Review of Finance, 2021, 819–861
doi: 10.1093/rof/rfaa025
Advance Access Publication Date: 3 October 2020

Managing Liquidity in Production Networks: The Role of Central Firms

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Abstract

Firms in the US economy are closely interconnected in a production network and are subject to shocks that propagate within the network. This study examines the liquidity management of firms centrally connected in the network. I show that, while central firms are more exposed to aggregate swings, they maintain higher cash holdings to protect themselves and connected firms against such exposure. Central firms' cash holding motives are alleviated by firm diversification but are aggravated by industry competition. Such motives are not explained by alternative determinants of cash policies. My findings suggest that systematically important firms proactively dampen the propagation of shocks in the production network.

Keywords: Production networks, Financial policies, Corporate liquidity, Trade credit

JEL classification: G32, G33, L14

Received June 14, 2018 by Editor Geoffrey Tate.

1. Introduction

A growing body of research posits that aggregate economic fluctuations can originate from micro-level shocks (e.g., Long and Plosser, 1987; Acemoglu et al., 2012; Barrot and Sauvagnat, 2016). As firms are connected through production linkages with complementary inputs, negative microeconomic shocks that occur to one firm can spill over to others

* I am thankful to Heitor Almeida, Fred Bereskin, Matthew Billett, Markus Broman, Murillo Campello, Andrew Ellul, Paul Gao, Yaniv Grinstein, Robert Jarrow, Maureen O'Hara, Joseph Pacelli, Uday Rajan, Carlos Ramirez, and Wenyu Wang for their valuable inputs. Comments from participants at the EFA 2014 doctoral consortium and the NFA 2013 annual meeting, and comments from seminar participants at Cornell University, Indiana University, Yale University, Notre Dame University, Emory University, University of Illinois at Urbana–Champaign, Imperial College London, University of Colorado Boulder, University of Connecticut, Georgia State University, Tulane University, DePaul University, University of Illinois at Chicago, Federal Reserve Board of Governors, and Cornerstone Research Boston are greatly appreciated. I also thank Andrea Frazzini, Lauren Cohen, and Edward Fee for sharing the data. All errors are my own.

and generate aggregate swings. Existing studies in this literature often assume that firms passively transmit shocks to one another, yet they do not consider the proactive role of firms in managing their liquidity reserves. If firms that are central to the production network conserve more liquidity, they may be able to alleviate the impact of negative shocks and decelerate the propagation of shocks in the network.

This study examines the cash holdings of firms that are central to the inter-sectoral production network of the US economy. I conjecture that central firms have an incentive to hoard liquidity to preempt the propagation of shocks. Central firms operate in sectors whose production depends heavily on other sectors. As micro-level shocks travel through inter-sectoral connections, they are likely to generate a greater impact on firms in central sectors. To the extent that such shocks are not diversified away, central sectors should be more exposed than peripheral sectors to the aggregate swings formed by micro shocks. By holding more cash, firms in central sectors can fare better during economic downturns. This is because cash reserves not only help firms sustain production during downturns, but they also allow firms to adjust trade credit and extend liquidity to their customers and suppliers, whose survival is key to the firms' own productivity. This logic predicts that central firms should have higher cash reserves than peripheral firms. This prediction, nonetheless, has not been taken to the data in a systematic fashion.

I empirically examine the relation between firms' cash holdings and their centrality in the US production network. The production network is constructed based on sectoral fund flows provided by the Bureau of Economic Analyses (BEA) 1997 input and output matrices. Based on the production network, I calculate the eigenvector centrality (Centrality) of each industry and assign an industry's centrality to all firms in that industry. Centrality is defined as a sector's dependence on the supply of productive input and the purchase of its output by all other sectors, including the dependence through higher order linkages. It thus captures the sector's exposure to all shocks that originate and propagate in the network.

In the first step of my analysis, I confirm that firms in central sectors are more exposed to aggregate shocks than firms in non-central sectors. The investment and profitability of central firms are more sensitive to business cycles: A one-standard-deviation increase in centrality is associated with a five-percentage-point greater increase in investment and a 16-percentage-point greater increase in profitability from low-growth to high-growth periods. Central firms also have higher equity betas than non-central firms. These results indicate that central firms are more exposed to aggregate economic fluctuations, which provides an incentive for them to maintain higher cash reserves.

My main finding is that central firms in the production network maintain higher cash holdings than non-central firms. The estimates suggest that a one-standard-deviation increase in centrality is associated with a one-percentage-point increase in cash holdings, which is around a 7% (13%) increase relative to the sample mean (median) for cash holdings. This finding is robust to controlling for broader industry dynamics through the inclusion of broader industry-year fixed effects. It also persists for a sector-level panel.

I next examine firm- and industry-level characteristics that could moderate central firms' cash policies. I start by considering the role of firm diversification. With internal capital market smoothing funding gaps across divisions, diversified firms have better access to capital and face lower deadweight losses during economic downturns (Stein, 1997; Dimitrov and Tice, 2006; Hann, Ogneva, and Ozbas, 2013). If central firms hold cash to hedge against downturns, their cash holding motives should be more mitigated by firm diversification than non-central firms. Consistent with this logic, I find that central firms hold less cash when they have multiple segments, especially when their segments face less correlated shocks. I next examine the role of industry competition. Firms facing more competitive pressures are more likely to lose customers or suppliers to their rivals during bad economic conditions. Given that cash holdings help firms fend off rivals' predatory behavior and maintain market share (Fresard, 2010), central firms should find cash holdings more valuable when facing stronger competition. In line with this prediction, I find that the cash-centrality relation intensifies in competitive industries. These cross-sectional analyses are informative in outlining the frictions that drive the way firms manage liquidity in relation to their exposure to shocks in the production network.

My base analysis relies on the sector-level correlation between centrality and cash holdings to draw the inference that central firms hold cash to mitigate their exposure to shocks. I test the robustness of my inference to controlling for various other determinants of cash holdings. I first consider the influence of external financing frictions. Firms that are smaller, younger, and operate with hard-to-pledge assets face more severe frictions in raising capital. I show that central firms do not differ from non-central firms along these dimensions. The cash-centrality relation is also unaffected by controlling for these proxies of external financing frictions. Next, I examine multinational firms' tax avoidance incentives. Multinational firms retain a high level of foreign income as cash holdings to avoid the tax cost arising from repatriating such income to the USA (Foley et al., 2007). If central sectors are dominated by multinational firms, their cash holdings could be driven by tax reasons. Finally, I evaluate the possibility that firms' governance structures could affect my results. I find no evidence that central firms have stronger tax avoidance motives or different governance quality from non-central firms. The base finding persists through the addition of controls for these explanations.

I design two analyses to test additional implications of my findings. First, I assess whether firms use trade credit to share liquidity with connected firms following negative shocks. I exploit the 9/11 terrorist attacks as an exogenous, negative shock to the airline industry and examine how this shock affects the trade credit usage of upstream firms. My analyses reveal several findings. First, following the attacks, suppliers of airline companies increase their receivables, providing liquidity to the airline industry. Critically, suppliers with low cash reserves prior to the attacks also increase their payables, suggesting that they receive liquidity from firms further upstream. In contrast, suppliers with high cash reserves do not increase their payables. This analysis provides unique micro-level evidence that trade credit allows firms to share liquidity, even with indirectly connected firms in the production chain.

In line with the above findings, I also expect central firms to extend more trade credit during aggregate downturns. This is because central firms are more reliant on other firms in the network and should have more incentives to support those firms during bad macroeconomic conditions. Consistent with this prediction, I find that central firms extend more trade credit during economic downturns. A one-standard-deviation increase in centrality is associated with a four-percentage-point larger increase in net receivables from low-growth to high-growth periods. Taken together, these results substantiate the argument that central firms conserve cash partly to provide liquidity during economic downturns.[1]

1 In the Online Appendix, I show that central firms help mitigate the transmission of negative shocks. Specifically, when a natural disaster hits a central firm and a non-central firm, customers of the central firm are less affected by the disaster than customers of the non-central firm.

In the second analysis, I investigate whether capital market investors incorporate the risk exposure of central firms and raise their funding costs accordingly. To this end, I look into firms' borrowing costs using credit spreads charged on privately placed bank loans. Firm centrality in the production network is associated with significantly higher credit spreads: High-centrality firms (at the 75th percentile of the sample) face 8 bps higher spreads than low-centrality firms (at the 25th percentile). Given the previous finding that central firms do not face greater financial frictions than non-central firms, this result suggests that investors price-in central firms' systematic exposure. Critically, this "centrality markup" in credit spreads increases during economic downturns, which likely enhances central firms' incentive to build up liquidity reserves *ex ante*.

In the last step of my analyses, I repeat my baseline test using a firm-level centrality measure, which helps mitigate the limitation that Centrality lacks variation within a census sector. I collect information regarding individual firms' principal customers and suppliers to build a supply-chain network. I then compute closeness centrality (Closeness), which gauges the average intensity of a firm's connections to all other firms in the production network. The granular information on inter-firm supply chains results in a measure of Closeness that exhibits rich variation across firms. The baseline results are robust to this firm-level measure.

This study makes several contributions to the literature. Critically, it is the first to explore the relation between firms' cash policies and their centrality in production networks. I find that firms that are central in the network conserve more cash, likely to hedge against aggregate economic downturns. This finding suggests that it is important to consider firms' proactive policy choices when assessing the cascading effect of shocks in input–output (IO) networks. My study thus complements existing research on the formation of business cycles in IO networks and the fragility of such networks (see, among others, Buraschi and Porchia, 2012; Barrot and Sauvagnat, 2016; Bigio and La'O, 2016).

This paper also relates to a growing body of work that links firm financial policies to customer–supplier relations (e.g., Titman, 1984; Fee and Thomas, 2004; Fee, Hadlock, and Thomas, 2006; Kale and Shahrur, 2007; Banerjee, Dasgupta, and Kim, 2008). These studies focus on the impact of direct customers and suppliers on firms' debt levels. My study examines a production network across all sectors in the economy. The network connections include not only direct customer–supplier relationships, but also indirect connections derived from those relationships. Considering all network linkages enables one to assess a firm's exposure to aggregate shocks, instead of idiosyncratic shock spillover from individual customers or suppliers. This study extends the literature on firms' supply-chain relationships by examining firms' role in preempting aggregate downturns.

Finally, this paper contributes to research on firms' conservative financial policy choices. In particular, my findings speak to studies documenting that even large, profitable firms have low leverage ratios and high cash holdings (e.g., Graham, 2000; Bates, Kahle, and Stulz, 2009; Strebulaev and Yang, 2013). While my study focuses on firms' cash reserves, it sheds light on the rationale for conservative policy choices: As larger firms tend to occupy more central positions in the network, their conservative financial policies can be partially explained by the intention to hedge against higher exposure to systematic shocks. Network centrality thus represents a new dimension of systematic risk and a novel determinant of financial policies that has not been explored in the literature.

The paper proceeds as follows. In Section 2, I develop testable hypotheses. In Section 3, I describe the data sources, sample construction, and empirical methodologies. Section 4 provides summary statistics and describes features of the network studied. Section 5 presents baseline results. In Section 6, I discuss endogeneity concerns. In Section 7, I explore additional implications. Section 8 provides robustness tests. Section 9 concludes.

2. Hypothesis Development

In this section, I discuss a conceptual framework to guide my empirical analyses on the relation between firms' cash holdings and their centrality in IO networks. This framework is supported by a stylized model in the Online Appendix. The model is purposefully parsimonious to deliver economic intuitions and describe the mechanisms. It contains two interconnected firms (sectors), which can be interpreted as a firm (sector) of interest and all other firms (sectors) in the network.

The framework relies on several assumptions. First, a firm's productivity depends positively on the production of the other firm. Such a dependence can differ between the two firms. Higher dependence suggests that a firm is more exposed to the spillover effect of shocks that occur in the production network.[2] In this two-firm framework, I define centrality as a firm's dependence on the other firm. In a production network with multiple sectors, centrality captures a sector's dependence on all other sectors in the network.

The second assumption is that both firms face external financial frictions, so that they cannot raise capital cheaply from external markets following negative shocks. The third assumption is that firms can provide liquidity to customers and suppliers by adjusting trade credit. This involves firms providing more receivables to customers or reducing payables to suppliers.[3]

Negative shocks randomly occur to firms. Such shocks refer to ones that decrease a firm's cash flows and tighten its budget constraint. They can arise from financial shocks such as a reduced bank credit supply, past productivity shocks that translate to lower current resources, or simply "bad luck" such as natural disasters and terrorist attacks. I do not, however, discuss certain technological shocks that may affect future investment opportunities but do not alter current budget conditions.

In the framework, firms choose cash policies prior to the realization of shocks. Their optimal cash holdings thus depend on the value they expect to derive from cash reserves in all future states of the world.

Given that firms' production functions are linked, they are affected not only by their own shock, but also the shock to their counterparty. This generates two reasons for central firms to maintain higher cash balances. First, firms internalize the liquidity need of their counterparty to a certain extent. Upon the realization of a negative shock, the firm not subject to the shock finds it beneficial to extend liquidity to the firm facing the shock. This is because the former firm's productivity hinges on the health of the latter firm. As a result of

2 Such a spillover effect is well documented in academic research (e.g., Cohen and Frazzini, 2008; Hertzel et al., 2008) and frequently observed by practitioners. For example, in 2008, Alan Mulally, the CEO of Ford, supported the request for government assistance from General Motors and Chrysler, two of Ford's rivals in the auto industry. He emphasized that the auto industry is "highly interdependent" due to a common supplier base and that the collapse of his competitors would have "devastating ripple effects" across the whole industry (Mulally, 2008).

3 This assumption is based on the evidence that customers demand trade credit from suppliers to a varying degree and that suppliers extend trade credit when their customers are in need (Garcia-Appendini and Montoriol-Garriga, 2013; Murfin and Njoroge, 2014). It rules out the extreme cases where one party has zero bargaining power in affecting the amount of trade credit it receives or extends.

the inter-firm liquidity extension, cash reserves become valuable to both firms even if the negative shock only occurs to one firm. As central firms are more dependent on other sectors, they internalize the liquidity need of other firms to a greater extent and have a stronger incentive to extend liquidity following negative shocks. This makes cash holdings more valuable to central firms prior to the occurrence of shocks.

The second reason is that central firms are more affected by aggregate downturns and need to hold cash to hedge such an exposure. In the two-firm framework, an aggregate downturn is a common negative shock that hits both firms. In this case, a firm's productivity decreases not only because of the direct impact of the shock, but also because of the negative spillover from the other firm. In other words, the cross-firm spillover amplifies the effect of economic downturns. Such an amplification effect is stronger for a central firm, which is more dependent on the other firm. Central firms' vulnerability to aggregate downturns provides an additional incentive for them to hold cash.

