The Epidemiology of Financial Constraints and Corporate Investment

Abstract

We show that production networks amplify the effects of a firm's financial constraints, generating substantive contagion effects on its partners' investment. We quantify these effects via a network multiplier whereby a one-dollar drop in the constrained firm's investment reduces total supply-chain investment by an additional dollar. To facilitate identification, we employ multiple financial-constraint measures, a Network Regression Discontinuity Design that accounts for covenant-violation spillovers, and an instrumented network of long-term partners. Consistent with production-driven spillovers, firms producing specific inputs generate larger investment spillovers and receive more trade credit. Overall, our results suggest that production networks aggregate firm-level financial frictions.

Keywords: Financial constraints, Corporate investment, Production networks, Supply chain, Spillovers, Contagion, Regression discontinuity, Spatial econometrics

JEL Codes: C21, D22, D85, E23, G31, L14, L21, L23, L25

Production is a highly interdependent process that requires coordination among several partners. Thus, one firm's investment opportunities are tied to those of its supply-chain partners, which raises an important yet unexplored question: when financing frictions force a firm to curtail its investment, what is the effect on other firms with interconnected investment opportunities? This study examines how financial constraints trigger a series of forgone investments that reverberate across the supply chain. We quantify a network multiplier, suggesting that contagion effects reduce total supply chain investment by roughly the same magnitude as the initial impact on the constrained firm.

Although investment spillovers are likely a fundamental feature of supply chains, estimating these spillovers is challenging for two reasons. First, propagation effects can accumulate over many potentially indirect linkages to affect macroeconomic activity on a larger scale than the direct impact of the shock (Morris, 2000; Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi, 2012; Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2017); thus identification requires methods that integrate essential features of the network structure (Bramoullé, Djebbari, and Fortin, 2009; Jackson, 2010; Boucher and Fortin, 2016). Second, firms' ability to diversify their supply chains may reduce the extent of the spillovers and imposes additional identification challenges (Lucas, 1977; Long and Plosser, 1983; Dupor, 1999).

To address these challenges, we first employ a network-based empirical approach that adapts spatial econometric regressions to non-spatial network settings (henceforth, *network regressions*) following Grieser et al. (2022a,b). Network regressions are analogous to a simultaneous equations model (SEM), where each equation represents a single firm's investment outcome as a function of connected firms' investments. While we defer technical details to the main text, identification comes from exploiting the network structure of firm-specific supply chain connections to solve for the reduced form of investment outcomes, akin to SEM exclusion restrictions.

Our network regression estimates indicate strong constraint-driven investment spillovers based on several financial constraint proxies used in the literature (e.g., Whited and Wu, 2006; Hadlock and Pierce, 2010; Hoberg and Maksimovic, 2015). Tightening a firm's constraints by one standard deviation curtails own-firm investment by 0.8 percentage points (12% of the sample average), which includes feedback effects through the production network. Additionally, the average network multiplier estimate of two implies that when a constrained firm reduces investment by $1, propagation effects *cumulatively* restrict total supply chain investment by an additional $1.

Most of our analysis treats the supply chain network as exogenous since quantifying spillovers with endogenous network formation in a unified framework is beyond the scope of extant econometric methods. This restriction may raise concerns regarding endogenous network formation. If partnerships are fluid and form among firms with similar constraints and investment levels, the effects we document may be attributed to selection effects as opposed to network spillovers. However, formal tests on network formation suggest that, if anything, similar investment and constraint levels *negatively* predict partnership formation. Additionally, supply-chain relationships are sticky (Barrot and Sauvagnat, 2016; Boehm, Flaaen, and Pandalai-Nayar, 2019), and our tests emphasize short-run spillover effects. Importantly, we document similar effects in analyses using long-term partnerships as an instrument for current supply chain networks.

Another concern is that financial constraint proxies may exhibit measurement error (Farre-Mensa and Ljungqvist, 2016). Accordingly, we follow a large volume of recent literature and exploit discrete jumps in constraints surrounding covenant violations in a regression discontinuity design (RDD).[1] The RDD approximates a randomized control trial (RCT) by comparing the outcomes of firms just above/below covenant violation thresholds, where firms' unobserved characteristics are plausibly similar. Moreover, covenant-driven constraints are arguably less prone to measurement error, and they directly influence investments through the transfer of control rights (Chava and Roberts, 2008).

[1]See: Chava and Roberts (2008); Roberts and Sufi (2009); Nini, Smith, and Sufi (2012); Falato and Liang (2016); Ferreira, Ferreira, and Mariano (2018); Akins, De Angelis, and Gaulin (2020); Ersahin, Irani, and Le (2021); Chodorow-Reich and Falato (2022).

Despite its promising features, the RDD relies strongly on the assumption that one firm's treatment cannot influence their partners' outcomes (Cox, 1958). We relax this assumption by employing a novel network RDD to evaluate the potential for covenant violations to trigger contagion effects in investment behavior (Cornwall and Sauley, 2021). We find that violations restrict own-firm investment by 1.7 percentage points, and contagion effects reduce total supply chain investment by an additional 1.2 percentage points. Thus, indirect treatment effects constitute roughly 70% of the total impact of violations. These results are robust to alternative RDD specifications that alleviate selection concerns in covenant enforcement.

We also assess how missing network linkages affect our estimates, recognizing that, due to data limitations, we may only capture a fraction of actual supply-chain connections. Using simulated data based on the complete set of supply-chain connections for all firms, we estimate peer effects by progressively omitting linkages from our analysis. The estimates only show a significant decline after randomly removing at least 75% of the network links. Additionally, since our data probably omit smaller linkages, the results bolster our confidence that the estimated peer-effect coefficients remain stable even with a considerable number of missing supply chain links.

Our study quantifies investment spillovers and offers micro-level evidence that bridges the gap between corporate investment and aggregate investment. Macroeconomists emphasize the role of financial accelerators in explaining the cyclicality of aggregate investment (see Bernanke and Gertler, 1989). We offer a similar mechanism whereby supply chain linkages amplify the effects of financial frictions. Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) provide a theoretical framework for the network effects that we document. However, this framework is subject to the standard criticism that firms can change partners and undo such effects (Lucas, 1977). Moreover, firms can extend trade credit to constrained partners to alleviate investment disruptions. In fact, we find firms that generate greater spillovers receive more favorable trade credit terms and retain longer partnerships. Yet, the extent to which firms take steps to undo spillover effects and how successful their efforts are is ultimately an empirical question.

Our baseline results reveal that strategic adjustments to the supply chain do not completely eliminate investment contagion. Importantly, we show that firms with high product specificity generate greater investment spillovers. This result is consistent with the view that partners using highly specific inputs cannot easily integrate alternate sources into their production process and hence cannot avoid investment disruptions. Prior studies highlight the role of input substitutability in supply-chain networks and show that relationships are generally very sticky in the short run (Barrot and Sauvagnat, 2016; Boehm et al., 2019). Our instrumented results using long-term relationships leverage this stickiness to further improve identification. Lastly, we find similar spillovers in market valuations of supply-chain partners, further affirming that the results are driven by spillover effects that financial markets recognize. Taken together, these findings explain firms' inability to (fully) respond to partners' investment disruptions.

Our study relates to a large literature quantifying the effect of financial constraints on own-firm investment.[2] We extend this literature by highlighting that a firm-centric model only captures the tip of the iceberg regarding the total consequences of financing frictions. Our findings also add to mounting empirical evidence that investments are strongly interdependent among firms (Dougal, Parsons, and Titman, 2015; Bustamante and Frésard, 2021; Grieser, LeSage, and Zekhnini, 2022b). Ultimately, empirical models restricting investment spending to depend solely on a firm's own decisions do not adequately describe firm behavior.

Our paper adds to a growing literature on production network effects. Specifically, recent studies focus on internal firm networks and document employment and productivity spillovers within firms (Giroud and Mueller, 2019; Giroud, Lenzu, Maingi, and Mueller, 2023). More broadly, a sizeable literature documents production spillovers across firms following natural

[2]See: Fazzari and Petersen (1988); Kaplan and Zingales (1997); Whited and Wu (2006); Hadlock and Pierce (2010); Hoberg and Maksimovic (2015); Bodnaruk, Loughran, and McDonald (2015); Catherine, Chaney, Huang, Sraer, and Thesmar (2022).

disasters (Barrot and Sauvagnat, 2016; Wu, 2016; Carvalho, Nirei, Saito, and Tahbaz-Salehi, 2021), import financing taxes changes (Demir Pakel, Javorcik, Michalski, and Ors, 2020), large tariff changes (Martin and Otto, 2021), and bank lending shocks (Costello, 2020; Alfaro, García-Santana, and Moral-Benito, 2021; Lenzu, Rivers, and Tielens, 2022). We show financial constraint shocks trigger contagion effects in investment roughly as influential as the initial impact of the shock.

A related literature provides evidence that bankruptcies inflict financial distress on a firm's competitors as well as their supply chain and joint venture partners.[3] Poor financial health can also invite opportunistic behavior from rivals (Rauh, 2006; Cookson, 2017), generating feedback loops that exacerbate industry downturns (Carvalho, Nirei, Saito, and Tahbaz-Salehi, 2021; Chen, Dou, Guo, and Ji, 2020; Dou, Johnson, Shao, and Wu, 2021). These literatures yield several important insights on financial health and supply chain spillovers. Our study emphasizes financial health when firms are constrained but not insolvent. This distinction is important for interpreting our results since (i) constrained firms lack capital but still have profitable investment opportunities, and (ii) covenant violations are roughly eight (63) times more frequent than a credit rating downgrade (bankruptcy) in our sample. Our findings therefore emphasize the importance of financial constraints and investment coordination even when firms are far from bankruptcy.[4]

Network-based methods offer economic insights in addition to improving identification. By amplifying or attenuating micro-level shocks, networks function as mediators between individual and aggregate economic behavior. Thus, network structures largely determine how individual shocks influence aggregate outcomes (Morris, 2000; Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2016b, 2017; Elliott, Golub, and Jackson, 2014). In our sample, only 0.8% of firm-pairs are direct partners, and only 7.8% of partnerships exhibit a mutual partnership with a third firm. Yet, 99% of firms are connected through at least one path, with most

[3]See: Hertzel, Li, Officer, and Rodgers (2008); Boone and Ivanov (2012); Hertzel and Officer (2012); Kolay, Lemmon, and Tashjian (2016); Bernstein, Colonnelli, Giroud, and Iverson (2019).

[4]We provide anecdotal evidence on investment coordination among supply-chain partners in the Internet Appendix.

connections only requiring a few intermediary relationships. Thus, the supply chain network is densely connected, which can lead to large network multiplier effects (Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi, 2012; Jackson, 2016). Importantly, our estimates represent the cumulative impact of many direct and indirect supply chain interactions that may each constitute a small effect in isolation. Effectively, network regressions capture the nuance of higher-order connections and feedback loops that characterize peer effects (Jackson, 2016). Overall, the network approach we employ likely has many insightful applications in corporate finance, asset pricing, personal finance, and social network settings.

1. Data

1.1. Supply chain network

We obtain customer-supplier relationships for public firms that are required to report customers that comprise at least 10% of the firm's total sales from Compustat Segment data. We gather additional relationships from FactSet Revere LiveData (available from 2003 to 2019). FactSet analysts review primary source documents, such as annual reports, investor presentations, and company websites, to identify supply chain relationships. While Revere data more than double the number of Compustat documented customer-supplier relationships, they likely miss several partnerships. To further reduce sparsity, we employ the *vertical text-based network industry classification* (VTNIC) developed by Frésard, Hoberg, and Phillips (2020). The authors combine vocabulary from 10-Ks and the Bureau of Economic Analysis's (BEA) input/output tables to create *vertical similarity scores* that indicate the propensity for two firms to form a supply chain partnership.

We combine these three data sources into a single *directed* network. For any two firms i and j with a customer-supplier relationship according to Compustat or FactSet, s_{ij} represents the percentage of supplier i's total sales to customer j, and s_{ji} represents the percentage of customer j's cost of goods purchased from supplier i. We scale s_{ij} to obtain a maximum value of 1 and a minimum value of 0.5. We use the VTNIC *vertical similarity scores* for s_{ij} and

s_{ji} when both Compustat and FactSet data are missing. We scale s_{ij} to obtain a maximum value of 0.1 for VTNIC relationships. This ad hoc scaling gives more weight to Compustat and Factset supply chain relationships, derived directly from firm-level documents, than to potential relationships defined in the VTNIC. We explore several alternative weighting schemes and network combinations in the Internet Appendix. We use the scaled, pairwise scores to define the directed supply chain matrix $S \equiv [s_{ij}]$. Panel A of Table 1, provides summary statistics for the supply chain network.[5]

1.2. Common financial constraint proxies

Empirical measures of constraints are typically designed to capture evidence of a wedge between the cost of a firm's internal and external capital (e.g., Kaplan and Zingales, 1997). Since we introduce multiple methodologies, we begin our analysis with several commonly used measures available for a broad cross section of firms. Thus, despite the potential limitations of these measures that we address in later sections, they provide a useful starting point and facilitate comparisons to prior studies.

We first employ the Whited and Wu (WW) index from Whited and Wu (2006). The authors estimate the shadow cost of raising new equity from an Euler equation using empirical measures of leverage, dividends, sales growth, firm size, the ratio of liquid assets to total assets, and the ratio of cash-flow to total assets. Second, we use the size-age (SA) index from Hadlock and Pierce (2010), whose approach is independent of various theoretical assumptions. The authors find that firm size and age most robustly predict financial constraints classified from discussions of constraints in management's letter to shareholders and the MD&A section of the firm's 10-K. Third, we define the portion of a firm's long-term debt coming due in one year (*LTD due*) from Almeida, Campello, Laranjeira, and Weisbenner (2012) and Carvalho (2015). These studies argue that there are frictions and fixed costs of refinancing debt, and that *LTD due* is plausibly exogenous to a firm's contemporaneous

[5]We calculate network statistics for the adjacency matrix $S^A \equiv [s^A_{ij}]$, where $s^A_{ij} = 1$ if $directed\ score_{ij} > 0$, and $s^A_{ij} = 0$ otherwise. Definitions for network statistics come from Jackson (2010).

policies since maturity choices on long-term loans are decided many years prior. We also use *Delay Inv* from Hoberg and Maksimovic (2015), who classify firms that mention curtailing, abandoning, or postponing investment because of liquidity problems in their 10-K. Lastly, we define (*FC combo*) as the sum of the standardized values of the first four continuous constraint measures.

1.3. Credit restrictions and financial constraints

The constraint measures described in the prior section are widely available and extensively studied. However, Farre-Mensa and Ljungqvist (2016) argue that indirect proxies often inadvertently "reflect differences in the growth and financing policies of firms at different stages of their life cycles." Thus, we build on an extensive literature emphasizing the advantages of covenant-based constraint measures.

First, debt covenants contain specific performance thresholds firms must meet to comply with contract terms, and therefore, they are less reliant on indirect imputations from financial statements. Second, covenant violations directly reduce firms' borrowing capacity and autonomy over investment decisions by transferring control rights to creditors (Baird and Rasmussen, 2006; Chava and Roberts, 2008; Nini et al., 2009; Roberts and Sufi, 2009; Chodorow-Reich and Falato, 2022). Third, since creditors tend to set strict covenant thresholds ex ante, violating firms are often not in financial distress. Approximately one in three firms (or about 4,000 firms) report a covenant violation at least once in our sample, yet only 60 subsequently (and perhaps selectively) default. Thus, covenant violations constitute significant credit events more indicative of constraints than financial distress.

Information on financial covenants for primary loan issues comes from Loan Pricing Corporation's DealScan. We match observations to Compustat using the link file provided by Chava and Roberts (2008). We calculate the distance from a covenant violation as the difference between the covenant threshold defined in DealScan and the respective financial information obtained from Compustat.[6] We use the earliest loan origination date and the latest maturity date to identify the period for which covenants are binding. Dealscan only provides covenant information at the initiation of a loan facility. This information may become stale if firms retire, refinance, or renegotiate their debt or if banks waive the technical violation (e.g., Gopalakrishnan and Parkash, 1995; Denis and Wang, 2014). Thus, technical violations based on DealScan covenant thresholds and Compustat data (*tech.viol*) may not always indicate realized violations. Accordingly, we identify firms that report confirmed (i.e., realized) covenant violations (*C.viol*) in their 10-K or 10-Q filings. Data on confirmed violations come from Nini, Smith, and Sufi (2012).

1.4. Firm financial information

Firm financial information comes from the CRSP–Compustat merged database. Our main sample period (2003–2019) is restricted by the availability of FactSet data.[7] We calculate investment (*CapEx/lagged assets*), the natural log of a firm's sales (*Ln(Sales)*), market-to-book ratio (Q), return on assets (*ROA*), cash holdings (*cash*), *Z-score*, and *Leverage*. We exclude firms in the utilities (SIC 4900–4999) and finance (SIC 6000–6999) sectors, firms headquartered outside the contiguous United States, and firms with missing data. We winsorize all non-dummy variables at the 1% level in each tail. Appendix A contains additional information on the construction of these variables.

Table 1 presents summary statistics for our main variables. Approximately 24% of the firms in the sample have an explicit restriction on capital investment (*C.CapEx*). Since loan contracts often involve multiple covenants with distinct thresholds, we calculate overall contract strictness (*C.strict*) as the probability of violating at least one covenant according to Murfin (2012). The ex ante probability of violating at least one covenant for the median firm in a given year is 23%. Roughly 10% of firms report confirmed violations of at least

[6] Covenant definitions often vary substantially across loans. Following Demerjian and Owens (2016), we restrict our attention to relatively homogeneous covenants with the most consistent definitions. In general, we follow the empirical choices in the referenced literature as closely as possible.

[7] Our sample includes firms whose fiscal year-end occurred in the first quarter of 2020.

one covenant in a given year, consistent with the statistics reported in Nini, Smith, and Sufi (2012).

2. Estimating investment spillovers of financial constraints

We represent a firm's investment as a function of its own constraints and policy choices, as well as its partners' investments, respectively, in scalar and matrix notation:

$$\begin{aligned} y_{i,t} &= \rho \sum_{j=1}^{N} s_{i,j,t} y_{j,t} + fc_{i,t-1}\delta + X_{i,t-1}\beta + \epsilon_{i,t}, \\ Y &= \rho SY + FC\delta + X\beta + \epsilon, \end{aligned} \tag{1}$$

where $y_{i,t}$, $fc_{i,t-1}$, and $X_{i,t-1}$ are, respectively, firm i's investment, financial constraints, and characteristics. The matrix $S \equiv [s_{i,j}]$ denotes the supply chain network, where element $s_{i,j}$ quantifies the relationship between firms i and j as constructed in Section 1.1. We row-normalize S (i.e., $\sum_{j \neq i} s_{ij} = 1$) and preclude firms from being their own partner ($s_{ii} \equiv 0$). The parameter ρ quantifies the strength of investment complementarity. Equation (1) reduces to the conventional firm-centric model when $\rho = 0$ (i.e., $y_{it} = fc_{i,t-1}\delta + X_{i,t-1}\beta + \epsilon_{it}$).

Equation (1) is analogous to an SEM, where each equation corresponds to a single firm's investment outcome as a function of partners' investments. Supply chain partners simultaneously influence each other's decisions (Y and SY are jointly determined). Thus, directly estimating Equation (1) induces a simultaneity bias. We exploit the network structure S, to solve for the reduced-form equation of the outcome variable Y:

$$Y = (I_N - \rho S)^{-1}(FC\delta + X\beta + \epsilon). \tag{2}$$

Identification of the structural parameters (ρ, β, δ) relies on firm-level variation in covariates and supply chain connections, akin to the exclusion restrictions in an SEM framework (Lee and Liu, 2010). A more challenging identification issue, often referred to as the Manski (1993) reflection problem, occurs when firms are equally connected within groups (see Berg, Reisinger, and Streitz, 2021, for an example of this issue in the context of industry peer groups). Linear estimators (e.g., OLS, 2SLS) are asymptotically inconsistent when applied to Equation (2), which is nonlinear in the structural parameters. Accordingly, we use numerical maximum likelihood estimation (MLE). Standard errors are calculated directly from the posterior distribution of parameter estimates (see the Internet Appendix for more details).

The partial derivative of own-firm investment on own-firm constraints takes the form

$$E[\partial y_i / \partial fc_i] = (I_N - \rho S)^{-1}_{i,i}\, \delta, \tag{3}$$

which explicitly quantifies feedback effects through the supply chain based on a firm's specific location in the network. For example, changing fc_i initially perturbs a firm's own investment y_i, which then influences partners' investments y_j through complementarity (i.e., ρ). Partners influence their partners' investment, many of whom may not be direct partners with firm i. This process perpetuates a chain reaction that can eventually return to influence y_i via feedback loops. The *own-firm* effect in Equation (3) summarizes the total equilibrium impact via the converging geometric sequence described in Equation (5).

The cross-partial effect of firm j's constraints on partners' investments takes the form

$$\sum_{j \neq i} E[\partial y_i / \partial fc_j] = \sum_{j \neq i} (I_N - \rho S)^{-1}_{i,j}\, \delta. \tag{4}$$

The cross-partial derivatives $\partial y_i / \partial fc_j$ in Equation (4) are potentially non-zero, even though y_i does not depend directly on fc_j for $i \neq j$ in Equation (1). Instead, fc_j affects y_i only through investment complementarity (i.e., ρ). Thus, the *indirect effects* in Equation (4) reference *cumulative* effects of ∂fc_j on total supply chain investment spending, which potentially accumulates through many firms in the network.

