Trade Credit and Sectoral Comovement during Recessions*

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October 30, 2024

Abstract

We examine sectoral output comovement during economic downturns, focusing on the impact of trade credit in exacerbating or alleviating crises. Analyzing nine US recessions from 1954 to 2022, we find increased comovement only during the Great Recession, driven by trade credit effects. Sectors experiencing reduced trade credit in 2008 showed a 40% higher comovement. Our multisectoral model reveals trade credit's asymmetric response to financial shocks, influenced by suppliers' financial health. Through calibration, we determine that trade credit, directly and indirectly through financial frictions, explains 81% of the comovement surge during the Great Recession. Compared to a fixed trade credit model, our findings reveal a 41% smaller increase in comovement and a 15-17% less severe GDP decline during the Great Recession. We also highlight trade credit's role as a buffer that mitigates sectoral spillovers, a pattern especially pronounced during the early 1980s recession.

Keywords: Trade Credit, Sectoral Comovement, Financial Frictions

JEL Classifications: C67, E23, E32, E44, E51, F40, G30

*We thank Eric van Wincoop and Eric Young, for their enormous support. We also thank David Baqaee, Huberto Ennis, Andrew Foerster, Jennifer Huang, Zhen Huo, Zhao Jin, Yang Jiao, Pete Klenow, Shaowen Luo, Toshihiko Mukoyama, Daniel Murphy, Jose Mustre-del-Rio, Jun Nie, Alessandro Rebucci, Christiern Rose, Pierre Sarte, Nicholas Sly, Kwok Ping Tsang, Kieran Walsh, Willem van Zandweghe, Tao Zha, and seminar participants at FRB Kansas City, FRB Cleveland, HKU, SUFE, Virginia Tech, SUSTech, Jinan, SED meetings, and Catholic University of Chile for helpful discussions and comments. We also thank Alvaro Castillo for outstanding research assistance. Zhang gratefully acknowledges financial support from the Bankard Fund for Political Economy and the ASEAN Business Research Initiative. We thank Egon Zakrajšek for providing us with the spread data. We also thank the editor and two anonymous referees for their insightful comments and suggestions.

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1 Introduction

The output growth of different sectors or firms can comove for at least two reasons. First, aggregate shocks are the main driver of aggregate fluctuations. Second, sectoral shocks propagate and amplify through production and credit linkages (see, for example, Lucas, 1981; Long and Plosser, 1983; Hornstein and Praschnik, 1997; Horvath, 1998; Shea, 2002; Foerster et al., 2011; Acemoglu et al., 2012; Barrot and Sauvagnat, 2016; Baqaee and Farhi, 2019; vom Lehn and Winberry, 2020). While previous work is crucial to explaining the average sectoral comovement (e.g., Raddatz, 2010), little has been done to understand the dynamics of sectoral comovement during different recessions (e.g., financial vs. economic recessions), which shapes the magnitudes of macroeconomic fluctuations. In this paper, we show that during periods of financial distress, sectoral shocks can generate large domino effects through the trade credit network, which then increases comovement and amplifies the downturn, as observed during the Great Recession in the US.

Using annual sectoral output growth from the Bureau of Economic Analysis (BEA), we find that sectoral output growth significantly comoves during the Great Recession and the COVID-19 recession but not in the early 1980s, which is comparable in magnitude to the Great Recession. After controlling for the size of recessions, the rise in sectoral comovement during the Great Recession, but not during the COVID-19 recession, is still pronounced. We then zoom into the Great Recession with quarterly data and find that sectoral comovement increased more for more-interconnected sectors. The average correlation rose from 0.02 to 0.25 between sectors trading intermediates one-way (only one sector providing intermediates to the other) and from 0.1 to 0.52 between sectors trading two-way (both sectors are intermediate input providers and users of each other).[1] Interestingly, this pattern is not observed between sectors in the no-trading group or during other recessions, indicating that a change in the nature of sectoral connections contributed to the rise in comovement during the Great Recession.

Next, we investigate the contraction in trade credit as a factor influencing changes in sectoral connections during the Great Recession. Our findings reveal that sectors experiencing a significant contraction in trade credit—defined as a decline in trade credit provision or reception exceeding the median decline among public firms—exhibited stronger comovement. Specifically, two-way trading pairs with such declines saw their correlation increase by 0.18 (or 40%) compared to sectors without a substantial reduction in trade credit. Among one-way trading groups, sectors with a trade credit contraction showed

[1] Notably, this relationship between pairwise correlations and input share (or the corresponding cell in the Leontief inverse matrix) is not monotonic, as the point estimate of a linear regression between the two is not statistically significant.

an increased correlation of 0.13 (or 50%) more than those without a significant decline in trade credit

To reconcile our sectoral observations and quantify the role of trade credit in the aggregate economy during recessions, we develop a model that combines the environments in Greenwood et al. (2010) and Bigio and La'O (2020). In particular, we construct a multisector model of production networks displaying firm-to-firm production and credit linkages. Trade credit arises in equilibrium as a way to verify the true quality of intermediates input, which, as in Smith (1987) and Kim and Shin (2012), is assumed to be uncertain *ex-ante* and privately known by the clients *ex-post*. The asymmetric information affects the suppliers, who must exert costly efforts to monitor their clients. Also, the input suppliers have pricing power in the intermediate input markets, as they customize their products for their clients. Finally, a collateral constraint is imposed on external funds. Firms need to finance the upfront payments for wages and a portion of input payments through perfectly competitive banks, which, in turn, require firms to pledge a fraction of their outputs as collateral.

The optimal trade credit contract offered by the supplier includes a price for the intermediate input, a deferred payment, and a penalty payment in case the client is found falsely claiming that the input was faulty. The penalty payment ensures that the client always tells the truth, even though the default is inevitable in the bad-realization case. The decision considers the benefit of increased sales and the cost of monitoring the client. A negative financial shock to the supplier reduces trade credit provision. In contrast, the same shock to the client has non-monotonic effects on trade credit, depending on whether the supplier is sufficiently financially constrained relative to the client. If so, such a shock to the client contracts trade credit provision, further tightening the client's financial constraint. Otherwise, the supplier extends more trade credit, alleviating the client's financial constraint. This asymmetry is consistent with the empirical evidence and is crucial to understanding the unique rise in sectoral comovement during the Great Recession. This mechanism is akin to the one proposed in Kiyotaki and Moore (1997a), in which a 'deep pocket' supplier is key to determining the response of trade credit to the adverse liquidity shocks to clients.

Through the lens of our model, we explore the data-generating process in the presence of endogenous trade credit. In particular, we calibrate the model to the US data and then use sectoral output and bond spreads to back out productivity and financial shocks. We find that during the Great Recession, the average correlations of both shocks rose by 0.13 and 0.18, respectively, and the median correlation of financial shocks only increased by 0.04, indicating that the deterioration of the financial condition was highly skewed and that only a few sectors were originally hit by the financial shocks. We then decompose the model-implied rise in pairwise correlations into four components: productivity shocks; trade credit adjustments; financial frictions due to collateral constraint and endogenous trade credit; and changes due to general-equilibrium effects. We find that the contraction in trade credit directly accounts for approximately 15% of the observed increase in average correlation. Additionally, when combined with financial frictions, it explains a further 65%.

To separate the effect of trade credit on sectoral comovement during the Great Recession from that of correlated productivity and financial shocks, we conducted a counterfactual analysis. In this analysis, we removed the correlation between productivity and financial shocks and examined sectoral comovement in simulated Great-Recession (GR) episodes under uncorrelated shocks. Using a VAR(1) model with a GR-specific factor, as in Li and Martin (2019), we separately estimated sectoral productivity and financial conditions, as well as the covariance matrix of the shocks. Simulating the economy and identifying GR episodes following the NBER definition, we find that sectoral comovement in these simulated GR episodes still significantly increases, accounting for 76% of the observed rise in comovement during the Great Recession. When we removed shock correlations, the increase in comovement remains substantial, representing 46% of the rise during the Great Recession.

Next, we conduct counterfactual exercises by fixing trade credit to the pre-recession level. We find that with our estimated shocks, the average rise in pairwise correlations with fixed trade credit is 42% lower than in our benchmark model. This implies that endogenous trade credit propagates highly skewed financial shocks to originally unaffected sectors. Moreover, the trade credit chain amplifies the financial shocks. Our results demonstrate that the fixed-trade-credit model produces a decline in GDP growth for 2008Q4 (2009Q1) that is 17% (15%) less than in our benchmark economy. Our model can also generate the two additional facts we document for the Great Recession: the rise in sectoral comovement is larger among i) more-interconnected sectors and ii) sectors that experienced a decline in trade credit. Next, we re-estimate the shocks using the fixed-trade-credit model and find that financial shocks need to be twice as correlated, along with substantially larger shocks to key sectors (such as manufacturing), to replicate the observed sectoral comovement.

We further investigate why sectoral comovement barely changed in the early 1980s recession and why the rise in comovement during the COVID-19 recession vanished after controlling for the size of the recession. Our calibrated model indicates that, during the 1980s, trade credit served as a cushion that dampened sectoral spillovers and, thus, comovement. As a result, real GDP did not decline as much as it would have with fixed trade credit. We then model the COVID-19 recession as a common negative productivity shock due to the public health crisis. We simulate a 1.5% decline in productivity for all sectors and show that sectoral output comovement increased substantially for all sectors, regardless of whether and how two sectors are interconnected. We also show that, as in the data, the rise in sectoral comovement during COVID-19 vanishes once we remove the aggregate component from the sectoral data. In our model, productivity shocks generate minor effects on collateral constraints and trade credit provision, implying no significant rise in sectoral comovement, conditional on the aggregate state of the economy.

Our paper builds on and contributes to three strands of the existing literature. The first studies the role of trade credit in the provision of liquidity or the propagation and amplification of financial shocks (see, for example, Smith, 1987; Kiyotaki and Moore, 1997a; Love et al., 2007; Giannetti et al., 2011; Jacobson and von Schedvin, 2016; Garcia-Marin et al., 2019; Costello, 2020; Giannetti et al., 2021; Adelino et al., 2023). Our paper explores the role of trade credit in determining the pairwise correlation over the US recessions. We demonstrate that trade credit can act as both a cushion and a conduit of shocks, depending on the supplier's financial condition relative to the client. On the theoretical front, we incorporate the uncertain quality setting from Smith (1987) into a multisector model and demonstrate the asymmetric role of trade credit as in Kiyotaki and Moore (1997a), in which a "deep pocket" supplier is key to determining the response of trade credit to adverse liquidity shocks to clients. Using the model, we quantify the role of trade credit as a driver of sectoral comovement during different recessions.

The second strand of related research examines how sectors comove over the business cycle and what drives these movements, (see, for example, Long and Plosser, 1983; Hornstein and Praschnik, 1997; Christiano and Fitzgerald, 1998; Raddatz, 2010; Li and Martin, 2019; Huo et al., 2019). Most papers in the existing literature study long-run comovement. An exception is Li and Martin (2019), which also focuses on the Great Recession and documents a large rise in sectoral comovement. The authors propose a dynamic factor model with a common factor, an additional aggregate factor during the Great Recession (GR factor), and sector-specific shocks with loading factors that can be specific to the Great Recession. They find that the loadings from 11 out of 16 sectors became smaller than the pre-recession ones. Thus, they attribute the rise in sectoral comovement mainly to a GR-specific common factor. We specify their reduced-form setting by incorporating a micro-founded structural model with state-dependent linkages. This specification is necessary and important for two reasons. First, the GR factor is a common shock during the Great Recession and cannot generate the differential rise in comovement among two-way, one-way, and no-trading groups. As we show, the rise in comovement of the two-way trading group is the most pronounced. Second, in our model, sectoral spillovers are time-varying and depend on the nature of shocks. We show that modestly correlated and highly skewed financial shocks are sufficient to trigger trade credit as a conduit and amplifier, further generating a significant rise in comovement.

The third strand of related literature incorporates financial frictions into multisector real business cycle models to study how financial frictions propagate and amplify sector-specific shocks in macroeconomic aggregates (see, for example, Bigio and La'O, 2020; Altinoglu, 2020; Luo, 2020; Reischer, 2020; Miranda-Pinto and Young, 2022; Shao, 2019; Cun et al., 2023). We make two main contributions to this literature. First, we show that the asymmetric role of trade credit provides a new channel to explain why financial crises are associated with severe recessions, as documented in Kaminsky and Reinhart (1999) and Reinhart and Rogoff (2011). Second, we provide empirical and quantitative results highlighting the asymmetric effects of trade credit over different recessions.

Our model is closely related to the models in Luo (2020) and Reischer (2020), which also display asymmetric effects—mitigation or amplification—of trade credit. Besides the fact that we micro-found trade credit, a key difference with respect to these two papers is what exactly generates the asymmetry in the model. Luo (2020) assumes that trade credit payments can be renegotiated and that the interest rate on the bank loans increases with the amount of trade credit forbearance, amplifying the effects of a negatively large financial shock. While her model predicts a reallocation from bank credit to trade credit, we observe the median ratio of trade credit relative to sales contracted during the Great Recession. In Reischer (2020), trade credit can amplify the negative financial shock as long as the increase in the interest rate for bank credit translates into an even larger increase in the rate for trade credit. Instead, our model generates an endogenous asymmetric relationship between trade credit provision and the financial condition, which depends on the supplier's and the client's relative financial conditions.

All in all, our paper contributes empirically, theoretically, and quantitatively to the literature studying comovement and trade credit by showing that the internal propagation forces during an economic recession can be very different from those triggered during a financial crisis and that trade credit adjustment is a crucial part of this mechanism.

2 Empirical Evidence

In this section, we document our main observations regarding the behavior of sectoral comovement during recessions. First, we find that output growth across sectors significantly comoved during the Great Recession, even after controlling for the size of recessions. In other post-war recessions, sectors either did not comove, or the comovement was not robust after filtering out the aggregate component. Second, the rise in sectoral comovement during the Great Recession was more pronounced in pairs of sectors that provide intermediate inputs to each other than in those in which only one provides inputs to the other, and much more than in ones without input-trading relations. Third, the pairs of sectors comoved more, by more than 40%, when they experienced a larger-than-median contraction in trade credit. Finally, we perform some robustness checks and discuss the results.

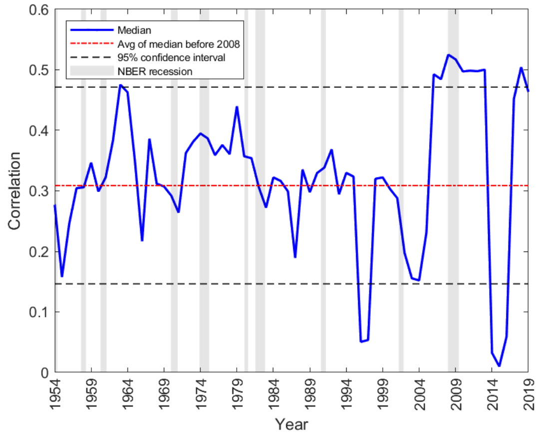
2.1 Observation I: rise in pairwise correlation

We begin by analyzing the annual growth rate of sectoral outputs from the BEA to investigate the dynamics of sectoral comovement following World War II (see Appendices A.1 and A.2 for detailed discussions of sector characteristics and measuring sectoral comovement). Panel (a) of Figure 1 shows the evolution of the median value of pairwise correlations over an eight-year rolling window, with the red dashed line representing the 1950-2005 average, and the black dashed lines indicating the 95% confidence interval. Our analysis reveals that the median generally fluctuated within the 95% confidence interval, except during the Great Recession and the COVID-19 recession, where significant increases are observed. This pattern is not evident in other recessions.

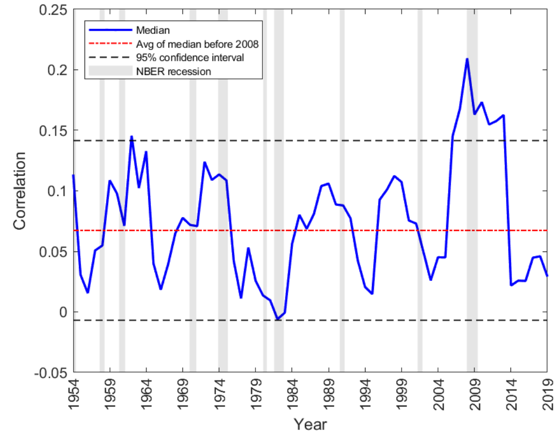
Due to the varying size and duration of each recession, we control for these factors by filtering out aggregate components. Specifically, we regress the logarithm of sectoral outputs on the logarithm of US GDP, take the residuals, compute their first differences, and then calculate the pairwise correlations.[2] Panel (b) of Figure 1 illustrates the evolution of median conditional correlations. Before 2008, the average conditional correlation decreased to 0.07 from the unconditional average of 0.31. During the Great Recession, the correlation significantly increased, with approximately 35% of the unconditional rise in comovement unexplained by aggregate components. Conversely, the conditional average correlation during the COVID-19 recession is statistically similar to the pre-recession level.[3] This suggests that inter-sector linkage significantly contributed to comovement

[2] Our approach implicitly considers the recession duration. However, since the duration of each recession within a fixed time window varies, we adjust the length of our time window to explicitly account for this. Direct comparisons across time windows are not possible due to differing statistical properties, so we standardize each sequence to the pre-Great Recession level. Figure B.1 shows that our results remain robust.

[3] In Table B.1, we show that, after accounting for the underlying autocorrelation of our data, the Great Recession is the only recession displaying a statistically significant shift in the distribution of conditional



(a) Unconditional correlation



(b) Conditional correlation

Note: Real gross outputs by industry from the BEA are used. Fifty-seven sectors cover all private non-farm business sectors, except for FIRE. The year on the horizontal axis corresponds to the fourth year of each time window. For the conditional correlations, we regress the logarithm of the sectoral outputs on the logarithm of the US GDP, take the residuals, use their first difference, and calculate the pairwise correlations over an eight-year rolling window.

Figure 1
Evolution of median pairwise correlations after WWII

during the Great Recession, whereas most sectors synchronized with the aggregate economy during the COVID-19 recession.

We now focus on sectoral comovement during the Great Recession using quarterly data, as annual data average out some sectors' activities within a year. Panel (a) of Figure 2 displays kernel densities before, during, and after the Great Recession. Following Kahle and Stulz (2013), we define the recession period as 2007Q3-2009Q2, with 2005Q3-2007Q2 and 2009Q3-2011Q2 representing the periods before and after the recession, respectively.[4] Consistent with annual growth data, we observe a significant rise in sectoral comovement during the Great Recession.

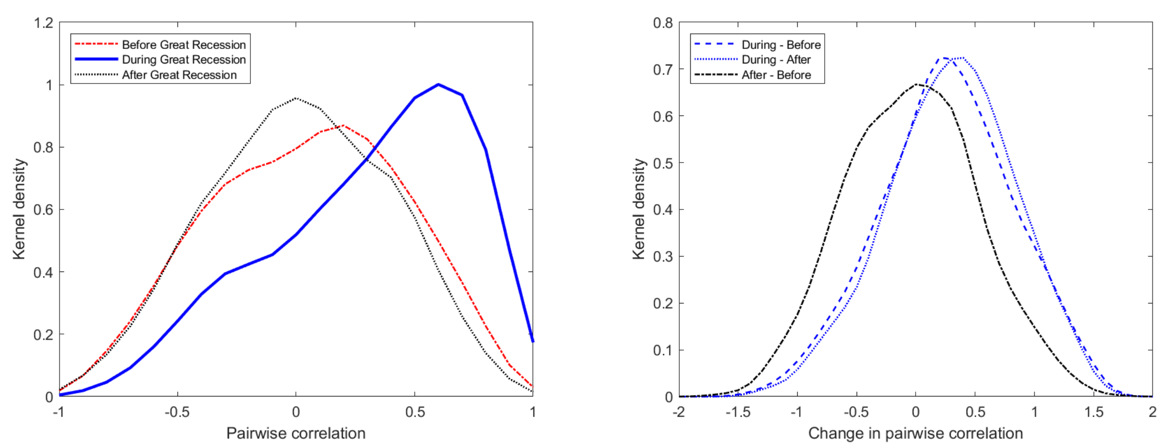
Figure 2 shows average correlation increases from 0.05 before the recession to 0.31 during the recession, and back to 0.01 afterward. Interestingly, changes in correlations varied significantly across pairs, as shown in Panel (b). Most pairs experienced an increase in comovement, with the density center around 0.31. The correlations of many pairs rose by more than 1, indicating that some pairs of sectors that previously comoved

pairwise correlations. For instance, during the Great Recession, the average rise in unconditional correlations was 0.34, compared to 0.12 for conditional correlations. In contrast, the average rise in unconditional correlations during the COVID-19 recession was 0.32, while the conditional average was 0.01.

[4]We use a bandwidth of 0.1, as Silverman's rule of thumb suggests an optimal bandwidth of 0.0956. We also vary the bandwidth values to 0.2 and 0.01, and Figure B.2 shows that the kernel density estimates mostly overlap. We thank the referee for this suggestion. Additionally, we used different coverage periods and lengths of time windows. All results presented here are robust.

negatively began moving together during the Great Recession. We conducted the two-sided Kolmogorov-Smirnov (KS) test to investigate whether pairwise correlations in two periods come from the same distribution. A problem with the KS test in our setup is that it assumes that the two samples under comparison are drawn from two independent and identically distributed (iid) distributions. However, a key characteristic of time series data is its persistence and autocorrelation. Indeed, the autocorrelation of the rolling-window pairwise correlation of a given pair fluctuates between 0.5 and 0.9. To correct this problem, we follow Lanzante (2021) and adjust the critical values of the KS test for the presence of autocorrelation.

Table 1 shows that the KS test rejects the null hypotheses at the 5% significance level, even if the underlying autocorrelation is very high. This result indicates that the average and distribution of pairwise correlations during the Great Recession were statistically significantly different from those before and after the recession.



(a) Pairwise correlation

(b) Change in pairwise correlation

Note: Real gross outputs by industry are seasonally adjusted series at annual rates from the BEA. Fifty-seven sectors cover all private non-farm business sectors, except for FIRE. The kernel density is taken with a bandwidth of 0.1. 2005Q3-2007Q2, 2007Q3-2009Q2, and 2009Q3-2011Q2 are chosen to represent before, during, and after the Great Recession.

Figure 2

Kernel density of pairwise correlation during the Great Recession

Additionally, we compute the kernel density of annual growth for all recessions, specifically those in 1960, 1970, 1973, 1990, and 2001, as well as the combined 1980 and 1981-1982 recessions, the Great Recession, and the COVID-19 recession (see Appendix B.1 for details). Consistent with the implications of Figure 1, the shift in kernel density is only statistically significant during the Great Recession. For all the other recessions, the shift is either insignificant or disappears after controlling for GDP.

Next, we analyze the role of intermediate input trading and trade credit—the firm-to-firm credit relied upon for input trading—in accounting for the increase in sectoral comovement during the Great Recession.