The two-firm framework does not discuss the source of aggregate fluctuations. In a multi-input production network, economy-wide shocks could arise from sources that are "exogenous" to the production network (such as changes in monetary policies or banking regulations), or could be formed by micro-level shocks. Central firms are more exposed to the first type of aggregate shocks than peripheral firms, for the same reason that is illustrated by the two-firm framework.

I argue that central firms are also more exposed to the second type of aggregate shocks, that is, those formed by micro-level shocks. This argument requires an additional assumption: For micro shocks that originate from specific sectors to spread and influence the economy, there needs to be a certain degree of complementarity among the inputs used by sectors. If inputs are perfectly substitutable, negative shocks to one sector may have little effect on downstream sectors as those sectors can switch to using other inputs. With input complementarity, sectoral shocks do not offset one another. Instead, they can propagate along production chains and form system-wide fluctuations (see, e.g., Jovanovic, 1987; Durlauf, 1993; Acemoglu *et al.*, 2012). Given that central firms are more dependent on other sectors, they are more affected by idiosyncratic shocks that travel through production linkages. As a result, they exhibit higher exposure to the systematic fluctuations formed by those idiosyncratic shocks.

This framework generates two testable implications. The main prediction is that central firms should have a greater incentive to conserve cash than peripheral firms:

Hypothesis 1. *Central firms have higher cash holdings than peripheral firms.*

The prerequisite condition for the main prediction is that central firms are more exposed to aggregate shocks. In the conceptual framework that I provide, this condition means that the investment and profitability of central firms are more sensitive to aggregate economic conditions. In testing its empirical implications, I also check whether the equity returns of central firms are more correlated with market returns (i.e., higher equity betas).

Hypothesis 2. *Central firms have more cyclical investment and profitability than peripheral firms. Central firms also have higher equity betas.*

3. Data, Measures, and Empirical Methodology

I construct an inter-sectoral production network using the IO matrices compiled by the BEA. Based on the IO matrices, I compute the dollar amount of trade exchanges between all industry pairs and calculate an industry's eigenvector centrality in the network (Ahern, 2015). Section 3.1 discusses the measurement in detail.

I extract firm fundamental information from the Compustat database. The variable of interest is firms' cash holdings (Cash). I exclude firms in the utility (SIC in 4900–4999) and financial (SIC in 6000–6999) industries, and require sample firms to have available information regarding their centrality, cash holdings, and control variables. The sample period runs from 1980 to 2010.

3.1 Measuring Inter-firm Connections and Firm Centrality

The BEA provides IO matrices that account for the commodities traded by all producers and purchasers in the US economy (including public and private firms). It publishes two matrices for 471 census industries for every five-year period: The Make table records commodities produced by each industry, and the Use table reports commodities purchased by each industry. The industry-level trade structures are persistent over time (which is verified in Section 4.2). Similar to Ahern and Harford (2014), I use the 1997 matrices as this year is around the midpoint of my sample period.

To estimate an industry's exposure to common liquidity shocks in the supply chain, I create an industry-to-industry adjacency matrix based on the fund flows between each pair of industries (Ahern, 2015). Specifically, I first calculate the amount of input an industry (i) purchases from another industry (j) and the amount of output that industry i supplies to industry j. I then net out the dollar amount of trades between the two industries to form an adjacency matrix A. Finally, I compute the eigenvector centrality for each industry as the corresponding entry in the principal eigenvector of matrix A.

The trade flows between industries are computed as follows: From the Make table, I create a percentage-production matrix (industry-by-commodity), where each entry $s_{i,c}$ shows the percentage of commodity c produced by industry i.[4] I then multiply this matrix with the Use table, in which each entry $p_{c,j}$ indicates the value of commodity c purchased by each industry j. The resulting matrix B represents industry-by-industry trade flows, whereby each entry $b(i, j)$ is the total estimated dollar sales of industry i to industry j. Formally, $b(i, j)$ is calculated as follows:

$$b(i,j) = \sum_{c=1}^{N} s_{i,c} p_{c,j},$$

where N is the total number of commodities in the IO tables.

I then calculate the fund flows between a pair of industries using the net amount of purchases and sales. Each industry is either a net seller or a net buyer to another industry. This procedure sharpens the measurement by focusing on the counterparty exposure against which an industry cannot "hedge." In other words, it precludes the possibility that an industry may reduce its purchase from another industry if the latter fails to make payments or reduce future purchase orders.

For every industry pair, I compute the exposure (weight) of the seller to the buyer as the percentage of sales the seller makes to the buyer. Analogously, I define the exposure of the buyer to the seller as the percentage of total purchases made by the buyer from the seller.

4 For example, suppose there are two industries that produce plastic materials: the petroleum industry produces \$300 million worth of plastic materials, and the chemicals industry produces \$2,700 million worth. The matrix entry will be 10% for the petroleum industry and 90% for the chemicals industry.

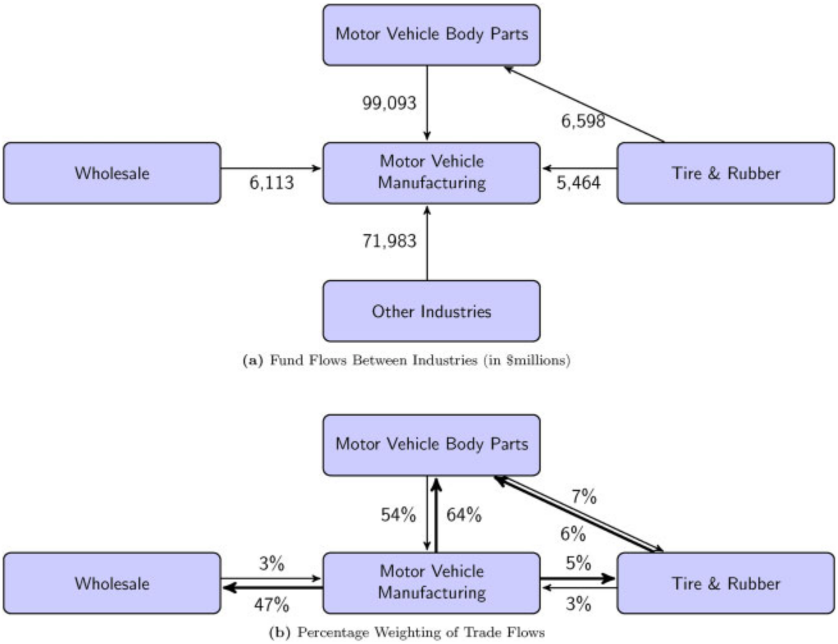

Figure 1. Construction of the production network. This figure illustrates how the weights of the connections in the network are determined. (**a**) The fund flows between several industries that are related to motor vehicle manufacturers (automakers). The numbers on the arrows represent dollar amounts of trades between industries (in $millions). The arrows indicate the supply of goods. (**b**) The weights assigned to those trade flows between industries. The arrows suggest the direction of potential contagious impact. The thick arrows point to the seller and bear the weight of the percentage of sales that the seller makes to the buyer (indicating that the seller is exposed to the buyer's shocks). The thin arrows point to the buyer and bear the weight of the percentage of purchases of the buyer from the seller. For example, motor vehicle manufacturers generate a net purchase of $99 billion from body part producers. This trade accounts for 54% of total purchases by motor vehicle manufacturers, but 64% of total sales made by body part manufacturers.

Figure 1 illustrates the definition of inter-industry connections. Figure 1(a) shows the trade flows among a few industries related to the motor vehicle manufacturing industry (automakers). The directions of the arrows indicate purchases. The automakers purchased input worth $99 billion from auto body part manufacturers, $5 billion from tire and rubber producers, and $6 billion from the wholesale industry. It also sourced $72 billion worth of input from other industries.

Accordingly, I define an adjacency matrix A that represents the trade relations between industries. Each entry $a(i, j)$ in the adjacency matrix stands for industry i's exposure to industry j. Specifically, if industry i purchases from j, then $a(i, j)$ equals the percentage purchases of industry i from industry j scaled by total purchases of i, and $a(j, i)$ equals the percentage sales of j to i scaled by all sales of j. As the adjacency matrix is not symmetric (i.e., $a(j, i)$ often differs from $a(i, j)$), the resulting production network is a directed network.

Figure 1(b) shows the weighting metric. The transaction between body parts producers and automakers accounts for 54% of total purchases ($183 billion) made by automakers, but 64% of total sales ($156 billion) made by body parts producers. The linkage between automakers and body parts manufacturers is thus represented by the weights on two directional arrows. In this figure, the directions of the arrows indicate directions of spillover effects. Specifically, thick arrows point to sellers and bear weights that equal the percentages of sales that sellers make to buyers, while thin arrows point to buyers and bear weights equal to the percentages of purchases that buyers make from sellers. For example, the thin arrow pointing from "Motor vehicle body parts" to "Motor vehicle manufacturing" suggests that automakers purchased 54% of their inputs from body parts producers. The thick arrow pointing from "Motor vehicle manufacturing" to "Motor vehicle body parts" bears a weight of 64%. It suggests that sales from the latter industry to the former account for 64% of total sales from body parts producers. Thus, the industry producing auto body parts has a 64% exposure to shocks occurring to auto-producers.

Figure 2 presents the inter-sectoral production network based on the trade flows reported by the 1997 BEA IO tables. The nodes represent census industries and the edges between nodes represent net trade flows between the corresponding pairs of industries. The thickness of the arrow represents the size of trade flows. The figure shows a connected and

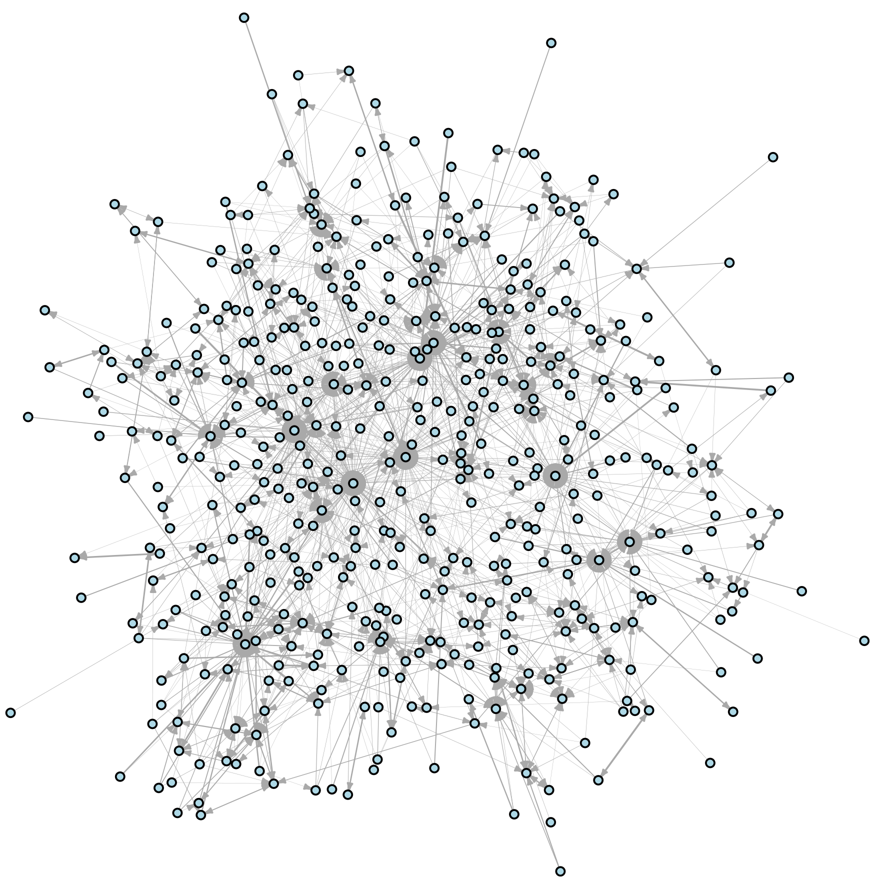

Figure 2. Industry-level network based on BEA matrices. This figure shows the input–output network based on 1997 BEA matrices. The nodes represent industries and the edges represent trade flows between industries.

directed network. In it, all of the industries are linked to one another, but they exhibit a wide variation in the level of connectedness.

I calculate eigenvector centrality for each industry (Centrality) as the entry in the principal eigenvector, e, of the adjacency matrix A. e solves the following relation:

$$Ae = \lambda e,$$

where λ is the largest eigenvalue of A. A higher value of Centrality indicates that an industry is more heavily reliant on all other industries. Such an industry is more exposed to undiversifiable shocks that propagate in the network.[5] Importantly, an industry can become more central if it is connected to a central industry (see Bonacich (1972) and Borgatti (2005) for more discussions). In other words, neighboring industries of a central industry are also more susceptible to the propagation of shocks. This property suggests that central firms are "systematically" important in their production networks.

3.2 Empirical Framework

I estimate the following panel regression model to test the relation between firms' cash holdings and centrality:

$$\text{Cash}_{i,t} = \beta \text{Centrality}_i + X_{i,t-1} + \xi_{k,t} + \epsilon_{i,t}, \quad (1)$$

where Centrality is the eigenvector centrality of the census industry to which a firm belongs, according to the crosswalk between firms' NAICS codes and census industry classifications (used in BEA IO matrices).[6] All explanatory variables are lagged by one year. I include one-digit SIC industry-year fixed effects ($\xi_{k,t}$), which remove dynamics at a broader industry level and the macroeconomy level that could affect firms' cash policies.[7] $\boldsymbol{X}_{i,t-1}$ is a vector of controls. Standard errors are clustered at the census industry level. I expect $\beta > 0$.

3.3 Control Variables

I control for a set of firm characteristics including Size, Market-to-Book, Tangibility, Profitability, R&D expenditures (R&D), and acquisition expenses (Acquisition). I further control for other financial policy variables such as Dividend Payer, an indicator variable for whether a firm pays dividends in a year, and a firm's leverage ratio. All variables are

5 Note that eigenvector centrality accounts for the concentration of the production network connections. Borgatti (2005) shows that eigenvector centrality is the row sum of a matrix S, which is the sum of all powers of the adjacency matrix A: $S = A + \lambda^{-1}A^2 + \lambda^{-2}A^3 + \cdots$, where λ is the largest eigenvalue of A. The row sum of A represents a firm i's exposure to shocks from all other directly connected firms (weighted by the intensity of their connections). Row sums of higher order adjacency matrices (e.g., A^2 and A^3) account for the concentration of higher order connections. For example, each entry of A^2, $A^2(i,j)$, describes all the ways in which firm k could be indirectly connected to firm i (e.g., a path $k \to j \to i$). This means that if j is an important customer or supplier to firm i, the influence of firm k will also be accounted more heavily. In light of these desirable features, Borgatti (2005) notes that eigenvector centrality is the most natural measure for describing the spillover effect among nodes in the network.

6 Firms in the construction industry (NAICS 23) can be matched to multiple IO industries. I create a separate observation for each of the matched IO industries for a construction firm. Only 2% of sample firms belong to this industry and Appendix B shows that my results remain largely unchanged to alternative sampling choices.