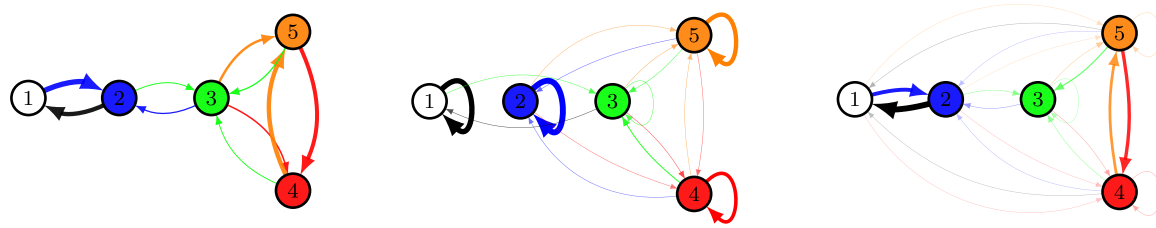
The infinite series expansion of $(I_N - \rho S)^{-1}$ in Equations (3) and (4) illustrates how a firm's investment decisions depend on those of connected firms:

$$Y = (I_N + \rho S + \rho^2 S^2 + \rho^3 S^3 + \ldots)(FC\delta + X\beta + \epsilon), \tag{5}$$

where S^K represents k^{th}-order connections. That is, a firm's constraints affect its own investment (I_N), as well as the investment of partners (ρS), partners of partners ($\rho^2 S^2$), and so on. Figure I presents the graph and matrix representations for the first three orders S^k for a simple five-firm network. The arrow (edge) width corresponds to the strength of relationships presented in the respective matrix.

Figure I: Orders S^k of a simple supply-chain network

(I.a) 1^{st}- order connections **(I.b)** 2^{nd}- order connections **(I.c)** 3^{rd}- order connections



$$\mathbf{S} = \begin{array}{c|ccccc} & 1 & 2 & 3 & 4 & 5 \\ \hline 1 & 0.00 & 1.00 & 0.00 & 0.00 & 0.00 \\ 2 & 0.82 & 0.00 & 0.18 & 0.00 & 0.00 \\ 3 & 0.00 & 0.24 & 0.00 & 0.29 & 0.47 \\ 4 & 0.00 & 0.00 & 0.17 & 0.00 & 0.83 \\ 5 & 0.00 & 0.00 & 0.25 & 0.75 & 0.00 \end{array}$$

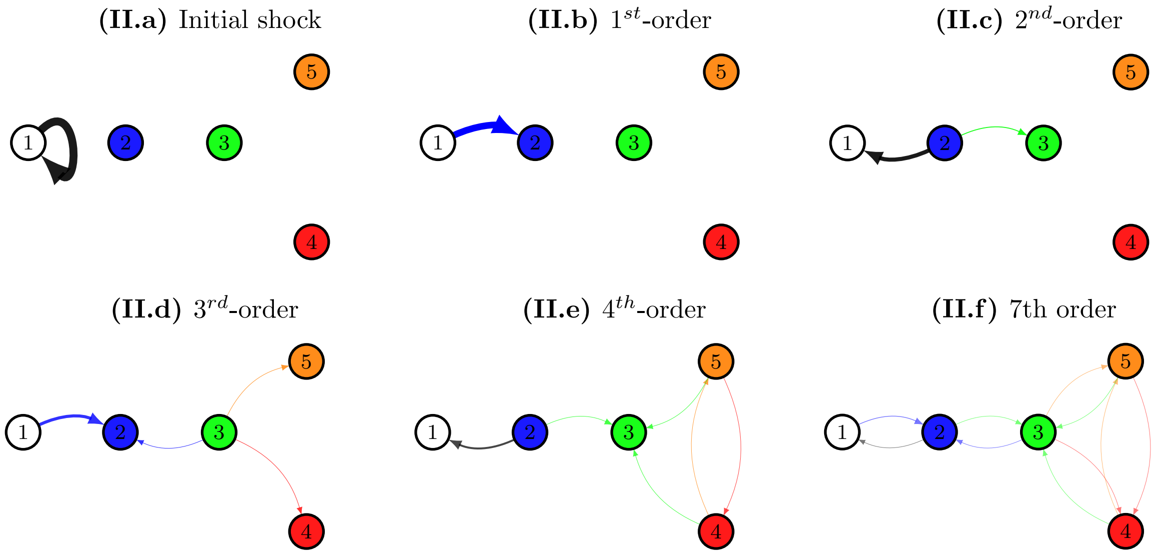
$$S^2 = \begin{array}{c|ccccc} & 1 & 2 & 3 & 4 & 5 \\ \hline 1 & 0.82 & 0.00 & 0.18 & 0.00 & 0.00 \\ 2 & 0.00 & 0.86 & 0.00 & 0.05 & 0.09 \\ 3 & 0.20 & 0.00 & 0.21 & 0.35 & 0.24 \\ 4 & 0.00 & 0.04 & 0.21 & 0.67 & 0.08 \\ 5 & 0.00 & 0.06 & 0.13 & 0.07 & 0.74 \end{array}$$

$$S^3 = \begin{array}{c|ccccc} & 1 & 2 & 3 & 4 & 5 \\ \hline 1 & 0.00 & 0.86 & 0.00 & 0.05 & 0.09 \\ 2 & 0.70 & 0.00 & 0.19 & 0.06 & 0.04 \\ 3 & 0.00 & 0.25 & 0.12 & 0.24 & 0.39 \\ 4 & 0.03 & 0.05 & 0.14 & 0.12 & 0.65 \\ 5 & 0.05 & 0.03 & 0.21 & 0.59 & 0.12 \end{array}$$

Figure II illustrates the propagation of a shock to firm 1 through the network. All arrows pointing toward firm 1 make up the own-firm effect, and all other arrows collectively constitute the indirect effect. Despite only directly interacting with firm 2, firm 1 influences all firms in the network, and they all influence firm 1 through feedback loops. Influence decays with the orders of separation since $|\rho| < 1$. The width of the arrows indicates the strength of transmission, according to ρ and the relationships presented in Figure (I.a). The cumulative influence through the network is summarized by the network multiplier $(1/(1-\rho))$. Intuitively, stronger investment complementarity (i.e., larger ρ) increases the network multiplier.

The contemporaneous relation in Equations (1)–(5) can be interpreted as firms interacting through a series of actions, reactions, reactions to reactions, and so on, all taking place within the frequency with which the data are observed (e.g., annually). Alternatively, equilibria may effectively occur instantaneously if firms form expectations based on higher-order beliefs

Figure II: Illustration of shock-propagation



about anticipated investment opportunities and supply chain responses. In either case, network regressions estimate the total propagation effect after an equilibrium is reached. We provide an extensive list of anecdotal evidence suggesting that partners' investment is interdependent in a contemporaneous manner consistent with these interpretations in the Internet Appendix.

3. Empirical Results

3.1. Network regressions

We estimate Equation (2), with an emphasis on the indirect effects defined in Equation (4). Table 2 reports estimates for eight models of corporate investment based on the eight measures of financial constraints (FC) defined in Section 1. We standardize all non-dummy variables in network regressions to facilitate the comparison of magnitudes across models.

Panel A reports estimates for (ρ), which indicates the strength of (short-run) investment complementarity as illustrated by Equation (5). The estimate for ρ is, on average, .485. This effect is economically large but consistent with extant literature that documents significant peer effects in production. For comparison, Boehm et al. (2019) analyze production spillovers as opposed to investment and report a one-for-one relationship among peer firms. With the exception of ρ, we report the partial derivatives rather than the structural coefficient estimates from Equation (2).

The magnitude of propagation effects is largely determined by the topology of a network Lamberson (2016). Panel A of Table 1 indicates that firms are direct partners, on average, with approximately 0.78% of all other firms (31 partners).[8] Additionally, the *shortest path length* indicates that firms are connected by only 3.28 degrees of separation, on average, and over 99% of firms are connected through at least one path. Thus, the supply chain network is densely connected, demonstrating potential for considerable network multiplier effects (Acemoglu et al., 2012, 2016b; Boucher and Fortin, 2016). Consistent with this notion, Table 2 estimates yield an average network multiplier $1/(1 - \bar{\rho}) = 1.94$, which is consistent with multipliers documented in recent studies (Elliott et al., 2014; Acemoglu et al., 2016a, 2017; Grieser et al., 2022b). This multiplier suggests that when a constrained firm reduces investment by \$1.00, contagion effects, including feedback effects to the focal firm, *cumulatively* curtail total supply chain investment by an additional \$0.94. Thus, total contagion effects are roughly equally important to the initial own-firm impact of constraints.

Panel B reports the own-firm effect from Equation (3), averaged across all firms and time periods.[9] The average statistically significant estimate suggests that tightening constraints by one standard deviation curtails own-firm investment by 0.08 standard deviations (or 0.83 percentage points). These magnitudes are consistent with those of mounting empirical studies of financial constraints on own-firm investment outcomes (e.g., Almeida and Campello, 2007; Hoberg and Maksimovic, 2015).

Panel C reports the indirect effects (cross-partial derivative) from Equation (4), averaged across all firms and periods. The indirect effects measure the *cumulative* external impact

[8] Figures (11.a) and (11.b) plot, respectively, the degree distribution for our main supply-chain network, and separately for FactSet-, Compustat-, and VTNIC-based relationships.

[9] The covenant-based proxies, ($C.viol$) in Column (6), a capital expenditure restrictions indicator ($C.CapEx$) in Column (7), and loan contract strictness ($C.strict$) in Column (8), all employ quarterly data. In the Internet Appendix, we find quantitatively similar estimates for specifications using annual data, which are analogous to Columns (6)–(8) in all other aspects.

of tightening a firm's financial constraints on partners, as well as the effect on partners of partners, and so on, as in Equation (4). Notably, capital expenditure restrictions, which directly indicate interventions in investment spending, yield economically and statistically significant results in Column (7). The indirect effects of financial constraints are highly significant across all models except for Column (4). The estimates indicate that, on average, tightening a firm's constraints by one standard deviation curtails total investment among all other firms in the supply chain network by 0.7 percentage points.

The consistency in evidence across eight distinct measures of constraints provides reassurance that our conclusions are not overly sensitive to the choice of financial constraint proxies. In the Internet Appendix, we report analyses for a longer sample period (1989–2019), for alternative network constructions, alternative measures of investment, and variations in control variables. In all cases, we find qualitatively similar results. Overall, robust evidence suggests ignoring contagion effects substantially understates the aggregate impact of financing frictions on investment.

4. Identification and endogeneity

Network transitivity, in our context, describes the degree to which firms share common supply chain relationships. Network regressions exploit heterogenous, firm-specific supply chain connections (i.e., Network intransitivity) to identify the key parameters (Grieser et al., 2022a). Greater intransitivity leads to more independent equations (i.e., units of observation) in the reduced form Equation (2), thus improving identification and statistical power.

The clustering coefficient reported in Panel A of 1 measures network transitivity via the fraction of partner firm-pairs i, j (i.e., $s_{ij} > 0$) that also share a common supply chain partner (i.e., $\exists\, k$ s.t. $s_{ik} > 0$ and $s_{jk} > 0$). The average clustering coefficient of 0.078 indicates that supply chain networks are highly intransitive: only 7.8% of partner-pairs share a common third partner. For reference, a perfectly transitive network exhibits a clustering coefficient of 1. Note that relationship intensities (rather than just the existence of connections) introduce even more heterogeneity. Thus, considerable supply chain intransitivity (i.e., partners do not frequently share common partners) yields substantial identifying variation. Notably, a high degree of intransitivity attenuates the influence of shocks common to many firms (e.g., industry year shocks), a topic we return to in Section 6.1.

While network regressions are well identified for a given model specification, potential endogeneity concerns may limit the interpretation of results. We address four main endogeneity challenges: (a) customer-supplier relationships form endogenously as a function of their financial health; (b) financial constraint measures are endogenous with respect to firm investment; (c) the empirical supply-chain network may be missing many links; (d) other confounding factors could muddle the interpretations of our results.

4.1. Endogeneity in network formation

Due to computational limitations, we take supply chain networks as exogenous in our baseline tests. Studies exploring tractable statistical models that simultaneously allow for endogenous network formation and propagation effects are only beginning to emerge (Jackson, 2016). Thus, empirical analyses of networks currently take one of two paths. First, research focuses on the economics of network formation directly (Inoue and Todo, 2019; Acemoglu and Azar, 2020; Boehm and Oberfield, 2020; Elliott et al., 2022). More commonly, researchers take a network as given to explore economic behavior, such as peer effects, learning, and diffusion (Boehm et al., 2019; Gofman et al., 2020; Crosignani et al., 2023). These studies argue that using endogenous networks to study economic behavior and acknowledging inherent limitations is more insightful than ignoring network effects.

In our setting, our interpretation of the results may be erroneous if firms with similar investment levels more frequently form partnerships the year before one of the partners' constraints become more binding. This problem, often referred to as homophily, is part of the Manski (1993) reflection problem, and it is clearly articulated by Leary and Roberts (2014) in the context of capital structure decisions. Homophily could introduce challenges in disentangling investment complementarity from selection effects. While ruling out the potential confounding effects of homophily entirely is not feasible, several features of our study mitigate such concerns.

First, we emphasize short-run investment spillovers one year after a firm's financial constraints tighten. A substantial body of evidence indicates substantial switching costs for supply-chain partnerships (e.g., Barrot and Sauvagnat, 2016; Boehm et al., 2019; Inoue and Todo, 2019). In our sample, partnerships last, on average, roughly 12 years according to Compustat and Factset data. Relationships defined according to the VTNIC last 3.3 years, on average.[10] Firms only turn over 4.5% of their partners, on average, each year.[11] Ultimately, supply chain relationships appear quite stable. Thus, it is unlikely that our results are driven by firms with low investment forming a partnership with a firm that also has a relatively low investment in the year before that partner becomes relatively constrained.

Second, we further address selection effects by restricting the network to long-term partnerships. Specifically, we build a network of partnerships that are at least five years old at time t (i.e., $s_{i,j,t} > 0$ and $s_{i,j,t-5} > 0$). Thus, selection decisions made five years prior are plausibly exogenous to contemporary financial constraints and investment outcomes. Table 3 presents estimates for this alternative network. While the economic effects are modestly attenuated, the results are highly consistent with the baseline results presented in Table 2. Thus, the contagion effects in investment behavior triggered by financial constraints continue to hold for stable partnerships.

Lastly, we estimate exponential random graph models (ERGMs), which are commonly used to study network formation (e.g., Robins et al., 2007; Ahern and Harford, 2014; Kim et al., 2016). ERGMs generalize logistic regressions by allowing for simultaneous dependence between all firms in a network when predicting whether two firms form a supply chain part-

[10]We report estimates for networks defined by each data source separately in the Internet Appendix.
[11]We tabulate the average annual turnover in the Internet Appendix.

nership.[12] Using ERGMs, we estimate the influence of distances between firms' investment and constraint levels on partnership formation. Evidence suggests firms are *less* likely to form partnerships when they exhibit similar investment and constraint levels (i.e., they exhibit heterophily with respect to the variables of interest). While not necessarily conclusive, this evidence assuages concerns that homophily drives our initial results.

4.2. Endogeneity in financial constraints: Introducing network RDD

The Table 2 estimates suggest financial constraints induce substantial contagion effects in forgone investment. In Section 4.1, we illustrate features of our study that assuage concerns regarding homophilly (i.e., selection effects). An additional concern is that financial constraint proxies exhibit measurement error that is correlated with investment opportunities (see Farre-Mensa and Ljungqvist, 2016). Importantly, this problem is likely less pervasive in our study, since financial constraints are arguably less endogenous with respect to partners' investments than with own-firm investments.

To further address these concerns, we employ an RDD strategy that exploits discrete jumps in financial constraints surrounding covenant violations (i.e., a treatment event). Treatment can be viewed as quasi-random within a bandwidth just above and below a covenant threshold, where firms plausibly exhibit similar characteristics other than treatment status. Thus, an RDD approximates an RCT, which mitigates the potential confounding effects driven by unobservable characteristics.

While RDDs offer attractive identifying assumptions, they also rely heavily on the stable unit treatment value assumption (SUTVA), which rules out the possibility that the treatment of one firm affects the potential outcome of other firms (Cox, 1958; Roberts and Whited, 2012). Violating SUTVA can lead to severely biased parameter estimates (Angrist and Pischke, 2008; Kolak and Anselin, 2020; Cornwall and Sauley, 2021). Thus, evaluating

[12] For example, Apple's decision to purchase processors from Intel is made simultaneously with its decision not to purchase processors from AMD. We discuss the estimation process and tabulate results in the Internet Appendix.

covenant-violation-induced investment spillovers in a standard RDD leads to a contradictory framework. To illustrate, covenant violations restrict investment for the violating firm, which can transmit to affect partners' investment opportunities. These spillovers present indirect treatments. If the control group is contaminated by indirect treatments, comparing the outcomes of the treatment and control groups yields an invalid estimate of the average treatment effect (ATE).

4.2.1. Network RDD: Local Linear Approach

We begin with the RDD first proposed by Chava and Roberts (2008) and later adopted by several studies, in which separate regressions are estimated for firms just above and below a violation threshold. To extend the model to allow for treatment spillovers, we use the Chava and Roberts (2008) framework in a network regression, which we label a local-linear network RDD.[13] To motivate local-linear network RDD, consider the following structural equation:

$$Y = \rho S Y + X\beta + \Phi D + \epsilon, \tag{6}$$

where D is a vector of treatment indicators for each firm. As in (Roberts and Whited, 2012), we use the running variable Z to create a deterministic treatment $D = [d_i]$:

$$d_i = \begin{cases} 1 & \text{if } z_i - z_0 < 0 \\ 0 & \text{otherwise,} \end{cases} \tag{7}$$

for all compliers. The covenant violation threshold for current ratio, net worth, and tangible net worth covenants is z_0 as in Chava and Roberts (2008). Treatment is quasi-random when focusing on observations within a narrow bandwidth around a threshold. The optimal bandwidth is calculated as per Imbens and Kalyanaraman (2012).

[13] For a list of papers using a discontinuity around covenant violations as an exogenous shock, see: Roberts and Sufi (2009); Hadlock and Pierce (2010); Falato and Liang (2016); Ferreira et al. (2018); Akins et al. (2020); Ersahin et al. (2021); Chodorow-Reich and Falato (2022). Our method builds on the Spatial RDD developed by Cornwall and Sauley (2021).

Investment complementarity implies that firms interact across treated, control, and non-complier groups. To obtain unbiased estimates, we follow (Cornwall and Sauley, 2021) and filter residuals to remove investment interdependence. Importantly, we include all firms in this step to fully account for investment complementarity. We estimate the following equation and filter residuals, respectively:

$$Y = (I_N - \rho S)^{-1}(X\beta + \hat{\Phi}D + \epsilon), \tag{8}$$

$$\tilde{\epsilon} = [I_N - \hat{\rho}S][Y - (I_N - \hat{\rho}S)^{-1}X\hat{\beta}]. \tag{9}$$

The residuals in Equation (9) are "filtered" in the sense that $(I_N - \hat{\rho}S)^{-1}X\hat{\beta}$ removes spillover effects from Y not due to the treatment. We then use $\tilde{\epsilon}$ in place of Y in the local-linear RDD by Hahn et al. (2001) to estimate the two equations for compliers:

$$\underline{\tilde{\epsilon}} = \underline{\theta} + \underline{\lambda}Z + \underline{u} \quad \text{if , } z_i - z_0 < 0 \tag{10}$$

$$\bar{\tilde{\epsilon}} = \bar{\theta} + \bar{\lambda}Z + \bar{u} \quad \text{if , } z_i - z_0 \geq 0. \tag{11}$$

The local average treatment effect (LATE) is defined as $\hat{\theta} = \underline{\theta} - \bar{\theta}$.

Table 4 presents estimates for the local-linear network RDD.[14] The ρ estimates are consistent with those in Table 2. The treatment effects, including feedback effects, indicate that a covenant violation decreases own-firm investment by 0.186 standard deviations. The indirect treatment effects indicate that a covenant violation leads to an additional 0.202 standard deviation decrease in total investment by all other firms in the network. These estimates suggest the ripple effects of violation-induced investment disruptions are roughly 109% of the own-firm treatment effect.

The local-linear network RDD employs technical violations based on DealScan and Compustat data, following Chava and Roberts (2008). Technical violations are inferred. Thus, some firms may be wrongly classified as treated if violations are waived or renegotiated.

[14] The estimation routine of a Network RDD employs an iterative process of estimating Equations (8)-(11), using the LATE in the last step as a proxy for the ATE for the following iteration. This process continues until sufficient draws have been sampled over the parameter distributions to approximate the joint parameter distribution. We provide more details regarding estimation in the Internet Appendix.

Accordingly, we employ information on confirmed covenant violations from Roberts and Sufi (2009) and Nini et al. (2012). One downside to confirmed violations is that bandwidths are not well-defined since the contractual level of the covenant being violated is often unobserved. Accordingly, we define a hybrid violation that utilizes the advantages of both data sources of violations. That is, $hybrid.viol = 1$ if a firm crosses a covenant threshold (technical violation) and it also has a confirmed violation, and $hybrid.viol = 0$ otherwise. Effectively, we assume that firms with technical violations that are not accompanied by a confirmed violation are effectively untreated.

Columns (2) and (8) in Table 4 present results for $hybrid.viol$. The own-firm and indirect treatment effects are roughly double the effects for $tech.viol$. This finding is reassuring since the hybrid violation classification will more likely capture consequential violations that are not waived or renegotiated.

4.2.2. Network RDD: Polynomial approach

To account for potential debt renegotiations and refinancing, Roberts and Sufi (2009) and Nini et al. (2012) study confirmed covenant violations ($C.viol$) on own-firm investment behavior and debt issuance, respectively. Because the contractual level of the exact covenant being violated is often unobserved for confirmed violations, the authors implement a polynomial RDD framework, which controls for a flexible, functional form of the running variables related to the performance criteria most commonly used in debt covenants. Both studies specify a 3^{rd}-degree polynomial.

We build on the framework of Roberts and Sufi (2009) and Nini et al. (2012) to allow for spillovers in the effects of covenant violations. The advantage of the polynomial approach is that all firms are used in the estimation (Angrist and Pischke, 2008). Thus, accounting for spillovers does not require an iterative procedure as for the local-linear network RDD. We estimate a modified version of Equation (1) that includes a third-degree polynomial of

Z (running variables) as follows:

$$Y = \rho SY + \Phi C.viol + Z\psi_1 + Z^2\psi_2 + Z^3\psi_3 + X\beta + \epsilon, \tag{12}$$

where Z is a matrix of financial ratios: *operating cash flow to lagged assets, total debt to assets, interest expense to lagged assets, net worth to assets, current assets to current liabilities,* and *market-to-book* value. $C.viol$ is a vector with elements equal to one for firm years with a confirmed covenant violation, keeping the other controls as in Table 2.

