Trade Credit and Sectoral Comovement during US Recessions

By Jorge Miranda-Pinto and Gang Zhang*

We find that sectoral comovement sharply increased during the Great Recession but did not change significantly during US economic recession. Trade credit is important to understand this asymmetry. During the Great Recession, trade credit contracted in response to the financial shock, contributing to more than 40% of the increase in comovement. We propose a multisector model in which trade can asymmetrically respond to financial shocks. Our model shows that modestly correlated financial shocks during the Great Recession triggered trade credit as an amplifier. In contrast, trade credit in the 1980s recession mitigated the spillover effects of financial shocks.

JEL: E32, E23, E44

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At the business cycle frequency, the output of different sectors or firms comoves. Two common explanations are either aggregate or sectoral shocks propagated and amplified through input-output 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; Baqaee and Farhi, 2019; Lehn and Winberry,

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2020). While previous work is crucial to explain the average sectoral comovement, 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 document that, unlike any other post-war US recession, sectoral comovement of output growth experienced an unprecedentedly large rise during the Great Recession. We provide empirical evidence and a theoretical framework to show that sectoral comovement is more prominent in the economy when a sufficient proportion of firms are financially constrained, triggering an adverse chain reaction in trade credit provision, which is propagated and amplified through the production network.

After controlling for the size and duration of different recessions, we only observe a significant increase in the pairwise correlations of annual sectoral output growth during the Great Recession but not in other recessions. Even though the early 1980s and the Covid-19 recession are comparable in magnitude to the Great Recession, we observe no change in comovement. We then zoom into the Great Recession with the unconditional correlations of quarterly growth and find sectoral comovement increased more for more interconnected sectors. The comovement 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 two-way (both sectors are intermediate input providers and users of each other).[1] Interestingly, this pattern is not observed in other recessions, regardless of whether we control for GDP, indicating that a change in the nature of sectoral connections contributed to the rise in comovement during the Great Recession.

We then investigate the role of the trade credit contraction in driving the change in interconnection during the Great Recession. We find that two sectors in the two-way trading group that experienced a significant contraction in their trade credit provision/reception—as defined by a decline in trade credit below the me-

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

dian decline during the Great Recession—also had a higher rise in comovement. In particular, the two-way trading pairs that displayed a significant reduction in trade credit had a larger rise in their correlation (by 0.18, on average) than the counterpart with no significant reduction in their trade credit intensity. The additional rise in the comovement of the two-way trade-credit-decline subgroup accounts for more than 40% of the average rise in the two-way trading group.

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 have to 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 is used to ensure 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.

We use the model to investigate the data-generating process in the presence of endogenous trade credit. In particular, we calibrate the model to the US data and then use sale output and bond spread to back out productivity and financial shocks. Then we conduct counterfactual exercises by fixing trade credit to the pre-recession level and find that with our estimated shocks, the average rise in pairwise correlations with fixed trade credit is 42.8% smaller than the one in our benchmark model. Moreover, we find the trade credit chain amplifies the financial shocks, where the fixed-trade-credit model generates a lower decline in GDP growth—17.3% (15.2%) smaller in 2008Q4 (2009Q1)—compared to 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 more interconnected sectors and among interconnected sectors that experienced a decline in trade credit. Next, we re-estimate the shocks with the fixed-trade-credit model and find that the fixed-trade-credit model requires more correlated financial shocks and substantially larger shocks to key sectors (e.g., manufacturing sector) to generate the observed sectoral comovement.

We then investigate why sectoral comovement barely changed during other US recessions. We focus on the early 1980s and the Covid-19 recessions, the other two large US recessions in terms of GDP decline. Our calibrated model indicates that, during the 1980s, trade credit adjustment 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. To understand the

Covid-19 recession, with our benchmark calibration, we simulate a 1.5% decline in productivity for all sectors. Due to the common shock, comovement increases substantially and universally, regardless of whether and how two sectors are interconnected. As in the data, conditional correlations for different interconnected sectors remain unchanged. Productivity shocks generate minor effects on sectoral collateral constraints and trade credit provision, implying no significant rise in sectoral spillovers.

Since the Great Recession is the only financial crisis in the US after WWII, we explore the cross-sectional variation across the US public firms to test the main mechanisms of our model. In particular, we use the collapse of Lehman Brothers (LB) as a quasi-natural experiment, along with a firm-to-firm and firm-to-bank network before the collapse. By restricting our sample to pairs where suppliers did not borrow from LB before 2008 but had at least one client doing so and another not, we examine how differently these common supplies comoved with their clients exposed differently to the LB shock. Furthermore, we adopt the bank-credit-shock index developed in Chodorow-Reich (2014) and then perform a two-stage least square regression with the change in pairwise correlation as the dependent variable and the trade credit intensity (the ratio of account payables to the operational cost, the AP-to-OC ratio), proxied by the **CR** index, as the key explanatory variable. We find supportive evidence in the two-stage regression. When the bank-credit shocks were more severe than the sample median, the AP-to-OC ratio declined, generating a significant rise in pairwise correlation. In contrast, the less shocked clients retained their trade credit and comoved less with the common supplier.

Our paper builds on three strands of existing literature. The first 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; Rebelo, 2005; Li and Martin, 2019). Most papers in the existing literature study long-run comovement. An exception is Li and Martin

(2019), who also focus on the Great Recession and document 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. We generalize their reduced-form setting by incorporating a micro-founded structural model with state-dependent linkages. This generalization is necessary and important for two reasons. First, the GR factor is a common shock during the Great Recession and cannot account for the differential rise in comovement across groups with different input connections. Second, although the authors also incorporate GR-specific loadings on sectoral shocks, they find 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. In our model, sectoral spillovers are time-varying and depend on the nature of shocks. We show that modestly correlated financial shocks are sufficient to trigger trade credit as a conduit and amplifier, further generating a significant rise in comovement.

The second strand of related research is the literature that incorporates financial frictions into multisector real business cycle models to study how financial frictions propagate and amplify sector-specific shocks to macroeconomic aggregates (see, for example, Bigio and La'O, 2020; Altinoglu, 2020; Luo, 2020; Reisher, 2020; Miranda-Pinto and Young, 2022; Shao, 2022). 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 Reisher (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 the two papers is what exactly generates the asymmetry in the model. Luo (2020) assumes that trade credit payments can be renegotiated and the interest rate on the bank loans increase with the amount of trade credit forbearance, amplifying the effects of a negatively large financial shock. While her model predicts a rise in trade credit, we show the median ratio of trade credit relative to sales contracted during the Great Recession. In Reisher (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 one on trade credit. The author derives a positive relationship between trade credit provision and the bank credit spread. Nevertheless, in data, the two displayed a negative relationship during the Great Recession. Instead, our model generates an endogenous asymmetric relationship between trade credit provision and the financial condition, which depends on the supplier's and client's relatively financial conditions.

The final strand of related literature studies the role of trade credit in propagating and amplifying the 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). Empirically, Jacobson and von Schedvin (2016) examines how the trade credit chain propagates the Swedish corporate bankruptcy. Costello (2020) studies the effects of the banking shock on trade credit provision and employment. Our paper explores the role of trade credit in determining the pairwise correlation over the US recessions. Moreover, we show that trade credit can also act as a cushion, depending on the supplier's financial condition relative to the client. In 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. Thus, the driver of sectoral comovement in our model can be quantified over different recessions.

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.

I. Empirical Evidence

In this section, we document our main observations regarding the behavior of sectoral comovement during recessions. First, after controlling for the aggregate GDP, sectoral comovement significantly rose during the Great Recession but not in any other US post-war recession. Second, the rise in sectoral comovement during the Great Recession is more significant in pairs of sectors that provide intermediate inputs to each other than in the ones in which only one sector provides inputs to the other, and much more in ones without input-trading relations. Third, the pairs of sectors connected through input-output linkages comoved more when experiencing a larger-than-median contraction in trade credit (TC). Last, we perform some robustness checks and discuss the results.

A. *Observation I: rise in opairwise correlation*

We first use the annual growth rate of sectoral outputs from BEA to examine the dynamics of sectoral comovement during eight US NBER recessions after WWII, namely the 1960, 1970, 1973, 1990, and 2001 recessions, the 1980 recession together with the 1981-1982 recession, the Great Recession, and the Covid-19 recession.[2] Because each recession may vary by size and duration, we control for them by filtering out the aggregate components in the dynamics of sectoral outputs. In doing so, we regress the logarithm of the sectoral outputs on the logarithm of the US GDP, take the residuals, and use their first difference as our measure for sectoral output growth. Then we calculate the pairwise correla-

[2]Note that the quarterly gross outputs from BEA are only available since 2005Q1.

tions over eight years, starting three years ahead of each recession (more details in Appendix A.A4).[3] Furthermore, we compare the kernel density of pairwise correlations during a recession to before or after.[4] Notably, controlling for the aggregate components reduces the value of pairwise correlations in general, regardless of whether it is normal time or in recession. During the Great Recession, the conditional average is about a third of the unconditional one.

Figure 1 shows the density in a recession (solid-blue line) only shifted significantly to the right during the Great Recession, implying a rise in sectoral comovement. As shown in Table B1 of our Appendix B.B1, the mean (median) correlation during the Great Recession increased to 0.14 (0.21), from the pre-recession average (0.02) and from the post-recession one (0.03).[5] Then two-sample t-test or Kolmogorov-Smirnov (KS) test is performed to examine whether the mean or density of pairwise correlations during the recession is the same as the one before or after. Both tests reject the null hypothesis at the 1% significance level.

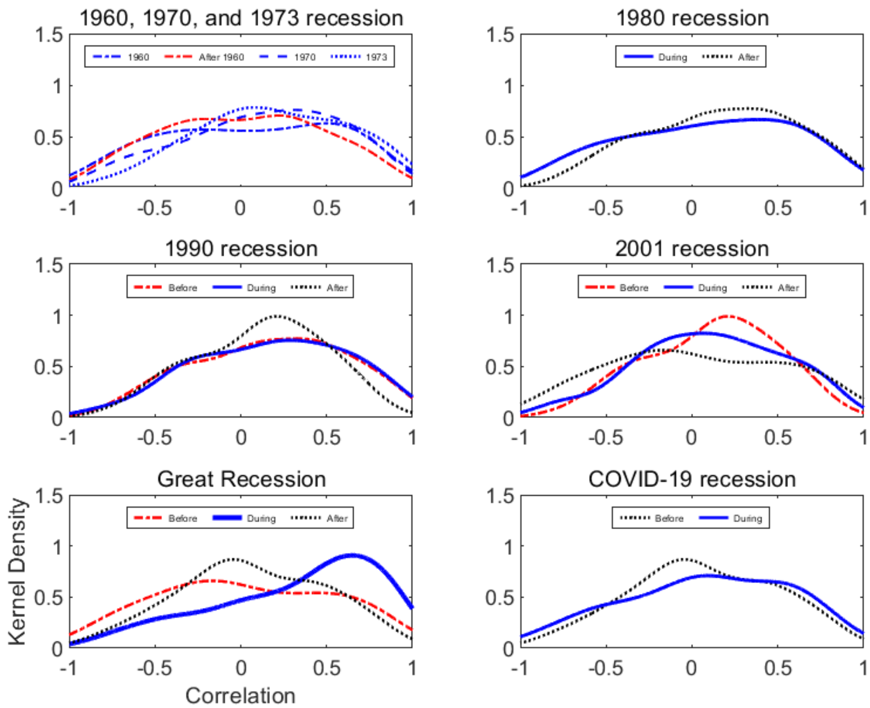
Following Chari et al. (2007), we take a close look at the 1980 recession as a contrast to the Great Recession since the aggregate economy then experienced a slightly lower but comparable decline in GDP than the one in the Great Recession.[6] However, as shown in the top-right panel, sectors then did not move together, some of which even moved oppositely as the density has a fat left tail. Neither the two-sample t-test nor the KS test can reject the null hypothesis. Moreover, during the Covid-19 recession, while we observe a significantly unconditional

[3]Our approach implicitly takes the recession duration into account. Still, since the period of each recession that stays in the fixed time window varies, we adjust the length of our time window to account for the duration explicitly. However, we cannot directly compare across time windows as they show different statistical properties. Thus, we standardize each sequence to the level before the Great Recession. As shown in Figure B2, we find our results here robust.

[4]In particular, we take 1962-1968 for the pre-1970 recession, 1983-1989 for both post-1980 and pre-1990 recessions, 1992-1999 for both post-1990 and pre-2001 recession, 2002-2007 for both post-2001 recession and pre-Great Recession, and 2011-2018 for both post-Great Recession and pre-COVID recession. The selection of time windows is solely to avoid any overlap with recession year. Unfortunately, we cannot find any time window suitable to compare with the 1973 recession.

[5]We also calculate the pairwise correlation of the growth rate of outputs by industry directly, without applying the linear regression to control for the recession size. As shown in Figure B4 of Appendix B.B2, we observe a significant rise in sectoral comovement during the Great Recession and the Covid-19 recession, while only small increases in other recessions.

[6]In 1982, the real GDP dropped by 1.9%, with the deepest drop being 6.5% in 1982Q1, whereas the real GDP contracted by 2.7% in 2008, with the largest contraction by 8.2% in 2008Q4.



Note: Real gross outputs by industry are calculated by dividing the nominal ones by the chain-type price indexes. Fifty-seven sectors cover all private non-farm business sectors, except for FIRE. Using Equation (A1), the correlation between any pair of two sectors is calculated over eight years, starting at three years ahead of six recessions, namely the 1960, 1970, 1973, and 1990 recession, the 1980 recession together with the 1981-1982 recession, and the Great Recession. In the control group, we take 1962-1968, 1983-1989, 1992-1999, 2002-2007, and 2011-2018 respectively, to represent the pre-1970, the post-1980 (pre-1990), the post-1990 (pre-2001) recessions, the post-2001 recession (the pre-Great Recession), and the post-Great Recession (the pre-COVID19 recession). The equal-weight kernel density is taken with a bin width of 0.001.

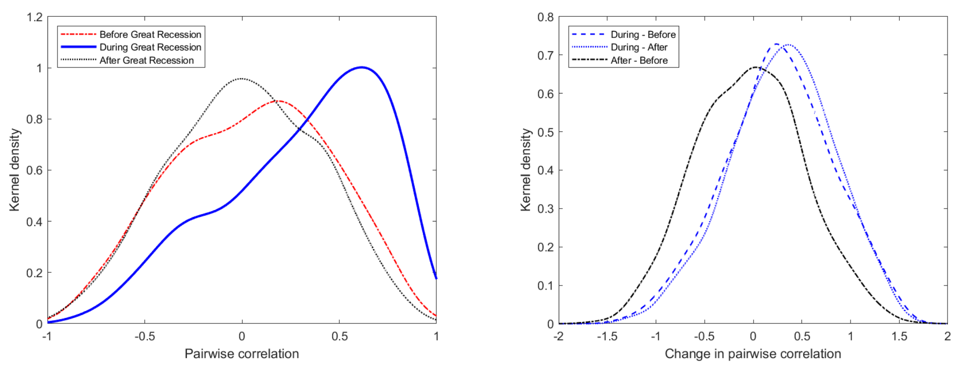
Figure 1. : Kernel Density for Pairwise Correlations in Recessions

rise in sectoral comovement, the rise in comovement vanishes after controlling for GDP. The two-sample t-test cannot reject the same-average hypothesis at the 1% significance level.[7] Later, we show the rise during the Covid-19 recession is mainly driven by a large decline in aggregate productivity, thus affecting majority pairs similarly regardless of whether and how they were interconnected.

We now zoom into the sectoral comovement during the Great Recession, with quarterly data, as some interactions among sectors are averaged out when using annual data. Instead of the conditional correlations (on GDP), we use the

[7]The KS test rejects the same-density hypothesis as the density during the recession has fatter tails on both ends.

unconditional ones for two reasons. First, we control for the GDP to compare sectoral comovement across recessions. Second, conditioning on GDP has the downside of confounding sectoral spillovers with aggregate shocks. Panel (a) of Figure 2 displays the kernel densities before, during, and after the Great Recession.[8] Consistent with the evidence using annual data, we observe a significant rise in sectoral comovement during the Great Recession. Interestingly, we find the changes in the correlations varied a lot. Panel (b) of Figure (2) shows that the majority of pairs experienced a rise in comovement, as the density is centered around 0.3. The correlations of many pairs rose by more than 1, implying that some pairs of sectors that used to comove negatively before moved together during the Great 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 correlation between any pair of two sectors is calculated using Equation (A1). The equal-weight kernel density is taken with a bin width of 0.001. 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

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

[8]Following Kahle and Stulz (2013), we choose 2007Q3-2009Q2 to cover the recession and 2005Q3-2007Q2 and 2009Q3-2011Q2 to represent before and after the recession, respectively. The different coverage periods and lengths of time windows are used. All results here are robust. Table B2 in Appendix B.B1 displays the main statistics.

contribute to the rise of sectoral comovement during the Great Recession.