7 In Table XI, I show that controlling for finer industry effects does not change my inference.

defined in Appendix A. To alleviate the impact of outliers, I restrict leverage to between 0 and 1 and winsorize other continuous variables at the 5th and 95th percentiles.

4. Univariate Analyses

4.1 Summary Statistics

Table I presents the summary statistics for Centrality and firm characteristics. The average level of Centrality in my sample is 0.076 and the standard deviation is 0.072. The average (median) firm in my sample has \$1.4 billion (\$108 million) in total assets, with 15% (8%) in cash and 30% (25%) in tangible assets.

Table II provides examples of the most central and the most peripheral industries. The most central industries include both producers of raw input such as oil and gas extraction and consumer-facing industries such as retail and restaurants. The most peripheral industries also include both business-facing and consumer-facing industries, such as refractory and furniture manufacturers.

4.2 The Stability of the Production Network

Figure 3 shows that firm centrality is highly stable over time. I first rank firms into three groups (low, medium, and high) based on their Centrality measured in IO matrices from each of the 1987, 1992, 1997, 2002, and 2007 surveys. Next, I calculate the cross-group transition matrix from one survey to the next. The x-axis shows the partitions based on a current survey (t, e.g., 1997) and the y-axis shows the partitions based on the next survey ($t+5$, e.g., 2002). The height of the columns suggests the likelihood that a firm switches from one group to another between surveys. For example, the solid column in the left lower corner suggests that nearly 70% of low-centrality firms remain in the low-centrality group. All the diagonal columns are significantly higher than off-diagonal columns, suggesting that firms' centrality evolves slowly, with their ranking being largely unchanged. This

Table I. Summary statistics

This table shows the summary statistics. The sample includes Compustat firms that have available information to calculate centrality and firm characteristics. The sample spans the period of 1980–2010. I require firms to have positive total asset values and exclude firms in financial (SIC in 6000–6999) and utility industries (SIC in 4900–4999).

Variable	Mean	Std. Dev.	25th Percentile	Median	75th Percentile
Centrality	0.076	0.072	0.009	0.041	0.182
Cash	0.149	0.173	0.024	0.078	0.208
Investment	0.059	0.054	0.019	0.042	0.081
Profitability	0.064	0.177	0.029	0.107	0.167
Size	4.943	2.035	3.394	4.926	6.456
Market-to-book	1.795	1.281	0.998	1.317	2.014
Tangibility	0.300	0.223	0.118	0.246	0.435
Research and development (R&D)	0.036	0.071	0	0	0.037
Acquisition	0.012	0.031	0	0	0.001
Leverage	0.247	0.230	0.055	0.207	0.364
Dividend payer	0.339	0.473	0	0	1

Table II. Examples of most central and peripheral industries

This table provides examples for the top ten and bottom ten industries according to their centrality. The left column shows the most central industries and the right column shows the least central (most peripheral) industries. The ranking is based on eigenvector centrality calculated using the 1997 BEA IO matrices.

Most central industries	Most peripheral industries
Oil and Gas Extraction	Traveler Accommodation
Paper and Paperboard Mills	Resilient Floor Covering Manufacturing
Automobile Manufacturing	Clay Product and Refractory Manufacturing
Telecommunications	Cutlery and Handtool Manufacturing
Truck Transportation	Industrial Machinery Manufacturing
Wholesale Trade	Facility Support Services
Retail Trade	Other General Purpose Machinery Manufacturing
Architectural and Engineering Services	Apparel Accessories and Other Apparel Manufacturing
Employment Services	Furniture Manufacturing
Food Services and Drinking Places	Metal Working Machinery Manufacturing

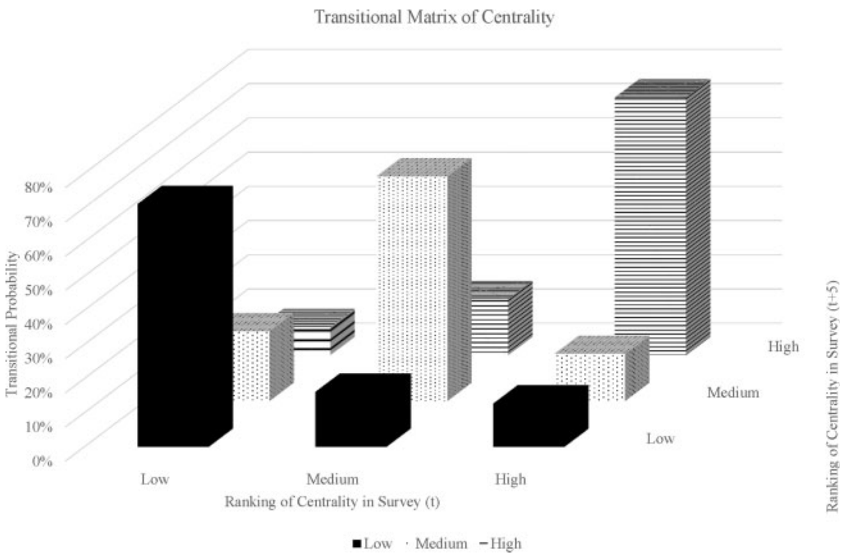

Figure 3. The transition matrix of firm centrality over time. This figure shows the evolution of firms' centrality over time. I rank all firms into three groups based on their centrality in networks constructed using each census survey, that is, IO tables in the years 1987, 1992, 1997, 2002, and 2007. The height of the columns indicates the transitional probability from one group to another group in the next survey. The *x*-axis (width) shows the partitions based on a current survey (*t*) and the *y*-axis (depth) shows the partitions based on the next survey ($t + 5$).

pattern indicates that the structure of the US production network is stable over time, and thus is unlikely to be changed by individual firms' cash policies.

Figure 4 illustrates the evolution of the production network over two decades, with snapshots in 1987, 1992, 2002, and 2007. For the visibility of the network structures, the

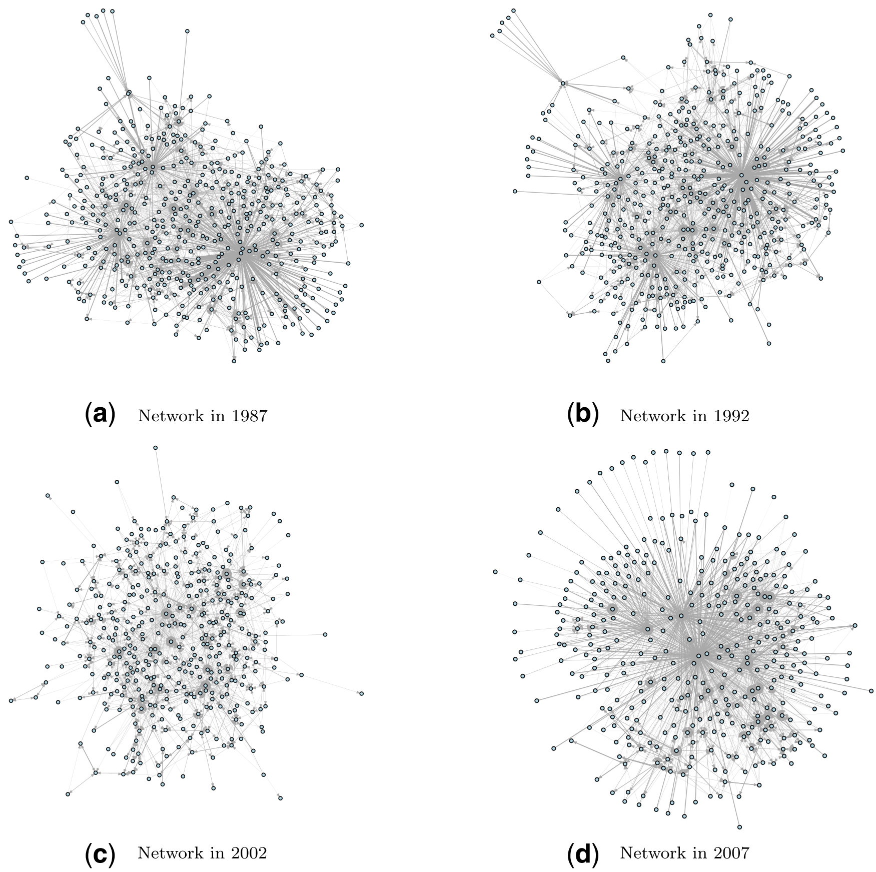

Figure 4. Construction of production network. This figure shows snapshots of the production network in the years (a) 1987, (b) 1992, (c) 2002, and (d) 2007. The network is constructed based on the industry-level IO matrices provided by the BEA. To maintain the clarity of the figures, I only keep industry connections with more than 10% of weights.

figures present only inter-sectoral connections with weights greater than 10%.[8] The snapshots suggest that the production network maintains a similar structure over time: every network contains several major clusters of industries that are closely connected to one another. It also contains some industries on the periphery of the network that are directly connected to only a few other industries.

5. Main Results

5.1 Exposure to Aggregate Shocks

I start by testing Hypothesis 2, which predicts that centrally connected firms are more sensitive to aggregate shocks. I test this hypothesis in two ways. First, I examine whether the

8 Note that the position of each industry may rotate from year to year, since the graph is designed to minimize the total distance of nodes to the center.

investment and profitability of central firms vary more along the business cycle than non-central firms. Second, I examine whether central firms have higher equity betas.

I investigate the cyclicality of central firms' investment and profitability using the following regression model:

$$Y_{i,t} = \delta \text{Centrality}_i \times \text{Business Cycle}_{i,t-1} + X_{i,t-1} + \alpha_i + \tau_t + \epsilon_{i,t}, \tag{2}$$

where $Y \in \{\text{Investment, Profitability}\}$. I use two proxies for business cycles. The first measure is the annual GDP growth rate (GDP Growth). GDP growth represents changes in aggregate output and reflects the propagation and aggregation of sectoral shocks in the production network (see Acemoglu *et al.*, 2012). I use the Chicago Fed National Activity Index (CFNAI) as a supplementary measure. CFNAI is a weighted average of eighty-five indicators of national economic activity, with a mean of 0 and a standard deviation of 1. Positive values of this index indicate above-average growth trends. The regression controls for firm-fixed effects (α_i) and year-fixed effects (τ_t). I expect $\delta > 0$.

Panel A of Table III reports results from Equation (2). The interaction terms of centrality and business cycle measures generate positive coefficients in both investment and profitability regressions, indicating that central firms are more sensitive to business cycle fluctuations. To better understand the coefficient estimates, I define high-growth periods as years when GDP growth is at least 4%, and low-growth periods as years when GDP growth is lower than 2%, based on the 25th and 75th percentiles of historical annual GDP growth rates. A one-standard-deviation increase in Centrality is associated with at least a 5-percentage-point greater increase in investment and a 16-percentage-point greater increase in profit from low-growth to high-growth periods.[9] These are large magnitudes compared with the sample standard deviation of investment of 5% and profitability of 18%.

I next compare the equity betas of central and non-central industries. For each census industry, I compute equal-weighted and value-weighted industry returns by aggregating monthly returns of firms in that industry. Excess returns are then defined as the difference between industry returns and the risk-free rate. I calculate an industry's equity beta by regressing excess returns on Fama–French 3 factors (Fama and French, 1993) and extracting the coefficient on the market factor. Alternatively, I compute betas using the CAPM model, regressing industry returns only on excess market returns. In each specification, I allow equity betas to vary over time by re-estimating betas every five years.[10]

After estimating equity betas, I classify census industries into terciles based on their centrality, and compare the average equity beta across centrality terciles. Panel B of Table III shows the results. Columns (1) and (2) report betas estimated based on equal-weighted industry returns, while Columns (3) and (4) report betas from value-weighted returns. Across both types of returns and benchmark models (Fama–French and CAPM), there is a positive correlation between equity betas and centrality. The equity betas of high-centrality industries are around 0.1 higher than those of low-centrality industries. The differences are statistically significant.

9 These estimates are based on the following calculation: investment changes from low-growth to high-growth periods $= 0.325 \times (4 - 2) \times 0.072$. Similarly, profitability changes $= 1.149 \times (4 - 2) \times 0.072$. The coefficients on CFNAI are generally smaller, likely because the index contains components that are not directly related to aggregate output.

10 Estimating betas every three years or using rolling-window regressions does not affect my inferences.

Table III. Exposure to aggregate shocks

This table examines central firms' exposure to aggregate shocks. Panel A shows results regarding the relation between centrality and the cyclicality of firms' investment and profitability. GDP Growth is the annual GDP growth rate. CFNAI is the Chicago Fed National Activity Index, the weighted average of eighty-five indicators that track economic activities. Control variables for investment regressions include size, market-to-book, leverage, tangibility, and profitability. Control variables for profitability regressions include size, market-to-book, leverage, tangibility, investment, and R&D. All explanatory variables are lagged by one year. Robust *t*-statistics are shown in parentheses. Regressions use firm- and year-fixed effects. Standard errors are clustered by census industry. Panel B shows the relation between centrality and equity market betas. An industry's equity beta is estimated by regressing the industry's monthly equity return on Fama–French 3 factors ("FF 3 Factor") or only on excess market returns ("CAPM"). Betas are coefficients on excess market returns. In Columns (1) and (2), equity betas are estimated using equal-weighted industry returns. In Columns (3) and (4), equity betas are estimated with value-weighted industry returns. Equity betas are re-estimated every five years. "Low Centrality" ("High Centrality") refers to industries whose centrality is at the bottom (top) tercile of the sample. *t*-statistics are based on Newey–West adjusted standard deviations. ***$p<0.01$, **$p<0.05$, *$p<0.10$.

Panel A: Cyclicality of investment and profitability

	(1)	(2)	(3)	(4)
Dependent variable:	Investment	Investment	Profitability	Profitability
Business Cycle measured by	GDP Growth	CFNAI	GDP Growth	CFNAI
Centrality × Business Cycle	0.325*	0.010	1.149**	0.027**
	(1.70)	(1.40)	(2.18)	(2.02)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	153,625	153,625	153,625	153,625
R-squared	0.579	0.579	0.752	0.752

Panel B Equity betas

Variable: Equity beta	(1)	(2)	(3)	(4)
Industry returns:	Equal-weighted		Value-weighted	
Regression model:	FF 3 factor	CAPM	FF 3 factor	CAPM
Low centrality	0.898	0.889	0.958	0.944
Medium centrality	0.957	0.965	1.018	1.012
High centrality	0.963	0.984	1.084	1.076
Difference (high–low)	0.065**	0.095***	0.126***	0.132***
t-statistics	2.26	3.09	4.00	3.79

Results from this section suggest that central firms exhibit more cyclical investment and profitability levels and have higher equity betas than peripheral firms. Such evidence is consistent with the argument that central firms are more subject to aggregate shocks.