2.2 Observation II: role of intermediate-input linkages

To identify the intermediate trading relationships between sectors, we adjust the input-output (IO) table of 71 industries from the BEA to match the sectors in our sample. We take the average data from 2003 to 2007 to avoid short-term variations and then calculate the IO matrix, where each cell represents the input share.[5] The pairs are then categorized into three groups based on their level of interconnectedness. Specifically, two sectors are classified into the two-way trading group if they both supply inputs to each other; into the one-way trading group if only one sector supplies inputs to the other; and into the no-trading group if no intermediate inputs are traded between them.[6] The groups contain 464, 796, and 336 pairs, respectively.

The way in which two sectors trade with each other significantly affects sectoral comovement. The top panel of Figure 3 displays the kernel densities of the three groups during the Great Recession. Specifically, the average (median) correlation within the two-way trading group is higher, by 0.19 (0.17), compared to the one-way trading group and much higher, by 0.32 (0.38), compared to the no-trading group, as shown in Table 1. The KS test rejects the null hypothesis that the means (densities) of the two-way trading groups are the same, at the 5% significance level, before/after and during the Great Recession. This is true for both levels of autocorrelation, mild and high.

The KS test indicates that the distribution of the one-way trading sectors also shifted during the Great Recession, at the 5% significance level. However, this is true only for the mild autocorrelation case. On the other hand, the no-trading sectors show no statistically significant shift in the distribution of pairwise correlation.

Moreover, as shown in the bottom panels of Figure 3, there is no statistical difference in the kernel densities of the three groups before and after the Great Recession. Our results indicate that network spillovers, rather than common shocks, are crucial for explaining the rise in comovement during the Great Recession. As demonstrated in Appendix E.5, the common shock hypothesis would predict a universal increase in comovement, regardless of the interconnectedness of sectors, which is not supported by our findings.

[5] If the input share is lower than 0.1%, we set it to 0. We also test different thresholds, such as 0.05% and 0.01%, and find our results robust across these variations.

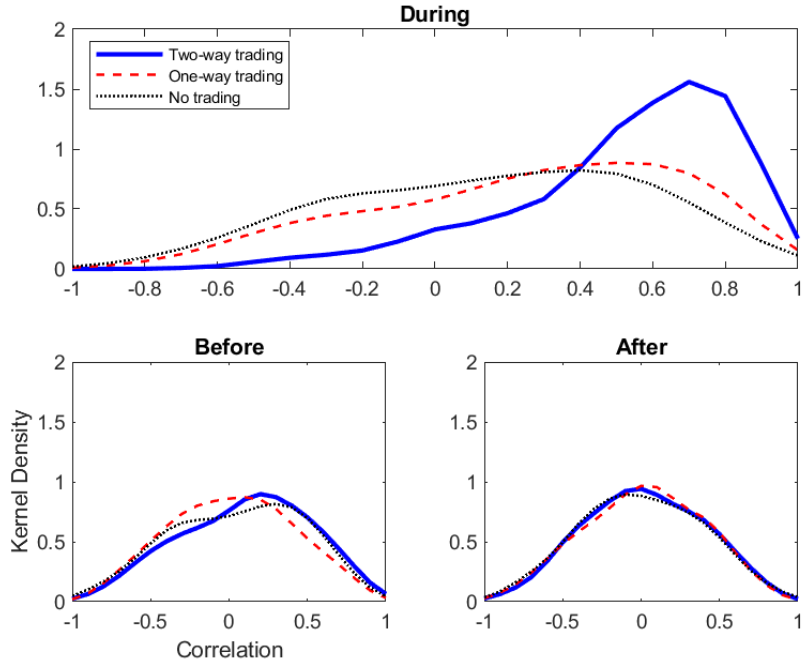
[6] We regress the pairwise correlations during the Great Recession or the change in correlations on the input share (or the Leontief influence factor) along with sectoral fixed effects and other controls. The coefficient is not statistically significant at the 90% significance level.

Table 1
SUMMARY STATISTICS: PAIRWISE CORRELATIONS (QUARTERLY GROWTH)

	Mean	Median	SE	Skewness	KS Stat (CV-KS*)
Overall					
Before the Great Recession	0.05	0.07	0.40	-0.11	0.28 (0.09, 0.21)
During the Great Recession	0.31	0.39	0.41	-0.58	
After the Great Recession	0.01	0.01	0.38	-0.07	0.32 (0.09, 0.21)
Two-way trading sectors					
Before the Great Recession	0.10	0.14	0.40	-0.23	0.48 (0.16, 0.39)
During the Great Recession	0.52	0.60	0.31	-1.10	
After the Great Recession	0.02	0.01	0.37	-0.03	0.56 (0.16, 0.39)
One-way trading sectors					
Before the Great Recession	0.02	0.02	0.39	0.00	0.27 (0.13, 0.30)
During the Great Recession	0.25	0.31	0.41	-0.46	
After the Great Recession	0.02	0.03	0.38	-0.12	0.27 (0.13, 0.30)
No trading sectors					
Before the Great Recession	0.05	0.09	0.41	-0.21	0.11 (0.19, 0.46)
During the Great Recession	0.15	0.17	0.41	-0.23	
After the Great Recession	0.00	-0.02	0.38	0.01	0.18 (0.19, 0.46)
Two-way trading and TC declined group					
Before the Great Recession	0.05	0.08	0.44	-0.03	0.63 (0.31, 0.74)
During the Great Recession	0.63	0.69	0.24	-1.43	
After the Great Recession	-0.01	-0.03	0.39	0.15	0.72 (0.19, 0.46)
Two-way trading and TC unchanged group					
Before the Great Recession	0.10	0.14	0.40	-0.29	0.39 (0.24, 0.58)
During the Great Recession	0.45	0.51	0.33	-0.81	
After the Great Recession	0.02	0.03	0.36	-0.06	0.49 (0.19, 0.46)
One-way trading and TC declined group					
Before the Great Recession	0.11	0.17	0.40	-0.26	0.35 (0.35, 0.83)
During the Great Recession	0.39	0.46	0.34	-0.59	
After the Great Recession	-0.02	0.01	0.37	0.08	0.49 (0.15, 0.37)
One-way trading and TC unchanged group					
Before the Great Recession	-0.02	-0.04	0.39	0.17	0.33 (0.17, 0.41)
During the Great Recession	0.26	0.35	0.43	-0.53	
After the Great Recession	0.02	0.02	0.38	-0.17	0.29 (0.15, 0.37)

Notes: *The critical values of the KS statistics (CV-KS) are reported in the last column. These critical values adjust for the presence of autocorrelation in the data, following Lanzante (2021). The critical value is for a 5% significance level. The first value in parenthesis is the critical value for mild underlying autocorrelation (AR(1) parameter of 0.6). The second critical value corresponds to mild underlying autocorrelation (AR(1) parameter of 0.6). Two sectors are classified as in the two-way trading group if they are both input supplier and client to each other; as in the one-way trading group if only one sector supplies inputs to the other but not vice versa; and as in the no-trading group if no intermediate input is traded between two. A pair of sectors is treated in the trade credit (TC) declined group if the change in the supplier's AR-to-sales ratio and the client's AP-to-OC ratio declined more than the corresponding median value across all public firms, respectively -1.6 and -1.3 percentage points.

Consistent with this, we apply the same categorization to the COVID-19 recession and examine sectoral comovement within each group. As shown in Figure B.5, the increase



Note: All pairwise correlations are calculated as in Figure 2. The kernel density is taken with a bin width of 0.1. Two sectors are classified into the two-way trading group if they both supply inputs to each other; into the one-way trading group if only one sector supplies inputs to the other; and into the no-trading group if no intermediate inputs are traded between them. The groups contain 466, 792, and 338 pairs, respectively.

Figure 3
PAIRWISE CORRELATION BY THE EXTENT OF INTERCONNECTEDNESS

in comovement during the COVID-19 recession was almost universal, regardless of interconnectedness. This suggests that the rise in sectoral comovement during the COVID-19 recession was likely due to a significant decline in aggregate productivity (a common shock from the public health crisis). We also examine other recessions (see Appendix B.2 for details) and do not observe a pattern similar to that of the Great Recession. This implies that an additional element must have contributed to the observed comovement during the Great Recession, which aligns with but is not explicitly addressed in Li and Martin (2019). We propose that the trade credit chain may be a contributing force.

2.3 Observation III: role of trade credit during the Great Recession

In addition to trading intermediate inputs, firms often defer some input payments to their clients and receive similar deferrals from their suppliers.[7] The Quarterly Financial Report (QFR), a survey of US firms' financial positions conducted by the US Census

[7] Claims against clients are recorded as suppliers' accounts receivable, while liabilities to their own suppliers are recorded as accounts payable.

Bureau, shows that the average ratios of accounts receivable (AR) and accounts payable (AP) to total assets for large firms (assets exceeding $250 million) were 7.9% and 6.3%, respectively, during 2012-2019, while for small firms, these ratios were 23.3% and 12.9%. Among short-term financing sources, large firms have significantly more AP, at least nine times more than short-term bank loans and commercial paper, whereas small firms hold twice as much AP as short-term bank loans.[8]

Since bilateral trade credit (TC) data are unavailable, we first create a variable to measure changes in TC between two sectors during versus prior to the recession. Using Compustat, we calculate the ratio of accounts receivable to average sales between the current and last quarters (the AR-to-sales ratio) to measure the intensity of TC provision, and the ratio of accounts payable to average operating cost (the AP-to-OC ratio) to measure the intensity of TC reception.[9] For each firm, we take the median value over two periods, 2005Q3–2006Q2 and 2008Q3–2009Q2, and then calculate their first difference. Finally, we use the median value across firms in each sector to represent the sectoral change in TC usage. Our sample is reduced to 44 sectors, retaining only those with more than three firms. Our measure is in line with that of Kiyotaki and Moore (1997a), who demonstrate that the supplier's ability to provide liquidity to its shocked clients, rather than the extent to which clients rely on the supplier's TC, is critical for the transmission of liquidity shocks.[10]

We then categorize pairs in the two-way (one-way) trading groups into two subgroups based on whether they experienced a decline in TC during the Great Recession. Specifically, a pair is considered to have experienced a TC decline (the TC-declined subgroup) if the supplier sector's AR-to-sales ratio and the client's AP-to-OC ratio both declined more than the corresponding medians across all public firms, which are -1.6 and -1.0 percentage points, respectively. Otherwise, the pair is categorized in the unchanged subgroup (the TC-unchanged subgroup).[11] In total, 189 pairs in the two-way trading group experienced a TC decline, and 128 did not, whereas the corresponding numbers for one-way trading pairs are 133 and 326.

The top panel of Figure 4 displays the kernel densities before, during, and after the

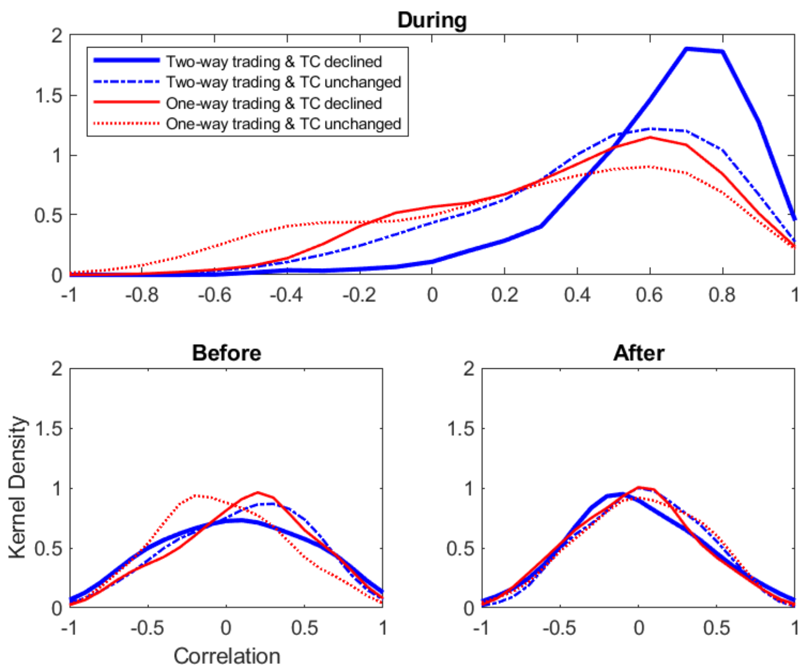
[8]Globally, firms in the Worldscope database typically finance about 20% of their working capital with trade credit, and in 60% of countries, firms use trade credit more than bank credit for short-term financing.

[9]We select the sample following Kahle and Stulz (2013). Please refer to Appendix A.3 for details. Note that both ratios are not bilateral but measure the total TC provision/reception to/from customers/suppliers.

[10]We use pre-recession TC usage to classify our pairs into TC-dependent and independent subgroups. However, we do not find that the TC-dependent subgroup significantly comoved more during the Great Recession.

[11]Since each sector can be both supplier and client in the two-way trading group, we classify the pair in the TC-declined subgroup if the TC-decline condition is satisfied in either direction.

Great Recession for the four subgroups described above. Given the interconnectedness, pairs that experienced a decline in TC comoved relatively more than those that did not. As shown in Table 1, the average correlation of the two-way trading pairs that experienced a decline in TC is 0.63 - 0.18 higher than in the unchanged subgroup. Within the one-way trading group, the TC decline group has an average correlation of 0.39 - 0.13 higher than for pairs that did not experience a TC decline. This additional rise accounts for 43% (57%) of the average rise in pairwise correlations of the two-way (one-way) trading group.[12]



Note: All pairwise correlations are calculated as in Figure 2. A pair is considered to have experienced a TC decline (the TC-declined subgroup) if the supplier sector's AR-to-sales ratio and the client's AP-to-OC ratio both declined more than the corresponding medians across all public firms, which are -1.6 and -1.0 percentage points, respectively. Otherwise, the pair is categorized in the unchanged subgroup (the TC-unchanged subgroup). The groups haves 189, 128, 133, and 326 pairs, respectively. The equal-weight kernel density is taken with a bandwidth of 0.1.

Figure 4
Pairwise correlation by whether trade credit declines

Moreover, as shown in the bottom panels of Figure 4, the kernel densities of the four subgroups before and after the Great Recession are not significantly different from each other, implying that TC adjustments during the Great Recession could be an important channel in explaining the rise in sectoral comovement. As a 'placebo test,' we also examine the kernel densities of the TC-declined and TC-unchanged subgroups within the

[12]Notably, the average correlation of the one-way trading pairs with available TC data is 0.29, slightly higher than the group average of 0.25.

no-trading group. Figure B.6 shows no difference between the two subgroups before, during, and after the Great Recession.

2.4 Discussion

Due to delivery delays, adjustment costs, search frictions, and other factors, two sectors may not comove contemporaneously, with one possibly leading the other. Thus, the rise in sectoral comovement during the Great Recession may simply result from synchronization in timing. To address this concern, we follow the method used in Christiano and Fitzgerald (1998), Hornstein (2000), and Kim and Kim (2006), calculating one-period lagged and lead correlations and then taking the maximum value among the three. As displayed in Panel (a) of Figure B.7, we find that, during the Great Recession, the kernel density of the maximal correlations still shifts significantly to the right. This result supports the hypothesis that the rise in sectoral comovement was driven primarily by structural factors linking the sectors, rather than synchronization in timing or common shocks.

Notably, our sectoral evidence points to the role of supply factors in driving the rise in comovement during the Great Recession. However, as Mian et al. (2013) argue, the collapse of house prices generated a negative wealth effect that decreased consumption, especially in states and cities with high mortgage debt. Consequently, sectors providing mainly final consumption goods or services should have comoved more strongly during the Great Recession. To test this hypothesis, we divide our sample of sectors into two groups, based on the share of output used for final consumption.[13] A sector is classified into the consumption-provider group if its share is larger than the median value of 36.8%. Otherwise, it is grouped as an input provider. Panel (b) of Figure B.7 displays the kernel densities for pairs within and between the two groups. During the Great Recession, we observe significantly higher comovement within the input-provider group, while the correlations among the consumption providers rose less strongly. The densities of the different groups almost overlap before and after the Great Recession. These results are consistent with our main observations.

Since the Great Recession was the only financial crisis in the US after World War II, we explore the cross-sectional variation among US public firms to test the main mechanisms of our model. Specifically, we use the collapse of Lehman Brothers (LB) as a quasi-natural experiment, utilizing firm-to-firm and firm-to-bank networks prior to the collapse. Restricting our sample to pairs where suppliers did not borrow from LB before 2008 but

[13] Please refer to Table E.2 for the specific values.

had at least one client who did and another who did not, we examine how these common suppliers comoved with their clients exposed differently to the LB shock. As shown in Appendix C, we find supportive evidence: LB-related clients comoved more with their common supplier than did LB-unrelated ones, especially when these clients experienced a decline in trade credit reception after the LB collapse.

3 Model

In this section, we develop a multisector model with endogenous TC adjustments to uncover the mechanism of the rise in sectoral comovement during the Great Recession. Our model economy combines elements from Greenwood et al. (2010) and Bigio and La'O (2020). Firms are *ex ante* uncertain about the quality of intermediate inputs, leading to TC demand as a way to verify the true quality of intermediates, as seen in Smith (1987) and Kim and Shin (2012). Suppliers have superior liquidation technology compared to banks, which implies that TC exists in equilibrium.

3.1 Firms' Production Plan

Suppose that the economy has n sectors, each with 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.[14] Here, firms providing inputs are suppliers, and those purchasing them are clients. Thus, sectors are interconnected via this firm-level network. The production function for any firm $h \in [0,1]$ in sector i takes a Cobb-Douglas form as:[15]

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

where z_i is sectoral TFP; l_i is labor employed; m_{ji} is intermediate inputs from a firm in sector j; ω_{ji} governs the input share with $\sum_{j=1}^{n} \omega_{ji} = 1$; and α_i and ν_i are labor and total input shares, respectively, with $\alpha_i + \nu_i < 1$.[16] Note that $\omega_{ji} = 0$ means that firms in sector i do not purchase inputs from any firm in sector j.

[14] This setup is not essential and only serves to avoid the coordination problem. We further assume that a firm cannot simultaneously be a supplier and a client for the same firm.

[15] For simplicity, the subscript for time is ignored in the discussion of the intratemporal features of the model.

[16] As in Bigio and La'O (2020), we can assume that firms use a fixed amount of capital with a capital share of $1 - \alpha - \nu$.

Products can be used as either intermediate inputs or consumption goods. Firms in any sector act as both suppliers and clients. Suppliers customize their products for use as inputs, enjoying some pricing power and charging q_{ij}. Alternatively, they can sell their products at price p_i in the consumption-good markets, assumed to be perfectly competitive. Following Smith (1987) and Kim and Shin (2012), we assume that the quality of customization is *ex ante* uncertain, with a probability $1-\eta$ that clients find delivered products unqualified as inputs.[17] In such cases, clients must purchase $\gamma > 1$ units from a secondary market to convert them into one unit of input. The price of sector i's products is p_i, the same as in the consumption-good market.

Each period is split into two stages. In the first stage, sectoral TFPs are realized, but the quality of ordered inputs remains uncertain. Firms order intermediate inputs and employ workers for later production. Due to uncertainty, it is ambiguous whether firms can make payments for labor and intermediate inputs. Hence, workers and suppliers demand upfront payment. Workers are compensated fully upfront, while intermediate input payments are divided into cash before delivery (CBD) and TC.[18] CBD is due in the first stage, while TC is deferred until clients realize their revenue. Suppliers decide the division endogenously. Suppose that no profits can be stored over periods. If the required working capital (wages plus paid CBD) exceeds the received CBD, suppliers need to borrow the difference from perfectly competitive banks, using products as collateral. Assuming that the liquidation ratio of collateral is θ_i for firm i, the amount of the loans that can be borrowed is limited by the following collateral constraint (CC):

$$b_i = \underbrace{wl_i}_{wage} + \underbrace{\sum_{j=1}^{n}(1-tc_{ji})q_{ji}m_{ji}}_{paid\ CBD} - \underbrace{\sum_{j=1}^{n}(1-tc_{ij})q_{ij}m_{ij}}_{received\ CBD} \leq \theta_i p_i y_i, \tag{CC}$$

where w is the wage; p_i is the price of the consumption goods in sector i; q_{ji} is the price of input from sector j to i; and tc_{ji} is the proportion of input payment deferred as TC. As in Kiyotaki and Moore (1997b) and Jermann and Quadrini (2012), we treat the change in θ_i as the sector-level financial shocks.

In the second stage, the quality of ordered inputs is realized, and all goods are produced and delivered. If the clients receive good-quality inputs, they pay back the TC,

[17] Giannetti et al. (2011) show empirical evidence of the importance of quality uncertainty as a driver of TC intensity.

[18] 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.

$tc_{ji}q_{ji}m_{ji}$; otherwise, they forfeit the paid CBD, default on TC, and pay γp_j per unit from the secondary market to produce. The expected unit cost of inputs for client i from supplier j is $(1-tc_{ji})q_{ji}+\eta tc_{ji}q_{ji}+(1-\eta)\gamma p_j$. The first term is the paid CBD; the second is the deferred payment in the good-quality case; and the third is the unit cost for alternative inputs. As for the supplier, if her products are of good quality, she receives the payment on TC while receiving nothing otherwise. When setting the input price, the supplier must ensure that clients do not incur a higher cost than they would in the secondary market, adhering to the no-arbitrage condition (NAC):

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

Note that the products sold in the consumption and secondary input market are not customized and can be delivered with certainty.

3.2 Optimal Contracts on Trade Credit

Assuming that the realization of product quality is private information for clients, when good quality is realized, clients have incentives to misreport and default on TC. To induce truth-telling, suppliers offer optimal contracts specifying input price q_{ij}, TC share tc_{ij}, and penalty payment g_{ij} for cheating. Clients receiving bad-quality inputs have no incentive to cheat, defaulting on TC. Therefore, the optimal contract is subject to two constraints: the resource constraint (RC) and the incentive-compatible constraint (ICC). The RC states that the penalty payment cannot exceed what the client makes after banks collect loans:

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

where ω_{ij} is the input share; $p_j y_j$ is the products' market value; and b_j is the bank loan amount. When cheating is detected, suppliers collect a penalty proportional to their input supply, $\omega_{ij}v_j$.

