves. Two common explanations are aggregate shocks and sectoral shocks propagated and amplified through input-output linkages (see, for example, Long and Plosser, 1983; Horvath, 1998; Acemoglu et al., 2012; Hornstein and Praschnik, 1997; Shea, 2002; Foerster et al., 2011; Baqaee and Farhi, 2019; Lehn and Winberry, 2020). While previous work is crucial to understanding average sectoral comovement, little work has been done to understand the state-dependency of sectoral comovement. In this paper, we document that, unlike any other post-war US recession, sectoral output comovement experienced a large and unprecedented shift in the US during the Great Recession. We argue that this shift was not merely a result of an aggregate financial shock but, instead, the result of domino effects generated by the endogenous response of trade credit—the main source of short-term credit among firms—to the initial financial 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 Great Recession and reverted to the pre-recession level in 2010. In particular, the average pairwise correlation among sectors rose from 0.08 to 0.38 (375% increase) and then declined to 0.02. Moreover, the rise in sectoral comovement is not a common feature of US recessions. With a subset of the quarterly data, we find that the distributions did not change during 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 decline in GDP.

Second, sectoral comovement increased more for the groups of sectors that had stronger input-output connections. While the comovement between sectors that did not trade intermediates increased by a factor of 3.1, the comovement between sectors trading intermediates one-way (only one sector providing intermediates for the other) and two-way (both sectors are intermediate providers and users of each other) rose by a factor of 5.5 and 8.3, respectively. Interestingly, the pairwise correlations for these three groups of sectors did not change during the Recessions of 1990 and 2001, indicating that a change in their relationship during the Great Recession, rather than their average connection, contributed to the shift in comovement.

Third, using sectoral data from the Quarterly Financial Report (QFR), we examine the role of trade credit adjustment in driving the shift in comovement. We show that two sectors in the two-way trading group that experienced a below-median decline in trade credit had a correlation of output growth that was 0.14 higher, on average, than the two-way pairs that did not. Similarly, a pair in the one-way trading group had a correlation 0.11 higher when the sectors experienced a below-median decline in trade, compared to the one that did not.

We complement our sectoral facts using firm-level evidence from COMPUSTAT and DealScan. We first show that, consistent with Costello (2020), and unlike the recessions in 1980, 1990, and 2001, trade credit reception and provision collapsed during the Great Recession. The intensity of trade credit provision (and reception), defined as the ratio of account receivables (payables) to sales (operation cost plus the change in inventory), declined by about ten percentage points during the Great Recession. We then take advantage of the quasi-natural experiment of the collapse of Lehman Brothers (henceforth, LB) to investigate the role of financial frictions and trade credit adjustment in increasing firm-level comovement during the Great Recession. We first focus on a set of firms for which suppliers were not connected to LB and at least one of their clients was. We find that direct exposure to LB significantly reduced the amount of trade credit reception by clients. We then show that firm-level pairwise correlation significantly increased when the client was directly or indirectly exposed to LB, and it increased even more when these clients had a lower accounts payable ratio. We found similar results when we considered the sample in which all clients were not directly connected to LB, but at least one of their suppliers was. This highlights the amplifying role that trade credit played in increasing comovement as a response to the initial financial shock during the Great Recession.

To uncover the mechanism and reconcile the facts that we document, we develop a model economy that combines the environments in Kiyotaki and Moore (1997), Greenwood et al. (2010), Kim and Shin (2012), and Bigio and La'O (2020). In particular, we construct a multisector model of production networks displaying firm-to-firm production and credit linkages. Due to the uncertainty about the quality of intermediate inputs, trade credit arises in equilibrium as a way to learn the true quality of intermediates. Thus, the model displays default risk on trade credit. Besides, there is pricing power in intermediate input markets, as producers customize their product for intermediate input uses. Finally, there is a collateral constraint on external funds. Firms need to finance the advance payments for wages and a portion of upfront payment for intermediates through competitive banks. Banks require firms' shareholders to pledge a fraction of their outputs as collateral.

The optimal trade credit contract offered by the supplier entails a price for the intermediate input, an amount of trade credit (delayed payment), and a penalty payment (in case the client misreports the quality of the input). The pricing decision weights the benefits of increasing sales—concave function of the price—against the cost of verifying the realized quality of the input—which is a convex function of the input price. The optimal amount of trade credit considers the supplier's desire for liquidity and the client's desire to learn the realized quality of the intermediate input. In addition, the client's and supplier's financial condition shape the intensity of trade credit provision. A negative financial shock to the supplier generates a reduction in trade credit provision, as less trade credit alleviates the tightened constraint due to the shock and partially recovers distorted outputs. This is consistent with Costello (2020). A negative financial shock to the client, all else equal, increases the amount of trade credit provided by the supplier, which increases the input sales. However, such a shock also leads the supplier's constraint to become tighter, as input revenue contracts. If the supplier is constrained to a certain extent, the negative financial shock to the client can trigger a reduction in trade credit provision by the supplier, which is in line with the empirical evidence we document.

We calibrate the model to the US economy to examine the role of endogenous trade credit adjustment in propagating and amplifying financial and productivity shocks during the Great Recession. First, we show that our calibrated model matches the rise in sectoral comovement during the Great Recession quite well. Also, the model-implied reduction in GDP growth during the Great Recession is close to that in the data. Moreover, even without any bilateral data on trade credit, we manage to derive such a relationship, and the sectoral accounts receivable and payable ratios are in line with the data. Next, we use the model-implied data to run a sectoral regression that mimics the ones that we run in the data. The results highlight the role of trade credit in driving the shift in comovement during the Great Recession. Negative financial shocks increase sectoral comovement the most when the clients receive a large shock and even more when their suppliers contract trade credit the most.

We then use the model to run several counterfactual exercises to quantify the role of trade credit in shifting the distribution of sectoral pairwise correlations and in amplifying the decline in aggregate GDP. In particular, we use the calibrated financial and productivity shocks and feed them to a model with trade credit structure (fixed to the pre-recession levels). The results shows no shift in sectoral comovement during the Great Recession, indicating that input-output linkages and financial frictions alone cannot explain the shift in comovement. Hence, the endogenous adjustment of trade credit is a crucial factor in the observed state-dependency of sectoral comovement during the Great Recession. In addition, the fixed-trade-credit model implies a decline in GDP growth that is 22% smaller than the one implied by our benchmark economy with endogenous-adjusted trade credit.

We also study the implied dynamics of sectoral shocks in a counterfactual model with fixed trade credit. In particular, we recalibrate the sequence of financial and productivity shocks in the version of our model in which trade credit stays fixed at the pre-recession level. We observe that, in order to match the evolution of sectoral sales, the fixed-trade-credit model requires a tightening of the collateral constraint that is up to 2.5 times larger than in the endogenous trade credit model. Thus, our model displays a strong internal propagation mechanism that is able to amplify milder financial negative shocks.

In our final section, we investigate the reasons that sectoral comovement barely shifted during US recessions before 2007. We focus on the recession in the early 1980s, a recession with a magnitude in GDP growth rate similar to that of the Great Recession. Our calibrated model indicates that trade credit adjustment served as a cushion that dampened sectoral spillovers and, therefore, reduced the decline in real GDP.

Our paper makes several contributions to the existing literature on sectoral comovement, financial crises, and trade credit (see, for example, Love et al., 2007; Costello, 2020; Li and Martin, 2019). On the empirical side, our paper documents the significant shift in sectoral comovement during the Great Recession as a unique feature of US business cycles. In addition, we provide sectoral and firm-level evidence supporting the idea that the response of trade credit to the initial banking shock to Lehman Brothers is at the heart of the shift in comovement.

On the theoretical front, our contribution is to build a macro-financial model displaying a network of producers that optimally decide to extend trade credit to each other due to the existence of banking credit constraints and asymmetry of information on the quality of inputs. While the literature - i.e., Luo (2020) and Reisher (2020) - typically abstracts from microfounding the existence of trade credit, in our model trade credit arises in equilibrium as a way to learn input quality. More generally, our model combines the structure in production network models with working capital constraints, as in Bigio and La'O (2020) and Miranda-Pinto and Young (2022), with models of endogenous trade credit linkages, as in Kiyotaki and Moore (1997), and with models of firm-financing and asymmetry of information as in Greenwood et al. (2010) and Kim and Shin (2012). Similar to Luo (2020), Shao (2020), and Reisher (2020), in our model, trade credit has asymmetric effects on sectoral comovement and aggregate economic activity. Different from previous papers, the asymmetry of trade credit is determined by the relative financial conditions of suppliers and clients in the production chain. Finally, our contribution is also quantitative. While we show that trade credit played a crucial role in shifting sectoral comovement and in amplifying the decline in GDP during the Great Recession, we also demonstrate that trade credit helped reduce the magnitude of the early 80s recession.

2 Three Stylized Facts

In this section, we document our main observations. We begin by describing how to construct the measurement of sectoral comovement. Then, we provide three stylized facts about sectoral comovement during the Great Recession: 1) sectoral comovement increased significantly during the Great Recession, and such a rise in comovement was not observed during any other recession after the WWII. 2) The level of sectoral comovement is more significant in pairs of sectors with a mutual trading partnership (the two sectors are intermediate input supplier and client to each other). 3) Sectors comoved even more when pairs experienced contraction in trade credit larger than the median.

2.1 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 gross output growth between two sectors, is applied to study inter–sector comovement. First, we combine sectoral sales from QFR with real gross industrial output, provided by the Bureau of Economic Analysis (BEA).[1] In total, the sample consists of 44 sectors, covering all private sectors in the United States except for Finance, Insurance, and Real Estate (FIRE).[2] Note that sales from the QFR are in nominal terms. To make that number 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 provided by the U.S. Census Bureau. 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

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

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 $\overline{\Delta y_i}$ and $\mathbf{std}\left(\Delta y_i\right)$ are, respectively, the sample mean and standard deviation of output growth rates over time window $\mathcal{T}$. Throughout the analysis in the paper, we use eight consecutive quarters for time window $\mathcal{T}$ unless otherwise stated.

2.2 Stylized fact I: shift in pairwise correlation

We first examine the sectoral comovement during the Great Recession. Following Kahle and Stulz (2013), we choose 2007Q3–2009Q2 to cover the recession.[3] To compare, we

[1] 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.

[2] Please refer to Table 5 in Appendix A.1 for the full list of sectors and their main characteristics.

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

also calculate the pairwise correlations before and after the recession, with 2005Q3–2007Q2 and 2009Q3–2011Q2 representing the periods before and after the recession, respectively. Figure 1 displays the kernel densities of 946 pairwise correlations for the three periods.[4] Before the recession, the density is hump-shaped with mean and median around 0.08, as shown in Table 8 in our Appendix B, 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 moved together than not. The density returned to the pre-crisis level soon after the recession. We perform the Kolmogorov-Smirnov (KS) test to determine whether the densities before and after the recession are statistically different from the density during the recession.[5] At the 0.1% significance level, the KS test rejects the null hypothesis that the density before (after) the recession is the same as that 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 in sectoral comovement still exists. In Sections 2.3 and 2.4, we conduct two decompositions based on the characteristics of sectors or pairs of sectors. We find that the trading in intermediates and the change in trade credit between two sectors are correlated with high sectoral comovement during the Great Recession.

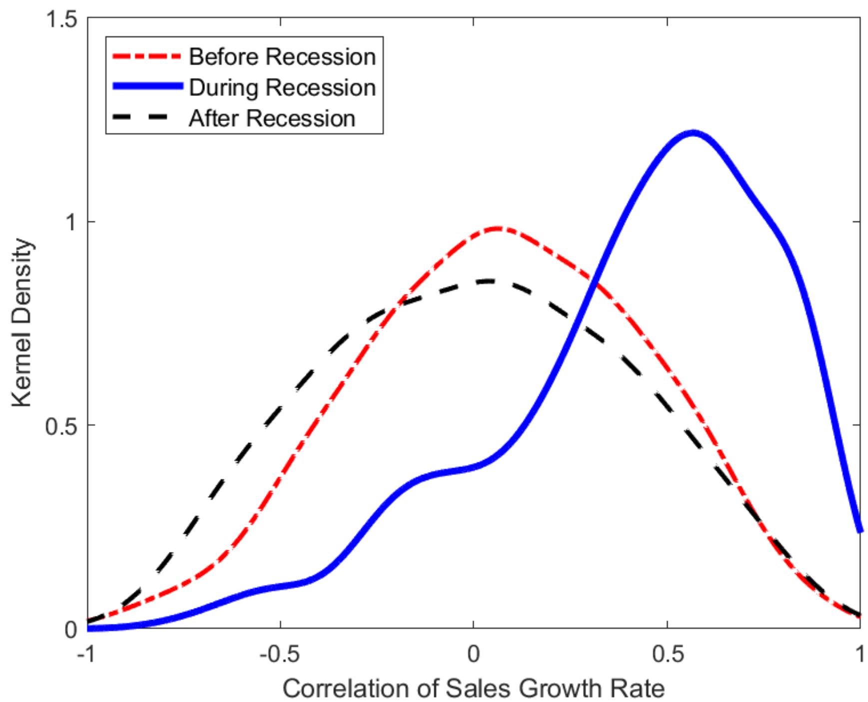
Is the high sectoral comovement a common feature of US recessions? The answer is no. Note that quarterly output data provided by BEA start only at 2005Q1, while all series from the QFR go back to 1987Q4. Utilizing the quarterly sales from the QFR, we show, as in Appendix B, that the kernel densities before, during, and after the 1990 and 2001 recessions almost overlap with each other. Moreover, 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 for FIRE, and study six recessions: the 1960, 1970, 1975, 1980, and 1990 recessions and the Great Recession.[6] We use 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 that occurred after the 1980 recession and before the Great Recession.[7] Figure

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

[5]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 the 0.1%, 1%, and 5% significance level are, respectively, 0.0616, 0.0515 and 0.0430 in this case.

[6]Note that we also try six- or twelve-year rolling windows. The main results remain.

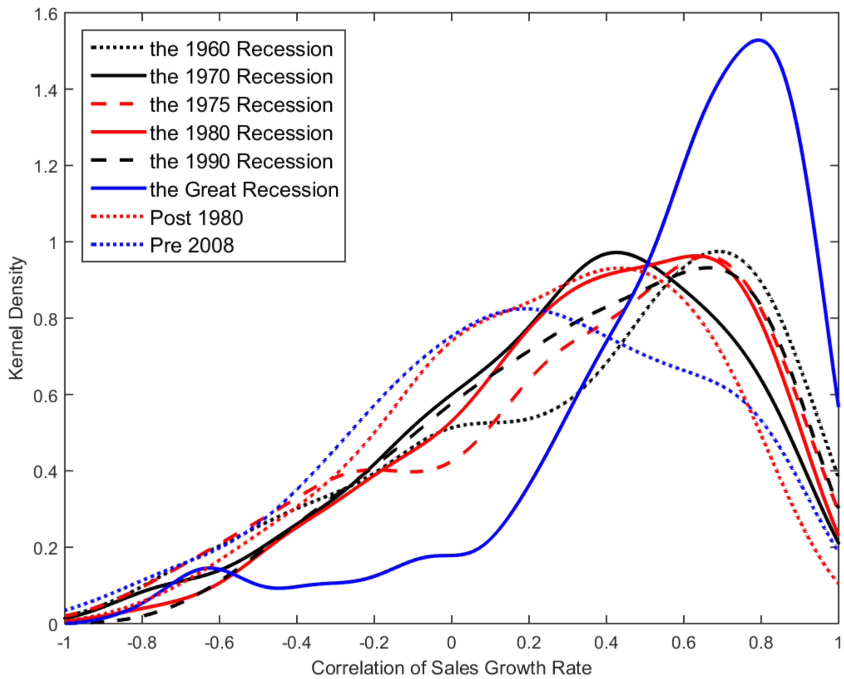
[7]The period starting points are, respectively, 1957, 1967,1972,1978,1988, and 2005 for the 1960, 1970, 1975, 1980, 1990 recessions, and the Great Recession, and 1983 for the post–1980 and 2000 for pre–2008 recession.



Note: The sectoral sales from the QFR are combined with the industrial gross output value by BEA (44 industries). 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

Figure 1
Kernel Density: Pairwise Correlations of Sales Growth

2 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 idiosyncratic fluctuations on a quarterly basis can be averaged out in the annual data. Second, the density during the Great Recession still shifts significantly toward the right, compared with the previous one, as shown by the dotted blue line. This observation is consistent with what we saw 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 Recession in terms of GDP drop. In 1982, the U.S. GDP dropped by 1.9%, with the deepest drop being 6.5% in 1982Q1, whereas GDP contracted by 2.7% in 2008, with the largest contraction by 8.2% in 2008Q4. Surprisingly, compared to the density after the recession, as displayed by the dotted red line, the density during the 1980 recession shifted toward the right only very modestly, if, indeed, at all.



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.

Figure 2
Kernel Density for Pairwise Correlations in Recessions

2.3 Stylized fact II: role of intermediate-input linkages

Next, we examine the role of trading in intermediate inputs in the increase of 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 44 private sectors, excluding 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 sector. If such a share is too low, namely 0.1%, we set it equal to 0.[8] Then, all pairs are categorized into three groups according to the extent of their interconnectedness. In particular, two sectors are classified as part of the two-way trading group if they are both input supplier and client to each other; the one-way trading group if only one sector supplies inputs to the other but not vice versa; and the no-trading group if no intermediate input is traded between two. Each group has 381, 410, and 155 pairs, respectively.

Figure 3 displays the comparison of kernel densities during the Great Recession across

[8]We also try a threshold share of 0.05% and 0.25%. All results here are robust.

the three groups. We observe that the way two sectors trade with each other largely matters for sectoral comovement during the recession. In particular, the two-way trading group has a 0.17 higher average correlation than the one-way group and a 0.31 higher correlation than the no-trading group, as Table 9 in Appendix B shows.[9] This outcome implies that the pairs with two-way interconnection were the main drivers of the rise in sectoral comovement during the Great Recession, and it also indicates that it is more likely that a sector-specific shock, transmitted via the production network, explains the rise in comovement. The aggregate shock hypothesis would imply, instead, an increase in comovement that is independent of the degree of interconnectedness across sectors.