5.2 Baseline Analyses

I examine the relation between a firm's centrality and its cash holdings using the model in Equation (1). Table IV reports the results. Column (1) presents results without controls for

Table IV. Network centrality and cash holdings

This table shows the regression results of firms' cash holdings on their centrality in the network. The dependent variable is Cash, defined as the ratio of cash and short-term investments over total assets. Centrality is measured using the 1997 BEA input–output table. All explanatory variables are lagged by one year. All regressions control for SIC1 industry-year fixed effects. Robust *t*-statistics are shown in parentheses. Standard errors are clustered by census industry. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Dependent Variable: Cash	(1)	(2)
Centrality	0.157**	0.141**
	(2.05)	(2.10)
Size	–0.003*	–0.001
	(–1.87)	(–0.46)
Market-to-book	0.020***	0.021***
	(10.96)	(12.26)
Tangibility	–0.209***	–0.161***
	(–8.72)	(–7.77)
Profitability	0.000	–0.067***
	(0.01)	(–3.38)
R&D	0.761***	0.649***
	(7.19)	(6.30)
Acquisition	–0.525***	–0.430***
	(–14.85)	(–12.64)
Leverage		–0.199***
		(–20.34)
Dividend payer		–0.014***
		(–2.91)
Industry-year FE	Yes	Yes
Observations	119,769	119,769
R-squared	0.342	0.422

other financial policies such as leverage and dividend payer dummy. Column (2) layers on those financial policy controls. Across both specifications, Centrality attracts positive and statistically significant coefficients ($p < 0.05$), suggesting that firms in central industries have higher cash holdings. The estimate from Column (2) indicates that a one-standard-deviation increase in Centrality is associated with a one-percentage-point increase in cash holdings. This effect is economically significant, accounting for a 7% increase relative to the sample average of cash holdings and a 13% increase relative to the median.

5.3 Cross-Sectional Analyses

I look into various firm- and industry-level characteristics that can moderate the relation between centrality and firms' cash holdings. This discussion sheds light on potential organizational and financial frictions that affect how firms manage liquidity to hedge against shocks permeating the production network.

First, I consider the role of firm diversification. Diversified firms operate in more than one industry segment and thus have the flexibility of redirecting their internal resources across divisions. The internal capital market of diversified firms helps alleviate the financial frictions faced by their divisions, allowing diversified firms to hold less cash (Stein, 1997; Matsusaka and Nanda, 2002; Duchin, 2010). Importantly, diversified firms fare better during economic downturns because they enjoy better credit access and suffer lower deadweight losses (Lewellen, 1971; Dimitrov and Tice, 2006; Hann, Ogneva, and Ozbas, 2013). If central firms hold cash to hedge against worse economic times, their cash holdings should decrease more with diversification than non-central firms.

I measure firm diversification across two dimensions. First, I count the number of business segments as the number of distinct three-digit NAICS industries in which a firm operates (Segments). Information on business segments comes from the Compustat Historical Segment database.[11] Second, I take into account the correlation of shocks across a firm's divisions. Firms whose segments face largely uncorrelated shocks have greater potential to smooth away those shocks. I calculate the correlation of cash flow and investment opportunities across a firm's divisions following the method introduced by Hann, Ogneva, and Ozbas (2013) (i.e., Cash Flow Correlation and Q Correlation). Both correlation measures take the value of one for standalone firms. Lower correlation indicates that a firm is more diversified.

Next, I investigate the role of industry competition. Firms facing greater competitive pressures are more substitutable to their customers and suppliers. This means that such firms are more likely to lose customers or suppliers to rivals when facing negative shocks. Existing research shows that cash reserves help firms defend against their product market rivals (Fresard, 2010). The role of cash in preserving market shares should be particularly valuable during bad economic conditions, which are associated with intense competitive pressures. Central firms, whose operations are more sensitive to economic downturns, should hold more cash as they face stronger competition.

I measure competition in two ways. First, I compute the Herfindahl index (HHI), defined as the sum of the squared percentage of sales generated by all public firms in an industry. HHI is calculated both for two-digit SIC industries and for census industries.[12] Next, following Fresard (2010), I exploit changes in US import tariffs as shocks to industry competition (Tariff Changes).[13] Lower (more negative) values of Tariff Changes suggest that an industry faces increased pressure from foreign penetration.

I regress firms' cash holdings on the interaction between Centrality and the abovementioned firm characteristics as follows:

$$\begin{aligned}\text{Cash}_{i,t} = {} & \gamma_1 \text{Centrality}_i + \gamma_2 \text{Centrality}_i \times \text{Characteristic}_{i,t-1} \\ & + \gamma_3 \text{Characteristic}_{i,t-1} + X_{i,t-1} + \xi_{k,t} + \epsilon_{i,t},\end{aligned} \tag{3}$$

where Characteristic $\in$ {Segments, Cash Flow Correlation, Q Correlation, HHI, Tariff Changes}. I expect the interactive coefficient γ_2 to be negative for Segments but positive for Cash Flow Correlation and Q Correlation. I also expect γ_2 to be negative for HHI and Tariff Changes.

Table V shows the results from this analysis. Panel A reports results regarding the effect of firm diversification. In Column (1), Centrality continues to generate a positive and statistically significant coefficient. Yet the interactive term between Centrality and Segments generates

11 NAICS codes for business segments are available starting in 1990.

12 Given that many census industries only contain a few public firms, I abbreviate the last digit of the industry code and use the first five digits to compute industry competition.

13 Tariff data are available for manufacturing industries (SIC 2000–3999) until 2005. Data come from Robert Feenstra's website and Peter Schott's website.

Table V. Cross-sectional analyses

This table examines the moderating effects of various industry and firm characteristics on the relation between firm centrality and cash holdings. Panel A reports the interactive results regarding firm diversification. Segments is the number of business segments (defined by three-digit NAICS codes) a firm has. Cash Flow Correlation and *Q* Correlation measure the extent to which a firm's cash flow and investment opportunities are correlated within its business segments. They are defined based on Hann, Ogneva, and Ozbas (2013). Panel B reports the interactive results related to industry competition. HHI stands for the Herfindahl index of sales among firms in an industry. In Column (1), I classify industries based on two-digit SIC codes and in Column (2), I calculate HHI in each of the five-digit census industries. All regressions control for SIC1 industry-year fixed effects. In Column (3), I examine the interactive effect of tariff cuts. Tariff Changes is changes in US import tariffs in a four-digit SIC industry. Data on US import tariffs are available for manufacturing industries (SIC 2000–3999) till 2005. Controls refers to the same set of control variables used in Column (2) of Table IV. Robust *t*-statistics are shown in parentheses. Standard errors are clustered by census industry.

Panel A: Effects of diversification

Dependent variable: Cash	(1)	(2)	(3)	(4)	(5)
Centrality	0.260**	–0.043	0.129	–0.036	0.124
	(2.33)	(–0.74)	(1.43)	(–0.60)	(1.32)
Centrality × Segments	–0.093**		–0.070*		–0.072**
	(–2.40)		(–1.96)		(–1.98)
Segments	–0.001		0.003		0.001
	(–0.35)		(0.88)		(0.42)
Centrality × Cash Flow Correlation		0.204**	0.108*		
		(2.23)	(1.79)		
Cash Flow Correlation		0.015*	0.020**		
		(1.91)	(2.13)		
Centrality × *Q* Correlation				0.196**	0.116*
				(2.19)	(1.94)
Q Correlation				0.015*	0.016
				(1.69)	(1.62)
Controls	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	86,211	86,211	86,211	86,211	86,211
R-squared	0.428	0.429	0.429	0.429	0.429

Panel B: Effects of Competition

Dependent variable: Cash	(1)	(2)	(3)
Centrality	0.396***	0.280*	0.216***
	(3.04)	(1.95)	(2.90)
Centrality × HHI (SIC)	–1.024***		
	(–3.05)		
HHI (SIC)	–0.011		
	(–0.36)		
Centrality × HHI (Census)		–0.568*	
		(–1.84)	

(continued)

Table V. Continued

Panel B: Effects of Competition

Dependent variable: Cash	(1)	(2)	(3)
HHI (Census)		–0.033*	
		(–1.72)	
Centrality × Tariff changes			–1.887**
			(–2.28)
Tariff changes			0.026
			(1.12)
Controls	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes
Observations	119,769	119,769	28,158
R-squared	0.425	0.408	0.409

a negative coefficient, suggesting that diversified firms hold less cash than standalone firms with the same level of centrality. In Columns (2) and (4), I interact a firm's centrality with the cash flow correlation and the *Q* correlation across its divisions. Both interactive terms generate positive coefficients. Recall that lower correlation values indicate more weakly correlated shocks across firms' divisions. This result thus suggests that, all else equal, central firms with diverse operations hold less cash than other firms that are equally central. In Columns (3) and (5), I further control for the interaction between Centrality and Segments. Both correlation measures continue to bear positive and economically meaningful coefficients, suggesting that the cross-divisional correlation of shocks generates additional explanatory power for central firms' cash holdings beyond the number of segments they have.

Panel B presents the results regarding the interactive effect of firm centrality and industry competition. While Centrality continues to generate a positive and significant coefficient, its interactive terms with measures of industry competition bears a negative sign. This suggests that central firms facing more competitive pressure (with low values of HHI or Tariff Changes) hold more cash than central firms in less competitive environments. The estimates from Column (1) indicate that, for firms with centrality at the 75th percentile of the sample, a one-standard-deviation increase in HHI (0.2) is associated with a 3.7-percentage point reduction in cash holdings ($= 1.024 \times 0.18 \times 0.2$).

6. Alternative Explanations

My baseline estimation relies on cross-sectoral variation in centrality to draw the inference that central firms in the network hold more cash. There remain challenges to making such an inference. For example, the observed relation between centrality and cash holdings may be driven by the external financing frictions that firms face. Alternatively, the cash-centrality relation can be influenced by firms' tax avoidance motives. It is also possible that firms' governance structures are correlated with both cash holdings and centrality, thus affecting my results. In this section, I discuss these alternative explanations in turn.

6.1 External Financing Frictions

One potential concern with the baseline finding is that central firms may hold cash because they face more severe frictions in accessing the external capital market, but not because they bear higher systematic risk. Such frictions can arise from various sources, including the level of information asymmetry between investors and shareholders, and the lack of pledgeability of firms' assets.

I look into the above sources of external financing frictions and investigate whether these characteristics can explain the cash-centrality relation. To start, I examine firms' size and age using the Hadlock–Pierce index (Hadlock and Pierce, 2010; henceforth "HP"). The HP index takes on higher values for smaller and younger firms, which face more information frictions in raising funds. I also examine firms' asset composition. Firms whose operations rely on intangible and customized assets face more difficulty in accessing the credit market, as those assets have a higher liquidation discount and lower collateral value (see, e.g., Titman and Wessels, 1988; Liberti and Mian, 2010). I employ two measures of asset composition, asset tangibility and input specificity. Input specificity is the percentage of inputs used by an industry that are neither exchange traded nor referenced in trade journals (Rauch, 1999; Nunn, 2007). This metric gauges firms' reliance on customized assets.

I check whether the above measures of external financing frictions are correlated with centrality. Panel A of Table VI presents the univariate relation between centrality and those characteristics. Results suggest that central firms do not seem to face more external financing frictions due to their size, age, or asset structure. For Panel B of Table VI, I include these characteristics as additional controls in the baseline estimation. Given that size (one input of the HP index) and tangibility are already included in the baseline model, I add input specificity and age (the other input of the HP index). My results are robust to these additional controls.

6.2 Firm's Tax Avoidance Incentives

A non-trivial amount of US firms' cash holdings is held by multinational companies (Foley *et al.*, 2007). The US tax system imposes corporate income taxes for earnings generated in foreign countries, but such taxes can be deferred until the earnings are repatriated. To avoid US corporate taxes, multinational firms retain their foreign income abroad, which largely translates into cash holdings. If the majority of central firms in the US production network are multinational firms, their tax avoidance incentive could bias my inference from the baseline finding.

I test this argument by controlling for various proxies of tax avoidance incentives. First, I construct an indicator for multinational firms (Multinational), which equals one if a firm has previously reported foreign segment sales that account for more than 25% of its total sales and zero otherwise (Pinkowitz, Stulz, and Williamson, 2013).[14] Second, I gauge the amount of foreign income a firm generates using the ratio of its foreign income over the firm's total assets. Higher foreign income is likely associated with stronger tax avoidance incentives. Finally, I measure the tax cost of repatriation (Repatriation Cost) following Foley *et al.* (2007). I first calculate the gap between the projected US corporate taxes a firm needs to pay if it repatriates all foreign income and the amount in foreign taxes it has paid. I then scale the maximum between this gap and zero by total assets. US corporate taxes are estimated as the product between a firm's foreign pre-tax income and its marginal effective tax rate according to Graham (2000). Higher values of this measure indicate that the firm would owe more taxes to the US government if it were to repatriate its foreign income.

14 Results do not change if multinational firms are defined as firms that report foreign income, or defined as firms that have reported foreign income in the past three years.

Table VI. Addressing omitted variables: financial frictions

This table addresses the concern that external financing frictions could drive the relation between centrality and firm cash holdings. In Panel A, I examine the relation between centrality and proxies of external financing frictions. In Panel B, I add controls for financial frictions in the baseline regression. Input Specificity is the percentage of inputs used in an industry that are neither exchange traded nor referenced in trade journals (Nunn, 2007). All regressions control for SIC1 industry-year fixed effects. Controls refer to the same set of control variables used in Column (2) of Table IV. Robust *t*-statistics are shown in parentheses. Standard errors are clustered by census industry. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Panel A: Centrality and external financing frictions

	(1)	(2)	(3)
Dependent variable:	HP index	Tangibility	Input specificity
Centrality	–0.192	0.515	0.029
	(–0.32)	(1.52)	(0.18)
Industry-year FE	Yes	Yes	Yes
Observations	154,048	154,048	90,512
R-squared	0.103	0.186	0.236

Panel B: Controlling for external financing frictions

Dependent variable: Cash	(1)	(2)	(3)
Centrality	0.135**	0.230***	0.223***
	(2.10)	(3.35)	(3.35)
Age	–0.001***		–0.001***
	(–4.36)		(–5.38)
Input specificity		–0.040**	–0.043**
		(–2.19)	(–2.31)
Controls	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes
Observations	119,764	70,653	70,651
R-squared	0.409	0.486	0.491

I show in Panel A of Table VII that central industries do not have more multinational firms than non-central industries.[15] Foreign income and repatriation cost also do not seem to increase with centrality. In Panel B of Table VII, I control for measures of firms' tax avoidance incentives in the baseline framework. Centrality continues to attract positive and statistically significant coefficients across all specifications, suggesting that multinational firms' tax avoidance is unlikely to drive my results.