The ICC ensures that clients always report their true state. As in Townsend (1979), Bernanke and Gertler (1986), Williamson (1986), and Carlstrom and Fuerst (1997), suppliers exert costly efforts to verify the reported state. The unit cost of verifying efforts for offering $q_{ij}m_{ij}$ dollars of inputs is e_{ij}, interpreted as verification intensity.[19] As in Greenwood et al. (2010) and Jiang et al. (2024), the supplier detects the true quality with probability $\mathbf{Pr}(e)$, which is assumed to be increasing and concave in e. The ICC is binding

[19] Following Greenwood et al. (2010), we establish that the total verification costs are proportional to the value of the delivery primarily for tractability, as we also model the payment division proportionally to the delivery value. With the same verification intensity, a higher delivery value results in higher costs for a supplier to ascertain the true status.

in equilibrium, and the exerted efforts are expressed as:

$$tc_{ij}q_{ij}m_{ij} \leq \mathbf{Pr}(e_{ij})g_{ij}, \tag{ICC}$$

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

$$e_{ij} = \mathbf{e}\left(\frac{tc_{ij}q_{ij}m_{ij}}{\omega_{ij}v_j\left(p_jy_j - b_j\right)}\right) \tag{2}$$

where the function $\mathbf{e}(\cdot)$ is the inverse function of $\mathbf{Pr}(e)$.[20]

3.3 Optimal Problem for Firms

In the first stage, all firms in the same sector make the same decisions, acting as both suppliers and clients. The firms will decide the production plan, taking as given the optimal contracts offered by their suppliers. Meanwhile, they act as suppliers and design their own optimal contracts for their clients, given the intermediate input demand function. The former specifies inputs, employees, and loans from banks, while the latter lays out the payment schedule, penalty payment, and verification efforts. In particular, taking as given the wage w, 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 optimal contract offered by the supplier $\left\{q_{ji}, tc_{ji}, g_{ji}\right\}$, a firm in sector i chooses the inputs $\left\{m_{ji}\right\}$, the labor l_i, the optimal contract $\left\{q_{ij}, tc_{ij}, g_{ij}\right\}$, and the efforts $\left\{e_{ij}\right\}$, to maximize her profits, subject to the collateral constraint (CC), resource constraint (RC), incentive-compatible constraint (ICC), and

[20] The optimal TC contract in our model is consistent with one observation from microdata: TC provision increases with relationship length (Garcia-Marin et al., 2019). Longer relationships allow suppliers to acquire more information on the ability of clients to honor their obligations. This is captured in our model with smaller monitoring costs. Hence, provided that one has access to more detailed firm-to-firm network data on production and credit, our model can match salient features of the microdata.

no-arbitrage condition (NAC), as,

$$\max_{l_i, m_{ji}, q_{ij}, tc_{ij}, g_{ij}, e_{ij}} p_i z_i l_i^{\alpha_i} \left(\prod_{j=1}^{n} m_{ji}^{\omega_{ji}} \right)^{\nu_i} - \sum_{j=1}^{n} \Big(p_i - \big(1 - (1-\eta) tc_{ij}\big) q_{ij} \Big) m_{ij} \tag{3}$$

$$- w l_i - \sum_{j=1}^{n} \Big((1 - tc_{ji}) q_{ji} + \eta tc_{ji} q_{ji} + (1-\eta) \gamma p_j \Big) m_{ji} - (1-\eta) \sum_{j=1}^{n} e_{ij} q_{ij} m_{ij}$$

$$s.t. \qquad CC,\ RC,\ ICC,\ and\ NAC$$

The expected revenue consists of input sales and consumption goods sales, accounting for a $1-\eta$ chance of TC default. Production costs include wages, expected input payments, and verification costs.

3.4 Households and market clearing condition

A representative household exists in the economy, choosing consumption bundles and labor to maximize utility subject to budget constraints:

$$\max_{c_t, l_t} \mathbf{E}_0 \left[\sum_{t=0}^{\infty} \beta^t \left(\log c_t - \psi \frac{l_t^{1+\xi}}{1+\xi} \right) \right] \ s.t. \ \ p_t c_t \leq w_t l_t + \pi_t + E_t \tag{4}$$

where c_t is the consumption bundle; l_t is the hours worked; ψ governs the degree of disutility from working; ξ is the inverse of Fischer elasticity; p_t is the price index; π_t is the total profits generated by all firms; and E_t is the total verification cost paid by firms. Moreover, the consumption bundle is defined as a composite of goods and services from all sectors, with a CES form, as in

$$c = \left(\sum_{i=1}^{n} \phi_i^{\frac{1}{\sigma}} c_i^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{5}$$

where σ is the elasticity of substitution, and ϕ_i is the share of the household's expenditure on sector i's goods with $\sum_{i=1}^{n} \phi_i = 1$. The price index is defined as

$$p = \left(\sum_{i=1}^{n} \phi_i p_i^{1-\sigma} \right)^{\frac{1}{1-\sigma}}, \tag{6}$$

Solving the optimal problem, a household's demand for goods in sector i is given as

$$c_i = \phi_i \left(\frac{p_i}{p} \right)^{-\sigma} c. \tag{7}$$

Labor supply is equal to labor demand across all firms as

$$l = \sum_{i=1}^{n} l_i. \tag{8}$$

Because firms' customization of their products has a probability η of being qualified for inputs, by the law of large numbers, a fraction η of input orders turn out to be of good quality. In contrast, the rest $(1-\eta)$ find inputs in the secondary market. Therefore, the market-clearing conditions for product market i can be written as

$$y_i = \sum_{j=1}^{n} m_{ij} + k_i + c_i, \ \forall i \tag{9}$$

where y_i is defined in equation (1) and $k_i = \sum_{j=1}^{n}(1-\eta)\gamma m_{ij}$.

4 Equilibrium Analysis

Now, we define the competitive equilibrium in our model as

Definition 1 *A **stationary Nash equilibrium** is defined as the product prices $\{p_i\}$, the wage w, the sectoral output $\{y_i\}$, the consumption goods $\{c_i\}$, the goods in the secondary input market $\{k_i\}$, the labor allocations $\{l_i\}$, the intermediate inputs $\{m_{ji}\}$, the optimal contracts $\{q_{ij}, tc_{ij}, g_{ij}\}$, and efforts to verify the 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 $\{q_{ji}, tc_{ji}, g_{ji}\}$, firms in sector i choose the labor l_i, the intermediate inputs $\{m_{ji}\}$, the optimal contracts for their own clients $\{q_{ij}, tc_{ij}, g_{ij}\}$, and the verifying efforts $\{e_{ij}\}$ to maximize the expected profit as in (3);*

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 (4);*

3. *the wage w clears the labor market (8); and*

4. *the product prices $\{p_i\}$ clear product markets in (9), and the aggregate price index p is normalized to 1.*

Next, we discuss the solution to the model and examine the role of TC 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 $\{q_{ji}, tc_{ji}, g_{ji}\}$, the optimal production plan for firms i satisfies the following conditions:*

$$\alpha_i v_i^L p_i y_i = w l_i, \tag{10}$$

$$\omega_{ji} \nu_i v_{ji}^M p_i y_i = q_{ji} m_{ji}, \; \forall\, j \tag{11}$$

where v_i^L and v_{ji}^M are defined as the labor and intermediate input wedges respectively as:

$$v_i^L = \frac{1+\theta_i \mu_i}{1+\mu_i}, \;\; and \;\; v_{ji}^M = \frac{1+\theta_i \mu_i}{1 - tc_{ji} + \eta tc_{ji} + (1-\eta)\frac{\gamma p_j}{q_{ji}} + \mu_i (1 - tc_{ji})}, \tag{12}$$

and μ_i is the Lagrangian multiplier for collateral constraint. Then the output y_i can be solved as

$$y_i = \left(z_i p_i^{\alpha_i + \nu_i} \left(\nu_i \prod_{j=1}^{n} \left(\frac{\omega_{ji} v_{ji}^M}{q_{ji}} \right)^{\omega_{ji}} \right)^{\nu_i} \left(\frac{\alpha_i v_i^L}{w} \right)^{\alpha_i} \right)^{\frac{1}{1-\alpha_i-\nu_i}} \tag{13}$$

Proof: see Appendix D.2.

Here, the labor and intermediate input wedges measure the extent to which the allocations of labor and intermediate inputs deviate from the first best. Note that three types of frictions are at play in our model: the uncertainty about quality (also, default risk on TC), the pricing power of suppliers, and the collateral constraint. These frictions interact with each other and affect the outputs through both labor and input wedges. The collateral constraint directly affects the labor wedge, while all three jointly determine the input wedge. A tighter collateral constraint (i.e., a higher μ_i) distorts the labor demand more and affects the input demand, where the latter effects depend on the size of received TC relative to the financial condition. Moreover, when the client finds the delivered goods unqualified for inputs, she bears 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 that 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, and the more the client's input demand is distorted. Equation (13) shows that the production in sector i is a function of their productivity and financial shocks, as well as their suppliers, through the labor and input wedges. Note that setting $\eta = 1$ and $\mu_i = 0$ for $\forall i$ eliminates the frictions in our model, and the allocations are the 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, for $\forall j$,

$$\mathbf{Pr}\left(e_{ij}\right) = \sqrt{\frac{e_{ij}}{\bar{e}_i}}, \ \ for \ \ e_{ij} \in [0, \bar{e}_i] \tag{14}$$

where $\bar{e}_i$ is the maximal effort level for firm i.[21] Here, we focus on the case in which collateral constraints are binding for all firms. In this case, the loans borrowed by firm j are equal to $\theta_j p_j y_j$. When the supplier finds out that the client j cheats, the penalty that all suppliers can capture is $(1-\theta_j)\nu_j p_j y_j$, of which the supplier i seizes a fraction ω_{ij}. 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}, the share of TC tc_{ij}, and the penalty payment g_{ij}, respectively, as:*

$$\begin{aligned} 3\gamma\bar{e}_i\left(\frac{(1-\eta)tc_{ij}v_{ij}^M}{1-\theta_j}\right)^2 &= (1+(1-\eta)\gamma)\left(1-tc_{ij}+\eta tc_{ij}\right) \\ &\quad +\left(\mu_j+(1-\eta)\gamma\mu_i\right)(1-tc_{ij}), \end{aligned} \tag{15}$$

$$\eta\frac{\gamma p_i}{q_{ij}} = \eta+(1-\eta)(1-tc_{ij}), \tag{16}$$

$$g_{ij} = \omega_{ij}\nu_j p_j y_j, \tag{17}$$

where v_{ij}^M is defined in equation (12) and y_j is given by equation (13).

Proof: see Appendix D.3.

When the firm makes the input price decision, it considers the input demand as in equation (11). As the relative input price rises, the input wedge increases due to the relatively lower cost of purchasing from the secondary market. The rising wedge partially offsets the decline in input demand caused by a higher price. As a result, as the input price rises, the input revenue increases, but increases less as the price rises, implying that the input revenue is a concave function in the price.

On the other hand, for the same verification intensity, the cost of verification increases with input sales. Moreover, the incentive to cheat (claim for bad-quality input) increases with input sales. Suppliers need to exert more effort to ensure truth-telling. As a result,

[21] 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 verification cost is convex in the input price. Therefore, the input price is determined to balance the concave sales and the convex verification costs.

Regarding the TC decision, the supplier wants to collect the input payment as early as possible. However, the supplier has to defer a proportion of the payment to compensate the client for the potential loss in the bad-quality case. Thus, the TC intensity is chosen until the unit cost of inputs is the same between ordering them from a supplier and purchasing them from the secondary market. A partial equilibrium analysis of Equation (16) implies that the TC intensity increases with the relative input price. As the relative input price increases, a higher revenue will be realized in the good-quality case. Thus, suppliers can afford to defer a larger fraction of payment as TC.

Next, we discuss the sufficient condition for the unique existence of TC intensity tc_{ij}. We also describe how TC 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 equation (15) given equation (12) and (16). Moreover, we have

$$\frac{\partial\, tc_{ij}}{\partial\, \mu_i} < 0, \ \ and \ \ \frac{\partial\, tc_{ij}}{\partial\, \theta_j} \begin{cases} \leq 0 & if \quad g\left(tc_{ij}, \mu_i, \mu_j, \theta_j\right) \leq 0 \\ > 0 & otherwise \end{cases}, \tag{18}$$

where the g function is defined in Appendix D.4.

Proof: see Appendix D.4.

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

Here is the intuition of Proposition 2. A tighter constraint for the supplier limits her production so that it can simply require more upfront payment to alleviate its financial constraint and increase production. For example, all else equal, a negative financial shock to the supplier results in a tighter constraint and, thus, less TC.

The intensity of TC given by a supplier to a client responds to the client's financial condition in a non-monotonic way. The response ultimately depends on the relative financial constraints of the supplier and client. A negative financial shock to the client can lead to more TC being extended to alleviate the client's constraint and increase input sales, or less TC being extended if the supplier's financial condition is sufficiently tight. In the latter case, requiring more input payments in advance benefits the supplier's production, at the cost of weakening the client's financial conditions and distorting her production in addition to the negative financial shock. TC is a cushion in the former case, while an amplifier in the latter. This asymmetry is particularly relevant to our observations of sectoral comovement during recessions in Section 2. During a financial recession, the amplifying role of TC can be triggered as a sufficient number of firms are financially constrained. In contrast, during an economic recession, TC works as a cushion to mitigate the spillover of sectoral shocks.

Next, we examine how TC affects sales growth. Lemma 1 implies that the values of the labor and input wedges rely on these binding financial constraints, which further depend on the exogenous financial conditions, θ. Given the sectoral productivity shocks $\{z_{it}\}$, TC intensities $\left\{tc_{ij,t}\right\}$, labor wedges $\left\{v_{it}^{L}\right\}$, and inputs wedges $\left\{v_{ij,t}^{M}\right\}$, we can decompose the real output growth at time t as

$$\Delta\log(p_t \circ y_t) = \Delta\tilde{z}_t + \Delta\tilde{tc}_t + \Delta\tilde{v}_t + \Delta\widetilde{GE}_t \tag{19}$$

where $\circ$ is the Hadamard product, and $\Delta\tilde{z}_t$, $\Delta\tilde{tc}_t$, $\Delta\tilde{v}_t$, and $\Delta\widetilde{GE}_t$ are defined, respectively, as the effects of productivity shocks, changes in TC, financial frictions, and the generate-equilibrium conditions on the real growth of sectoral outputs as

$$\begin{aligned}
\Delta\tilde{z}_t &= \left(\mathbf{I}_n + \frac{1}{\sigma-1}\mathbf{M}_{py}\right)^{-1}(\mathbf{I}_n - \mathbf{D}_\alpha - \mathbf{D}_\nu)^{-1}\Delta\log z_t, &(20)\\
\Delta\tilde{tc}_t &= \left(\mathbf{I}_n + \frac{1}{\sigma-1}\mathbf{M}_{py}\right)^{-1}(\mathbf{I}_n - \mathbf{D}_\alpha - \mathbf{D}_\nu)^{-1}\mathbf{D}_\nu\mathbf{M}_\omega\Delta\log\left(1-(1-\eta)tc_t\right), &(21)\\
\Delta\tilde{v}_t &= \left(\mathbf{I}_n + \frac{1}{\sigma-1}\mathbf{M}_{py}\right)^{-1}(\mathbf{I}_n - \mathbf{D}_\alpha - \mathbf{D}_\nu)^{-1}\left(\mathbf{D}_\alpha\Delta\log v_t^L + \mathbf{D}_\nu\mathbf{M}_\omega\Delta\log v_t^M\right), &(22)\\
\Delta\widetilde{GE}_t &= \left(\mathbf{I}_n + \frac{1}{\sigma-1}\mathbf{M}_{py}\right)^{-1}(\mathbf{I}_n - \mathbf{D}_\alpha - \mathbf{D}_\nu)^{-1}\left(-\frac{\xi}{1+\xi}\Delta\log\left(\mathbf{1}_n' v^L \circ p_t \circ y_t\right)\mathbf{D}_\alpha\mathbf{1}_n\right.\\
&\quad \left. +\Delta\log\left(\mathbf{1}_n'\left(\eta\mathbf{I}_n - \frac{1}{\eta\gamma}\mathbf{D}_\nu\mathbf{M}_{xt}\right)p_t \circ y_t\right)\left(\frac{1}{\sigma-1}(\mathbf{I}_n - \mathbf{D}_\nu\Omega') - \frac{1}{1-\xi}\mathbf{D}_\alpha\right)\mathbf{1}_n\right), &(23)
\end{aligned}$$

and as shown in Appendix D.5, $\mathbf{D}_\alpha$, $\mathbf{D}_\nu$, $\mathbf{M}_\omega$, $\mathbf{M}_{py}$, $\mathbf{M}_{xt}$, and Ω are matrices of structural parameters, and p_t, y_t, z_t, v_t^L, v_t^M and tc_t are vectors of state or endogenous variables across sectors. Notably, endogenous TC can affect the sectoral output growth in both a direct and an indirect way. The TC component $(\tilde{tc}_{it})$ captures the direct effects. Moreover, TC is adjusted in response to the exogenous shocks discussed in Proposition 2, which further alters other firms' financial constraints. Thus, TC can indirectly influence output growth through labor and input wedges.

Therefore, the observed sectoral comovement can be attributed to four sources. First, sectoral productivity shocks can generate comovement through input-output linkage. Second, endogenous TC also alters outputs directly, as we demonstrate in Proposition 2. Third, due to the financial frictions and endogenous TC, labor and input wedges arise, which further vary over time as the financial shocks hit. Last, as a common factor, the GE effects lead sectors to comove homogeneously across sectors. As we will show later, the asymmetrical response of TC can account for a substantial proportion of sectoral comovement during the Great Recession, which Li and Martin (2019) attribute mainly to a reduced-formed GR-specific common factor .

5 Quantitative model

In this section, we apply our model, along with the outputs and bond spread of the US sectors, to back out the sectoral productivity and financial shocks. We then conduct several exercises to highlight the role of endogenous TC and its interaction with financial shocks in accounting for the large rise in sectoral comovement and the dynamics of the aggregate economy during the Great Recession. Next, we study how the two shocks differ from the ones implied by a fixed-trade-credit model. Finally, we study the model implied evolution of comovement for the early 1980s recession and the COVID-19 recession.

5.1 Calibration

We follow a three-stage calibration strategy. First, we select the value of some parameters by either following the existing literature or matching the data moments. Second, we use equilibrium conditions to calibrate the maximal verification efforts to match the sectors' AR-to-sales ratios. Last, we apply our model to back out productivity and financial shocks with the sectoral outputs and bond spread.

Following standard practices in the literature, we set the importance of labor disutility ψ to 1, the elasticity of substitution among consumption goods σ to 2.5, and the inverse of the Frisch elasticity ξ to 0.36. The TC delinquent/default rate in the US is not directly observed. Using payment-level data, Boissay and Gropp (2013) report that 18.5% of firms in France default at least once per quarter, on average, and Jacobson and von Schedvin (2016) find that the TC failure frequency in Sweden was about 10% between 1992 and 2005. Therefore, we average these two rates and set the probability that clients receive qualified inputs, η, at 0.86.[22] Moreover, the premium in the secondary market (γ) can be interpreted as the reduced form of costs associated with finding alternative inputs, including search costs, transportation costs, and others. However, these costs are not directly observable. Therefore, we set γ to 2.73, which corresponds to the average trade cost within the US, as derived from the estimates by Caliendo et al. (2018).[23]

As shown in Table 2, 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.[24]

Table 2

Calibration for sectoral parameters

Sectors	ν	α	ϕ	$\bar{e}$
Mining	0.44	0.52	0.01	11.95
Utilities	0.56	0.39	0.02	10.36
Construction	0.49	0.30	0.13	7.41
Manufacturing	0.65	0.19	0.16	10.62
Wholesale trade	0.37	0.40	0.09	7.40
Retail trade	0.37	0.44	0.11	7.41
Transportation and warehousing	0.51	0.31	0.05	8.95
Information	0.45	0.22	0.08	8.25
Professional and business services	0.37	0.45	0.09	7.40
Educational services, and health care	0.39	0.50	0.16	7.41
Arts, and recreation services	0.47	0.36	0.07	8.30
Other services	0.38	0.43	0.04	7.41

Notes: All parameters are calibrated from the 12-sector input-output table in 2005. $\{\nu_i\}$ are the intermediate input share over the total output. $\{\alpha_i\}$ are labor share. $\{\phi_i\}$ are consumption shares. $\{\bar{e}_i\}$ are calibrated maximal value of efforts.

Next, we use our model solution to calibrate the maximal verification effort parameters $\{\bar{e}_i\}$. Since we do not observe bilateral TC issuance, for our calibration on $\{\bar{e}_i\}$, we first assume that a given supplier provides the same TC intensity to all clients - i.e., $tc_{ij} = \overline{tc}_i$ - for $\forall j$. We take the median AR-to-sales ratio between 2005Q3 and 2006Q2 for each firm and the median again across firms in the corresponding industry as $\overline{tc}_i$.[25] We then use

[22] This value is also close to the one-year survival rate of new startups in the US.

[23] Specifically, we use the point estimates from the model without fixed effects in Table A7.1 of Caliendo et al. (2018), calculating their weighted average using sectoral value-added shares as weights. The trade cost ratio is then imputed using equation (A.6). This value is also consistent with the estimated trade cost between the US and Canada in Anderson and Van Wincoop (2003) with $\sigma = 2.5$.

[24] 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 operating surplus to the total output as α for these two sectors.

[25] In practice, since firms usually provide either inputs or final goods while sectors in our model do both,

equation (15) to solve for e_{ij}, out of which $\bar{e}_i$ is selected as the maximal value, across all clients. Once $\{\bar{e}_i\}$ are calibrated, we can deviate from the assumption that the supplier issues the same proportion of payments as TC to all clients and let TC be endogenously determined. When the calibrated $\bar{e}$ is lower than the threshold in Assumption (#1), we replace it with the threshold value. The fourth column of Table 2 displays the results for $\{\bar{e}_i\}$. The mining and manufacturing industries exhibit the highest values, suggesting that with the same effort e, it is least likely to detect the true state due to the relative complexity of their products or services. Conversely, $\bar{e}$ for the retail, construction, and education sectors is the lowest, indicating that with the same effort e, it is most likely to detect the true state, as their products or services are comparatively simpler. Notably, the average verification cost relative to sales across all sectors is 5%, with a standard deviation of 4.1%.

Following Bigio and La'O (2020) and Miranda-Pinto and Young (2022), 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 (12).[26] Imposing this condition, along with sectoral real gross output, we can solve the system to obtain the implied sectoral productivity $\{z_{it}\}$ and financial shock $\{\theta_{it}\}$. Table 3 displays the pairwise correlations of calibrated productivity and financial shocks. Before the Great Recession, the mean (median) of pairwise correlations among the productivity shocks was -0.03 (0.05) and -0.01 (0.06) for the financial shocks. During the Great Recession, the correlation of productivity shocks significantly rose, by 0.13, to 0.1, and that of the financial shocks increased from -0.01 to 0.17. Interestingly, the average correlation of financial shocks rose more than the median (rising by 0.04), which implies that the deterioration of financial conditions during the Great Recession was highly skewed. That is, a few sectors' financial conditions, rather than the majority, moved together. Between the two types of shocks—productivity and financial—we observe a positive correlation before the Great Recession and a negative correlation during it. However, the average correlation magnitude remained small even during the Great Recession, indicating that productivity and financial shocks play distinct roles.[27]

Finally, we verify how well our calibration matches the data we do not target. As shown in Appendix E.2, our model can reasonably account for the decline in aggregate GDP/consumption and the reduction in sectoral TC, as measured by AR-to-sales ratios, during the Great Recession.[28]

thus, $\overline{tc}_i \kappa_i$ is used, where κ represents the share of products used as intermediate inputs.