Note: Two-way trading group, in which two sectors are both inteprmediate 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. The top panel shows data for the Great Recession. The bottom left panel shows data before the Great Recession, while the bottom right panel shows data after the Great Recession.

Figure 3
Kernel Density during the Great Recession by Extent of Interconnectedness

We then keep the same categorization and calculate the pairwise correlations before and after the Great Recession for each group. In Figure 15 of Appendix C, we can see that

[9]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.

the densities before and after the Great Recession almost overlap across the three subgroups and are statistically indistinguishable. Hence, the fact that linkages are important only during the Great Recession indicates that it is not the average interconnectedness that matters, but an endogenous mechanism that alters the extent of interconnectedness among sectors.

2.4 Stylized fact III: role of trade credit during the Great Recession

In addition to trading in intermediate inputs, firms simultaneously defer some input payments to their clients and receive such deferral from their suppliers. Claims against clients are recorded as suppliers' account receivables, while liabilities to their own suppliers are recorded as their 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 were 6.6% and 6.0%, respectively, for big corporations with assets exceeding $250 million, while the counterpart ratios were 23.2% and 11.8% for small firms.[10] Moreover, trade credit is the most important source of short–term finance. Account payables among big corporations are eight 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 three times as much as a short-term bank loan and 15 times other short–term loans. Firms in Worldscope typically finance about 20% of their working capital with trade credit, and firms in 60% of countries use trade credit more than bank credit for short–term financing.

We use sectoral data on account payables and receivables from the QFR. Due to data limitations, we restrict our analysis to the manufacturing, wholesale, and retail sectors. For each sector, we calculate the ratio of account receivables to average sales between current and past quarters (henceforth, the AR-to-sales ratio) as intensities of trade credit provision and the ratio of account payables over average operating cost (henceforth, the AP-to-OC ratio) as the intensities of trade credit reception.[11] For each ratio, we take the mean value over 2005Q3–2007Q2 and over 2008Q3–2009Q1, respectively, to represent the corresponding ratios before and during the Great Recession. We then calculate the first difference between two periods as the changes in trade credit provision or reception.[12] Note that the difference measures only the change in gross trade credit provision to all clients or reception from its suppliers. Therefore, a pair is considered to have been experiencing a trade credit decline during the Great Recession (thenceforth the TC

[10] Author's calculation from the QFR.

[11] The ratios of account receivables (payables) over current sales (operating cost) are calculated. The main results stay the same.

[12] From now on, we refer the average of one variable between 2005Q3 and 2007Q2 as the pre-recession average, and the average between 2008Q3 and 2009Q1 as the recession average.

decline group) if both the change in the supplier's AR-to-sales ratio and the client's AP-to-OC ratio both declined more than the corresponding median value across all sectors, which are, respectively, -1.4 and -0.4 percentage points. Otherwise, the pair is categorized as belonging to the control group. Define

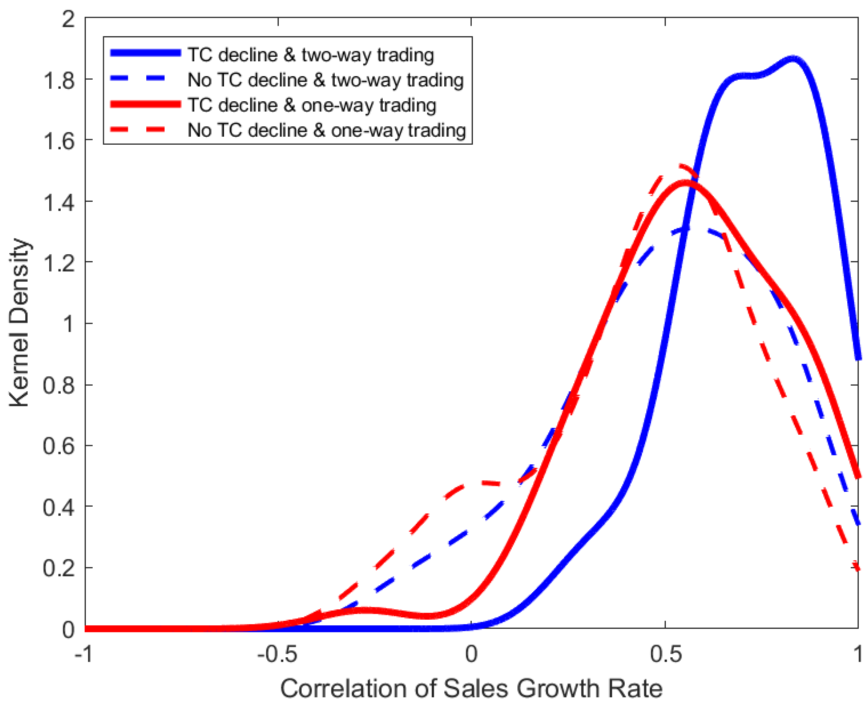
$$\mathbf{D}_{ij}^{tc} = \mathbf{1}\left(\Delta \frac{AR_i}{S_i} < \mathbf{median}\left(\Delta \frac{AR}{S}\right) \textit{ and } \Delta \frac{AP_j}{OC_j} < \mathbf{median}\left(\Delta \frac{AP}{OC}\right)\right), \tag{2}$$

where $\Delta\frac{AR}{S}$ and $\Delta\frac{AP}{OC}$, respectively, , respectively, the first difference of the AR-to-sales and the AP-to- OC ratio. Combined with the division based on the trading relationship in Section 2.3, we categorize all pairs of sectors into four subgroups, according to whether two sectors are two-way or one-way trading partners and whether they experience a decline in trade credit as defined by $\mathbf{D}_{ij}^{tc}$. Notably, in the two-way trading group, a pair belongs to the TC-decline group if the condition is satisfied in either direction. In sum, 145 two-way trading pairs are left in the subsample, in which 66 experienced a TC decline during the Great Recession and 79 did not, whereas the counterpart numbers of one-way trading pairs are 53 and 132.

Figure 4 exhibits the kernel densities of the pairwise correlations during the Great Recession for these four groups. Conditional on the trading relationship, a pair that experienced a decline in trade credit comoved relatively more than one that did not. As Table 10 in Appendix B shows, the two-way trading pairs that experienced a decline in trade credit have a correlation of 0.18 higher, on average, than the pairs that did not. Within the one-way trading group, the trade-credit decline group has a correlation 0.09 higher than the control group. The similarity of two densities is rejected by the KS test at the 0.1% significance level. Moreover, as shown in Figure 16 in Appendix B, the kernel densities of the four subgroups before and after the Great Recession are not significantly different from each other, reinforcing the idea that, during the Great Recession, endogenous changes in trade credit, rather than the level, were instrumental in shifting sectoral comovement.

3 Firm-level Evidence

In this section, we complement the results in Section 2 using firm-level data. We use the collapse of Lehman Brothers as a quasi-natural experiment to highlight the role of trade credit in propagating individual shocks along the production chain. First, we show that the median value of the AR-to-sales and AP-to-OC ratios at the listed-firm level experienced a sharp decline during the Great Recession. Second, we show that for pairs of firms trading intermediate inputs, the fact that the client or the supplier had direct or indirect



Note: A pair is considered to have experienced a trade credit decline during Great Recession if both the supplier's AR-to-sales ratio declined more than 2.9% and the client's AP-to-OC ratio declined more than 1.5%.. Otherwise, the pair is categorized as belonging to 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.

Figure 4
KERNEL DENSITY DURING THE GREAT RECESSION BY WHETHER TRADE CREDIT DECLINES

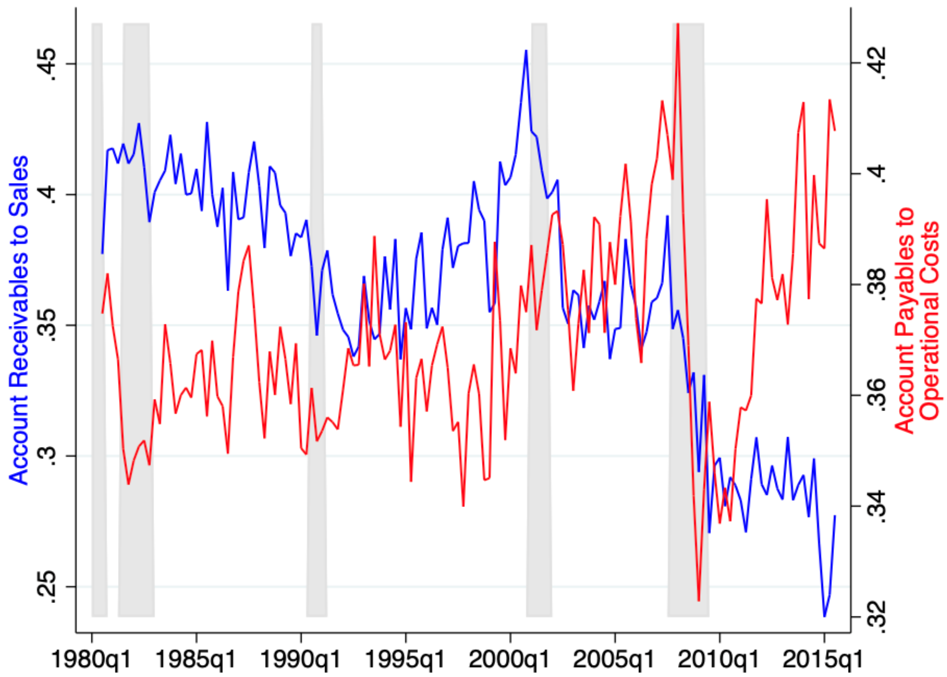
exposure to Lehman Brothers implied a contraction in trade credit and an increase in firm-level comovement.

3.1 Trade credit provision and reception during the Great Recession

We use US public firms' data from COMPUSTAT and calculate the AR-to-sales and AP-to-OC ratios, as defined in Section 2.4, for each selected firm in each quarter.[13] We then adjust these ratios for seasonality using moving-average methods at the firm level. Figure 5 displays the evolution of the median value for both ratios from 1980Q3 to 2016Q3. The two ratios fluctuate modestly over time, even throughout the 1990 and 2001 recessions. During the Great Recession, they went up at the beginning and plummeted by roughly 15 to 20 percentage points starting in 2008Q3. This pattern indicates that, in addition to the reduced demand for inputs, more firms requested more downpayment for new input orders and wrote off the existing trade credit. This is consistent with the evidence

[13]We select non-financial firms, following Kahle and Stulz (2013). See Appendix A.2 for details.

in Costello (2020) for the US during the Great Recession and the evidence in Love et al. (2007) for the Mexican and Asian crises in 1994 and 1997, respectively.



The AR-to-sales and AP-to-OC ratios are calculated as defined in Section 2.4. Seasonality of both sequences of ratios 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.

Figure 5
Evolution of Intensities of Trade Credit Provision and Reception

3.2 Quasi-natural experiment: Lehman Brothers' collapse

The collapse of Lehman Brothers (henceforth, LB) provides us with an ideal setting in which to study how banking shocks can affect trade credit provision and then propagate along the production network. We start by constructing a firm-to-firm production network to then identify direct and indirect linkages between firms and LB. Using Form 10-K, we are able to construct the firm-level production network among suppliers and their top ten clients. After filtering the data with criteria in Appendix A.2, we identify 641 supplier-client pairs, containing 426 suppliers and 176 clients.

To establish the relationship between listed firms and LB, we use the syndicated loan data from DealScan, which allow us to select those firms that were directly connected to LB prior to its collapse, as in Chodorow-Reich (2014) and Ivashina and Scharfsteinb

(2010).[14] Additionally, we identify lenders that were directly connected to LB through the syndicated loan market by the following requirements: (1) the lender and LB participated in a syndicated loan that was due after 2008Q3; (2) the lender was the arranger, which is a leading role in a syndicated loan; (3) the loan was made for the purpose of working capital. We then categorize a firm as indirectly connected to LB if that firm did not borrow directly from LB but borrowed from lenders connected to LB. The combination of these two datasets—firm-to-firm and firm-to-LB linkages— results in 19 out of 426 suppliers being directly connected to LB; 237 indirectly connected to LB through their lenders; and 150 without a relationship with LB through the syndicated loan market. However, we find that, out of the 176 clients, 40 borrowed directly from LB; 120 were indirectly connected to LB; and 16 had no relationship with LB. Later, we will utilize this variation to demonstrate the trade credit in determining the sales comovement between two firms. Note that we classify these firms using only information in the syndicated loan market, and we do not exclude any other financial connection that firms may have had with LB, either directly or indirectly.

Table 11 in Appendix C provides relevant descriptive statistics for the resulting firm-to-firm network. Using Equation (1), we find that, consistent with the evidence at the sector level, the average pairwise correlation between suppliers and clients increased significantly during the Great Recession. The average pairwise correlation increased from 0.04 between 2005Q3 and 2007Q2 to 0.20 during the Great Recession—that is, between 2007Q3 and 2009Q2.

Next, we investigate whether the LB shock contributed to the rise in comovement among firms through the trade credit channel. We focus on two different subsamples. The first subsample focuses on suppliers that were not directly connected to LB and that had clients with different degrees of exposure to LB (directly connected, indirectly connected and not connected to LB). This way, we aim to capture how negative financial shocks affecting clients had an effect on suppliers' trade credit provision. We also study how this upstream propagation (from client to supplier) was amplified by the supplier's indirect exposure to LB. The second subsample focuses on the group of clients that were not directly exposed to LB, as well as their suppliers with different degrees of exposure to LB. This sample is intended to capture the downstream propagation (from suppliers to clients) of financial shocks and its interaction with trade credit.

3.3 Transmission of the LB Shock

The sample contains all suppliers that were not directly connected to LB, but that had at least one client that borrowed directly from LB and one client that did not. We exclude

[14] Please refer to Appendix A.3 for selection standard.

the suppliers that presented only one client and those that had all their clients exposed directly to LB. With these adjustments, we end up with 175 pairs that consist of 66 suppliers and 69 clients. Among the suppliers, 17 of them had no relationship with LB in the syndicated loan market, and the rest of them were indirectly connected. Among the clients, six had no relationship with LB; 42 were indirectly connected to LB; and 21 borrowed from LB directly.[15]

First, we study how the clients' AP-to-OC ratios respond to the LB shock. We run the following regression:

$$\Delta \frac{AP_j}{OC_j} = \alpha_0 + \alpha_1 \mathbf{1}^{LB}_{j,dir} + \alpha_2 \mathbf{1}^{LB}_{j,indir} + \gamma \Delta X_j + \beta \frac{AP_{j,before}}{OC_{j,before}} + \epsilon_j, \tag{3}$$

where j is an index for client; $\mathbf{1}^{LB}_{j,dir}$ is an indicator variable that takes the value of 1 when the client is directly connected to LB in the syndicated loan market; $\mathbf{1}^{LB}_{j,indir}$ is an indicator variable that takes the value of 1 when the client is indirectly connected to LB in the syndicated loan market; X is the control variables listed in Table 11; and ΔX is the first difference between the recession and pre-recession averages of X.

Table 1 reports the point estimates for Equation (3). In Column (1), the coefficients of the direct and indirect indicators are negative, indicating that, unconditionally, clients exposed to LB experienced a decline in trade credit reception (AP-to-OC ratio). Then, we add control variables, and the result for the direct indicator remains negative and statistically significant (at the 95% confidence level). Only the direct effect is statistically significant, with 95% confidence, implying that the AP-to-OC ratio decreased by 6.3 percentage points more for clients connected to LB than for other clients.

Further, in Column (3), we study whether the change in the AP-to-OC ratio is different for the subsample of clients with suppliers indirectly connected to LB. We observe that the point estimate for $\mathbf{1}^{LB}_{j,dir}$ is statistically significant at the 95% confidence level and increases in magnitude from -6.3 to -10.1 percentage points, while the coefficient of the indirectly-connected indicator switches from a positive to a negative sign. Therefore, we conclude that it is not just the negative financial shock to the customer, but also the financial constraint of the supplier, that determines the adjustment of trade credit.

In Columns (4)-(6), we study the behavior of other short-term financial variables as a response to the LB shock. The results show that being connected to LB has no significant effects on clients' AR-to-sales ratio and short-term debt to assets. Clients connected to LB experienced a decline in the cash-to-assets ratio. These results are consistent with Kahle and Stulz (2013), indicating that public firms, on average, might have become more financially constrained after LB collapsed, but such constraints vary across firms, and, thus,

[15] In our Appendix C, we construct a similar dataset for the subsample of customers tat were not directly connected to LB. The results are similar.

no significant coefficient is found. This variation enables us to explore the relationship between trade credit and sales comovement between two firms.

Table 1
REGRESSION RESULTS OF EQUATION (3)

	$\Delta\frac{AP_j}{OC_j}$			$\Delta\frac{AR_j}{sales_j}$	$\Delta\frac{debt_j}{TA_j}$	$\Delta\frac{cash_j}{TA_j}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbf{1}_{j,dir}^{LB}$	-7.67*	-6.3**	-10.1**	-.292	3.6	-4.55*
	(3.94)	(2.61)	(3.26)	(2.3)	(2.13)	(2.05)
$\mathbf{1}_{j,indir}^{LB}$	-.156	2.07	-3	2.3	2.93	-2.7
	(2.27)	(3.25)	(6.7)	(1.82)	(2.1)	(2.5)
obs	64	62	51	62	62	62
control var	No	Yes	Yes	Yes	Yes	Yes
adjusted R^2	.052	.277	.15	.238	.176	.18

Notes: Column (3) shows the results for the subsample in which the suppliers are indirectly connected to LB. All errors are clustered at the sectoral level. All control variables are listed in Table 11. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Next, we examine how the pairwise correlation between two firms is associated with the LB shock and its interaction with trade credit. We run the following regression

$$\Delta\mathbf{corr}_{ij} = \alpha_0 + \alpha_1\mathbf{1}_i^{LB} + \alpha_2\mathbf{1}_j^{LB} + \alpha_3\mathbf{1}_i^{LB} \times \Delta\frac{AR_i}{S_i} + \alpha_4\mathbf{1}_j^{LB} \times \Delta\frac{AP_j}{OC_j} + \beta_1' X_i + \beta_2' X_j + \epsilon_{ij}, \tag{4}$$

where i is an index for the supplier; $\Delta\mathbf{corr}_{ij}$ is the change in the pairwise correlation between firms before and during the Great Recession; X includes industry dummy; and the first differences between the recession and pre-recession averages of the variables listed in Table 11.[16]

Table 2 reports the OLS coefficients of Equation (4). The results in Column (1) and (2) show a strong positive relationship between the client's exposure to LB, both directly and indirectly, and the change in pairwise correlation during the Great Recession.[17] We find that, during the Great Recession, a supplier's sales comoved much more with LB-related clients compared to LB-unrelated clients. In particular, we observe that the pairwise correlations of pairs with clients that were LB borrowers rose more than three times the average increase (0.23) and rose two times for pairs with indirectly LB-connected clients.