B. Observation II: role of intermediate-input linkages

To identify the intermediate trading relationship between two sectors, we adjust the input-output (IO) tables of 71 industries from the BEA to match the sectors in our sample, take the average between 2003 and 2007 to avoid any short-term variation, and then calculate the IO matrix with each cell equal to the input share.[9] Then, all pairs are categorized into three groups according to the extent of their interconnectedness. In particular, two sectors are classified into the two-way trading group if they are both input supplier and client to each other; the one-way trading group if only one sector supplies inputs to the other but not vice versa; and the no-trading group if no intermediate input is traded between two. Each group has 466, 792, and 338 pairs, respectively.

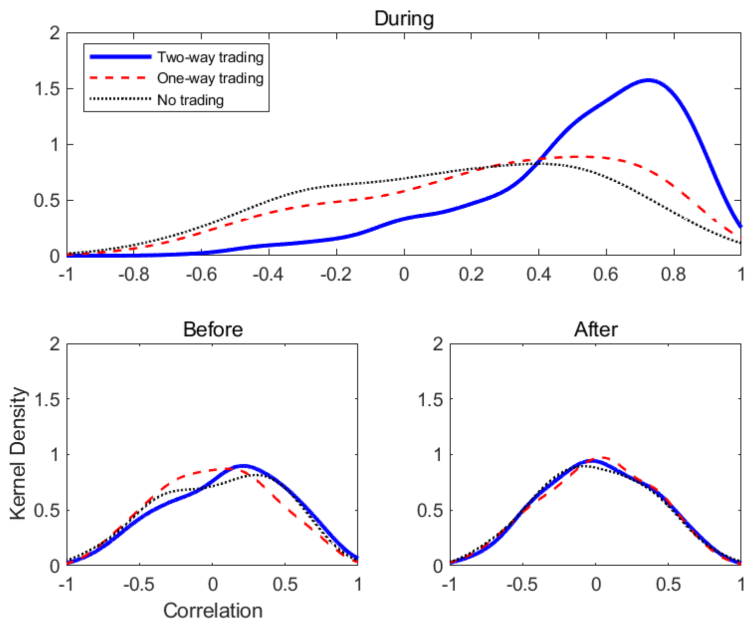
The way two sectors trade with each other matters for sectoral comovement. The top panel of Figure 3 displays the kernel densities of three groups during the Great Recession.[10] In particular, the average (median) correlation within the two-way trading group is higher, by 0.27 (0.29), than that in the one-way group and much higher, by 0.37 (0.43), than that in the no-trading group, as Table B2 in Appendix B.B1 shows.[11] This outcome implies the pairs with two-way interconnection were the main drivers of the rise in sectoral comovement during the Great Recession. Moreover, as seen in the bottom panels of Figure 3, before and after the Great Recession, the three groups present no statistical difference in their kernel densities.

Our results here indicate that network spillovers, rather than common shocks, are critical to explaining the rise in comovement during the Great Recession. As

[9] If the input share is lower than 0.1%, we set it to 0. We also try different thresholds, like 0.05% and 0.01%. All results here are robust.

[10] We regress the pairwise correlations during the Great Recession or the change in correlations on the input share (the corresponding cell of the Leontief inverse matrix) along with sectoral fixed effects and other controls. The coefficient is not statistically significant.

[11] The KS statistics is 0.31 between the two and one-way trading group, 0.42 between the two-way and no-trading group, and 0.12 between the one-way and no-trading group. All tests reject the null hypothesis that two densities are the same at the 1% significance level.



Note: All pairwise correlations are calculated as in Figure 2. The equal-weight kernel density is taken with a bin width of 0.001. Two sectors are classified as in the two-way trading group if they are both input supplier and client to each other; the one-way trading group if only one sector supplies inputs to the other but not vice versa; and the no-trading group if no intermediate input is traded between two. Each group has 466, 792, and 338 pairs, respectively.

Figure 3. : PAIRWISE CORRELATION BY THE EXTENT OF INTERCONNECTEDNESS

we demonstrate in Section IV.E, the common shock hypothesis would not deliver the fact we present here but rather increase comovement universally, regardless of whether and how sectors are interconnected. In line with this finding, we apply the same categorization to the Covid-19 recession and examine whether and how sectors within each group comove. Overall, we find sectoral comovement rose significantly during the Covid-19 recession, even more than that during the Great Recession.[12] However, Figure B6 in Appendix B.B3 shows that the increase in comovement was almost universal during the Covid-19 recession, regardless of their degree of interconnectedness. It implies that the rise in sectoral comovement during the Covid-19 recession is likely caused by a large decline in aggregate productivity (common shock due to the public health crisis).

[12]Note that, unlike the bottom-right panel in Figure 1, we use the unconditional pairwise correlations of the quarterly sectoral output growth here. The recession periods are 2019Q3-2021Q2, while the pre-recession periods are 2017Q3-2019Q2.

We perform the same exercise for other recessions with annual data. However, we do not observe any significant rise in sectoral comovement for all three groups during any recession before 2008.[13] Thus, an additional linkage must exist that contributes to the observation we document here. This is also advocated but silent in Li and Martin (2019). Thus, we propose a changing connection originating in the trade credit chain. Later, we will show that our model generalizes their setting by incorporating the endogenous TC chain, the role of which depends on the nature of shocks.

C. *Observation III: role of trade credit during the Great Recession*

In addition to trading in intermediate inputs, firms simultaneously defer some input payments to their clients and receive such deferral from their suppliers.[14] The quarterly financial report (QFR), a survey of the US firms' financial positions conducted by the US Census Bureau, shows that the average ratio of account receivables and account payables relative to total assets are 7.9% and 6.3% from 2012 to 2019 for big firms (assets exceeding $250 million) and 23.3% and 12.9% for small ones. Among short-term financing sources, the big firms had more account payables, at least by a factor of 9, than short-term bank loans, commercial paper, and other short-term loans, whereas small firms held two times more account payables than their short-term bank loans.[15]

Since bilateral TC is unavailable, we first create a variable to measure how the TC between two sectors changed in the recession compared to the pre-recession level. In particular, we take the financial variables for the US public firms from Compustat.[16] Here, the ratio of account receivables to average sales between the current and last quarters (the AR-to-sales ratio) is calculated to measure

[13]Please refer to Appendix B.B3 for detail.

[14]Claims against clients are recorded as suppliers' account receivables, while liabilities to their own suppliers as their account payables.

[15]From a global perspective, 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.

[16]We select the sample following the filters in Kahle and Stulz (2013). Please refer to Appendix A.A2 for details.

the intensity of TC provision, while the ratio of account payables over average operating cost (the AP-to-OC ratio) as the intensity of TC reception.[17] For each firm, we take the median value over two periods, namely 2005Q3–2006Q2 and 2008Q3–2009Q2, and then calculate the first difference between the two periods. Last, we use the median across firms in each sector to represent the sectoral change in TC usage. It leaves us 44 out of 57 sectors, where only sectors with more than three firms are kept. Our measure stays in line with Kiyotaki and Moore (1997a). They show whether the supplier can provide enough liquidity to its shocked clients, rather than how much the clients rely on the supplier's TC, matters for whether the liquidity shock will be transmitted.[18]

Then, we further 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. In particular, 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 median across all public firms, which are, respectively, -1.6 and -1.0 percentage points. Otherwise, the pair is categorized in the unchanged subgroup (the TC unchanged subgroup).[19] In sum, 189 pairs in the two-way trading group experienced TC decline, and 128 did not, whereas the corresponding numbers for one-way trading pairs are 133 and 326.

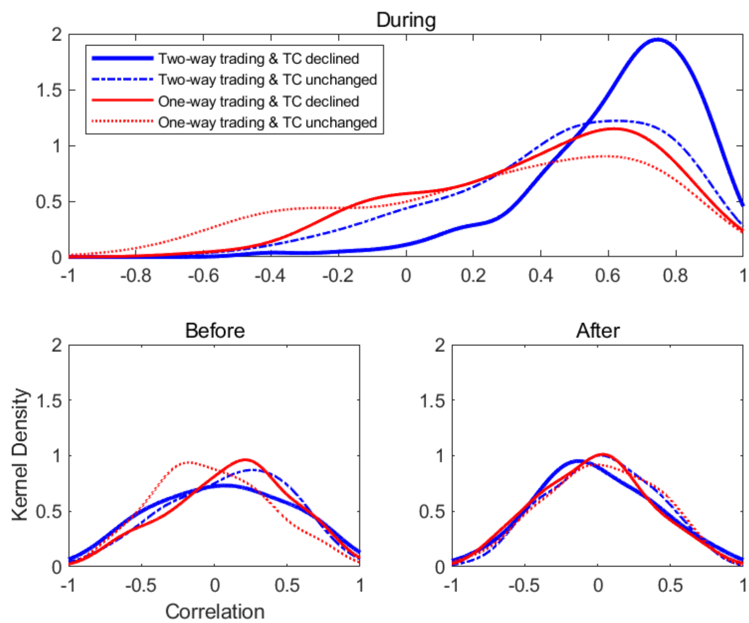
The top panel of Figure 4 exhibits the kernel densities before, during, and after the Great Recession for the four subgroups described above. Given the extent of interconnectedness, a pair that experienced a decline in TC comoved relatively more than the one that did not. As Table B2 in Appendix B.B1 shows, the mean correlation of the two-way trading pairs that experienced a decline in TC is 0.63,

[17]Note that both ratios are not bilateral, but rather measure the total provision/reception of TC to/from customers/suppliers.

[18]We also use the pre-recession TC usage to classify our pairs into the TC-dependent and independent subgroups. However, we do not observe the TC-dependent subgroup significantly comove more during the Great Recession.

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

which is higher by 0.18 than that in the unchanged subgroup. Within the one-way trading group, the TC decline group has an average correlation of 0.39, which is 0.13 higher than that for pairs that did not experience TC decline. The additional rise accounts for 43.2% (54.1%) of the average rise in pairwise correlations of the two-way (one-way) trading group.[20]



Note: All pairwise correlations are calculated as in Figure 2. A pair of sectors is treated in the 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. Each group has 189, 128, 133, and 326 pairs. The equal-weight kernel density is taken with a bin width of 0.001.

Figure 4. : Pairwise correlation by Whether Trade Credit Declines

Moreover, as shown in the bottom panel 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 the TC adjustment during the Great Recession can be an important channel in accounting for the rise in sectoral comovement. As a 'placebo test', we also examine the kernel densities of the TC decline and

[20]Notably, the average correlation of the one-way trading pairs with available trade credit data is 0.29, slightly higher than the group average (0.25).

unchanged subgroups for the no-trading group.[21] As shown in Figure B3 of Appendix B.B3, no difference between the two subgroups is observed during the Great Recession.

D. Discussion

Due to delivery, adjustment cost, search frictions, and other factors, two sectors may not comove contemporaneously, and instead, one may lead to another. Thus, the rise in sectoral comovement during the Great Recession may be just a result of synchronization in timing.[22] To address this concern, we follow the method used in Christiano and Fitzgerald (1998), Hornstein (2000), and Kim and Kim (2006), calculate one-period lagged and leaded correlations, and then take the maximum value among the three. As displayed in Figure B7 in Appendix B.B4, we find that, during the Great Recession, the kernel density of the maximal correlations still shifts significantly towards the right. This result complements the hypothesis that the rise in sectoral comovement was mainly driven by structural factors linking the sectors rather than the synchronization in timing due to some common shocks.

Notably, our sectoral evidence points to the role of supply factors driving the rise in comovement during the Great Recession. However, as argued by Mian et al. (2013), the collapse of house prices generated a negative wealth effect that decreased consumption, especially in states/cities with high mortgage debt. Thus, sectors that mainly provide 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 according to the share of output used as the final consumption.[23] Here, one sector is classified into the consumption-provider group if its share is larger than the median value, namely 36.8%. Otherwise, this sector would be grouped as the input provider. The top panel of

[21] Similarly with the two-way trading group, the TC decline pair is identified if the TC declined condition is satisfied in either direction.
[22] We thank the referee to point this out.
[23] Please refer Table A1 for the specific values.

Figure B8 in Appendix B.B5 displays the kernel densities for pairs within and connecting two groups. Surprisingly, during the Great Recession, we observe a significantly higher comovement within the input-provider group, while the correlations among the consumption providers rose the least on average. The densities of the different groups almost overlap before and after the Great Recession. The results are consistent with the main observations we document.

II. Model

In this section, we develop a multisector model with input-output linkages and endogenous TC adjustment to uncover the mechanism of the rise in sectoral comovement during the Great Recession. Our model economy combines the environments in Greenwood et al. (2010) and Bigio and La'O (2020). Firms are *ex ante* uncertain about the quality of intermediate inputs, and thus TC arises in equilibrium as a way to learn the true quality of intermediates.

A. Firms' Production Plan

Suppose that the economy has n sectors, each of which has a continuum of firms on the interval $[0, 1]$. Each firm hires labor and purchases intermediate inputs to produce. Suppose that each firm purchases inputs from, at most, one firm in each sector.[24] Here, we refer to firms providing inputs as suppliers and purchasing them as clients. Thus, sectors are interconnected via this vertical firm-level network. Suppose that the production of any firm $h \in [0, 1]$ in sector i takes a Cobb-Douglas form as

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

[24]This setup is not essential and only serves to avoid the coordination problem.

where z_i is the sectoral TFP, l_i is the employed labor, m_{ji} is the intermediate inputs purchased from a firm in sector j, ω_{ji} governs its share over total expenditures on inputs with $\sum_{j=1}^{n} \omega_{ji} = 1$, and α_i and ν_i are, respectively, the labor and input share with $\alpha_i + \nu_i < 1$.[25] Note that $\omega_{ji} = 0$ means that firms in sector i do not purchase inputs from any firm in sector j.

Products can be used as either intermediate inputs or consumption goods. Thus, firms in any sector simultaneously act as both a supplier to provide and a client to receive inputs.[26] After receiving orders, suppliers customize their products to be used as inputs. Thus, they enjoy some pricing power and charge q_{ij}. Alternatively, they can sell their products at a price p_i in the consumption-good markets, which is assumed to be perfectly competitive. Moreover, following Smith (1987) and Kim and Shin (2012), we assume that the quality of the customization is *ex ante* uncertain.[27] There exists a probability of $1-\eta$ that the clients will find the delivered products not qualified for inputs. In this case, these inputs perish, and the clients must purchase $\gamma > 1$ units from a secondary market and convert them into one unit of input. We assume that the price of sector i's products is p_i, the same as that in the consumption-good market.

Each period is split into two stages. In the first stage, sectoral TFPs are realized, but firms still need to be determined about the quality of their ordered inputs. Nevertheless, they now need to put in an order for intermediate inputs and employ workers to produce later. Due to the uncertainty, it is ambiguous whether firms can make payments for labor and intermediate inputs. Hence, workers and suppliers demand to be paid in advance. We assume that workers have strong bargaining power over firms and are, therefore, compensated upfront at the full amount.[28] The intermediate input payments are divided into cash

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

[26] We assume that a firm cannot be simultaneously both supplier and client for the same firm.

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

[28] 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

before delivery (CBD) and trade credit (TC). The former is due in the first stage, while the latter is deferred until their clients realize their revenue. Suppliers endogenously decide the division, and its details will be specified later. Suppose that no profits can be stored over periods. If the required working capital, the summation of the wages and paid CBD, exceeds the received CBD, the supplier needs to borrow the difference from perfectly competitive banks. To secure the loans, banks require firms' products as collateral. Assuming that the liquidation ratio of collateral is θ_i for the firm i, the amount of the loans that can be borrowed should be equal to or smaller than $\theta_i p_i y_i$ as

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

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 θ_i here as the sector-level financial shocks.

In the second stage, the quality of their ordered inputs is realized, and all goods are produced and delivered. If the client receives good-quality inputs, then she pays back the TC, i.e., $tc_{ji}q_{ji}m_{ji}$. Otherwise, she forgoes the paid CBD, defaults on TC, and then effectively pays γp_j per unit of input from the secondary market to produce. Thus, the expected unit cost of inputs paid by the client i to the supplier j is given as $(1-tc_{ji})q_{ji} + \eta tc_{ji}q_{ji} + (1-\eta)\gamma p_j$. 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 turn out to be of good quality, she receives the payment on TC, while receiving nothing otherwise. Therefore, when setting the input price, a supplier must ensure that the clients pay at most what they effectively pay from the secondary market.

through the input-output network.

Thus we set the no-arbitrage condition as

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

Note that the products sold in the consumption and secondary input market are not customized and thus can be delivered without any uncertainty.

B. Optimal Contracts on Trade Credit

Suppose that the realization of product quality is private information for clients. Thus, when good quality is realized, clients have incentives to misreport their status and default on TC. To induce truth-telling, every supplier will offer an optimal contract to each client separately. In the contract to the client j, the supplier i specifies the input price q_{ij}, the share of TC tc_{ij}, and the penalty payment g_{ij} when it finds out the client cheats. Notably, clients that receive bad-quality inputs have no incentives to cheat because they default on TC. Therefore, this contract is designed to satisfy two constraints: the resource constraint (RC) and the incentive-compatible constraint (ICC). The former requires that the penalty payment cannot exceed what the client makes after banks collect their loans as

$$\text{(RC)} \qquad g_{ij} \leq \omega_{ij}v_j\left(p_jy_j - b_j\right),$$

where ω_{ij} is input share, p_jy_j is the products' market value, and b_j is the bank loan amount. When the supplier detects the client misreports, she can collect a penalty payment proportional to their input supply, namely $\omega_{ij}v_j$.