6.3 Governance Quality

I next consider the possibility that a firm's governance structures may be correlated with both its centrality and its cash holdings. Previous studies suggest that governance quality

15 Industries with the highest prevalence of multinationals include fabric production, wholesale trade, agriculture, and mining machinery manufacturing. The agriculture and fabric industries, for example, have relatively low centrality in the production network.

Table VII. Addressing omitted variables: tax avoidance incentives

This table addresses the concern that multinational firms' tax avoidance incentives could drive the relation between centrality and cash holdings. In Panel A, I examine the relation between centrality and measures of multinational firms' tax avoidance incentives. In Panel B, I add controls for tax avoidance incentives in the baseline regression. Multinational is an indicator that equals to one if a firm has reported at least 25% foreign sales in its geographical segments before, and zero otherwise. Foreign Income is the ratio of foreign pre-tax income to total assets. Given a firm's pre-tax foreign income, Repatriation Cost is computed as the difference between a firm's projected US taxes based on the US marginal effective tax rate and the tax it paid for its foreign income. The maximum between this difference and zero is scaled by total assets. Foreign Income and Repatriation Cost are available only for multinational firms, that is, firms that report foreign income. All regressions control for SIC1 industry-year fixed effects. Controls refer to the same set of control variables used in Column (2) of Table IV. Robust *t*-statistics are shown in parentheses. Standard errors are clustered by census industry. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Panel A: Centrality and tax avoidance incentives

	(1)	(2)	(3)
Dependent variable:	Multinational	Foreign income	Repatriation cost
Centrality	–0.076	–0.012	0.004
	(–0.69)	(–0.53)	(1.09)
Industry-year FE	Yes	Yes	Yes
Observations	154,048	35,501	20,370
R-squared	0.459	0.019	0.016

Panel B: Controlling for firms' tax avoidance incentives

Dependent variable: Cash	(1)	(2)	(3)
Centrality	0.141**	0.201**	0.258**
	(2.10)	(2.12)	(2.41)
Multinational	0.001		
	(0.13)		
Foreign income		0.025	
		(1.42)	
Repatriation cost			0.932**
			(2.34)
Controls	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes
Observations	119,769	31,298	18,538
R-squared	0.403	0.455	0.476

affects cash holdings (Harford, Mansi, and Maxwell, 2008). If central firms' governance structures differ significantly from those of non-central firms, the observed relation between centrality and cash could be biased.

To assess this argument, I examine the governance quality of central and non-central firms using an array of corporate governance metrics. First, I look at two indices of antitakeover provisions. Gompers, Ishii, and Metrick (2003) constructed an index of twenty-four antitakeover provisions (G-index). Bebchuk and Cohen (2005) later developed a management entrenchment index using a subset of provisions (E-index). Higher values of both indices suggest weaker shareholder rights. Next, I consider management compensation incentives proxied by Pay Sensitivity, which is defined as the average equity-based compensation for top management (Core, Guay, and Rusticus, 2006). I also include the percentage of firms' outstanding shares owned by institutional investors (Institutional Ownership). Higher institutional ownership is associated with stronger monitoring from institutional investors over management. Finally, I use board characteristics including Board Size, the ratio of the number of directors on a board over the log of firm assets, and Board Independence, the percentage of outside directors on the board. These characteristics could be correlated with the monitoring effectiveness of the board.

In Panel A of Table VIII, I examine the relation between centrality and governance quality, but do not find evidence that central firms have significantly different governance structures from non-central firms. I further control for the above-mentioned governance metrics in the baseline regression. Panel B of Table VIII reports the results. In Columns (1)–(6), I include one governance measure in each regression. In Column (7), I add all six measures in the same regression. Given that these governance measures are generally available for a subset of firms and over limited sample periods, the number of observations substantially reduces from the baseline sample and varies across regressions.[16] Despite the inclusion of various governance indices, Centrality continues to generate positive and statistically significant coefficients, with magnitudes similar to those of the baseline results.

Overall, the results in this section suggest that the documented relation between centrality and cash holdings is unlikely to be driven by central firms facing more severe external financial frictions, having stronger tax avoidance incentives, or having different governance structures. Admittedly, it is challenging to entirely rule out all possibilities that firms' cash holdings might reflect certain unobservable firm-level conditions. However, to the extent that those unobservables do not correlate with both firms' precautionary motives and industry-level IO structures, they should not limit my inferences.

7. Additional Implications

I test two additional implications of my framework described in Section 2. First, central firms hoard cash partly because they extend trade credit to support connected firms following negative shocks. I verify this channel in the context of both idiosyncratic and aggregate shocks. Second, if capital market investors recognize central firms' exposure to aggregate shocks, they should incorporate such an exposure by marking-up those firms' financing costs. I test this prediction in the setting of credit markets.

7.1 Liquidity Transfer along the Supply Chain: Evidence from 9/11 Attacks

I study the role of trade credit as a channel through which firms share liquidity to support counterparties that face negative shocks. I do so in two different contexts. First, I exploit an idiosyncratic, negative shock to the airline industry and examine how firms directly or indirectly connected to airlines adjust their trade credit. Second, I examine whether central

16 For example, G-index and E-index are available for around 1,000 large firms in my sample from 1990 to 2006. Data on pay sensitivity start in 1992. Institutional ownership data start in 1999. Board data are obtained from MSCI and are available for around 1,500 large firms in my sample since 2001.

Table VIII. Addressing omitted variables: governance structures

This table examines whether governance structures could influence the relation between centrality and firms' cash policies. In Panel A, I examine the relation between centrality and proxies for governance quality. In Panel B, I add controls for governance quality in the baseline regression. G-index and E-index account for the level of antitakeover provisions in place. G-index is based on Gompers, Ishii, and Metrick (2003). E-index is developed by Bebchuk *et al.* (2005). Pay Sensitivity is the pay-for-performance sensitivity of a firm's top management. Institutional Ownership is the percentage of a firm's equity shares owned by institutional investors. Board Size is the ratio between the number of directors to the log of assets. Board Independence is the percentage of outside directors over the total number of directors. All regressions control for SIC1 industry-year fixed effects. Controls refer to the same set of control variables used in Column (2) of Table IV. Robust *t*-statistics are shown in parentheses. Standard errors are clustered by census industry. ***$p<0.01$, **$p<0.05$, *$p<0.10$.

Panel A: Centrality and corporate governance structures

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	G-index	E-index	Pay sensitivity	Institutional ownership	Board size	Board independence
Centrality	–1.030	–0.874	116.671	0.013	–0.246	–0.048
	(–0.57)	(–0.89)	(1.06)	(0.08)	(–0.78)	(–0.99)
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,483	16,663	20,618	42,899	14,753	14,720
R-squared	0.022	0.021	0.055	0.098	0.404	0.059

Panel B: Controlling for corporate governance structures

Dependent variable: Cash	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Centrality	0.156**	0.140**	0.216**	0.163*	0.153*	0.155*	0.226**
	(2.11)	(2.07)	(2.31)	(1.84)	(1.68)	(1.67)	(2.16)
G-index	–0.003***						–0.002
	(–3.36)						(–1.01)
E-index		–0.007***					–0.008**
		(–3.92)					(–2.35)
Pay sensitivity			0.000				–0.000
			(0.19)				(–0.09)
Institutional ownership				0.024			0.064***
				(1.60)			(3.81)
Board size					–0.008		–0.029***
					(–1.56)		(–2.66)
Board independence						0.011	–0.002
						(0.63)	(–0.07)
Observations	14,149	16,316	19,583	37,243	14,061	14,031	4,598
R-squared	0.507	0.509	0.530	0.528	0.554	0.554	0.506

firms provide more liquidity through trade credit during aggregate downturns, that is, negative shocks that affect all firms connected in the network.

In the first analysis, I use the September 11, 2001, terrorist attacks (9/11) as a negative shock to the airline industry (SIC = 4512). The terrorist attacks led to significant reductions in consumer demand for the airlines and even resulted in the bankruptcies of several major airline companies and large-scale layoffs across the whole industry. As airlines are in distress, I expect their direct suppliers to increase their receivables following the attacks. I also expect those suppliers to pass on the liquidity shortage further upstream by increasing their accounts payable. Such a transmission mechanism should be mitigated by suppliers' liquidity reserves prior to the shock.[17]

I compare the trade credit of immediate suppliers to airline companies (treated) and that of firms indirectly connected to airlines up to the 4th degree (control). I use September 11, 2001, as the event date, the four years after the event as the post-event window, and the four years prior to the event as the pre-event window. I estimate changes in trade credit usage using the following difference-in-differences model:

$$\mathrm{TC}_{i,t} = \theta \mathrm{Supplier}_i \times \mathrm{Post}_t + \boldsymbol{X}_{i,t} + \alpha_i + \tau_t + \epsilon_{i,t}, \tag{4}$$

where TC includes receivables and payables, both scaled by total assets; Post is an indicator variable that equals one if a firm's reporting date falls after September 11, 2001, and zero otherwise; Supplier is an indicator that equals one if a firm is a direct supplier of at least one of the airlines during the pre-event period. The estimation controls for firm-fixed effects (α_i) and year-fixed effects (τ_t). The non-interactive terms, Supplier and Post are thus absorbed by fixed effects. Control variables include firm size, market-to-book, tangibility, leverage, profitability, investment, sales, log of firm age, and the square of log age (Petersen and Rajan, 1997). Standard errors are clustered by firm.

Panel A of Table IX shows the results from this analysis. Results reported in Column (1) show that direct suppliers of airline companies provide liquidity by increasing receivables by two percentage points following the attacks. This increase is economically sizable, accounting for an 18% increase over the sample average.

I then examine the trade credit demand of airlines' suppliers from their own upstream firms. In this investigation, I split the sample into terciles based on firms' pre-event liquidity reserves, which are defined as the firm-level average of residuals from regressing pre-event cash holdings on characteristics that have been shown to influence cash demand, such as size, tangibility, leverage, and so on. Columns (2) and (3) report results for firms with bottom-tercile and top-tercile pre-event cash reserves, respectively. Suppliers with low cash reserves pass on the liquidity shortage to upstream firms by increasing their payables by around two percentage points, while suppliers with high cash reserves do not increase trade credit financing from their own upstream firms. In the Online Appendix, I show that these changes in trade credit usage do not predate the attacks. These results provide evidence consistent with the conjecture that negative shocks propagate along the supply chain and that firms pass on their liquidity shortages by "borrowing" from upstream firms. However, such an effect is mitigated if firms have high liquidity reserves. This finding adds further credence to the argument that corporate cash holdings can dampen the spillover effects along the supply chain.

17 Prior literature shows that firms rely on trade credit when bank credit is in short supply (e.g., Garcia-Appendini and Montoriol-Garriga, 2013). This analysis differs from that of Garcia-Appendini and Montoriol-Garriga (2013) in that it does not focus on the effects of an aggregate credit crunch. It also looks at the liquidity transfer across indirectly connected firms (e.g., suppliers of suppliers).

Table IX. Propagation of shocks and trade credit

This table shows the provision of trade credit following negative shocks. Panel A examines trade credit usage by upstream firms of the airline industry around the 9/11 terrorist attacks. Supplier is an indicator that equals one if a firm is an immediate supplier of an airline company. Post is an indicator for whether a firm's reporting date falls after 9/11/2001. Column (1) examines the trade credit extension of upstream firms to airlines. Receivables stands for accounts receivable scaled by total assets. Columns (2) and (3) examine the trade credit demand of upstream firms to their own suppliers. Payables stands for accounts payable scaled by total assets. Low (high) cash reserves indicate the sample of firms that have bottom- (top-) tercile cash holdings prior to the attacks. Pre-event cash holdings are defined as firm-specific average residuals from regressing cash holdings on a set of firm characteristics in the pre-event period. Panel B reports results on firms' trade credit extension over the business cycle. Net Receivables is calculated as the difference between accounts receivable and accounts payable scaled by total assets. The sample for this panel contains all firms with available information on Centrality. All regressions use firm-fixed effects and year-fixed effects. Standard errors are clustered by firm in Panel A and by census industry in Panel B. *t*-statistics are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Panel A: Trade credit usage around 9/11

	(1)	(2)	(3)
Dependent variable:	Receivables	Payables	Payables
Sample:	All	Low cash reserves	High cash reserves
Supplier × Post	0.020*	0.022***	0.003
	(1.73)	(2.59)	(0.19)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	7,138	2,520	2,374
R-squared	0.875	0.870	0.847

Panel B: Trade credit over business cycles

	(1)	(2)	(3)	(4)
Dependent variable:	Receivables	Receivables	Net receivables	Net receivables
Business cycle measured by:	GDP growth	CFNAI	GDP growth	CFNAI
Centrality × Business Cycle	−0.241	−0.012**	−0.306**	−0.009**
	(−1.47)	(−2.34)	(−2.18)	(−2.18)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	132,551	132,551	132,531	132,531
R-squared	0.769	0.769	0.747	0.747

My second analysis studies central firms' provision of trade credit across business cycles. Given that central firms are more dependent on other firms, they should have a greater incentive to support other firms during downturns. To test this conjecture, I follow the regression framework outlined in Equation (2), substituting the outcome variable for Receivables and Net Receivables (receivables − payables). Net receivables capture the amount of liquidity provided by a firm that is not sourced from its suppliers. Panel B of Table IX reports the results from this analysis. The interaction term between Centrality and Business Cycle generates negative coefficients for both measures of receivables and business cycles, suggesting that central firms provide more trade credit during low-growth periods. The estimate from Column (3) suggests that a one-standard-deviation increase in Centrality is associated with firms providing four percentage points more trade credit from high- to low-growth periods.

Overall, results from this section suggest that trade credit is an important channel through which firms share liquidity and smooth shocks along the supply chain. For central firms, cash not only provides a cushion against their own shock, but also helps them support trade counterparties during aggregate downturns. This likely enhances their incentives to maintain high cash reserves.

7.2 Borrowing Costs

Do investors in the capital market incorporate centrality in determining firms' costs of financing? While central firms do not face more severe financial frictions than non-central firms, it is plausible that investors demand compensation for central firms' systematic risk exposure. To test this conjecture, I examine the credit spreads charged on privately placed debt contracts. The private debt market serves as an ideal setting for studying the relationship between centrality and external financing costs because this market is one of the most important sources of funding for US public firms, where detailed information is available regarding borrower identities and loan contract terms.

Information on credit spreads comes from the LPC Dealscan database. I use three measures of credit spreads to gauge a firm's financing costs. The first measure is loan spreads in basis points over LIBOR, which represents interest rate markups charged by lenders to compensate for credit risk. The other two measures are excess spreads relative to benchmarks based on "comparable loans." These measures incorporate the fact that corporate lenders often price loans based on deals with similar characteristics issued in the recent past (Murfin and Pratt, 2019). Excess spreads capture a firm's borrowing costs relative to other borrowers with similar characteristics. The first version of the benchmark is the average spreads charged on loans issued to borrowers in the same ratings category and the same industry, having the same loan type, and issued during the one-year window prior to the origination of the loan of interest.[18] The second benchmark is the predicted spreads from a credit score model, which utilizes a wide range of predictors, including borrower characteristics, loan contract characteristics (i.e., maturity, type, and loan size), and industry-year fixed effects. The credit score model is estimated using all Dealscan loans extended to US public firms.