[26] We thank Gilchrist and Zakrajsek for kindly sharing their data with us.

[27] Please see Figure E.2 for the kernel densities of pairwise correlation for two shocks.

[28] By construction, our estimated shocks generate the same sectoral output growth as in the data and,

Table 3
PAIRWISE CORRELATIONS OF CALIBRATED SHOCKS

	endogenous TC		fixed TC	
	mean	median	mean	median
before the Great Recession				
corr$(\Delta z_{it}, \Delta z_{jt})$	-0.03	0.05	0.23	0.24
corr$(\Delta \theta_{it}, \Delta \theta_{jt})$	-0.01	0.06	0.04	0.06
corr$(\Delta z_{it}, \Delta \theta_{jt})$	0.03	-0.01	-0.02	0.00
during the Great Recession				
corr$(\Delta z_{it}, \Delta z_{jt})$	0.10	0.14	0.32	0.41
corr$(\Delta \theta_{it}, \Delta \theta_{jt})$	0.17	0.10	0.41	0.43
corr$(\Delta z_{it}, \Delta \theta_{jt})$	-0.07	-0.10	-0.13	-0.22

Notes: The sectoral bond spreads and real sectoral outputs are used to impute productivity and financial shocks, using the solution of the model with or without endogenous trade credit. 2005Q3-2007Q2 and 2007Q3-2009Q2 are respectively the time windows before and during the Great Recession.

5.2 Decomposition of sectoral comovement

Now we apply our calibration to decompose pairwise correlations of sectoral output growth before and during the Great Recession. In particular, we use the calibrated productivity shocks, model-implied TC, and labor and input wedge, along with structural parameters, to impute these four components in equation (19). Therefore, the pairwise correlation of sectoral output growth between sectors i and j over a certain period, shown in Table 3, can be expressed as

$$\mathbf{corr}\left(\Delta \log p_{it} y_{it}, \Delta \log p_{jt} y_{jt}\right) = \sum_{x,x' \in \left\{\tilde{z}, \tilde{tc}, \tilde{v}, \widetilde{GE}\right\}} \frac{\sigma_i^{\Delta x} \sigma_j^{\Delta v}}{\sigma_i^{\Delta py} \sigma_j^{\Delta py}} \mathbf{corr}\left(\Delta x_{it}, \Delta x'_{jt}\right) \tag{24}$$

where $\sigma_i^{\Delta x}$ is the standard deviation of the component Δx for sector i over the same period.

Table 4 reports the average correlation of corresponding components and their contributions to the average correlation of sectoral output growth.[29] The average correlation of sectoral output growth in our sample increases from 0.04 before to 0.5 during the

thus, the observed rise in sectoral comovement.

[29]Even though the loading of the GE component ($\widetilde{GE}$) varies across sectors, the loading for one sector is fixed over time, and, thus, the correlation of the GE components between two sectors is equal to one. We also ignore the pairwise correlations between the two components.

Great Recession, consistent with, but higher than, what we find with 57 sectors in Section 2.1. The average correlation of the productivity component - i.e., $\mathbf{corr}\left(\Delta\tilde{z}_{it}, \Delta\tilde{z}_{jt}\right)$ - rose from 0.18 before to 0.3 during the Great Recession, driven mainly by the change in the correlation of underline shocks, as shown in Table 3. However, the contribution of the comovement generated by productivity shocks, $\frac{\sigma_i^{\Delta\tilde{z}}\sigma_j^{\Delta\tilde{z}}}{\sigma_i^{\Delta py}\sigma_j^{\Delta py}}\mathbf{corr}\left(\Delta\tilde{z}_{it}, \Delta\tilde{z}_{jt}\right)$ rose only from 0.06 to 0.11, which accounts for 11% of the rise in the output-growth correlation.

Table 4
Decomposition of pairwise correlations

	before Great Recession		**during Great Recession**		
	average corr	contribution	average corr	contribution	Δ in contribution
$\Delta \log py$	0.04		0.50		
$\Delta\tilde{z}$	0.18	0.06	0.30	0.11	0.05
$\Delta\tilde{tc}$	0.01	-0.01	0.37	0.06	0.07
$\Delta\tilde{v}$	0.29	0.06	0.89	0.36	0.30

Notes: The average correlation reports the pairwise correlation of corresponding components, i.e., $\mathbf{corr}\left(\Delta x_{it}, \Delta x_{jt}\right)$ for $x \in \{\tilde{z}, \tilde{tc}, \tilde{v}\}$. The contribution reports the contribution of each component to the average correlation of the sectoral output growth, i.e., $\frac{\sigma_i^{\Delta x}\sigma_j^{\Delta x}}{\sigma_i^{\Delta py}\sigma_j^{\Delta py}}\mathbf{corr}\left(\Delta x_{it}, \Delta x_{jt}\right)$ for $x \in \{\tilde{z}, \tilde{tc}, \tilde{v}\}$. 2005Q3-2007Q2 and 2007Q3-2009Q2 are respectively the time windows before and during the Great Recession.

Endogenous TC can affect the output-growth correlation in both a direct and an indirect way. The direct effects are captured by the comovement of the TC component - i.e., $\mathbf{corr}\left(\Delta\tilde{tc}_{it}, \Delta\tilde{tc}_{jt}\right)$ - which increased by 0.36 during the Great Recession and contributed 15% of the rise in the output-growth correlation. Moreover, in response to financial shocks during the Great Recession, TC adjusted in a way that tightened financial constraints for certain sectors. This adjustment further generated more synchronized labor and input wedges, with the average correlation rising from 0.29 to 0.89 during the Great Recession, accounting for 65% of the increase in output-growth correlation. This finding highlights the role of TC in determining the sharp rise in sectoral comovement during the Great Recession.

Moreover, we use the model-implied data to perform a sectoral regression (see Appendix E.3 for details). The results confirm the role of TC in driving the rise in comovement during the Great Recession. Sectoral comovement increases when the clients receive a negative financial shock and even more when their suppliers contract TC. In contrast, we find that productivity shocks play little role.

5.3 Correlated versus uncorrelated shocks

During the Great Recession, the increased comovement of labor and input wedges might have been indirectly influenced by the more correlated productivity and financial shocks. To disentangle these effects, we perform a counterfactual analysis by imposing uncorrelated productivity and financial shocks.[30] We then examine the pairwise correlations under both correlated and the counterfactually uncorrelated shocks.

First, we use a VAR model to separately estimate imputed productivity and financial shocks as, for $\mathbf{x} \in \{z, \theta\}$,

$$\log \mathbf{x}_t = \mathbf{D}_\rho^x \log \mathbf{x}_{t-1} + \epsilon_t^x + \mathbf{1}_{(\mathbf{07}-\mathbf{09})} \nu_t^x \tag{25}$$

where $\mathbf{x}_t = [x_{1t}, \ldots, x_{nt}]^T$ is a vector of imputed productivity ($\{z_{it}\}$) or financial conditions ($\{\theta_{it}\}$). $\mathbf{D}_\rho^x$ is a diagonal matrix with autocorrelation coefficients on the diagonal.[31] $\epsilon_t^x = \left[\epsilon_{1t}^x, \ldots, \epsilon_{nt}^x\right]^T$ is a vector of error terms that are serially independent and identically distributed, following a joint normal distribution $\mathbf{N}\left(\mathbf{0}, \Omega_{normal}^x\right)$. As in Li and Martin (2019), $\nu_t^x = \left[\nu_{1t}^x, \ldots, \nu_{nt}^x\right]^T$ is a vector of GR-specific error terms, which are also serially independent and identically distributed, following a joint normal distribution as $\mathbf{N}\left(\mathbf{0}, \Omega_{GR}^x\right)$. Also, we assume that ϵ_t^x and ν_t^x are independent.

Assuming that the economy begins at a steady state, we simulate both productivity and financial shocks over an 8-period window. To ensure comparability between the correlated and uncorrelated shock cases, we randomly draw the underlying shocks from a joint standard normal distribution. These draws are then adjusted using the Cholesky decomposition of the estimated covariance matrix, $\widehat{\Omega}_{normal}^x$, for the pre-Great Recession (GR) simulation, and $\widehat{\Omega}_{normal}^x + \widehat{\Omega}_{GR}^x$ for the GR simulation. Subsequently, we solve our model and compute the pairwise correlations over the 8 periods, as detailed in Section 2. This procedure is repeated 1000 times. In the GR simulation, according to the NBER's definition of a recession, an 8-period simulation is identified as experiencing a GR episode if the GDP growth rate falls below one standard deviation from zero (i.e., -0.97%) for any two consecutive periods, and the minimum GDP growth rate is below two standard deviations from zero (i.e., -1.95%).[32] Overall, 368 out of the 1000 simulations are identified as GR episodes.

Table 5 presents the average pairwise correlations for both pre-GR simulations and

[30] We thank the referee for this suggestion.

[31] The model can be easily extended to incorporate cross-sectional autocorrelations, which generate naturally correlated sectoral productivity or financial conditions. Here, we maintain a minimal setting to compare correlated and uncorrelated shocks, thus excluding cross-sectional autocorrelations.

[32] Note that the standard deviation of GDP growth rate is 0.97% across all pre-GR simulations.

GR episodes, where the standard deviation is reported in parentheses. Notably, in the GR simulations, only the GR episodes are considered in the calculation.[33] First, we observe that the average correlations in our simulations with correlated shocks align with the empirical data. Specifically, the average pairwise correlation increases by 0.35 during GR episodes, accounting for 76% of the observed rise in sectoral comovement during the Great Recession. Second, using equation (24), we decompose the pairwise correlation of sectoral output growth into correlations of various components. Our findings indicate that the term encompassing labor and input wedges exhibits the highest average correlation, whereas the sectoral comovement of the productivity shocks is the lowest.

Table 5
Pairwise correlation: data, simulation, and decomposition

	before Great Recession				**during Great Recession**			
	$\Delta \log py$	$\Delta\tilde{z}$	$\Delta\tilde{fc}$	$\Delta\tilde{v}$	$\Delta \log py$	$\Delta\tilde{z}$	$\Delta\tilde{fc}$	$\Delta\tilde{v}$
Data	0.04	0.18	0.01	0.29	0.50	0.30	0.37	0.89
Correlated shocks	0.06	-0.02	0.02	0.09	0.41	0.02	0.08	0.48
	(0.05)	(0.03)	(0.06)	(0.07)	(0.11)	(0.06)	(0.07)	(0.14)
Uncorrelated shocks	0.06	0.00	0.01	0.12	0.27	0.00	0.05	0.31
	(0.10)	(0.04)	(0.07)	(0.13)	(0.12)	(0.04)	(0.07)	(0.13)

Notes: Equation (25) is estimated for the covariance matrix of error terms. Assuming that the economy begins at a steady state, both productivity and financial shocks are simulated over an 8-period window, where the estimated covariance matrix, $\widehat{\Omega}^x_{normal}$, is employed for the pre-GR simulation and $\widehat{\Omega}^x_{normal} + \widehat{\Omega}^x_{GR}$ for the GR simulation. The procedure is repeated 1000 times. A simulation is identified as experiencing a GR episode if the GDP growth rate falls below -0.97% for any two consecutive periods within the 8-period simulation and the minimum GDP growth rate is below -1.95%. Simulation with uncorrelated shocks is conducted with the same underlying shock but adjusted only for diagonal elements of the corresponding covariance matrix in the pre-GR and GR simulations. The average correlation reports the pairwise correlation of corresponding components, i.e., $\mathbf{corr}\left(\Delta x_{it}, \Delta x_{jt}\right)$ for $x \in \{\tilde{z}, \tilde{fc}, \tilde{v}\}$. Standard deviations are reported in the parenthesis.

Next, we perform a counterfactual exercise by eliminating the covariance of both productivity and financial shocks, focusing solely on the diagonal elements of the estimated covariance matrix for both pre-GR and GR simulations. Using the same random draws as in the correlated-shock case, we recompute productivity and financial conditions, solve the model, and calculate the pairwise correlations. The fourth row of Table 5 displays the average pairwise correlations in both the pre-GR simulation and GR episodes, with the GR episodes being the same simulations as in the correlated-shock case. We find that even with uncorrelated shocks, the average pairwise correlation in the GR episodes significantly increases, accounting for 60% of the rise in sectoral comovement observed

[33] Correspondingly, in the pre-GR simulations, the average pairwise correlation of sectoral output growth is 0.06 for the simulations identified as GR episodes in the GR simulations.

in the correlated-shock case (46% of the observed increase in the data). In the pre-GR simulations, the average pairwise correlation with uncorrelated shocks remains similar to that in the correlated-shock case. Using equation (24), we decompose the pairwise correlations of sectoral output growth, finding that the sectoral comovements of each component are similar to those in the correlated-shock case. These results indicate that even in the absence of correlated productivity and financial shocks, TC still significantly affects sectoral comovement in the Great-Recession scenario, both directly and indirectly.

5.4 Counterfactual exercise with fixed trade credit

In this section, we conduct several counterfactual exercises to examine the role of endogenous TC and its interaction with financial and productivity shocks in explaining the sharp increase in comovement during the Great Recession. By considering a counterfactual economy in which TC is fixed at the pre-recession average, we compare this scenario with our benchmark model under the imposition of both productivity and financial shocks, separately and together. The summary statistics of the pairwise correlation implied by our model are presented in Table 6.

First, fixing the TC intensity to its pre-recession average, we impose the same productivity and financial shocks calibrated in Section 5.1. In Figure 5, Panel (a) shows that the average pairwise correlations in the fixed-TC model rose by 0.27 during the Great Recession, which is 42% lower than the increase with the endogenous model (from 0.04 to 0.5). This result is consistent with our sectoral evidence in Section 2.3, where the difference in the rise of pairwise correlations between the TC-declined and unchanged subgroups is more than 40% of the group average. The intuition is straightforward. In the presence of financial shocks during the recession, sufficiently constrained suppliers do not extend TC to their shocked clients as they normally would but, rather, contract TC, making their clients more constrained. Fixed TC limits suppliers' response, thus dampening the comovement between the two parties.[34]

Additionally, the fixed TC model generates a milder decline in aggregate GDP, where the decline in GDP growth is 17.3% smaller in Q4 2008 and 15.2% smaller in Q1 2009 than in our benchmark model. This is because, in the fixed TC case, the clients' production is not further distorted by a more tightened constraint caused by the contraction in TC.

[34] Specifically, we regress the change in pairwise correlation, with endogenous and fixed TC, on the one-way and two-way indicators, along with other control variables. We find that 1) the two-way group comoves more in both models, and the rise in comovement is larger in the endogenous TC model; 2) the rise in the endogenous TC model is due to the contraction in TC provision, while the rise in the fixed TC model is due mainly to the correlations of the underlying shocks. Please refer to Appendix E.3 for more detail.

Table 6

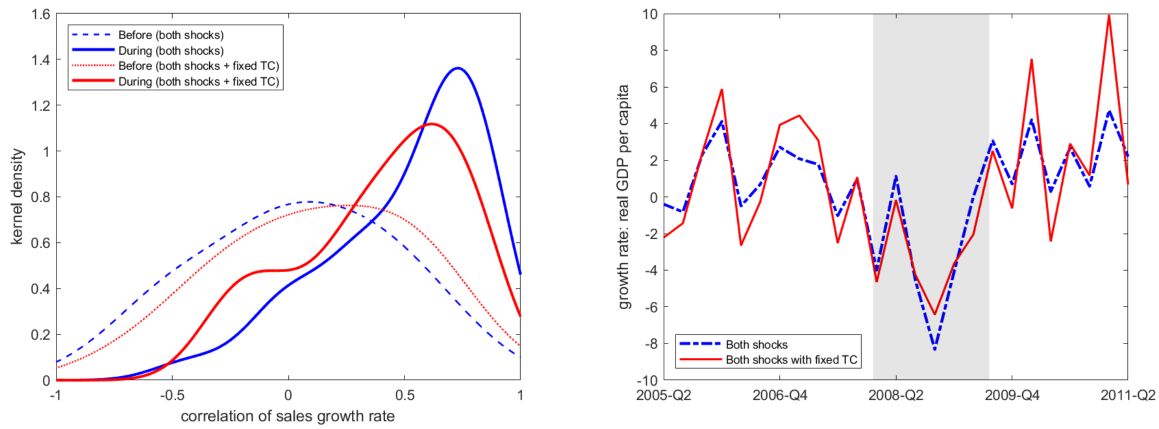
Model-implied pairwise correlations of output growth rates

	mean	median	std	skewness	KS stat. (CV-KS)
Data / model-implied with both shocks					
Before the Great Recession	0.04	0.03	0.42	-0.11	0.48 (0.43, 1.04)
During the Great Recession	0.50	0.62	0.34	-0.95	
Model-implied with both shocks and fixed TC					
Before the Great Recession	0.13	0.16	0.41	-0.25	0.33 (0.43, 1.04)
During the Great Recession	0.40	0.49	0.35	-0.57	
Model-implied with only θ					
Before the Great Recession	0.13	0.16	0.41	-0.25	0.50 (0.43, 1.04)
During the Great Recession	0.65	0.73	0.24	-0.67	
Model-implied with only θ and fixed TC					
Before the Great Recession	0.19	0.21	0.39	-0.41	0.17 (0.43, 1.04)
During the Great Recession	0.32	0.28	0.37	0.04	
Model-implied with only z					
Before the Great Recession	-0.03	-0.02	0.40	-0.02	0.52 (0.43, 1.04)
During the Great Recession	0.47	0.60	0.39	-0.88	
Model-implied with only z and fixed TC					
Before the Great Recession	0.00	0.00	0.41	-0.09	0.58 (0.43, 1.04)
During the Great Recession	0.52	0.66	0.38	-1.06	

Notes: The table presents summary statistics of pairwise correlations, generated with the model, before and during the Great Recession. The 'both shocks' case includes both productivity and financial shocks, calibrated as detailed in Section 5.1, aligning with observed data. The 'financial shocks only' case is generated using solely financial shocks, while the 'productivity shocks only' case includes only productivity shocks. In cases labeled 'fixed trade credit,' the trade credit (TC) intensity is held constant at its pre-recession average, with the relevant shocks applied accordingly. The critical values of the KS statistics (CV-KS) are reported in the last column. These critical values adjust for the presence of autocorrelation in the data, following Lanzante (2021). The critical value is for a 5% significance level. The first value in parenthesis is the critical value for mild underlying autocorrelation (AR(1) parameter of 0.6). The second critical value corresponds to mild underlying autocorrelation (AR(1) parameter of 0.6).

Next, we examine the role of financial and productivity shocks in driving sectoral comovement during the Great Recession. To do this, we introduce one set of shocks at a time into the model while keeping the other fixed at the pre-recession average. Panel (a) of Figure 6 displays the kernel density for the endogenous TC structure with only financial shocks (red) and for the fixed-TC case (black). With endogenous TC, the average correlation rises from 0.13 to 0.65 during the Great Recession, which is higher than that implied by our benchmark model (blue).

Notably, this sharp rise in pairwise correlations of sectoral output growth is generated



(a) Kernel density of pairwise correlation

(b) Growth rate: real GDP per capita

Note: The fixed TC case is the one where the TC intensity is fixed to its pre-recession average. The blue lines represent variables in the endogenous TC case, while the red ones describe the variables in the fixed TC case.

Figure 5

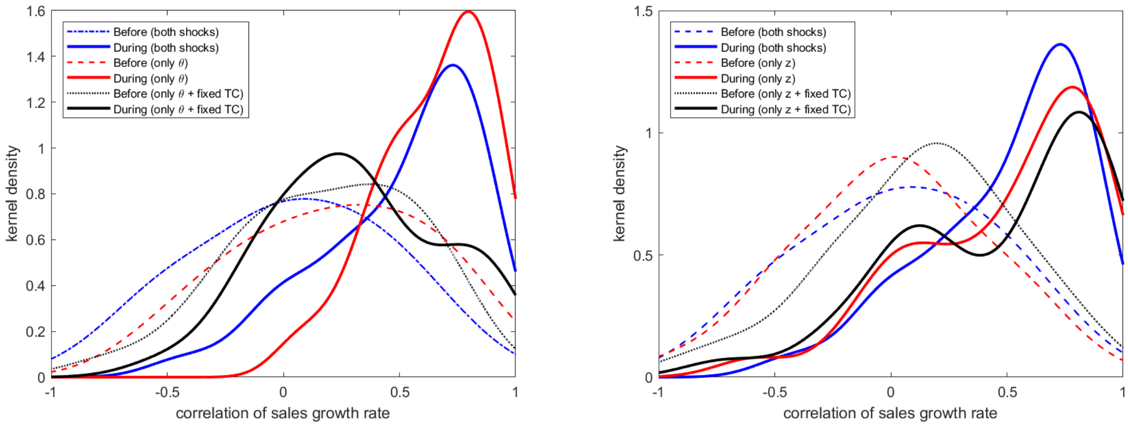
Both shocks: endogenous vs fixed trade credit

by modestly correlated and highly skewed financial shocks, where the average increasd from -0.01 before the recession to 0.17 during the Great Recession, and the median rose by only 0.04. This indicates that trade credit acts as a conduit, propagating and amplifying shocks from a few sectors to many others that were not originally affected. When we fix the TC intensity, the rise in sectoral comovement contracts by 75%.

Finally, we introduce productivity shocks only into the economy. Panel (b) of Figure 6 displays the kernel density for the endogenous TC model (red) and the fixed TC model (black). Due to the higher correlated productivity shocks during the Great Recession, we observe a rise in sectoral comovement in both models. Since productivity shocks affect TC provision primarily through the tightness of the financial constraint, and TC responds minimally to productivity shocks, both models exhibit similar behavior. In fact, we observe more comovement in the fixed-TC model, as the negative productivity shocks alleviate the financial constraint in the endogenous TC model.

5.5 Recalibrating sectoral shocks in the fixed trade credit model

Now, we investigate how the data generation process in a fixed-TC model differs from that in an endogenous TC model. Notably, the former model is isomorphic to the one used in Bigio and La'O (2020). To determine the difference, we re-calibrate the financial and productivity shocks while keeping the TC intensities at the pre-recession average and taking all other parameters as given.