The ICC ensures that the client always reports its true state. As in Townsend (1979), Bernanke and Gertler (1986), Williamson (1986), and Carlstrom and Fuerst (1997), we assume that any supplier exerts costly efforts to verify the state reported by each of its clients. Denote the unit cost of the verifying efforts for offering $q_{ij}m_{ij}$ dollars of inputs as e_{ij}, which can be interpreted as the verification intensity. For the same verification intensity, the more inputs the supplier provides, or the higher the price it charges, the more costly it is for a supplier to find out the true status. As in Greenwood et al. (2010) and De Nicolo et al. (2021), we assume that suppliers can detect the true quality with only a certain probability $\mathbf{Pr}(e)$, which is assumed to be increasing and concave in e. Thus, in the optimal contract, the incentive-compatible constraint is given as

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

where the left-hand side is TC to be paid, 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 the efforts are costly, suppliers will make enough efforts 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 $\mathbf{Pr}(e)$.[29]

C. Optimal Problem for Firms

In the first stage, all firms in the same sector are ex ante the same, making the same decisions. Note that all firms are simultaneously 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

[29]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 that 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 one has access to more detailed firm-to-firm network data on production and credit, our model can match salient features of the microdata.

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 $\{p_j\}$, the banks loans by other firms $\{b_j\}$, the outputs by other firms $\{y_j\}$, the optimal contract offered by the supplier $\left\{q_{ji}, tc_{ji}, g_{ji}\right\}$, a firm in sector i chooses the inputs $\{m_{ji}\}$, the labor l_i, the optimal contract $\left\{q_{ij}, tc_{ij}, g_{ij}\right\}$, and the efforts $\{e_{ij}\}$, to maximize her profits, subject to the collateral constraint (CC), resource constraint (RC), incentive-compatible constraint (ICC), and no-arbitrage condition (NAC), as,

$$\begin{aligned}
(3) \qquad & \max_{l_i, m_{ji}, q_{ij}, tc_{ij}, g_{ij}, e_{ij}} p_i z_i l_i^{\alpha_i} \left(\prod_{j=1}^{n} m_{ji}^{\omega_{ji}}\right)^{\nu_i} - \sum_{j=1}^{n} \left(p_i - (1-(1-\eta)tc_{ij})\, q_{ij}\right) m_{ij} \\
& \quad - w l_i - \sum_{j=1}^{n} \left((1-tc_{ji})q_{ji} + \eta tc_{ji} q_{ji} + (1-\eta)\gamma p_j\right) m_{ji} - (1-\eta)\sum_{j=1}^{n} e_{ij} q_{ij} m_{ij} \\
& s.t. \qquad CC, \;\; RC, \;\; ICC, \;\; and \;\; NAC
\end{aligned}$$

The expected revenue consists of revenue from offering inputs and sales in the consumption goods and secondary input market, where with a $1-\eta$ chance, she cannot collect TC due to default. The costs to produce consist of wages and expected input payments and verification cost.

D. Households and Market clearing condition

Suppose that a representative household exists in the economy. The household's objective is to choose a consumption bundle and labor to maximize her utility subject to her budget constraint as

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

where c is the consumption bundle, l is the hours worked, the parameter ψ governs the degree of disutility from working, ξ is the Fischer elasticity, p is the price index, π is the total profit generated by all firms, and E is the total verification cost paid by firms.

Labor supply is equal to labor demand across all firms as

$$l = \sum_{i=1}^{n} l_i. \tag{5}$$

Because firms' customization of their products has a probability η of being qualified for inputs, by law of large number, a fraction η of input orders are turned 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

$$y_i = \sum_{j=1}^{n} m_{ij} + k_i + c_i, \ \forall i \tag{6}$$

where y_i is defined in Equation (1) and $k_i = \sum_{j=1}^{n}(1-\eta)\gamma m_{ij}$. Moreover, we denote the actual sales by firms in sector i as

$$sales_i = p_i\left(c_i + k_i\right) + \sum_{j=1}^{n}\left(1-(1-\eta)tc_{ij}\right) q_{ij} m_{ij} \tag{7}$$

where the sales consist of revenues from consumption goods and inputs from both direct orders and the secondary market.

III. Equilibrium Analysis

Now we define the competitive equilibrium in our model as

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

1) *Given a vector of prices* $\{p_i\}$, *the wage* w *and the contracts offered by suppliers* $\{q_{ji}, tc_{ji}, g_{ji}\}$, *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 (5);*

4) *The commodity prices* $\{p_i\}$ *clear commodity markets in (6), 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:*

$$\alpha_i v_i^L p_i y_i = w l_i, \tag{8}$$

$$\omega_{ji} \nu_i v_{ji}^M p_i y_i = q_{ji} m_{ji}, \ \forall\ j \tag{9}$$

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

$$v_i^L = \frac{1+\theta_i\mu_i}{1+\mu_i}, \ \ \textit{and} \ \ v_{ji}^M = \frac{1+\theta_i\mu_i}{1 - tc_{ji} + \eta tc_{ji} + (1-\eta)\frac{\gamma p_j}{q_{ji}} + \mu_i(1-tc_{ji})}. \tag{10}$$

Then the output y_i can be solved as

$$y_i = \left(z_i p_i^{\alpha_i + \nu_i} \left(\nu_i \prod_{j=1}^{n} \left(\frac{\omega_{ji} v_{ji}^M}{q_{ji}} \right)^{\omega_{ji}} \right)^{\nu_i} \left(\frac{\alpha_i v_i^L}{w} \right)^{\alpha_i} \right)^{\frac{1}{1-\alpha_i-\nu_i}} \tag{11}$$

Proof: see Appendix C.C2.

Here, the labor and the intermediate input wedges measure to which extent the allocations of the labor and intermediate inputs deviate from the first best. Note that three types of frictions are at play in our model: the uncertainty about the quality (also, default risk on TC), the pricing power by suppliers, and the collateral constraint. These frictions interact with each other and affect the outputs through both labor and input wedges. The collateral constraint directly affects the labor wedge, while all three jointly determine the input wedge. In particular, 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 relative size of received TC to the financial condition. Moreover, when the client finds the delivered goods unqualified for inputs, she bears the additional costs of finding alternatives in the secondary market. When the default risk is higher - i.e., η is lower - or when the relative price of input to the one in the secondary market is lower - i.e., $\frac{q_{ji}}{\gamma p_j}$ is smaller, the additional costs are higher. The higher such costs are, the smaller the input wedge is, and the more the client's input demand is distorted more. Equation (11) shows that the output 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 $\mu_i = 0$ eliminates the frictions in our model, and the allocations are at first best. As discussed in detail later, TC responds to firms' productivity and financial conditions, which provides an additional channel of propagating shocks through the input and labor wedge, along with the production network.

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 $\forall j$,

$$\mathbf{Pr}\left(e_{ij}\right) = \sqrt{\frac{e_{ij}}{\bar{e}_i}}, \quad for \;\; e_{ij} \in [0, \bar{e}_i] \tag{12}$$

where $\bar{e}_i$ is the maximal effort level for firms i.[30] Here, we focus on the case in which collateral constraints are binding for all firms. In this case, the loans borrowed by the firm j are equal to $\theta_j p_j y_j$. When the supplier finds out 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 trade credit tc_{ij}, and the penalty payment g_{ij}, respectively, as:*

$$\begin{aligned}
3\gamma\bar{e}_i\left(\frac{(1-\eta)tc_{ij}v_{ij}^M}{1-\theta_j}\right)^2 &= (1+(1-\eta)\gamma)\left(1-tc_{ij}+\eta tc_{ij}\right) \\
&\quad + \left(\mu_j + (1-\eta)\gamma\mu_i\right)(1-tc_{ij}), && (13)\\
\eta\frac{\gamma p_i}{q_{ij}} &= \eta + (1-\eta)(1-tc_{ij}), && (14)\\
g_{ij} &= \omega_{ij}\nu_j p_j y_j, && (15)
\end{aligned}$$

where v_{ij}^M is defined in Equation (10) and y_j is given by Equation (11).
Proof: see Appendix C.C3.

When the firm makes the input price decision, it considers the input demand

[30] 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.

as in Equation (9). 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 the input demand caused by a higher price. As a result, as the input price rises, the input revenue increases, but the increase becomes smaller due to disproportionally lower input demand, implying the input revenue that is a concave function in the price.

On the other hand, for the same verification intensity, the cost of verification increases in input sales. Moreover, the incentive to cheat (claim for bad-quality input) increases with the input sales. Thus, suppliers need to exert more effort to ensure truth-telling. As a result, 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 up to the point at which the unit cost of inputs is the same between ordering it from a supplier and purchasing from the secondary market. A partial equilibrium analysis of Equation (14) implies that the TC intensity increases in 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 proportion 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*

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

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 (13) given Equation (10) and (14). Moreover, we have

$$\frac{\partial\, tc_{ij}}{\partial\, \mu_i} < 0, \;\; and \;\; \frac{\partial\, tc_{ij}}{\partial\, \theta_j} \begin{cases} \leq 0 & if \quad g\left(tc_{ij}, \mu_i, \mu_j, \theta_j\right) \leq 0 \\ > 0 & otherwise \end{cases}, \tag{16}$$

where the g function is defined in Appendix C.C4.

Proof: see Appendix C.C4.

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 guarantee the existence of equilibrium.

Here is the intuition of Proposition 2. A tighter constraint limits the supplier's production so that it can simply require more upfront payment to alleviate its financial constraint and increase production. All else equal, a negative financial shock results a tighter constraint and, thus, less TC. Also, the productivity shock affects the value of the received CBD relative to the total value of output, i.e. $\frac{\sum_{j=1}^{n}(1-tc_{ij})q_{ij}m_{ij}}{p_i y_i}$, and, thus, the constraint is likely to become looser after a negative productivity shock. Therefore, the TC issuance decreases as the supplier receives either a negative financial shock or a positive productivity shock.

The intensity of TC given by a supplier to a client responds to the client's financial condition in a non-monotonic way. A negative financial shock can either 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 also negatively affected. The response ultimately depends on the relative financial constraints of the supplier and client. Consider a negative financial shock hits the client. If the supplier is sufficiently tightened, requiring more input payments in advance is more beneficial to its own production. Thus, the supplier chooses to extend less TC to its client, further weakening the client's financial conditions and distorting production. Otherwise, more input payments are deferred to alleviate the client's financial constraint and partially restore its production and input demand. TC serves as an amplifier in the former case while as a cushion in the latter. This asymmetry is particularly relevant to our observations of the sectoral comovement during recessions in Section I. During a financial recession, the amplifying role of TC can be triggered as firms are more likely to be financially constrained. In contrast, in an economic recession, TC works as a cushion to mitigate the spillover of sectoral shocks.

As shown in Equation C13 in Appendix C.C5, the sectoral output growth in our model generalizes the one used in Li and Martin (2019), where a common factor, sector-specific shocks with addition GR loadings, and the GR-specific factor are considered in reduced form. In our case, we decompose the real sectoral output growth into four components: sectoral productivity shocks, labor and input wedges, the TC adjustment, and the general equilibrium (GE) effects.[31] Thus, the observed sectoral comovement can be attributed to four sources. First, sectoral productivity shocks can generate comovement through input-output linkage. Second, due to the financial frictions, labor and input wedges arise, which further vary over time as the financial shocks hit. Moreover, the loading matrix is time-varying as TC endogenously responds. Thus, the effects of financial shocks on sectoral comovement depend not only on the correlations of the underline shocks but also on the endogenous response of TC and tightness of collateral constraint. Third, endogenous TC also alters sales directly. Last, as a common factor, the GE effects lead sectors to comove homogeneously across sectors. Our quantitative results in the next section will point to the relevance of considering labor and inputs wedges and endogenous TC.

[31] Please refer to Appendix C.C5 for details.

IV. 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 with a fixed-trade-credit model. Last, we study the model implied evolution of comovement, and TC, for the early 1980s recession and the Covid-19 recession.

A. Calibration

We follow a three-stage calibration strategy. First, we select the value of some parameters either following 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 the common practice in the literature, we set the importance of labor disutility ψ to be 1, the elasticity of substitution among consumption goods σ to be 2.5, and the inverse of Frisch elasticity ξ to be 0.36. We set the cost of replacing faulty inputs γ to be 2.89 so that the premium in the secondary market is equivalent to the trading cost between the US and Canada as estimated in Anderson and Van Wincoop (2003).[32] The probability that clients receive qualified inputs, η, is 0.85 to match the one-year survival rate of new startups in the US. As shown in Table D1, we calibrate the total shares of inputs to output ($\{\nu_i\}$), labor shares ($\{\alpha_i\}$), input-output matrix ($\{\omega_{ij}\}$), and consumption shares ($\{\phi_i\}$) using the 2005 12-sector input-output table from the BEA.[33]

[32] The value is calculated, based on Table 2 in Anderson and Van Wincoop (2003) with $\sigma = 2.5$.

[33] 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.

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 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 $\overline{tc}_i$.[34] We then use Equation (13) to solve for e_{ij}, out of which $\bar{e}_i$ is selected as the median value, across all clients j.[35] When this median value is lower than the threshold in Assumption (#1), we replace it with the threshold value. The fifth column of Table D1 displays the results for $\{\bar{e}_i\}$. The mining and manufacturing industries have the highest values, which implies that the states of their products are relatively more complex to verify. On the other hand, for the retail, construction, and education services is the lowest, indicating that it is more straightforward to monitor their states.

Following in 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 (10).[36] Imposing this condition, along with sectoral real gross output and the binding collateral constraint, we can solve the system to obtain the implied sectoral productivity $\{z_{it}\}$ and financial shock $\{\theta_{it}\}$. Panel (a) of Figure D1 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 D1 shows the normalized financial shocks. After the collapse of Lehman Brothers, compared to the pre-recession average, construction, manufacturing, and educa-

[34] In practice, since firms usually provide either inputs or final goods while sectors in our model do both, thus, $\overline{tc}_i \kappa_i$ is used, where κ represents the share of products used as intermediate inputs.

[35] Once $\{\bar{e}_i\}$ are calibrated, we can deviate away from the assumption that the supplier issues the same proportion of payments as TC to all clients, and let Equation (C6) endogenously determine the TC intensity tc_{ij}.

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

tion & healthcare were hit the most in 2008Q4 and 2009Q1. In Appendix D.D2 we show that our model reasonably matches the decline in aggregate GDP and other untargeted variables during the Great Recession.[37]

B. Counterfactual exercise with fixed trade credit

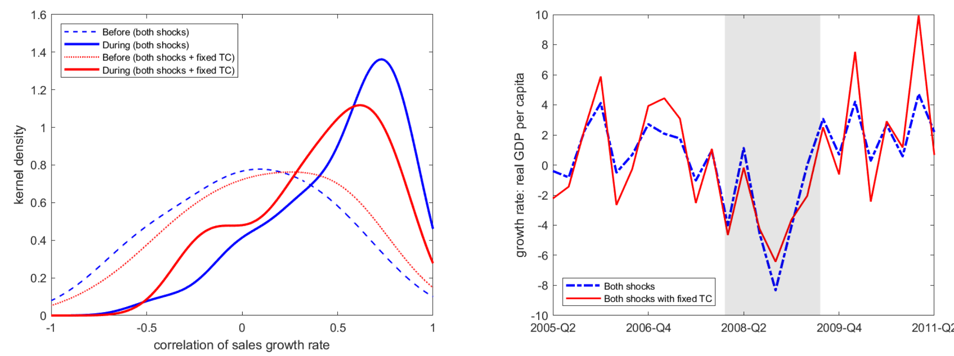
In this section, we perform several counterfactual exercises to study the role of endogenous TC and its interaction with financial and productivity shocks in explaining the sharp increase in comovement during the Great Recession. Considering a counterfactual economy in which TC is fixed to the pre-recession average, we compare this economy with our benchmark model after imposing productivity and financial shocks, together and separately.

We first fix the TC intensity to its pre-recession average. Given all parameters, we impose the same productivity and financial shocks calibrated in Section IV.A. 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 42.6% lower than the increase with the endogenous one (from 0.04 to 0.5). This result is consistent with our sectoral evidence in Section I.C, where the difference of rises in pairwise correlations between the TC-declined and unchanged subgroup is more than 40% of the group average. The intuition is straightforward. In the presence of financial shocks during the recession, the sufficiently constrained suppliers do not extend TC to their shocked clients as they normally do, but rather contract TC, making their clients more constrained. Fixed TC limits the response of suppliers and, thus, it dampens the comovement between the two parties.[38] In addition, the fixed trade-credit model generates a milder decline in aggregate GDP, where the decline in GDP growth is 17.3% smaller in 2008Q4 and 15.2% smaller in 2009Q1 than

[37]By construction, our estimated shocks generate the same sectoral output growth as in the data. Thus, we can also match the observed rise in sectoral comovement.