Table X reports the results. Across all measures of borrowing costs, Centrality generates positive and statistically significant coefficients. Estimates from Column (3) suggest that high-centrality firms (at the 75th percentile of the sample) face an 8-basis-point higher excess spreads on their loans than low-centrality firms (at the 25th percentile), a 10% increase

18 Consistent with Murfin and Pratt (2019), I classify a borrower of an existing deal to be in the same ratings category as the firm of interest if they are within the same major ratings category (e.g., a BB+ rating is considered to be in the same category as ratings ranging from B+ to BBB+) and the difference in numerical ratings between matches is at most three.

Table X. Cost of borrowing

This table presents results for firms' credit spreads. The variable of interest is the interest rate spreads for corporate loans in basis points over LIBOR (*Source*: LPC Dealscan). The unit of observation is a loan facility. The dependent variable in Column (1) is the raw credit spreads. The dependent variable in Column (2) is the excess spread relative to a benchmark group of same-type loans issued to borrowers in the same industry and ratings group during the one-year window prior to the issuance of the loan of interest. The dependent variable in Column (3) is the excess spread relative to a credit score model, which controls for industry-year fixed effects, firm characteristics (i.e., same set as in Column (2) of Table IV), and loan contract characteristics (loan maturity, loan size, and loan type fixed effects). All firm characteristics are lagged by one year. Robust *t*-statistics are reported in parentheses. Standard errors are clustered by census industry. ***$p<0.01$, **$p<0.05$, *$p<0.10$.

	(1)	(2)	(3)
Dependent variable:	Spreads	Excess spreads	Excess spreads
Benchmark:	LIBOR	Comparables	Credit score model
Centrality	47.389**	28.872*	44.033**
	(2.46)	(1.89)	(2.32)
Controls	Yes	Yes	No
Other loan terms controls	Yes	No	No
Industry-year FE	Yes	Yes	Yes
Observations	19,223	18,396	19,223
R-squared	0.531	0.239	0.033

relative to the sample standard deviation of excess spread. This result is consistent with creditors marking up interest rates to reflect central firms' systematic risk exposure.

Importantly, the "centrality markup" in credit spreads heightens during economic downturns. Figure 5 illustrates this point using estimates from the following model:

$$\text{Excess Spreads}_{l,i,t} = \sum_m \beta_m \text{Centrality}_i \times I_{m,t} + \xi_{k,t} + \epsilon_{i,t}, \quad (5)$$

where Excess Spreads refers to the loan spreads over a benchmark spread predicted by the credit score model. l indicates a loan facility. $I_{m,t}$ are indicators of economic conditions, with m representing high-growth, moderation, or low-growth periods. Figure 5 plots the coefficients of the interaction terms β_m. The solid dots represent point estimates of the coefficients and the dashed lines represent 90% confidence intervals. The coefficient of Centrality × High Growth Periods is close to zero while that of Centrality × Low Growth Periods is economically large and statistically significant. This difference in coefficients suggests that, from economic booms to busts, high-centrality firms experience an additional 13-basis-point increase in borrowing costs compared to low-centrality firms.[19]

Overall, the results in this section suggest that investors in the capital market recognize the systematic risk borne by central firms and incorporate such risk exposure into their funding costs. More importantly, the markup associated with centrality aggravates during busts and ameliorates during booms. The counter-cyclicality of financing costs may create

19 The 75th percentile of centrality is 0.180 while the 25th percentile is 0.009. Accordingly, the differential funding cost between booms and busts is estimated as $(68-(-6)) \times (0.180-0.009)$.

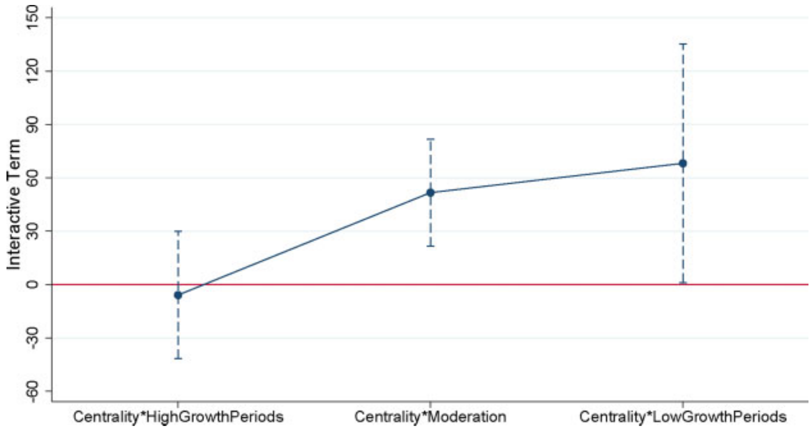

Figure 5. Excess loan spreads of central firms. This figure shows the coefficients of interactive terms between firm centrality and economic conditions in a regression of excess credit spreads. The dependent variable is the excess loan spreads relative to the benchmark spreads predicted by the credit score model. The solid dots represent point estimates for the interactive coefficients and the dashed lines represent 90% confidence intervals around the coefficient estimates. The regression controls for industry-year fixed effects. Standard errors are clustered by census industry.

an additional incentive for central firms to build up liquidity reserves prior to the realization of economic conditions.

8. Robustness

I conduct various robustness tests to verify that the baseline findings are not sensitive to certain empirical specifications or measurement choices.

8.1 Industry Classification and Measurement

The baseline analyses remove time-varying conditions of broadly defined industries (one-digit SIC). I test the robustness of my analyses by imposing fixed effects based on more refined industry classifications. Table XI shows the results. Column (1) controls for "matching industry"-year fixed effects, where matching industries are defined as two-digit SIC industries for observations prior to 1997 and three-digit NAICS industries for observations starting in 1997. This corresponds to the crosswalk between census industries and public firms at the time of observation. Column (2) controls for two-digit SIC-year fixed effects and Column (3) controls for three-digit NAICS-year fixed effects throughout the sample period. In Column (4), I repeat the baseline analysis using a census sector-year panel. For this analysis, cash holdings and control variables are calculated as the average level across all firms in an industry. The base result is robust across all the above specifications.

8.2 Production Networks and Centrality at the Firm Level

Network centrality calculated using the BEA IO matrices captures comprehensive information on the trade flows across all economic entities, including public and private firms as well as major and minor supply-chain relations. However, it also faces the limitation that it is an industry-level statistic and allows no within-industry and little time-series variation.

Table XI. Other industry-year effects

This table shows the robustness of the baseline test to controlling for alternative industry-year fixed effects or changing the sample structure. In Column (1), I control for matching industry-year fixed effects, whereby matching industries are defined as two-digit SIC industries prior to 1997 and three-digit NAICS industries after 1997. In Column (2), I impose two-digit SIC-year fixed effects throughout the sample period. In Column (3), I impose three-digit NAICS-year fixed effects throughout the sample period. In Column (4), I use a census industry-year panel and impose one-digit SIC-year fixed effects. Cash holdings and all control variables are the industry average level in a given year. Controls refer to the same set of control variables used in Column (2) of Table IV. Standard errors are clustered by census industry.

Dependent variable: Cash	(1)	(2)	(3)	(4)
Sample:	Firm-year	Firm-year	Firm-year	Sector-year
Centrality	0.122**	0.123**	0.151**	0.073*
	(2.54)	(2.57)	(2.58)	(1.80)
Controls	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes
Industry type	Matching Ind	SIC2	NAICS3	SIC1
Observations	119,771	119,769	119,771	16,500
R-squared	0.448	0.446	0.437	0.405

To overcome this limitation, I gather more granular information regarding firm-to-firm linkages based on customer–supplier relationships. This information comes from the Compustat Segment database and the Factset Revere database. The Segment data are sourced from firms' mandatory reporting of customers that account for more than 10% of total sales, according to the Statement of Financial Accounting Standard (SFAS) No. 14. FactSet gathers supply-chain information from companies' conference calls, capital market presentations, press releases, and websites, in addition to 10-K disclosures.[20]

Using these data sources, I construct firm-level production networks for each fiscal year. Those networks are generally disconnected, that is, there are clusters of firms that are not connected to the rest of the network. Given that eigenvector centrality is not well defined for disconnected networks, I use closeness centrality (Closeness) to gauge the centrality of firms in a production network. Similar to eigenvector centrality, closeness centrality also measures a firm's exposure to shocks occurring to other firms in the network. Yet it relies on the shortest "distance" between a pair of firms to determine the likelihood and intensity of spillover effects.[21] The distance between each pair of firms reflects the inverse of their

20 The two data sources each have its advantages. The Segment data contain a longer time series and provide annual sales numbers between firms. Yet it does not include minor customers to whom firms attribute less than 10% of sales. The FactSet data cover a more comprehensive set of supply-chain relations, but it reports customer relations only from 2003 onward. It also does not document sales numbers. I thank Andrea Frazzini and Ted Fee for sharing data on customer identities from the Segment data.

21 Closeness takes into account only the "shortest path," that is, the path of contagion with the strongest impact. In other words, if there are two ways in which a shock occurring to firm k will affect firm i, $k \rightarrow j_1 \rightarrow i$ and $k \rightarrow j_2 \rightarrow i$, and that j_1 is a less important customer of firm i than j_2, then only the second path will be considered in the calculation.

Table XII. Robustness: closeness centrality

This table shows the relation between firm-level closeness centrality and cash holdings. Panel A shows the summary statistics for samples using closeness centrality in this study. The Segment sample includes all firms that report a major customer or are reported as major customers by other firms in their 10-K reports. The sample period runs from 1976 to 2010. The FactSet sample includes firms with available customer or supplier information from the FactSet Revere database to construct closeness centrality. The sample period runs from 2004 to 2011. Both samples require firms to have positive total asset values and exclude firms in financial (SIC in 6000–6999) and utility industries (SIC in 4900–4999). In Panel B, I repeat the baseline tests for closeness centrality. In Column (1), I use Closeness measured using the Segment data, and in Column (2), I use FactSet data. All regressions control for industry-year fixed effects. Controls refers to the same set of control variables used in Column (2) of Table IV. Robust *t*-statistics from the regressions are shown in parentheses. Standard errors are clustered by firm. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.10$.

Panel A: Summary of closeness

	Mean	Median	Std. Dev.	25th Percentile	75th Percentile
Closeness (Segment)	0.013	0.010	0.013	0.002	0.022
Closeness (FactSet)	0.280	0.050	0.283	0.253	0.312

Panel B: Baseline results using closeness

Sample:	Segment	FactSet
Dependent variable: Cash	(1)	(2)
Closeness	0.426***	0.124**
	(2.97)	(2.19)
Controls	Yes	Yes
Industry-Year FE	Yes	Yes
Observations	20,364	18,812
R-squared	0.490	0.367

dependence. In other words, a shorter distance describes greater reliance of one firm on the other and thus higher exposure to shocks occurring to the other firm. Closeness centrality is the average of the inverse distance between a firm to every other firm in the network. It thus gauges a firm's exposure to common shocks in the network. A detailed definition of Closeness is provided in Appendix C.

Panel A of Table XII reports the summary statistics for closeness centrality. The average Closeness in the Segment sample is 0.013 and the average level in the FactSet sample is 0.28.[22] Panel B repeats baseline tests using closeness centrality. Column (1) shows results with Closeness based on the Segment data and Column (2) shows results with the FactSet data. Across both samples, Closeness attracts positive and significant coefficients for cash holdings.

In the Appendix, I provide several validation tests regarding closeness centrality. First, I show that the relation between cash and centrality in the firm-level network is unlikely to

22 The closeness centrality calculated using the FactSet data is larger in magnitude, as the network linkages are not weighted by percentage sales or purchases.

be biased by the reporting threshold of 10% (Online Appendix, Section IA4). Second, I address endogeneity issues related to closeness centrality by exploiting mergers of secondary network neighbors as shocks to local network structure (Appendix C2). The rationale behind this test is that mergers between a firm's network neighbors enhance the connections between the firm and other firms connected to the merging entities, thus increasing the firm's centrality.[23] Using secondary neighbors helps alleviate the concern that mergers can alter the bargaining dynamics between the firm of interest and the merging entities. Network neighbors of merging entities (the treated group) are further compared with neighbors of withdrawn mergers from the same industry as the completed mergers (the control group) to control for confounding effects related to the life-cycle of the merging entities (e.g., mergers may be conducted by dominant, mature firms in the industry). This test produces results consistent with those in Table XII: Firms' centrality increases following mergers of network neighbors, which in turn leads to higher cash holdings.

Admittedly, inferences from the merger analysis are valid to the extent that the mergers in my sample do not systematically occur for the purposes of changing secondary network neighbors' cash policies. One example of such a concern is that firms may decide to merge in order to pressure secondary neighbors to hold more cash and reduce supply-chain risk. I discuss this particular concern in Appendix C2, but do not find evidence suggesting that network neighbors become less risky following mergers.

Taken together, the findings based on inter-firm network connections corroborate the evidence from the inter-sectoral network that central firms maintain higher cash reserves.

9. Conclusion

In the US economy, firms are closely connected in a production network and are exposed to the spillover effects of negative shocks from their connected firms. Recent research suggests that even small, idiosyncratic shocks can generate system-wide fluctuations. Centrally connected firms could be particularly sensitive to these shocks, endangering other firms during economic downturns. However, the extant literature has largely overlooked the stabilizing role of firms' liquidity management policies. My study bridges the gap in the literature by proposing that systematically important firms in the economy conserve liquidity to preempt aggregate shocks.

This paper is the first to study firms' liquidity management policies in relation to their position in the production network. I find that central firms maintain higher cash holdings to hedge against their exposure to aggregate shocks. In bad economic times, cash holdings not only help central firms sustain their own production, but also allow them to extend liquidity to support their trade counterparties. My study sheds light on the proactive role that firms play in dampening the propagation of shocks inside their production networks.

23 Recall that closeness centrality relies on the shortest path between a pair of firms to trace the propagation of shocks. A merger can provide a shorter path as it combines two neighboring firms into one. Although in some cases, the shortest path may already exist without the merger, the test only requires that with some probability, mergers of neighboring firms can create a shorter path.

Data availability

The data underlying this article were provided by the third-party data vendors under license, funded by Indiana University. Data will not be shared without permission of the data vendors and the funding institutions.