[16]By studying the change in pairwise correlation, instead of the level during the Great Recession, we eliminate any unobserved fixed effects for the supplier, client, and the pair.

[17]Column (1) includes the control variables in the regression and Column (3) adds client and supplier industry dummies.

Table 2
REGRESSION RESULTS OF EQUATION (4)

	$\Delta\mathbf{corr}_{ij}$			$\mathbf{corr}_{ij,before}$	$\Delta\mathbf{corr}_{ij}$
	(1)	(2)	(3)	(4)	(5)
$\mathbf{1}_{j,dir}^{LB}$	1.01***	.916***	.767***	-.0281	.781**
	(.147)	(.245)	(.277)	(.748)	(.329)
$\mathbf{1}_{j,indir}^{LB}$	.835***	.621***	.531*	-.168	.556*
	(.142)	(.21)	(.269)	(.716)	(.275)
$\mathbf{1}_{j,2nd}^{LB}$					.675**
					(.296)
$\mathbf{1}_{j,dir}^{LB} \times \Delta\frac{AP_j}{OC_j}$	-.336***	-.313***	-.251**	-.00145	-.312*
	(.0889)	(.113)	(.12)	(.011)	(.172)
$\mathbf{1}_{j,indir}^{LB} \times \Delta\frac{AP_j}{OC_j}$	-.342***	-.305***	-.257**	.000156	-.373**
	(.0896)	(.115)	(.124)	(.011)	(.173)
$\Delta\frac{AP_j}{OC_j}$	.337***	.302***	.25**	.0000288	.255
	(.0891)	(.115)	(.121)	(.0109)	(.156)
$\mathbf{1}_{i,indir}^{LB}$	.0801	.0299			
	(.119)	(.153)			
$\mathbf{1}_{i,indir}^{LB} \times \Delta\frac{AR_i}{S_i}$	.0183	.0355			
	(.0169)	(.0215)			
$\Delta\frac{AR_i}{S_i}$	-.0139	-.0191			
	(.0153)	(.0183)			
obs	175	156	160	162	67
client control	No	Yes	Yes	Yes	Yes
supplier control	No	Yes	No	No	No
supplier dummy	No	No	Yes	Yes	Yes
adjusted R^2	.0392	.0737	.122	.0431	.0883

Notes: All control variables are listed in Table 11. Industrial dummies are constructed at the 2-digit industry level. All variables used in Column (4) are the corresponding pre-recession averages instead of difference ones in Equation (4). Errors from Column (1) through (3) are robust ones, and from (4) through (6) are clustered at the client level. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

The results for the interaction between clients' exposure to LB ($\mathbf{1}_j^{LB}$) and clients' AP-to-OC ratio (AP/OC) indicates hat the pairwise correlation increases even further when the client exposed to LB also experienced a decline in the AP-to-OC ratio (i.e., when the suppliers defer a smaller proportion as trade credit, or the client manages to write off some of the existing trade credit). We find that the correlation between a LB borrower and its supplier increases by 0.31 for each percentage point decline in the client's AP-to-OC ratio. Given that the ratio declines by 6.3 percentage points for the LB borrower, as shown in Column (2) of Table 1, the additional comovement between such a pair increases by about 0.07, which is 30% of the average increases in correlation and also accounts for 7% of the total difference between being a LB borrower and being a non-related firm.

It is still possible that the estimation of Equation (4) is biased by some unobserved and time-varying supplier characteristics. To tackle this issue, we include the supplier dummies and show the results in Column (3). We find similar results with slightly smaller magnitudes. Interestingly, we find a positive and statistically significant coefficient for the AP-to-OC ratio, which indicates potentially asymmetric responses of different clients to the decline in the AP-to-OC ratios. A client with no connection to LB could have fulfilled the requirement for more early payment or writing off of the existing trade credit, which would not have disrupted the input sales. Clients connected to LB may not have done so without transmitting the shock to their suppliers by reducing input demand.

A 'placebo test' is conducted by replacing all the difference variables with the corresponding pre-recession average. In Column (4), we do not observe that the pairwise correlations between LB-connected firms with their suppliers were any different from those of other firms before the Great Recession. In Column (5), we examine whether the LB shocks could have been be transmitted further, to the LB-unrelated suppliers' suppliers (second-round network effects captured by $\mathbf{1}^{LB}_{j,2nd}$). In doing so, we select all the LB-unrelated suppliers and their own suppliers that were not directly connected to LB, but that also had at least one LB-related client and one non-LB-related client. The results in Column (5) show a positive and statistically significant estimate of $\mathbf{1}^{LB}_{j,2nd}$. The point estimate is slightly lower than the direct indicator and higher than the indirect indicator, showing that the LB shock transmitted further along with the production chain to affect firm-level comovement.

In Appendix C, we run regressions (3)-(4) with an alternative sample of firms. We use the sample of suppliers that were exposed heterogeneously to LB (directly, indirectly, and not related) and clients that did not borrow from LB. While this sample is smaller, the results are qualitatively similar.

To sum up, the evidence presented in this section shows that the rise in firm-level comovement during the Great Recession was significantly amplified by the exposure of firms to LB and by the implied adjustment in trade credit provision. These facts support the interpretation of our facts in Section 2 - using industry data - that an important driver of the sharp increase in sectoral comovement during the Great Recession was the tightening of financial conditions, via bank credit and trade credit.

4 Model

In this section, we develop a multisector model with input-output linkages and endogenous trade credit adjustment to uncover the mechanism of the rise in sectoral comovement during the Great Recession. Our model economy combines the environments in Kiyotaki and Moore (1997), Greenwood et al. (2010) and Kim and Shin (2012). Firms are uncertain about the quality of intermediate inputs. Thus, trade credit arises in equilibrium as a way to learn the true quality of intermediates.

4.1 Firms' Production Plan

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 to produce. Suppose that each firm purchases inputs from, at most, one firm in each sector.[18] Here, we refer to firms providing inputs as suppliers and firms receiving them as clients.[19] Thus, sectors are interconnected via this vertical firm-level network. Suppose that the production of any firm $h \in [0,1]$ in sector i takes a Cobb-Douglas form as

$$y_i(h) = z_i \left(\prod_{j=1}^{n} m_{ji}^{\omega_{ji}} \right)^{\nu_i} l_i^{\alpha_i}, \tag{5}$$

where z_i is the TFP; m_{ji} is the intermediate inputs purchased from a firm in sector j; ω_{ji} governs its share over total expenditures on inputs with $\sum_{j=1}^{n} \omega_{ji} = 1$; l_i is the employed labor; and α_i and ν_i are, respectively, the labor and input share with $\alpha_i + \nu_i < 1$.[20] Note that $\omega_{ji} = 0$ means no input purchase from firms in sector j.

Products can be used as either intermediate inputs or consumption goods. Thus, firms in any sector will simultaneously act as both a supplier to provide and a client to receive inputs. After receiving orders, suppliers will customize their products so that they can be used as inputs. Thus, suppliers enjoy some pricing power as monopolistic competitors, and charge a price q_{ij}. Or they can sell their products at price p_i in the consumption good markets, which is assumed to be perfectly competitive. Moreover, we follow Kim and Shin (2012) and assume that the quality of the intermediate inputs is *ex ante* uncertain. There exists a probability of $1-\eta$ that the clients will find the delivered products not qualified for inputs. In this case, the clients have to order $\gamma > 1$ units of goods from a secondary market and convert them into one unit of input.

Each period is split into two stages. In the first stage, sectoral TFPs are realized, but

[18] This setup is not essential, and only served to avoid the coordination problem.

[19] Here we assume that the supplier and client of any firm cannot be the same one.

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

firms are still uncertain about the quality of their products. Nevertheless, they now need to put in an order for intermediate inputs and employ workers to produce later. Due to the uncertainty, whether firms are able to make payments for labor and intermediate inputs is ambiguous. Hence, workers and suppliers demand to be paid in advance. We assume that workers have strong bargaining power over firms and are, therefore, compensated upfront at the full amount.[21] The payments for intermediate inputs are divided into two parts: cash before delivery (CBD) and trade credit. The former is due in the first stage, while the latter is deferred until their clients realize their revenue. The division is endogenously decided by suppliers, and its details will be specified later. Suppose that no profits can be stored over periods. If the required working capital, the summation of the wages and paid CBD, exceeds the received CBD, the supplier needs to borrow the difference from perfectly competitive banks. To secure the loans, banks require firms' products as collateral. Assuming that the liquidation ratio of collateral is θ_i for the firms in sector i, the amount of the loans that can be borrowed should be equal to or smaller than $\theta_i p_i y_i$ as

$$b_i = \underbrace{wl_i}_{wage} + \underbrace{\sum_{j=1}^{n} d_{ji} q_{ji} m_{ji}}_{paid\ CBD} - \underbrace{\sum_{j=1}^{n} d_{ij} q_{ij} m_{ij}}_{received\ CBD} \leq \theta_i p_i z_i \left(\prod_{j=1}^{n} m_{ji}^{\omega_{ji}} \right)^{\nu_i} l_i^{\alpha_i}, \tag{6}$$

where w is the wage; p_i is the price of the consumption goods; q_{ji} is the input price; and d_{ji} is the proportion of input payment as CBD. Note that the total input payment $q_{ji} m_{ji}$ is divided into two parts: $d_{ji} q_{ji} m_{ji}$ as CBD and $(1 - d_{ji}) q_{ji} m_{ji}$ deferred as trade credit. As in Kiyotaki and Moore (1997) and Jermann and Quadrini (2012), we treat θ_i here as the sector-level financial shocks.

In the second stage, the quality of their ordered inputs is realized, and all goods are produced and delivered. Any client either receives good-quality inputs or not. In the former case, the client pays backs the trade credit - i.e., $(1 - d_{ji}) q_{ji} m_{ji}$ - whereas pays γp_j from the secondary market in the latter. Thus, the expected unit cost of the inputs paid by the client in sector i to the supplier in sector j is given as

$$d_{ji} q_{ji} + \eta (1 - d_{ji}) q_{ji} + (1 - \eta) \gamma p_j, \tag{7}$$

where the first term is the paid CBD; the second is the deferred payment in the good-quality case; and the third is the payment for alternative inputs. If the products of any

[21] Miranda-Pinto and Young (2022) show that in input-output models featuring working capital constraints, whether or not labor is paid upfront makes little quantitative difference. The authors show that the constraint on intermediate input purchases is the crucial element that amplifies financial frictions through the input-output network.

supplier turn out to be high-quality, then she receives the payment on trade credit and revenue from the household. Otherwise, nothing is received.

Moreover, when setting the input price, a supplier needs to ensure that the clients pay no more than what they effectively pay from importing as

$$d_{ji}q_{ji} + \eta(1-d_{ji})q_{ji} + (1-\eta)\gamma p_j \leq \gamma p_j. \tag{8}$$

Here, we denote this constraint as the no-arbitrage condition.

4.2 Optimal Contracts on Trade Credit

Suppose that the realization of product quality is private information for clients. Thus, when good quality is realized, clients have incentives to misreport their status and default on trade credit. To induce truth-telling, every supplier will separately offer each of its clients an optimal contract. In such a contract offered by the supplier in sector i to the client in sector j, the supplier will specify the input price q_{ij}, the share of CBD d_{ij}, and the penalty payment g_{ij} when it find out that the client cheats. Notably, clients that receive a low-quality good have no incentives to cheat because they can simply default on trade credit when they tell the truth. This contract is designed to satisfy two constraints: the resource constraint (RC) and the incentive-compatible constraint (ICC). The former requires that the penalty payment cannot exceed what the client actually makes after banks collect their loans as

$$g_{ij} \leq \omega_{ij} v_j \left(p_j y_j - b_j\right). \tag{9}$$

where ω_{ij} is input share; $p_j y_j$ is products' market value; and b_j is the amount of the bank loan.

The ICC ensures that the client always reports its true state. As in Bernanke et al. (1999), we assume that any supplier exerts costly efforts to verify the state reported by each of its clients. Denote the unit cost of the verifying efforts for offering $q_{ij}m_{ij}$ dollars of inputs as e_{ij}, which can be interpreted as the verification intensity. For the same verification intensity, the more inputs the supplier provides, or the higher the price it charges, the more costly it is for a supplier to find out the true status. As in Greenwood et al. (2010), we assume that suppliers can detect the true quality with only a certain probability $\mathbf{Pr}(e)$, which is assumed to be increasing and concave in e. Thus, in the optimal contract, the incentive-compatible constraint is given as

$$(1-d_{ij})q_{ij}m_{ij} \leq \mathbf{Pr}(e_{ij})g_{ij}. \tag{10}$$

where the left-hand side is trade credit to be paid, while the right-hand side is the expected payment of cheating. It is straightforward to show that the RC is binding since the marginal benefit of raising the penalty payment is positive, while the marginal cost is zero. Also, because the efforts are costly, suppliers will make just enough effort to induce clients to report the true status. This implies that the ICC is binding, as well. Thus, the exerted efforts can be expressed as

$$e_{ij} = e\left(\frac{(1-d_{ij})q_{ij}m_{ij}}{\omega_{ij}v_j\left(p_j y_j - b_j\right)}\right) \tag{11}$$

where the function e is the inversed function of $\mathbf{Pr}(e)$.

4.3 Optimal Problem for Firms

In the first stage, all firms in the same sector are ex ante the same, so they make the same decisions. Note that all firms are simultaneously a supplier and a client. The client will decide the production plan, taking as given the optimal contracts offered by the suppliers. Meanwhile, the client acts as a supplier to design her own optimal contracts to her clients, given the input demand function. The former specifies inputs, employees, and loans from banks in order to produce in the second stage, while the latter lays out the payment schedule, penalty payment, and verification efforts. In particular, taking as given the input prices $\left\{q_{ji}\right\}$, the shares of the CBD $\left\{d_{ji}\right\}$, the consumption good prices $\left\{p_j\right\}$, the banks loans by other firms $\left\{b_j\right\}$, the outputs by other firms $\left\{y_j\right\}$, and the wage w, a firm in sector i chooses the inputs $\left\{m_{ji}\right\}$, the labor l_i, the goods sold in the consumption goods market c_i and in the secondary market k_i, the optimal contract $\left\{q_{ij}, d_{ij}, g_{ij}\right\}$, and the efforts $\left\{e_{ij}\right\}$ to verify the states, to maximize her profits as

$$\begin{aligned}
\max_{l_i, m_{ji}, k_i, c_i, q_{ij}, d_{ij}, g_{ij}, e_{ij}} \quad & \sum_{j=1}^{n}\left(d_{ij} + \eta\left(1-d_{ij}\right)\right)q_{ij}m_{ij} + p_i k_i + p_i c_i \\
& -wl_i - \sum_{j=1}^{n}\left(d_{ji}q_{ji} + \eta(1-d_{ji})q_{ji} + (1-\eta)\gamma p_j\right)m_{ji} \\
& -(1-\eta)\sum_{j=1}^{n} e\left(\frac{(1-d_{ij})q_{ij}m_{ij}}{\omega_{ij}v_j\left(p_j y_j - b_j\right)}\right)q_{ij}m_{ij} && (12) \\
s.t. \quad & z_i\left(\prod_{j=1}^{n} m_{ji}^{\omega_{ji}}\right)^{\nu_i} l_i^{\alpha_i} = \sum_{j=1}^{n} m_{ij} + k_i + c_i && (13) \\
& wl_i + \sum_{j=1}^{n} d_{ji}q_{ji}m_{ji} \le \theta_i p_i z_i\left(\prod_{j=1}^{n} m_{ji}^{\omega_{ji}}\right)^{\nu_i} l_i^{\alpha_i} + \sum_{j=1}^{n} d_{ij}q_{ij}m_{ij} && (14) \\
& d_{ij}q_{ij} + \eta(1-d_{ij})q_{ij} + (1-\eta)\gamma p_i \le \gamma p_i, \ \ \forall j. && (15)
\end{aligned}$$

The expected revenue consists of revenue from offering inputs and sales in the consumption goods market, where with a $1-\eta$ chance, she cannot collect trade credit due to default. The costs to produce consist of wages and expected input payments and verification cost. Condition (13) is the allocation of outputs. Constraints (14) and (15) are, respectively, the collateral and the no-arbitrage constraints.