[38]More specifically, we regress the change in the pairwise correlation, with endogenous and fixed TC, on the one-way and two-way indicators, along with other control variables. We find 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 mainly due to the correlations of the underline shocks. Please refer to Appendix D.D4 for more detail.

our benchmark model. This is because, in the fixed case, the clients' production is not further distorted by a more tightened constraint caused by the contraction in TC.



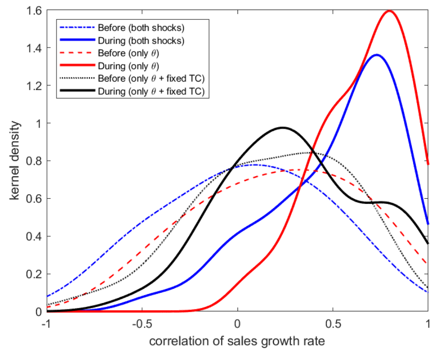
(a) Kernel density of pairwise correlation (b) Growth rate: real GDP per capita

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.

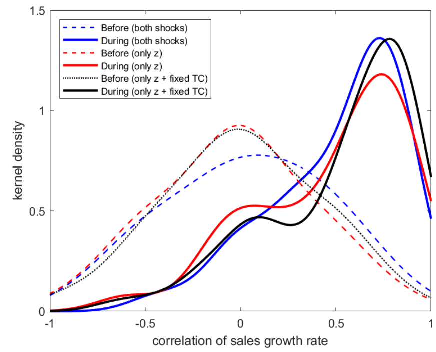
Figure 5. : Both shocks: endogenous vs fixed trade credit

Next, we study the role of financial and productivity shocks in driving sectoral comovement during the Great Recession. In doing so, we feed the model with one set of shocks at a time while keeping the other fixed at the pre-recession average. Panel (a) of Figure 6 displays the kernel density with only financial shocks for the endogenous TC structure (red) and the one in the fixed-TC case (black). With endogenous TC, the average correlation rises from 0.17 to 0.58 during the Great Recession, which is slightly higher than the one implied by our benchmark model (blue). Surprisingly, when we fix the TC intensity, the rise in comovement vanishes, highlighting the role of TC in propagating financial shocks. The intuition is similar as above.

Last, we feed the economy with productivity shocks only. Panel (b) of Figure 6 displays the kernel density in the endogenous TC model (red) and the one in the fixed TC model (black). We observe a rise in sectoral comovement in both models. Since productivity shocks only affect the TC provision through the



(a) only financial shocks



(b) only productivity shocks

Note: The fixed TC case is the one where the trade credit 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 red ones describe the fixed TC case with only financial (productivity) shocks.

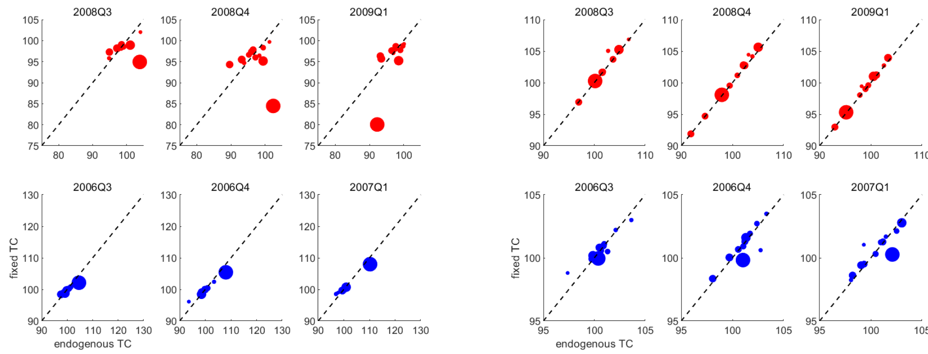
Figure 6. : Pairwise correlation: endogenous vs fixed trade credit

tightness of the financial constraint, and given that TC responds quantitatively little to productivity shocks, both models behave alike. We even observe more comovement in the fixed-TC model as the negative productivity shocks loose the financial constraint in the endogenous trade credit model.

C. *Recalibrating sectoral shocks in the fixed trade credit model*

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

Figure 7 displays the scatter plots of sectoral shocks–the relative size to their pre-recession average, where a bubble represents one sector, its size reflects the sales share in 2005, and the horizontal and vertical axes stand for the endogenous and fixed TC models, respectively. In Panel (a), the financial shocks are quite different between the two models. For example, manufacturing in the endogenous TC model only received a negative financial shock in 2009Q1, and the size of



(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

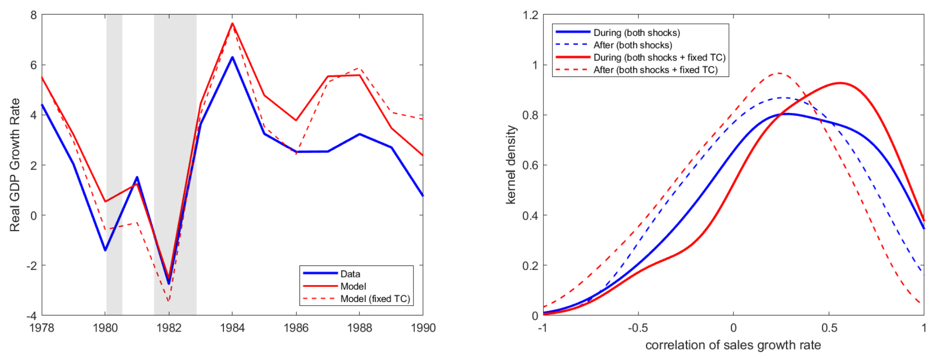
shocks (7.7% decline in 2009Q1) is much smaller than that with fixed TC (15.5% decline in 2008Q4 and 19.9% in 2009Q1). Instead, as shown in the bottom panel of Figure D5, more correlated financial shocks are needed in the fixed TC model. To compare, we also plot pre-recession scatter for three quarters before 2008, where we cannot find significant differences between the two series.

Moreover, Panel (b) displays the scatter plot for the productivity shocks. All bubbles line up along the 45-degree line, indicating the limited interaction between productivity shocks and endogenous TC.

D. *The early 80s recession*

In this section, we analyze an important question: why did not sectoral co-movement 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 annual data. Following the same strategy, we back out two shocks to match sectoral outputs and spreads between 1978 and 1989.[39] Using the same set of parameters calibrated in Section IV.A, we then compare the sectoral comovement, and GDP decline with those generated by a model with TC fixed to the level in 1978.[40] 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.



(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, while 1983-1989 as the post-recession one.

Figure 8. : The Early 80s Recession: endogenous vs exogenous trade credit

Panel (b) of Figure 8 plots the kernel density of pairwise correlation of sectoral sales growth. Without controlling the aggregate GDP, we find the sectoral comovement (blue) slightly rose, consistent with the unconditional correlations in Appendix B.B2. The model with the fixed TC generates an even larger rise in sectoral comovement. Different from the Great Recession, TC during the early 1980s was adjusted to mitigate the negative shocks by smoothing negative

[39]As shown in Figure D8 of Appendix D.D6, we observe a large variation across pairs in the correlations of two shocks. As in Section I.A, we use 1978-1985 as the in-recession window, while 1983-1989 as the post-recession one.

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

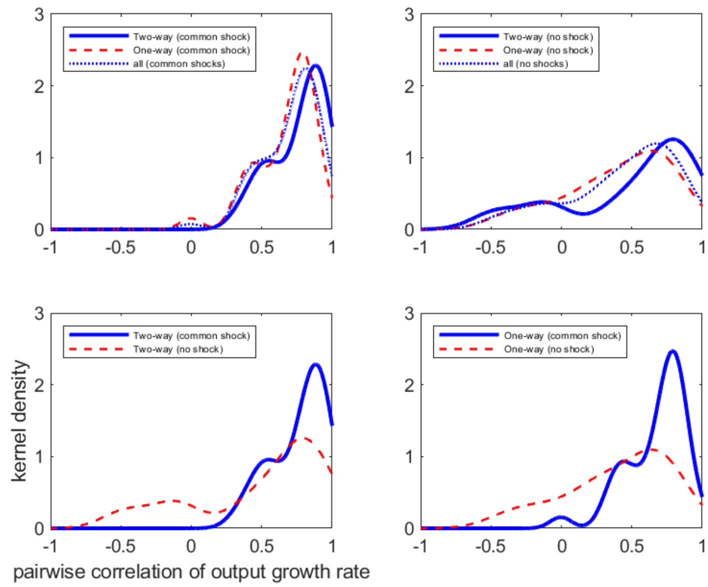
spillover effects among sectors, reducing the decline in GDP.

E. Covid-19 as an aggregate decline in productivity

Finally, 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 between 2005Q1 and 2007Q2 and then simulate a 1.5% decline in productivity for all sectors in 2006Q1. The top left panel of Figure 9 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 I.B. 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. These results are in line with the dynamics of unconditional comovement during Covid-19 in Figure B6 of Appendix B.B3.

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, Figures D9 and D10 in Appendix D.D7 show that the same results hold in a model with non-unitary elasticity of substitution in production as in Atalay (2017) and Carvalho et al. (2021).[41] An aggregate decline in productivity generates a rise in comovement that is very similar for the one-way and two-way trading groups.

[41] Figure D9 assumes an elasticity of substitution between inputs of 0.6, while Figure D10 assumes an elasticity of 0.2. There is no apparent difference in comovement as a result of the elasticity of substitution.



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 9. : Sectoral comovement under common shocks

V. Firm-level evidence on role of trade credit

Since the Great Recession is the only financial crisis that occurred in the US after WWII, we explore the cross-sectional variation across the US public firms during the Great Recession and highlight our main mechanism in the model. In particular, we use the collapse of Lehman Brothers (LB) as a quasi-natural experiment and examine whether and how the trade credit during the Great Recession was triggered as an amplifier of shocks along the production network.

First, we use the 10-K form from Compustat and the syndicated loan from DealScan to construct a firm-to-firm and firm-to-bank network before 2008. We further restrict our sample to pairs where suppliers did not borrow from LB before 2008 but had at least one client doing so and another not. Moreover, we identify firms that did not borrow from LB before 2008 but from lenders that led a syndicated loan with LB before 2008. Thus, by contrasting the difference in comovement between the common suppliers and their clients, we examine whether the LB shock plays any role in driving the rise in comovement and whether and how much trade credit contributes to such a rise. To mitigate the effects of time-varying unobservables on the suppliers' side, we use the change in pairwise correlation as our dependent variable. This method is also in line with the difference-in-difference estimation setting.[42]

We first regress the change in pairwise correlations on the indicators for borrowing from LB and LB-related lenders before 2008 and their interactions with the change in the client's AP-to-OC ratio, along with other control variables. We find that clients connecting to LB directly or indirectly through the financial network significantly comoved more with their suppliers during the Great Recession. Furthermore, the comovement was even higher as the LB-related clients experienced a contraction in the AP-to-OC ratio.

To deal with the endogeneity issue of the change in the client's AP-to-OC ratio, we adopt the bank-credit shocks developed by Chodorow-Reich (2014) (**CR** index) as an instrument. This index measures the firm's exposure to credit shocks during the Great Recession. Then, we perform a two-stage least square regression with the change in pairwise correlation as the dependent variable and the AP-to-OC ratio, proxied by the **CR** index, as the key explanatory variable. We treat trade credit as proximate causes, determined by and acting as channels of influence for such shocks, for the rise in comovement. We find the response of the AP-to-OC ratio is not monotonic with the degree of exposure. However, once the **CR** index is lower than the sample median, the AP-to-OC ratio starts to contract. Then we examine how the credit shocks were transmitted into the change in comovement between the supplier and client through the trade credit chain. We find that a one percentage point decline in the proxied AP-to-OC ratio generates a 0.028 rise in correlation, which is 16.5% of the average rise across the pairs of the US public firms.

Our findings here highlight the propagating and amplifying role of trade credit

[42]Please see Appendix E for detail.

in increasing comovement as a response to the initial financial shocks during the Great Recession and also indicate the circumstance under which such a role is triggered.

VI. 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 adjustment play a key role in driving comovement during financial crises.

We then construct a multisector model with input-output linkages, financial frictions, and endogenous trade credit adjustment and highlight the importance of trade credit adjustment in driving sectoral comovement during post-war US recessions. Our model emphasizes the asymmetric role of trade credit. When financial conditions are loose, suppliers with "deep pockets" have incentives to extend more trade credit to clients facing tighter financial conditions. However, when financial conditions are adverse to suppliers too, trade credit provision collapses. We show that this mechanism is crucial to explain the significant increase in sectoral comovement during the Great Recession in the US. Moreover, through this mechanism, our model suggests that trade credit amplifies the effect of financial shock on GDP growth. Using our model, we show that during the early 1980 recession, which is comparable to the Great Recession in magnitude, trade credit acted as a cushion that mitigated negative spillovers and prevented the shift in comovement and, therefore, mitigated the recession.

More generally, our paper emphasizes the relevance of considering the internal propagation forces and the endogenous trade credit 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 - compared to a model with exogenous trade credit - can generate large sectoral cascades. A milder and well-targeted stabilization policy should be able to stabilize the macroeconomy in the presence of negative financial shocks.

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Data Description

A1. Sectors from BEA and their characteristics

For the annual outputs, we adopt the nominal gross output by industry, provided by the Bureau of Economic Analysis (BEA), adjusted for the sectoral chain-type price indexes. We adopt the real gross output by industry (seasonal-adjusted at annual rates) for the quarterly ones. The quarterly series started in 2005Q1, while the annual ones started in 1947. For both series, after excluding agriculture, forestry, fishing, and hunting (AFFH), finance, insurance, real estate (FIRE), and public sectors, we end up with a sample consisting of 57 sectors and 1596 pairs.

The sectors' list and characteristics are shown in Table A1. All pairwise correlations of output growth are calculated using Equation (A1). 2005Q3-2007Q2, 2007Q3-2009Q2, and 2009Q3-2011Q2 are respectively used to represent before, during, and after the Great Recession. $c\bar{o}rr_{before}$, $c\bar{o}rr_{in}$, and $c\bar{o}rr_{after}$ are the average for the corresponding sector with all others.

The two or one-way linkages show the number of sectors with which the corresponding sector has a two or one-way trading relationship. Two sectors are classified as in the two-way trading group if they are both input suppliers and clients to each other. The one-way trading group if only one sector supplies inputs to the other but not vice versa.

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

Table A1—: List of sectors and characteristics

Sector	# two-way	# one-way	$\tilde{corr}_{before}$	$\tilde{corr}_{in}$	$\tilde{corr}_{after}$	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%

The ratio of account receivables to average sales between the current and past quarters (henceforth, the AR-to-sales ratio) is calculated to measure the intensity of trade credit provision, while the ratio of account payables over average operating cost (henceforth, the AP-to-OC ratio) as the intensity of trade credit reception. We take the median value of both ratios for each firm from Compustat, respectively, over 2005Q3–2006Q2 and 2008Q3–2009Q2, further calculate the first difference between 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 -1.3 percentage points.

A2. Compustat

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

- Observations with negative total assets (atq), negative sales (saleq), negative cash and marketable securities, cash and marketable securities greater than total assets;
- Firms not incorporated in the US;
- All financial firms (firms with standard industrial classification(SIC) codes between 6000 and and 6999);
- Firms with 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
- Observations which have cash and marketable securities greater than total assets;

Table A2 displays the summary statistics of all selected firms.

Table A2—: Summary statistics of selected Compustat firms

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

A3. Syndicated loan from Dealscan

Following Chodorow-Reich (2014), we use Deals can 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

A4. Measure of sectoral comovement

The correlation of real GDP growth between two countries is widely used to study the business cycle comovement across countries (see, for example, Frankel and Rose, 1998; Clark and van Wincoop, 2001). Here, a similar measure, the pairwise correlation of gross output growth between two sectors, is applied to study intersectoral comovement. Then, we take the growth rates of the sectoral outputs and calculate the correlation of the growth rates between any pair of sectors over a certain time window as

$$\mathbf{corr}\left(\Delta y_i, \Delta y_j\right) = \frac{\sum_{t\in\mathcal{T}}\left(\Delta y_{it} - \overline{\Delta y_i}\right)\left(\Delta y_{jt} - \overline{\Delta y_j}\right)}{\left(\#\mathcal{T}-1\right)\mathbf{std}\left(\Delta y_i\right)\ \mathbf{std}\left(\Delta y_j\right)}, \tag{A1}$$

where i and j with $i \neq j$ stand for two sectors, $\mathcal{T}$ is the time window, Δy_{it} is the growth rate from the previous period at time t, and $\overline{\Delta y_i}$ and $\mathbf{std}\left(\Delta y_i\right)$ are, respectively, the sample mean and standard deviation over $\mathcal{T}$. Throughout the analysis in the paper, we use eight consecutive periods (either quarters or years) for time window $\mathcal{T}$ unless otherwise stated. Li and Martin (2019) use the same measurements for the sectoral comovement but over a different time window. Here we use an eight-year time window and also try a six- and ten-year time window. The main results here are robust.

The previous literature, such as Christiano and Fitzgerald (1998), Hornstein (2000), and Kalemli-Ozcan et al. (2013), introduce another approach to measure the comment. They firstly regress one sector's employment on the other's and then take R^2 to measure the comovement, which assesses how much one sector's employment can be accounted for by the other's. Both approaches are similar, except theirs is only normalized by the standard deviation of the targeted sector, while ours accounts for both sectors' variation.