(a) only financial shocks

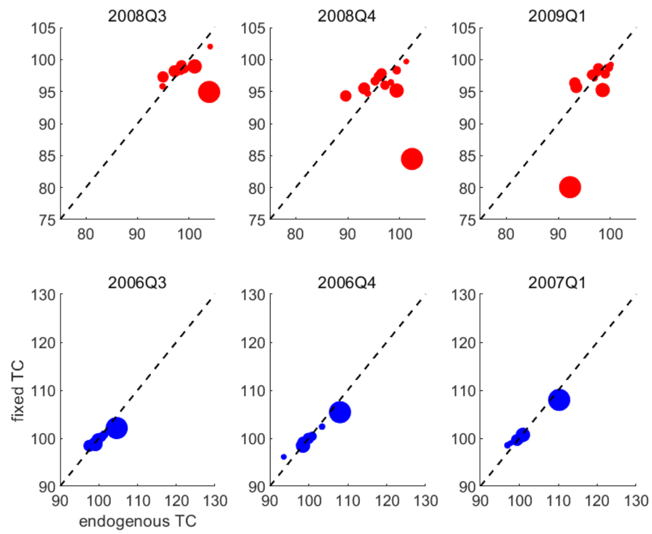
(b) only productivity shocks

Note: The fixed TC case is the one in which the TC intensity is fixed to its pre-recession average. The blue lines represent the benchmark case, the red lines show the economy with only financial (productivity) shocks and the endogenous TC case, and the black ones describe the fixed TC case with only financial (productivity) shocks.

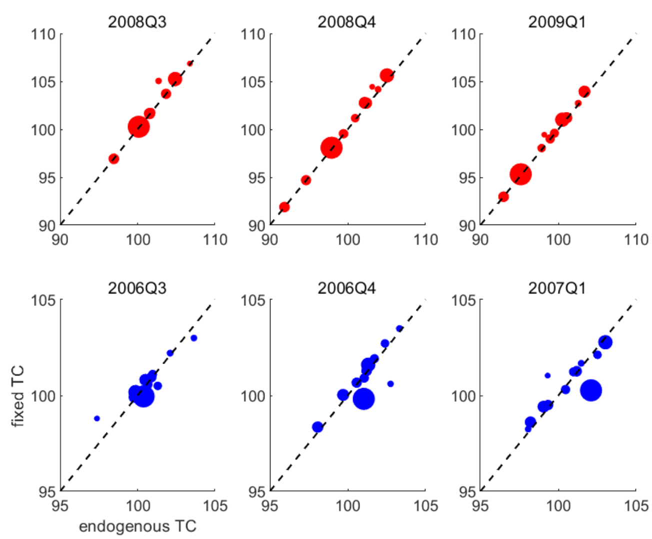
Figure 6
Pairwise correlation: endogenous vs fixed trade credit

Columns (3) and (4) in Table 3 report the summary statistics of the productivity and financial shocks. Before the Great Recession, both models, with or without endogenous TC, imply similarly correlated sequences of shocks. However, to generate the same dynamics of sectoral output during the Great Recession, the model with fixed TC requires financial shocks that are more than twice as correlated as those in the endogenous-TC case, while the productivity shocks need to be only slightly more correlated.

Figure 7 displays scatter plots of sectoral shocks relative to their pre-recession average, where each bubble represents one sector; its size reflects the sales share in 2005; and the horizontal and vertical axes correspond to the endogenous and fixed TC models, respectively. In Panel (a), the financial shocks differ significantly between the two models. For example, in the endogenous TC model, manufacturing received a negative financial shock only in Q1 2009, with a 7.7% decline, whereas, in the fixed TC model, manufacturing experienced a 15.5% decline in Q4 2008 and a 19.9% decline in Q1 2009. For comparison, we plot the pre-recession scatter for the three quarters before 2008 and observe no significant differences between the two series. Panel (b) displays the scatter plot for productivity shocks. All bubbles align along the 45-degree line, indicating the limited interaction between productivity shocks and endogenous TC.



(a) Financial shocks



(b) Productivity shocks

Note: A bubble represents a sector. Each bubble's coordinate value is the shocks' size relative to their pre-recession average. The size of the bubble reflects the sales share in 2005. The horizontal and vertical axes stand for the endogenous and fixed TC models, respectively. In the fixed TC model, the TC intensity is set to its pre-recession average.

Figure 7

Calibrated financial and productivity shocks: endogenous vs fixed trade credit

5.6 The other recessions

In this section, we analyze an important question: why did sectoral comovement not rise significantly in the recessions before 2008? Following Chari et al. (2007), we take the case of the early 1980s recession, which displayed a comparable decline in real GDP to the one during the Great Recession.

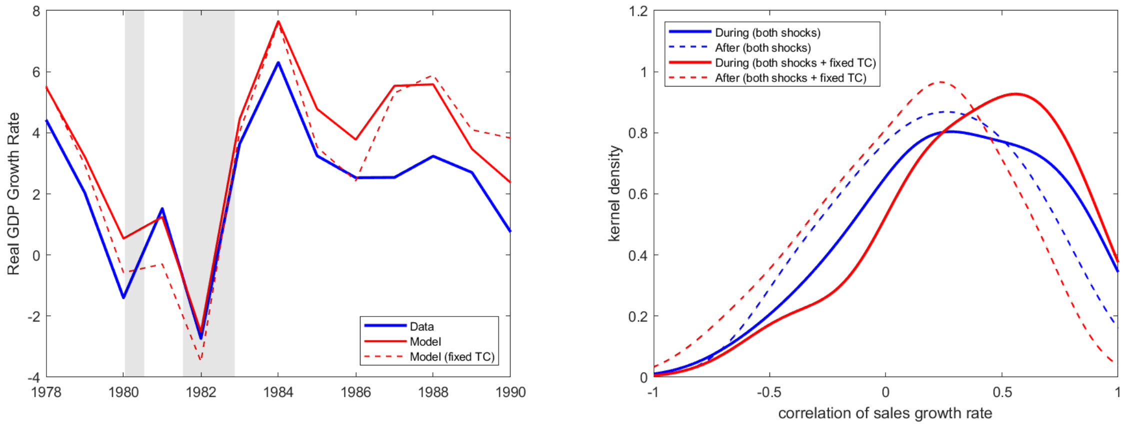
We answer this question through the lens of our model with sectoral annual growth. Following the same strategy, we back out two shocks to match sectoral outputs and spreads between 1978 and 1989.[35] Using the same set of parameters calibrated in Section 5.1, we then compare the sectoral comovement and GDP decline with those generated by a model with TC fixed to the 1978 level.[36] Panel (a) of Figure 8 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 TC model implies a larger decline in GDP growth in both recessions, indicating that TC dampened the magnitude of the recessions in 1980 and 1982. These results resonate with the evolution of trade credit during the early 80s in Figure C.1. We observe that accounts receivable indeed increased in 1980 and then declined slightly at the end of the recession. These results are also consistent with the evolution of the model-implied financial shocks shown in Figure E.7. The decline in financial conditions during the 1980s recession was significantly milder than that observed during the Great Recession (see Figure E.1). Consequently, the financial shocks of the 1980s recession did not trigger domino effects from suppliers cutting trade credit to clients.

Panel (b) of Figure 8 plots the kernel density of pairwise correlation of sectoral sales growth. The sectoral comovement (blue) rises slightly, while the model with the fixed TC generates an even larger rise in sectoral comovement. Unlike the Great Recession, TC during the early 1980s was adjusted to mitigate the negative shocks by smoothing negative spillover effects among sectors, reducing the decline in GDP.

In Appendix E.5, we use our calibrated model to confirm the following intuition behind the dynamics of sectoral comovement during COVID-19: if common shocks are the driver, sectoral comovement should rise ubiquitously, regardless of the degree of interconnection among sectors. In doing so, we feed the model with the productivity and financial shocks for the pre-GR period 2005Q1-2007Q2 and then simulate a 1.5% decline in productivity for all sectors in 2006Q1. We find that two-way, one-way, and no-trading groups all comove substantially and universally, consistent with our observation in the COVID-19 recession. We also apply the shocks to the production functions with non-unitary elasticity as in Atalay (2017). The results remain robust, the common shock

[35] As shown in Figure E.6 of Appendix E.4 there is a decline in the average productivity and financial shock. The decline is milder compared to that in the GR. Also, in Figure E.7, we observe a large variation across pairs in the correlations of two shocks. As in Section 2.1, we use 1978-1985 as the in-recession window and 1983-1989 as the post-recession window.

[36] Notably, we assume that the economy's structure of the early 1980s was similar to that before the Great Recession. This is a rather strong assumption, but it allows us to focus on the data-generating process rather than on the economic structure change over time.



(a) Growth rate: real GDP per capita

(b) Kernel density of pairwise correlation

Note: Sectoral productivity and financial shocks are backed out to match sectoral sales and spreads annually for 1978-1989. 1978-1985 is used as the in-recession window and 1983-1989 as the post-recession window.

Figure 8

The Early 80s Recession: endogenous vs exogenous trade credit

shifts sectoral comovement regardless of the degree of sectoral interconnectedness.

6 Conclusion

We document a defining feature of sectoral comovement over the business cycle in the US. The distribution of sectoral output growth correlations, conditional on aggregate GDP, is acyclical, except during the Great Recession, when it shifted significantly to the right. In other words, sectoral comovement does not significantly change during economic recessions but rises during financial crises. We use sectoral and firm-level data to show that input-output linkages and trade credit (TC) adjustment are key in driving comovement during financial crises.

We then construct a multisector model with endogenous TC adjustment and highlight the importance of TC adjustment in driving sectoral comovement during post-war US recessions. Our model emphasizes the asymmetric role of TC. When financial conditions are loose, suppliers with “deep pockets" have incentives to extend more TC to clients facing tighter financial conditions. However, when financial conditions are adverse to suppliers, too, TC provision collapses. We show that this mechanism is crucial in explaining the significant increase in sectoral comovement during the Great Recession in the US. Moreover, through this mechanism, our model suggests that TC amplifies the effect of financial shock on GDP growth. Using our model, we show that during the early

1980 recession, comparable to the Great Recession in magnitude, TC acted as a cushion that mitigated negative spillovers, prevented the shift in comovement, and mitigated the recession.

More generally, our paper emphasizes the relevance of considering the internal propagation forces and the endogenous TC chain when interested in aggregate and sectoral dynamics. Our results have important implications for business cycle stabilization policies. In particular, mild sectoral financial shocks in our model can generate large sectoral cascades compared to a model with exogenous TC. A milder and well-targeted stabilization policy should stabilize the macroeconomy in the presence of negative financial shocks.

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Online Appendix (not for publication)

A Data Description

A.1 Sectors' characteristics

For the annual outputs, we use the nominal gross output by industry, provided by the Bureau of Economic Analysis (BEA), adjusted for sectoral chain-type price indexes. For the quarterly outputs, we use the real gross output by industry (seasonally adjusted at annual rates). The quarterly series began in 2005Q1, while the annual series began in 1947. After excluding the agriculture, forestry, fishing and hunting (AFFH), finance, insurance and real estate (FIRE), and public sectors, our sample consists of 57 sectors and 1596 pairs.

The list and characteristics of the sectors are shown in Table E.2. All pairwise correlations of output growth are calculated using equation (A.1). The periods 2005Q3-2007Q2, 2007Q3-2009Q2, and 2009Q3-2011Q2 represent the times before, during, and after the Great Recession, respectively. $\overline{corr}_{before}$, $\overline{corr}_{in}$, and $\overline{corr}_{after}$ are the average correlations for the corresponding sector with all others.

The two-way or one-way linkages indicate the number of sectors with which the corresponding sector has a trading relationship. Two sectors are classified as part of the two-way trading group if they are both input suppliers and clients to each other. They are classified as part of the one-way trading group if only one sector supplies inputs to the other.

The consumption share for each sector is equal to the share of personal consumption expenditure over the sum of total intermediate input and personal consumption expenditure.

The ratio of accounts receivable to average sales between the current and past quarters (the AR-to-sales ratio) is calculated to measure the intensity of trade credit (TC) provision, while the ratio of accounts payable to average operating cost (the AP-to-OC ratio) measures the intensity of TC reception. We take the median value of both ratios for each firm from Compustat over 2005Q3–2006Q2 and 2008Q3–2009Q2, calculate the first difference between these two windows, and use the median as the representation for each sector with more than three firms. The median decline in the AR-to-sales ratio and the client's AP-to-OC ratio are -1.6 and -1.0 percentage points, respectively.

A.2 Measurement for sectoral comovements

The correlation of real GDP growth between two countries is commonly used to study business cycle comovement across countries (see, for example, Frankel and Rose, 1998; Clark and van Wincoop, 2001). In this study, we apply a similar measure, the pairwise correlation of gross output growth between two sectors, to examine intersectoral comovement. We calculate the growth rates of sectoral outputs and then determine the correlation of these growth rates between any pair of sectors over a specified time window, as follows:

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

where i and j with $i \neq j$ represent two different sectors; $\mathcal{T}$ is the time window; Δy_{it} is the output growth rate from the previous period at time t; and $\overline{\Delta y_i}$ and $\mathbf{std}(\Delta y_i)$ are, respectively, the sample mean and standard deviation over $\mathcal{T}$. For this analysis, we use a time window $\mathcal{T}$ of eight consecutive periods (either quarters or years) unless otherwise specified. Li and Martin (2019) use the same measurements for sectoral comovement but over a different time window. In this study, we use an eight-year time window and also test six- and ten-year time windows. The main results are robust across these time windows.

Previous literature, such as Christiano and Fitzgerald (1998), Hornstein (2000), and Kalemli-Ozcan et al. (2013), introduce another approach to measuring comovements. They regress one sector's employment on another's and use the R^2 value to measure comovement, assessing how much one sector's employment can be explained by the other's. Both approaches are similar, but theirs is normalized only by the standard deviation of the targeted sector, while ours accounts for the variation in both sectors.

A.3 Compustat

Following Kahle and Stulz (2013), we use the 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 a market capitalization less than \$50 million and with a book value of assets less than \$10 million;
- firms with a quarterly asset or sales growth greater than 100% at some point during the sample period; and
- observations which have cash and marketable securities greater than total assets.

Table A.1 displays the summary statistics of all selected firms.

Table A.1
SUMMARY STATISTICS OF SELECTED COMPUSTAT FIRMS

		Before		**During**		**Difference**	
	Obs	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

A.4 Syndicated loan from Dealscan

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

- firms not incorporated in the US;
- all financial firms (firms with standard industrial classification(SIC) codes between 6000 and and 6999);

- loans due before October 2008;
- the main purpose of loans is not working capital or corporate purpose

B Additional Sectoral Evidence

B.1 Pairwise correlations during US post-war recessions

By regressing the logarithm of sectoral output on the logarithm of the US GDP, our approach implicitly accounts for the duration of recessions. However, since the duration of each recession within the fixed time window varies, we adjust the length of our time window to explicitly account for this variation. Direct comparisons across different time windows are not possible due to differing statistical properties. Therefore, we standardize each sequence to the level prior to the Great Recession. As shown in Figure B.1, our results remain robust, consistent with Panel (b) of Figure 1.

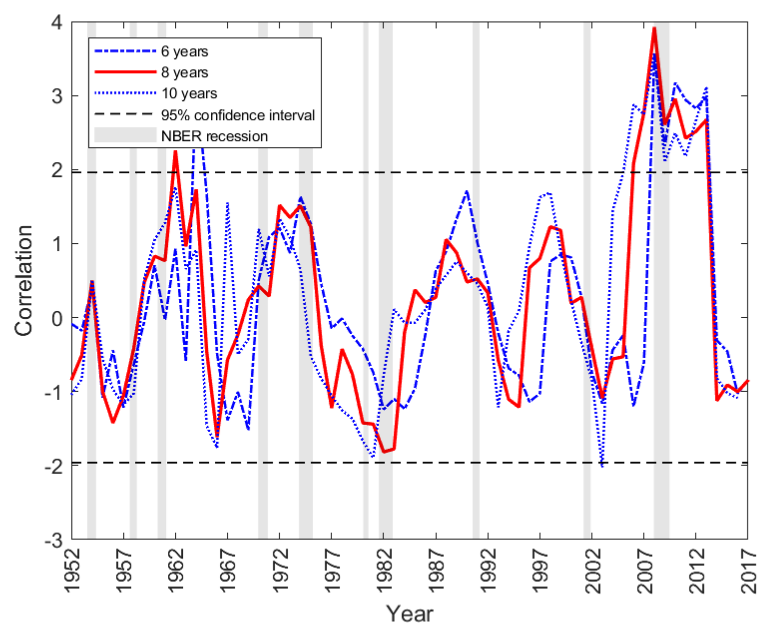
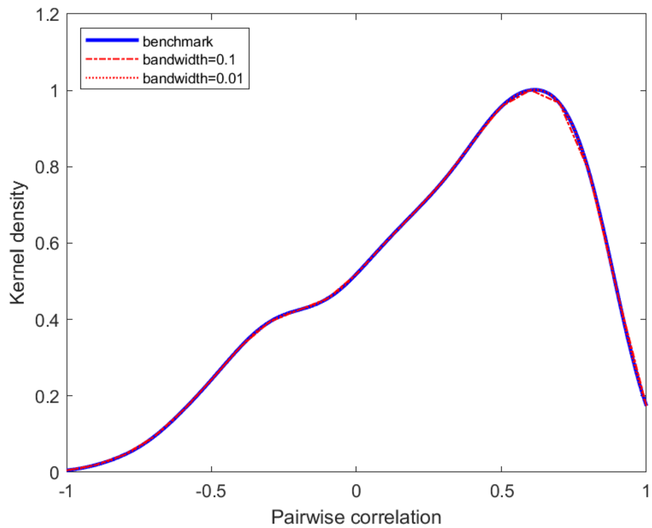


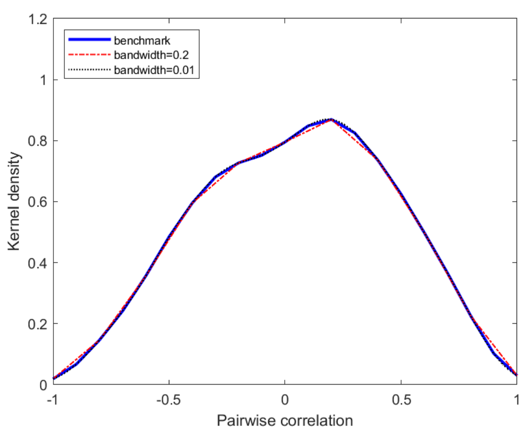
Figure B.1
Median of pairwise correlation standardized to pre-GR

To estimate the kernel density, we use Silverman's rule of thumb for bandwidth selection, given by $1.06\hat{\sigma}n^{-1/5}$, where $\hat{\sigma} = 0.4$ is the standard deviation of the pairwise correlations before the Great Recession, and $n = 1596$ is the number of pairs in our sample. As a robustness check, we also use bandwidth values of 0.2 and 0.01. As shown in Figure

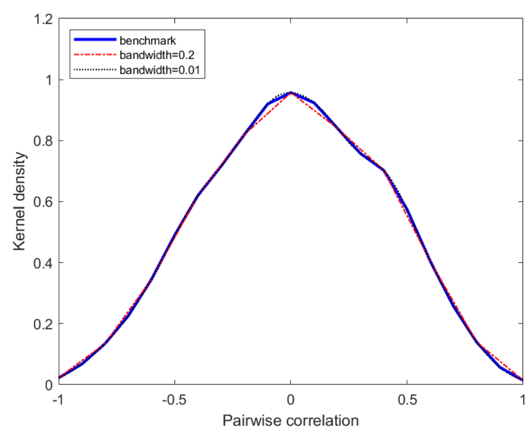
B.2, the three kernel density estimates mostly overlap, with the one using a bandwidth of 0.01 showing a slightly smoother peak compared to the other two.



(a) during GR



(b) before GR



(c) after GR

Figure B.2
Kernel density during GR with different bandwith

As shown in Figure 2 in Section 2.1, we compare the kernel density of pairwise correlations for eight US recessions after WWII: the 1960, 1970, 1973, 1990, and 2001 recessions, the combined 1980 and 1981-1982 recessions, the Great Recession, and the COVID-19 recession. These correlations are calculated with annual growth over eight years, starting three years before each recession. For comparison, we use the periods 1962-1968, 1983-1989, 1992-1999, 2002-2007, and 2011-2018 to represent the pre-1970, post-1980 (pre-1990), post-1990 (pre-2001), post-2001 (pre-Great Recession), and post-Great Recession (pre-COVID-19) periods, respectively. These time windows are selected to avoid any overlap with recession years. Unfortunately, we could not find a suitable time window for comparison with the 1973 recession.

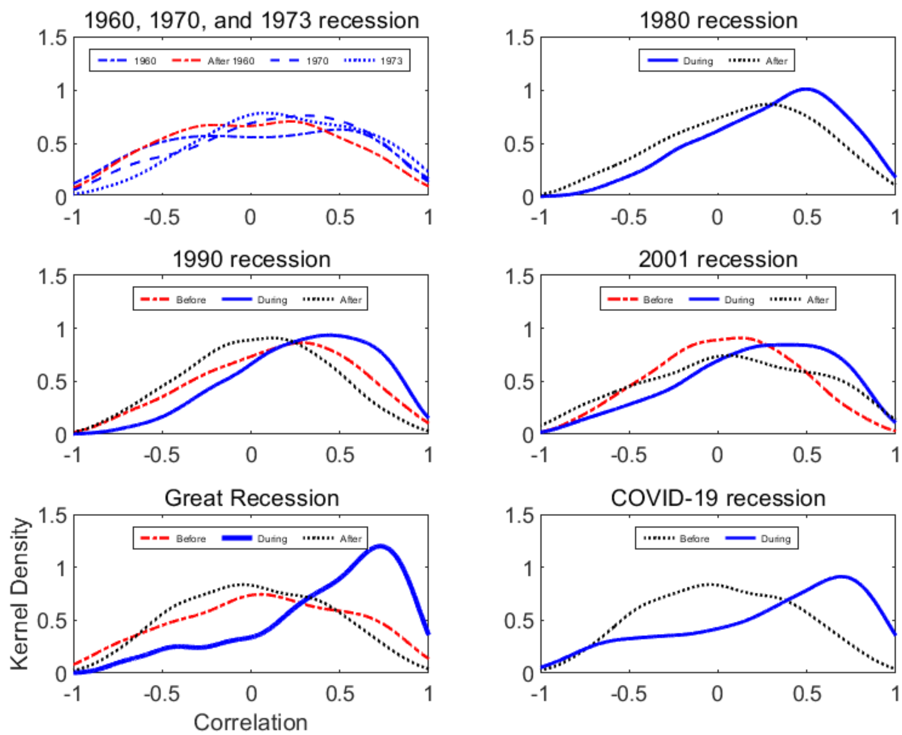


Figure B.3
Kernel density of pairwise correlation in US recessions (Unconditional correlations)

Figure B.3 shows the kernel density of unconditional pairwise correlations, while Figure B.4 displays the kernel density after removing the aggregate component. Table B.1 presents the summary statistics and results for the mean difference of the two-sample t-test and the KS statistics (with p-values in parentheses). Consistent with the findings in Figure 1, the density shifts only slightly to the right, if at all, before the 2008 recession. However, the density shifts significantly to the right during the Great Recession.