4.4 Households

Suppose that a representative household exists in the economy with utility as

$$\mathbf{U}(c,l) = \log c - \psi \frac{l^{1+\xi}}{1+\xi}, \tag{16}$$

where c is the consumption bundle; l is hours worked; the parameter ψ governs the degree of disutility from working; and ξ is the Frischer elasticity. Given the prices of consumption goods and wages, the household's objective is to choose a consumption bundle and labor to maximize her utility subject to her budget constraint as

$$\max_{c_t, l_t} \mathbf{E}_0 \left[\sum_{t=0}^{\infty} \beta^t \left(\log c_t - \psi \frac{l_t^{1+\xi}}{1+\xi} \right) \right] \tag{17}$$

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

where p is the price index; π is the total profit generated by all firms; and T is the total verification cost paid by firms. The first order conditions on consumption and labor supply yield

$$pc = \frac{w}{\psi l^{\xi}}. \tag{18}$$

Moreover, the consumption bundle is defined as a composite of goods and services from all sectors as in

$$c = \left(\sum_{i=1}^{N} \phi^{\frac{1}{\sigma}} c_i^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{19}$$

and the price index is defined as

$$p = \left(\sum_{i=1}^{N} \phi p_i^{1-\sigma} \right)^{\frac{1}{1-\sigma}}, \tag{20}$$

where ϕ_i is the share of the household's expenditure on sector i's goods and $\sum_{i=1}^{N} \phi_i = 1$. Solving the optimal problem, a household's demand for goods in sector i is given as

$$c_i = \phi_i \left(\frac{p_i}{p}\right)^{-\sigma} c. \tag{21}$$

4.5 Market clearing condition

Because firms' products have a probability η of being qualified for inputs, by law of large number, a fraction η of firms will produce output y_i, to be used as input and consumption good of good quality. Therefore, the market-clearing conditions for product market i can be written as

$$y_i = \eta \sum_{j=1}^{n} m_{ij} + k_i + c_i, \ \forall i \tag{22}$$

where y_i is defined in Equation (5) and $k_i = \sum_{j=1}^{n}(1-\eta)\gamma m_{ij}$. Finally, labor supply is equal to labor demand across all firms as

$$l = \sum_{i=1}^{n} l_i. \tag{23}$$

Moreover, we denote the actual sales by firms in sector i as

$$sales_{it} = p_{it}c_{it} + \sum_{j=1}^{n}\Big(1-(1-\eta)tc_{ij}\Big)q_{ij}m_{ij} \tag{24}$$

where the sales consist of revenues from both inputs and consumption-goods.

5 Equilibrium Analysis

Now we define the competitive equilibrium in our model as

Definition 1 *A **Stationary Nash equilibrium** is defined as the commodity prices $\{p_i\}$, the wage w, the sectoral output $\{y_i\}$, the consumption goods $\{c_i\}$, the goods in the secondary market the consumption goods $\{k_i\}$, the labor allocations $\{l_i\}_i$, the intermediate inputs $\{m_{ji}\}$, the optimal contracts $\{q_{ij}, d_{ij}, g_{ij}\}$, and efforts to verify status reported by clients $\{e_{ij}\}$, such that*

1. *Given a vector of prices $\{p_i\}$, the wage w and the contracts offered by suppliers $\{q_{ji}, d_{ji}, g_{ji}\}$, firms in sector i choose the labor l_i, the intermediate inputs $\{m_{ji}\}$, the optimal contracts for their own clients $\{q_{ij}, d_{ij}, g_{ij}\}$, and the verifying efforts $\{e_{ij}\}$ to maximize the expected profit as in (12);*

2. *Given $\{p_i\}$ and w, the representative household chooses the consumption goods $\{c_i\}$ and the labor supply l to maximize its utility as in (17);*

3. *The wage w clears the labor market (23);*
4. *The commodity prices $\{p_i\}$ clear commodity markets in (22), and the aggregate price index p is normalized to 1.*

Next, we discuss the solution to the model, and examine the role of trade credit in transmitting shocks. We start with the case in which the firm acts as a client and determines its production plan, as shown in Lemma 1 as:

Lemma 1 (Production plan) *Given a vector of the consumption-good prices $\{p_i\}$, the wage w, and the optimal contracts offered by their suppliers $\{q_{ji}, d_{ji}, g_{ji}\}$, the optimal production plan for firms in sector i satisfies the following conditions:*

$$\alpha_i v_i^L p_i y_i = w l_i, \tag{25}$$

$$\omega_{ji} \nu_i v_{ji}^M p_i y_i = q_{ji} m_{ji}, \ \forall\, j \tag{26}$$

where μ_i is the Lagrangian multiplier for collateral constraint, and v_i^L and v_{ji}^M are defined as the labor and intermediate input wedges respectively as:

$$v_i^L = \frac{1+\theta_i \mu_i}{1+\mu_i}, \ \ and \ \ v_{ji}^M = \frac{1+\theta_i \mu_i}{d_{ji} + \eta(1-d_{ji}) + (1-\eta)\frac{\gamma p_j}{q_{ji}} + \mu_i d_{ji}}. \tag{27}$$

Then the output y_i can be solved as

$$y_i = \left(z_i p_i^{\alpha_i+\nu_i} \left(\nu_i \prod_{j=1}^{n} \left(\frac{\omega_{ji} v_{ji}^M}{p_j} \right)^{\omega_{ji}} \right)^{\nu_i} \left(\frac{\alpha_i v_i^L}{w} \right)^{\alpha_i} \right)^{\frac{1}{1-\alpha_i-\nu_i}} \tag{28}$$

Proof: see Appendix D.1.

Here, the labor and the intermediate input wedges measure the extent to which the allocations of the labor and intermediate inputs, respectively, deviate from the first best. Note that three types of frictions are at play in our model: the uncertainty about the quality (i.e., default risk on trade credit); the pricing power by suppliers; and the collateral constraint. These frictions interact with each other and affect the outputs through both labor and input wedges. The labor wedge is affected only by the collateral constraint, while all three types directly affect the intermediate input wedge. In particular, a tighter collateral constraint (i.e., a higher μ_i) distorts the labor demand more and also affects the input demand, but due to trade credit, the effects depend on the relative size of received trade credit (d_{ji}) to the financial condition (θ_i). Moreover, when the client finds the delivered goods unqualified for inputs, she bears the additional costs of finding alternatives in the secondary market. When the default risk is higher - i.e., η is lower - or when the relative price of input to the one in the secondary market is lower - i.e., $\frac{q_{ji}}{\gamma p_j}$ - is smaller, the additional costs are higher. The higher such costs are, the smaller the input wedge is, and the more the client's input demand is distorted from the first best. As discussed in detail later, the intermediate input wedge is also affected by trade credit. In turn, trade credit responds to firms' productivity and financial conditions, which provides an additional channel of propagation of shocks. Equation (28) shows that the output of firms in sector i is a function of their own productivity and financial shocks, as well as their suppliers', through the intermediate input wedges. Note that, setting $\eta = 1$ and $\mu_i = 0$ eliminates the frictions in our model and the allocations are first best.

We now examine how firms, as input suppliers, design optimal contracts with their clients. First, we assume that the probability of detecting a true state is

$$\mathbf{Pr}\left(e_{ij}\right) = \sqrt{\frac{e_{ij}}{\bar{e}_i}}, \ \forall j, \tag{29}$$

where $\bar{e}_i$ is a scalar that governs the size of the average effort.[22] Here, we focus on the case in which collateral constraints are binding for all firms. In this case, the loans borrowed by firms in sector j are equal to $\theta_j p_j y_j$. Thus, the revenue left for all suppliers of firms in sector j is $(1-\theta_j)\nu_j p_j y_j$. A specific supplier in sector i seizes a fraction ω_{ij} of the revenue left. Proposition 1 characterizes the details of the optimal contract.

Proposition 1 (Optimal contract) *Consider the case in which $\{\theta_i\}$ are sufficiently small - i.e., $\mu_i > 0$ for $\forall i$. Given the consumption-good prices $\{p_i\}$, the financial condition $\{\theta_i\}$, and the tightness of collateral constraints $\{\mu_i\}$, the optimal contract, offered by a firm in sector i to a client in sector j, specifies the input price q_{ij} and the share of CBD d_{ij}, respectively, as:*

$$\begin{aligned} 3\gamma\bar{e}_i\left(\frac{(1-\eta)(1-d_{ij})v_{ij}^M}{1-\theta_j}\right)^2 &= (1+(1-\eta)\gamma)\left(d_{ij}+\eta(1-d_{ij})\right)+\mu_j d_{ij}+(1-\eta)\gamma\mu_i d_{ij} && (30)\\ \gamma\eta\frac{p_i}{q_{ij}} &= \eta+(1-\eta)d_{ij}, \ \ for \ \ d_{ij}\in(0,1), && (31)\end{aligned}$$

where v_{ij}^M is defined in Equation (27) and y_j is given by Equation (28).
Proof: see Appendix D.2.

Here, we discuss the intuition in Proposition 1. When the firm makes the intermediate input price decision, it acts as a monopolistic competitor, taking into account the demand for intermediates in Equation (26). As the relative input price rises, the input wedge increases, due to the relatively lower cost of purchasing from the alternative sources. Therefore, the decline in the quantity demanded of intermediate inputs (due to

[22]Note that the square root functional form is selected simply for analytical tractability, and the main results remain, as long as the function is increasing and concave in the effort.

the higher price) is partially offset by the rise in the wedge. As a result, the intermediate input revenue increases as the price rises, implying a revenue function that is concave in intermediate input prices.

On the other hand, for the same verification intensity, the cost of verification increases with the size of input sale. Moreover, the incentives to cheat (claim bad quality input) and, therefore, fail to meet the trade credit contract, increases with the size of the sale. Thus, suppliers need to exert more effort to ensure truth–telling. As a result, the combination of these two effects makes the verification cost a convex function in the input price. The intermediate input price in Equation (31) is then determined to balance the amount of sales and the verification costs.

Regarding the trade credit decision, the supplier wants to collect the input payment as early as possible. However, as in Kim and Shin (2012), the supplier has to defer a proportion of the payment to compensate the client for the potential loss in the low-quality case. Thus, the cash before delivery (CBD) is required up to the point at which the unit cost of inputs is the same for domestic intermediates and intermediates purchased abroad. Define the trade credit intensity as

$$tc_{ij} = 1 - d_{ij}. \tag{32}$$

A partial equilibrium analysis of Equation (31) implies that the trade credit intensity increases in the relative input price. As the relative input price increases, a higher revenue will be realized in the good-quality case, and, thus, suppliers can afford to defer a larger proportion of payment as trade credit.

Next, we discuss the sufficient condition for the unique existence of trade credit intensity tc_{ij}. We also describe how trade credit responds to changes in the financial conditions of suppliers and clients.

Proposition 2 *Suppose that*

$$\bar{e}_i \geq \frac{\eta(1+(1-\eta)\gamma)}{3\gamma(1-\eta)^2}, \ \ \forall i. \tag{\#1}$$

Therefore, for any $\theta_i, \theta_j \in (0,1)$ and $\mu_i, \mu_j > 0$, there exists a unique $tc_{ij} \in (0,1)$ that solves

$$3\gamma\bar{e}_i\left(\frac{\eta(1-\eta)(\eta+\theta_j\mu_j)tc_{ij}}{(1-\theta_j)\left(1+\eta\mu_j-(1-(1-\mu_j)\eta)tc_{ij}\right)}\right)^2 = (1+(1-\eta)\gamma)\left(1-(1-\eta)tc_{ij}\right)+\left(\mu_j+(1-\eta)\gamma\mu_i\right)(1-tc_{ij}). \tag{33}$$

Moreover, we have

$$\frac{\partial\, tc_{ij}}{\partial\, \mu_i} < 0, \ \ and \ \ \frac{\partial\, tc_{ij}}{\partial\, \theta_j}\begin{cases} \leq 0 & if \ \ g\left(tc_{ij}, \mu_i, \mu_j, \theta_j\right) \leq 0 \\ > 0 & otherwise \end{cases}, \tag{34}$$

where the g function is defined as

$$
\begin{aligned}
g\left(tc_{ij},\mu_i,\mu_j,\theta_j\right) \;=\;& \left(\frac{2\eta(1-tc_{ij})}{1+\eta\mu_j-(1-(1-\mu_j)\eta)tc_{ij}}+\frac{(1-tc_{ij})}{(1+(1-\eta)\gamma)\left(1-(1-\eta)tc_{ij}\right)+\left(\mu_j+(1-\eta)\gamma\mu_i\right)(1-tc_{ij})}\right)\frac{\partial\,\mu_j}{\partial\,\theta_j}\\
&-\frac{2\theta_j}{\eta+\theta_j\mu_j}\frac{\partial\,\mu_j}{\partial\,\theta_j}-2\left(\frac{1}{1-\theta_j}+\frac{\mu_j}{\eta+\theta_j\mu_j}\right)\\
&+\frac{(1-\eta)\gamma(1-tc_{ij})}{(1+(1-\eta)\gamma)\left(1-(1-\eta)tc_{ij}\right)+\left(\mu_j+(1-\eta)\gamma\mu_i\right)(1-tc_{ij})}\frac{\partial\,\mu_i}{\partial\,\theta_j}
\end{aligned}
\tag{35}
$$

Proof: see Appendix D.3.

Proposition 2 states that, all else equal, the supplier does not need to exert any effort if it issues no trade credit, whereas it makes maximal effort when it defers the entire payment. Assumption (#1) ensures that the marginal cost of verification at $tc_{ij} = 1$ should be at least as much as its marginal revenue and, thus, guarantee the existence of equilibrium.

We now analyze the connection between the empirical facts documented in Section 3.3 and the results in Proposition 2. Our firm-level evidence indicates that trade credit is determined by both suppliers' and clients' operational and financial conditions. In particular, as the supplier's financial constraint becomes tighter, it extends less trade credit to its clients. The intuition is straightforward. A tighter constraint limits the supplier's production so that it can simply require a larger fraction as CBD to alleviate its financial problem and increase production. Notably, both financial and productivity shocks can affect the supplier's financial constraint. The financial shock affects firms by changing the value of the collateral, implying that a negative shock results in a tighter constraint. The productivity shock affects the relative value of the received CBD to the total value of output, i.e. $\frac{\sum_{j=1}^{n} d_{ij}q_{ij}m_{ij}}{p_i y_i}$, and, thus, the constraint is likely to become looser after a negative productivity shock that lowers the value of total output, as indicated in Equation (28). Therefore, the trade credit issuance decreases as the supplier receives a negative financial shock or a positive productivity shock.

Moreover, the trade credit intensity also responds to the clients' financial condition. Interestingly, the response is non monotonic. On the one hand, a negative financial shock makes the client more financially constrained, which distorts her production and, therefore, her input demand. All else equal, the supplier extends more trade credit to alleviate the client's constraint and partially recover some input sales. Moreover, a negative financial shock reduces the amount of debt, which then lowers the effort that the supplier needs to make in order to verify the status of the input. This also tends to cause the supplier to increase the proportion of input payment that can be deferred.

On the other hand, a negative financial shock to the client, via reducing demand, can worsen the financial condition of the supplier and give the supplier incentives to require a higher fraction of cash before delivery (CBD). Therefore, in equilibrium, the response of trade credit to the client's financial shocks hinges on how elastic the client's and supplier's Lagrange multipliers are to the client's financial shock. If the client is relatively more financially constrained, the supplier extends more trade credit, which then serves as a cushion for the negative shock. In contrast, if the supplier presents a relatively tighter financial constraint than the client does, the client receives less trade credit, which weakens her financial conditions and distorts her production further. In this case, the trade credit channel acts like an amplifier of shocks.

The asymmetric effects of trade credit are present in Kiyotaki and Moore (1997), Luo (2020), and Reisher (2020). However, the asymmetry in our model is fundamentally different. Trade credit amplifies financial shocks from the supplier side and mitigates financial shocks from the client side. However, during a financial crisis in which suppliers are relatively more financially constrained than clients, trade credit amplifies only the effects of negative financial shocks, generating domino effects, as in Kiyotaki and Moore (1997).[23]

In the next section, we investigate the quantitative importance of trade credit adjustment in shaping the state dependency observed in sectoral comovement. In addition, we study the role of trade credit in amplifying or mitigating the effects of financial and productivity shocks on aggregate GDP growth.[24]

6 Quantitative model

In this section, we calibrate our model to the U.S. data. We conduct several exercises to highlight the role of endogenous trade credit and its interaction with financial and productivity shocks in accounting for the large shift in sectoral comovement, as well as the dynamics of the aggregate economy, during the Great Recession.

6.1 Calibration

We follow a three-stage calibration strategy. First, we select the value of some parameters following the existing literature. Second, we calibrate productivity shocks using sectoral TFP estimates from the KLEMS dataset. Third, we calibrate sectoral financial shocks and

[23]In Luo (2020), on the one hand, trade credit acts as a substitute for bank credit which helps mitigate the financial shock. On the other hand, the introduction of trade credit forbearance (costly renegotiation), implies that trade credit can amplify the negative financial shock. In Reisher (2020), the asymmetric effect of trade credit depends on the shape of the credit management cost function and the whether the financial shock is idiosyncratic or aggregate.

[24]In Appendix E, we show how trade credit affects sectoral sales growth and, therefore, sectoral comovement. Sectoral sales growth is a complex function of trade credit adjustment, productivity shocks, financial shocks, and wedges.

the verification efforts using the model and data on sectoral bond spreads from Gilchrist and Zakrajšek (2012) and the sectors' average AR-to-sales ratios from the QFR.