Additional Sectoral Evidence

B1. *Summary statistics of pairwise correlation*

Figure B1 displays the evolution of the median value of the pairwise correlations, where the red dotted line is the average from 1950-2005 and the dashed one is the 95% confidence interval. The year on the horizontal axis corresponds to the fourth year of each point estimate. The median fluctuates within the 95% confidence interval for most of the years, except the Great Recession and 1962. Also, we find the median of unconditional pairwise correlation is acyclical over the business cycle.

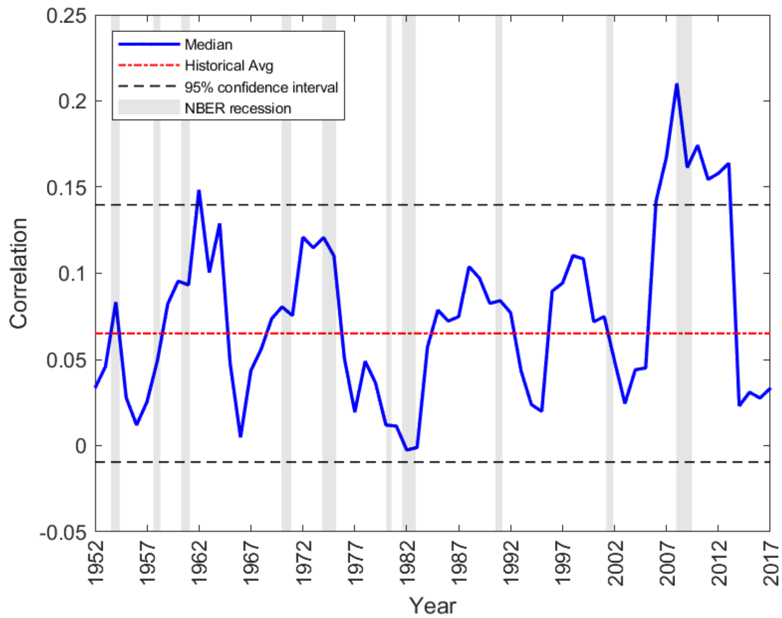


Figure B1. : Kernel density of unconditional correlations (eight-year rolling window)

Moreover, we calculate the summary statistics for the pairwise correlations in Figure 1. Six recessions after WWII are considered, namely 1960, 1970, 1973, and 1990 recessions, the 1980 recession with the 1981-1982 recession, and the Great Recession. Using Equation (A1), we calculate the pairwise correlations over eight years, starting three years ahead of each recession. Also, we take 1962-1968 as the representation for the pre-1970 recession, 1983-1989 for both post-1980 and pre-1990 recessions, 1992-1999 for the post-1990 recession, 2002-2007 for the pre-Great Recession, and 2011-2018 for the post-Great Recession. Furthermore, we perform a two-sample t-test to examine whether the mean of pairwise correlations during a recession is the same as the pre- or post-recession average. Also, to test whether pairwise correlations from two different periods come from the same distribution, we perform the Kolmogorov-Smirnov (KS) test. Table B1 reports the results, where we report the mean difference of the two-sample t-test and the KS statistics, both with the p-value in parentheses. Only during the Great Recession, we reject both null hypothesises at 1% significance level.

Table B1—: Summary statistics: conditional pairwise correlations (annual growth)

	Mean	Median	Std	Skewness	T Test	KS Test
The 1960 recession						
During the 1960 recession	0.05	0.09	0.50	-0.13		
After the 1960 recession	0.00	0.01	0.45	0.00	0.04(0.07)	0.09(0.01)
The 1970 recession						
Before the 1970 recession	0.00	0.01	0.45	0.00	0.06(0.00)	0.08(0.02)
During the 1970 recession	0.07	0.08	0.42	-0.12		
The 1973 recession						
During the 1973 recession	0.09	0.12	0.44	-0.21		
The 1980 recession						
During the 1980 recession	0.01	0.01	0.47	0.00		
After the 1980 recession	0.09	0.09	0.43	-0.11	-0.08(0.99)	0.01(0.75)
The 1990 recession						
Before the 1990 Recession	0.09	0.09	0.43	-0.11	-0.01(0.61)	0.02(0.42)
During the 1990 recession	0.08	0.08	0.42	-0.08		
After the 1990 Recession	0.06	0.09	0.40	-0.15	0.01(0.17)	0.04(0.07)
The 2001 recession						
Before the 2001 Recession	0.06	0.09	0.40	-0.15	-0.03(0.95)	0.01(0.85)
During the 2001 recession	0.06	0.07	0.40	-0.09		
After the 2001 Recession	0.02	0.00	0.48	-0.01	0.02(0.09)	0.07(0.00)
The Great Recession						
Before the Great Recession	0.02	0.00	0.48	-0.01	0.12(0.00)	0.14(0.00)
During the Great Recession	0.14	0.21	0.50	-0.31		
After the Great Recession	0.03	0.03	0.41	0.01	0.11(0.00)	0.17(0.00)
The Covid-19 recession						
Before the Covid-19 recession	0.03	0.03	0.41	0.01	0.00(0.40)	0.08(0.00)
During the Covid-19 Recession	0.04	0.05	0.51	-0.07		

Here our approach implicitly takes the recession duration into account. Since the fraction that each recession stays in the fixed time window varies, we adjust the length of our time window to account for the duration explicitly. However, we cannot directly compare across time windows as they may come from different underline distributions. Thus, we standardize each sequence with the corresponding average and standard deviation before the Great Recession. As shown in Figure B2, We find our results here robust.

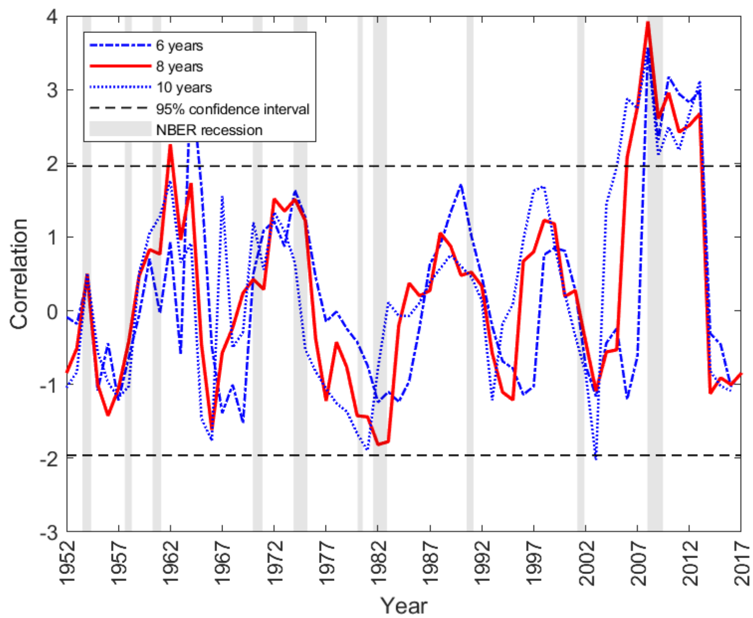


Figure B2. : Median of pairwise correlation standardized to pre-GR

Furthermore, we zoom into the Great Recession with the quarterly growth. With the same set of sectors, we report the summary statistics of pairwise correlation from Section I.A through I.C. To test whether pairwise correlations from two different periods come from the same distribution, we perform two-sample t-test and the KS test. Table B2 reports the results, where we report the mean difference of the two-sample t-test and the KS statistics, both with the p-value in parentheses.

Following the categorization as in Section I.C, a pair is considered to have experienced a trade credit decline during the Great Recession (henceforth, the TC declined group) if both the change in the supplier's AR-to-sales ratio and the

Table B2—: Summary statistics: unconditional pairwise correlations (quarterly growth)

	Mean	Median	Std	Skewness	T-Test	KS Stat
Overall						
Before the Great Recession	0.05	0.07	0.40	-0.11	0.25(0.00)	0.28(0.00)
During the Great Recession	0.31	0.39	0.41	-0.58		
After the Great Recession	0.01	0.01	0.38	-0.07	0.29(0.00)	0.32(0.00)
Two-way trading sectors						
Before the Great Recession	0.10	0.14	0.40	-0.23	0.41(0.00)	0.48(0.00)
During the Great Recession	0.52	0.60	0.31	-1.10		
After the Great Recession	0.02	0.01	0.37	-0.03	0.50(0.00)	0.56(0.00)
One-way trading sectors						
Before the Great Recession	0.02	0.02	0.39	0.00	0.23(0.00)	0.27(0.00)
During the Great Recession	0.25	0.31	0.41	-0.46		
After the Great Recession	0.02	0.03	0.38	-0.12	0.23(0.00)	0.27(0.00)
No trading sectors						
Before the Great Recession	0.05	0.09	0.41	-0.21	0.09(0.00)	0.11(0.01)
During the Great Recession	0.15	0.17	0.41	-0.23		
After the Great Recession	0.00	-0.02	0.38	0.01	0.15(0.00)	0.18(0.00)
Two-way trading and TC declined group						
Before the Great Recession	0.05	0.08	0.44	-0.03	0.57(0.00)	0.63(0.00)
During the Great Recession	0.63	0.69	0.24	-1.43		
After the Great Recession	-0.01	-0.03	0.39	0.15	0.64(0.00)	0.72(0.00)
Two-way trading and TC unchanged group						
Before the Great Recession	0.10	0.14	0.40	-0.29	0.35(0.00)	0.39(0.00)
During the Great Recession	0.45	0.51	0.33	-0.81		
After the Great Recession	0.02	0.03	0.36	-0.06	0.42(0.00)	0.49(0.00)
One-way trading and TC declined group						
Before the Great Recession	0.11	0.17	0.40	-0.26	0.27(0.00)	0.35(0.00)
During the Great Recession	0.39	0.46	0.34	-0.59		
After the Great Recession	-0.02	0.01	0.37	0.08	0.41(0.00)	0.49(0.00)
One-way trading and TC unchanged group						
Before the Great Recession	-0.02	-0.04	0.39	0.17	0.28(0.00)	0.33(0.00)
During the Great Recession	0.26	0.35	0.43	-0.53		
After the Great Recession	0.02	0.02	0.38	-0.17	0.24(0.00)	0.29(0.00)
No trading and TC declined group						
Before the Great Recession	0.20	0.26	0.34	-0.35	0.02(0.35)	0.18(0.11)
During the Great Recession	0.23	0.32	0.44	-0.33		
After the Great Recession	-0.02	-0.07	0.41	-0.01	0.25(0.00)	0.28(0.00)
One-way trading and TC unchanged group						
Before the Great Recession	0.04	0.06	0.41	-0.26	0.10(0.01)	0.14(0.03)
During the Great Recession	0.15	0.21	0.43	-0.29		
After the Great Recession	0.00	0.01	0.39	-0.02	0.14(0.00)	0.19(0.00)

client's AP-to-OC ratio both declined more than the corresponding median value across all public firms, which are, respectively, -1.6 and -1.0 percentage points. Otherwise, the pair is categorized as in the unchanged group (henceforth, the TC unchanged group). Notably, in the no trading group, this pair is classified into the TC declined group if the TC decline condition is satisfied in either direction. Figure B3 reports the results. No significant shift is observed in both subgroup.

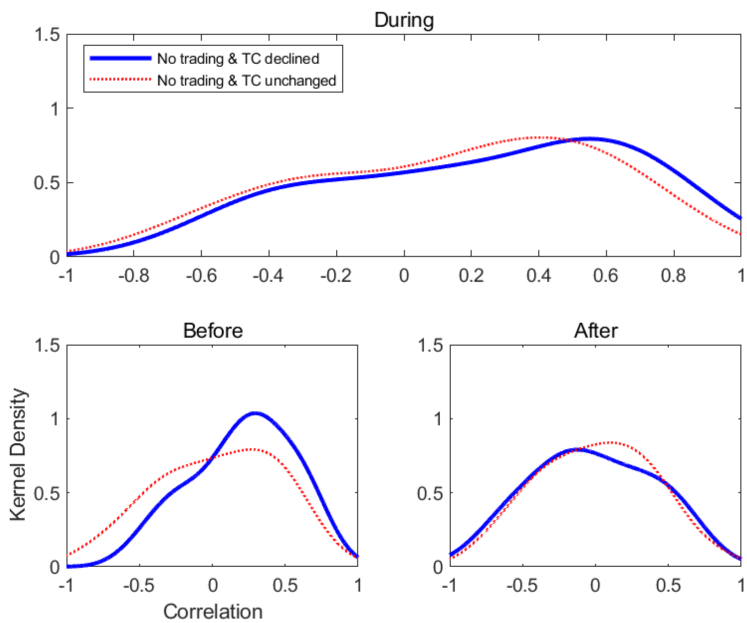


Figure B3. : Kernel density for no trading group by the TC subgroup

B2. *Pairwise correlation in other recession without controlling for GDP*

We calculate the unconditional pairwise correlation of the annually sector growth, without controlling for the recession size. The same time windows are applied for recession and normal period, as in Section I.A. Figure B4 display the densities for eight recessions and the corresponding normal periods to be compared.

Moreover, we calculate the summary statistics for the pairwise correlations in

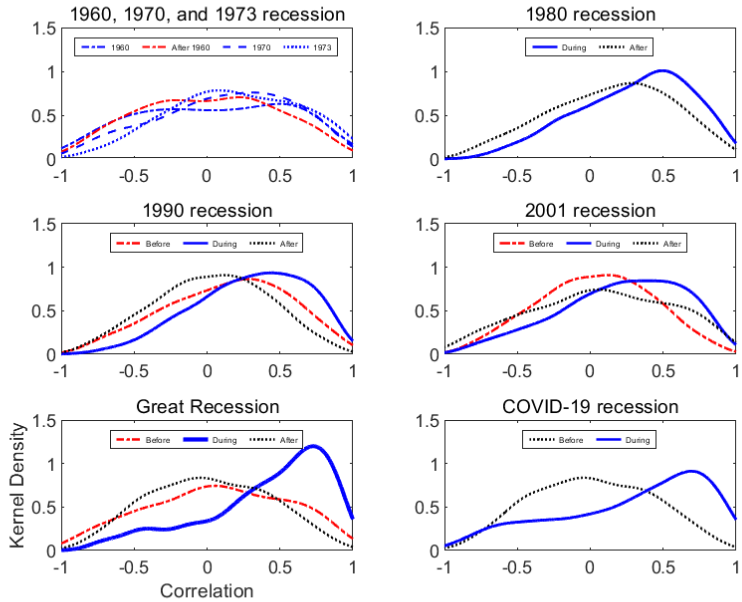


Figure B4. : Kernel density in other recession without controlling for GDP

Figure B4. Table B3 reports the results, where we report the mean difference of the two-sample t-test and the KS statistics, both with the p-value in parentheses.

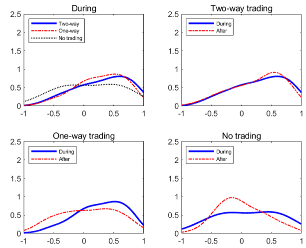
B3. Role of IO linkage in the other recessions

Following the categorization as in Section I.B, two sectors are classified as in the two-way trading group if they are both input supplier and client to each other; the one-way trading group if only one sector supplies inputs to the other but not vice versa; and the no-trading group if no intermediate input is traded between two. Then we apply the division to the all other recessions except the Great Recession. Figure B5 reports the results. We find the two-way trading group modestly shift toward the right during the 1980 and 1990 recession, but not as much as the Great Recession. The sectoral comovement universally rose across three groups during the Covid-19 recession.

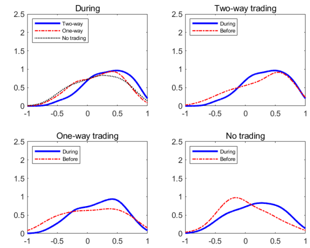
Table B3—: Summary statistics: unconditionally pairwise correlations (annual growth)

	Mean	Median	Std	Skewness	T Test	KS Test
The 1960 recession						
During the 1960 recession	0.27	0.32	0.43	-0.43		
After the 1960 recession	0.16	0.19	0.45	-0.26	0.11(0.00)	0.09(0.01)
The 1970 recession						
Before the 1970 recession	0.16	0.19	0.45	-0.26	0.08(0.00)	0.08(0.01)
During the 1970 recession	0.24	0.28	0.38	-0.29		
The 1973 recession						
During the 1973 recession	0.36	0.39	0.35	-0.59		
The 1980 recession						
During the 1980 recession	0.30	0.35	0.39	-0.45		
After the 1980 recession	0.14	0.17	0.42	-0.24	0.15(0.00)	0.01(0.75)
The 1990 recession						
Before the 1990 Recession	0.14	0.17	0.42	-0.24	0.15(0.00)	0.02(0.42)
During the 1990 recession	0.29	0.33	0.38	-0.43		
After the 1990 Recession	0.03	0.05	0.39	-0.09	0.26(0.00)	0.04(0.07)
The 2001 recession						
Before the 2001 Recession	0.03	0.05	0.39	-0.09	0.17(0.00)	0.01(0.85)
During the 2001 recession	0.24	0.29	0.41	-0.52		
After the 2001 Recession	0.07	0.08	0.47	-0.13	0.13(0.00)	0.07(0.00)
The Great Recession						
Before the Great Recession	0.07	0.08	0.47	-0.13	0.33(0.00)	0.14(0.00)
During the Great Recession	0.41	0.52	0.44	-0.94		
After the Great Recession	0.01	0.00	0.41	0.03	0.39(0.00)	0.17(0.00)
The Covid-19 recession						
Before Covid-19 recession	0.01	0.00	0.41	0.03	0.31(0.00)	0.08(0.00)
During Covid-19 recession	0.33	0.46	0.49	-0.83		

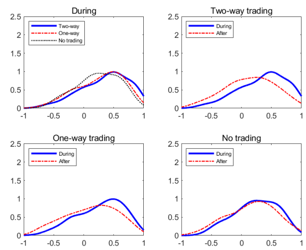
Now we zoom into the Covid-19 recession with quarterly data. Figure B6 reports the kernel density of output growth before and during Covid-19. We divide the pairs of sectors based on their degree of interconnections. It is clear from the figure that: i) comovement increased significantly during Covid-19; ii) comovement increased for all pairs of sectors, regardless of their degree of interconnections. Therefore, we interpret the large shift in comovement as the result of a large aggregate shock.