We estimate Equation (12) using network regressions, which we refer to as a network polynomial RDD. Like a polynomial RDD, the network polynomial RDD achieves identification by controlling for a flexible functional form of the running variables (Z). Thus, Φ isolates the discontinuity that occurs at the violation threshold.[15]

Column (3) of Table 4 presents the network polynomial RDD results. Estimates for the strength of supply chain partner investment complementarity (ρ) are consistent with our prior analysis. The own-firm treatment effect and indirect treatment effects are analogous to Equations (3) and (4), respectively. The estimates suggest that a confirmed covenant violation decreases own-firm investment by 1.5 percentage points, or 20% of the mean investment level (Chava and Roberts, 2008; Nini et al., 2009). The average indirect treatment effect of a covenant violation on supply chain partners' investment is also economically significant: the cumulative network effect of a covenant violation is roughly equivalent to a 1.7 percentage points reduction in supply chain partners' investment, or 24% of the average investment level. Again, the average *cumulative* indirect treatment effect represents the aggregate drop in investment across supply chain partners and is roughly the same magnitude as the own-firm treatment effect. This result highlights the importance of accounting for spillovers in

[15]The specification in Equation (12) follows Nini et al. (2012), with the exception that we do not first-difference the outcome variable, and we only include time fixed effects. Nini et al. (2012) highlight that the polynomial RDD "works identically to a sharp RDD if all firms have covenants written at the same level since the level of the covenant control variables will perfectly determine a violation." Although this criterion is unlikely to hold perfectly, the polynomial RDD reasonably approximates an RDD. Roberts and Sufi (2009) and Nini et al. (2012) argue that violations induce large and discrete changes in financial constraints that are arguably exogenous to the violating firms. Notably, these discrete changes are even more likely to be exogenous to a firm's supply chain partners. In this sense, the identifying assumptions of the network polynomial RDD are less restrictive than those of the polynomial RDD.

treatment effects. In addition to the control variables employed in Column (3), we control for *tech.viol* as well as a 3rd-degree polynomial of the distances from violation thresholds for *current ratio, net worth,* and *tangible net worth* covenants (i.e., 10 total variables). The treatment effects in Column (4) are quantitatively similar to those of Column (3).

To account for further potential differences in violating and non-violating firms, we estimate specifications that impose entropy balancing (Hainmueller, 2012), a method that generalizes propensity score matching through re-weighting observations. Specifically, we impose entropy balancing on the first two moments (mean and variance) of the control variables and ratio polynomials in Column (5) and also for the distance polynomials in Column (6). This technique creates a near-perfect covariate distribution balance between treatment and control firms. The own-firm effects effects are quantitatively similar to those of specifications without entropy balancing. However, the estimate for ρ (indirect effects) in Columns (5) and (6) are roughly 60% (50%) of the magnitudes reported in Columns (3) and (4). Therefore, the entropy balancing results continue to support the conclusion that financial constraints induce significant investment spillovers.

The network RDD analysis addresses the identification challenges related to the exogeneity of firms' covenant violations. However, exogenous firm shocks may influence how firms choose supply chain partners to reduce their exposure to partners' shocks. For this reason, our analysis focuses on short-term spillovers. Firms' ability to substitute between different inputs strategically is near zero in the short run (Barrot and Sauvagnat, 2016; Boehm et al., 2019). Importantly, to mitigate the influence of selection further, we exploit supply chain partnerships established five years before and thus are unlikely driven by credit shocks.

In Panel B of Table 4, we apply the same network RDD approach as in Panel A, using only long-term supply chain relationships in the production network. Even though the estimates are again slightly attenuated, we still find evidence of extensive spillover effects in investment across supply-chain partners across almost all specifications. The consistency in the results after adding a large set of variables strongly associated with *C.viol* mitigates concerns regarding differences in potential outcomes surrounding covenant violations.

4.3. Missing network links

To investigate the potential role of missing supply-chain links in the peer network characterization, we conduct the following simulation exercise. Specifically, we generate simulated data for firms' investment levels, assuming the network we observe contains the complete set of supply-chain connections for all firms. By removing links from this network randomly, we ascertain the sensitivity of our estimation approach to errors resulting from missing parts in firms' production networks.

To this end, we first simulate firms' investment using the Network Regression model in Equation (1) as the data generating process. We fix the parameter ρ at 0.450, in line with the average ρ found in Panel A of Table 2. Using the simulated sample, we randomly eliminate edges from the network. Specifically, we use five alternative supply chain matrices, each missing 0%, 25%, 50%, 75%, and 95% of the true connections, respectively, and estimate the model's parameters (i.e., ρ and β). We repeat the simulation 100 times for each incomplete network and report the average estimate in Figure 2.

The estimate of investment complementarity on the simulated sample using the complete network (i.e., removing 0% of network edges) is 0.445, which aligns closely with the set parameter (0.45). Eliminating 25% of the edges, the estimated investment complementarity drops slightly to 0.38, and the model's estimates remain stable. Importantly, even after missing 50% of the network's edges, the estimated peer-effect coefficient remains fairly large (0.30). Only after removing at least 75% (95%) of the supply chain links in the network, do we start observing a significant drop in the estimates of complementarity in the simulated sample (0.18 and 0.05, respectively).

The simulation results, taken in tandem with the likelihood that omitted linkages not captured by databases such as Compustat or Factset are often smaller in scale, indicate that the effect of missing connections within the network is likely small. Therefore, these findings further increase our confidence that the estimated peer-effect coefficients do not exhibit high sensitivity to a reasonable degree of missing supply chain links.

5. Investment spillovers in production networks

A wealth of theoretical and empirical research, including the influential works of Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012); Gabaix (2011); Carvalho, Nirei, Saito, and Tahbaz-Salehi (2021), has underscored the role of production networks in amplifying microeconomic idiosyncratic shocks. Nonetheless, several theoretical studies such as Lucas (1977); Long and Plosser (1983); Dupor (1999), suggest that sectoral linkages might not lead to substantial spillovers in large production networks given agents' ability to diversify exposure to idiosyncratic shocks. Therefore, the magnitude of the estimated effect, as well as the mechanisms underlying these effects, merit further investigation.

To help establish that the investment spillover effects we document stem from intertwined investment opportunities, we explore a range of additional tests. These tests include investigating: (a) similar spillovers in market valuations, which suggest that the results are driven by economic effects that markets recognize and respond to; (b) firms producing highly specific inputs create, on average, greater investment spillovers; and (c) firms that generate greater externalities also receive more generous trade credit terms. The latter result suggests that the intuition behind Lucas (1977) is indeed possibly valid, but firms' ability to adapt and change trade partners in the short run is fairly limited, and thus the externalities are greater.

5.1. Market response to investment disruptions

Our results suggest that financing constraints induce a series of supply-chain investment disruptions of partners linked through the production process. This section considers whether the stock market recognizes these investment disruptions. To the extent that spillovers affect partners' economic fundamentals, they should also affect partners' stock returns.

We construct abnormal quarterly stock returns according to Daniel et al. (1997). We estimate spillover effects of financial constraints on abnormal stock returns by first applying the network RDD framework in Sections 4.2.2 and 4.2.1 to abnormal stock returns as in Table 4. Specifically, we compare the abnormal returns of firms with violations to those of firms without violations. The units of comparison consist of all firms within a narrow bandwidth around the covenant violation threshold.

Table 5, Panel A, presents the estimates of stock return complementarity (ρ), as well as the own-firm and indirect effects of financial constraints on partners' returns. The analysis shows that covenant violations negatively affect both own-firm and partner-firm stock returns. In all specifications, the parameter ρ is positive and statistically significant, ranging from 0.067 to 0.144. Consistent with prior literature, the own-firm effects of financial constraints on stock returns are, on average, negative. In addition, the indirect effects of financial constraints on returns are also negative, on average, and statistically significant in four of the six models.

To address the partner selection issue, we repeat our analysis in Panel B after replacing the main supply chain network with the network of long-term supply chain partners and find similar results. In this setting, the extent of the investment spillovers comes from supply chain linkages that also existed five years ago. Therefore, the relationships that form the production network are less likely driven by the focal firm's financial constraints. The results indicate that financially constrained firms exhibit low returns, which transmit to supply chain partners. Taken together, these findings in the two panels of Table 5 indicate that market values mirror the fundamental spillovers into investment decisions documented in the prior sections.[16]

[16]The magnitudes for returns are smaller than those for investment outcomes. One potential explanation is that we observe the timing of corporate decisions (i.e., investment spending) with a reasonable degree of accuracy, whereas it is not possible to know when markets learn about financial constraint shocks. Thus, the timing is more challenging for stock returns. Nonetheless, the results corroborate our primary analysis.

5.2. Spillovers of firms producing highly specific inputs

Several studies provide evidence that input specificity in production networks can generate substantive switching costs that amplify the propagation of idiosyncratic shocks (Barrot and Sauvagnat, 2016; Carvalho et al., 2021). In our context, relatively high costs of switching suppliers/customers may inhibit a firm's ability to respond to a partner's constraint-induced investment disruptions, especially in the short run (Antras et al., 2017; Boehm et al., 2019). Thus, we expect more substantial indirect effects of financial constraints from firms producing highly specific inputs.

To test this hypothesis, we first create four measures of asset specificity. First, following Barrot and Sauvagnat (2016), we calculate the ratio of a firm's R&D to sales, and the ratio of its patents to sales. We also employ a firm's *Total Similarity*, defined by Hoberg and Phillips (2016) as a firm's total product market similarity score with other firms. A higher *Total Similarity* indicates that it produces inputs likely to be more substitutable. To facilitate comparison to our other measures of asset specificity, we define *differentiation* as the negative value of *Total Similarity*. Lastly, we use the Herfindahl-Hirschmann sum of squared market shares, calculated from firm-specific TNIC from Hoberg and Phillips (2010b, 2016). For each of these four variables, we use the raw values, as well as indicator variables for values above the annual median of the firm's SIC-3 industry distribution.[17] These measures are built on the intuition that firms that produce differentiated goods also engage in high levels of R&D and tend to hold more patents, and are thus more likely to produce specific inputs/outputs.

Next, we calculate for each firm the total indirect effect of its financial constraints on partners' investment. The indirect effect in Equation (4) describes the *cumulative* impact of a one standard deviation change in firm j's financial constraints on investment spending of all other firms in the supply chain network. Thus far, we report the average indirect

[17] Consistent with high switching costs, we show that each measure is associated with longer partnerships. We tabulate the result of this analysis in the Internet Appendix.

effect across all firms in the sample. However, our estimation routine calculates the partial derivative in Equation (4) separately for each firm before calculating the scalar average value that we report. Consistent with other literature, we refer to firm-specific estimates as the "emanating effect" from unit j to other firms (Kelejian and Piras, 2017).

Table 6 presents the results from this analysis. On average, we show that firms with higher levels of product-specificity generate substantively larger spillover effects, ranging between 0.03 and 0.44 standard deviations in investment. These findings are consistent with the hypothesis that a firm's financial constraints induce a stronger effect if its supply chain partners have fewer input-substitution options (or highly specific inputs).

Taken together, these findings provide strong corroborating evidence that our results are driven by investment spillovers in production networks among partners with intertwined business opportunities. This channel is intuitively a plausible economic explanation mechanism that drives our findings, and it is supported by theoretical and empirical studies, as well as anecdotal evidence and numerous media references (detailed in the Internet Appendix) that highlight how investment opportunities are highly interdependent among business partners.

5.3. Investment spillovers and trade credit

Extending trade credit is an alternative to avoiding partnerships with constrained firms. Trade credit potentially alleviates partners' constraints (Petersen and Rajan, 1997), minimizing disruptions to the quality and quantity of inputs the partner produces (purchases). Although plausible, this proposition is not apparent, as highlighted by some evidence that less financially constrained firms receive more trade credit from small (and more credit-constrained) suppliers (Dasgupta and Kim, 1997; Murfin and Njoroge, 2015). We consider these possibilities by examining how the indirect effects of firms' financial constraints affect the extent of trade credit they receive and provide.[18]

[18]The trade-credit analysis is more indirect than our analyses of corporate investment decisions. Investments represent a *common* outcome variable that supply-chain partners jointly determine. The common outcome variable yields Equation (1), which allows us to solve the ensuing simultaneity problem, as in Equation (2). Although trade credit is also jointly determined by supply-chain partners, the outcome variable is

We define the average number of days it takes the firm to pay suppliers (*Payable Days*), the average number of days it takes customers to pay the firm (*Receivable Days*), and the difference between *Payable Days* and *Receivable Days* (*Net Trade Days*).[19] Table 7 reports OLS regression results and suggests a standard deviation increase in firms' indirect effect on supply-chain investment is, on average, associated with 5–7 additional accounts *payable days*. That is, firms that induce higher spillovers receive more trade credit by paying their suppliers later. The evidence in Columns (2), (4), and (6) further validate this result, suggesting that firms receive less trade credit (i.e., pay earlier) when their partners' investment decisions are more consequential for their peers.

Although the estimates warrant notable caveats, the pattern highlighted in Table 7 helps validate our earlier analysis. In particular, the findings are consistent with firms extending trade credit to mitigate the potential disruptions in production networks. The results suggest that extending trade credit may indeed be an alternative to avoiding partnerships with constrained firms.[20]

6. Confounding mechanisms

6.1. Common industry shocks

We hypothesize that financial constraints curtail a firm's investment spending, initiating a series of reactive changes in investment spending through the supply chain network. Since we emphasize firm-specific financial constraint shocks, we employ a series of tests to substantiate that industry-level shocks do not drive our results.

For our network regressions, we do not employ fixed effects at the firm or industry level for several important reasons. First, our analysis is primarily cross-sectional in nature (in-

not common across partners since one firm's receivables are a partner's payables. Thus, trade credit lacks a natural network regression specification, which precludes the ability to directly model financial constraint spillovers through trade credit decisions, as we did for investment decisions.

[19] We construct the variables in this analysis following Murfin and Njoroge (2015). Our distinct naming convention emphasizes that the regressions presented in Table 7 estimate a firm-centric relation.

[20] We provide a more extensive discussion on how financial constraints may affect firms' choice of supply chain partners using ERG models in the Internet Appendix.

cluding across industry), thus fixed effects are not suitable for our analysis and can lead to over-differencing the data (Roberts and Whited, 2012). Second, the intransitive (and persistent) nature of supply chain networks makes it unclear how industry fixed-effect transformations impact the relation between a firm's outcome variables and that of the entire supply chain. Specifically, industry shocks to the focal firm must correlate with the investment of a unique set of partners across unrelated industries to explain these patterns. Importantly, our analysis primarily concerns the effects of a firm's constraints on *partners*' investment, thus mitigating unobserved heterogeneity concerns regarding the constrained firm. Finally, strict exogeneity does not hold for corporate investment decisions and unobserved heterogeneity is unlikely constant in our context. Thus, fixed effects transformations induce severe biases without addressing concerns regarding unobserved heterogeneity (Grieser and Hadlock, 2019). In the Internet Appendix, we also provide a more extended discussion of the costs and benefits of imposing fixed effects transformations in a network setting.

Considering these challenges, we address the possibility that industry trends drive the changes in investment by explicitly controlling in our regressions for average industry characteristics based on TNIC-3 industry definitions from Hoberg and Phillips (2010a, 2016). This empirical approach has several important advantages. First, instead of using a fixed industry classification, each firm has its own set of competitors; prior studies suggest that text-based network industry classifications capture firms' industry peers more accurately. Second, the dynamic nature of the TNIC industry definitions allows us to control for time-varying industry trends and growth opportunities directly. In Table 8, we show that controlling for industry effects does not qualitatively alter the estimates of investment spillovers. Specifically, the average complementarity in investment drops slightly from 0.5 to 0.45, but it remains economically large.[21]

[21] We tabulate all estimates for the complete set of control variables included in the network regressions in the Internet Appendix.

6.2. Financial constraint spillovers and common-lender networks

The main premise of our study is that investment opportunities among supply chain partners are naturally intertwined. However, a possible concern in our estimation of the level of interdependence in their investment derives from the possibility that production networks have a large overlap with banking networks. For instance, the financial struggles of one firm may create unfavorable terms for linked partners via a common lender. More broadly, our estimates may obtain from financial constraints that propagate throughout the supply chain, shaping investment decisions along the way and potentially intensifying under shared economic shocks. As a result, a positive ρ parameter may not imply coordinated investment but rather reflect the spread and correlation of these financial constraints.

Several empirical facts suggest, however, that these channels cannot explain the estimated degree of investment complementarity in the data. First, we examine the hypothesis that financial constraints propagate among supply chain partners by a shared lender. To test this hypothesis, we match for every firm and its partners all lenders in Dealscan that extend loans to both. However, we find that the unconditional probability two supply chain partners have a common lender in a given year is approximately 2.5%, and the probability they have a common lender at any point in our sample is approximately 6%. The overlap between the two networks is particularly small, and thus, it is highly unlikely that common-lender networks are a plausible confounding mechanism.

Furthermore, in Table 9, we explore whether financial constraints impact not only a company's own investment but also whether they bear direct implications on their partners' investments. For seven out of eight proxies of financial constraints, a firm's investment correlates positively or is not significantly related to the financial constraints of its supply chain partners. This trend aligns with the evidence of heterophily in financial constraint levels among partners in Section 4.1. Importantly, we estimate network regressions Equation (1) to study how financial constraints, rather than investment, spread through production network linkages (i.e., $\text{FC} = \rho S\text{FC} + X\beta + \epsilon$) and plot the estimates of financial-constraint complementarities ρ in Figure 3.[22] We find economically small estimates of complementarity in financial constraints, ranging between -0.02 and 0.06. This evidence suggests that, unlike investment spending, firms' financial constraints do not propagate via supply chain linkages. Therefore, these findings further support the hypothesis that financial constraints do not disseminate directly across firms.

6.3. Additional analyses

Given that we employ novel methods in a finance setting, we dedicate much of the paper to validating the methods and mapping technical details to economic intuition. To keep the paper at a reasonable length, we relegate several discussions to the Internet Appendix. Most notably, we provide several anecdotes highlighting supply-chain partners' coordination as well as additional robustness results. As an overview of the remaining analyses, our main findings are robust to alternative supply-chain network constructions, sample periods, winsorization schemes, and control variables (including specifications without controls). Overall, the extra analyses support the notion that financial constraints propagate through the supply chain network via corporate investment externalities.

The Internet Appendix also addresses additional questions regarding network regressions, such as the sensitivity of our analyses to the precise construction of the supply chain network and details regarding standard error calculations. We also provide simple illustrations of network propagation and higher-order effects. Lastly, we compare network regressions to relevant alternative techniques used in recent studies.

7. Conclusion

Supply chain partners depend heavily on each other to turn capital expenditures into profitable business ventures. Recent studies emphasize how complex and interdependent supply chain networks amplify disruptions in the production process. However, capital investment

[22]We also present the complete set of estimates for each network regression in the Internet Appendix.

typically precedes production, and thus, the interdependence in production naturally implies that supply-chain partners' investment opportunities are highly interdependent as well. To our knowledge, this is the first study that examines the role of production networks in amplifying investment distortions. Specifically, we ask the following question: If financing frictions force a firm to curtail its investment, what is the overall impact on the investment of production partners with intertwined investment opportunities?

We show that tightening a firm's financial constraints generates a cumulative network effect on supply chain partners' investments that is roughly as important as the effect on the firm's own investment. Firms producing highly specific inputs, despite receiving more lenient trade credit terms, generate more substantive investment spillovers. We also show that equity markets recognize the investment distortions across supply chain partners. These estimates are robust to using numerous measures of financial constraint, definitions of production networks, and alternate specifications that facilitate identification and rule out confounding mechanisms.

The quantities we estimate are important in understanding how firm-level financial frictions can accumulate to affect aggregate investment. In fact, the substantial spillover effects in investment we document imply an amplification role for the supply-chain network. This amplification is due, at least in part, to the inability of firms to change production partners in the short run. The spillover effects are more pronounced for firms with specialized inputs that are less likely to switch partners. Overall, our results offer new evidence in favor of production networks serving as a conduit for financial shocks. This network mechanism is a likely connection between financial conditions and investment in the macroeconomy. Our results have potential implications for ongoing debates regarding the multiplier effects of monetary policy on corporate investments. Further research is therefore needed to better understand supply-chain spillovers and their overall impact on the economy.

Bibliography

Acemoglu, D., U. Akcigit, and W. Kerr. 2016a. Networks and the macroeconomy: An empirical exploration. *NBER Macroeconomics Annual* 30:273–335.

Acemoglu, D., and P. D. Azar. 2020. Endogenous production networks. *Econometrica* 88:33–82.

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

Acemoglu, D., A. Ozdaglar, and A. Tahbaz-Salehi. 2016b. Networks, shocks, and systemic risk. In *The Oxford Handbook of the Economics of Networks*, chap. 21, pp. 569–605. Oxford University Press.

Acemoglu, D., A. Ozdaglar, and A. Tahbaz-Salehi. 2017. Microeconomic origins of macroeconomic tail risks. *American Economic Review* 107:54–108.

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

Akins, B., D. De Angelis, and M. Gaulin. 2020. Debt contracting on management. *Journal of Finance* 75:2095–2137.

Alfaro, L., M. García-Santana, and E. Moral-Benito. 2021. On the direct and indirect real effects of credit supply shocks. *Journal of Financial Economics* 139:895–921.

Almeida, H., and M. Campello. 2007. Financial constraints, asset tangibility, and corporate investment. *Review of Financial Studies* 20:1429–1460.

Almeida, H., M. Campello, B. Laranjeira, and S. Weisbenner. 2012. Corporate debt maturity and the real effects of the 2007 credit crisis. *Critical Finance Review* 1:3–58.

Angrist, J. D., and J.-S. Pischke. 2008. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Antras, P., T. C. Fort, and F. Tintelnot. 2017. The margins of global sourcing: Theory and evidence from us firms. *American Economic Review* 107:2514–2564.

Baird, D. G., and R. K. Rasmussen. 2006. Private debt and the missing lever of corporate governance. *University of Pennsylvania Law Review* pp. 1209–1251.

Banerjee, S., S. Dasgupta, and Y. Kim. 2004. Buyer-supplier relationships and trade credit. Working Paper, Lancaster University.