Appendix A: Variable Definitions

Dependent Variables

- Cash: Cash and equivalent securities (Data #1)/total assets (Data #6).
- Investment: Capital expenditure (Data #128)/total asset.
- Profitability: Operating income (Data #13)/total assets.
- Receivables: Accounts receivable (Data #2)/total assets.
- Payables: Accounts payable (Data #70)/total assets.
- Net receivables: (Accounts receivable - Accounts payable) (Data #2 – #70)/total assets.
- Spreads: The annual average interest rate spreads a firm receives, in basis points over LIBOR.
- Excess spread (Comparables): The annual average level of excess spreads, where excess spread = Spreads – average loan spreads across all loans of the same type issued to firms in the same two-digit SIC industry in the same credit rating group that are originated during the year prior to the loan of interest. The borrower of an existing deal is considered to be in the same rating category as the firm of interest if they are within the same major ratings category (e.g., a BB+ rating is considered to be the same category as ratings ranging from B+ to BBB+), and that the difference in numerical ratings between matches are at most three (see Murfin and Pratt, 2019).
- Excess spread (Credit score model): The annual average level of excess spreads, where excess spread = *Spreads* – fitted credit spread from a credit score model that includes firm characteristics (including firm size, market-to-book, tangibility, profitability, and leverage ratio), and loan contract characteristics (including loan maturity, loan size, and loan type fixed effects). The credit score model is estimated using all Dealscan loans.

Control Variables

- Size: Log(total assets).
- Market-to-book: (total assets + (share price (#24) × shares outstanding (#25))—book equity (#60)—deferred tax (#74))/total assets.
- Tangibility: Property, plant, and equipment (Data #8)/total assets.
- R&D: Firms' R&D expenditures (Data #46)/total assets.
- Acquisition: Acquisitions (Data #129)/sales (#12).
- Leverage: Book leverage (Data #9 + #34)/total assets.
- Dividend payer: A dummy for whether the firm pays dividend.

Conditioning Variables

- Segments: The number of distinct three-digit NAICS industries a firm reports as business segments.
- Cash flow correlation: The correlation among the cash flows of industry segments in which a firm operates, defined as $\Sigma_p \Sigma_q \omega_{ip} \omega_{iq} Corr_{[t-10,t-1]}(p,q)$. ω_{ip} is the percentage of

sales a firm generates in industry p relative to its total sales of a given year. $\text{Corr}_{[t-10,t-1]}(p,q)$ is the estimated correlation of industry cash flows between industries p and q over the 10-year period before year t (See Hann, Ogneva, and Ozbas, 2013).

- Q correlation: The correlation of Tobin's Q across industry segments in which a firm operates, defined analogously as Cash Flow Correlation. Tobin's Q is defined as market value of assets/(0.9 $\times$ total assets + 0.1 $\times$ market value of assets). The market value of assets is calculated as (total assets (Data #6) + (share price (#24) $\times$ shares outstanding (#25)) – book equity (#60) – deferred tax (#74))
- HHI: Herfindahl index of an industry based on sales generated by public firms in the industry.
- Tariff changes: Changes in US import tariffs in a four-digit SIC industry. Data on tariffs come from Robert Feenstra's and Peter Schott's websites.
- Age: The number of years since a firm first appears in Compustat database.
- Input specificity: The percentage of inputs used by an industry that are neither sold on an organized exchange nor reference priced. See Nunn (2007).
- HP index: Hadlock–Pierce index of financial constraint, introduced by Hadlock and Pierce (2010).
- Multinational: An indicator that equals one if a firm has previously reported foreign segment sales that account for more than 25% of its total sales and zero otherwise.
- Foreign income: The ratio of foreign pre-tax income to total assets.
- Repatriation cost: max{Pre-tax foreign income $\times$ US marginal effective tax rates (provided by Graham, 1996) – tax paid for foreign income, 0}/total assets.
- G-index: Antitakeover index developed by Gompers, Ishii, and Metrick (2003). Data come from Andrew Metrick's website.
- E-index: Antitakeover index developed by Bebchuk *et al.* (2009). Data come from Lucian Bebchuk's website.
- Pay sensitivity: Pay-for-performance sensitivity of a firm's top management. Data come from Lalitha Naveen's website.
- Institutional ownership: The percentage of a firm's equity shared owned by institutional investors.
- Board size: The ratio between the number of directors to the log of assets.
- Board independence: The percentage of outside directors over the total number of directors.

Appendix B: Multiple Observations

In constructing the base sample, I create a separate observation for each of the matched IO industries for firms in the construction industry (NAICS 23). I check how this sampling choice influences my results using three alternative empirical specifications. Table BI reports the results.

First, I double-cluster standard errors by firm and IO industry (Columns (1) and (2)). Second, I remove firms in the construction industry from the sample (Columns (3) and (4)). Third, I collapse multiple industry matches to a unique firm-year observation (Columns (5) and (6)). In doing so, I assign the average centrality across all matched IO industries to a firm and assign all construction firms in the same industry cluster. My baseline findings persist throughout these alternative specifications.

Table BI. Alternative sampling choices

This table shows the results from my baseline analyses while applying the alternative specifications to the standard errors and sampling. In Columns (1) and (2), I double-cluster standard errors by firm and I-O industry. In Columns (3) and (4), I remove firms from the construction industry (NAICS 23) from the sample. In Columns (5) and (6), I collapse observations for a same firm-year into a unique observation. Centrality is the average centrality across all matched industries. In Columns (3)–(6), standard errors are clustered by census industry.

Dependent variable: Cash	(1)	(2)	(3)	(4)	(5)	(6)
Centrality	0.157**	0.141**	0.144**	0.129**	0.153**	0.137**
	(2.04)	(2.10)	(1.98)	(2.04)	(2.06)	(2.12)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Financial policy controls	No	Yes	No	Yes	No	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	119,769	119,769	105,064	105,064	106,194	106,194
R-squared	0.342	0.403	0.362	0.425	0.359	0.423

Appendix C: Closeness Centrality

C1. Definition

Within each fiscal year, I connect all reported customer–supplier pairs to form a directed network, in which firms are represented as "nodes" and customer–supplier pairs are represented as "edges" that connect the nodes. For each customer–supplier connection, I assign weights in an analogous fashion as in the industry-level network: The weight of the direction from the supplier to the customer is the percentage of sales made to this customer divided by the total sales of the supplier. The weight of the direction from the customer to the supplier is the percentage of purchases made from this supplier divided by all of the customer's purchases.[24]

For a pair of firms that are not directly connected, the calculation of closeness centrality requires one to identify the "shortest path" between the two. The shortest path is defined as the way in which economic shocks can travel from one firm to the other over the smallest geodesic distance. The shorter the distance, the stronger is the contagious impact between those firms.

Figure C1 illustrates the definition of geodesic distances using the example of GM and Lear. In 2004, Lear sold \$5.3 billion worth of goods to GM, which represented 31% of its total sales of \$17 billion during the fiscal year. GM, on the other hand, had total purchases of \$48 billion from all of its suppliers, with Lear representing 11% of these purchases. Geodesic distance measures how insulated a firm is from the shocks originating from connected firms. The distance between immediate customers and suppliers is the inverse of the weight on their connections. In Figure C1, the distance from GM to Lear is 9.1 (1/0.11), while the distance from Lear to GM is 3.2 (1/0.31). Between indirectly connected firms, the geodesic distance is the total distance of the shortest path connecting the two firms. For

24 FactSet does not provide the value of sales between firms, so every edge derived from that database has a weight of 1.

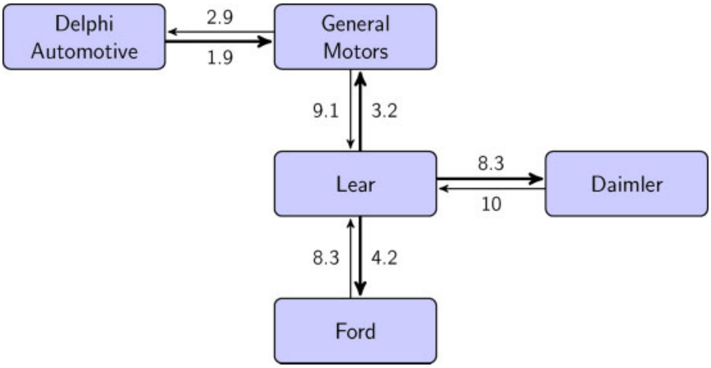

Figure C1. Geodesic distances of network connections. This figure shows an example of how the geodesic distances of the connections in the network are defined. The thick arrows indicate "sales to," and the thin arrows indicate "purchases from." In 2004, Lear sells \$5.3 billion worth of goods and services to General Motors. This transaction accounts for 31% of total sales for Lear, but accounts for only 11% of General Motors' total purchases. The path from Lear to General Motors thus is 3.2, while the path from General Motors to Lear has a distance of 9.1.

example, the geodesic distance of the path from GM to Ford will be 13.3 (9.1 + 4.2), while the distance from Ford to GM will be 11.5 (8.3 + 3.2).

Closeness centrality (Closeness) measures the average level of a firm's inverse geodesic distances from all other firms in the network (see Freeman, 1978; Jackson, 2010; Opsahl, Agneessens, and Skvoretz, 2010). In the context of a network, Closeness describes a firm's exposure to a common shock within the network. Closeness is computed as

$$\text{Closeness}_i = \frac{1}{g-1} \sum_{j=1, j \neq i}^{g} \frac{1}{d(i,j)},$$

where g is the number of firms in the network; $d(i,j) = \sum_{(l,k) \in \sigma(i,j)} d(l,k)$ is the geodesic distance from firm i to firm j; $\sigma(i,j)$ is the shortest path from i to j, consisting of sequentially connected nodes (e.g., l, k); and (l, k) represents the directed edges on the shortest path from i to j.

Closeness centrality is a suitable measure of firms' exposure to shocks in the firm-level supply-chain network, which is directed, weighted, and disconnected. Moreover, this measure focuses on the shortest paths between firms, gauging the first-order impact of inter-firm contagion (Borgatti, 2005).

In the Online Appendix, I further discuss concerns related to the measurement of Closeness centrality, and present empirical tests to address those concerns.

C2. Addressing Endogeneity Concerns with Closeness

The calculation of Closeness could induce endogeneity concerns as that measure relies on firm-level customer–supplier relations. To alleviate potential concerns, I explore variation in the network structure that is plausibly outside the control of the firm of interest. In particular, I look at M&A activity of secondary network neighbors, that is, firms that are indirectly connected to the firm of interest through an intermediate trade partner. Focusing on the secondary neighbor creates an additional degree of separation, thus preventing the

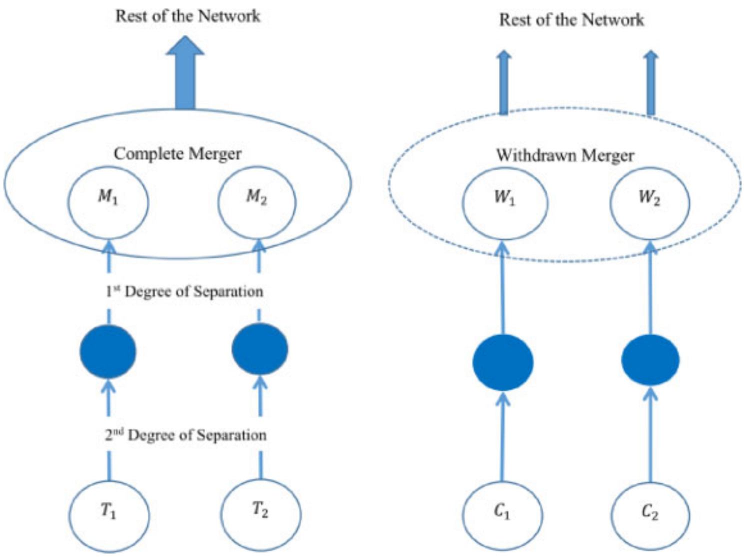

Figure C2. Comparison between subnetworks. This figure demonstrates the network structure changes around mergers for firms that are secondary neighbors to merging entities.

shock from systematically affecting the bargaining dynamics between the firm of interest and its suppliers or customers. To maintain comparability of unobservable characteristics, such as firms' life cycles and growth opportunities, I use the secondary neighbors of withdrawn mergers as a benchmark.

Figure C2 illustrates this testing approach. I examine the merger of two firms, M_1 and M_2, and consider firms T_1 and T_2, which are secondarily connected to M_1 and M_2, as my treated sample. I then choose a failed merger by W_1 and W_2 and consider secondary connections to those entities, C_1 and C_2, as my control sample. All else equal, I conjecture that treated firms should become more central following the merger, as they are connected to more firms through the merger.[25] Accordingly, I expect the treated firms to increase cash holdings as they become more connected.

I collect complete and withdrawn merger deals from the SDC database. Reasons for withdrawal include failure of gaining shareholders' approval, cessation of hostile bids, superior bids, and anti-trust concerns. I then apply the following filters: (i) Both the target and acquirer are public firms, and at least one has a secondary neighbor in my sample. (ii) I exclude horizontal and vertical mergers by requiring that the acquirer and the target do not belong to the same industry or operate in industries with relatedness higher than 0.01 (see Fan and Goyal, 2006). These filters alleviate the concern that mergers induce significant changes in industry concentration. (iii) I exclude the withdrawn merger deals in which the

25 In Figure C2, *T1* and *T2* become more connected following the merger as T_1 is connected to T_2 through the merged entities. However, C_1 is not connected to C_2 as the proposed target and acquirer in the withdrawn merger remain separate from each other. The additional connections created by the merger increase the weights between treated firms to the subnetwork surrounding the other merging entity from zero to a positive number, thus increasing the connectivity of treated firms.

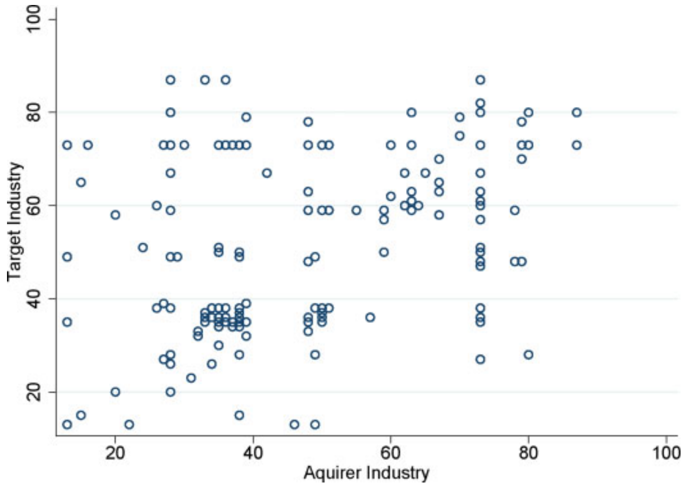

Figure C3. Industry distribution of the merger sample. This figure demonstrates the network structure changes around mergers for firms that are secondary neighbors to merging entities. The horizontal axis shows acquirers' industries and the vertical axis shows target industries.

target or acquirer later merged with another company during the same year. (iv) I require the target or acquirer in a withdrawn deal to operate in the same industry as the target or acquirer of a complete merger during the same year. This criterion maintains the similarity between the firms involved in withdrawn and complete mergers.