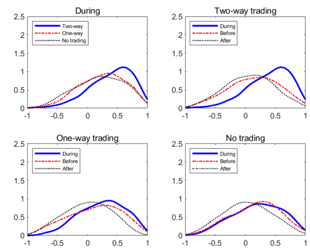
(a) the 1960 recession



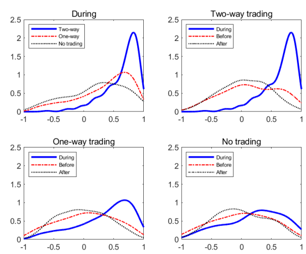
(b) the 1970 recession



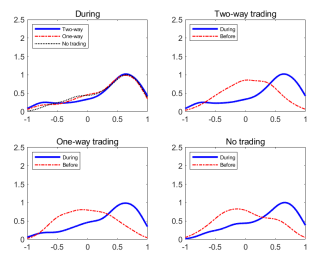
(c) the 1980 recession



(d) the 1990 recession



(e) the Great Recession



(f) the Covid-19 recession

Figure B5. : Kernel density for the earlier recessions: unconditional pairwise correlation by interconnectedness

B4. Maximal correlations

Due to delivery, adjustment cost, search frictions, and other factors, two sectors may not comove contemporaneously, and instead, one may lead to another. Thus, the rise in sectoral comovement during the Great Recession may be just a result of synchronization in timing. In addition to the contemporaneous correlation, we calculate one-period lagged and leaded correlations and then take the maximum

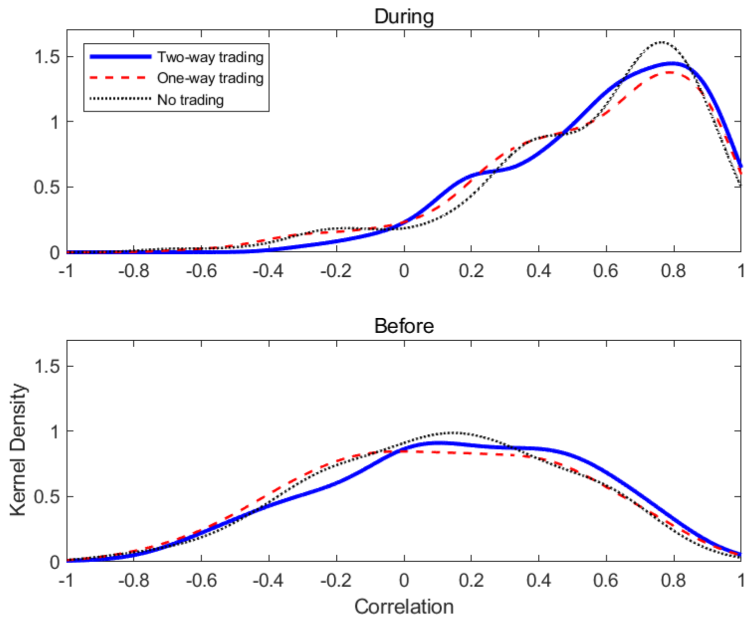


Figure B6. : Kernel density of output growth before and during Covid-19.

value among the three. Figure B7 reports the results before, during, and after the Great Recession. We find 1) the maximal correlations still significantly rose during the Great Recession; 2) the maximal correlations are higher than the contemporaneous ones for before, during and after the Great Recession; 3) the rise in the maximal correlations is more concentrated than the contemporaneous ones, where the latter has a fatter right tails.

B5. Comovement among consumption providers

We divide our sample of sectors into two groups according to the share of output used as the final consumption. Please refer Table A1 for the specific values. Here, one sector is classified into the consumption-provider group if its share is larger than the median value, namely 36.8%. Otherwise, this sector would be grouped as the input provider. Figure B8 shows the results.

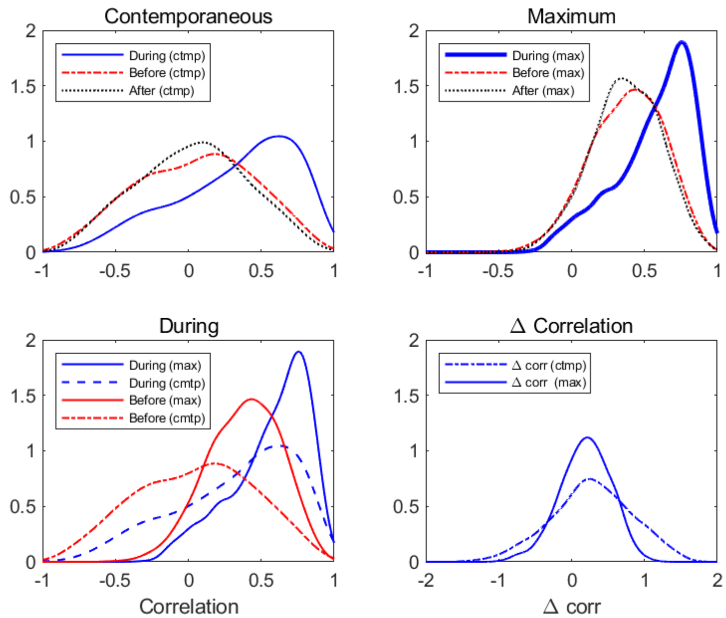


Figure B7. : Kernel density for maximum and contemporaneous correlations

Model details: proof for propositions and lemmas

C1. Solutions

The first-order conditions on consumption and labor supply yield

$$pc = \frac{w}{\psi l^{\xi}}. \tag{C1}$$

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

$$c = \left(\sum_{i=1}^{n} \phi_i^{\frac{1}{\sigma}} c_i^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{C2}$$

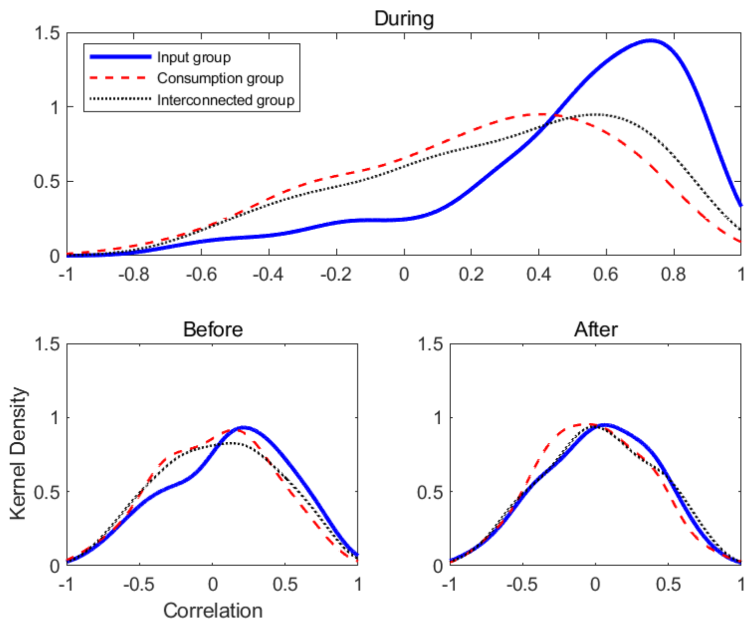


Figure B8. : Kernel density grouped by the final consumption exposure subgroups

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

$$p = \left(\sum_{i=1}^{n} \phi_i p_i^{1-\sigma} \right)^{\frac{1}{1-\sigma}}, \tag{C3}$$

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

$$c_i = \phi_i \left(\frac{p_i}{p} \right)^{-\sigma} c. \tag{C4}$$

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 the efforts are costly, suppliers will make enough efforts 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

$$
\begin{aligned}
\text{(C5)} \quad \mathcal{L} \quad = \quad & p_i z_i \left(\prod_{j=1}^{n} m_{ji}^{\omega_{ji}} \right)^{\nu_i} l_i^{\alpha_i} - \sum_{h=1}^{n} \left(p_i - (1 - (1-\eta)\, tc_{ih})\, q_{ih} \right) m_{ih} \\
& - w l_i - \sum_{j=1}^{n} \left(1 - (1-\eta) tc_{ji} + (1-\eta)\gamma \frac{p_j}{q_{ji}} \right) q_{ji} m_{ji} \\
& - (1-\eta)\bar{e}_i \sum_{h=1}^{n} \left(\frac{tc_{ih} q_{ih} m_{ih}}{(1-\theta_h)\omega_{ih} v_h p_h y_h} \right)^2 q_{ih} m_{ih} + \mu_i \left(\theta_i p_i z_i \left(\prod_{j=1}^{n} m_{ji}^{\omega_{ji}} \right)^{\nu_i} l_i^{\alpha_i} \right. \\
& \left. z + \sum_{h=1}^{n} (1 - tc_{ih}) q_{ih} m_{ih} - w l_i - \sum_{j=1}^{n} (1 - tc_{ji}) q_{ji} m_{ji} \right) \\
& + \sum_{h=1}^{n} \lambda_{ih} \left(\gamma p_i - d_{ih} q_{ih} - \eta (1 - d_{ih}) q_{ih} - (1-\eta)\left(\gamma - \theta_i\right) p_i \right)
\end{aligned}
$$

C2. Proof of Lemma 1

PROOF:

Taking the derivatives of Equation (C5) with respect to l_i and m_{ji}, we have the first order conditions as in Equation (8) and (9), and then use Equation (1) to derive the solution for y_i as in Equation (11).

C3. 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 payament as in Equation (15). Taking solution of m_{ij} from Lemma 1 as given, we have $\frac{tc_{ih} q_{ih} m_{ih}}{(1-\theta_h)\omega_{ih} v_h p_h y_h} = \frac{tc_{ij} v_{ij}^{M}}{1-\theta_j}$. Since the firm has pricing power over the input client, we take the first order conditions of q_{ij} as in Equation (C5). And the firm set the TC intensity to the extent where the no-arbitrage constraint as shown in the NAC constraint is just binding.

C4. Proof of Proposition 2

PROOF:

Combining Equation (13) with (10) and (14), we have

$$3\gamma\bar{e}_i\left(\frac{\eta(1-\eta)(\eta+\theta_j\mu_j)tc_{ij}}{(1-\theta_j)\left(1+\eta\mu_j-(1-(1-\mu_j)\eta)tc_{ij}\right)}\right)^2 \tag{C6}$$

$$= \quad (1+(1-\eta)\gamma)\left(1-(1-\eta)tc_{ij}\right)+\left(\mu_j+(1-\eta)\gamma\mu_i\right)(1-tc_{ij}).$$

At $tc_{ij}=0$, we have the left-hand side (LHS) of Equation (C6) equal to 0, while the right-hand side (RHS) is positive. Clearly, the LHS is increasing in tc_{ij}, while the RHS is decreasing in tc_{ij}. Moreover, Assumption (#1) ensures the LHS is larger than the RHS at $tc_{ij}=1$. Therefore, the solution exists for any $\theta\in(0,1)$ and $\mu>0$, and the uniqueness is guaranteed due to monotonicity.

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

$$\begin{aligned} g\left(tc_{ij},\mu_i,\mu_j,\theta_j\right) \quad = \quad & \Bigg(\frac{2\eta(1-tc_{ij})}{1+\eta\mu_j-(1-(1-\mu_j)\eta)tc_{ij}}+ \\ & \frac{(1-tc_{ij})}{(1+(1-\eta)\gamma)\left(1-(1-\eta)tc_{ij}\right)\left(\mu_j+(1-\eta)\gamma\mu_i\right)(1-tc_{ij})}\Bigg)\frac{\partial\,\mu_j}{\partial\,\theta_j} \\ & -\frac{2\theta_j}{\eta+\theta_j\mu_j}\frac{\partial\,\mu_j}{\partial\,\theta_j}-2\left(\frac{1}{1-\theta_j}+\frac{\mu_j}{\eta+\theta_j\mu_j}\right) \\ & +\frac{(1-\eta)\gamma(1-tc_{ij})}{(1+(1-\eta)\gamma)\left(1-(1-\eta)tc_{ij}\right)+\left(\mu_j+(1-\eta)\gamma\mu_i\right)(1-tc_{ij})}\frac{\partial\,\mu_i}{\partial\,\theta_j} \end{aligned} \tag{C7}$$

C5. 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, which details are specified in appendix, and let

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

Then we denote

$$x_t = [x_{1t}, \dots, x_{nt}]', \quad for \ \ x \in \left\{p, y, z, sales, v^L, \right\} \tag{C8}$$

$$x_t = [x_{11,t}, \dots, x_{1n,t}, \dots, x_{n1,t}, \dots, x_{nn,t}]', \quad for \ \ x \in \left\{tc, q, v^M\right\} \tag{C9}$$

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

(C10)

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

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

$$\mathbf{M}_{xt} = \begin{bmatrix} (1-(1-\eta)tc_{11,t})\,\omega_{11}v^M_{11,t} & \dots & (1-(1-\eta)tc_{1n,t})\,\omega_{1n}v^M_{1n,t} \\ & \ddots & \\ (1-(1-\eta)tc_{n1,t})\,\omega_{n1}v^M_{n1,t} & \dots & (1-(1-\eta)tc_{nn,t})\,\omega_{nn}v^M_{nn,t} \end{bmatrix}. \tag{C11}$$

Moreover, 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 $\{z_{it}\}$, Lagrangian multipliers for collateral constraints $\{\mu_{it}\}$, the financial conditions $\{\theta_{it}\}$, labor wedges $\{v^L_{it}\}$, inputs wedges $\left\{v^M_{ij,t}\right\}$, and trade credit intensities and $\{d_{ij,t}\}$, the vector of sectoral sales growth rates can be expressed as

$$\Delta \log(sales_t) = \Delta \log\left(\left(\eta \mathbf{I}_n + \left(1 - \frac{1}{\eta\gamma}\right)\mathbf{D}_\nu \mathbf{M}_{xt}\right) p_t \circ y_t\right) \tag{C12}$$

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

$$\begin{aligned}
\Delta \log(p_t \circ y_t) \quad = \quad & (\mathbf{I}_n - \mathbf{D}_\alpha - \mathbf{D}_\nu)^{-1} \Big(\underbrace{\Delta \log z_t}_{\%\,\Delta\ in\ prod} + \underbrace{\mathbf{D}_\nu \mathbf{M}_\omega \Delta \log\left(1 - (1-\eta)tc\right)}_{TC\ \ effects} \\
& + \underbrace{\mathbf{D}_\alpha \Delta \log v_t^L + \mathbf{D}_\nu \mathbf{M}_\omega \Delta \log v_t^M}_{financial\ \ frictions} \\
& + \underbrace{\Delta \log\left(\mathbf{1}_n'\left(\eta \mathbf{I}_n - \frac{1}{\eta\gamma}\mathbf{D}_\nu \mathbf{M}_{xt}\right) p_t \circ y_t\right)\left(\frac{1}{\sigma - 1}\left(\mathbf{I}_n - \mathbf{D}_\nu \Omega'\right) - \frac{1}{1-\xi}\mathbf{D}_\alpha\right)\mathbf{1}_n}_{wage\ \ effects} \\
& - \underbrace{\frac{1}{\sigma - 1}\left(\mathbf{I}_n - \mathbf{D}_\nu \Omega'\right)\Delta \log\left(\left(\eta \mathbf{I}_n - \frac{1}{\eta\gamma}\mathbf{D}_\nu \mathbf{M}_{xt}\right) p_t \circ y_t\right)}_{pricing\ \ effects} \\
& - \underbrace{\frac{1}{1-\xi}\Delta \log\left(\mathbf{1}_n' \mathbf{D}_\alpha v^L \circ p_t \circ y_t\right)\mathbf{1}_n}_{aggregate\ \ labor\ \ effects}
\end{aligned} \tag{C13}$$

Equation (C13) illustrates four types of sources that can affect the growth rates of sectoral sales: sectoral productivity shocks, financial frictions, endogenous trade credit channel and GE effects.