Following Chari et al. (2007), we closely examine the 1980 recession as a contrast with the Great Recession since the overall economy experienced a slightly smaller but comparable decline in GDP. In 1982, real GDP dropped by 1.9%, with the steepest decline of 6.5% occurring in Q1 1982. In comparison, real GDP contracted by 2.7% in 2008, with the largest contraction of 8.2% in Q4 2008. However, during the 1980 recession, we do not

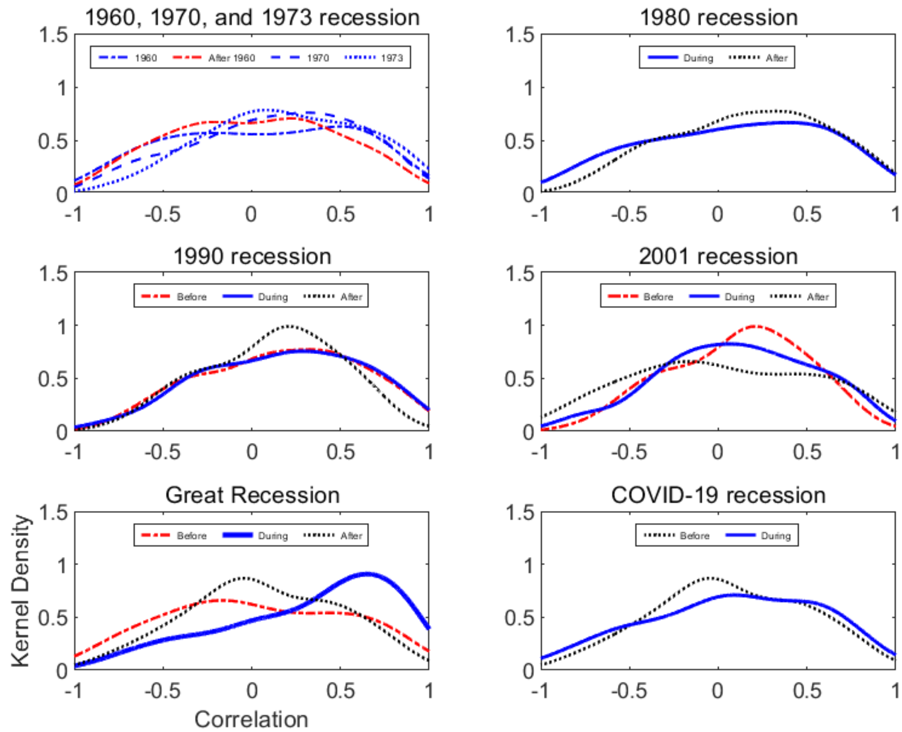


Figure B.4
Kernel density of pairwise correlation in US recessions (Conditional correlations)

observe a shift in the density of pairwise correlations as pronounced as the GDP decline. Furthermore, after filtering out the aggregate component, the comovement disappears, and some pairs even moved in opposite directions, indicated by the density having a fat left tail. Both the t-test and KS test fail to reject the null hypothesis.

During the COVID-19 recession, we observe a significant unconditional rise in sectoral comovement, increasing from 0.01 before the recession to 0.33 during it. However, after controlling for GDP, this increase in comovement disappears.

B.2 Role of IO linkage in the other recessions

We apply the same classification for sector pairs as in Section 2.2 to all other recessions. Figure B.5 presents the kernel densities for three groups, comparing them before and after the recessions.

First, the kernel density for the three groups does not change during the 1960 and 1970 recessions. Second, the two-way and one-way trading groups shift modestly to the right during the 1980 and 1990 recessions. These two groups account for most of the rise

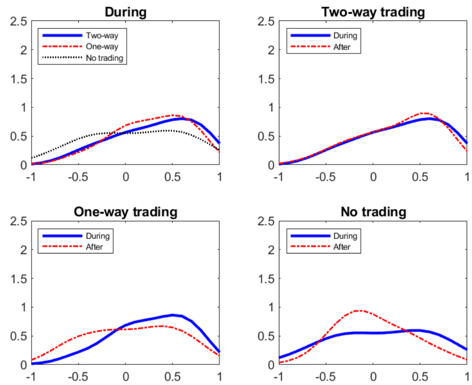
Table B.1

Summary statistics: conditional pairwise correlations (annual growth)

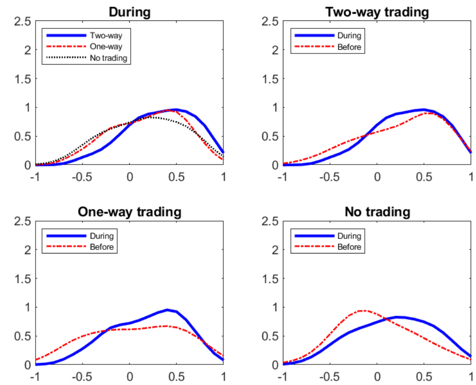
	Unconditional			Conditional		
	Mean	Median	KS Stat (CV*)	Mean	Median	KS Stat (CV)
The 1960 recession						
During	0.27	0.32		0.05	0.09	
After	0.16	0.19	0.09(0.09,0.21)	0.00	0.01	0.09(0.09,0.21)
The 1970 recession						
Before	0.16	0.19	0.08(0.09,0.21)	0.00	0.01	0.08(0.09,0.21)
During	0.24	0.28		0.07	0.08	
The 1973 recession						
During	0.36	0.39		0.09	0.12	
The 1980 recession						
During	0.30	0.35		0.01	0.01	
After	0.14	0.17	0.01(0.09,0.21)	0.09	0.09	0.01(0.09,0.21)
The 1990 recession						
Before	0.14	0.17	0.02(0.09,0.21)	0.09	0.09	0.02(0.09,0.21)
During	0.29	0.33		0.08	0.08	
After	0.03	0.05	0.04(0.09,0.21)	0.06	0.09	0.04(0.09,0.21)
The 2001 recession						
Before	0.03	0.05	0.01(0.09,0.21)	0.06	0.09	0.01(0.09,0.21)
During	0.24	0.29		0.06	0.07	
After	0.07	0.08	0.07(0.09,0.21)	0.02	0.00	0.07(0.09,0.21)
The Great Recession						
Before	0.07	0.08	0.14(0.09,0.21)	0.02	0.00	0.14(0.09,0.21)
During	0.41	0.52		0.14	0.21	
After	0.01	0.00	0.17(0.09,0.21)	0.03	0.03	0.17(0.09,0.21)
The COVID-19 recession						
Before	0.01	0.00	0.08(0.09,0.21)	0.03	0.03	0.08(0.09,0.21)
During	0.33	0.46		0.04	0.05	

Notes: *The critical values of the KS statistics (CV), for a 5% significance level, are reported in parenthesis. These critical values adjust for the presence of autocorrelation in the data, following Lanzante (2021). The first element of the parenthesis is the critical value for mild underlying autocorrelation (AR(1) parameter of 0.6). The second value in the parenthesis is the critical value for high underlying autocorrelation (AR(1) parameter of 0.9).

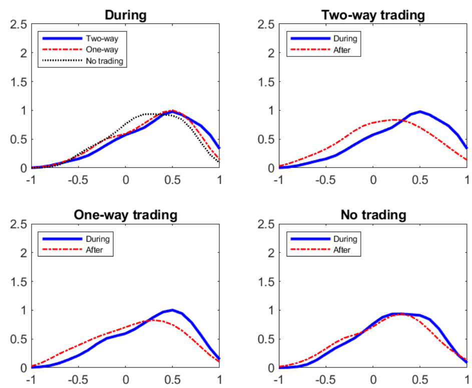
in unconditional correlations, similar to, but not as pronounced as, that during the Great Recession. Third, the three groups during the Great Recession exhibit the same pattern observed with quarterly growth. Fourth, during the COVID-19 recession, comovement among the three groups increased significantly, with the rise in comovement being similar in scale for all sector pairs, regardless of their degree of interconnection.



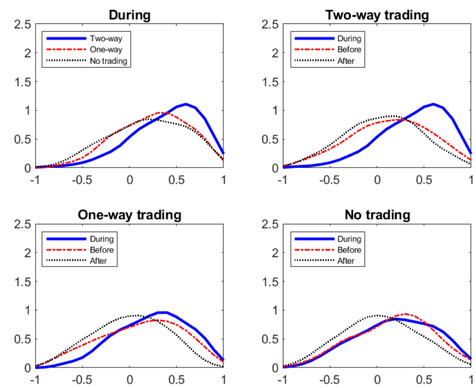
(a) the 1960 recession



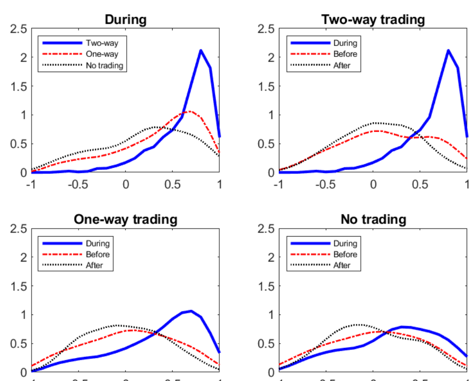
(b) the 1970 recession



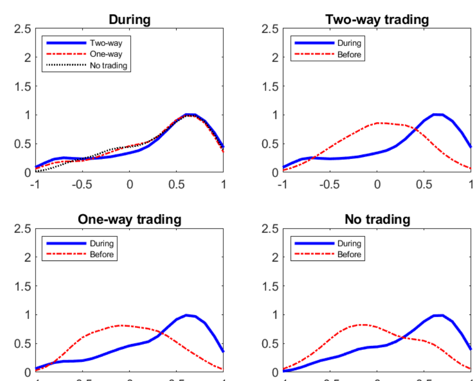
(c) the 1980 recession



(d) the 1990 recession



(e) the Great Recession



(f) the COVID-19 recession

Figure B.5

KERNEL DENSITY OF UNCONDITIONAL CORRELATION BY INTERCONNECTEDNESS

B.3 Role of trade credit in the no-trading group

Following the categorization in Section 2.3, a pair is considered to have experienced a trade credit decline during the Great Recession (henceforth, the TC-declined group) if both the supplier's AR-to-sales ratio and the client's AP-to-OC ratio declined more than the corresponding median values across all public firms, which are -1.6 and -1.0 percentage points, respectively. Otherwise, the pair is categorized as part of the unchanged group (henceforth, the TC unchanged group). Notably, in the no trading group, a pair is classified into the TC declined group if the TC decline condition is met in either direction. Figure B.6 reports the results. No significant shift is observed in either subgroup, whether during, before, or after the Great Recession.

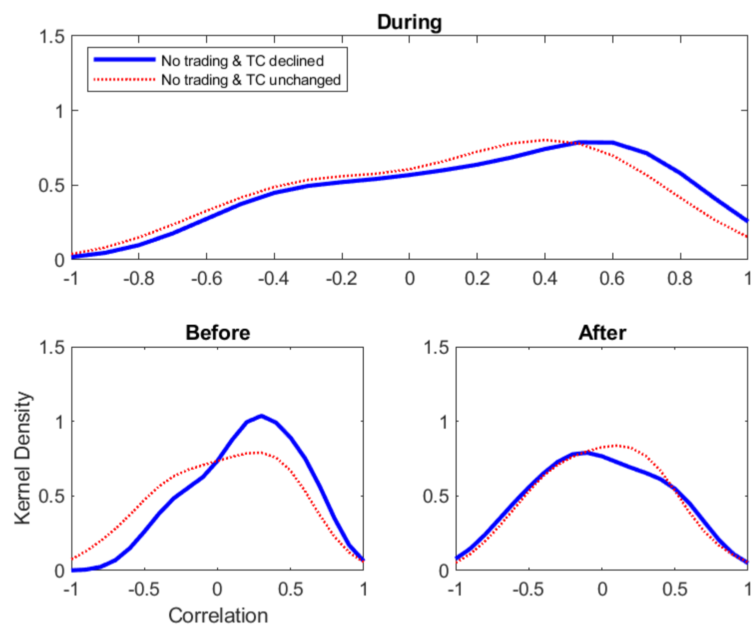
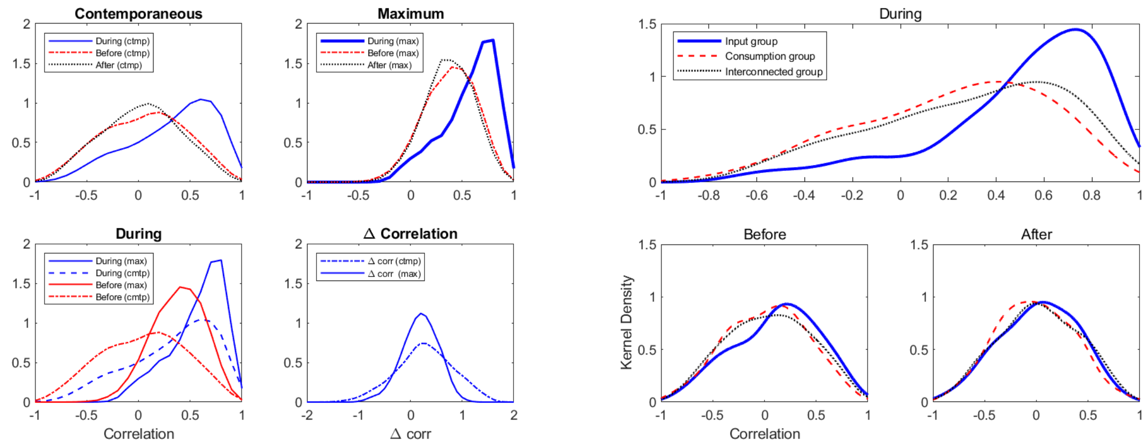


Figure B.6
KERNEL DENSITY FOR NO TRADING GROUP BY THE TC SUBGROUP

B.4 Robustness check

Due to delivery delays, adjustment costs, search frictions, and other factors, two sectors may not comove contemporaneously; instead, one may lead the other. Therefore, the rise in sectoral comovement during the Great Recession may result from synchronization in timing. In addition to contemporaneous correlation, we calculate one-period lagged and lead correlations and then take the maximum value among the three. Panel (a) of Figure

B.7 reports the results before, during, and after the Great Recession. We find that: 1) the maximal correlations still significantly rose during the Great Recession; 2) the maximal correlations are higher than the contemporaneous ones before, during, and after the Great Recession; and 3) the rise in maximal correlations is more concentrated than that of the contemporaneous correlations, with the latter having fatter right tails.



(a) Maximum and contemporaneous correlations

(b) Consumption exposure subgroups

Figure B.7

Kernel density of unconditional correlation by interconnectedness

We further divide our sample of sectors into two groups based on the share of output used for final consumption. Table E.2 provides the specific values. A sector is classified into the consumption-provider group if its share is larger than the median value of 36.8%. Otherwise, the sector is grouped as an input provider. Panel (b) of Figure B.7 shows the results. Only the kernel density of the input-provider group significantly shifts to the right.

C Firm-level evidence on role of trade credit

Given that the Great Recession is the only financial crisis in the US post-World War II, we explore the cross-sectional variation among US public firms during this period, using the collapse of Lehman Brothers (LB) as a quasi-natural experiment. We then examine whether and how TC played an asymmetric role in transmitting or mitigating shocks within the production network during the Great Recession.

C.1 Data and sample selection

We first construct a firm-to-firm production network using Form 10-K, following the method in Garcia-Appendini and Montoriol-Garriga (2013). We identify 641 supplier-client pairs, comprising 426 suppliers and 176 clients. To establish relationships between listed firms and LB, we use syndicated loan data from DealScan. Following Ivashina and Scharfstein (2010), we select firms for which LB led or joined a syndicated loan before its collapse. Additionally, in line with the literature on financial networks, such as Allen and Gale (2000), Elliott et al. (2014), and Acemoglu et al. (2015), among others, we identify lenders that share a direct financial network with LB through the syndicated loan market. Thus, a firm is considered indirectly connected to LB if it did not borrow directly from LB but from lenders connected to LB. Overall, we have 19 out of 426 suppliers directly connected to LB; 237 indirectly connected through their lenders; and 150 without a connection to LB through the syndicated loan market. Among the 176 clients, 40 borrowed directly from LB; 120 were indirectly connected; and 16 had no relationship with LB. It is important to note that we classify these firms based only on information from the syndicated loan market and do not exclude any other potential financial connections they may have had with LB.

We use the Compustat database to acquire financial variables for the listed firms, with summary statistics displayed in Table C.1. We calculate pairwise correlations at the firm level, finding a significant increase of 0.17 during the Great Recession, consistent with our sector-level findings. We select financial variables, using median values from 2005Q3-2006Q2 and 2008Q3-2009Q2 to represent periods before and during the Great Recession, respectively. Before the recession, compared to the average firm in Compustat, the suppliers in our sample are smaller in terms of total assets, extend less TC, and hold more cash, whereas the clients are larger, receive less TC, and have less cash. This is mainly because the suppliers report the clients as their top 10 clients in Form 10-K. As observed in the QFR data, smaller firms rely more on TC, leading to a smaller decline in clients' TC compared to the suppliers' TC. Consistent with Kahle and Stulz (2013), we find that typical financial variables, such as ratios of investment, cash, and short-term and long-term debt over total assets for suppliers and clients before and during the recession, are not significantly different. The size of firms, in terms of sales and total assets, also shows little difference over the two periods. However, profitability and growth perspectives (growth rates of sales and total assets) are significantly lower during the recession. This decline is reflected in their market value, resulting in a lower Tobin's Q during the recession.

Table C.1
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)
CR	452	1.07	0.86				
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)
CR	185	0.66	.71				

C.2 Trade credit provision and reception during the Great Recession

We use data from US public firms in Compustat to study the evolution of trade credit, calculating the AR-to-sales and AP-to-OC ratios as defined in Section 2.3. These ratios are then adjusted for seasonality using moving-average methods at the firm level. Figure C.1 shows the evolution of the median values for both ratios from 1980Q3 to 2016Q3. The ratios exhibit modest fluctuations over time, even during the 1990 and 2001 recessions. During the Great Recession, both ratios initially increased but then plummeted by approximately 10 to 20 percentage points starting in 2008Q3. This pattern suggests that, in addition to reduced demand for inputs, more firms began requesting upfront payment for new orders and wrote off existing trade credit. This finding is consistent with evidence from Costello (2020) for the US during the Great Recession and Love et al. (2007) for the Mexican crisis in 1994 and the Asian flu in 1997.

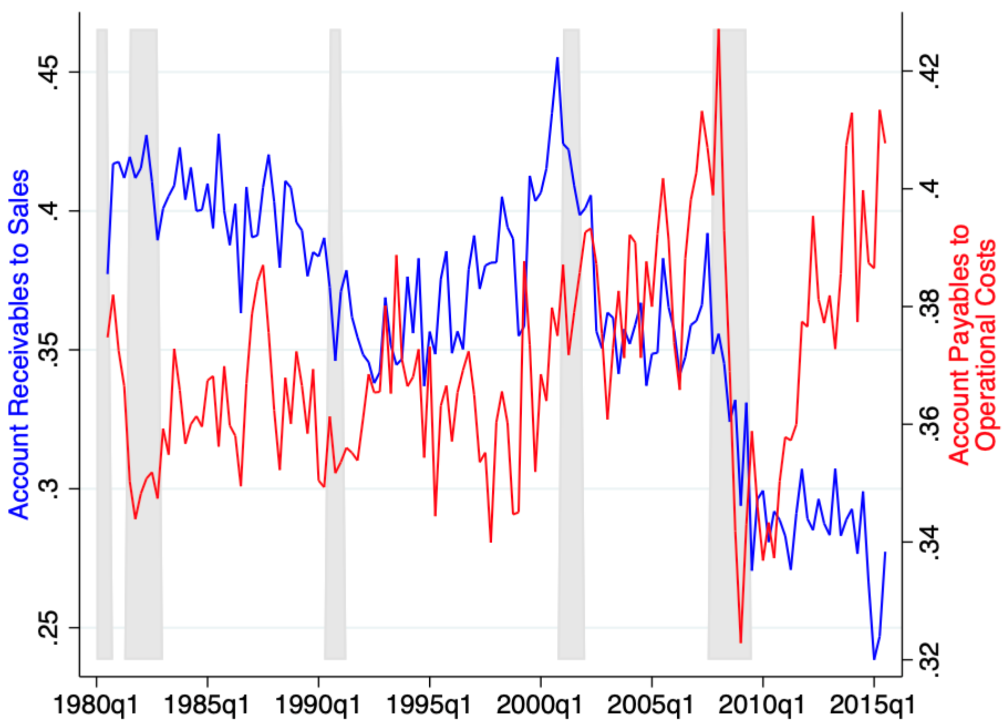


Figure C.1
Evolution of Intensities of Trade Credit Provision and Reception

We then test how the clients' financial positions responded to the LB shock. In particular, we regress the change in financial measures on whether the clients were directly or indirectly connected to LB before its collapse, along with other control variables, as

$$\Delta y_j = \alpha_0 + \alpha_1 \mathbf{1}^{LB}_{j,dir} + \alpha_2 \mathbf{1}^{LB}_{j,indir} + \gamma \Delta X_j + \beta y_{j,before} + \epsilon_j, \tag{C.1}$$

where j is an index for a client; y is the financial variable of interest; Δ stands for the first difference; $\mathbf{1}^{LB}_{j,dir}$ 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 C.1; and ΔX is the first difference between the in and pre-recession median of X.

Table C.2 presents the point estimates for equation (C.1), with robust standard errors reported in parentheses. Column (1) shows that in the regression of the AP-to-OC ratio, the coefficient for the indicator of a direct connection to LB is negative and statistically significant, indicating a 6.5-percentage-point decrease in the ratio for LB-connected clients. This suggests that, during the recession, either LB-connected clients wrote off some of the existing trade credit, or their suppliers deferred a smaller proportion of new sales as trade credit. The coefficient for the indirect connection is negative but not statistically significant. This may be because other lenders connected to LB absorbed the shocks, preventing systematic transmission to their own borrowers.

Table C.2
Regression Results of equation (C.1)

	$\Delta\frac{AP_j}{OC_j}$	$\Delta\frac{AR_j}{sales_j}$	$\Delta\frac{debt_j}{TA_j}$	$\Delta\frac{cash_j}{TA_j}$
	(1)	(2)	(3)	(4)
$\mathbf{1}^{LB}_{j,dir}$	-6.52***	-.981	3.15	-8.05***
	(.956)	(3.15)	(2.73)	(1.68)
$\mathbf{1}^{LB}_{j,indir}$	-6.55	3.2	3.07	-6.55***
	(4.81)	(2.93)	(2.21)	(1.26)
obs	58	58	58	58
adjusted R^2	.477	.352	.321	.416

Notes: $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$.

In columns (2)-(4), we analyze other short-term financial measures, such as the AR-to-sales ratio, short-term debt, and the cash ratio. The LB shock shows no significant effects on the AR-to-sales and short-term debt ratios. However, compared to the average cash-to-assets ratio of 10.7% before the recession, LB borrowers experienced a sharp decline in cash, while LB-unrelated firms increased their cash holdings by 8.7 percentage points (the point estimate of the constant term). This result aligns with Kahle and Stulz (2013), who found that, compared to firms with low leverage, bank-dependent firms did not decrease net debt issuance and instead hoarded cash during the recession.