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

Berg, T., M. Reisinger, and D. Streitz. 2021. Spillover effects in empirical corporate finance. *Journal of Financial Economics* .

Bernanke, B., and M. Gertler. 1989. Agency Costs, Net Worth, and Business Fluctuations. *American Economic Review* 79.

Bernstein, S., E. Colonnelli, X. Giroud, and B. Iverson. 2019. Bankruptcy spillovers. *Journal of Financial Economics* 133:608–633.

Bodnaruk, A., T. Loughran, and B. McDonald. 2015. Using 10-K text to gauge financial constraints. *Journal of Financial and Quantitative Analysis* 50:623–646.

Boehm, C. E., A. Flaaen, and N. Pandalai-Nayar. 2019. Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tōhoku earthquake. *Review of Economics and Statistics* 101:60–75.

Boehm, J., and E. Oberfield. 2020. Misallocation in the Market for Inputs: Enforcement and the Organization of Production. *Quarterly Journal of Economics* 135:2007–2058.

Boone, A. L., and V. I. Ivanov. 2012. Bankruptcy spillover effects on strategic alliance partners. *Journal of Financial Economics* 103:551–569.

Boucher, V., and B. Fortin. 2016. Some challenges in the empirics of the effects of networks. In *The Oxford Handbook of the Economics of Networks*, chap. 12, pp. 277–302. Oxford University Press.

Bramoullé, Y., H. Djebbari, and B. Fortin. 2009. Identification of peer effects through social networks. *Journal of Econometrics* 150:41–55.

Bramoullé, Y., H. Djebbari, and B. Fortin. 2020. Peer effects in networks: A survey. *Annual Review of Economics* 12:603–629.

Bustamante, M. C., and L. Frésard. 2021. Does firm investment respond to peers' investment? *Management Science* 67:4703–4724.

Carvalho, D. 2015. Financing constraints and the amplification of aggregate downturns. *Review of Financial Studies* 28:2463–2501.

Carvalho, V. M., M. Nirei, Y. U. Saito, and A. Tahbaz-Salehi. 2021. Supply chain disruptions: Evidence from the great east Japan earthquake. *Quarterly Journal of Economics* 136:1255–1321.

Catherine, S., T. Chaney, Z. Huang, D. Sraer, and D. Thesmar. 2022. Quantifying Reduced-Form Evidence on Collateral Constraints. *Journal of Finance* 77:2143–2181.

Chava, S., and M. R. Roberts. 2008. How does financing impact investment? The role of debt covenants. *Journal of Finance* 63:2085–2121.

Chen, H., W. Dou, H. Guo, and Y. Ji. 2020. Feedback and contagion through distressed competition. Working Paper, University of Pennsylvania.

Chodorow-Reich, G., and A. Falato. 2022. The loan covenant channel: How bank health transmits to the real economy. *Journal of Finance* 77:85–128.

Cookson, J. A. 2017. Anticipated entry and entry deterrence: Evidence from the American casino industry. *Management Science* 64:2325–2344.

Cornwall, G., and B. Sauley. 2021. Indirect effects and causal inference: Reconsidering regression discontinuity. *Journal of Spatial Econometrics* 2:1–28.

Costello, A. M. 2020. Credit market disruptions and liquidity spillover effects in the supply chain. *Journal of Political Economy* 128:3434–3468.

Cox, D. R. 1958. *Planning of Experiments.* Wiley & Sons, New York.

Crosignani, M., M. Macchiavelli, and A. F. Silva. 2023. Pirates without borders: The propagation of cyberattacks through firms' supply chains. *Journal of Financial Economics* 147:432–448.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers. 1997. Measuring mutual fund performance with characteristic-based benchmarks. *Journal of Finance* 52:1035–1058.

Dasgupta, S., and Y. Kim. 1997. Vertical buyer-supplier relationships and capital structure. Working paper, Hong Kong University of Science and Technology.

Demerjian, P. R., and E. L. Owens. 2016. Measuring the probability of financial covenant violation in private debt contracts. *Journal of Accounting and Economics* 61:433–447.

Demir Pakel, B., B. S. Javorcik, T. K. Michalski, and E. Ors. 2020. Financial constraints and propagation of shocks in production networks. Working Paper, Bilkent University.

Denis, D. J., and J. Wang. 2014. Debt covenant renegotiations and creditor control rights. *Journal of Financial Economics* 113:348–367.

Dou, W., S. A. Johnson, M. A. Shao, and W. Wu. 2021. Competition network, distress propagation, and stock returns. Working Paper, University of Pennsylvania.

Dougal, C., C. A. Parsons, and S. Titman. 2015. Urban vibrancy and corporate growth. *Journal of Finance* 70:163–210.

Dupor, B. 1999. Aggregation and irrelevance in multi-sector models. *Journal of Monetary Economics* 43:391–409.

Elliott, M., B. Golub, and M. O. Jackson. 2014. Financial networks and contagion. *American Economic Review* 104:3115–53.

Elliott, M., B. Golub, and M. V. Leduc. 2022. Supply network formation and fragility. *American Economic Review* 112:2701–47.

Ersahin, N., R. M. Irani, and H. Le. 2021. Creditor control rights and resource allocation within firms. *Journal of Financial Economics* 139:186–208.

Falato, A., and N. Liang. 2016. Do creditor rights increase employment risk? Evidence from loan covenants. *Journal of Finance* 71:2545–2590.

Farre-Mensa, J., and A. Ljungqvist. 2016. Do measures of financial constraints measure financial constraints? *Review of Financial Studies* 29:271–308.

Fazzari, S. M., and B. C. Petersen. 1988. Financing constraints and corporate investment. *Brookings Papers on Economic Activity* 1988:141–195.

Ferreira, D., M. A. Ferreira, and B. Mariano. 2018. Creditor control rights and board independence. *Journal of Finance* 73:2385–2423.

Frésard, L., G. Hoberg, and G. M. Phillips. 2020. Innovation activities and integration through vertical acquisitions. *Review of Financial Studies* 33:2937–2976.

Gabaix, X. 2011. The granular origins of aggregate fluctuations. *Econometrica* 79:733–772.

Giroud, X., S. Lenzu, Q. Maingi, and H. Mueller. 2023. Propagation and amplification of local productivity spillovers. Tech. rep.

Giroud, X., and H. M. Mueller. 2019. Firms' internal networks and local economic shocks. *American Economic Review* 109:3617–3649.

Gofman, M., G. Segal, and Y. Wu. 2020. Production networks and stock returns: The role of vertical creative destruction. *Review of Financial Studies* 33:5856–5905.

Gopalakrishnan, V., and M. Parkash. 1995. Borrower and lender perceptions of accounting information in corporate lending agreements. *Accounting Horizons* 9:13.

Grieser, W., C. Hadlock, J. LeSage, and M. Zekhnini. 2022a. Network effects in corporate financial policies. *Journal of Financial Economics* 144:247–272.

Grieser, W., and C. J. Hadlock. 2019. Panel-data estimation in finance: testable assumptions and parameter (in)consistency. *Journal of Financial and Quantitative Analysis* 54:1–29.

Grieser, W., J. LeSage, and M. Zekhnini. 2022b. Industry networks and the geography of firm behavior. *Management Science* 68:6163–6183.

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

Hahn, J., P. Todd, and W. Van der Klaauw. 2001. Identification and estimation of treatment effects with a regression-discontinuity design. *Econometrica* 69:201–209.

Hainmueller, J. 2012. Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political Analysis* 20:25–46.

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

Hertzel, M. G., and M. S. Officer. 2012. Industry contagion in loan spreads. *Journal of Financial Economics* 103:493–506.

Hoberg, G., and V. Maksimovic. 2015. Redefining financial constraints: A text-based analysis. *Review of Financial Studies* 28:1312–1352.

Hoberg, G., and G. Phillips. 2010a. Product market synergies and competition in mergers and acquisitions: A text-based analysis. *Review of Financial Studies* 23:3773–3811.

Hoberg, G., and G. Phillips. 2016. Text-based network industries and endogenous product differentiation. *Journal of Political Economy* 124:1423–1465.

Hoberg, G., G. Phillips, and N. Prabhala. 2014. Product Market Threats, Payouts, and Financial Flexibility. *Journal of Finance* 69:293–324.

Hoberg, G., and G. M. Phillips. 2010b. Text-based network industries and endogenous product differentiation. Tech. rep., National Bureau of Economic Research.

Imbens, G., and K. Kalyanaraman. 2012. Optimal bandwidth choice for the regression discontinuity estimator. *Review of Economic Studies* 79:933–959.

Inoue, H., and Y. Todo. 2019. Firm-level propagation of shocks through supply-chain networks. *Nature Sustainability* 2:841–847.

Jackson, M. O. 2010. *Social and Economic Networks*. Princeton University Press.

Jackson, M. O. 2016. The past and future of network analysis in economics. In *The Oxford Handbook of the Economics of Networks*, chap. 4, pp. 71–79. Oxford University Press.

Kaplan, S. N., and L. Zingales. 1997. Do investment-cash flow sensitivities provide useful measures of financing constraints? *Quarterly Journal of Economics* 112:169–215.

Kelejian, H., and G. Piras. 2017. *Spatial Econometrics*. Academic Press.

Kim, J. Y., M. Howard, E. Cox Pahnke, and W. Boeker. 2016. Understanding network formation in strategy research: Exponential random graph models. *Strategic Management Journal* 37:22–44.

Kolak, M., and L. Anselin. 2020. A spatial perspective on the econometrics of program evaluation. *International Regional Science Review* 43:128–153.

Kolay, M., M. Lemmon, and E. Tashjian. 2016. Spreading the misery? Sources of bankruptcy spillover in the supply chain. *Journal of Financial and Quantitative Analysis* 51:1955–1990.

Lamberson, P. 2016. Diffusion in networks. In *The Oxford Handbook of the Economics of Networks*, chap. 18, pp. 479—-503. Oxford University Press.

Leary, M. T., and M. R. Roberts. 2014. Do peer firms affect corporate financial policy? *Journal of Finance* 69:139–178.

Lee, L.-f., and X. Liu. 2010. Efficient GMM estimation of high order spatial autoregressive models with autoregressive disturbances. *Econometric Theory* 26:187–230.

Lenzu, S., D. A. Rivers, and J. Tielens. 2022. Financial Shocks, Productivity, and Prices pp. Working Paper, NYU.

LeSage, J., and K. Pace. 2009. *Introduction to Spatial Econometrics*. Florida CRC Press.

LeSage, J. P., and R. K. Pace. 2011. Pitfalls in higher order model extensions of basic spatial regression methodology. *Review of Regional Studies* 41:13–26.

Liker, J. K., and T. Y. Choi. 2004. Building deep supplier relationships. *Harvard Business Review* 82:104–113.

Long, J. B., and C. Plosser. 1983. Real business cycles. *Journal of Political Economy* 91:39–69.

Lucas, R. E. 1977. Understanding business cycles. *Carnegie-Rochester Conference Series on Public Policy* 5:7–29.

Maksimovic, V., and S. Titman. 1991. Financial policy and reputation for product quality. *Review of Financial Studies* 4:175–200.

Manski, C. F. 1993. Identification of endogenous social effects: The reflection problem. *The Review of Economic Studies* 60:531–542.

Martin, T., and C. A. Otto. 2021. The downstream impact of upstream tariffs: Evidence from investment decisions in supply chains. Working Paper, Bocconi University.

Morris, S. 2000. Contagion. *Review of Economic Studies* 67:57–78.

Murfin, J. 2012. The supply-side determinants of loan contract strictness. *Journal of Finance* 67:1565–1601.

Murfin, J., and K. Njoroge. 2015. The implicit costs of trade credit borrowing by large firms. *Review of Financial Studies* 28:112–145.

Nini, G., D. C. Smith, and A. Sufi. 2009. Creditor control rights and firm investment policy. *Journal of Financial Economics* 92:400–420.

Nini, G., D. C. Smith, and A. Sufi. 2012. Creditor control rights, corporate governance, and firm value. *Review of Financial Studies* 25:1713–1761.

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

Rauh, J. D. 2006. Investment and financing constraints: Evidence from the funding of corporate pension plans. *Journal of Finance* 61:33–71.

Roberts, M. R., and A. Sufi. 2009. Control rights and capital structure: An empirical investigation. *Journal of Finance* 64:1657–1695.

Roberts, M. R., and T. M. Whited. 2012. Endogeneity in empirical corporate finance. Working paper, University of Rochester.

Robins, G., P. Pattison, Y. Kalish, and D. Lusher. 2007. An introduction to exponential random graph (p*) models for social networks. *Social Networks* 29:173–191.

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

Whited, T. M., and G. Wu. 2006. Financial constraints risk. *Review of Financial Studies* 19:531–559.

Wu, D. 2016. Shock spillover and financial response in supply chain networks: Evidence from firm-level data. Working Paper.

Appendix A: Variable Definitions

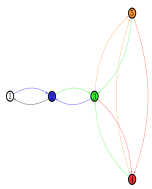
Variable names	Description
Assets	Total assets (in $ billions)
Sales	Total sales (in $ billions)
CapEx/Assets	Capital expenditures / Lagged total assets
Cash	Cash and short term investments / Total assets
Leverage	Total debt / Book assets
MB	(Assets + market equity - book equity) / Assets
Return on Assets (ROA)	Net income / Lagged book assets
Altman-Z	3.3*(Pretax income/assets) + 0.999*(Sales/assets) + 1.4 *(Retained Earnings/Assets) + 1.2*(Current assets - current liabilities)/assets +0.6*(Mkt equity/Total liabilities)
Emanating effects	The value of the cross-partial derivative in Equation (4), or $\sum_{j\neq i}(I_N - \rho S)^{-1}_{i,j}\,\delta$ for each firm. It is equivalent to the *cumulative* impact of a one standard deviation change in firm j's financial constraints on investment spending of all other firms in the supply chain network. The average emanating effect across all firms each year is equivalent to the indirect effects reported in the Tables. Consistent with other literature, we refer to firm-specific estimates as the "emanating effect" from unit j to other firms (Kelejian and Piras, 2017)
Buyer payable days	360*(Accounts payable/Costs of goods sold + inventory)
Seller receivable days	360*(Accounts receivable/Total sales)
Net trade days	Buyer payable days - Seller receivable days
Accounting measures of financial constraints	
Whited-Wu (WW)	-.091*(cash flow) - .062*(dividend payer) + .021*(total long-term debt/assets) - .044*Log(assets) + .102*(SIC-3 sales growth) - .035*(sales growth)
Size-age (SA)	-.737*ln(assets) + .043*ln(assets)^2 - .040*(age)
Long-term debt due (LTD due)	Long term debt due in one year/(Current + long-term debt)
Delay Inv	Measure of financial constraints constructed by Hoberg and Maksimovic (2015), who provide the following definition: "higher values are more similar to a set of firms known to be at risk of delaying their investments due to issues with liquidity and indicate plans to issue debt"
FC combo	Sum of standardized (demeaned and divided by standard deviation) of *WW, SA, LTD Due* and *Delay Inv*
Debt-based measures of financial constraints	
C. viol	An indicator variable that equals one if the firm reports a confirmed (i.e., realized) technical covenant violation in a given year, and zero otherwise
Tech. viol	An indicator variable that equals one if the firm violates a current ratio, net worth, or tangible net worth covenant in a given quarter as in Chava and Roberts (2008), and zero otherwise
Hybrid viol	An indicator variable that equals one if the firm crosses a covenant threshold (tech. viol=1) *and* it also has a confirmed (C. viol=1), and zero otherwise
C. CapEx	An indicator variable that equals one if the firm has a financial covenant that restricts its investment, and zero otherwise
C. strict	Indicates the probability that the firm will violate at least one of its covenants in the next year. To construct the measure we follow the methodology of Murfin (2012), and financial covenant definitions as used in Demerjian and Owens (2016)

Appendix B: A Simple Illustration of Network Propagation

Figure B.1 plots graphical and matrix representations for a simple supply-chain network. We plot the first, second, and third orders, and the cumulative network effects in sub-figures (a), (b), (c), and (d), respectively. The cumulative effects are determined by the inverse term $(I_n - \rho S)^{-1}$. For this example, we set $\rho = 0.5$.

Figure B.1

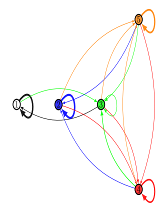
(a)



$$\mathbf{S}$$

$$\begin{array}{c} \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} \begin{array}{c} \begin{array}{ccccc} 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{pmatrix} 0.00 & 1.00 & 0.00 & 0.00 & 0.00 \\ 0.82 & 0.00 & 0.18 & 0.00 & 0.00 \\ 0.00 & 0.24 & 0.00 & 0.29 & 0.47 \\ 0.00 & 0.00 & 0.17 & 0.00 & 0.83 \\ 0.00 & 0.00 & 0.25 & 0.75 & 0.00 \end{pmatrix} \end{array}$$

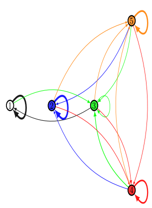
(b)



$$S^2$$

$$\begin{array}{c} \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} \begin{array}{c} \begin{array}{ccccc} 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{pmatrix} 0.82 & 0.00 & 0.18 & 0.00 & 0.00 \\ 0.00 & 0.86 & 0.00 & 0.05 & 0.09 \\ 0.20 & 0.00 & 0.21 & 0.35 & 0.24 \\ 0.00 & 0.04 & 0.21 & 0.67 & 0.08 \\ 0.00 & 0.06 & 0.13 & 0.07 & 0.74 \end{pmatrix} \end{array}$$

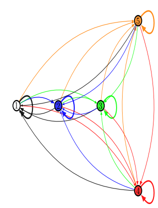
(c)



$$S^3$$

$$\begin{array}{c} \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} \begin{array}{c} \begin{array}{ccccc} 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{pmatrix} 0.00 & 0.86 & 0.00 & 0.05 & 0.09 \\ 0.70 & 0.00 & 0.19 & 0.06 & 0.04 \\ 0.00 & 0.25 & 0.12 & 0.24 & 0.39 \\ 0.03 & 0.05 & 0.14 & 0.12 & 0.65 \\ 0.05 & 0.03 & 0.21 & 0.59 & 0.12 \end{pmatrix} \end{array}$$

(d)



$$(I_n - \rho S)^{-1} \text{ for } \rho = .5$$

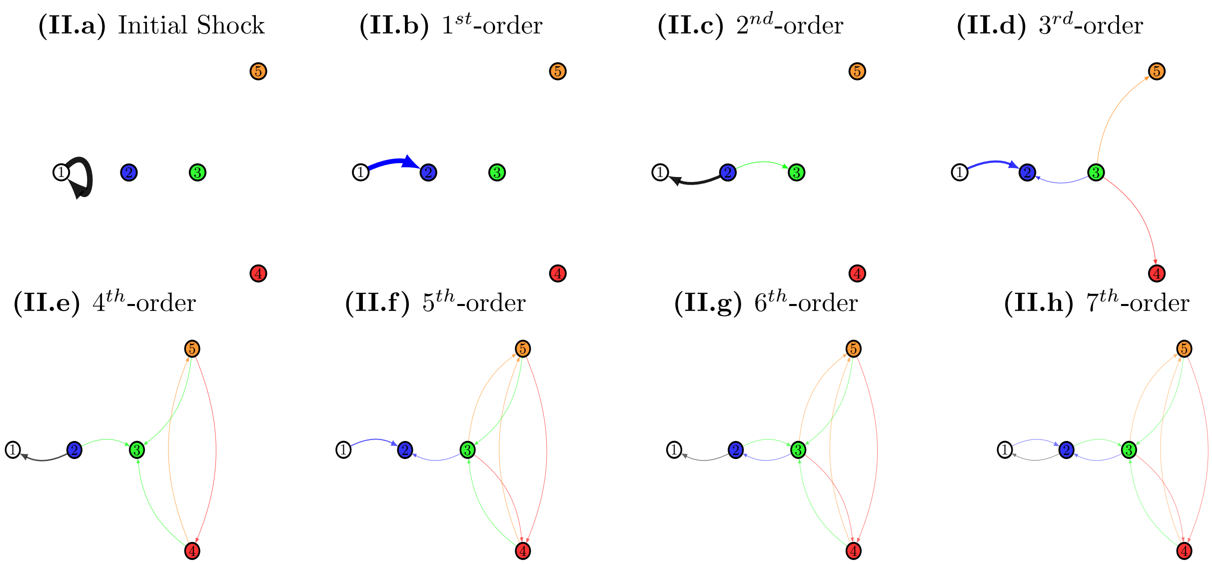
$$\left(\begin{array}{c|ccccc} & 1 & 2 & 3 & 4 & 5 \\ 1 & 1.26 & 0.64 & 0.06 & 0.02 & 0.02 \\ 2 & 0.52 & 1.28 & 0.12 & 0.03 & 0.04 \\ 3 & 0.07 & 0.16 & 1.09 & 0.30 & 0.38 \\ 4 & 0.01 & 0.03 & 0.18 & 1.23 & 0.55 \\ 5 & 0.02 & 0.03 & 0.20 & 0.50 & 1.26 \\ \hline \textit{Total} & 1.88 & 2.14 & 1.65 & 2.08 & 2.25 \end{array} \right)$$

In Sub-figure (a) of Figure (B.1), the matrix illustrates that firm 1 only depends on firm 2, and thus $S_{1,2} = 1$. Firm 2 depends on both firms 1 and 3 with respective strengths of $S_{2,1} = 0.82$ and $S_{2,3} = 0.18$, and so on. Sub-figure (b) shows that firm 1 exhibits second-order connections to itself and to firm 3, despite not having direct connections for these relationships. Similarly, firm 1 has third-order connections to firms 2, 4, and 5. The network becomes more densely connected for higher orders of the network, and all firms are connected by the seventh-order (unreported).

Sub-figure (d) illustrates the final, cumulative transmission effects for $\rho = 0.5$. The column sums illustrate the effects from firm i to other firms (out-degree effects). The row sums indicate the effects received by other firms (in-degree effects). While each firm exhibits unique out-degree and in-degree effects, the average in-degree effect across all firms equals the average out-degree effect across all firms, by definition. The network multiplier $1/(1 - \rho) = 1/(1 - 0.5) = 2$ summarizes these average effects.