We set the importance of labor disutility ψ to be 1, the elasticity of substitution among consumption goods σ to be 2.5, and the inverse of Frisch elasticity ξ to be 0.36. Following Anderson and Van Wincoop (2003), we set the cost of replacing faulty inputs γ to be 2.83 so that the premium in the secondary market is equivalent to the trading cost between the U.S. and the rest of world. The probability that clients receive qualified inputs, η, is 0.85 to match the one-year survival rate of new startups in the U.S. As shown in Table 3, we calibrate the total shares of inputs to output ($\{\nu_i\}$), labor shares ($\{\alpha_i\}$), input–output matrix $\left(\left\{\omega_{ij}\right\}\right)$, and consumption shares ($\{\phi_i\}$) using the 2005 12-sector input-output table from the BEA.[25]

Table 3
Calibration

Sectors	ν	α	ϕ	$\bar{e}$	κ
Mining	0.44	0.52	0.01	17.66	0.86
Utilities	0.56	0.39	0.02	15.70	0.47
Construction	0.49	0.30	0.13	9.62	0.03
Manufacturing	0.65	0.19	0.16	16.72	0.69
Wholesale trade	0.37	0.40	0.09	10.16	0.06
Retail trade	0.37	0.44	0.11	9.53	0.00
Transportation and warehousing	0.51	0.31	0.05	14.39	0.35
Information	0.45	0.22	0.08	11.91	0.31
Professional and business services	0.37	0.45	0.09	13.31	0.62
Educational services, and health care	0.39	0.50	0.16	9.68	0.02
Arts, and recreation services	0.47	0.36	0.07	13.64	0.19
Other services	0.38	0.43	0.04	12.32	0.25

Next, we use our model solution to calibrate the verification effort parameters ($\{\bar{e}_i\}$) and the sectoral financial shocks ($\{\theta_{it}\}$). In particular, we use Equation (33) to pin down the verification efforts. We do not observe bilateral trade credit issuance, which is why, for the purpose of our calibration, we assume that a given supplier provides the same proportion of trade credit to all clients - i.e., $tc_{ij} = \overline{tc}_i$ - for $\forall j$. For each sector in each quarter, we take the median AR-to-sales ratio across all listed firms in the corresponding industry

[25] Note that α in the mining and utility sector is small, because many of the inputs are imported. This would generate a negative θ for the corresponding sectors. To avoid this, we use the ratio of the sum of employees' compensation and operation surplus to the total output as α for these two sectors.

and then calculate the sectoral average between 2005Q3 and 2007Q2 as $\overline{tc}_i$.[26] We then use Equation (33) to solve for $\bar{e}_{ij}$, out of which $\bar{e}_i$ is selected as the median value of $\bar{e}_{ij}$, across all clients j.[27] When this median value is lower than the threshold in Assumption (#1), we replace it with the threshold value. The fifth column of Table 3 displays the results for $\{\bar{e}_i\}$. The mining and manufacturing industries have the highest values, which implies that the states of their products are relatively more complex to verify. On the other hand, for the retail, construction, and education services is the lowest, indicating that it is more straightforward to monitor their states.

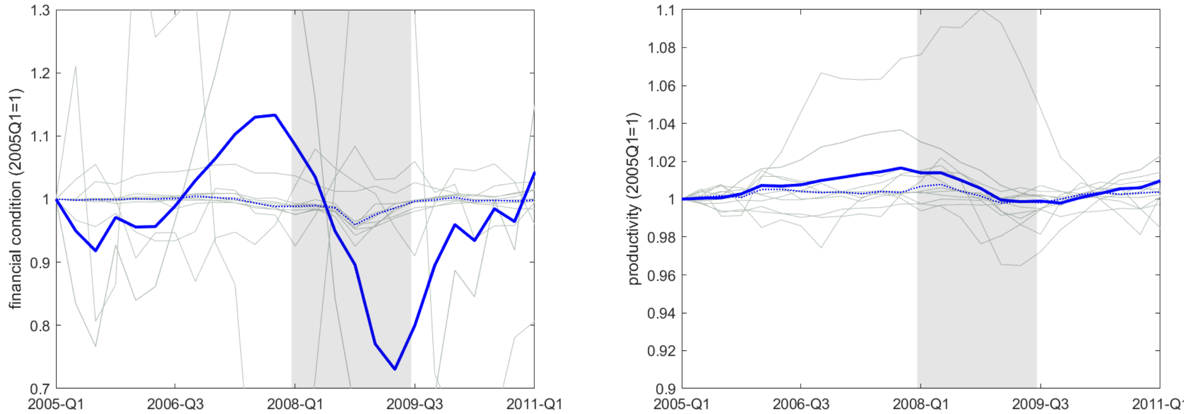
We calibrate sectoral financial shocks extending the approach in Bigio and La'O (2020) and Miranda-Pinto and Young (2022). In particular, we use the sectoral bond spreads from Gilchrist and Zakrajšek (2012) to guide the value for the inverse of the labor wedge, defined in Equation (27).[28] Combining this condition with the binding collateral constraint, we can obtain the implied sectoral financial shock $\{\theta_i\}$ and Lagrangian multiplier $\{\mu_i\}$ at every time t. The top and bottom right of Figure 6 show the normalized financial shocks, with each grey line standing for one sector, and the solid and dashed blue line, respectively, standing for the weighted average (2005 sales share as weights) and median across all sectors. After the collapse of Lehman Brothers, compared to the pre-recession average, more than three quarters of sectors receive negative financial shocks. Manufacturing was hit the most, with θ declining, compared to the pre-recession average, by 7.5%, 23.8%, 65.8% and 76.3% from 2008Q3 through 2009Q2.

Lastly, we calibrate sectoral TFP using KLEMS data. KLEMS productivity data are in annual frequency. We construct quarterly productivity data combining two sources of data. First, we use data on the contribution of labor, capital and inputs to output growth from KLEMs. These data are annual, and we convert them to quarterly frequency using linear extrapolation. Then, we use quarterly data on output growth and the contribution by labor with the data from BEA and BLS, respectively. TFP growth rates are calculated as a Solow residual. Panel (b) of Figure 6 depicts our sectoral TFP data. Compared to the financial shocks, the productivity shocks were less volatile and experienced a smaller decline during the Great Recession.

[26] In practice, since firms usually provide either inputs or consumption goods while sectors in our model do both, thus, $\overline{tc}_i j \kappa_i$ is used, where κ represents the shares of products used as inputs over the total outputs.

[27] Once $\{\bar{e}_i\}$ are calibrated, we can deviate away from the assumption that the supplier issues the same proportion of payments as trade credit to all clients, and let Equation (33) endogenously determine the trade credit intensity tc_{ij}.

[28] The sectoral bond spreads are also constructed by taking the sectoral median. We thank Gilchrist and Zakrajsek for kindly sharing their data with us.



(a) Sectoral Financial Shocks $\{\theta_{it}\}$ (b) Sectoral Productivity Shocks $\{z_{it}\}$

Figure 6
Normalized Financial and Productivity Shocks (2005Q1=1)

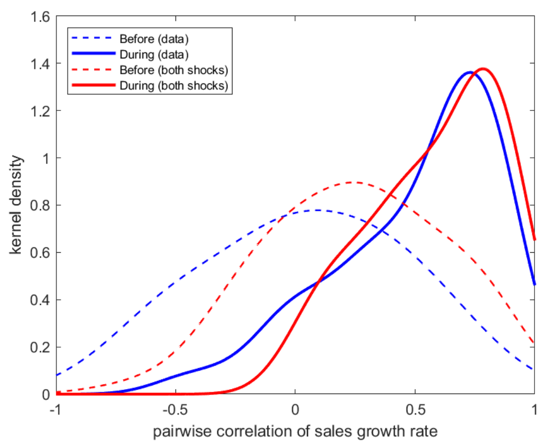
6.2 Fit of the model

Before performing a series of counterfactual exercises, we begin by verifying the ability of our calibrated model in matching key empirical moments. First, we check its ability to match the evolution of real GDP per capita growth for the period 2005-2011. In our model, real GDP is measured by aggregate consumption c. Figure 7 displays the quarter-to-quarter annualized growth rate of real GDP between 2005Q2 and 2011Q2. The blue and red lines represent the data and the model-implied growth rate, respectively, and the shaded area represents the Great Recession period as defined by the NBER. The model-implied growth rate tracks the data closely. The correlation between the two sequences is 0.76, and the model accounts for 86.3% and 74.1% of the observed decline in GDP in 2008Q4 and 2009Q1, respectively.

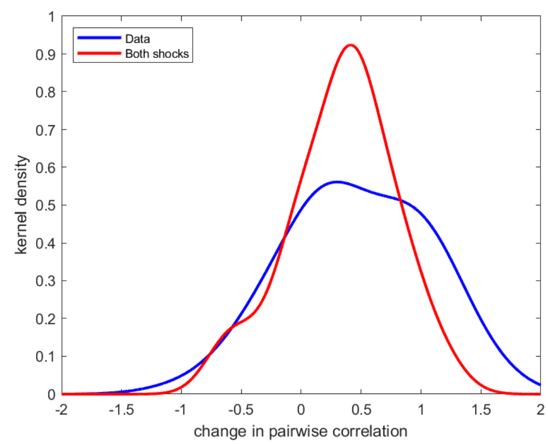
Second, we contrast the pairwise correlations of the sectoral output growth rate generated from the model and the data. To construct the pairwise correlation, we follow the same strategy as in Section 2.1. Figure 8, Panel (a) displays the kernel density of pairwise correlations before and during the Great Recession. In panel (b), we show the difference in pairwise correlations between the periods during and before the Great Recession. We can see in panel (a) that the model-implied density during the Great Recession is slightly higher— by 0.06, on average—than that observed in the data. The model slightly overestimates the pre-recession correlations (by 0.19, on average), but it matches very well the change in pairwise correlations during the Great Recession, as shown in Panel (b) of Figure 8.

Third, we compare the model fit in matching sectoral trade credit issuance and re-

Figure 7
Growth Rate of Real GDP per Capita: Model vs Data



(a) Pairwise Correlation: before and during



(b) Change in Pairwise Correlation

Figure 8
Kernel Density of Pairwise Correlation of Output Growth Rate: Model vs Data

ception. In the data, following the same definition as in Section 2, we take the average AR-to-sales and AP-to-OC between 2005Q3 and 2007Q2 for each sector. As for the model, we first define the account receivables and payables as

$$AR_i = \sum_{j=1}^{n} tc_{ij} q_{ij} m_{ij}, \ \ and \ \ AP_i = \sum_{j=1}^{n} tc_{ji} q_{ji} m_{ji} \tag{36}$$

where tc_{ij} is determined, for all i and j, by Equation (33). Then, the AR-to-sales and

AP-to-OC ratios implied by model can be defined, respectively, as

$$\frac{AR_i}{sales_i} = \frac{\sum_{j=1}^{n} tc_{ij} q_{ij} m_{ij}}{p_i y_i + \sum_{j=1}^{n}\left(1-(1-\eta)tc_{ij} - \frac{p_i}{q_{ij}}\right) q_{ij} m_{ij}}, \tag{37}$$

$$\frac{AP_i}{OC_i} = \frac{\sum_{j=1}^{n} tc_{ji} q_{ji} m_{ji}}{wl_i + \sum_{j=1}^{n} q_{ji} m_{ji}}. \tag{38}$$

where $sales_i$ is defined in Equation (24), and operational costs are equal to the sum of the wage bill and intermediate input payments. Figure 17 in the Appendix displays the scatter plots of both ratios for the model and the data. The horizontal and vertical axes present the data and model-implied ratio, respectively. The size of the bubble indicates the relative size of a sector in 2005, and the black dashed line is the 45-degree line. Panel (a) displays the AR-to-sales ratio, while Panel (b) depicts the AP-to-OC ratio. Except for the mining and professional services sectors, all bubbles line up around the 45-degree line, implying that our model is able to match the data relatively well.

6.3 Trade credit and model-implied sectoral comovement

In this section, we investigate the role of trade credit tc_{ij}, endogenously determined in the model, in driving the rise in sectoral comovement during the Great Recession. We construct an empirical experiment that resembles our empirical evidence in Section 3.3, where we show that sectors comove more during the Great Recession through the disruption of trade credit. We create an indicator, denoted as $\mathbf{1}_{\Delta \log \theta_j < \mathbf{med}}$, for the sectors receiving severe financial shocks during the Great Recession. In particular, the indicator is equal to one when a sector received a financial shock below the median, which is -2.65% across all sectors. This is comparable to the our LB-related group in the empirical sections. We interact the indicator with the change in trade credit intensity to capture the propagating effects through the trade credit channel. We run the following regression

$$\Delta \mathbf{corr}_{ij} = \alpha_0 + \alpha_1 \mathbf{1}_i + \alpha_2 \mathbf{1}_j + \alpha_3 \mathbf{1}_i \times \Delta tc_{ij} + \alpha_4 \mathbf{1}_j \times \Delta tc_{ij} + \alpha_5 \Delta tc_{ij} + \beta_i' \Delta S_i + \beta_j' \Delta S_j + \gamma' X_{ij} + \epsilon_{ij}, \tag{39}$$

where ΔS_i represents financial or productivity shocks for sector i, and X is a vector or control variables capturing either suppliers' or clients' characteristics. These controls include, among others, the pre-recession financial conditions, productivity, sales, input share, etc.

Table 4 reports the point estimates for Equation (39). In Column (1), where no control variables are included, we find that the coefficient of the client's interacted term is negative and statistically significant. It implies that the rising comovement is not sim-

Table 4
Regression: Role of Input-output Linkage and Trade Credit

	(1)	(2)
	$\Delta\mathbf{corr}_{ij}$	$\Delta\mathbf{corr}_{ij}$
$\mathbf{1}_{\Delta\log\theta_i<\mathbf{med}}$	-.29	-.479*
	(.224)	(.259)
$\mathbf{1}_{\Delta\log\theta_j<\mathbf{med}}$	.379	.995**
	(.34)	(.373)
$\mathbf{1}_{\Delta\log\theta_i<\mathbf{med}}\times\Delta tc_{ij}$	.0161	.053
	(.0458)	(.0364)
$\mathbf{1}_{\Delta\log\theta_j<\mathbf{med}}\times\Delta tc_{ij}$	-.554***	-1.31***
	(.19)	(.315)
Δtc_{ij}	-.109	.0993
	(.199)	(.167)
$\Delta\log\theta_i$	-.02***	-.0284***
	(.00613)	(.00717)
$\Delta\log\theta_j$	-.0289	.0509
	(.0294)	(.0321)
$\Delta\log z_i$	.0475	.207
	(.05)	(.128)
$\Delta\log z_j$	.0653	.0707
	(.147)	(.103)
obs	66	66
control	No	Yes
adjusted R^2	.319	.523

ply in the disruption of the trade credit channel but, rather, is only when the client receives a sufficiently severe financial shock. This result highlights the asymmetric role of the trade credit channel, suggesting an environment under which it switches from a cushion to an amplifier. Also, we consider that the coefficient of the supplier's financial shock is insignificant and argue that the supplier's financial shocks affect the comovement mostly through the trade credit channel. Moreover, the coefficient of the supplier's financial shock is negative and statistically significant, implying that the suppliers' financial shocks play direct roles in affecting the sectoral comovement. Next, we incorporate control variables in Column (2), and the main results stay the same qualitatively. Quantitatively, we find that the suppliers comove significantly more, 0.995 on average, with the clients receiving more severe shocks. In addition, the decline in the trade credit intensity has larger marginal effects on sectoral comovement. We find that the correlation rises by 0.013 for each percentage point decline in tcij, compared to a 0.006 rise when we omit the control variables.

6.4 Counterfactual exercise with fixed trade credit

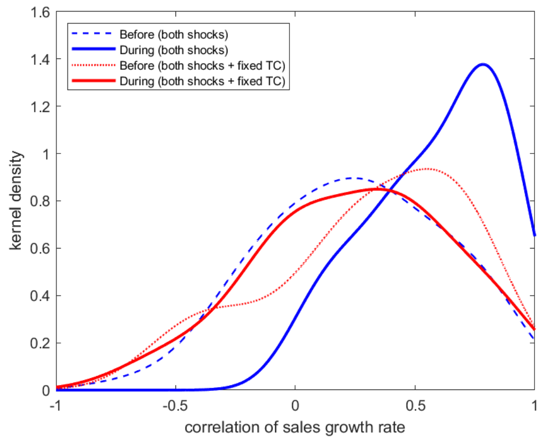
In this section, we perform several counterfactual exercises to study the role of endogenous trade credit, financial shocks, and productivity shocks in explaining the sharp increase in comovement during the Great Recession. We study a counterfactual economy in which trade credit is fixed to the pre-recession average.[29] We then compare that economy with our benchmark endogenous trade-credit model under three scenarios: 1) the case in which financial and productivity shocks are both imposed; 2) the case in which only financial shocks hit the economy; and 3) the case in which only productivity shocks operate.

Figure 9, panel (a) shows the importance of the trade credit channel in matching the shift in sectoral comovemet during the Great Recession. The blue lines correspond to our calibrated benchmark model in Figure 8, while the red lines describe the model-implied distribution of pairwise correlation for the case in which trade credit stays fixed at its pre-recession average - i.e., $tc_{ij,t} = \overline{tc}_{ij}$ - for $\forall t$, where $\overline{tc}_{ij}$ is the pre-recession average for supplier i and client j. As in our benchmark calibration, we feed the fixed trade credit model with the same sequence of financial and productivity shocks calibrated from Section 6.1.[30]

The results in Figure 9 indicate that given two sequences of shocks, the fixed trade credit model is not capable of generating the observed state-dependency in sectoral comovement. In addition, that model generates a milder decline in aggregate GDP. In particular, as observed in Table 13, while the endogenous trade credit model implies a rise in average comovement from 0.22 to 0.52, the fixed trade credit model generates a decrease from 0.29 to 0.21. On the other hand, the fixed trade credit model generates a decline in GDP growth that is 23% smaller than in our benchmark model. Therefore, as our empirical results suggest, trade credit adjustment is instrumental to quantitatively explain the

[29] Once we impose that trade credit is fixed, our model is akin to the model in Bigio and La'O (2020).

[30] Note that in the fixed case, no arbitrage constraint may not be held binding, and we adjust equilibrium equations accordingly.