C.3 Transmission of the LB Shock

We investigate whether and how the pairwise correlation between two firms responds to the LB shock through the TC channel. Specifically, we calculate the first difference of pairwise correlations between two periods to eliminate fixed effects associated with suppliers, clients, and pairs. By comparing the change in the correlation of a common supplier with different clients, our approach resembles a difference-in-difference framework, reducing the likelihood that time-varying unobservables, other than the connection to LB, affect the change in comovement over time. Our empirical strategy is specified as follows:

$$\Delta\mathbf{corr}_{ij} = \alpha_0 + \alpha_1 \mathbf{1}_j^{LB} + \alpha_2 \mathbf{1}_j^{LB} \times \Delta\frac{AP_j}{OC_j} + \gamma D_i + \beta' \Delta X_j + \epsilon_{ij}, \tag{C.2}$$

where i and j are, respectively, indexes for the supplier and client; $\Delta\mathbf{corr}_{ij}$ is the change in the pairwise correlation before and during the recession; $\mathbf{1}_j^{LB}$ is the indicator that the client j is either directly or indirectly connected to LB; D_i is the dummy variable for the supplier i; and X are characteristics for a firm j, including the first-difference of financial measurements listed in Table C.1. To highlight the role of TC in propagating and amplifying the LB shocks, we incorporate the interaction term of the LB indicator and the change in the AP-to-OC ratio. Since clients connected to LB experienced a contraction in TC, on average, a negative coefficient is expected for the interaction term, which implies that the TC channel amplifies the LB shock. Last, we add the dummies for the suppliers to control the time-varying effects for suppliers.

Table C.3 reports the point estimates. Column (1) exhibits the results of the benchmark model in equation (C.2). We find that, during the Great Recession, the correlation of a supplier with its client connected to LB increased more, by 0.88, than that of an unconnected one. Such a rise is higher than the sample average (0.17) by a factor of 5.2. Also, the coefficient of the interaction term is negative and statistically significant, implying that the TC channel indeed amplified the LB shock after the collapse of LB and increasing the comovement between the two firms.

We also test whether clients that relied more on TC before the Great Recession comoved more during the Great Recession. In doing so, we replace the change in AP-to-OC ratio in equation (C.2) with the pre-recession ratio AP_j^{pre}/OC_j^{pre}. The point estimates in column (2) show that the level of the pre-recession ratios fails to predict the change in pairwise correlations. Lastly, we perform a 'placebo test' by comparing the change in cor-

Table C.3
POINT ESTIMATES FOR EQUATION (C.2)

	Δ**corr**$_{ij}$	placebo test	
	(1)	(2)	(3)
$\mathbf{1}^{LB}_{j,dir}$	.875*	-.172	-.167
	(.345)	(1.12)	(.296)
$\mathbf{1}^{LB}_{j,indir}$	.687^	-.501	-.0439
	(.36)	(1.15)	(.3)
$\mathbf{1}^{LB}_{j,dir} \times \Delta \frac{AP_j}{OC_j}$	-.393**		
	(.143)		
$\mathbf{1}^{LB}_{j,indir} \times \Delta \frac{AP_j}{OC_j}$	-.392**		
	(.142)		
$\mathbf{1}^{LB}_{j,dir} \times \frac{AP^{pre}_j}{OC^{pre}_j}$		.00736	
		(.0177)	
$\mathbf{1}^{LB}_{j,indir} \times \frac{AP^{pre}_j}{OC^{pre}_j}$		.00952	
		(.018)	
obs	148	148	150
adjusted R^2	.125	.0881	.0522

Notes: $^{+}p < 0.10$ $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$.

relations between two regular periods, namely 2003Q3-2005Q2 versus 2005Q3-2007Q2. As shown in column (3), we do not find evidence that the control and the treatment group had pre-existing differences in comovement before the Great Recession.

D Model details: proof of propositions and lemmas

D.1 Solutions

The first-order conditions on consumption and labor supply yield

$$pc = \frac{w}{\psi l^{\xi}}. \tag{D.1}$$

It is straightforward to show that the RC constraint is binding in equilibrium since the marginal benefit of raising the penalty payment is positive, while the marginal cost is zero. Also, because efforts are costly, suppliers will make enough effort to induce clients to report the true status. This implies that the ICC constraint is also binding. Given the form of the probability, we have the $e_{ij} = \bar{e}_i \left(\frac{tc_{ij} q_{ij} m_{ij}}{(1-\theta_j)\omega_{ij} v_j p_j y_j} \right)^2$. The Lagrangian for Problem

(3) is given by

$$\begin{aligned}\mathcal{L} \quad = \quad & p_i z_i \left(\prod_{j=1}^{n} m_{ji}^{\omega_{ji}}\right)^{\nu_i} l_i^{\alpha_i} - \sum_{h=1}^{n} \left(p_i - (1-(1-\eta)tc_{ih})q_{ih}\right) m_{ih} \\ & -wl_i - \sum_{j=1}^{n} \left(1-(1-\eta)tc_{ji} + (1-\eta)\gamma \frac{p_j}{q_{ji}}\right) q_{ji} m_{ji} \\ & -(1-\eta)\bar{e}_i \sum_{h=1}^{n} \left(\frac{tc_{ih} q_{ih} m_{ih}}{(1-\theta_h)\omega_{ih}\nu_h p_h y_h}\right)^2 q_{ih} m_{ih} + \mu_i \left(\theta_i p_i z_i \left(\prod_{j=1}^{n} m_{ji}^{\omega_{ji}}\right)^{\nu_i} l_i^{\alpha_i}\right. \\ & \left. z + \sum_{h=1}^{n} (1-tc_{ih}) q_{ih} m_{ih} - wl_i - \sum_{j=1}^{n} (1-tc_{ji}) q_{ji} m_{ji}\right) \\ & + \sum_{h=1}^{n} \lambda_{ih} \left(\gamma p_i - d_{ih} q_{ih} - \eta(1-d_{ih}) q_{ih} - (1-\eta)(\gamma - \theta_i) p_i\right)\end{aligned} \tag{D.2}$$

D.2 Proof of Lemma 1

Proof. Taking the derivatives of equation (D.2) with respect to l_i and m_{ji}, we have the first order conditions as in equation (10) and (11), and then use equation (1) to derive the solution for y_i as in equation (13). ■

D.3 Proof of Proposition 1

Proof. Since the RC constraint is binding, we have $g_{ih} = \omega_{ih}\nu_h p_h y_h$. Under the assumption that all CC constraints are binding, we obtain the penalty payment as in equation (17). Taking the solution of m_{ij} from Lemma 1 as given, we have $\frac{tc_{ih} q_{ih} m_{ih}}{(1-\theta_h)\omega_{ih}\nu_h p_h y_h} = \frac{tc_{ij} v_{ij}^M}{1-\theta_j}$. Since the firm has pricing power over the input client, we take the first-order conditions of q_{ij} as in equation (D.2). And the firm set the TC intensity to the extent that the no-arbitrage constraint, as shown in the NAC constraint is just binding. ■

D.4 Proof of Proposition 2

Proof. Combining equation (15) with (12) and (16), we have

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

At $tc_{ij} = 0$, we have the left-hand side (LHS) of equation (D.3) 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 that 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 sides, we have that tc_{ij} is decreasing in θ_j if g function is negative, where g function is given as

$$\begin{aligned} g\left(tc_{ij},\mu_i,\mu_j,\theta_j\right) \quad = \quad & \left(\frac{2\eta(1-tc_{ij})}{1+\eta\mu_j-(1-(1-\mu_j)\eta)tc_{ij}}+\right. \\ & \left.\frac{(1-tc_{ij})}{(1+(1-\eta)\gamma)\left(1-(1-\eta)tc_{ij}\right)\left(\mu_j+(1-\eta)\gamma\mu_i\right)(1-tc_{ij})}\right)\frac{\partial\,\mu_j}{\partial\,\theta_j} \\ & -\frac{2\theta_j}{\eta+\theta_j\mu_j}\frac{\partial\,\mu_j}{\partial\,\theta_j}-2\left(\frac{1}{1-\theta_j}+\frac{\mu_j}{\eta+\theta_j\mu_j}\right) \\ & +\frac{(1-\eta)\gamma(1-tc_{ij})}{(1+(1-\eta)\gamma)\left(1-(1-\eta)tc_{ij}\right)+\left(\mu_j+(1-\eta)\gamma\mu_i\right)(1-tc_{ij})}\frac{\partial\,\mu_i}{\partial\,\theta_j} \end{aligned} \tag{D.4}$$

■

D.5 Sales Growth Decomposition

We examine how trade credit affects sales growth. First, let $\mathbf{D}_\alpha$ and $\mathbf{D}_\nu$ be the diagonal matrix for α and ν, 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

$$x_t = [x_{1t},\dots,x_{nt}]', \;\; for \;\; x \in \left\{p, y, z, sales, v^L,\right\} \tag{D.5}$$

$$x_t = [x_{11,t},\dots,x_{1n,t},\dots,x_{n1,t},\dots,x_{nn,t}]', \;\; for \;\; x \in \left\{tc, q, v^M\right\} \tag{D.6}$$

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

$$\Delta \log p_t = \frac{1}{1-\sigma}\left(\log\left(\left(\eta \mathbf{I}_n - \frac{1}{\eta\gamma}\mathbf{D}_\nu \mathbf{M}_{xt}\right) p_t \circ y_t\right) - \mathbf{1}_n \log\left(\mathbf{1}_n'\left(\eta \mathbf{I}_n - \frac{1}{\eta\gamma}\mathbf{D}_\nu \mathbf{M}_{xt}\right) p_t \circ y_t\right)\right) \tag{D.7}$$

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

$$
\mathbf{M}_{xt} = \begin{bmatrix} (1-(1-\eta)tc_{11,t})\,\omega_{11}v^M_{11,t} & \dots & (1-(1-\eta)tc_{1n,t})\,\omega_{1n}v^M_{1n,t} \\ & \ddots & \\ (1-(1-\eta)tc_{n1,t})\,\omega_{n1}v^M_{n1,t} & \dots & (1-(1-\eta)tc_{nn,t})\,\omega_{nn}v^M_{nn,t} \end{bmatrix}, \tag{D.8}
$$

and $p \circ y$ is the fixed vector for the following equation:

$$
\begin{aligned}
& \Delta\log(p_t \circ y_t) + \frac{1}{\sigma-1}(\mathbf{I}_n - \mathbf{D}_\nu\Omega')\Delta\log\left(\left(\eta\mathbf{I}_n - \frac{1}{\eta\gamma}\mathbf{D}_\nu\mathbf{M}_{xt}\right)p_t \circ y_t\right) \\
= \; & (\mathbf{I}_n - \mathbf{D}_\alpha - \mathbf{D}_\nu)^{-1}\Big(\Delta\log z_t + \mathbf{D}_\nu\mathbf{M}_\omega\Delta\log(1-(1-\eta)tc) + \mathbf{D}_\alpha\Delta\log v_t^L + \mathbf{D}_\nu\mathbf{M}_\omega\Delta\log v_t^M \\
& + \Delta\log\left(\mathbf{1}_n'\left(\eta\mathbf{I}_n - \frac{1}{\eta\gamma}\mathbf{D}_\nu\mathbf{M}_{xt}\right)p_t \circ y_t\right)\left(\frac{1}{\sigma-1}(\mathbf{I}_n - \mathbf{D}_\nu\Omega') - \frac{1}{1-\xi}\mathbf{D}_\alpha\right)\mathbf{1}_n - \frac{\xi}{1+\xi}\Delta\log\left(\mathbf{1}_n'\mathbf{D}_\alpha v^L \circ p_t \circ y_t\right)\mathbf{1}_n\Big)
\end{aligned}
$$

Moreover, using the first-order Taylor expansion, we can derive the left hand side of the equation above as

$$
\mathbf{LHS} = \left(\mathbf{I}_n + \mathbf{M}_{py}\right)\Delta\log(p_t \circ y_t) \tag{D.9}
$$

where the matrix $\mathbf{M}_p y$ is defined as

$$
\mathbf{M}_{py} = \frac{1}{\sigma-1}(\mathbf{I}_n - \mathbf{D}_\nu\Omega')\left(\eta\mathbf{I}_n - \frac{1}{\eta\gamma}\mathbf{D}_\nu\mathbf{M}_{xt}\right)\left(\mathbf{1}_n' \otimes \left(\eta\mathbf{I}_n - \frac{1}{\eta\gamma}\mathbf{D}_\nu\mathbf{M}_{xt}\right)(p_{t-1} \circ y_{t-1})\right)^{-1}, \tag{D.10}
$$

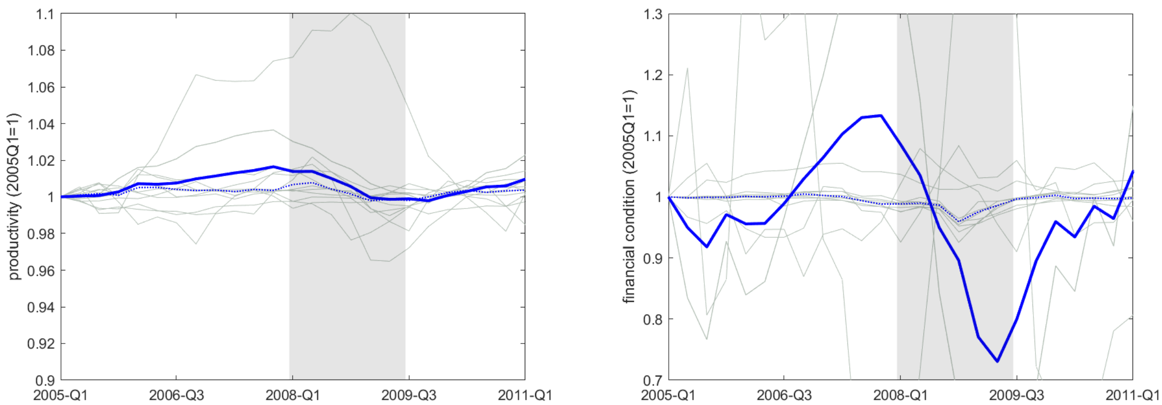
and $\circ$ is the Hadamard product; and $\otimes$ is the Kronecker product.

E More Results from Quantitative Analysis

E.1 More about calibrated shocks

Panel (a) of Figure E.1 depicts sectoral TFP normalized to 2005Q1, with each grey line standing for one sector and the solid and dashed blue line, respectively, standing for the weighted average (sales share in 2005 as weights) and median across all sectors. Compared to the pre-average between 2005Q3 and 2007Q2, manufacturing, retail and wholesale, and transportation experienced a large drop in productivity in 2008Q4 and 2009Q1. Panel (b) of Figure E.1 shows the normalized financial shocks. After the collapse of Lehman Brothers, compared to the pre-recession average, construction, manufacturing, and education and healthcare were hit the most in 2008Q4 and 2009Q1.

Once we impose the fixed trade credit on the economy, our model becomes one akin to Bigio and La'O (2020). In this case, the sectoral sales should highly comove with underlying shocks. In Figure E.2, 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



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

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

Figure E.1
NORMALIZED FINANCIAL AND PRODUCTIVITY SHOCKS (2005Q1=1)

and solid lines, respectively, stand for the kernel density before and during the Great Recession. Here we observe a modest rise in the comovement of productivity shocks during the Great Recession. In contrast, we also calculate the TFP implied by our model, as shown by 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 most of the rise in sectoral comovement observed in the data. As for financial shocks, we cannot observe a systematic rise in pairwise correlation during the Great Recession. Instead, for a few pairs of sectors, financial shocks indeed comoved during the Great Recession, as we observe a fat right tail, while other pairs stay more or less the same as before.

E.2 Fit of the model

Before performing a series of counterfactual exercises, we begin by verifying the ability of our calibrated model to match key empirical moments. First, we check its ability to match the real GDP per capita growth evolution for 2005-2011. In our model, real GDP is measured by aggregate consumption c. Figure E.3 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; the dark dashed line stands for the consumption growth; and the shaded area represents the Great Recession period defined by the NBER. The model-implied growth rate tracks both growth rates in

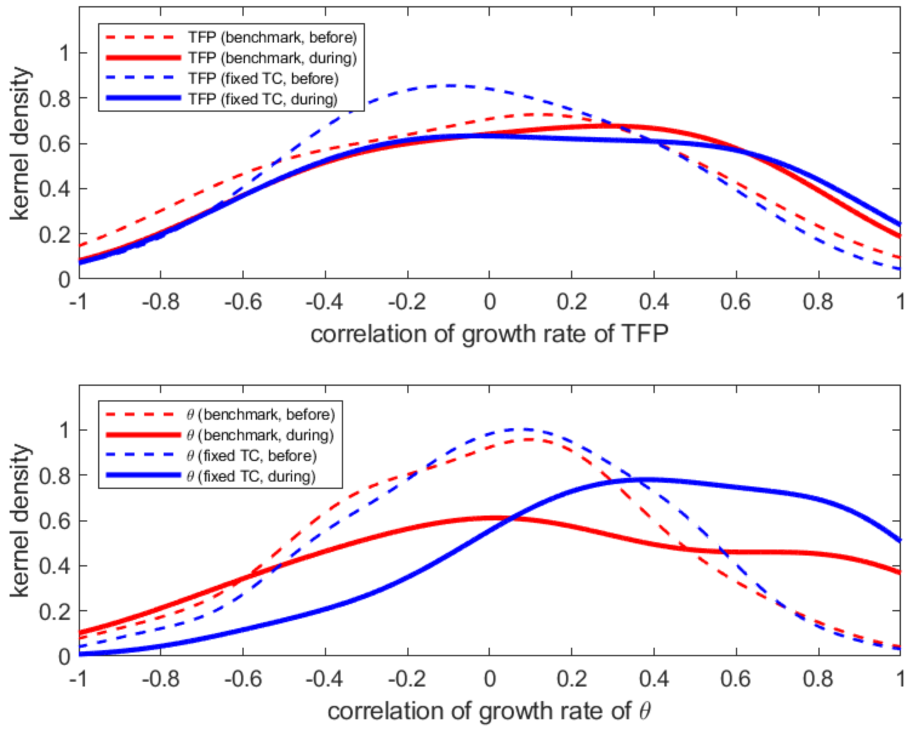


Figure E.2
Pairwise correlations of financial and productivity shocks

the data closely.

Second, we examine the model in matching sectoral trade credit issuance and reception. In the data, we take the median of AR-to-sales and AP-to-OC ratios between 2005Q3 and 2006Q2 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 $ap_i = \sum_{j=1}^{n} tc_{ji} q_{ji} m_{ji}$, where tc_{ij} is determined, for all i and j, by equation (D.3). Then, the AR-to-sales and AP-to-OC ratios implied by the model can be defined, respectively, as

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

$$\frac{ap_i}{oc_i} = \frac{\sum_{j=1}^{n} tc_{ji} q_{ji} m_{ji}}{wl_i + \sum_{j=1}^{n} q_{ji} m_{ji}}. \tag{E.2}$$

where operational costs are equal to the sum of the wage bill and input payments.

Panel (a) and (b) of Figure E.4 present scatter plots comparing both ratios for the model and the data before the Great Recession. The horizontal axis shows the data ratio,

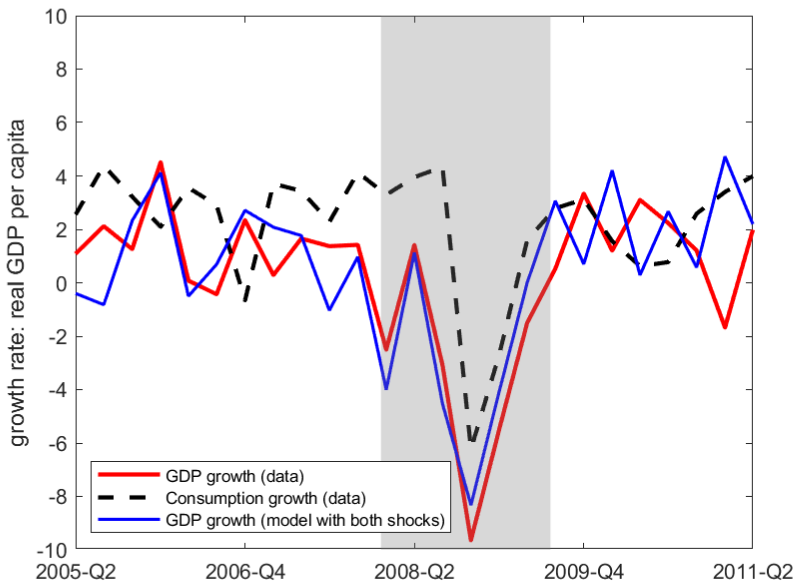
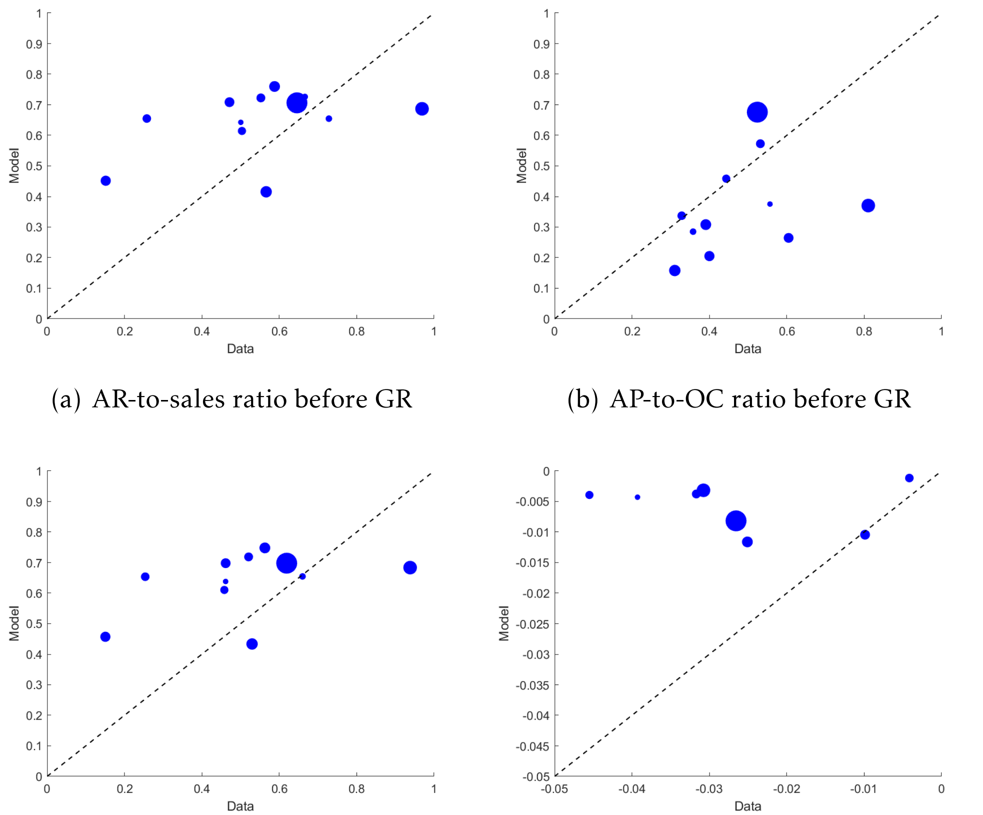


Figure E.3
Growth rate of real GDP per capita: model vs data

while the vertical axis displays the model-implied ratio. The size of each bubble represents the sector's relative size in 2005, and the black dashed line indicates the 45-degree line. Panel (a) illustrates the AR-to-sales ratios, with the horizontal axis representing the average ratio from 2005Q3 to 2007Q2, and the vertical axis showing the model-implied ratio in the steady state. Except for the mining and professional services sectors, all bubbles align closely with the 45-degree line. This indicates that our model effectively matches the data. The AR-to-sales ratio is used to calibrate the maximal efforts - i.e., $\{\bar{e}_t\}$. The model-implied ratios do not always align perfectly with the data due to the endogenously determined bilateral trade credit intensity.