Continuing with the example from Figure B.1, we trace how an initial shock shock that causes firm 1 to curtail investment by \$1 transmits through the network. The primary interest is on the final, cumulative effect of this \$1 in forgone investment on investment for the rest of the supply chain network. Figure B.2 presents the orders of transmission:

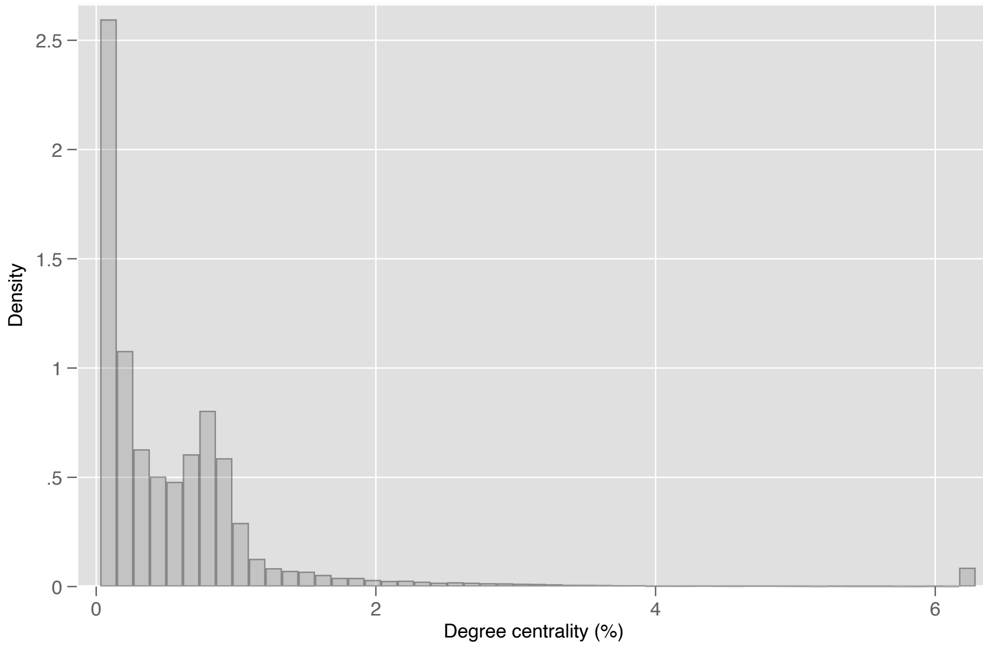
Figure B.2



Sub-figure (a) illustrates the initial \$1 shock to firm 1. Sub-figure (b) shows the first-order transmission of this shock to firm 2, which cuts investment by $\$\rho \times .82 = \$.41$. Sub-figure (c) shows the second-order transmission, where the effect on firm 2 feeds back to firm 1, which cuts investment by $\$\rho^2 \times 1 \times .82 = \$0.21$ and firm 3, which cuts investment by $\$\rho^2 \times .24 \times .82 = \$0.05$. In the third-order transmission illustrated in Sub-figure (d), firm 2 cuts investment by an additional $\$\rho^3 \times .82 \times 1 \times .82 + \$\rho^3 \times .18 \times .82 \times .24$, firm 4 cuts investment by $\$\rho^3 \times .17 \times .82 \times .24$, and firm 5 cuts investment by $\$\rho^3 \times .25 \times .82 \times .24$. This process can either describe a series of reactions, reactions to reactions, and so on, or it could describe the higher order beliefs that firms form about partners actions. In either case, the final equilibrium effect of cutting \$1 in investment spending for firm 1 leads to a total cumulative loss of \$1.82 through the entire supply chain. Column (1) in Sub-figure (d) of Figure B.1 illustrates the effect on each firm. Firm 1 ultimately cuts investment by \$1.26, where the additional \$0.26 comes from feedback effects through the network. In this example the own-firm effect = \$1.26 and the indirect effects sum to \$0.62.

Figure 1

(1.a) This figure plots the overall distribution of firms' annual degree centrality according to the supply chain network that combines all three sources of supply chain relationships (i.e., Compustat, FactSet Revere, and VTNIC).



(1.b) This figure plots the distribution of firms' average annual degree centrality in the supply chain network for each source of supply chain relationships separately. The centrality distribution based on Compustat relationships is plotted in black transparent boxes, the centrality distribution based on FactSet is plotted in grey, and the centrality distribution based on VTNIC relationships is plotted in light blue.

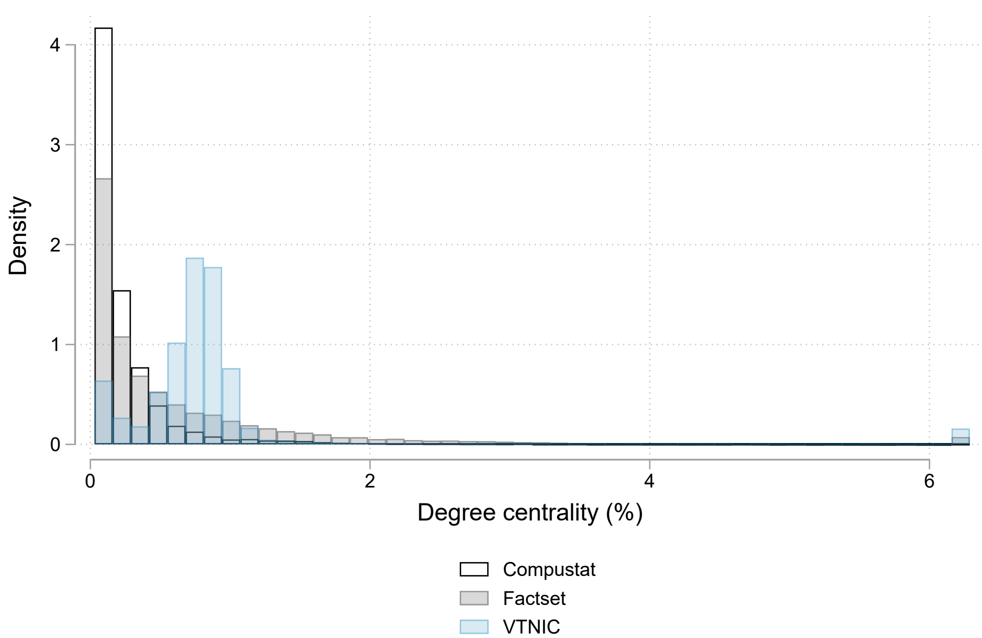


Figure 2: Investment Complementarity with Missing Links

This figure plots the network regression estimates partners' financial constraints complementarity parameter ρ (i.e., $FC = \rho S\,FC + X\beta + \epsilon$) using a simulated sample with investment complementarity fixed at 0.45. Each bar represents the estimate when we randomly remove 0%, 25%, 50%, 75%, and 95% of the edges from the supply chain network. Above each bar, we report the log-likelihood values to assess each model's fit.

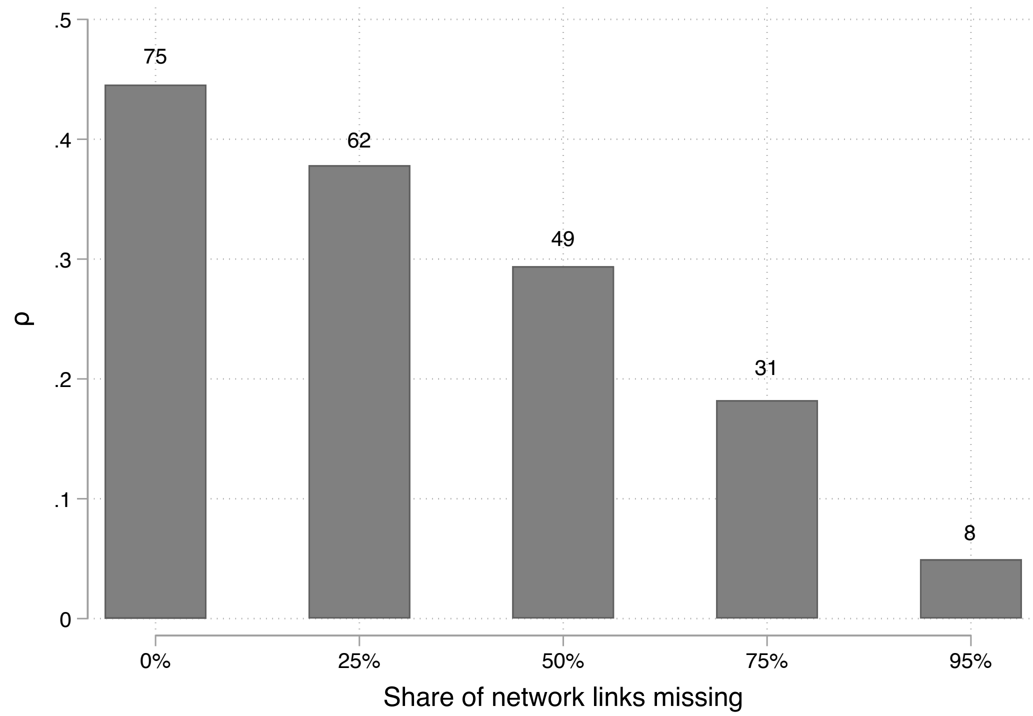


Figure 3: Financial Constraints Complementarity in Production Networks

This figure plots the network regression estimates for partners' financial constraints complementarity parameter ρ. Each point represents an estimate for ρ from the network regression $\mathrm{FC} = \rho S\,\mathrm{FC} + X\beta + \epsilon$. The horizontal axis shows the measure of financial constraints FC used in each model: the financial constraints index from Whited and Wu (2006) (WW); the size-age index (SA) from Hadlock and Pierce (2010); the proportion of long-term debt due (*LTD due*) from Almeida et al. (2012); the text-based measure (*Delay Inv*) from Hoberg and Maksimovic (2015); the sum of the first four (standardized) financial constraint measures (*FC combo*); an indicator variable equal to one if a firm reports a covenant violation in its 10-K or 10-Q (*C.viol*); an indicator variable equal to one if a firm has a capital expenditure covenant (*CapexCov*) from Nini et al. (2009); and the probability that a firm violates at least one covenant in the next quarter (*C.strict*) from Murfin (2012). We present the complete set of estimates for each network regression in the Internet Appendix.

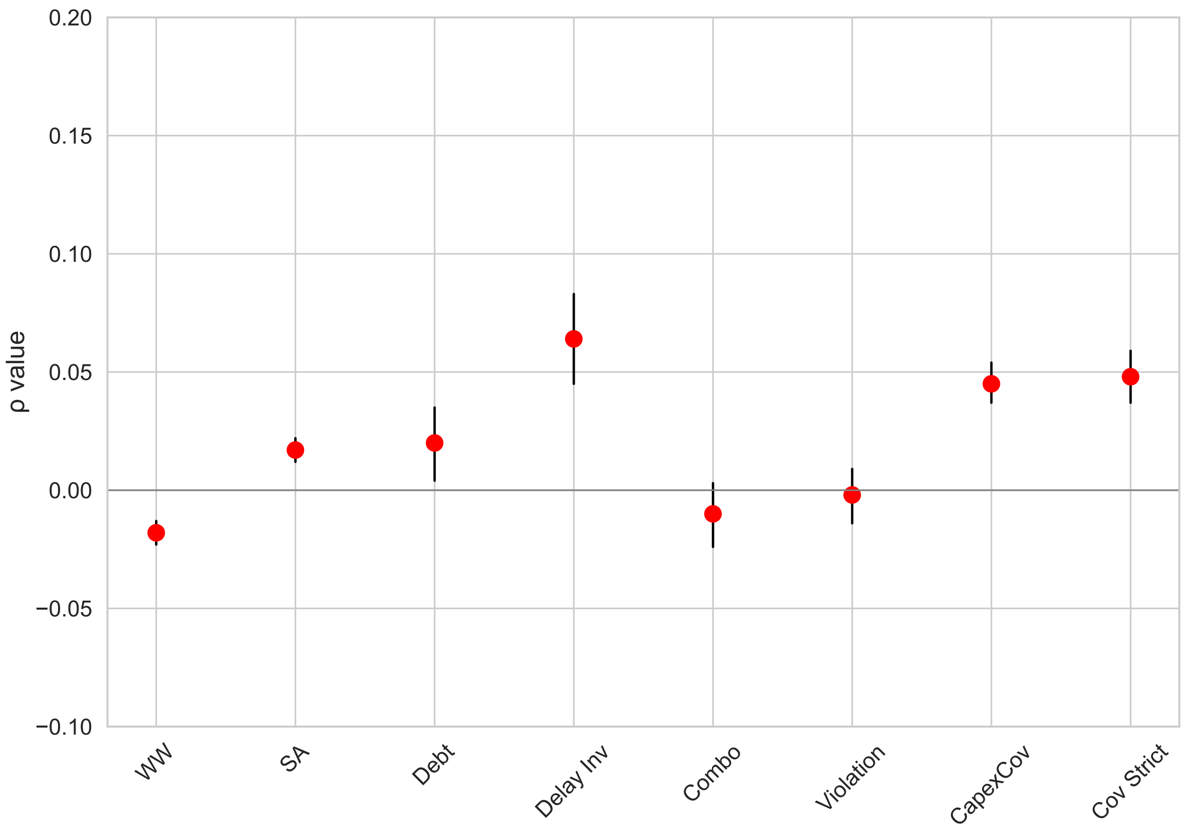


Table 1: Summary Statistics

This table presents summary statistics for the supply chain network (Panel A) and firm-level characteristics (Panel B). In Panel A, degree centrality is reported separately for each supply chain data source (i.e., Compustat segment, FactSet Revere, and VTNIC). Degree centrality (in %) is normalized by the total number of nodes in the network. Accounting information is obtained from Compustat, and loan covenant information is obtained from LPC DealScan. All variables are defined in detail in the Appendix.

	N	Mean	SD	P10	P50	P90
Panel A: Network characteristics						
Degree (%) - All networks	203,823	0.786	3.275	0.049	0.365	1.130
Degree (%) - Compustat	64,186	0.285	0.522	0.048	0.143	0.569
Degree (%) - Factset	76,326	0.716	1.294	0.043	0.311	1.694
Degree (%) - VTNIC	63,311	1.379	5.623	0.216	0.771	1.028
Clustering (%)	203,823	7.779	15.205	0.000	0.000	21.739
Shortest path	203,823	3.280	0.622	2.248	3.151	3.923
Panel B: Firm characteristics						
Annual Observations						
CapEx/Lagged assets	154,641	0.068	0.097	0.004	0.037	0.155
Assets	154,641	1.909	6.440	0.005	0.118	3.520
Sales	154,641	1.704	5.668	0.001	0.104	3.240
Cash	154,641	0.211	0.244	0.008	0.110	0.604
Altman-Z	154,641	0.424	13.053	-13.144	2.973	9.762
ROA	154,641	-0.260	1.235	-0.573	0.021	0.152
MB	154,641	3.212	6.917	0.875	1.542	5.082
Leverage	154,641	0.232	0.243	0.000	0.176	0.549
Whited-Wu	144,301	-0.142	0.225	-0.353	-0.164	0.038
Size-Age	154,641	-2.707	1.030	-3.837	-2.871	-1.395
LTD due	117,211	0.163	0.243	0.000	0.059	0.500
Delay Inv	60,251	-0.001	0.056	-0.068	-0.007	0.075
FC combo	45,203	-0.005	2.310	-2.593	-0.309	2.909
C.viol	77,218	0.100	0.300	0.000	0.000	0.000
C.CapEx	33,814	0.243	0.429	0.000	0.000	1.000
C.strict (%)	33,814	27.484	26.411	0.000	23.584	67.166
Emanating effects	63,949	1.689	1.275	1.000	1.288	2.548
R&D/Sales	130,523	0.429	2.226	0.000	0.003	0.285
Product sim.	105,073	4.315	8.427	1.006	1.470	9.670
TNIC-3 HHI	103,013	0.335	0.295	0.063	0.221	0.896
Patents/Sales	36,322	0.992	19.773	0.001	0.017	0.255
Relationship length	63,949	5.678	3.631	1.622	5.000	10.976
Buyer payable days	147,610	102.009	249.79	14.82	44.18	158.72
Supplier receivable days	145,790	58.093	47.40	6.89	52.02	103.37
Quarterly Observations						
CapEx/Lagged assets	485,157	0.071	0.14	0.000	0.028	0.166
C.viol	292,180	0.051	0.22	0.000	0.000	0.000
tech.viol	52,178	0.198	0.40	0.000	0.000	1.000
hybrid.viol	52,178	0.066	0.25	0.000	0.000	0.000

Table 2: Financial Constraint-Induced Investment Spillovers

This table presents network regression estimates of the spillovers of financial constraints on supply chain partners' investment, as specified in Equation (1). The dependent variable is firm investment *(CapEx/L.Assets)* in all models. In columns (1)-(5), the independent variable *FC* represents five measures of financial constraints: the *WW* index from Whited and Wu (2006), the size-age (SA) index from Hadlock and Pierce (2010), the proportion of long-term debt due *(LTD due)* from Almeida et al. (2012), a text-based measure *(Delay Inv)* from Hoberg and Maksimovic (2015), and the sum of the first four (standardized) financial constraint measures *(FC combo)*. In columns (6)-(8), *FC* represents three measures of covenant-induced financial constraints: *C.viol* is an indicator variable equal to one if a firm reports a covenant violation in its 10-K or 10-Q; *C.CapEx* is an indicator variable equal to one if a firm has a capital expenditure covenant; *C.strict* is the probability that a firm violates at least one covenant in the next quarter. Panel A reports estimates for ρ, which quantifies supply chain partners' investment complementarity. Panel B reports estimates of the average direct effect of own-firm financial constraints and other covariates on own-firm investment. Panel C reports estimates of the average indirect effect of financial constraints and other covariates on partners' investments. All non-dummy variables are standardized, and all models include year fixed effects. In parentheses, we report t-statistics based on standard errors calculated directly from the posterior distribution of MCMC parameter estimates.

	CapEx/L.Assets (Annual)					*CapEx/L.Assets (Qtr.)*		
	WW	SA	LTD due	Delay Inv	FC combo	C.viol	C.CapEx	C.strict
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Investment Complementarity								
ρ	0.403	0.431	0.440	0.480	0.460	0.557	0.486	0.619
	(56.409)	(61.095)	(48.633)	(47.884)	(39.729)	(107.132)	(125.122)	(103.154)
Panel B: Own-firm Effects								
FC	-0.294	-0.024	-0.030	-0.006	-0.086	-0.164	-0.024	-0.021
	(-31.003)	(-3.205)	(-6.284)	(-1.084)	(-9.887)	(-15.579)	(-3.77)	(-6.509)
ln(Sales)	-0.257	-0.096	-0.084	-0.058	-0.116	-0.049	-0.074	-0.147
	(-34.168)	(-14.149)	(-15.242)	(-8.919)	(-13.447)	(-23.303)	(-19.848)	(-44.851)
Cash	-0.182	-0.164	-0.120	-0.158	-0.131	-0.156	-0.168	-0.107
	(-38.421)	(-35.71)	(-24.306)	(-24.708)	(-18.724)	(-60.46)	(-80.428)	(-31.462)
Z-score	0.077	0.085	0.087	0.082	0.097	0.041	0.056	-0.036
	(14.275)	(17.249)	(14.615)	(12.797)	(11.839)	(17.052)	(29.581)	(-8.514)
ROA	-0.147	-0.012	-0.016	0.002	-0.036	0.030	0.036	0.079
	(-21.357)	(-2.377)	(-2.807)	(0.347)	(-4.481)	(9.343)	(14.419)	(23.829)
MB	0.112	0.094	0.076	0.099	0.094	0.052	0.052	0.118
	(23.756)	(18.226)	(13.66)	(16.222)	(12.601)	(17.533)	(21.917)	(28.895)
Leverage	0.005	0.005	-0.006	0.009	0.003	0.004	-0.010	0.010
	(1.018)	(1.175)	(-1.228)	(1.57)	(0.479)	(1.753)	(-4.8)	(2.735)
Panel C: Indirect Effects								
FC	-0.193	-0.017	-0.022	-0.005	-0.071	-0.204	-0.022	-0.034
	(-22.694)	(-3.197)	(-6.158)	(-1.084)	(-8.745)	(-14.512)	(-3.762)	(-6.376)
ln(Sales)	-0.169	-0.071	-0.064	-0.052	-0.096	-0.061	-0.069	-0.234
	(-23.717)	(-13.269)	(-13.345)	(-8.316)	(-10.889)	(-17.712)	(-32.596)	(-29.501)
Cash	-0.120	-0.120	-0.091	-0.141	-0.108	-0.195	-0.156	-0.170
	(-25.935)	(-24.827)	(-17.78)	(-17.714)	(-13.807)	(-37.449)	(-50.102)	(-24.843)
Z-score	0.051	0.062	0.066	0.073	0.080	0.051	0.052	-0.058
	(13.114)	(15.666)	(12.961)	(11.15)	(10.402)	(16.151)	(26.997)	(-8.116)
ROA	-0.096	-0.009	-0.012	0.002	-0.030	0.037	0.033	0.126
	(-17.904)	(-2.379)	(-2.813)	(0.343)	(-4.406)	(9.174)	(14.16)	(19.679)
MB	0.073	0.069	0.058	0.088	0.078	0.065	0.049	0.187
	(19.523)	(16.292)	(11.973)	(14.184)	(10.867)	(16.187)	(20.532)	(22.435)
Leverage	0.003	0.004	-0.005	0.008	0.003	0.005	-0.010	0.016
	(1.016)	(1.175)	(-1.226)	(1.563)	(0.476)	(1.752)	(-4.778)	(2.728)

Table 3: Financial Constraint-Induced Investment Spillovers for Long-term Partners

This table presents network regression estimates of the spillovers of financial constraints on supply chain partners' investments, as specified in Equation (1). We restrict the supply chain network to partnerships at least five years old. The dependent variable is firm investment *(CapEx/L.Assets)* in all models. In columns (1)-(5), the independent variable *FC* represents five measures of financial constraints: the *WW* index from Whited and Wu (2006), the size-age (SA) index from Hadlock and Pierce (2010), the proportion of long-term debt due *(LTD due)* from Almeida et al. (2012), a text-based measure *(Delay Inv)* from Hoberg and Maksimovic (2015), and the sum of the first four (standardized) financial constraint measures *(FC combo)*. In columns (6)-(8), *FC* represents three measures of covenant-induced financial constraints: *C.viol* is an indicator variable equal to one if a firm reports a covenant violation in its 10-K or 10-Q; *C.CapEx* is an indicator variable equal to one if a firm has a capital expenditure covenant; *C.strict* is the probability that a firm violates at least one covenant in the next quarter. Panel A reports estimates for ρ, which quantifies supply chain partners' investment complementarity. Panel B reports estimates of the average own-firm effect of financial constraints and other covariates on own-firm investment. Panel C reports estimates of the average indirect effect of financial constraints and other covariates on partners' investments. All non-dummy variables are standardized, and all models include year fixed effects. In parentheses, we report t-statistics based on standard errors calculated directly from the posterior distribution of MCMC parameter estimates.