Calibration and Results from Quantitative Analysis

D1. *Calibrated parameters and shocks*

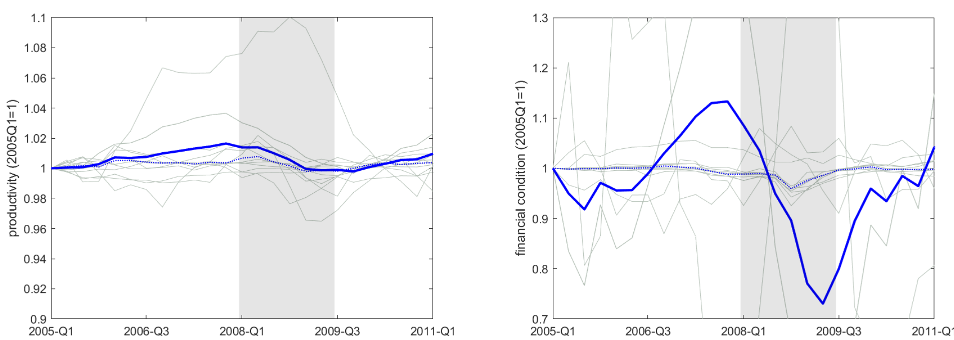
Table D1 shows our calibration for ν, α, ϕ and κ, which are all calculated as the counterpart as in the US input-output table. $\bar{e}$ is solved using the equilibrium conditions.

Figure D1 shows the evolution of calibrated productivity and financial shocks, where all series are normalized to 1 at 2005Q1. Productivity shocks are calculated with external sources, while financial shocks are calibrated with the equilibrium equation. Each grey line stands for one sector, and the solid and dashed blue line,

Table D1—: Calibration

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

respectively, stand for the weighted average (sales share in 2005 as weights) and median across all sectors.



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

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

Figure D1. : Normalized financial and productivity shocks (2005Q1=1)

We further estimate the sectoral productivity as the Solow residual. In doing so, we firstly take the sectoral value added (VA) from BEA, capital usage from KLEMs, hours worked from BLS, and the corporate bond spread constructed by Gilchrist and Zakrajšek (2012). The annual usage of capital is interpolated, using Denton's method, into the quarterly frequency, and the bond spread is aggregated into the sectoral level by taking the median value. Then we regress the logarithm of VA on the logarithm of capital, the hours worked, and the bond spread, and then predict the residuals as the sectoral TFP. As shown in Bigio and La'O (2020), the productivity does not respond to the financial distortions at the first order, but the labor wedge does. Thus, we include the bond spread in our estimation to control for the effects of financial distortions on the TFP. Figure D2 display the kernel density of the estimated productivity and financial shocks. The model-implied productivity are much less correlated than the Solow residuals.

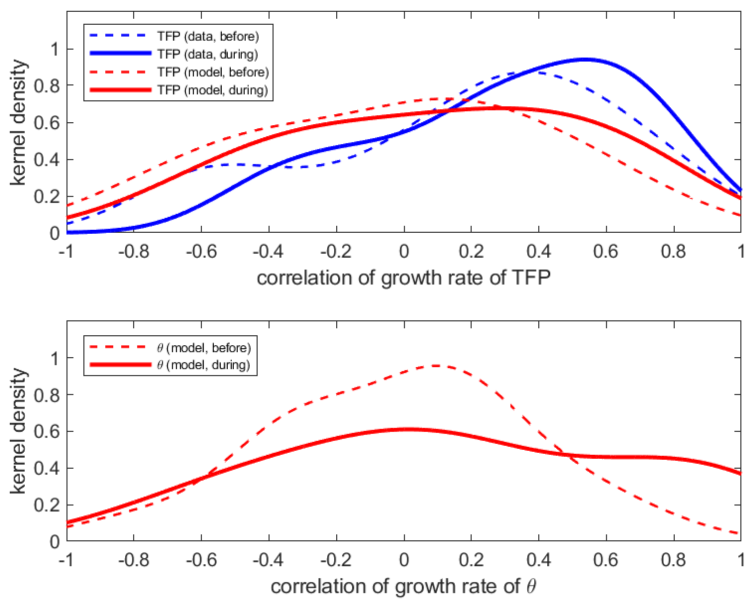
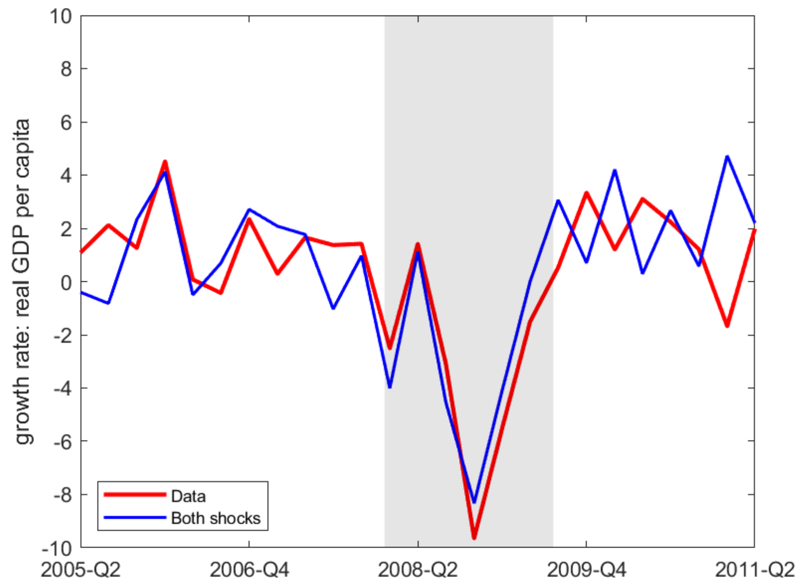


Figure D2. : Pairwise correlation of sectoral productivity and financial shocks

D2. *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 D3 displays the quarter-to-quarter annualized growth rate of real GDP between 2005Q2 and 2011Q2. The blue and red lines represent the data and the model-implied growth rate, respectively, and the shaded area represents the Great Recession period defined by the NBER. The model-implied growth rate tracks the data closely.



Note: The blue line represents the growth rate of real GDP per capita in data, while the one implied by our model is displayed in the red one.

Figure D3. : Growth rate of real GDP per capita: model vs data

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 (C6). Then, the AR-to-sales and AP-to-OC ratios implied by the model can be defined, respectively, as

$$\text{(D1)} \qquad \frac{AR_i}{sales_i} = \frac{\sum_{j=1}^{n} tc_{ij} q_{ij} m_{ij}}{p_i y_i + \sum_{j=1}^{n} \left(1 - (1-\eta) tc_{ij} - \frac{p_i}{q_{ij}}\right) q_{ij} m_{ij}},$$

$$\text{(D2)} \qquad \frac{AP_i}{OC_i} = \frac{\sum_{j=1}^{n} tc_{ji} q_{ji} m_{ji}}{wl_i + \sum_{j=1}^{n} q_{ji} m_{ji}}.$$

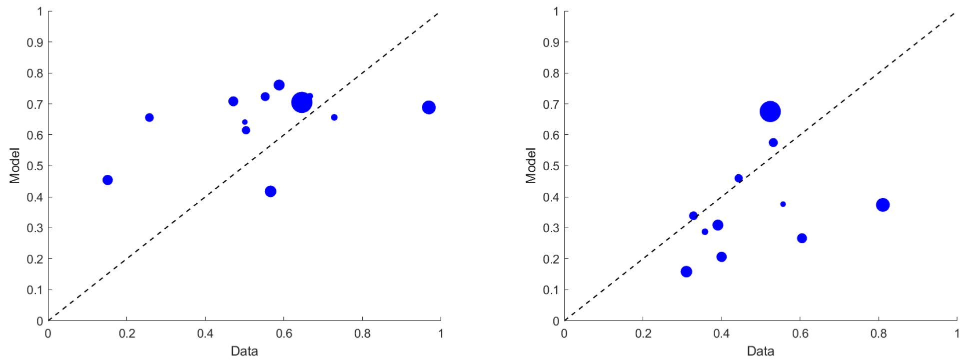
where $sales_i$ is defined in Equation (7), and operational costs are equal to the sum of the wage bill and input payments. Figure D4 displays the scatter plots of both ratios for model and data, where the horizontal and vertical axis respectively present data and mode-implied ratio, the size of the bubble indicate the sectoral relative size in 2005, and the black dashed line is the 45-degree line. Panel (a) displays the AR-to-sales ratio, while the AP-to-OC ratio is shown in Panel (b). Except for mining and professional services sectors, all bubbles are lined up around the 45-degree line in both cases. It implies that our model does a decent job to match the data. Even though we use the AR-to-sales ratio to calibrate the maximal efforts, i.e., $\{\bar{e}_t\}$, the model-implied ratios do not necessarily stay in line with data, since the bilateral trade credit intensity now is endogenously determined. Moreover, the model-implied AP-to-OC ratios, which are not targeted, match the data fairly well.

D3. Summary statistics of model-implied pairwise correlations

We report the summary statistics of pairwise correlation, implied by our model. To test whether how two densities are statistically insignificantly different from each other, we perform the KS test. Table D2 reports the results, where the p-value for the KS test is shown in parentheses.

D4. 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.



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

Figure D4. : Comparison of AR-to-sales and AP-to-OC ratios: Model vs Data

Table D2—: Model-implied pairwise correlations of output growth rates

	Mean	Median	Std	Skewness	KS Statistics
Data or model-implied with both shocks					
Before the Great Recession	0.04	0.03	0.42	-0.11	0.48 (0.00)
During the Great Recession	0.50	0.62	0.34	-0.95	
Model-implied with both shocks and fixed trade credit					
Before the Great Recession	0.13	0.16	0.41	-0.25	0.33 (0.00)
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(0.00)
During the Great Recession	0.65	0.73	0.24	-0.67	
Model-implied with only θ and fixed trade credit					
Before the Great Recession	0.19	0.21	0.39	-0.41	0.17(0.29)
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 (0.00)
During the Great Recession	0.47	0.60	0.39	-0.88	
Model-implied with only z and fixed trade credit					
Before the Great Recession	0.00	0.00	0.41	-0.09	0.58 (0.00)
During the Great Recession	0.52	0.66	0.38	-1.06	

In particular, we specify the

$$\begin{aligned}\Delta\mathbf{corr}_{ij} &= \alpha_0 + \alpha_1 \mathbf{1}_{ij}^{two-way} + \alpha_2 \mathbf{1}_{ij}^{one-way} + \alpha_3 \mathbf{1}_{ij}^{two-way} \times \Delta tc_{ij} + \\ &\quad + \alpha_4 \mathbf{1}_{ij}^{one-way} \times \Delta tc_{ij} + \beta' X_{ij} + \epsilon_{ij}, \end{aligned} \tag{D3}$$

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 D3 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 model. However, there still exists variation between two model. To see this, we include control variables in Column (2), 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. 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.

D5. Pairwise correlation of shocks

Once we impose the fixed trade credit to the economy, our model becomes one akin to Bigio and La'O (2020). In this case, the sectoral sales should highly comove with underline shocks. In Figure D5, we plot the kernel density of the pairwise correlations for both shocks, where the top panel is for productivity shocks and the bottom for financial shocks, all red lines represent the shocks we used for our exercise, and all dashed and solid lines respectively stand for the kernel density before and during the Great Recession. Here we observe a

Table D3—: Regression Results of Equation (D3)

	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 Va	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 $^{***}p < 0.001$.

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 in the blue lines of the top panel. Surprisingly, the kernel density during the Great Recession does not shift significantly, compared to the one before. It implies that the endogenous trade credit along with the financial shocks can account for 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, their financial shocks indeed comove during the Great Recession as we observe a fat right tail, while other pairs stay more or less the same as before.

D6. 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 out sectoral productivity and financial shocks. The annual data is used instead of the quarterly one, where the period 1978-1985 is used as the in-recession window, while the post-recession one covers 1983-1989. Figure D7

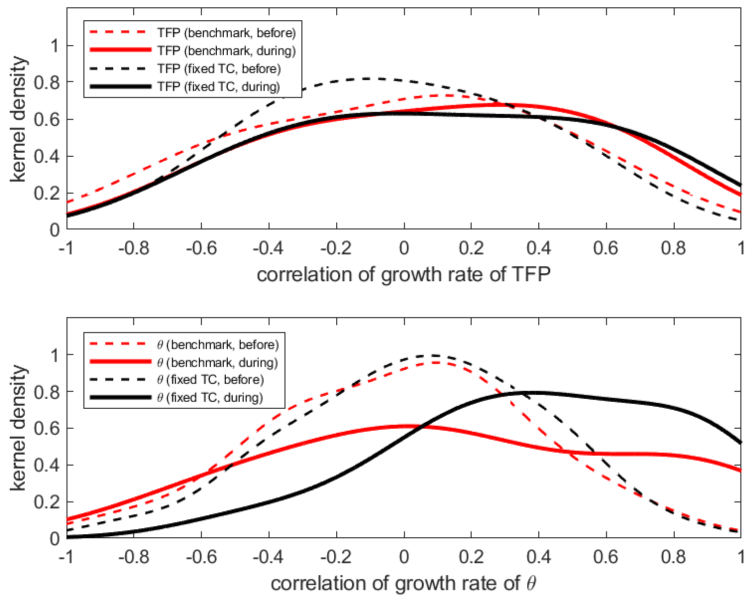


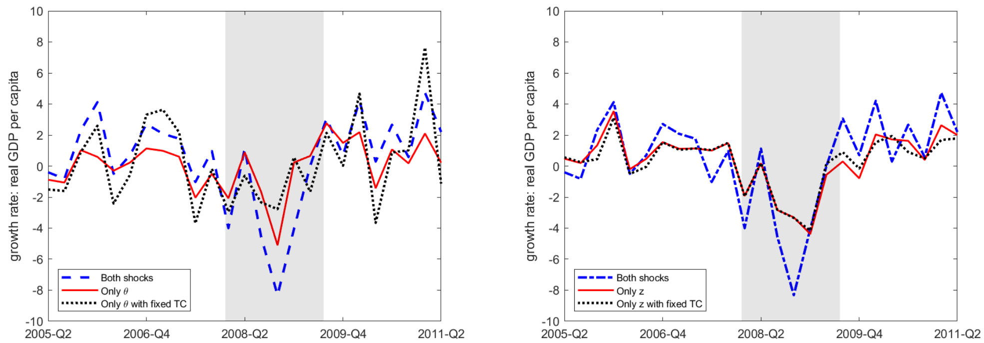
Figure D5. : Pairwise correlations of financial and productivity shocks

reports the normalized shocks, and Figure D8 displays the kernel densities for the underline shocks.

D7. *Commovement with CES production technologies*

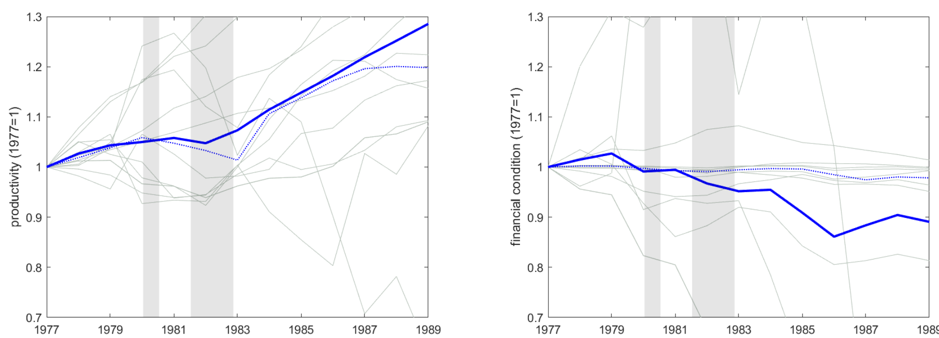
Firm-level Evidence

Since the Great Recession is the only financial crisis after the WWII, here we explore the cross-sectional variation across the US public firms to highlight the mechansim in our model. In particular, we use the collapse of Lehman Brothers (LB) as a quasi-natural experiment. First, we show that the median value of the AR-to-sales and AP-to-OC ratios at the listed-firm level experienced a sharp decline during the Great Recession, unlike any other previous recession in the sample. Second, we show that an input supplier comoved more, in terms of sales growth, with a client connected to LB than with an unrelated one. Moreover, the



(a) Kernel density of pairwise correlation (b) Growth rate: real GDP per capita

Figure D6. : Only productivity shocks: endogenous vs fixed trade credit



(a) Productivity Shocks (b) Financial Shocks

Figure D7. : Shocks in the Early 80s Recession

correlation rose even more if the LB-connected client experienced a contraction in trade credit reception.