Panel (b) compares the average AP-to-OC ratios with the steady-state ratios. These model-implied ratios, which were not specifically targeted, also align well with the data. Panel (c) presents the AR-to-sales ratio during the Great Recession, while Panel (d) shows the change in the AR-to-sales ratio from the period before the Great Recession to the recession itself. Similar to Figure C.1, we use the average ratio from 2008Q4 to 2009Q1 to represent the empirical ratio on the horizontal axis, while the average model-implied ratios over the same period are on the vertical axis. These model-implied ratios generally follow the empirical ones.



(a) AR-to-sales ratio before GR (b) AP-to-OC ratio before GR

(c) AR-to-sales ratio during GR (d) Change in AR-to-sales ratio during GR

Figure E.4
Comparison of AR-to-sales and AP-to-OC ratios: Model vs Data

E.3 Trade credit and model-implied sectoral comovement

We examine whether and how the pairwise correlation between the two firms responds to the financial and productivity shocks through the trade credit channel. In particular, we specify the

$$\begin{aligned}\Delta \mathbf{corr}_{ij} \quad = \quad & \alpha_0 + \alpha_1 \mathbf{1}_{ij}^{two-way} + \alpha_2 \mathbf{1}_{ij}^{one-way} + \alpha_3 \mathbf{1}_{ij}^{two-way} \times \Delta tc_{ij} + \\ & + \alpha_4 \mathbf{1}_{ij}^{one-way} \times \Delta tc_{ij} + \beta' X_{ij} + \epsilon_{ij}, \end{aligned} \tag{E.3}$$

where i and j are, respectively, indexes for the supplier and client; $\Delta\mathbf{corr}_{ij}$ is the change in the pairwise correlation before and during the recession; $\mathbf{1}_j^{two-way}$ ($\mathbf{1}_j^{one-way}$) is the indicator for the two-way (one-way) connection; Δtc_{ij} is the change in TC intensity; and X_{ij} are sectoral or pair characteristics, such as input share for the pair, the share of input usage for each sector, the output share, the corresponding cell of the Leontief inverse matrix, the logarithm of financial and productivity before 2008, and the change in the logarithm of financial and productivity before 2008.

Table E.1 reports the point estimates. Column (1) and (4) display the point estimate without control variables. Thus, the corresponding point estimates are equal to the sample mean. We observe a higher rise in the two-way trading group in both models. However, there still exists variation between the two models. To see this, we include control variables in column (2) and (5). We find that the rise in sectoral comovement is also through the contraction in trade credit, whereas the point estimates in the fixed-TC model become insignificant once we include more control variables. We further perform a two-stage least square regression with the change in pairwise correlation as dependent variable and the change in the TC intensity, proxied by pairwise and sectoral characteristics, as the explanatory variables. As shown in column (3), the negative and statistically significant coefficient indicates that the trade credit chain indeed plays an important role in accounting for the rise in sectoral comovement.

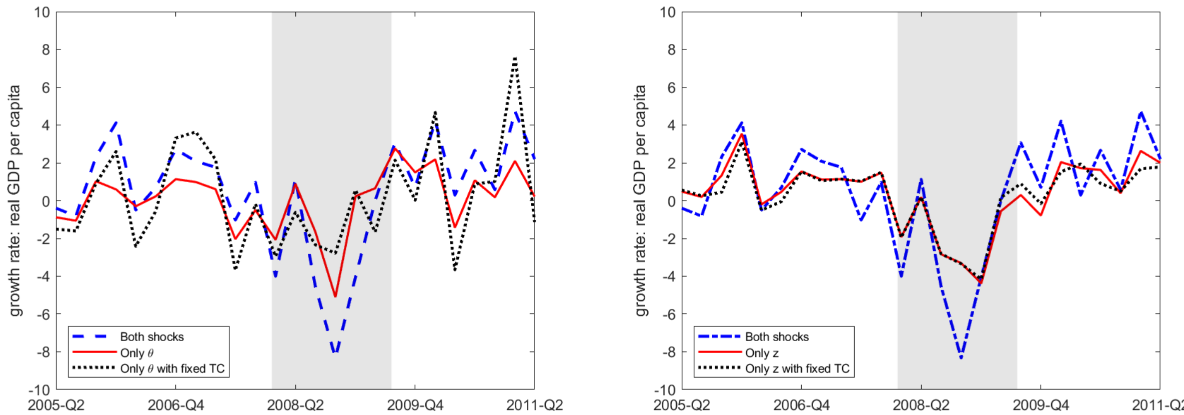
Table E.1
REGRESSION RESULTS OF EQUATION (E.1)

	benchmark shocks			benchmark shocks with fixed TC		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbf{1}_{ij}^{one-way}$	.52*	2.1***	.1	.39***	.0077	-.1
	(.27)	(.57)	(.43)	(.13)	(1)	(.39)
$\mathbf{1}_{ij}^{two-way}$	.81***	2.4***	.18	.67***	.26	.16
	(.26)	(.57)	(.45)	(.11)	(.97)	(.44)
$\mathbf{1}_{ij}^{one-way} \times \Delta tc_{ij}$		-1.3***				-.069
		(.29)				(.56)
$\mathbf{1}_{ij}^{two-way} \times \Delta tc_{ij}$		-1.3***				-.056
		(.26)				(.53)
$\Delta \hat{tc}_{ij}$			-1.6***			
			(.6)			
Control var	No	Yes	Yes	No	Yes	Yes
N	66	66	66	66	66	66
Adjused R^2	.08	.15	.3	.053	.27	.31

Notes: $^{\dagger}p < 0.10$ $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$.

E.4 Shocks in the Early 1980s Recession

We calibrate the model to match sectoral sales and spreads on an annual basis for the period 1978-1985. We instead use the equilibrium conditions from our model to back

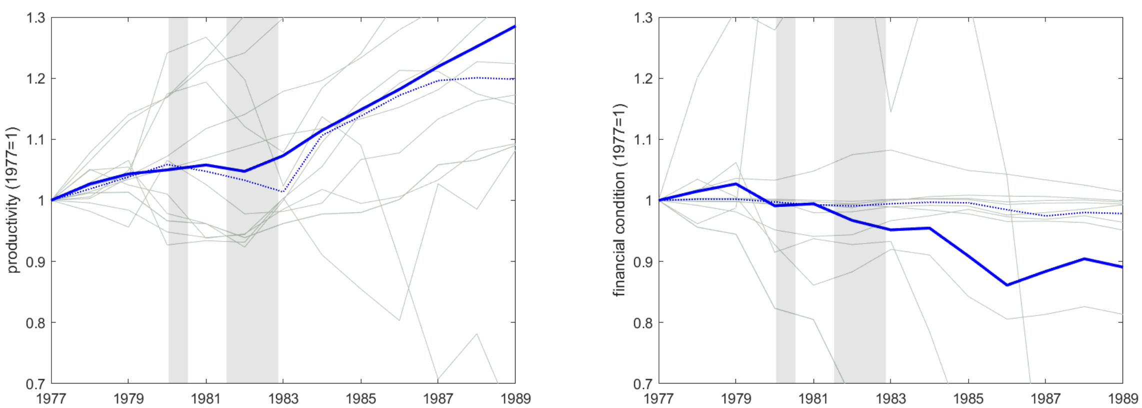


(a) Kernel density of pairwise correlation

(b) Growth rate: real GDP per capita

Figure E.5
Only productivity shocks: endogenous vs fixed trade credit

out sectoral productivity and financial shocks. We use the annual data rather than the quarterly data, with the period 1978-1985 used as the in-recession window, while the post-recession one covers 1983-1989. Figure E.6 reports the normalized shocks, and Figure E.7 displays the kernel densities for the underlying shocks.



(a) Productivity Shocks

(b) Financial Shocks

Figure E.6
Shocks in the Early 80s Recession

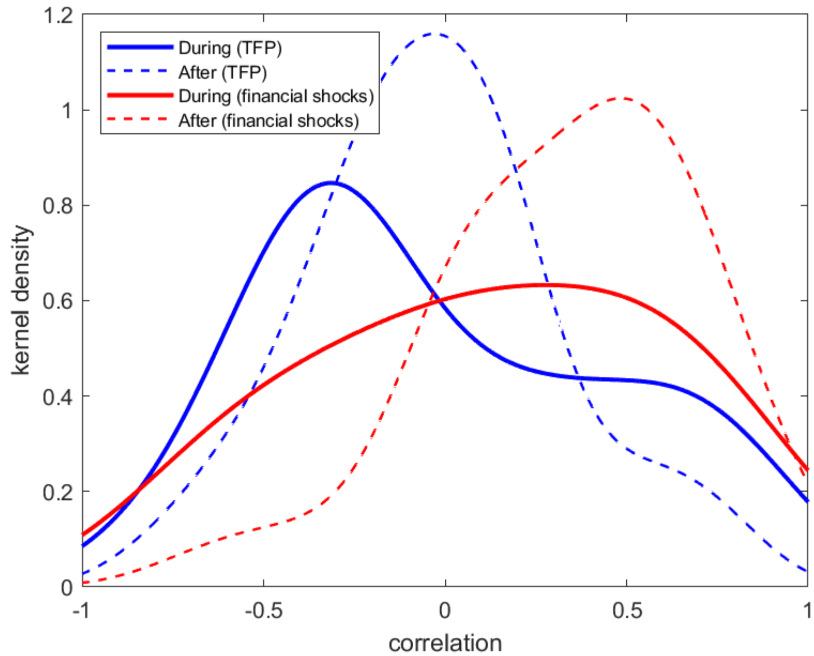
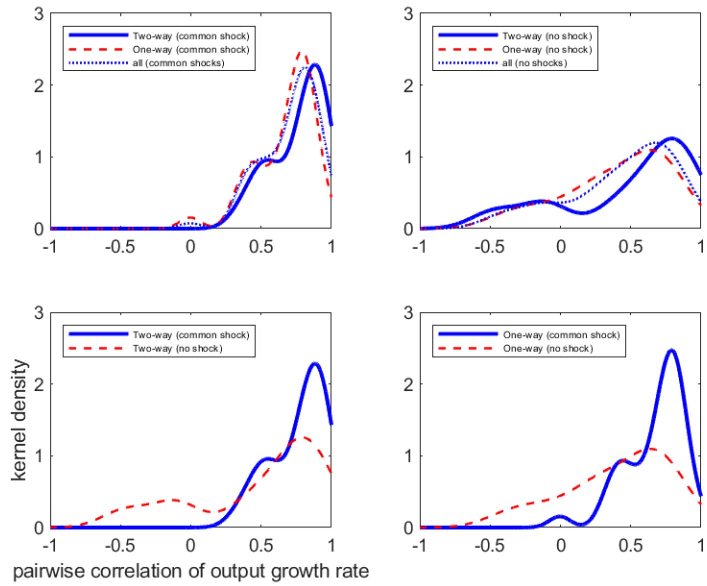


Figure E.7
PAIRWISE CORRELATIONS OF SECTORAL SHOCKS: THE EARLY 1980S RECESSION

E.5 Role of common shocks

We use our calibrated model to confirm the following intuition behind the dynamics of sectoral comovement during COVID-19: if common shocks were the driver, sectoral comovement should have risen ubiquitously, regardless of the degree of interconnection among sectors. In doing so, we feed the model with the productivity and financial shocks between 2005Q1 and 2007Q2 and then simulate a 1.5% decline in productivity for all sectors in 2006Q1. The top left panel of Figure E.8 plots the kernel densities of pairwise correlations for pairs in two-way and one-way trading groups, where we use the same classification as in Section 2.2. Compared to the densities without common shocks in the top-right panel, we observe a significant rise in sectoral comovement for both groups. While the two-way trading group appears to rise more with the common shock, it is also the one comoving more without. In Figure B.5 of Appendix B.2, these results stay in line with the dynamics of unconditional comovement during COVID-19.

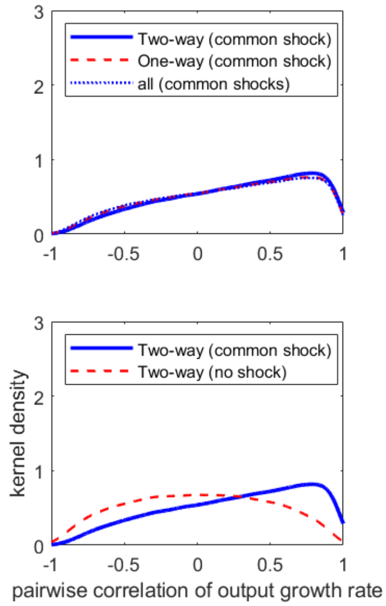
The bottom panels compare the kernel density without common shocks to that of common shocks. In both groups, the densities significantly shift to the right, highlighting the irrelevance of input-output linkages for comovement with common shocks. Moreover, Figure E.9 shows that the same results hold in a model with non-unitary elasticity of sub-



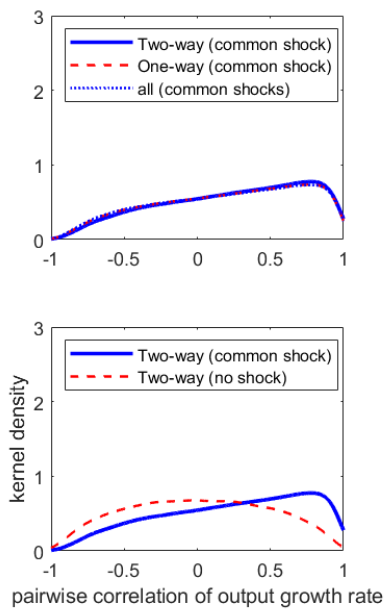
Note: The model is fed with the productivity and financial shocks between 2005Q2 and 2007Q2, and then a 1.5% decline in productivity for all sectors is imposed in 2006Q2.

Figure E.8
Sectoral comovement under common shocks

stitution in production, as in Atalay (2017) and Carvalho et al. (2021), where in Panel (a), we assume an elasticity of substitution between inputs of 0.6, while in Panel (b), with an elasticity of 0.2. There is no apparent difference in comovement as a result of the elasticity of substitution. An aggregate decline in productivity generates a rise in comovement that is very similar for the one-way and two-way trading groups.



(a) elasticity = 0.6



(b) elasticity = 0.2

Figure E.9
Kernel density: CES production with common shocks

Table E.2
List of sectors and characteristics

Sector	# two-way	# one-way	$\bar{corr}_{before}$	$\bar{corr}_{in}$	$\bar{corr}_{after}$	cmp share	$\frac{AR_{before}}{sales_{before}}$	$\frac{AP_{before}}{OC_{before}}$	$\Delta \frac{AR}{sales}$	$\Delta \frac{AP}{OC}$
Oil and gas extraction	5	15	0.034	-0.218	-0.048	0.0%	55.4%	163.7%	-2.8%	-57.9%
Mining, except oil and gas	15	22	0.138	0.245	0.001	0.9%	N.A.	N.A.	N.A.	N.A.
Support activities for mining	1	27	0.138	0.206	0.085	0.0%	85.4%	39.5%	-3.5%	-3.3%
Utilities	21	35	-0.169	0.425	0.066	44.8%	45.9%	42.1%	-3.1%	-0.1%
Construction	24	31	0.134	0.481	0.002	0.0%	73.8%	33.9%	1.9%	-3.1%
Wood products	21	26	0.122	0.419	-0.017	5.0%	23.0%	18.3%	4.5%	-1.0%
Nonmetallic mineral products	26	21	0.192	0.516	0.092	11.5%	N.A.	N.A.	N.A.	N.A.
Primary metals	18	22	0.103	0.505	0.046	0.6%	52.6%	31.8%	-3.8%	-0.5%
Fabricated metal products	27	26	0.199	0.519	0.020	7.4%	68.7%	44.5%	-2.5%	0.8%
Machinery	28	25	-0.030	0.380	0.006	10.1%	70.3%	47.9%	-3.8%	-1.2%
Computer and electronic products	25	27	0.127	0.496	0.032	34.2%	66.9%	52.6%	-2.6%	-1.1%
Electrical equipment and appliances	22	25	0.038	0.486	0.066	35.9%	61.8%	45.9%	-2.5%	-1.0%
Motor vehicles, bodies and trailers	19	33	-0.023	0.424	0.002	51.6%	N.A.	N.A.	N.A.	N.A.
Other transportation equipment	2	31	-0.069	0.242	-0.012	33.8%	N.A.	N.A.	N.A.	N.A.
Furniture and related products	8	30	0.192	0.482	0.023	69.2%	61.2%	46.5%	-4.8%	-3.4%
Miscellaneous manufacturing	20	24	-0.143	0.485	-0.019	72.5%	64.5%	48.8%	-4.4%	-2.4%
Food and beverage and tobacco products	11	31	0.084	-0.076	0.067	70.4%	39.3%	32.5%	-1.2%	-1.5%
Textile mills and textile product mills	15	32	0.109	0.395	-0.039	49.6%	67.8%	31.7%	-0.3%	-1.6%
Apparel and leather and allied products	9	26	0.146	0.086	-0.157	93.4%	68.6%	39.9%	-4.0%	8.7%
Paper products	27	27	0.105	0.431	-0.057	18.7%	63.1%	40.3%	-4.5%	-2.9%
Printing and related support activities	19	27	-0.122	0.452	0.052	6.4%	46.1%	26.1%	1.3%	0.7%
Petroleum and coal products	9	47	-0.064	-0.210	0.003	40.4%	35.4%	29.4%	1.8%	1.8%
Chemical products	27	27	-0.032	0.345	0.108	40.3%	60.9%	46.8%	-0.9%	0.2%
Plastics and rubber products	30	22	0.061	0.464	0.028	18.8%	58.4%	40.0%	-5.2%	0.3%
Wholesale trade	21	25	0.016	0.542	0.074	0.0%	49.3%	38.3%	0.4%	-0.7%
Motor vehicle and parts dealers	0	36	0.004	0.405	0.130	N.A.	37.7%	51.9%	2.0%	0.5%
Food and beverage stores	0	37	0.011	0.496	0.005	N.A.	5.8%	37.4%	0.2%	-0.1%
General merchandise stores	0	31	-0.012	-0.184	-0.132	N.A.	14.5%	33.6%	0.4%	-0.8%
Other retail	0	41	0.153	0.256	0.017	59.7%	11.2%	29.8%	0.3%	0.2%
Air transportation	16	29	-0.085	0.357	-0.058	60.8%	17.9%	18.9%	-1.7%	-2.0%
Rail transportation	2	26	0.198	0.461	0.060	17.6%	47.5%	66.6%	-6.9%	-1.5%
Water transportation	0	20	0.115	-0.047	0.099	71.8%	N.A.	N.A.	N.A.	N.A.
Truck transportation	9	26	0.208	0.320	0.128	24.8%	46.9%	16.7%	-4.4%	-2.3%
Transit and ground passenger transportation	12	30	0.011	0.240	-0.097	53.8%	41.1%	61.0%	-1.7%	-3.2%
Pipeline transportation	1	23	-0.081	0.288	-0.022	0.0%	44.9%	58.7%	-6.1%	4.0%
Other transportation and support activities	22	29	0.045	0.176	0.101	6.4%	65.4%	29.8%	-0.8%	-2.0%
Warehousing and storage	19	30	0.076	0.349	0.029	0.6%	N.A.	N.A.	N.A.	N.A.
Publishing industries, except internet	13	28	0.062	0.425	-0.062	70.8%	74.4%	49.1%	-3.0%	-5.1%
Motion picture and sound recording industries	7	28	-0.075	-0.012	-0.024	43.7%	66.9%	28.2%	-1.1%	-1.6%
Broadcasting and telecommunications	30	26	0.048	0.426	-0.060	44.1%	48.6%	38.5%	-2.0%	-2.5%
Data processing and internet publishing	32	19	-0.063	0.424	0.031	11.4%	65.4%	32.5%	-1.2%	-1.7%
Legal services	25	31	-0.036	0.318	-0.016	37.8%	70.4%	21.0%	-0.7%	-1.7%
Computer systems design and related services	27	27	-0.003	0.418	0.024	0.0%	81.8%	32.4%	-4.8%	-4.4%
Professional, scientific, and technical services	37	19	0.077	0.435	0.009	5.3%	71.4%	31.3%	-2.6%	-1.1%
Management of companies and enterprises	28	26	0.065	0.310	-0.057	0.0%	N.A.	N.A.	N.A.	N.A.
Administrative and support services	36	20	0.084	0.491	-0.062	7.6%	69.2%	15.6%	-1.3%	-0.4%
Waste management and remediation services	29	26	0.040	0.262	0.065	17.7%	48.0%	112.2%	3.7%	-5.8%
Educational services	4	39	-0.025	-0.024	0.074	94.3%	N.A.	N.A.	N.A.	N.A.
Ambulatory health care services	1	35	-0.043	0.354	0.066	96.6%	60.9%	25.3%	-5.0%	-2.1%
Hospitals	0	33	-0.019	-0.120	0.021	99.6%	59.8%	35.1%	-5.0%	-1.8%
Nursing and residential care facilities	0	35	0.137	0.276	0.003	98.0%	41.5%	9.2%	-0.7%	-0.6%
Social assistance	0	41	0.037	-0.076	0.074	99.1%	N.A.	N.A.	N.A.	N.A.
Performing arts, spectator sports, and museums	18	22	0.156	0.258	-0.050	48.3%	9.9%	18.6%	0.5%	-1.5%
Amusements, gambling, and recreation industries	13	32	0.099	0.385	-0.054	92.9%	N.A.	N.A.	N.A.	N.A.
Accommodation	28	19	0.229	0.464	0.032	66.7%	34.6%	36.1%	-2.9%	-1.2%
Food services and drinking places	35	18	0.097	0.402	0.030	78.4%	6.0%	17.7%	0.7%	-1.4%
Other services, except government	38	18	-0.015	0.488	0.034	68.7%	59.1%	34.5%	-1.1%	-2.0%