(a) Kernel density of pairwise correlation

(b) Growth rate: real GDP per capita

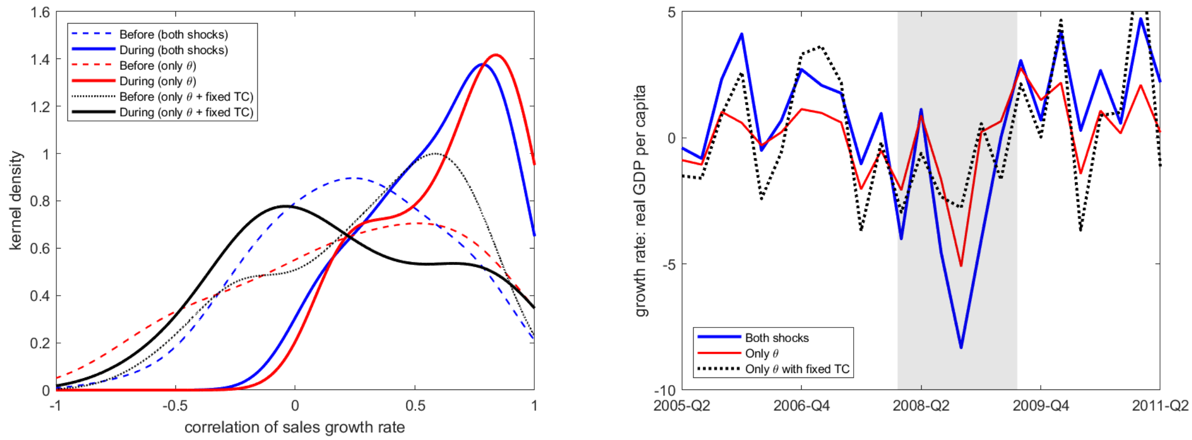
Figure 9

Both shocks: endogenous vs exogenous trade credit

shift in comovement during the Great Recession. The domino effects generated by trade credit adjustment not only shape comovement but also amplify the recession by 23%.

6.4.1 The role of financial shocks

We now study the role that financial shocks, as opposed to productivity shocks, play in driving the results in Figure 9. We feed the model with the same sequence of financial shocks calibrated from Section 6.1, while keeping sectoral productivity at the pre-recession average - i.e., $z_{it} = \bar{z}_i$ - for $\forall t$, where $\bar{z}_i$ is the pre-recession average for sector i.



(a) Kernel density of pairwise correlation

(b) Growth rate: real GDP per capita

Figure 10

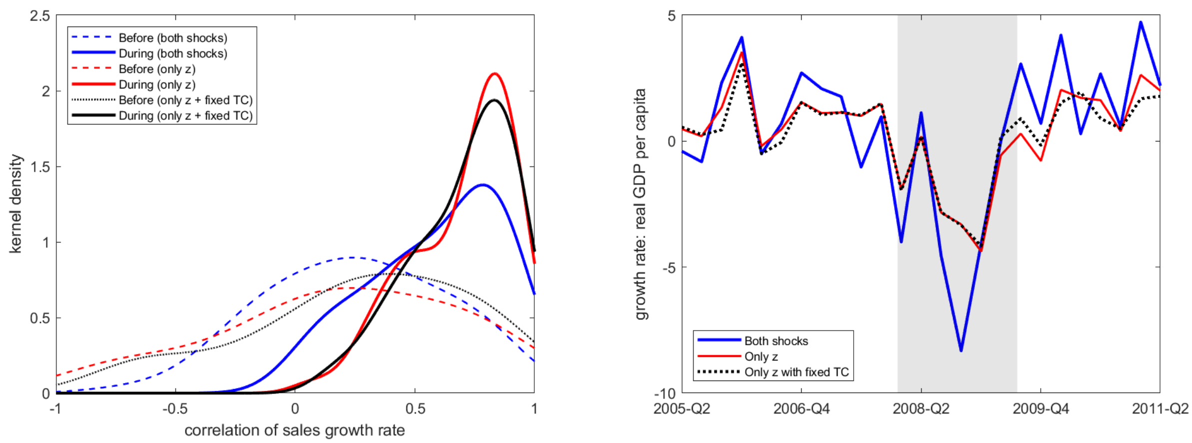
Only financial shocks: endogenous vs exogenous trade credit

Panel (a) of Figure 10 displays the kernel density of sectoral output growth for our benchmark model (blue line) and for the model with fixed trade credit (black line), which are set to the pre-recession average in the presence of only financial shocks. We can see that, when the economy is hit only by sectoral financial shocks, our model with endogenous trade credit is able to generate a shift in sectoral comovement that is similar to that implied by our benchmark model. On the other hand, the fixed trade credit model implies a reduction in sectoral comovement during the Great Recession. This counterfactual decline in comovement implied by the fixed trade credit model is explained by the nature of our calibrated financial shocks. In Figure 18, we show the pairwise correlation of our calibrated financial (and productivity) shocks. We observe that during the Great Recession, the pairwise correlation of financial shocks displays a bi modal distribution. In effect, only a few pairs of sectors experienced a rise in the comovement of the underlying financial shocks.

We can also see in Panel (b) of Figure 10 that, compared to the fixed trade credit model, the endogenous response of trade credit amplified the aggregate effect of financial shocks by a factor of 1.8 in 2008Q4. Overall, the results in Figure 10 indicate that, with endogenous trade credit, it is sufficient that a few sectors receive a negative financial shock to generate strong domino effects that significantly increase sectoral comovement and reduce aggregate economic activity.

6.4.2 The role of productivity shocks

In this section, we study the role of productivity shocks and their interaction with trade credit adjustment. We impose that only productivity shocks hit the economy and assume that financial shocks remain at their pre-recession level. Figure 11, Panel (a) displays the kernel density of sectoral output growth. We observe a substantial rise in sectoral comovement. The rise in comovement occurs in the endogenous trade credit model (red line) and in the fixed trade credit model (black line). The reason is simple. As shown in Figure 18, sectoral productivity shocks calibrated from KLEMS were substantially more correlated during the Great Recession. The fact that the endogenous trade credit model and the fixed trade credit model display similar comovement dynamics demonstrates that trade credit does not respond to productivity shocks but respond mainly to financial shocks, as shown in Figure 10.



(a) Kernel density of pairwise correlation

(b) Growth rate: real GDP per capita

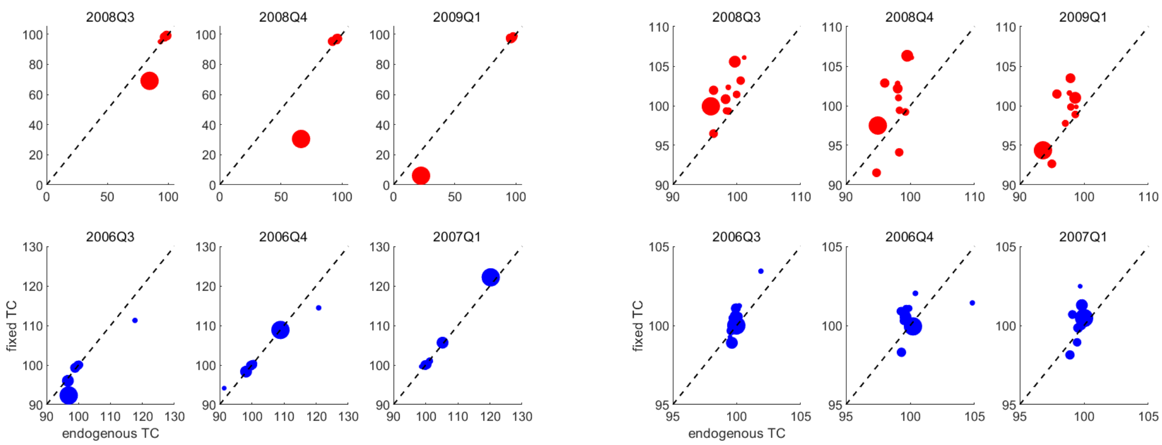
Figure 11
ONLY PRODUCTIVITY SHOCKS: ENDOGENOUS VS EXOGENOUS TRADE CREDIT

In terms of GDP growth, productivity shocks alone can account for 39.7% of the decline in GDP growth during 2008Q4. The evolution of GDP growth is the same for the model with fixed trade credit, confirming the fact that, unlike the case of financial shocks, trade credit does not amplify the effect of productivity shocks.

6.5 Recalibrating sectoral shocks in the fixed trade credit model

In this section, we emphasize the role of trade credit from a different perspective. We ask the following question: what does a model with production networks, working capital constraints, and fixed trade credit provision tell us about the drivers of the Great Recession? In particular, we investigate how sectoral financial and productivity shocks differ in a calibrated model with fixed trade credit compared to our benchmark model.

We re calibrate financial and productivity shocks, while keeping the trade credit intensities at the pre-recession average, following the same strategy we used in Section 6.1. Figure 12 is a scatter plot of sectoral shocks—the relative size to their pre-recession average. A bubble represents one sector, and its size reflects the sales share in 2005. The horizontal and vertical axes stand for the endogenous trade credit model and the fixed trade credit model, respectively.



(a) Financial shocks (b) Productivity shocks

Figure 12
Calibrated financial and productivity shocks: endogenous vs exogenous trade credit

In Panel (a) of Figure 12, we plot the financial shocks. We observe that for the largest sector in our sample, Manufacturing, the bubble lies significantly below the 45-degree line. Therefore, in order to match the sectoral sales and interest spread, the fixed trade credit model needs a much larger negative financial shock to a key upstream sector in the production network. Between 2008Q3 and 2009Q1, the financial shocks to the manufacturing sector in the fixed case was 2.5 times larger, on average, than in the endogenous case. For other sectors, the difference between the relative size in both cases was less than 2%. In contrast, we do not observe any significant differences between the shocks for the period before the Great Recession, where most of bubbles lie around the 45-degree line.

Moreover, we perform the same analysis on productivity shocks. As shown in Panel (b), we do not observe any significant different between sectoral productivity imputed from models with endogenous and fixed trade credit.

6.6 The early 80s recession

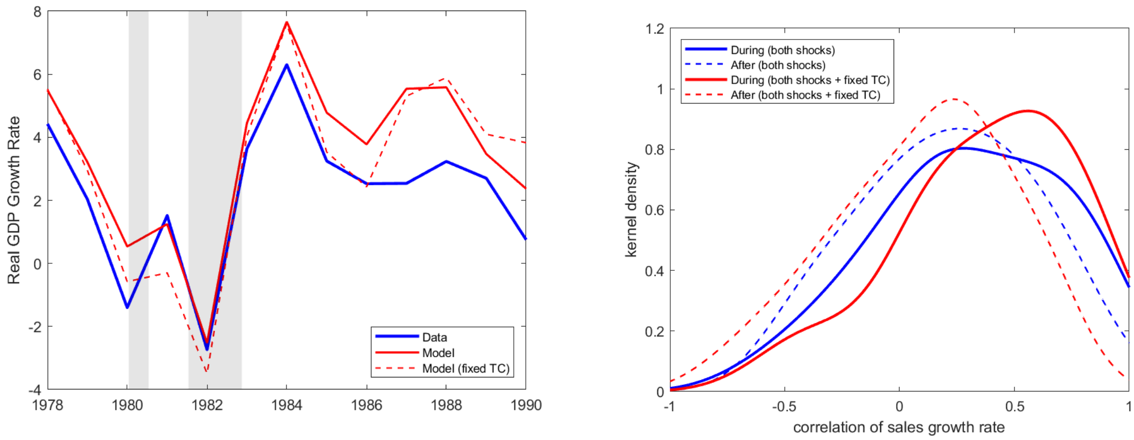
In this final section, we analyze an important question left out: why didn't sectoral comovement shift significantly during US recessions prior to 2007? We take the case of the early 80s recession, which displayed a decline in real GDP that is comparable to that of the Great Recession.

We answer this question through the lens of our model. In particular, we calibrate the model to match sectoral sales, and sectoral spreads for the period 1978-1985. Since KLEMs data provide only estimated sectoral TFP from 1987, we use the equilibrium conditions from our model to back out sectoral productivity and financial shocks. There are two caveats to using this approach. First, we adopt the same set of parameters calibrated in Section 6.1. In this way, we assume that the economy's structure of the early 1980s was the same as before the Great Recession. This is a rather strong assumption, but it allows us to compare, through the lens of the model, the dynamics of sectoral comovement across different US recessions. Second, we must use annual data since quarterly data are not available for the period 1978-1990. We use the period 1978-1985 as the"during" recession window, while the "after" window is the period 1983-1990.

We study the role of trade credit in shaping comovement during the early 80s recession by comparing the evolution of the real GDP growth and sectoral comovement from our benchmark calibration with the evolution implied by a model that assumes that trade credit stays constant at its average level. Panel (a) of Figure 13 plots the evolution of the real GDP growth rate. The model matches the GDP decline in 1982 quite well but slightly underestimates the decline in 1980. The fixed trade credit model implies a higher decline in GDP growth in both recessions, indicating that trade credit dampened the magnitude of the recessions in 1980 and 1982. Thus, unlike in the Great Recession, and as predicted by our model, trade credit can also act as a buffer rather than an amplifier of economic recessions.

Panel (b) of Figure 13 plots the kernel density of pairwise correlation of sectoral sales growth. We can see that in our benchmark calibration, and consistent with the empirical results in Figure 2, the kernel density of output growth slightly only shifted to the right during the recession period (blue line). On the other hand, we can see that the fixed trade credit model amplifies the shift in sectoral comovement. Hence, different from the Great Recession—in which trade credit generated strong negative spillover effects, shifting sectoral comovement and amplifying the decline in GDP during the early 80s—trade credit adjustment mitigated the magnitude of the early 80s recession by smoothing negative spillover effects among sectors and, therefore, reducing the decline in GDP.[31]

[31] Figures 19 and 20 in our Appendix F.1 depict the evolution of sectoral shocks and the kernel density of sectoral shocks during and after the early 80s recessions.



(a) Growth rate: real GDP per capita

(b) Kernel density of pairwise correlation

Figure 13
The Early 80s Recession: endogenous vs exogenous trade credit

7 Conclusion

We document a defining feature of the US business cycle during the Great Recession. Unlike any other post-war recession, the distribution of sectoral and firm-level comovement shifted significantly to the right during the Great Recession. Using sectoral and firm-level data, we show that trade credit adjustment played an important role in shifting comovement.

We then construct a multisector model with input-output linkages, financial frictions and endogenous trade credit adjustment and highlight the importance of trade credit adjustment in driving the state-dependency of sectoral comovement. Our model emphasizes the asymmetric role of trade credit. In normal times, when suppliers have “deep pockets", they have incentives to extend more trade credit to clients facing tighter financial conditions. However, when financial conditions are adverse to suppliers, too, trade credit provision collapses. We show that this mechanism is crucial to explain the significant increase in sectoral comovement during the Great Recession in the US. Moreover, through this mechanism, our model suggests that trade credit amplified the effect of financial shock on GDP growth by a factor of 1.22.

More generally, our paper emphasizes the relevance of considering internal propagation forces, endogenous trade credit chain, when one is interested not only in aggregate dynamics but also in sectoral dynamics. Our results have important implications for business cycle stabilization policies. In particular, in the same way that mild sectoral financial shocks in our model - compared to a model with exogenous trade credit - are able to generate large sectoral cascades, a milder and well-targeted stabilization policy should be able to stabilize the macroeconomy in the face of negative financial shocks.

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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 5 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 respectively in Equation (37) and (38).

A.2 Compustat

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

- Observations with negative total assets (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

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

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

Table 6 display the summary statistics of all selected firms.

Table 5
List of Sectors and Characteristics

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

A.3 Syndicated loan from Dealscan

Following Chodorow-Reich (2014), we use Dealscan Database and create our firm-bank connection by filtering out

Table 6
Summary Statistics of Selected Compustat Firms

		Before		During		Difference	
	Nobs	Mean	Std	Mean	Std	Mean	Std
$AR/Sales$	1246	63	80.2	60.8	79.6	-2.3	27.5
$AP/Cost$	1248	66.9	184.0	59.2	173.9	-7.7	118.6
$Investment/TA$	1249	1.4	1.5	1.1	1.3	-0.2	0.9
$Cash/TA$	1249	17.2	18.3	15.9	16.2	-1.3	9.9
$Short-term\,debt/TA$	1235	2.3	4.4	2.8	5.1	0.5	4.4
$Long-term\,debt/TA$	1243	16.5	17.8	19.2	19.5	2.6	11.8
$OIBDP/TA$	1241	3.7	2.7	2.9	3.2	-0.7	2.4
$Tobin's\ Q$	1249	1.86	0.71	1.44	0.60	-0.43	0.47
$Inventory/TA$	1241	11.5	12.5	11.4	11.6	-0.1	4.3
g_{sales}	1249	2.9	4.3	-2.9	7.4	-5.8	8.1
g_{assets}	1249	2.1	2.7	-1.1	3.7	-3.2	4.2
$log(TA)$	1249	7.2	1.6	7.3	1.6	0.1	0.3

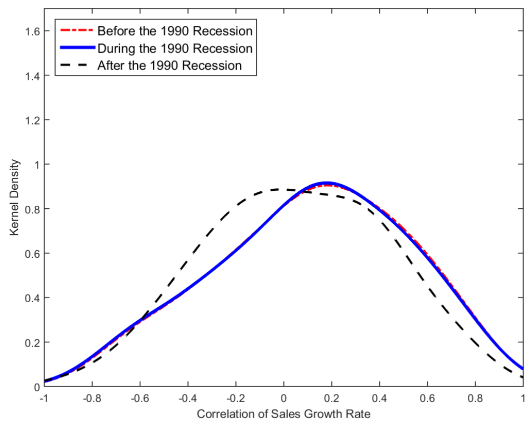
Notes: select financial variables from COMPUSTAT following Kahle and Stulz (2013), and take the median value of these variables 2005Q3-2007Q2 and 2008Q3-2009Q2 respectively to represent the value

- Firms not incorporated in the US;
- All financial firms (firms with standard industrial classification(SIC) codes between 6000 and and 6999);
- Loans due before Octbor 2008
- The main purpose of loans are not working capital or corporate purpose

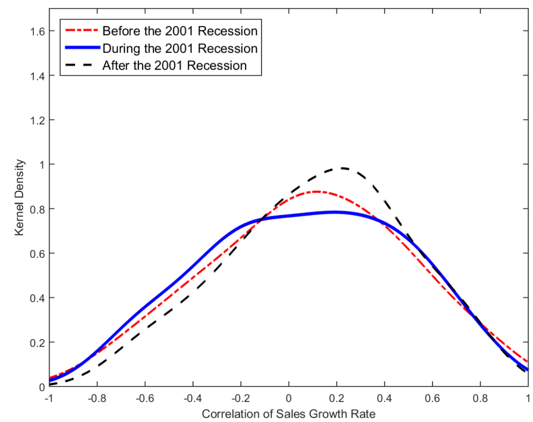
B Additional Sectoral Evidence

Here 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. Note that 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 classification is consistent when we calculate the kernel densities throughout the 2001 recession. We adopt the same approach to calculate the pairwise correlations. 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 14 respectively shows the kernel densities of pairwise correlations before, during, and after the 1990 and 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 and 2001 recession is akin to the one during the Great Recession.