E1. Trade credit provision and reception during the Great Recession

We use the US public firms' data from Compustat to study how trade credit has evolved and calculate the AR-to-sales and AP-to-OC ratios, defined in Section

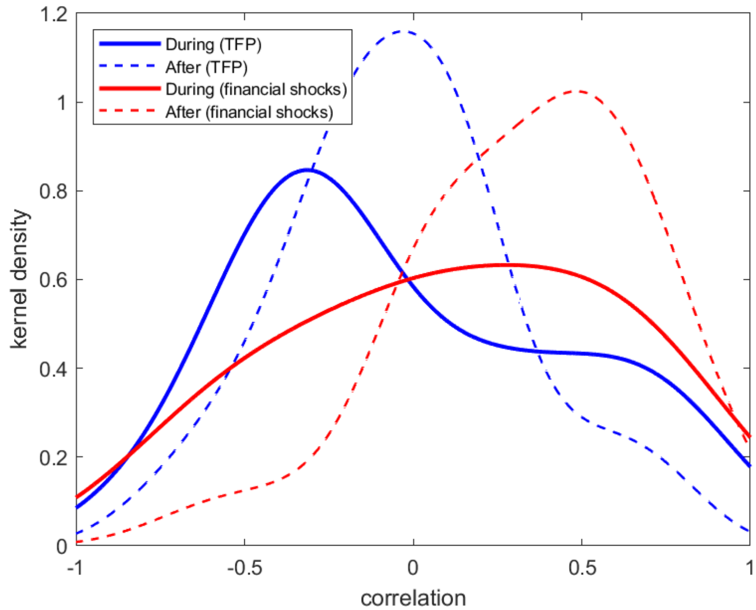
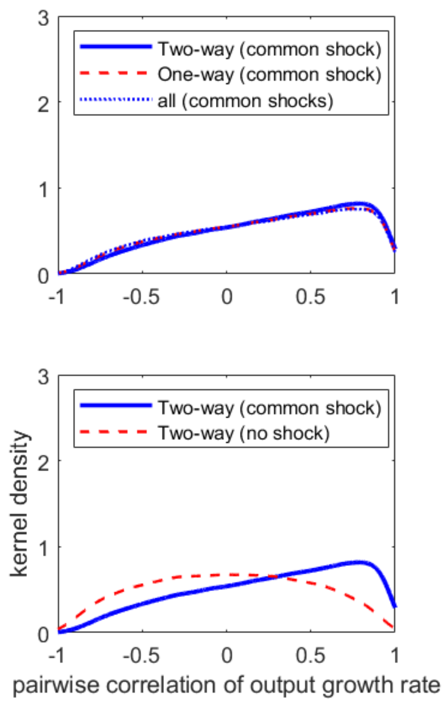


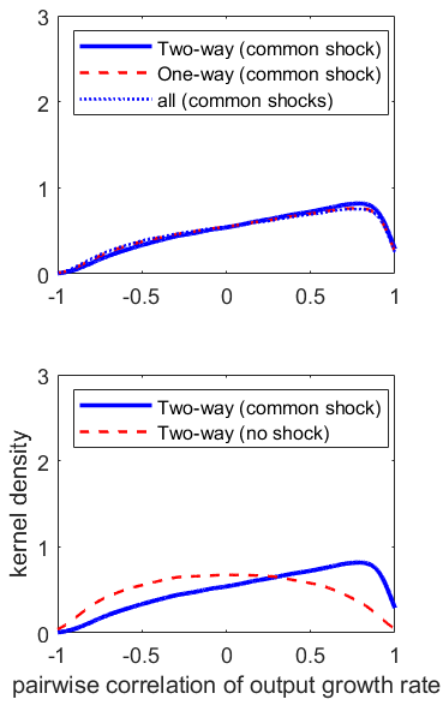
Figure D8. : Pairwise correlations of sectoral shocks: the early 1980s recession

I.C. We then adjust these ratios for seasonality using moving-average methods at the firm level. Figure ?? displays the evolution of the median value for both ratios from 1980Q3 to 2016Q3. The two ratios fluctuate modestly over time, even throughout the 1990 and 2001 recessions. During the Great Recession, they went up at the beginning and plummeted by roughly 10 to 20 percentage points starting in 2008Q3. This pattern indicates that, in addition to the reduced demand for inputs, more firms requested more upfront payment for new input orders and wrote off the existing trade credit. This is consistent with the evidence in Costello (2020) for the US during the Great Recession, and the one in Love et al. (2007) for the Mexican crisis in 1994 and the Asian flu in 1997.



This figure plots the kernel density of pairwise correlations of a CES production network model (as in Carvalho et al. (2021)). The elasticity of substitution between inputs is 0.6.

Figure D9. : Sectoral comovement and common shock CES model (elasticity of 0.6)



This figure plots the kernel density of pairwise correlations of a CES production network model (as in Carvalho et al. (2021)). The elasticity of substitution between inputs is 0.2.

Figure D10. : Sectoral comovement and common shock CES model (elasticity of 0.2)

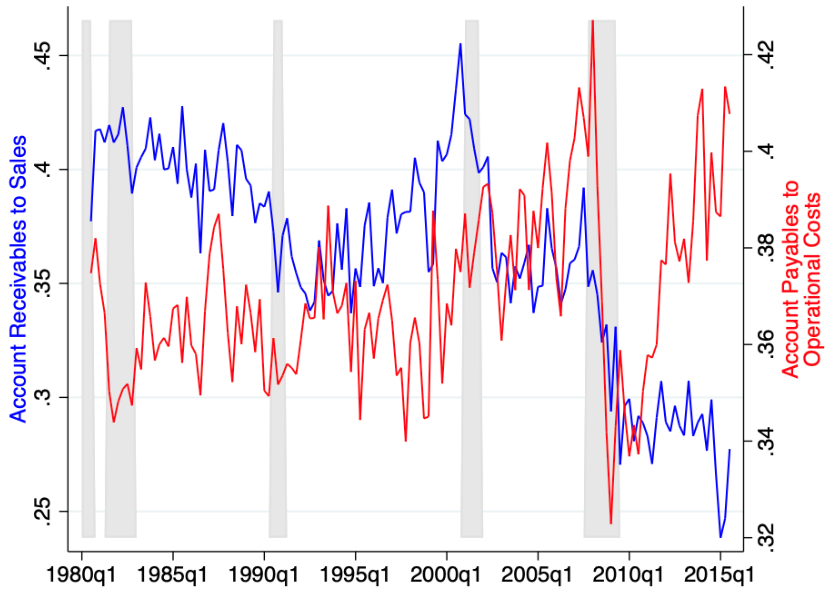


Figure E1. : Evolution of Intensities of Trade Credit Provision and Reception

E2. Quasi-natural experiment: Lehman Brothers' collapse

The collapse of Lehman Brothers (henceforth, LB) provides an ideal setting to study how banking shocks can affect trade credit provision and then propagate along the production network. We start by constructing a firm-to-firm production network using Form 10-K, as in Garcia-Appendini and Montoriol-Garriga (2013). In total, we identify 641 supplier-client pairs, with 426 suppliers and 176 clients.

To establish the relationship between listed firms and LB, we use the syndicated loan data from DealScan. Following Ivashina and Scharfsteinb (2010), we select firms of which LB led or joined a syndicated loan before its collapse. Additionally, in the spirit of the literature on financial networks, such as Allen and Gale (2000), Elliott et al. (2014), Acemoglu et al. (2015), among others, we find lenders that directly share the financial network with LB through the syndicated loan market. In particular, we identify whether (1) the lender and LB participated in a syndicated loan that was due after 2008Q3; (2) the lender was the arranger, a leading role in a syndicated loan; (3) the loan was used as working capital. Thus, a firm is treated as indirectly connected to LB if that firm did not borrow directly from LB but from lenders connected to LB. Combining both datasets, we have 19 out of 426 suppliers directly connected to LB, 237 indirectly connected to LB through their lenders, and 150 without a connection to LB through the syndicated loan market. Also, out of the 176 clients, 40 borrowed directly from LB, 120 were indirectly connected to LB, and 16 had no relationship with LB. Note that we classify these firms only using the information in the syndicated loan market. We do not exclude any other financial connection firms may have had with LB, either directly or indirectly.

Table E1 displays the summary statistics of all paired suppliers and clients. Using Equation (A1) over the same time window as used with the quarterly data in Section I.A, we confirm that the pairwise correlations at the firm level significantly increased, by 0.17, during the Great Recession. This is consistent with our findings at the sector level. Furthermore, we select financial variables, where the median values of 2005Q3-2006Q2 and 2008Q3-2009Q2 are taken respectively to represent before and during the Great Recession. Before the recession, compared to the average firm in Compustat, the suppliers in our sample are smaller in terms of total assets, extend less trade credit, and hold more cash, whereas the clients are larger, receive less trade credit, and have less cash. It is mainly because the suppliers report the clients as their top 10 clients in Form 10-K. As seen in the QFR data, smaller firms rely more on trade credit, and thus we observe a smaller decline in clients' trade credit compared to the suppliers'. As in Kahle and Stulz (2013), we find those typical financial variables, such as ratios of investment, cash, and short-term and long-term debt over total assets, of both suppliers and clients before and during the recession are all not significantly different. Also, the size of firms, in terms of sales and total assets, is not very different over the two windows. However, we find profitability and growth perspectives (growth rate of sales and total assets) to be significantly lower during the recession. Such a decline is reflected in their market value, resulting in a lower Tobin's Q during the recession.

Table E1—: 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				

E3. Transmission of the LB Shock

Did the LB shock contribute to the rise in comovement among firms through the trade credit channel? We use the variation in the degree of connections to LB to examine the role of trade credit in explaining the sales comovement between two firms. In particular, we focus on suppliers that did not directly borrow from

LB before 2008 but had clients with different degrees of exposure to LB (directly, indirectly, and not connected to LB through the syndicated loan market). In total, our sample has 162 pairs that consist of 62 suppliers and 65 clients. Seventeen of the suppliers had no relationship with LB, and 45 were indirectly connected, while 20, 39, and 6 clients were directly, indirectly, and not connected to LB.

We first 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

$$\Delta y_j = \alpha_0 + \alpha_1 \mathbf{1}^{LB}_{j,dir} + \alpha_2 \mathbf{1}^{LB}_{j,indir} + \gamma \Delta X_j + \beta y_{j,before} + \epsilon_j, \tag{E1}$$

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 E1, and ΔX is the first difference between the in and pre-recession median of X. Table E2 reports the point estimates for Equation (E1), where the robust standard errors are reported in the parentheses.

Table E2—: Regression Results of Equation (E1)

	$\Delta\frac{AP_j}{OC_j}$	$\Delta\frac{AR_j}{sales_j}$	$\Delta\frac{debt_j}{TA_j}$	$\Delta\frac{cash_j}{TA_j}$
	(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 $^{***}p < 0.001$.

As shown in Column (1), we find that in the regression of the AP-to-OC ratio, the coefficient of the indicator for the direct connection is negative and statistically significant, meaning that the ratio of the LB-connected clients decreased by 6.5 percentage points. It implies that, during the recession, either the 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 of the indirect connection is negative but not statistically significant. It may be because other lenders connected to LB absorbed the LB shocks, so they did not systematically transmit the shocks to their own borrowers. In Columns (2)-(4), we examine other short-term financial measures, such as the AR-to-sales, short-term debt, and cash ratio. The LB shock has no significant effects on the AR-to-sales and short-term debt ratio. However, compared to the average cash-to-assets ratio (10.7%) before the recession, the LB borrowers did experience a sharp decline in cash, while the LB-unrelated firms hoarded more cash by an 8.7 percentage points (the point estimate of constant term) rise in the cash-to-asset ratio. The latter result is consistent with Kahle and Stulz (2013), who find that compared to firms with low leverage, bank-dependent ones did not decrease net debt issuance and instead hoarded cash during the recession.

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

$$\Delta\mathbf{corr}_{ij} = \alpha_0 + \alpha_1 \mathbf{1}_j^{LB} + \alpha_2 \mathbf{1}_j^{LB} \times \Delta\frac{AP_j}{OC_j} + \gamma D_i + \beta' \Delta X_j + \epsilon_{ij}, \tag{E2}$$

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 E1. To eliminate the suppliers', clients', and pairs' fixed effects, we take the first difference of correlation before and during the recession. Moreover, comparing the change in the correlation of the common supplier with different clients makes our approach similar to the difference-in-difference method, as we mitigate the possibility that some time-varying unobservables, other than the connection to LB, influence the change in comovement over time. To highlight the role of trade credit in transmitting 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, on average, in trade credit, a negative coefficient of the interaction term implies the trade credit channel amplifies the LB shock, while a positive one suggests mitigating effects. Last, we add the dummies for the suppliers to control the time-varying effects for suppliers.

Table E3 reports the point estimates. Column (1) exhibits the results of the benchmark model in Equation (E2). We find that, during the Great Recession, the correlation of a supplier with its client connected to LB increased more, by 0.88, than the one with an unconnected one. Such a rise is higher than the sample average (0.17) by a factor of 5.2. Also, the indirect-connected clients comoved more with their suppliers but with a slightly lower scale. In addition, the coefficient of the AP-to-OC ratio is positive and statistically significant. It implies that if the client is not related to LB, it comoves less with its supplier as the AP-to-OC ratio declines. Combining this coefficient with the coefficients of interaction terms, we find that the role of trade credit is switched for these LB-connected clients. To be concrete, for each percentage point decline in the AP-to-OC ratio, a directly (indirectly) connected client is associated with a 0.011 (0.01) higher correlation of sales growth with its supplier. This cross-sectional comparison suggests that trade credit responded to the financial shocks, affecting the comovement between the two firms.

If the contraction in the clients' payables is not passed through to the suppliers' receivables, the propagation of shocks through the trade credit channel is stopped at the clients' end. Otherwise, it works as a conduit and possibly tightens the

Table E3—: Regression Results of Equation (E2)

	$\Delta\mathbf{corr}_{ij}$					placebo test
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbf{1}^{LB}_{j,dir}$	.875*	.841**	-1.8		-.172	-.167
	(.345)	(.285)	(1.57)		(1.12)	(.296)
$\mathbf{1}^{LB}_{j,indir}$	.687^	.799*	-2.19		-.501	-.0439
	(.36)	(.308)	(1.88)		(1.15)	(.3)
$\mathbf{1}^{LB}_{j,dir} \times \Delta\frac{AP_j}{OC_j}$	-.393**	-.461*	.0144			
	(.143)	(.191)	(.0189)			
$\mathbf{1}^{LB}_{j,indir} \times \Delta\frac{AP_j}{OC_j}$	-.392**	-.457*	-.0154			
	(.142)	(.189)	(.019)			
$\Delta\frac{AP_j}{OC_j}$	.383**	.448*				
	(.141)	(.186)				
$\Delta\widehat{\frac{AP_j}{OC_j}}$				-.0276*		
				(.0137)		
$\mathbf{1}^{LB}_{j,dir} \times \frac{AP^{pre}_j}{OC^{pre}_j}$					.00736	
					(.0177)	
$\mathbf{1}^{LB}_{j,indir} \times \frac{AP^{pre}_j}{OC^{pre}_j}$					.00952	
					(.018)	
obs	148	95	53	148	148	150
adjusted R^2	.125	.0424	.11	.128	.0881	.0522

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

suppliers' financial constraints. To examine this, we restrict our sample to suppliers that experienced a decline in the AR-to-sales ratio that is more severe than the sample median (-1.67 percentage points). The results are shown in Column (2) and are consistent with our benchmark results.[43] However, when we focus on the subsample where the suppliers' AR-to-sales ratio did not reduce more than the median, as shown in Column (3), we find that there is no significant rise in co-movement between the supplier and LB-connected clients. Our finding indicates the circumstance under which the trade credit chain is triggered as a conduit and amplifier. It is more likely when the financial shocks hit a sufficient number of firms and make them financially constrained.

To deal with the endogeneity issue of the change in the client's AP-to-OC ratio, we adopt the bank-credit shocks developed by Chodorow-Reich (2014) (**CR**

[43]We further examine whether the LB shocks could be transmitted further to the LB-unrelated suppliers' suppliers (second-round network effects). In doing so, we select all the LB-unrelated suppliers and their own suppliers that were not directly connected to LB but had at least one LB-related client and an unrelated one. We find positive and statistically significant effects of this second round.

index) as an instrument. This index measures the firm's exposure to credit shocks during the Great Recession. Then, we perform a two-stage least square regression with the change in pairwise correlation as the dependent variable and the AP-to-OC ratio, proxied by the **CR** index, as the key explanatory variable. We treat trade credit as proximate causes, determined by and acting as channels of influence for such shocks, for the rise in comovement. We find the response of the AP-to-OC ratio is not monotonic with the degree of exposure. However, once the **CR** index is lower than the sample median, the AP-to-OC ratio starts to contract. Then we examine how the credit shocks were transmitted into the change in comovement between the supplier and client through the trade credit chain. We find that a one percentage point decline in the proxied AP-to-OC ratio generates a 0.028 rise in correlation, which is 16.5% of the average rise across the pairs of the US public firms.

We also test whether clients that relied more on trade credit before the Great Recession comoved more during the Great Recession. In doing so, we replace the change in AP-to-Oc ratio $\Delta\frac{AP_j}{OC_j}$ in Equation (E2) with the pre-recession ratio $\frac{AP_j^{pre}}{OC_j^{pre}}$. The point estimates in Column (5) 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 correlations between two regular periods, namely 2003Q3-2005Q2 versus 2005Q3-2007Q2. As shown in Column (6), we do not find evidence that the control and the treatment group had pre-existing differences in comovement before the Great Recession.