	CapEx/L.Assets (Annual)					*CapEx/L.Assets (Qtr.)*		
	WW	SA	LTD due	Delay Inv	FC combo	C.viol	C.CapEx	C.strict
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Investment Complementarity								
ρ	0.389	0.399	0.408	0.412	0.407	0.402	0.398	0.403
	(57.112)	(59.227)	(48.727)	(46.856)	(37.777)	(36.895)	(38.251)	(37.319)
Panel B: Own-firm effects								
FC	-0.273	-0.066	-0.026	-0.003	-0.081	-0.071	-0.094	-0.011
	(-25.820)	(-8.877)	(-5.072)	(-0.567)	(-9.701)	(-8.592)	(-13.317)	(-1.421)
ln(Sale)	-0.226	-0.095	-0.064	-0.037	-0.102	-0.137	-0.152	-0.134
	(-27.442)	(-13.084)	(-11.219)	(-5.547)	(-11.944)	(-17.174)	(-21.821)	(-18.819)
Cash	-0.172	-0.155	-0.116	-0.154	-0.133	-0.126	-0.125	-0.126
	(-36.043)	(-31.088)	(-22.068)	(-22.936)	(-18.739)	(-15.081)	(-17.453)	(-16.375)
Z-score	0.054	0.050	0.068	0.070	0.082	-0.050	-0.037	-0.038
	(10.710)	(9.506)	(11.047)	(10.044)	(9.814)	(-5.796)	(-4.485)	(-4.743)
ROA	-0.106	0.012	0.009	0.029	0.000	0.074	0.077	0.075
	(-14.940)	(2.132)	(1.432)	(4.166)	(-0.048)	(8.857)	(9.919)	(9.285)
MB	0.103	0.098	0.071	0.103	0.093	0.119	0.110	0.114
	(20.292)	(18.325)	(11.575)	(15.501)	(11.764)	(14.682)	(14.958)	(15.258)
Leverage	0.010	0.010	0.003	0.018	0.013	0.009	0.016	0.008
	(2.131)	(2.271)	(0.492)	(2.697)	(1.682)	(1.036)	(2.039)	(1.000)
Panel C: Indirect effects								
FC	-0.168	-0.042	-0.017	-0.002	-0.053	-0.045	-0.059	-0.007
	(-21.31)	(-8.520)	(-4.953)	(-0.568)	(-8.894)	(-8.041)	(-11.287)	(-1.419)
ln(Sale)	-0.139	-0.061	-0.042	-0.025	-0.067	-0.088	-0.096	-0.086
	(-22.042)	(-12.193)	(-10.366)	(-5.457)	(-10.66)	(-13.914)	(-15.693)	(-14.199)
Cash	-0.106	-0.099	-0.077	-0.103	-0.087	-0.081	-0.079	-0.081
	(-25.134)	(-23.830)	(-17.336)	(-17.978)	(-14.699)	(-12.954)	(-14.013)	(-13.006)
Z-score	0.033	0.032	0.045	0.047	0.054	-0.032	-0.023	-0.024
	(10.208)	(9.224)	(10.432)	(9.281)	(8.988)	(-5.595)	(-4.456)	(-4.699)
ROA	-0.065	0.008	0.006	0.019	0.000	0.047	0.049	0.048
	(-14.111)	(2.132)	(1.425)	(4.134)	(-0.049)	(8.2)	(9.243)	(8.751)
MB	0.063	0.063	0.047	0.069	0.061	0.077	0.069	0.073
	(17.016)	(16.179)	(10.897)	(13.292)	(10.449)	(12.388)	(12.442)	(12.528)
Leverage	0.006	0.007	0.002	0.012	0.008	0.006	0.010	0.005
	(2.131)	(2.278)	(0.494)	(2.679)	(1.675)	(1.030)	(2.006)	(0.996)

Table 4: Network RDD: Covenant Violations and Investment Spillovers

This table presents network regression discontinuity design estimates of the strength of the spillovers of financial constraints on supply chain partners' investment. The dependent variable is firm investment *(CapEx/L.Assets)* in all models. The estimates in Columns (1) - (4) are based on the network polynomial RDD from Equation (12). The treatment in Column (1) is based on the *C.viol*, which is an indicator variable equal to one if a firm reports a covenant violation in its 10-K or 10-Q during quarter $t-1$, and zero otherwise. Column (2) repeats the analysis of Column (1) and includes a 3rd-degree polynomial of the distances from violation thresholds for *current ratio, net worth,* and *tangible net worth* covenants. Columns (1) and (2) include a 3rd-degree polynomial of the five covenant variables: *cash-flow/assets, leverage ratio, int.expense/assets, net worth/assets, current ratio, and market-to-book*. The estimates in Columns (5)–(6) are based on the network local-linear RDD. In Column (5), treatment is based on *tech.viol*, which indicates whether a financial ratio in Compustat has crossed the corresponding contractual covenant violation threshold for *net worth*, *tangible net worth*, and *current ratio* covenants. In Column (6), treatment is based on *hybrid.viol*, which is a hybrid definition of violations from Columns (3) and (5) where *hybrid.viol* equals one if *tech.viol*=1 and *C.viol*=1, and equals zero otherwise. Panel A reports estimates for ρ, which quantifies supply chain partners' investment complementarity. Panel B reports estimates of the average direct effect of own-firm treatment on own-firm investment and the average indirect effect of own-firm treatment on partners' investments. All non-dummy variables are standardized, and all models include year fixed effects. In parentheses, we report t-statistics based on standard errors calculated directly from the posterior distribution of MCMC parameter estimates.

Panel A: Main Supply Chain Network

	CapEx/L.Assets					
	Local Linear Network RDD		Polynomial Network RDD			
	(1)	(2)	(3)	(4)	(5)	(6)
Inv. Complementarity (ρ)	0.526	0.537	0.534	0.514	0.326	0.284
	(107.722)	(112.01)	(98.343)	(96.624)	(61.891)	(56.485)
Own-firm Treatment Effect	-0.186	-0.335	-0.153	-0.180	-0.183	-0.177
	(-2.982)	(-3.32)	(-15.551)	(-18.294)	(-47.782)	-(48.107)
Indirect Treatment Effect	-0.202	-0.396	-0.174	-0.151	-0.088	-0.070
	(-2.983)	(-3.33)	(-14.417)	(-16.911)	(-31.810)	(-31.023)

Panel B: Long-term Partner Network

	CapEx/L.Assets					
	Local Linear Network RDD		Polynomial Network RDD			
	(7)	(8)	(9)	(10)	(11)	(12)
Inv. Complementarity (ρ)	0.466	0.465	0.465	0.401	0.263	0.231
	(101.343)	(98.116)	(100.435)	(87.087)	(56.005)	(50.861)
Own-firm Treatment Effect	-0.270	-0.237	-0.170	-0.197	-0.195	-0.189
	(-3.713)	(-3.713)	(-16.165)	(-18.829)	(-43.246)	(-46.387)
Indirect Treatment Effect	-0.258	-0.224	-0.145	-0.130	-0.069	-0.056
	(-2.071)	(-2.071)	(-15.451)	(-17.898)	(-29.517)	(-31.465)
Ratio polynomials	No	No	Yes	Yes	Yes	Yes
Entropy balancing	No	No	No	No	Yes	Yes
Distance polynomials	No	No	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Treatment variable	*tech.viol*	*hybrid.viol*	*C.viol*	*C.viol*	*C.viol*	*C.viol*

Table 5: Network RDD: Market Valuations of Covenant Violation and Investment Spillovers

This table presents network regression discontinuity design estimates of the strength of the spillovers of financial constraints on supply chain partners' stock returns. The dependent variable in all models is a firm's annual characteristics-adjusted stock return *(DGTW)* following Daniel et al. (1997). The estimates in Columns (1) - (4) are based on the network polynomial RDD from Equation (12). The treatment in Column (1) is based on the *C.viol*, which is an indicator variable equal to one if a firm reports a covenant violation in its 10-K or 10-Q during quarter $t-1$, and zero otherwise. Column (2) repeats the analysis of Column (1) and includes a 3rd-degree polynomial of the distances from violation thresholds for *current ratio, net worth,* and *tangible net worth* covenants. Columns (1) and (2) include a 3rd-degree polynomial of the five covenant variables: *cash-flow/assets, leverage ratio, int.expense/assets, net worth/assets, current ratio, and market-to-book.* The estimates in Columns (5)–(6) are based on the network local-linear RDD. In Column (5), treatment is based on *tech.viol*, which indicates whether a financial ratio in Compustat has crossed the corresponding contractual covenant violation threshold for *net worth*, *tangible net worth*, and *current ratio* covenants. In Column (6), treatment is based on *hybrid.viol*, which is a hybrid definition of violations from Columns (3) and (5) where *hybrid.viol* equals one if *tech.viol*=1 and *C.viol*=1, and equals zero otherwise. Panel A reports estimates for ρ, which quantifies supply chain partners' stock return complementarity. Panel B reports estimates of the average direct effect of own-firm treatment on own-firm stock returns and the average indirect effect of own-firm treatment on partners' stock returns. All non-dummy variables are standardized, and all models include year fixed effects. In parentheses, we report t-statistics based on standard errors calculated directly from the posterior distribution of MCMC parameter estimates.

Panel A: Main Supply Chain Network

	Stock Returns (DGTW)					
	Local Linear Network RDD		Polynomial Network RDD			
	(1)	(2)	(3)	(4)	(5)	(6)
Inv Complementarity (ρ)	0.100	0.099	0.144	0.143	0.068	0.067
	(9.771)	(9.621)	(12.960)	(11.856)	(5.283)	(5.028)
Own-firm Treatment Effect	-0.017	-0.221	-0.237	-0.236	-0.074	-0.071
	(-0.422)	(-3.855)	(-21.392)	(-22.088)	(-24.962)	(-23.534)
Indirect Treatment Effect	-0.002	-0.023	-0.040	-0.039	-0.005	-0.003
	(-0.422)	(-3.855)	(-9.811)	(-8.856)	(-4.919)	(-3.192)

Panel B: Long-term Partner Network

	Stock Returns (DGTW)					
	Local Linear Network RDD		Polynomial Network RDD			
	(7)	(8)	(9)	(10)	(11)	(12)
Inv Complementarity (ρ)	0.072	0.072	0.094	0.094	0.036	0.036
	(8.625)	(8.653)	(9.673)	(10.238)	(3.373)	(3.286)
Own-firm Treatment Effect	-0.032	-0.029	-0.231	-0.231	-0.071	-0.070
	(-0.771)	(-0.702)	(-19.088)	(-19.173)	(-23.534)	(-22.784)
Indirect Treatment Effect	-0.002	-0.002	-0.024	-0.024	-0.003	-0.003
	(-0.771)	(-0.702)	(-7.952)	(-8.628)	(-3.192)	(-3.117)
Ratio polynomials	No	No	Yes	Yes	Yes	Yes
Entropy balancing	No	No	No	No	Yes	Yes
Distance polynomials	No	No	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Treatment variable	*tech.viol*	*hybrid.viol*	*C.viol*	*C.viol*	*C.viol*	*C.viol*

Table 6: Investment Spillovers and Product Specificity

This table presents OLS regressions of firm-specific emanating effects on firm-level measures of product specificity. In all models, the dependent variable is *Emanating Effects*, defined as the aggregate investment spillovers originating from a given firm j to all other firms in its supply chain network. We compute this variable using the sum of the indirect effects emanating from a firm, represented by the formula $\sum_{j\neq i}(I_N - \rho S)^{-1}_{i,j}\beta$. For the primary independent variables, we use four measures of firms' product specificity: The ratio of its R&D expenses to sales *R&D/Sales* (Column 1); The negative value of the firms' product similarity measure from Hoberg et al. (2014) (Column 3); The *TNIC-3 HHI* from Hoberg et al. (2014) (Column 5); And the ratio of the firms' total patents to sales (Column 7); In columns (2), (4), (6), and (8), a firm is considered to produce a high-specificity input if each respective measure of product specificity used above lies above the SIC-3 and year industry median of the share of differentiated goods. All non-dummy variables are standardized, and all models include SIC-3 industry and year fixed effects. Standard errors are clustered at the SIC-3 industry and year levels. We report t-statistics in parentheses.

	Emanating effects							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R&D/Sales	0.035							
	(15.717)							
R&D/Sales high		0.115						
		(8.392)						
Product diff.			0.019					
			(2.465)					
Product diff. high				0.064				
				(5.008)				
TNIC-3 HHI					0.019			
					(3.643)			
TNIC-3 HHI high						0.033		
						(2.717)		
Patents/Sales							0.017	
							(3.587)	
Patents/Sales high								0.445
								(14.277)
ln(Sales)	0.541	0.533	0.596	0.601	0.593	0.590	0.652	0.687
	(62.482)	(63.861)	(59.143)	(58.799)	(62.324)	(64.010)	(53.287)	(52.794)
Cash	0.042	0.035	0.082	0.083	0.071	0.069	0.086	0.061
	(8.073)	(7.493)	(12.953)	(13.920)	(11.715)	(11.658)	(10.422)	(7.516)
Altman-Z	-0.078	-0.074	-0.066	-0.068	-0.074	-0.073	-0.064	-0.056
	(-17.678)	(-16.866)	(-14.530)	(-14.610)	(-16.596)	(-16.608)	(-10.568)	(-9.152)
ROA	-0.024	-0.027	-0.054	-0.054	-0.052	-0.052	-0.056	-0.054
	(-10.727)	(-12.129)	(-14.695)	(-15.055)	(-15.090)	(-15.128)	(-9.840)	(-9.999)
MB	0.023	0.022	0.017	0.017	0.018	0.018	0.028	0.025
	(7.559)	(7.149)	(4.082)	(4.138)	(3.976)	(3.958)	(3.250)	(3.130)
Leverage	-0.024	-0.023	-0.040	-0.039	-0.042	-0.042	-0.025	-0.019
	(-5.869)	(-5.476)	(-8.299)	(-8.305)	(-8.904)	(-8.896)	(-3.755)	(-2.887)
SIC-3, Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58240	58240	47253	47253	46110	46110	16873	16873
Adjusted R^2	0.272	0.272	0.319	0.319	0.321	0.321	0.397	0.409

Table 7: Investment Spillovers, Product Specificity, and Trade Credit

This table presents OLS regressions of firms' trade credit on firm-specific emanating effects. In columns (1)-(2), (3)-(4), and (5)-(6), the dependent variable is, respectively: the average number of days it takes the firm to pay suppliers (*Payable Days*), the average number of days it takes customers to pay the firm (*Receivable Days*), and the difference between *Payable Days* and *Receivable Days* (*Net Trade Days*). The variable *Emanating effects* of firm j describes the cumulative investment spillovers originating from firm j to all other firms in the supply chain network, calculated as the sum of the indirect effects, i.e., $\sum_{j \neq i} (I_N - \rho S)^{-1}_{i,j} \beta$. All non-dummy variables are standardized, and all models include SIC-3 industry and year fixed effects. Standard errors are clustered at the SIC-3 industry and year levels. We report t-statistics in parentheses.

	Payable Days		Receivable Days		Net Trade Days	
	(1)	(2)	(3)	(4)	(5)	(6)
Emanating effects	0.031	0.024	-0.014	-0.016	0.035	0.028
	(10.770)	(8.840)	(-4.484)	(-5.098)	(12.628)	(10.794)
Partners' emanating effects		-0.039		-0.001		-0.043
		(-7.399)		(-0.225)		(-7.725)
ln(Sales)	-0.155	-0.156	-0.079	-0.074	-0.136	-0.138
	(-17.472)	(-17.309)	(-9.918)	(-9.101)	(-15.893)	(-15.670)
ROA	-0.080	-0.082	-0.012	-0.010	-0.077	-0.081
	(-5.965)	(-5.748)	(-1.330)	(-1.121)	(-5.865)	(-5.621)
MB	0.178	0.177	-0.040	-0.037	0.182	0.181
	(13.094)	(12.737)	(-6.126)	(-5.345)	(14.468)	(14.186)
Leverage	0.049	0.044	-0.010	-0.006	0.053	0.047
	(6.771)	(6.152)	(-2.074)	(-1.257)	(7.327)	(6.601)
SIC-3, Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61004	59473	61004	59473	61004	59473
Adjusted R^2	0.151	0.148	0.178	0.180	0.146	0.143

Table 8: Accounting for Industry Shocks

This table presents network regression estimates of the spillovers of financial constraints on supply chain partners' investment, as specified in Equation (1). The dependent variable is firm investment *(CapEx/L.Assets)* in all models. In columns (1)-(5), the independent variable *FC* represents five measures of financial constraints: the *WW* index from Whited and Wu (2006), the size-age (SA) index from Hadlock and Pierce (2010), the proportion of long-term debt due *(LTD due)* from Almeida et al. (2012), a text-based measure *(Delay Inv)* from Hoberg and Maksimovic (2015), and the sum of the first four (standardized) financial constraint measures *(FC combo)*. In columns (6)-(8), *FC* represents three measures of covenant-induced financial constraints: *C.viol* is an indicator variable equal to one if a firm reports a covenant violation in its 10-K or 10-Q; *C.CapEx* is an indicator variable equal to one if a firm has a capital expenditure covenant; *C.strict* is the probability that a firm violates at least one covenant in the next quarter. All regressions include industry-peer annual averages of the control variables of a firm's industry peer group (-i), as defined by firm i's Network Industry Classification (TNIC-3) in year t. Panel A reports estimates for ρ, which quantifies supply chain partners' investment complementarity. Panel B reports estimates of the average own-firm effect of own-firm financial constraints and other covariates on own-firm investment. Panel C reports estimates of the average indirect effect of financial constraints and other covariates on partners' investments. All non-dummy variables are standardized, and all models include year fixed effects. In parentheses, we report t-statistics based on standard errors calculated directly from the posterior distribution of MCMC parameter estimates.

	CapEx/L.Assets							
	WW	SA	LTD due	Delay Inv	FC combo	C.viol	C.CapEx	C.strict
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Investment Complementarity							
ρ	0.465	0.528	0.500	0.440	0.416	0.410	0.404	0.417
	(43.652)	(50.748)	(41.57)	(39.545)	(32.691)	(30.499)	(33.592)	(36.267)
	Panel B: Own-firm effects							
FC	-0.125	0.054	-0.017	-0.006	-0.045	-0.050	-0.058	-0.001
	(-12.245)	(6.517)	(-3.041)	(-0.961)	(-5.88)	(-6.64)	(-8.183)	(-0.067)
	Panel C: Indirect effects							
FC	-0.106	0.059	-0.017	-0.004	-0.031	-0.033	-0.038	0.000
	(-11.256)	(6.273)	(-3.017)	(-0.958)	(-5.644)	(-6.238)	(-7.588)	(-0.067)

Table 9: Contextual Effects: Investment and Partners' Financial Constraints

This table presents OLS regressions of firm investment on own-firm financial constraints (*Own-firm FC*) and the financial constraints of their supply-chain partners *(SC-Ptn FC)*. The dependent variable is firm investment *(CapEx/L.Assets)* in all models. In columns (1)-(5), we use five measures of financial constraints: the *WW* index from Whited and Wu (2006); the size-age (SA) index from Hadlock and Pierce (2010); the proportion of long-term debt due *(LTD due)* from Almeida et al. (2012); the text-based measure *(Delay Inv)* from Hoberg and Maksimovic (2015); and the sum of the first four (standardized) financial constraint measures *(FC combo)*. In columns (6)-(8), *FC* represents three measures of covenant-induced financial constraints: *C.viol* is an indicator variable equal to one if a firm reports a covenant violation in its 10-K or 10-Q; *C.CapEx* is an indicator variable equal to one if a firm has a capital expenditure covenant; *C.strict* is the probability that a firm violates at least one covenant in the next quarter. All models include lagged controls for firm *sales, cash holdings, Z-score, ROA, Market-to-book, and book leverage*. All non-dummy variables are standardized, and all models include year fixed effects. We report t-statistics in parentheses.

	CapEx / L.Assets							
	WW	SA	LTD Due	Delay Inv	FC Combo	C.Viol	C.CapEx	C.Strict
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Own-firm FC	-0.237	-0.097	-0.016	-0.003	-0.088	-0.049	-0.086	-0.023
	(-8.926)	(-5.080)	(-3.461)	(-0.328)	(-6.769)	(-9.399)	(-11.703)	(-1.827)
SC-Ptn FC	0.006	0.037	-0.019	0.018	0.007	0.031	-0.020	0.041
	(1.330)	(7.716)	(-3.633)	(2.782)	(0.964)	(5.359)	(-1.338)	(3.758)
ln(Sales)	-0.200	-0.124	-0.040	-0.051	-0.118	-0.065	-0.169	-0.160
	(-9.460)	(-7.809)	(-5.001)	(-5.408)	(-7.796)	(-7.582)	(-11.864)	(-12.611)
Cash	-0.161	-0.146	-0.099	-0.161	-0.136	-0.163	-0.119	-0.119
	(-20.478)	(-20.304)	(-14.359)	(-14.955)	(-11.609)	(-19.988)	(-11.973)	(-12.846)
Altman-Z	0.059	0.063	0.063	0.085	0.081	0.075	-0.006	-0.007
	(7.221)	(8.039)	(8.801)	(9.281)	(7.650)	(8.741)	(-0.624)	(-0.780)
ROA	-0.061	0.018	0.040	0.019	0.022	0.014	0.061	0.060
	(-3.987)	(2.246)	(3.713)	(1.565)	(1.780)	(1.503)	(4.420)	(4.285)
MB	0.135	0.135	0.118	0.128	0.118	0.126	0.125	0.124
	(10.181)	(8.618)	(8.464)	(5.873)	(6.177)	(6.179)	(6.848)	(6.808)
Leverage	-0.015	-0.019	-0.024	0.001	-0.002	0.009	-0.010	-0.012
	(-2.243)	(-2.625)	(-3.334)	(0.113)	(-0.160)	(1.101)	(-0.968)	(-1.495)
Observations	114216	122400	92843	52025	39113	67071	31402	31402
Adjusted R^2	0.059	0.053	0.042	0.051	0.044	0.055	0.075	0.070

Internet Appendix

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Internet Appendix Overview

The goal of this study is to quantify financial constraint spillovers via corporate investment externalities using a network approach. To increase confidence in our conclusions, we explore several variations in the specifications reported in the main text. We present many of these results in this Internet Appendix. All other results are available upon request. The Internet Appendix also addresses additional questions that the reader may have regarding our methods, such as the sensitivity of our analysis to the precise construction of the supply chain network, fixed effects transformations, and details regarding standard error calculations.