(c) The 1990 Recession



(d) The 2001 Recession

Note: Output data are from the QFR (20 industries). 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. 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 1990 recession, respectively

Figure 14

Kernel Density for Pairwise Correlations during the 1990 and 2001 Recession

Before the recession, the density is hump-shaped with mean and median around 0.08, as shown in Table 8, 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.[32] 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.

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

32

Table 7

PAIRWISE CORRELATIONS OF OUTPUT GROWTH RATES DURING THE 1990 AND 2001 RECESSION

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

Notes: All kernel densities f are calculated on unit interval $[-1,1]$ with bandwidth 0.001. 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. 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 8

SUMMARY STATISTICS OF PAIRWISE CORRELATIONS

	Mean	Median	Std	Skewness	KS Statistics
Before	0.07	0.08	0.38	-0.11	0.21 (0.00)
During	0.40	0.48	0.36	-0.76	
After	0.01	0.01	0.41	0.02	0.26 (0.00)

Notes: All kernel densities f are calculated on unit interval $[-1,1]$ with bandwidth 0.001. 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. 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.

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. 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.

Table 9

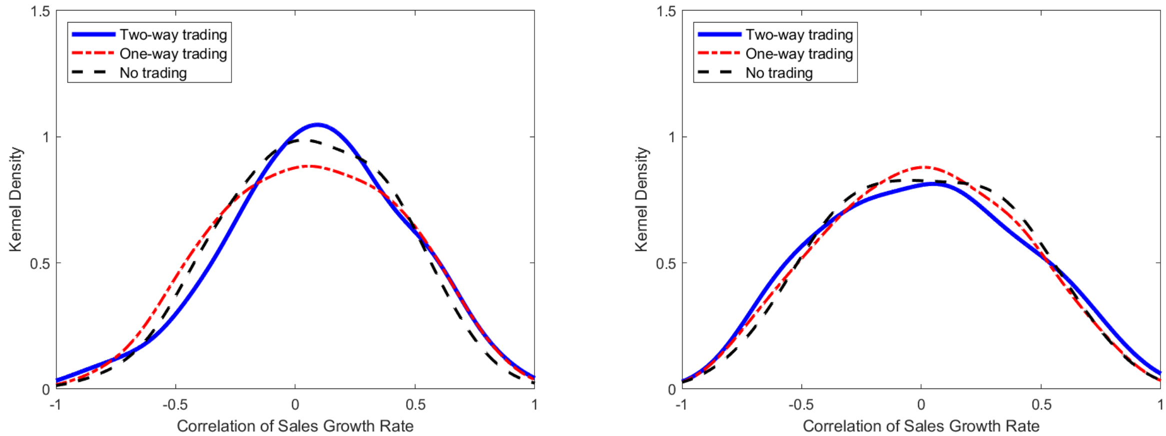
Summary Statistics of Pairwise Correlations, by Extent of Interconnectedness

	Mean	Median	Std	Skewness	KS Statistics
Two–way Trading Group					
Before	0.10	0.12	0.39	-0.20	0.27 (0.00)
During	0.50	0.60	0.34	-1.21	
After	0.01	0.01	0.44	0.05	0.36 (0.00)
One–way Trading Group					
Before	0.06	0.07	0.40	-0.04	0.17 (0.00)
During	0.33	0.40	0.37	-0.53	
After	0.01	0.03	0.41	-0.01	0.19 (0.00)
No Trading Group					
Before	0.06	0.07	0.36	-0.06	0.11 (0.00)
During	0.19	0.24	0.39	-0.35	
After	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. 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. 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.

We then fix the categorization and, for each group, we calculate the pairwise correlations before and after the Great Recession. As we can see in Figure 15, the densities before (left) and after (right) the Great Recession have very similar statistical moments across three groups. Hence, the fact that linkages are important only during the Great

Recession indicates that it is not the average interconnectedness what matters but an endogenous mechanism that alter the extent of interconnectedness among sectors.



(a) Before (b) After

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. The top panel shows data for the Great Recession. The bottom left panel shows data before the Great Recession, while the bottom right panel shows data after the Great Recession.

Figure 15
Kernel Density before and after the Great Recession
by Extent of Interconnectedness

As Table 10 shows, two sectors in the two-way traded group that experienced a decline in trade credit have correlation 0.14 higher, on average, than the two-way pairs that did not. Similarly, a pair in the one-way traded group has a correlation 0.11 higher when they reduced their trade credit significantly, compared to the one did not. The similarity of two densities is rejected by the KS test at the 0.1% significance level. Moreover, these pairs that have two-way trading relationship but managed to keep trade credit intact during Great Recession have a similar degree of comovement with these that traded in one direction but did experience the decline in trade credit.

Figure 16 show the kernel densities of the different groups before (left) and after the Great Recession (right). We can see that these groups presented kernel densities that are more or less the same before and after Great Recession.

C Additional Micro Evidence

Table 11 display the summary statistics of all selected suppliers and clients. We confirm that the pairwise correlations at the firm level significantly increased during Great Recession, although it is slightly lower compared to the shift at the sector level. In particular, using Equation (1) with the same time window, we find the pairwise correlations between suppliers and clients rose by 0.25, from 0.04 prior to Great Recession. To investigate what factors can account for the change in comovement, we select financial variables

Table 10

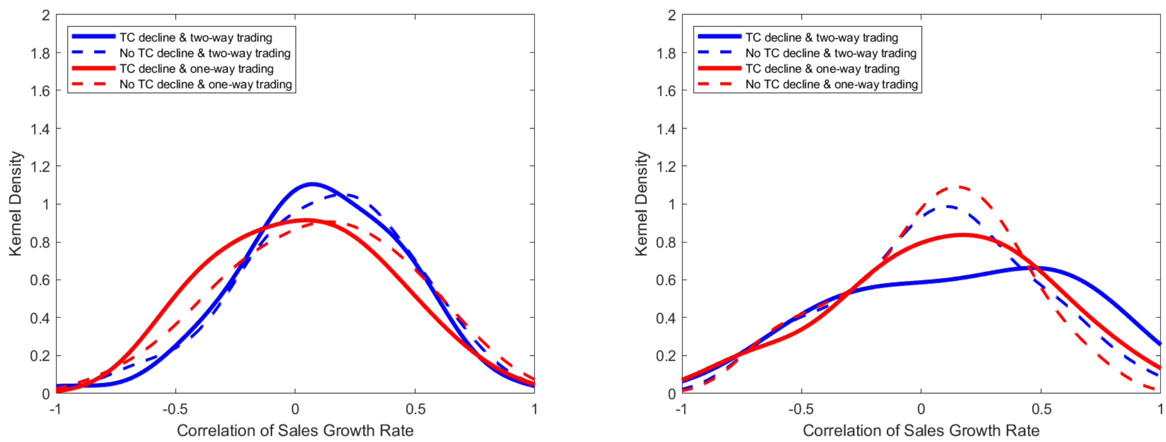
Summary Statistics of Pairwise Correlations by Whether Trade Credit Declines

	Mean	Median	Std	Skewness	KS Statistics
Group I: $\mathbf{D}_{ij}^{tc}$ *or* $\mathbf{D}_{ji}^{tc} = 1$ and two-way traded					
Before	0.16	0.21	0.32	-0.37	0.54 (0.00)
During	0.70	0.79	0.18	-0.37	
After	0.08	0.16	0.47	-0.05	0.61 (0.00)
Group II: $\mathbf{D}_{ij}^{tc}$ *or* $\mathbf{D}_{ji}^{tc} = 1$ and one-way traded					
Before	0.09	0.10	0.36	-0.09	0.46 (0.00)
During	0.60	0.64	0.20	0.00	
After	0.15	0.20	0.41	-0.28	0.48 (0.00)
Group III: $\mathbf{D}_{ij}^{tc}$ *and* $\mathbf{D}_{ji}^{tc} = 0$ and two-way traded					
Before	0.13	0.18	0.43	-0.18	0.46 (0.00)
During	0.56	0.66	0.23	0.24	
After	0.09	0.13	0.42	-0.02	0.47 (0.00)
Group IV: $\mathbf{D}_{ij}^{tc}$ *and* $\mathbf{D}_{ji}^{tc} = 0$ and one-way traded					
Before	0.11	0.13	0.38	-0.19	0.30 (0.00)
During	0.49	0.56	0.29	-0.48	
After	0.12	0.14	0.40	-0.24	0.27 (0.00)
KS Test across Groups during the Great Recession					
Group I vs Group III					0.40 (0.00)
Group II vs Group IV					0.24 (0.00)

Notes: All kernel densities f are calculated on unit interval $[-1,1]$ with bandwidth 0.001. 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. 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.

from COMPUSTAT following Kahle and Stulz (2013), and take the mean value of these variables over 2005Q3-2007Q2 and 2008Q3-2009Q1 respectively to represent before and during Great Recession. We collect data on account payable, account receivable, investment to total assets (TA), cash to assets ratio, short-term and long-term debt to assets ratio, among others.

Analogously, we examine the role of trade credit in propagating and amplifying the LB shock downstream, from supplier affected by LB to a customer. In particular, we focus on a subsample of firms in which some LB and non-LB borrowers have a common client that is not directly borrower from LB. We consider indirect-LB client just for purpose of observation, since we do not have any pair where supplier directly borrows from LB but client has no relationship with LB in syndicated loan market. Then we contrast the pairwise correlations of this common client and these suppliers, and test how clients'



(a) Before (b) After

Note: A pair is considered as experiencing trade credit decline during Great Recession if both the supplier's AR-to-sales ratio declines more than 2.9% and the client's AP-to-OC ratio does more than 1.5%.. 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.

Figure 16
Kernel Density before and after the Great Recession
by Whether Trade Credit Declines

trade credit reception affected their comovement with the same supplier. Here we have 62 pair in total, which is consist of 8 clients and 49 suppliers. Then we study the relevance of financial frictions and the change in trade credit in driving the rise in comovement through the following linear regression:

$$\Delta\mathbf{corr}_{ij}-\overline{\Delta\mathbf{corr}}_j = \alpha_0+\alpha_1\mathbf{1}^{LB}_{i,dir}+\alpha_2\mathbf{1}^{LB}_{i,indir}+\alpha_3\mathbf{1}^{LB}_{i,dir}\times\Delta\frac{AR_i}{Sales_i}+\alpha_4\mathbf{1}^{LB}_{i,indir}\times\Delta\frac{AR_i}{Sales_i}+\beta_1'\Delta X_i+\epsilon_i, \tag{40}$$

where $\overline{\Delta\mathbf{corr}}_j = \frac{1}{n}\sum_{i=1}^{n}\Delta\mathbf{corr}_{ij}$ is the average change in pairwise correlation for supplier j over all her clients. In doing so, we can eliminate the unobservables from clients.

Despite the small number of observations, the results in Table 12 indicate that the client-supplier comovement during the Great Recession was amplified by the exposure of a supplier to LB and by the contraction in the supplier's account receivables. The results on the effect of LB in financial variables are qualitatively similar, although not statistically significant (not reported here), which is not surprising given the smaller sample size.

Table 11
Summary Statistics: Paired Supplier and Client

		Before		During		Difference	
	Obs	Mean	Std	Mean	Std	Mean	t-stats
corr$_{ij}$	641	.035	.44	.20	.46	0.17***	(7.14)
Suppliers							
$AR/Sales$	426	59.92	24.78	59.34	24.74	-0.58	(-0.34)
$AP/Cost$	426	58.16	53.18	54.28	36.11	-3.88	(-1.25)
$Investment/TA$	426	1.46	1.82	1.33	1.62	-0.12	(-1.04)
$Cash/TA$	426	20.00	19.78	18.00	18.32	-1.99	(-1.53)
$Short-term\ debt/TA$	425	2.90	4.73	3.30	5.94	0.41	(1.10)
$Long-term\ debt/TA$	426	16.39	18.81	18.23	20.65	1.85	(1.36)
$OIBDP/TA$	423	3.33	3.03	2.23	3.86	-1.10***	(-4.61)
$Tobin's\ Q$	423	1.88	0.73	0.14	0.57	-0.52***	(-11.48)
$Inventory/TA$	426	11.98	10.42	12.50	10.61	0.52	(0.73)
g_{sales}	426	2.94	3.45	0.24	3.71	-2.71***	(-11.03)
g_{assets}	426	2.89	3.91	0.18	3.88	-2.71***	(-10.13)
$log(TA)$	426	6.48	1.69	6.61	1.73	0.13	(1.09)
$log(sales)$	426	5.07	1.73	5.18	1.73	0.11	(0.92)
Clients							
$AR/Sales$	176	51.67	39.94	52.69	42.66	1.02	-0.23
$AP/Cost$	176	62.74	49.32	62.1	47.62	-0.63	(-0.12)
$Investment/TA$	176	1.55	1.48	1.49	1.53	-0.06	(-0.35)
$Cash/TA$	176	11.75	13.7	10.28	11.88	-1.47	(-1.07)
$Short-term\ debt/TA$	176	3.95	5.91	4.55	8.16	0.6	-0.79
$Long-term\ debt/TA$	176	20.32	17.43	23.59	18.48	3.28	-1.71
$OIBDP/TA$	176	3.83	2.08	3.31	2.36	-0.52*	(-2.19)
$Tobin's\ Q$	175	0.18	0.64	0.14	0.5	-0.36***	(-5.88)
$Inventory/TA$	176	13.21	12.99	13.23	12.95	0.02	-0.01
g_{sales}	176	2.61	2.77	0.48	3.59	-2.12***	(-6.21)
g_{assets}	176	2.69	3.16	0.94	2.84	-1.75***	(-5.48)
$log(TA)$	176	9.04	1.59	9.2	1.56	0.16	-0.92
$log(sales)$	176	7.72	1.6	7.83	1.58	0.11	-0.63

Notes: All sample are selected using the requirement in Kahle and Stulz (2013) and pairwise are matched using the 10-K form. The values in the 'before' column are the pre-recession average between 2005Q3 and 2007Q2 and the 'during' ones are the average between 2008Q3 and 2009Q1.

Table 12
Results: Regression (40)

	$\Delta\textbf{corr}_{ij} - \overline{\Delta\textbf{corr}}_i$				$\textbf{corr}_{ij,05} - \overline{\textbf{corr}}_{i,05}$
	(1)	(2)	(3)	(4)	placebo test
$\mathbf{1}^{LB}_{i,dir}$	.43†	.22	.053	.082	.33
	(.25)	(.22)	(.18)	(.3)	(.29)
$\mathbf{1}^{LB}_{i,indir}$	.44*	.43*	.64**	.65**	-.072
	(.2)	(.19)	(.19)	(.22)	(.17)
$\mathbf{1}^{LB}_{i,dir} \times \Delta\frac{AR_i}{Sales_i}$		.052*	.025	.032	
		(.02)	(.013)	(.029)	
$\mathbf{1}^{LB}_{i,indir} \times \Delta\frac{AR_i}{Sales_i}$		-.0063	-.035†	-.057*	
		(.019)	(.018)	(.022)	
$\Delta\frac{AR_i}{Sales_i}$ or $\frac{AR_{i,05}}{Sales_{i,05}}$		-.015	.019†	.028†	.005
		(.013)	(.011)	(.016)	(.0035)
N	62	62	58	58	60
Control var	No	No	ΔX	ΔX	X_{05}
Industry dummy	No	No	No	Yes	Yes
R^2	.11	.19	.53	.64	.45

Notes: $^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.01$.

D Proof for propositions and lemmas

Given Equation (13), we can replace the k_i and c_i in the objective function in Problem (12), and derive the Lagrangian as

$$\begin{aligned}\mathcal{L} \;=\; & \eta\left[\sum_{h=1}^{n}\left(d_{ih}+\eta\left(1-d_{ih}\right)-\frac{p_i}{q_{ih}}\right)q_{ih}m_{ih}+p_i z_i\left(\prod_{h=1}^{n} m_{hi}^{\omega_{hi}}\right)^{\nu_i} l_i^{\alpha_i}-wl_i\right.\\ & \left.-\sum_{h=1}^{n}\left(\eta+(1-\eta)d_{ih}+(1-\eta)\gamma\frac{p_h}{q_{hi}}\right)q_{hi}m_{hi}\right]-(1-\eta)\sum_{h=1}^{n}\left(\frac{(1-d_{ij})q_{ij}m_{ij}}{\omega_{ij}v_j\left(p_j y_j-b_j\right)}\right)^2\bar{e}_i q_{ih}m_{ih}\\ & +\mu_i\left(\theta_i p_i z_i\left(\prod_{h=1}^{n} m_{hi}^{\omega_{hi}}\right)^{\nu_i} l_i^{\alpha_i}+\sum_{h=1}^{n} d_{ih}q_{ih}m_{ih}-wl_i-\sum_{h=1}^{n} d_{hi}q_{hi}m_{hi}\right)\\ & +\sum_{h=1}^{n}\lambda_{ih}\left(\gamma p_i-d_{ih}q_{ih}-\eta(1-d_{ih})q_{ih}-(1-\eta)(\gamma-\theta_i)p_i\right) \qquad (41)\end{aligned}$$

D.1 Proof of Lemma 1

Proof. Taking the derivatives against l_i and m_{hi}, we have the first order conditions as in Equation (25) and (26), and then use Equation (26) to derive the solution for y_i as in Equation (28). ■

D.2 Proof of Proposition 1

Proof. Taking solution of $m_{ij}$from Lemma 1 as given, we have $\frac{(1-d_{ij})q_{ij}m_{ij}}{\omega_{ij}v_j(p_jy_j-b_j)} = \frac{(1-d_{ij})v_{ij}^M}{1-\theta_j}$. Since the firm acts like a monopolistic competitor, we take the first order conditions of q_{ij} as in Equation (30). And the firm set the CBD intensity to the extent where the no arbitrage constraint as shown in Equation (15) is just binding. ■

D.3 Proof of Proposition 2

Proof. Combining Equation (30) with (31), we have Equation (33) with the replacement $tc_{ij} = 1 - d_{ij}$. At $tc_{ij} = 0$, we have the left hand side (LHS) is equal to 0, while the right hand side (RHS) is positive. Clearly, the LHS is increasing in tc_{ij}, while the RHS is decreasing in tc_{ij}. Moreover, Assumption (#1) ensures the LHS is larger than the RHS at $tc_{ij} = 1$. Therefore, the solution exists for any $\theta \in (0,1)$ and $\mu > 0$, and the uniqueness is guaranteed due to monotonicity.