To be included in the sample, a firm needs to have available financial information and Closeness for at least two years prior to the merger (pre-event window) and two years following the merger (post-event window). Importantly, I exclude sample firms on which the merger could have a direct product market impact, including industry peers, customers, or suppliers of the merging entities. I also exclude control firms whose industries experience a merger wave.[26] These restrictions effectively limit the linkage between the mergers and the firms of interest to supply-chain network connections only. With these restrictions, I construct a matched sample consisting of eighty-one withdrawn mergers with 1,407 control firms, and 233 completed mergers with 3,072 treated firms. Figure C3 depicts the distribution of industry pairs inside my merger sample. Among all the completed mergers, about 17% are within-industry mergers, while the rest have acquirers and targets operating in different industries (two-digit SIC level).

To examine how firms' policies are affected by mergers in the network, I adopt an instrumental variable (IV) approach combined with difference-in-differences estimators, thus using two-stage regressions to estimate changes in centrality and cash. Formally, I estimate the following two-stage regressions:

$$d(\text{Closeness})_i = \beta_0 + \beta_1 \text{NeighborMerger}_i + \beta_2 \text{Controls}_i + u_i \qquad (6)$$

26 Specifically, I exclude firms in my control group that belong to industries that are ranked in the top three in terms of the number of merger deals in a given year.

$$d(\text{Cash})_i = \gamma_0 + \gamma_1 d(\widehat{\text{Closeness}})_i + \gamma_2 \text{Controls}_i + v_i, \tag{7}$$

where NeighborMerger indicates treatment. It equals one if a firm is a secondary neighbor of a completed merger, and zero if the firm is a secondary neighbor of a withdrawn merger. $d(\widehat{\text{Closeness}})_i$ is the predicted change in Closeness from the first stage; d(Cash) represents the change in a firm's cash holdings from the pre-event window to the post-event window; and Controls include pre-event size, tangibility, cash flow volatility, the changes in profitability, and market-to-book over the event period, and industry fixed effects. I also include in the set of control variables the pre-event cash levels and Closeness to allow for differential speed of adjustment following the mergers. Finally, I control for macroeconomic conditions, including aggregate stock market returns, merger waves (measured as the total number of merger deals in a year), GDP growth, and credit spreads. I expect $\beta_1 > 0$, and γ_1 should have the same signs as in the baseline regressions.

Panel A of Table CI presents results from the two-stage estimations.[27] Column 1 reports results from first-stage regressions. Following a merger conducted by secondary neighbors, firms become more centrally connected. Treated firms experience a 20-basis-point increase in Closeness, which is around a 15% increase relative to the sample average. Column 2 reports the second-stage results. Consistent with the OLS results, the instrumented changes in closeness centrality attract a positive coefficient for cash holdings and negative coefficients for leverage and total payout. The estimates suggest that, following a merger, the increased connectivity of treated firms leads to around a one-percentage-point larger increase in cash holdings (0.2×0.05) than in control firms.

To refine the merger analyses, I restrict the sample of failed mergers to ones withdrawn for reasons plausibly unrelated to supply-chain conditions of the acquirers and targets (see, e.g., Savor and Lu, 2009; Malmendier, Opp, and Saidi, 2016).[28] Specifically, I consider only mergers withdrawn due to regulatory objections and competing offers, but not those withdrawn owing to fundamental news related to the acquirer or target. To further maintain the comparability of treated and control firms, I keep only manufacturers in the sample (two-digit SIC codes of 20–39).[29] Using this matched sample of firms, I employ a difference-in-differences approach to examine the differential changes in firms' connectivity and cash policies between treated and control firms.

Panel B of Table CI shows the results. Being connected to merging entities increases a firm's closeness centrality in the network by about 0.5 percentage point.

Granted, mergers do not occur randomly, and the validity of this test rests on the assumption that the merger deals used in my sample do not systematically occur because of the cash holdings of secondary network neighbors. One potential concern related to this assumption is that firms may choose to merge because they consider their secondary network neighbors to be too risky. Following the mergers, the merged entity may pressure those network neighbors to adopt more conservative policies so as to reduce their riskiness. I test the plausibility of this concern by examining the changes in riskiness of my sample firms after

27 Given the small magnitude of d(Closeness), I multiply this variable by 100 to display the nonzero digits from the estimation.

28 I thank Farzad Saidi for kindly sharing this data.

29 Most other industries include only treated or control firms for my test. Including these other industries generates qualitatively similar results.

Table CI. IV estimation: mergers of secondary network neighbors

This table shows the effects of secondary network neighbor mergers on firms' centrality and cash policies. Panel A shows two-stage regression results from the IV analysis using the average merger activity in the industries of a firm's secondary network neighbors as an instrument. The second-stage dependent variables is changes in cash holdings (d(Cash)). $d(\widehat{Closeness})$ is the projected changes in closeness centrality from the first-stage regressions. The dependent variable in the first stage is the changes in closeness (d(Closeness)). Macro variables include GDP growth, credit spreads, stock market returns. Panel B shows the difference-in-difference results using a matched sample of completed and withdrawn mergers. In both panels, changes in centrality and cash holdings are calculated as the differences between the two-year window following the mergers and the two-year window prior to the mergers. Robust *z*-statistics are reported in parentheses. Standard errors are clustered by firm. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Panel A: IV analyses

	(1)	(2)
Regression	First stage	Second stage
Dependent variable:	d(Closeness)	d(Cash)
NeighborMerger	0.192***	
	(5.99)	
$d(\widehat{Closeness})$		0.050***
		(2.67)
Under-identification test		
p-value		<0.01
Weak identification test		
Kleibergen–Paap LM *p*-value		<0.01
Controls	Yes	Yes
Pre-event closeness control	Yes	Yes
Pre-event cash control	Yes	Yes
Macroeconomic variables	Yes	Yes
Industry FE	Yes	Yes
Observations	4,041	4,041

Panel B: DID analyses

	(1)	(2)
Dependent variable:	d(Closeness)	d(Cash)
NeighborMerger	0.005***	0.024*
	(2.71)	(1.95)
Pre-event closeness control	Yes	Yes
Pre-event cash control	Yes	Yes
Macroeconomic variables	Yes	Yes
Industry FE	Yes	Yes
Observations	536	613
R-squared	0.64	0.19

mergers. Using equity volatility as a measure of firm risk, I regress changes in firms' equity volatility directly on the indicator variable NeighborMerger, together with the same set of controls used in Equation (6). Table CII shows the results. There is no evidence that

Table CII. Changes in risk following mergers

This table examines whether firms become riskier once their secondary network neighbor experienced a merger. The dependent variable is changes in equity volatility measured from the pre-event window to the post-event window. Equity volatility is defined as the annual volatility of daily equity returns.

Dependent variable: d(Equity Vol)	(1)	(2)	(3)
Neighbor merger	0.022	0.064	0.018
	(0.36)	(1.07)	(0.32)
Firm control	No	Yes	Yes
Macroeconomic variables	No	No	Yes
Industry FE	Yes	Yes	Yes
Observations	2,782	2,587	2,587
R-squared	0.041	0.104	0.197

mergers decrease the riskiness of secondary connected firms. If anything, firms' risk level increases (insignificantly) after mergers.

Overall, results from merger-based shocks provide additional credence for the base findings that firms hold more cash as they become more central in the network. Using downstream mergers as an instrument builds on the premise that acquisition decisions are not driven primarily by conservative policies of the secondary neighbors of the target or the acquirer.

References

Bebchuk, L., Cohen, A., and Ferrell A. (2009): What matters corporate governance?. *Review of Financial Studies* 22, 783–827.

Acemoglu, D., Carvalho, V., Ozdaglar, A., and Tahbas-Salehi, A. (2012): The network origins of aggregate fluctuations, *Econometrica* 80, 1977–2016.

Ahern, K. R. (2015): Network centrality and the cross section of stock returns. Working paper.

Ahern, K. R. and Harford, J. (2014): The importance of industry links in merger waves, *Journal of Finance* 69, 527–576.

Banerjee, S., Dasgupta, S., and Kim, Y. (2008): Buyer–supplier relationships and the stakeholder theory of capital structure, *Journal of Finance* 63, 2507–2552.

Barrot, J. N. and Sauvagnat, J. (2016): Input specificity and the propagation of idiosyncratic shocks in production networks, *Quarterly Journal of Economics* 131, 1543–1592.

Bates, T. W., Kahle, K. M., and Stulz, R. M. (2009): Why do US firms hold so much more cash than they used to?, *Journal of Finance* 64, 1985–2021.

Bebchuk, L. A. and Cohen, A. (2005): The costs of entrenched boards, *Journal of Financial Economics* 78, 409–433.

Bigio, S. and La'O, J. (2016): Financial frictions in production networks. Working paper.

Bonacich, P. (1972): Factoring and weighting approaches to status scores and clique identification, *Journal of Mathematical Sociology* 2, 113–120.

Borgatti, S. P. (2005): Centrality and network flow, *Social Networks* 27, 55–71.

Buraschi, A. and Porchia, P. (2012): Dynamics networks and asset pricing. Working paper.

Cohen, L. and Frazzini, A. (2008): Economic links and predictable returns, *Journal of Finance* 63, 1977–2011.

Core, J. E., Guay, W. R., and Rusticus, T. O. (2006): Does weak governance cause weak stock returns? An examination of firm operating performance and investors' expectations, *Journal of Finance* 61, 655–687.

Dimitrov, V. and Tice, S. (2006): Corporate diversification and credit constraints: real effects across the business cycle, *Review of Financial Studies* 19, 1465–1498.

Duchin, R. (2010): Cash holdings and corporate diversification, *Journal of Finance* 65, 955–992.

Durlauf, S. N. (1993): Nonergodic economic growth, *Review of Economic Studies* 60, 349–366.

Fama, E. F. and French, K. R. (1993): Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fan, J. and Goyal, V. (2006): On the patterns and wealth effects of vertical mergers, *Journal of Business* 79, 877–902.

Fee, E., Hadlock, C., and Thomas, S. (2006): Corporate equity ownership and the governance of product market relationship, *Journal of Finance* 61, 1217–1251.

Fee, E. and Thomas, S. (2004): Sources of gains in horizontal mergers: evidence from customer, supplier, and rival firms, *Journal of Financial Economics* 74, 423–460.

Foley, C. F., Hartzell, J. C., Titman, S., and Twite, G. (2007): Why do firms hold so much cash? A tax-based explanation, *Journal of Financial Economics* 86, 579–607.

Freeman, L. (1978): Centrality in social networks conceptual clarification, *Social Networks* 1, 215–239.

Fresard, L. (2010): Financial strength and product market behavior: the real effects of corporate cash holdings, *Journal of Finance* 65, 1097–1122.

Garcia-Appendini, E. and Montoriol-Garriga, J. (2013): Firms as liquidity providers: evidence from the 2007–2008 financial crisis, *Journal of Financial Economics* 109, 272–291.

Gompers, P., Ishii, J., and Metrick, A. (2003): Corporate governance and equity prices, *Quarterly Journal of Economics* 118, 107–156.

Graham, J. R. (1996): Proxies for the corporate marginal tax rate, *Journal of Financial Economics* 42, 187–221.

Graham, J. R. (2000): How big are the tax benefits of debt?, *Journal of Finance* 55, 1901–1941.

Hadlock, C. J. and Pierce, J. R. (2010): New evidence on measuring financial constraints: moving beyond the KZ index, *Review of Financial Studies* 23, 1909–1940.

Hann, R. N., Ogneva, M., and Ozbas, O. (2013): Corporate diversification and the cost of capital, *Journal of Finance* 68, 1961–1999.

Harford, J., Mansi, S. A., and Maxwell, W. F. (2008): Corporate governance and firm cash holdings in the US, *Journal of Financial Economics* 87, 535–555.

Hertzel, M., Li, Z., Officer, M., and Rodgers, K. (2008): Inter-firm linkages and the wealth effects of financial distress along the supply chain, *Journal of Financial Economics* 87, 374–387.

Jackson, M. O. (2010): *Social and Economic Networks*, Princeton, New Jersey: Princeton University Press.

Jovanovic, B. (1987): Micro shocks and aggregate risk, *Quarterly Journal of Economics* 102, 395–409.

Kale, J. and Shahrur, H. (2007): Corporate capital structure and the characteristics of suppliers and customers, *Journal of Financial Economics* 83, 321–365.

Lewellen, W. G. (1971): A pure financial rationale for the conglomerate merger, *Journal of Finance* 26, 521–537.

Liberti, J. M. and Mian, A. R. (2010): Collateral spread and financial development, *Journal of Finance* 65, 147–177.

Long, J. B. and Plosser, C. I. (1987): Sectoral vs. aggregate shocks in the business cycle, *American Economic Review* 77, 333–336.

Malmendier, U., Opp, M. M., and Saidi, F. (2016): Target revaluation after failed takeover attempts: cash versus stock, *Journal of Financial Economics* 119, 92–106.

Matsusaka, J. and Nanda, V. (2002): Internal capital markets and corporate refocusing, *Journal of Financial Intermediation* 11, 176–211.

Mulally, A. R. (2008): Examining the state of the domestic automobile industry, hearing, United States. Congress. Senate. Committee on Banking, Housing, and Urban Affairs.

Murfin, J. and Njoroge, K. (2014): The implicit costs of trade credit borrowing by large firms, *Review of Financial Studies* 28, 112–145.

Murfin, J. and Pratt, R. (2019): Comparables pricing, *Review of Financial Studies* 32, 688–737.

Nunn, N. (2007): Relationship–specificity, incomplete contracts, and the pattern of trade, *Quarterly Journal of Economics* 122, 569–600.

Opsahl, T., Agneessens, F., and Skvoretz, J. (2010): Node centrality in weighted networks: generalizing degree and shortest paths, *Social Networks* 32, 245–251.

Petersen, M. A. and Rajan, R. G. (1997): Trade credit: theories and evidence, *Review of Financial Studies* 10, 661–691.

Pinkowitz, L., Stulz, R., and Williamson, R. (2013): Is there a US high cash holdings puzzle after the financial crisis? Working paper.

Rauch, J. E. (1999): Networks versus markets in international trade, *Journal of International Economics* 48, 7–35.

Savor, P. and Lu, Q. (2009): Do stock mergers create value for acquirers?, *Journal of Finance* 64, 1061–1097.

Stein, J. (1997): Internal capital markets and the competition for corporate resources, *Journal of Finance* 52, 111–133.

Strebulaev, I. A. and Yang, B. (2013): The mystery of zero-leverage firms, *Journal of Financial Economics* 109, 1–23.

Titman, S. (1984): The effect of capital structure on a firm's liquidation decision, *Journal of Financial Economics* 13, 137–151.

Titman, S. and Wessels, R. (1988): The determinants of capital structure choice, *Journal of Finance* 43, 1–19.