This Internet Appendix is divided into the following sections. Section A provides anecdotal evidence on the coordination of investment decisions among supply chain partners. Section B describes the role of fixed effects in identifying financial constraint spillovers in the context of our study. Section C provides detailed information about the network characteristics described in Section 1.1 of the main text and describes additional characteristics. Section D provides the analysis using alternative supply chain network constructions. Section E describes homophily/heterophily in firms' investment levels. Section F describes how financial constraints affect their propensity to form new partnerships. Section G details the calculation and validity of standard errors in our MCMC estimation procedure. Section H provides a description of firms' trade credit. Finally, Section I includes a brief discussion of additional robustness tests.

A. Anecdotal Evidence

Capital investment is one of the most important processes in industrial production and economic growth. Production involves several firms that each produce unique inputs that contribute to the final product. A large literature on the boundaries of the firms considers when each input should be produced by the same firm or by distinct firms. When inputs are produced by distinct firms, the firms must coordinate investment and share information about demand and capacity constraints to synchronize production.

The following articles provide anecdotal evidence from various outlets regarding the coordination in investment of supply chain partners, as well as the role of partners' financial constraints on firms' investment policy. While these anecdotes do not prove that similar coordination and constraint patterns occur for a broad cross-section of firms, they support the premise and conclusions of our analysis as well as the modeling choices we adopted. Specifically, these anecdotes support the modeling of a contemporaneous relation in supply-chain partners' investment spending in Equations (2) and (5) of the main text.

- Liker and Choi (2004) highlight the strategic interactions between automakers and their supply chain partners. Many automakers hold annual meetings with suppliers to coordinate their investment and production strategies. For example, "Honda invites one supplier from each region to the global jikon in Tokyo every year; it held one-on-one meetings with 35 North American suppliers in 2003. The discussions don't extend to operational matters but instead cover only top-level strategic issues. Honda tells the suppliers what kinds of products it intends to introduce and what types of markets it plans to cultivate in the coming years. The company then discusses the supplier's strategic direction in terms of technology, globalization, major investments (such as capital goods and plant expansion), and ideas about new products."

  In the article, Liker and Choi (2004) add that "when Toyota decided to make cars in Kentucky, it picked Johnson Controls to supply seats. Johnson Controls wanted to expand its nearby facility, but Toyota stipulated that it shouldn't, partly because an expansion would require a large investment and eat into the supplier's profits. Instead, the Japanese manufacturer challenged Johnson Controls to make more seats in an existing building. That seemed impossible at first, but with the help of Toyota's lean-manufacturing experts, the supplier restructured its shop floor, slashed inventories, and was able to make seats for Toyota in the existing space."

- Wal-Mart has been one of the driving forces behind the adoption of radio-frequency identification tags (RFID) technology. Back in 2004, the retail giant coordinated with hundreds of suppliers to facilitate the introduction of the technology across all distribution networks. "Wal-Mart expects the number of suppliers tagging cases and pallets to expand every few weeks – particularly those selling electronics or large items such as bicycles or lawnmowers."[23]

- Despite the surge in consumer demand during the Covid-19 pandemic, firms have been reluctant to invest and increase their capital spending that is necessary to raise output, arguing that rising costs and limited access to raw inputs would not be able to convert into increased production. "While economists expect companies would have sunk money into expanding capacity, investment spending in many of the world's largest economies has instead stalled [...] Matilde Poggi, a winegrower based in Cavaion Veronese, in northern Italy, says that many of the country's vineyard owners just can't expand because they are struggling to get their hands on needed equipment and materials."[24]

- To meet increasing demand for their products during the pandemic, firms co-invest with their suppliers. "[Black & Decker] is seeking electric battery and computer chip makers that would agree to supply components in return for an investment." According to Chief Financial Officer Donald Allan Jr. "Black & Decker, which has budgeted for roughly $500 million in capital expenditures this year, plans to dedicate about 10% to 15% of that to supply-chain partnerships and other related initiatives." "We will co-invest," Mr. Allan said. "If it costs $100 million to set up a line, we will put in $50 million."[25]

- The global COVID pandemic has caused a rise in demand for goods due to a substitution away from services. This shift in demand patterns resulted in upstream propagation in investment through supply chain partnerships. For example, ship owners are investing heavily in vessels to accommodate this surge in demand. The shipowners' investment spending led to and increase in shipyards' investment spending in order to raise production capacity to meet demand for new vessels.[26] At the same time, investment spending into expanding shipyard and other facilities also affected the suppliers of the crane rail clamps market.[27]

[23] See https://www.wsj.com/articles/SB108491126556814808.
[24] See https://on.wsj.com/35eiJDd
[25] See https://on.wsj.com/3G2oTmE.
[26] See https://on.wsj.com/349G6xa.
[27] See https://bit.ly/3IBKDaP.

- Suppliers' credit constraints affect customers' production and investment decisions."[Miguel] Patricio, who took over as Kraft Heinz's CEO last year, said its packaged food units are working in three shifts to meet high demand. Patricio said he considers Kraft Heinz to be a "safe haven" but is worried about the effect of credit constraints on its suppliers, adding that he is looking at ways to address the issue."[28]

- The global surge in demand for chips affects Intel's decision to exploit its financial position and expand production capacity of chips with aggressive investment spending. "Everything is becoming more digital and we are saying Intel is stepping into that gap aggressively to help provide the capacity that's needed," Intel Chief Executive Pat Gelsinger said as he rolled out his turnaround plan for the company. The embrace of more digital tools fueling that demand, he said, was only accelerated by the pandemic.[...] Microsoft Corp. CEO Satya Nadella, joining his Intel counterpart by video at the chipmaker's strategy rollout, said that "we're entering a complete new era as computing becomes embedded in our world."[29]

B. Discussion on Fixed Effects Transformations

Throughout our analysis, we employ year fixed-effects transformations. Our lack of fixed effects at the firm- or industry-level may appear somewhat jarring relative to the growing convention in corporate finance (see Grieser and Hadlock, 2019). However, incorporating firm- and industry-level fixed effects in a network framework introduces various challenges about the sources of variation. In our setting, these transformations attenuate the main results, albeit all the primary results remain statistically significant. Yet this pattern is not surprising given the relationships between firms or industries and the supply chain. Ultimately, it is worth weighing the benefits and the costs of imposing fixed effects transformations on the data before drawing conclusions based on the corresponding estimates.

In our setting, there are valid concerns regarding unobserved heterogeneity that may be related to financial constraints, such as managerial quality or risk tolerance. Or, as illustrated by Farre-Mensa and Ljungqvist (2016), financial constraints may be correlated with unobservable charac-

[28]See https://reut.rs/3u33xTU.
[29]See https://on.wsj.com/3u3iaXu.

teristics relating to the stage of a firm's life cycle. The extent to which the investment spillovers of financial constraints that we document reflect a nuanced relation between these omitted characteristics and partner firm investment decisions is ambiguous. Fixed effects transformations are theoretically appealing because they can *purge* these potential sources of confounding variation. However, this solution is subject to several practical limitations, and therefore, should be applied with caution (Roberts and Whited, 2012).

First, fixed effects transformations only eliminate potentially confounding heterogeneity if it is perfectly constant. Grieser and Hadlock (2019) illustrate that estimates become highly unstable if this assumption is even moderately violated. Potentially confounding variation in our setting (e.g., a firm's stage of life cycle) is likely to evolve over time, suggesting that fixed effects are unlikely to address heterogeneity concerns. Second, firm and industry fixed effects transformations impose a strict exogeneity assumption. Strict exogeneity is violated in our setting if corporate investment decisions depend on anticipated financial constraints, which, based on anecdotal evidence, is likely to be the case. We also find empirical evidence that this assumption is violated according to the tests outlined in Grieser and Hadlock (2019). The authors demonstrate that fixed effects transformations induce in a severe and unpredictable estimation bias when strict exogeneity fails. Collectively, these two points suggest that imposing fixed effects transformations provide little benefit in our setting since the required assumptions are not met.

Third, notwithstanding violations of the underlying assumptions, granular fixed effects transformations can lead to an over-differencing of the data, in which variation necessary for identification is purged along with potentially confounding unobserved heterogeneity. In our analysis, network regressions primarily rely on cross-sectional variation for identification LeSage and Pace (2009). Firm and industry fixed effects transformations, however, eliminate a substantive portion of this variation, which can lead to weak identification. This problem is articulated by Roberts and Whited (2012), who state "if the research question is inherently aimed at understanding cross-sectional variation in a variable, then fixed effects defeat this purpose."

Fourth, as discussed in Section 2, identification in a network regression comes from structure of the underlying network. Grieser et al. (2022a) illustrate that network intransitivity enhances identification in a network regression by exploiting the variation in each firm's unique set of supply chain relationships. Intransitivity, implies that a partner of a partner is not necessarily a direct partner. Since the supply chain network does not exhibit a group structure (firm membership into groups is binary and transitive), common shocks to a supply chain for instance, cannot drive all the network effects that we document. More intransitive networks make it less likely for common shocks to drive complementarity in investment decisions for the full cross section of supply chain partners. The network statistics in Table 1 illustrate that our supply chain network is highly intransitive with a clustering coefficient of 0.072, thus lending confidence that our estimates cannot be driven by common shocks, that would potentially be controlled for via fixed effects transformations.

Finally, our focus is on the *indirect effects* of financial constraints imposed on supply chain partner' investment behavior. Hence, endogeneity concerns regarding unobserved heterogeneity for firm i must relate to its entire set of supply chain partners' investment behavior in order to affect our analysis. While this relation is plausible, it is less clear what specific problem fixed effects are meant to address in the context of *indirect effects*. Furthermore, supply chain network regressions—by construction—exploit variation stemming from partner firms' covariates. A firm's supply chain partners i) are typically unique, ii) change through time, iii) come from many different industries, and iv) may consist of firms that enter and exit the sample for different periods. Thus, it is unclear how a simple difference imposed by a fixed effects transformation at the firm or industry level will impact the relation between a firm's variables and the variables of its entire supply chain for such a complex and evolving web of supply chain connections.

We do not intend to dismiss the problems that fixed effects transformations are typically meant to address. However, given the collective problems associated with fixed effects transformations in our setting, we opt for alternative identification techniques. First, we employing 11 different proxies for financial constraints throughout our analysis. Each measure exhibits unique strengths and weaknesses. For example, *CapEx. Cov* contains explicit restrictions on capital investment, which increases confidence that the effects we document operate through investment externalities. The variable *LTD due* is plausibly exogenous to the focal firm at the time the debt is coming due, and accordingly, is the primary (exogenous) independent variable of interest in recent studies

(Almeida et al., 2012; Carvalho, 2015). For a given endogeneity concern to explain all of our results, it must be the case that all 11 measures of financial constraints that we employ are subject to highly correlated concerns. It is also worth reiterating that variables that are plausibly exogenous to the focal firm are even more likely to be exogenous to a firm's supply chain partner.

To bolster our analysis, we also implement two novel network RDD approaches that model spillovers in treatment effects for covenant violations in Section 4.2. These approaches compare the outcomes of firms just above and below a covenant threshold (based on a variety of observable characteristics in the polynomial approach). The identifying assumption of the network RDD (polynomial network RDD) analysis is that the function linking potentially confounding variation to investment decisions for firm i and partner j does not simultaneously satisfy the following four criteria: i) it is discontinuous exactly at the covenant threshold for firm i, ii) it is also discontinuous at partner j's a priori investment level, iii) the discontinuity in unobservable variation decreases investment for both firm i and firm j, and iv) the intensity of the discontinuity effect in confounding variation increases with the proportions of firm i's and firm j's partners that are treated. Consequently, the network RDD strongly mitigates concerns that the effects we document are driven by unobservable characteristics that relate a firm's constraints and its investments to partner firms' investment.

While each of the tests that we employ may exhibit some shortcomings, we believe the totality of our evidence offers strong support for investment spillovers induced by financing constraints. Nonetheless, fixed effects transformations impose a distinct set of assumptions compared to our analysis, and therefore, may illustrate the robustness of our estimates. As such, we repeat our analysis using firm-, industry-, and industry $\times$ year fixed effects transformations. We find that, in most cases, the *indirect effects* of financial constraints remain statistically significant, but the economic magnitudes of the estimates for investment complementarity among supply chain partners that operate in a specific SIC industry are, as expected, smaller.

C. Supply Chain Network Topology

The premise of our study is that firm investment decisions are influenced by those of other firms. In the main text, we emphasize the necessity of a network approach in studying this topic: even if firms only interact with direct peers, corporate decisions can depend on the entire supply chain network through higher-order chains of connection. Acemoglu et al. (2012) illustrate that the cumulative impact of these higher-order interconnections can be substantial. Networks provide a natural way to represent the structure of these firm interactions and to account for higher-order connections. For a more in depth review of measures of network topology, we refer the reader to Jackson (2010).

For the summary statistics provided in this section, we use an adjacency matrix $S^A \equiv [s^A_{ij}]$, where $s^A_{ij} = 1$ if $\textit{directed score}_{ij} > 0$, and $s^A_{ij} = 0$ otherwise. We start by summarizing how well connected the average node (firm) is in the adjacency network S^A. For each firm i in year t we calculate *degree centrality* as:

$$\text{degree centrality} = \frac{d_i^k}{n-1}, \qquad d_i^k = \#\{j : p_{i,j} > 0\}. \tag{1}$$

Degree centrality measures the number of direct (first order) supply chain relationships, expressed as a fraction of the total number of possible first order relationships in the network. Thus, degree centrality ranges in value from 0 to 1. A value of 1 indicates that a node has first order connections with all other nodes, and a value of 0 indicates that a firm has no first order relations. In Table 1, Panel A, we report the average Degree centrality (calculated each year) across all firm-years separately for the Compustat, FactSet, and VTNIC networks, along with the combined network. The distribution of degree centrality using the three different sources produce relatively similar distributions of degree centrality. Networks that use actual supply chain relationship data (i.e., Compustat and FactSet) are more similar and relatively more sparse than networks based on estimated relationships (i.e., VTNIC).

Average *degree centrality* represents the average centrality across all firms in the supply chain network. In a given year, the average firm in our sample is directly connected to approximately 0.6% of all other firms in Compustat (or 45 partners, on average). This summary measure obfuscates whether the average is driven by a few firms with very large (low) degree centralities, or several firms with a modest degree centralities, and so on. In Figure (11.a) we plot the degree distribution across all firms. Most firms exhibit low degrees (only directly connected to a few firms) with few firms having very high degrees. As illustrated in Figure (11.b), the combined network substantively reduces the number of firms with low degrees, thus reaffirming the value in combining multiple sources of information on the supply chain network.

Another common measure of interest is the *clustering coefficient* (also known as the *transitivity* of the network), which measures the probability that two randomly selected nodes with a common link are also directly linked, i.e., the fraction of firms with a common supply chain partner that are also partners. Formally, the individual clustering coefficient of firm i is defined as

$$IC_i = \frac{\sum_{j \neq i; k \neq j; k \neq i} s^A_{ij} s^A_{ik} s^A_{jk}}{\sum_{j \neq i; k \neq j; k \neq i} s^A_{ij} s^A_{ik}}, \tag{2}$$

The individual clustering coefficient ranges in value from 0 to 1. A value of 1 indicates that all of firm i's first order peers are also first order peers of each other (i.e., a firm belongs to a transitive group). In Table 1 we report the average individual clustering coefficient, which ranges from 0-66%. A related measure is the *overall clustering coefficient* which extends the sum over all firms

$$IC_i = \frac{\sum_{i; j \neq i; k \neq j; k \neq i} s^A_{ij} s^A_{ik} s^A_{jk}}{\sum_{i; j \neq i; k \neq j; k \neq i} s^A_{ij} s^A_{ik}}. \tag{3}$$

The overall clustering coefficient describes the degree of transitivity of the entire network in a scalar summary. A perfectly transitive network would exhibit a clustering coefficient of 1. There is a wide range of values for the overall clustering coefficient, ranging from 2.2%-3.7%. While the two measures are related, the overall clustering coefficient gives more weight to high-degree nodes than the average individual clustering coefficient. Importantly, in nearly all cases the clustering coefficients are below 3.7% for the overall clustering coefficient and below 8% for the average individual clustering coefficient. Overall, the data indicate that supply chain networks are highly intransitive.

Next we consider the average shortest path length to connect two firms. A *path* is a sequence of nodes with the property that each consecutive pair is connected by an edge (relation). The *shortest path* between nodes i and j is the fewest number of edges required to create a connection. A path length of 1 suggests that two firms are direct peers. The concept that a path length can be greater than 1 illustrates the importance of using a network structure. A network structure allows for the ability to study indirect relationships whereby firms are indirectly connected through common peers, common peers of peers, and so on. For instance, if firm i is related to firm j and k, but firms j and k are not directly related, they may still exert influence on each other through their influence on firm i. In this case, j and k would have a path length of 2. The average shortest path length is summarized in Table 1, Panel A. We find that the average (shortest) path length throughout the sample is 2.92, and it ranges from 1-7.

Finally, while the clustering coefficients provide summary measures of the degree of transitivity within first order relationships, they do not describe the degree to which all firms are connected in the network. A network is *fully connected* if every node can reach every other node through at least one path. We create the variable *connected* to represent the percentage of node pairs that have at least one path connecting them. The average *connected* value in the sample is 0.99, which means that 99% of all nodes are connected through at least one path. The *largest component* of a network is the largest subset of nodes that create a fully connected group. We also present summary measures of the diameter (i.e., the largest path required to connect firms within a component) of the largest component for each year.

D. Alternative Supply Chain Network Constructions

Spatial econometric methods offer substantial advantages over traditional techniques for studying externalities by relaxing the assumption of cross-sectional independence. However, making assumptions regarding the structure of firm networks is unavoidable in order to achieve identification in the presence of firm interaction (Bramoullé et al., 2020). Thus, a natural concern is how well our results hold up under alternative supply chain network specifications. For robustness, we consider several variations in sample periods and construction of the supply chain network.

In Table IA.1 we report estimates of the specifications in Table 2 using the full network that includes all firms' partners for the entire sample period (1989-2020), rather than the 2003-2020 period (FactSet linkages are available only after 2003). In Table IA.2 we repeat our baseline specification using a supply chain network defined only for Compustat and FactSet relationships, and in Table IA.3 we repeat our baseline specification using only the closest 30 supply chain relationships based on VTNIC.[30] Finally, in Table IA.4, we consider an alternative equal weighting scheme for the supply chain network that we employ in our main analysis. That is, rather than weighting each relationship by their sales intensity, every partner receives $1/N_i$ weight where N_i is firm i's number of partners. This structure is effectively an adjacency matrix that is then row-normalized to have row sums of unity. Each of these alternatives yields qualitatively similar results to those of Table 2 of the main text. These results increase our confidence that our estimates are not driven by a specific construct that we have chosen to employ for the bulk of our analysis.

The similarity in estimates for alternative supply chain constructs is consistent with econometric theory. Indeed, LeSage and Pace (2011) show that if W_y and $\tilde{W}_y$ are highly correlated, then "it would seem difficult to reach materially different conclusions about the partial derivative impact of changes in the explanatory variables in the matrix X on the dependent variable y (which LeSage and Pace (2009) label effects estimates) from models based on W_y and $\tilde{W}_y$." Additionally, Grieser et al. (2022a) illustrate with simulated data estimates are not overly sensitive to the precise choice of their competitor network in the context of peer effects in corporate financial policies. They argue the main reason is that the networks are highly correlated. In additional analysis, the authors add noise to the network, and show that the differences in results become larger as the noise added to the network increases.

To further explore this point, we consider the overlap in the supply chain network that we consider in the main text and in the alternative constructs that we consider in the Internet Appendix. For a more in depth discussion of network correlations, see Grieser et al. (2022b), which we follow in this section. We start by considering firm outcomes that, by construction, are independent. That is, we assign each firm a random outcome $\mu_j \overset{\text{i.i.d.}}{\sim} N(0,1)$, $j = 1, \dots, N$. We then calculate the average outcome across each firm's supply chain partners: $S\mu$. The final result $S\mu$ is merely a vector. Thus, we can calculate the correlations between $S\mu$ for different choices of S.

In the extreme case that a firm does not have any supply chain partners in common across different choices of S (say S and $\tilde{S}$), then the two averages $S_i\mu$ and $\tilde{S}_i\mu$ will not contain any common μ_j terms. If this is the case for all firms, then $corr(S\mu, \tilde{S}\mu) = 0$. However, greater consistency in supply chain partner assignment across different choices of S will lead to $S_i\mu$ and

[30]This specification is computationally intensive and not feasible to repeat for all of our analysis.

$\tilde{S}_i\mu$ containing more common nonzero weights on the same μ_j. Thus, the final sums across partner firms will be closer in value for the different constructs. Overall, greater consistency in supply chain partner assignment will lead to a higher correlations between $S_i\mu$ and $\tilde{S}_i\mu$. As previously discussed, higher correlations in network outcomes will expectedly yield similar estimates.