Moreover, it is straightforward to show that trade credit intensity tc_{ij} is decreasing in μ_i. Taking the total differentiation on both side, we have tc_{ij} is decreasing in θ_j if g function is negative. ■

E Sales Growth Decomposition

We examine how the trade credit affect the sales growth. First, let $\mathbf{D}_\alpha$ and $\mathbf{D}_\nu$ be the diagonal matrix for α and ν, which details are specified in appendix, and let

$$\Omega = \begin{bmatrix} \omega_{11} & \dots & \omega_{1n} \\ \vdots & \ddots & \vdots \\ \omega_{n1} & \dots & \omega_{nn} \end{bmatrix}, \ and\ \mathbf{M}_\omega = \begin{bmatrix} \omega_{11} & & & \dots & \omega_{n1} & & \\ & \ddots & & \dots & & \ddots & \\ & & \omega_{1n} & \dots & & & \omega_{nn} \end{bmatrix}.$$

Then we denote

$$x_t = [x_{1t}, \dots, x_{nt}]',\ for\ x \in \left\{p, y, z, sales, v^L,\right\} \tag{42}$$

$$x_t = [x_{11,t}, \dots, x_{1n,t}, \dots, x_{n1,t}, \dots, x_{nn,t}]',\ for\ x \in \left\{tc, q, v^M\right\} \tag{43}$$

Using the goods market clearing condition in Equation (22) and the FOC of household as in Equation (18), we have

$$\Delta \log p_t = \frac{1}{1-\sigma}\left(\log\left(\left(\eta \mathbf{I}_n - \frac{1}{\eta\gamma}\mathbf{D}_\nu \mathbf{M}_{xt}\right) p_t \circ y_t\right) - \mathbf{1}_n \log\left(\mathbf{1}_n'\left(\eta \mathbf{I}_n - \frac{1}{\eta\gamma}\mathbf{D}_\nu \mathbf{M}_{xt}\right) p_t \circ y_t\right)\right) \tag{44}$$

where $\mathbf{1}_n$ is a 1-by-n unit vector, $\mathbf{I}_n$ is the n dimension identity matrix, $\circ$ stands for Hadamard product, and the input-usage weighted matrix $\mathbf{M}_{xt}$ is defined as

$$\mathbf{M}_{xt} = \begin{bmatrix} (1-(1-\eta)tc_{11,t})\,\omega_{11} v_{11,t}^M & \dots & (1-(1-\eta)tc_{1n,t})\,\omega_{1n} v_{1n,t}^M \\ & \ddots & \\ (1-(1-\eta)tc_{n1,t})\,\omega_{n1} v_{n1,t}^M & \dots & (1-(1-\eta)tc_{nn,t})\,\omega_{nn} v_{nn,t}^M \end{bmatrix}. \tag{45}$$

Moreover, Lemma 1 implies that the values of the labor and input wedges rely on these binding financial constraints, which further depend on the exogeneous financial conditions, θ. Proposition 3 describes a solution for the vector of sectoral output growth rate.

Proposition 3 *Given the sectoral productvity shocks $\{z_{it}\}$, Lagrangian multipliers for collateral constraints $\{\mu_{it}\}$, the financial conditions $\{\theta_{it}\}$, labor wedges $\left\{v_{it}^L\right\}$, inputs wedges $\left\{v_{ij,t}^M\right\}$, and trade credit intensities and $\left\{d_{ij,t}\right\}$, the vector of sectoral sales growth rates can be expressed as*

$$\Delta \log(sales_t) = \Delta \log\left(\left(\eta \mathbf{I}_n + \left(1 - \frac{1}{\eta\gamma}\right)\mathbf{D}_\nu \mathbf{M}_{xt}\right) p_t \circ y_t\right) \tag{46}$$

where $p \circ y$ are the fixed vector for the following equation

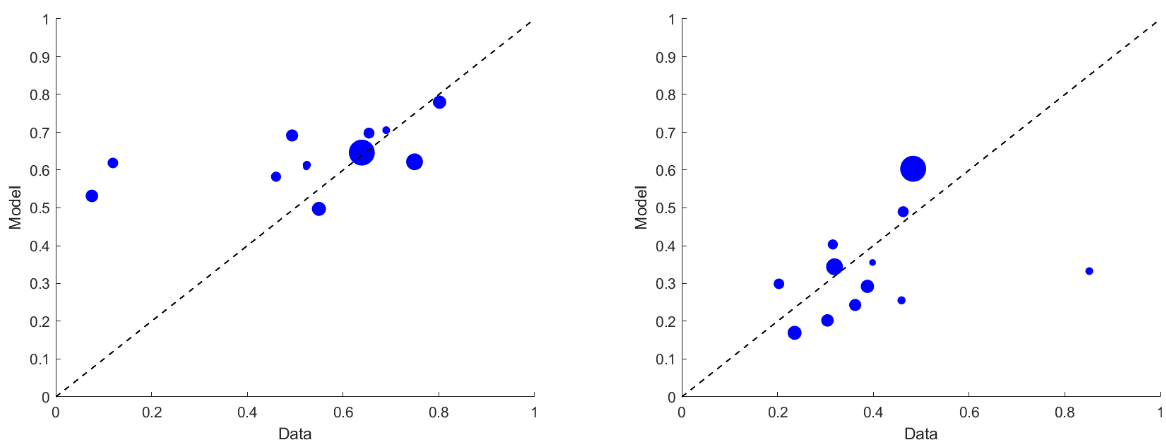
$$\begin{aligned}
\Delta \log(p_t \circ y_t) \quad = \quad & (\mathbf{I}_n - \mathbf{D}_\alpha - \mathbf{D}_\nu)^{-1} \Bigg(\underbrace{\Delta \log z_t}_{\%\,\Delta\, in\, prod} + \underbrace{\mathbf{D}_\nu \mathbf{M}_\omega \Delta \log(1-(1-\eta)tc)}_{TC\ effects} \\
& + \underbrace{\mathbf{D}_\alpha \Delta \log v_t^L + \mathbf{D}_\nu \mathbf{M}_\omega \Delta \log v_t^M}_{financial\ frictions} \\
& + \underbrace{\Delta \log\left(\mathbf{1}_n'\left(\eta \mathbf{I}_n - \frac{1}{\eta\gamma}\mathbf{D}_\nu \mathbf{M}_{xt}\right) p_t \circ y_t\right)\left(\frac{1}{\sigma-1}(\mathbf{I}_n - \mathbf{D}_\nu \Omega') - \frac{1}{1-\xi}\mathbf{D}_\alpha\right)\mathbf{1}_n}_{wage\ effects} \\
& - \underbrace{\frac{1}{\sigma-1}(\mathbf{I}_n - \mathbf{D}_\nu \Omega')\Delta \log\left(\left(\eta \mathbf{I}_n - \frac{1}{\eta\gamma}\mathbf{D}_\nu \mathbf{M}_{xt}\right) p_t \circ y_t\right)}_{pricing\ effects} \\
& - \underbrace{\frac{1}{1-\xi}\Delta \log\left(\mathbf{1}_n' \mathbf{D}_\alpha v^L \circ p_t \circ y_t\right)\mathbf{1}_n}_{aggregate\ labor\ effects}
\end{aligned} \tag{47}$$

Proposition 3 illustrates three types of sources that can affect the growth rates of sectoral sales: sectoral productivity shocks, financial frictions, and GE effects.

F Additional Results from Quantitative Analysis

We contrast the pairwise correlations of sectoral output growth rate generated from two sources. To construct the pairwise correlation, we follow the same strategy as in Section 2.1. Figure 8 displays the kernel density of pairwise correlations before and during the Great Recession as in Panel (a), and their first difference between during and before the Great Recession as in Panel (b). In Panel (a), the model-implied density during the Great Recession is similar with the one using data, while slightly overestimates the pre-recession correlations. This is also confirmed in Table 13, which shows both average and median correlations in model are 0.07 higher than the one in data before the Great Recession, while comparable during. In online Appendix, we also examine the composition of density, and find the difference of correlation are mostly bunched around zeros for the model-implied and data, implying the shifting order is also preserved. Panel (b) displays the kernel density of the changes in pairwise correlation from during to before the Great Recession. The shift generated by model is similar with the one by data, but more concentrated around the average.

Figure 17 displays the scatter plots of both ratios for model and data, where the horizontal and vertical axis respectively present data and mode-implied ratio, the size of bubble indicates the sectoral relative size in 2005, and the black dash line is the 45 degree line. Panel (a) displays the AR-to-sales ratio, while the AR-to-sales ratio is shown in Panel (b). Except mining and professional services sectors, all bubbles are lined up around the 45 degree line in both cases. It implies that our model does a decent job to match the data.



(a) Ratios of Account Receivables to Sales

(b) Ratios of Account Payables to Operation Cost

Figure 17
COMPARISON: MODEL VS DATA

Once we impose the fixed trade credit to the economy, our model becomes the one akin to Bigio and La'O (2020). In this case, the sectoral sales should highly comove with underline shocks. In Figure 18, we plot the kernel density of the pairwise correlations for both shocks, where the top panel is for productivity shocks and the bottom for financial shocks, all red lines represent the shocks we used for our exercise, and all dashed and solid lines respectively stand for the kernel density before and during the Great Recession. Here we observe a modest rise in comovement of productivity shocks during the Great Recession. In contrast, we also calculate the TFP implied by our model as shown in the blue lines of the top panel. Surprisingly, the kernel density during the Great Recession does not shift significantly, compared to the one before. It implies that the endogenous trade credit along with the financial shocks can account for the most of the rise in sectoral comovement observed in the data. As for financial shocks, we cannot observe systematic rise in pairwise correlation during the Great Recession as well. Rather, for a few pairs of sectors, their financial shocks indeed comove during the Great Recession as we observe a fat right tail, while other pairs stay more or less the same as before.

Table 13
Model-implied Pairwise Correlations of Output Growth Rates

	Mean	Median	Std	Skewness	KS Statistics
Data					
Before the Great Recession	0.034	0.063	0.440	-0.082	
During the Great Recession	0.460	0.582	0.348	-0.683	0.000 (0.485)
Model-implied with both shocks					
Before the Great Recession	0.223	0.252	0.386	-0.159	
During the Great Recession	0.522	0.629	0.275	-0.149	0.000 (0.409)
Model-implied with both shocks and fixed trade credit					
Before the Great Recession	0.335	0.467	0.404	-0.429	
During the Great Recession	0.394	0.442	0.304	-0.088	0.000 (0.227)
Model-implied with only θ					
Before the Great Recession	0.184	0.305	0.461	-0.285	
During the Great Recession	0.528	0.694	0.269	0.179	0.000 (0.379)
Model-implied with only θ and fixed trade credit					
Before the Great Recession	0.387	0.506	0.379	-0.519	
During the Great Recession	0.223	0.260	0.389	0.096	0.056 (0.227)
Model-implied with only z					
Before the Great Recession	0.140	0.249	0.465	-0.276	
During the Great Recession	0.641	0.745	0.216	-0.252	0.000 (0.516)
Model-implied with only z and fixed trade credit					
Before the Great Recession	0.261	0.426	0.452	-0.520	
During the Great Recession	0.666	0.806	0.199	0.285	0.000 (0.563)
KS Test across Groups during the Great Recession					
Model-implied vs Data					0.405 (0.152)
Both shocks with and without endogenous trade credit					0.003 (0.303)
Only θ with and without endogenous trade credit					0.000 (0.424)
Only z with and without endogenous trade credit					0.034 (0.242)

Notes: All kernel densities f are calculated on unit interval $[-1,1]$ with bandwidth 0.001. 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. 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.

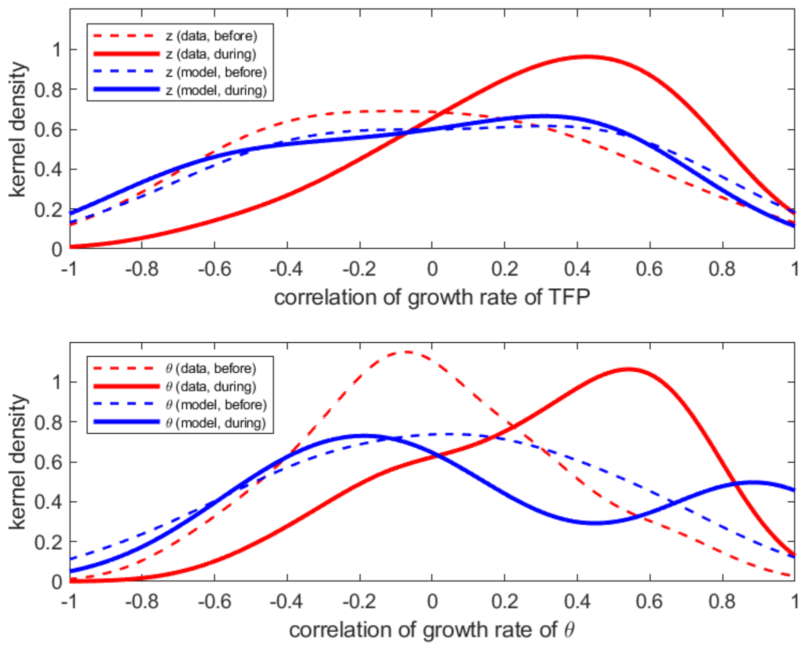
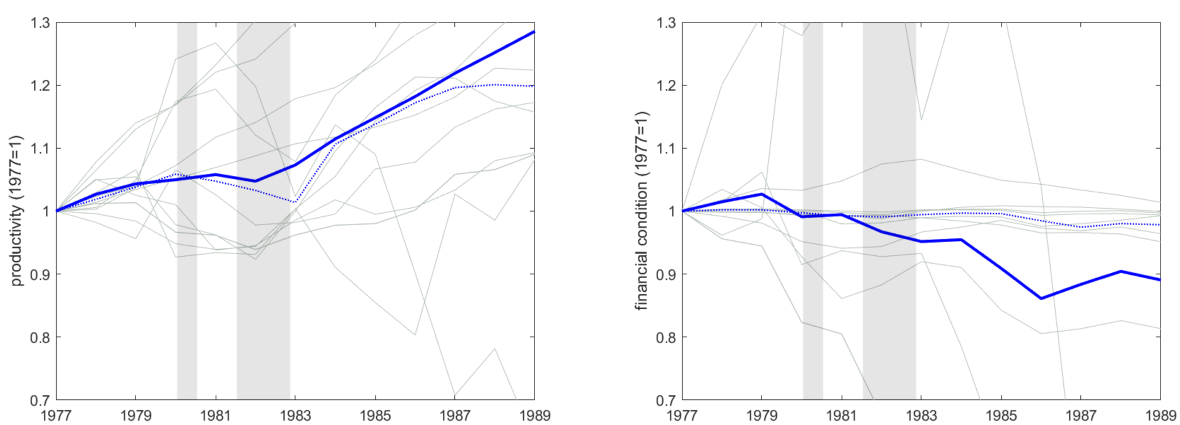


Figure 18
PAIRWISE CORRELATIONS OF GROWTH RATE OF FINANCIAL AND PRODUCTIVITY SHOCKS

F.1 Shocks in the Early 1980s Recession



(a) Productivity Shocks

(b) Financial Shocks

Figure 19
SHOCKS IN THE EARLY 80S RECESSION

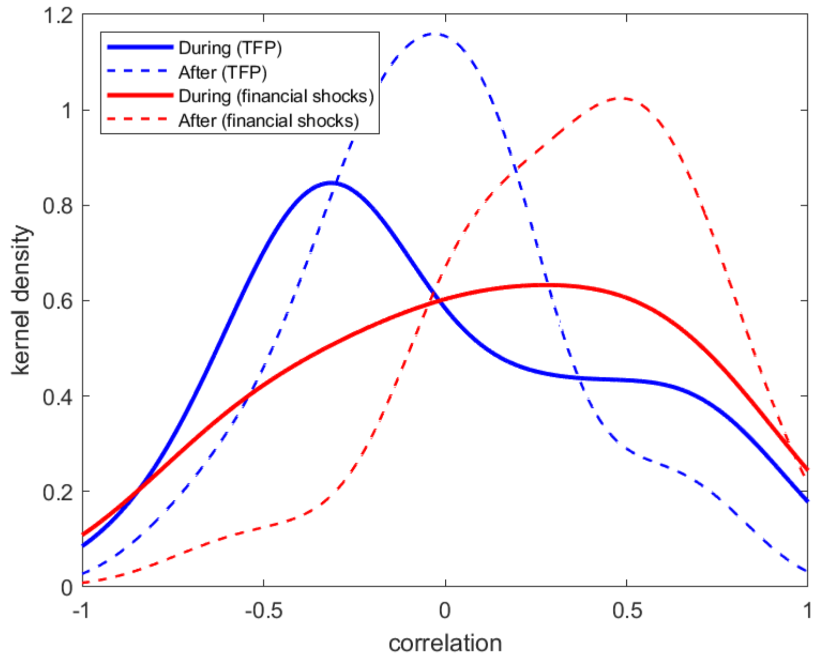


Figure 20
Pairwise correlations of sectoral shocks: the early 1980s recession

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