Table IA.5 presents correlation estimates from the exercise described above for our main network specification (Main Network), the suppliers (downstream flow) network, customers (upstream flow) network, the network of Compustat and FactSet relationships, Compustat only, FactSet only VTNIC, and the full network using all three sources and that does not exclude any partners (Full Network). The main network and supplier network exhibit the largest correlation ($corr = 0.9$), which loosely interpreted, indicates that 90% of partners in our main network are also partners in the Downstream network. The lowest correlation is between VTNIC and the Main Network ($corr = 0.49$), and most correlations are above 0.7. As in Grieser et al. (2022b), we repeat the randomization procedure 1,000 times for each estimate and we report the average estimate across all draws. The subsequent Columns of IA.5 report the correlations in second order and third order supply chain partnerships. Again, most of the correlations are quite high, suggesting that there is substantial consistency across different constructs.

The investment outcomes that we observe are not random, and they take all orders of connection into account. Accordingly, we repeat the exercise for investment spending, rather than randomly assigned outcomes. Specifically, we compute the average investment outcomes for each firm–year according to each of the row normalized supply chain network definitions. We summarize the correlations in these vectors for corporate investment in Table IA.5. The correlations for investment outcomes is substantially higher than for random outcomes in virtually all cases. One explanation is that firms may improperly be classified as 4th order peers when they are really 2nd or 3rd order peers. Thus, they would not enter the calculations for the randomization procedure, but they would impact the final investment outcome through the cumulative process highlighted in Section 2 of the main text. In a sense, using a real outcome variable mitigates some imperfections in the assignment of supply chain partners, since unclassified partners could still be connected through higher order connections.

E. Network Homophily

In this section, we aim to demonstrate that our results are not solely driven by the formation of networks, but rather by the interactions that occur between firms after the network is formed. To achieve this goal, we utilize exponential random graph models (ERGMs), which are commonly used to analyze network formation (e.g., Robins et al., 2007; Ahern and Harford, 2014; Kim et al., 2016). ERGMs generalize logistic regression models by incorporating simultaneous dependence between all nodes (i.e., firms) in a network when predicting binary outcomes (i.e., whether two firms become trade partners). Unlike logistic regression models, ERGMs account for effects on (potential) higher-order supply chain connections. For instance, when firm A creates a trade partnership with firm B, it systematically excludes the possibility of forming a partnership with firm C. In other words, when Apple or Dell choose to purchase processors from Intel, they simultaneously choose not to purchase processors from AMD or other manufacturers, and thus influence how other connections are formed. By taking into account these higher-order connections, ERGMs can provide a more accurate understanding of how decisions to form supply chain partnerships are interrelated.

Table IA.6 presents ERGM estimates for the impact of investment and constraint level similarity on partnership formation. We include two edge (firm-pair-level) characteristics. In Column (1) we consider the absolute value of the difference in investment levels for firms i and j. Column (2) includes the absolute value of the difference in financial constraint levels for firms i and j. Column (3) includes both edge characteristics.

The estimates represent the marginal effect of the level difference on the conditional log-odds that two firms form a supply chain partnership. For example, in Column (1), a standard deviation difference in investment between two firms increases the probability of being partners by 0.5% (i.e., a 0.15 standard deviation increase in the probability of being connected).[31] Evaluating the log-odds ratio at the intercept estimate (*edges*) captures the homogeneous probability of forming a marginal tie (partnership) if a random *edge* (firm) is added to the network (see Ahern and Harford, 2014).

[31] To calculate the average marginal effect of a one standard deviation change in $|I_i - I_j|$, we employ the delta method ($\Delta X = 1\sigma$), evaluated at the median, for the inverse logit function: $\text{p(new tie)} = exp(\text{edges} + \beta|I_i - I_j|)/(1 + exp(\text{edges} + \beta|I_i - I_j|)$.

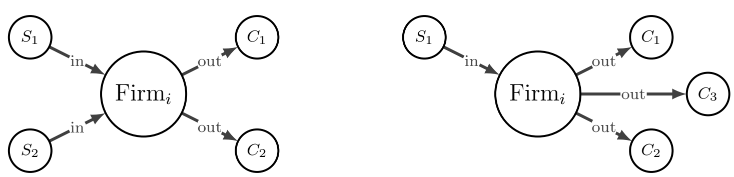
While this evidence may not be conclusive, it does offer some preliminary support in allaying concerns regarding homophily.

F. Upstream vs. Downstream Network Formation

Our analysis provides robust evidence that financial constraints generate considerable spillovers for supply chain partners' investment decisions. Accordingly, firms plausibly consider potential spillover effects when deciding whether to partner with a constrained customer or supplier. To examine this possibility, we estimate an ERGM with nodal (i.e., firm-level) characteristics.

Table IA.7 reports ERGM estimates for the effects of financial constraints on supply chain network formation. For a given firm, we separate network ties (partnerships) into upstream ties (i.e., buying inputs from new suppliers) and downstream ties (i.e., distributing inputs to new customers). This distinction allows us quantify the effects of constraints on upstream and downstream network formation separately. The estimates for *FC-upstream* and *FC-downstream* describe the effect of financial constraints on the propensity to form partnerships with new suppliers and new customers, respectively. Tightening financial constraints for a given firm leads to fewer upstream connections and to more downstream connections. Figure IA.1 depicts this relationship: firm i loses supplier S_2 but gains customer C_3 after becoming constrained.

Figure IA.1: Directed Supply Chain Network Formation



(1.a) Unconstrained **(1.b)** Constrained

The upstream network formation results are consistent with suppliers avoiding constrained customers that may not be able to pay for inputs promptly (a supply-side effect) and with constrained firms seeking out fewer suppliers when they have less capital for purchasing inputs (a demand-side effect). The downstream network formation results suggest either that constrained firms seek out other customers (a supply-side effect) or that firms prefer to buy from constrained suppliers (a demand-side effect). The supply-side effect is consistent with constrained firms engaging in myopic behavior, perhaps by reducing prices to generate more short-run cash flows. The demand-side effect is consistent with firms exploiting bargaining power with weaker partners (Dasgupta and Kim, 1997; Murfin and Njoroge, 2015).

Table IA.7 also provides indirect evidence that firms minimize potential disruptions to investment opportunities by avoiding financially constrained customers. These effects can be exacerbated if switching partners is costly, as argued by Titman and Wessels (1988) and Boehm et al. (2019). Additionally, firms concerned with quality or reputation may avoid forming relationships with constrained partners that may have less of an incentive or ability to maintain certain standards (Maksimovic and Titman, 1991).

G. Standard Errors in Network Regressions

Network regressions cannot be estimated using standard methods such as OLS due to the presence of nonlinear parameters in the model. We use an MCMC approach that exploits numerical features of the likelihood function for a large range of proposed parameter values to estimate these models. A key advantage of the MCMC procedure is that it produces an entire distribution of parameter estimates proportional to their likelihood of explaining the observed data. Thus, the estimates can be considered samples from the true probability distribution of the parameters under the assumption that the data provide a representative sample from the population. Consequently, calculating confidence intervals around the mean (median) estimates from the parameter distribution is straightforward and akin to bootstrapped confidence intervals. The standard errors for the structural parameters are simply the standard deviation of the corresponding parameter estimates over 1,000 iterations of the MCMC procedure. The confidence intervals and t-statistics are derived from these standard errors without the need for any further adjustments.

We also report scalar summary measures of the non-linear direct and indirect effects estimates. These estimates are a function of the structural parameter estimates and the supply chain matrix S. For the case of the SAR model, the point estimates correspond to the partial derivative:

$$E[\partial y/\partial X_r] = (I_N - \rho S)^{-1}\beta_r \tag{4}$$

This partial derivative is a matrix so that the (i, j) entry is the effect of perturbing firm j's r^{th} covariate on firm i's outcome variable. The average of the diagonal elements of this matrix provides a scalar summary point estimate for the direct effect, whereas the sum of the off-diagonal elements from each row (averaged across all rows) is the summary point estimate for the indirect effect.

Note that based on the MCMC procedure we obtain 1,000 draws of the parameters (ρ, β, σ^2). We therefore implement the following approach to calculate empirical estimates of dispersion:

1. Use the 1,000 parameter values to calculate 1,000 matrices of marginal effects based on the analytical matrix expressions for the model partial derivatives shown in (4). Note that each matrix represents one possible draw of the parameters, and hence one possible value of the marginal effects.

2. For each of the 1,000 different matrices reflecting all marginal effects, calculate the scalar summary estimates of the direct effects using the average of the main diagonal elements, and the average of the cumulative sum of off-diagonal elements from each row as the indirect effect estimate.

3. Use the set of 1,000 scalar summary estimates to calculate an empirical measure of dispersion (e.g., standard deviation or variance) for the scalar summary estimates of the direct and indirect effects. These can be used to construct $t-$statistics, lower and upper confidence intervals, etc.

H. Trade Credit and Partner Constraints

Extending trade credit is an alternative to avoiding partnerships with constrained firms. Trade credit potentially alleviates partners' constraints, minimizing disruptions to the quality and quantity of inputs the partner produces (purchases). Although plausible, this proposition is not apparent, as highlighted by evidence that firms may prefer to exploit partners' financial constraints to gain bargaining power (Dasgupta and Kim, 1997; Murfin and Njoroge, 2015). We consider these possibilities by examining the relationship between a firm's financial constraints and trade credit received from supply-chain partners.

We define *accounts payable days* as the average number of days it takes the firm to pay suppliers, and we define *accounts receivable days* as the average number of days it takes customers to pay the firm.[32] Table IA.8 reports OLS regression results of own-firm *accounts payable days* and own-firm *accounts receivable days* on own-firm financing constraints, respectively, in Panels A and B. The models employ the eight financial constraint measures from Table 2. The estimates suggest that tightening a firm's constraints by one standard deviation is, on average, associated with 15 additional *accounts payable days* (i.e., constrained buyers pay later) and 5 fewer *accounts receivable days* (i.e., suppliers receive payment faster).

Although the estimates warrant notable caveats (discussed below), the pattern highlighted in Table IA.8 helps validate our earlier analysis. In particular, although the evidence is indirect, the findings are consistent with firms extending trade credit to mitigate the potential effects of partners' constraints on own-firm investment opportunities. The results also support recent evidence that principal customers pay more promptly when suppliers are in financial distress (Banerjee et al., 2004). Moreover, trade credit serves a financial-intermediation role whereby well-capitalized firms extend financing to partner firms with insufficient access to credit markets Petersen and Rajan (1997). The evidence suggests that extending trade credit may indeed be an alternative to avoiding partnerships with constrained firms. Thus, these results may potentially attenuate the effects presented in Table IA.7.

The trade-credit analysis is more indirect than our analyses on corporate investment decisions. Investments represent a *common* outcome variable that supply-chain partners jointly determine. The common outcome variable yields Equation 1, which allows us to solve out the ensuing simultaneity problem, as in Equation 2. Although trade credit is also jointly determined by supply-chain partners, the outcome variable is not common across partners since one firm's receivables is a partner's payables. Thus, trade credit lacks a natural network regression specification, which precludes the ability to directly model financial constraint spillovers through trade credit decisions, as we did for investment decisions.

[32] We construct the variables in this analysis following Murfin and Njoroge (2015). The variables *accounts receivable* and *accounts payable* days correspond, respectively, to *buyer payable* and *supplier receivable* days. Our distinct naming convention emphasizes that the regressions presented in Table IA.8 estimate a firm-centric relation. The Internet Appendix provides additional details regarding the analysis in this section.

I. Additional Tests

Our main results are also robust to the alternative sample period 1998-2020, alternative winsorization schemes, and most variations in control variables (including specifications without controls). In our setting, contextual effects refer to the situation in which a firm's outcomes depend directly on partners' covariates. Overall, our findings in these extra analyses continue to strongly support the notion that financial constraints generate substantive supply chain spillovers.

- Table IA.9: This table presents OLS regressions of supply-chain partners' length of relationship on measures of input specificity.
- Table IA.10: This table presents the complete set of estimates used for the plot in Figure 3 of the main text.
- Table IA.11: This table presents the annual share of firms' supply chain partners that do not extend a supply-chain relationship from the previous year.
- Table IA.12: This table presents the annual share of firms' supply chain partners that do not extend a supply-chain relationship from the previous year.
- Table IA.13: This table shows summary statistics for Compustat's quarterly dataset.
- Figure IA.2: This figure plots the residuals from a local linear network RDD of investment on firms' distance from covenant thresholds as outlined in Section 4.2.1.
- Figure IA.3: This figure plots the propagation of a shock through a simple supply-chain network.

Table IA.1: Financial Constraints Spillovers - Extended Sample Period (1989-2020)

This table presents network regression estimates of financial constraint spillovers via supply chain partners' investments, as specified in Equation (1). The dependent variable is firm investment *(CapEx/L.Assets)* in all models. The independent variable *FC* represents five measures of financial constraints: the *WW* index from Whited and Wu (2006), the size-age (SA) index from Hadlock and Pierce (2010), the proportion of long-term debt due *(LTD due)* from Almeida et al. (2012), a text-based measure *(Delay Inv)* from Hoberg and Maksimovic (2015), and the sum of the first four (standardized) financial constraint measures *(FC combo)*. Panel A reports estimates for ρ, which quantifies supply chain partners' investment complementarity. Panel B reports estimates of the average direct effect of own-firm financial constraints and other covariates on own-firm investment. Panel C reports estimates of the average indirect effect of financial constraints and other covariates on partners' investments. All non-dummy variables are standardized, and all models include year fixed effects. In parentheses, we report t-statistics based on standard errors calculated directly from the posterior distribution of MCMC parameter estimates.

	CapEx/L.Assets				
	WW	SA	LTD DUE	Delay Inv	FC (combo)
	Panel A: Investment Complementarity				
ρ	0.287	0.307	0.299	0.364	0.356
	(53.083)	(60.665)	(48.074)	(44.557)	(36.09)
	Panel B: Own-firm Effects				
FC	-0.211	-0.081	-0.016	-0.003	-0.075
	(-34.391)	(-14.369)	(-4.656)	(-0.585)	(-11.68)
ln(Sale)	-0.192	-0.114	-0.054	-0.048	-0.102
	(-36.408)	(-20.798)	(-13.48)	(-9.132)	(-14.5)
Cash	-0.158	-0.144	-0.105	-0.151	-0.125
	(-47.019)	(-42.881)	(-28.839)	(-28.421)	(-22.469)
Z-score	0.060	0.061	0.069	0.083	0.092
	(17.473)	(16.796)	(16.899)	(16.533)	(14.415)
ROA	-0.051	0.010	0.030	0.008	-0.013
	(-11.928)	(2.839)	(7.161)	(1.571)	(-2.168)
MB	0.142	0.140	0.128	0.131	0.122
	(43.421)	(43.715)	(31.961)	(25.694)	(21.018)
Leverage	-0.013	-0.018	-0.023	-0.002	-0.004
	(-3.714)	(-5.609)	(-5.917)	(-0.456)	(-0.753)
	Panel C: Indirect Effects				
FC	-0.083	-0.035	-0.006	-0.001	-0.040
	(-26.295)	(-13.831)	(-4.608)	(-0.586)	(-10.468)
ln(Sale)	-0.075	-0.049	-0.023	-0.027	-0.055
	(-26.839)	(-18.912)	(-12.479)	(-8.793)	(-12.635)
Cash	-0.062	-0.062	-0.043	-0.084	-0.067
	(-29.311)	(-29.165)	(-21.491)	(-21.164)	(-16.872)
Z-score	0.024	0.027	0.029	0.046	0.050
	(15.815)	(15.546)	(14.728)	(14.274)	(12.497)
ROA	-0.020	0.004	0.012	0.005	-0.007
	(-11.58)	(2.835)	(7)	(1.571)	(-2.168)
MB	0.056	0.061	0.053	0.073	0.066
	(27.471)	(29.671)	(23.197)	(19.312)	(15.439)
Leverage	-0.005	-0.008	-0.009	-0.001	-0.002
	(-3.676)	(-5.55)	(-5.787)	(-0.457)	(-0.753)

Table IA.2: Financial Constraints Spillovers - Excluding VTNIC

This table presents network regression estimates of financial constraint spillovers via supply chain partners' investments, as specified in Equation (1). The dependent variable is firm investment *(CapEx/L.Assets)* in all models. The independent variable *FC* represents five measures of financial constraints: the *WW* index from Whited and Wu (2006), the size-age (SA) index from Hadlock and Pierce (2010), the proportion of long-term debt due *(LTD due)* from Almeida et al. (2012), a text-based measure *(Delay Inv)* from Hoberg and Maksimovic (2015), and the sum of the first four (standardized) financial constraint measures *(FC combo)*. Panel A reports estimates for ρ, which quantifies supply chain partners' investment complementarity. Panel B reports estimates of the average direct effect of own-firm financial constraints and other covariates on own-firm investment. Panel C reports estimates of the average indirect effect of financial constraints and other covariates on partners' investments. All non-dummy variables are standardized, and all models include year fixed effects. In parentheses, we report t-statistics based on standard errors calculated directly from the posterior distribution of MCMC parameter estimates.

	CapEx/L.Assets				
	WW	SA	LTD due	Delay Inv	FC combo
	Panel A: Investment Complementarity				
ρ	0.383	0.407	0.419	0.436	0.425
	(57.601)	(57.709)	(51.011)	(46.901)	(41.412)
	Panel B: Own-firm Effects				
FC	-0.306	-0.032	-0.030	-0.003	-0.087
	(-29.679)	(-4.068)	(-6.088)	(-0.488)	(-10.162)
ln(Sale)	-0.259	-0.098	-0.077	-0.052	-0.110
	(-33.611)	(-13.483)	(-13.794)	(-7.782)	(-12.489)
Cash	-0.175	-0.157	-0.115	-0.148	-0.126
	(-37.588)	(-31.834)	(-23.026)	(-22.194)	(-17.316)
Z-score	0.076	0.084	0.083	0.082	0.095
	(15.456)	(16.109)	(13.411)	(12.098)	(11.304)
ROA	-0.155	-0.017	-0.018	-0.001	-0.039
	(-21.697)	(-3.397)	(-2.898)	(-0.106)	(-4.84)
MB	0.111	0.093	0.074	0.100	0.096
	(22.06)	(17.907)	(13.069)	(15.173)	(11.542)
Leverage	0.005	0.005	-0.006	0.012	0.009
	(1.095)	(1.061)	(-1.149)	(1.921)	(1.251)
	Panel C: Indirect Effects				
FC	-0.184	-0.021	-0.021	-0.002	-0.062
	(-23.412)	(-4.031)	(-5.956)	(-0.486)	(-9.197)
ln(Sale)	-0.156	-0.065	-0.054	-0.039	-0.078
	(-24.949)	(-12.463)	(-12.457)	(-7.507)	(-10.898)
Cash	-0.105	-0.104	-0.080	-0.110	-0.089
	(-25.86)	(-23.032)	(-17.65)	(-16.637)	(-14.176)
Z-score	0.046	0.056	0.058	0.061	0.067
	(14.108)	(14.656)	(12.128)	(11.206)	(10.084)
ROA	-0.093	-0.012	-0.012	-0.001	-0.028
	(-19.179)	(-3.393)	(-2.88)	(-0.106)	(-4.779)
MB	0.066	0.062	0.052	0.074	0.068
	(18.161)	(15.521)	(11.849)	(12.875)	(10.157)
Leverage	0.003	0.003	-0.004	0.009	0.006
	(1.095)	(1.063)	(-1.153)	(1.921)	(1.248)

Table IA.3: Financial Constraints Spillovers - Only VTNIC

This table presents network regression estimates of financial constraint spillovers via supply chain partners' investments, as specified in Equation (1). The dependent variable is firm investment *(CapEx/L.Assets)* in all models. The independent variable *FC* represents five measures of financial constraints: the *WW* index from Whited and Wu (2006), the size-age (SA) index from Hadlock and Pierce (2010), the proportion of long-term debt due *(LTD due)* from Almeida et al. (2012), a text-based measure *(Delay Inv)* from Hoberg and Maksimovic (2015), and the sum of the first four (standardized) financial constraint measures *(FC combo)*. Panel A reports estimates for ρ, which quantifies supply chain partners' investment complementarity. Panel B reports estimates of the average direct effect of own-firm financial constraints and other covariates on own-firm investment. Panel C reports estimates of the average indirect effect of financial constraints and other covariates on partners' investments. All non-dummy variables are standardized, and all models include year fixed effects. In parentheses, we report t-statistics based on standard errors calculated directly from the posterior distribution of MCMC parameter estimates.

	CapEx/L.Assets				
	WW	SA	LTD due	Delay Inv	FC combo
	Panel A: Investment Complementarity				
ρ	0.269	0.273	0.249	0.200	0.187
	(11.724)	(12.64)	(10.096)	(7.237)	(6.375)
	Panel B: Own-firm Effects				
FC	-0.280	0.003	-0.036	-0.010	-0.097
	(-26.964)	(0.312)	(-6.066)	(-1.591)	(-12.035)
ln(Sale)	-0.310	-0.105	-0.128	-0.106	-0.169
	(-31.863)	(-12.267)	(-18.48)	(-14.585)	(-18.341)
Cash	-0.230	-0.207	-0.158	-0.215	-0.176
	(-37.261)	(-34.335)	(-22.908)	(-31.561)	(-22.848)
Z-score	0.041	0.055	0.050	0.052	0.047
	(7.28)	(9.643)	(7.371)	(7.708)	(6.011)
ROA	-0.052	0.027	0.046	0.046	0.055
	(-7.773)	(4.836)	(6.827)	(6.766)	(7.001)
MB	0.130	0.120	0.123	0.126	0.135
	(23.613)	(21.927)	(19.802)	(19.057)	(17.544)
Leverage	0.027	0.036	0.028	0.036	0.023
	(4.997)	(6.506)	(4.56)	(5.67)	(3.129)
	Panel C: Indirect Effects				
FC	-0.104	0.001	-0.012	-0.003	-0.022
	(-8.102)	(0.305)	(-4.543)	(-1.53)	(-4.665)
ln(Sale)	-0.114	-0.039	-0.043	-0.027	-0.039
	(-8.294)	(-7.202)	(-6.982)	(-5.364)	(-4.965)
Cash	-0.085	-0.078	-0.053	-0.054	-0.041
	(-8.365)	(-8.848)	(-7.282)	(-5.692)	(-5.175)
Z-score	0.015	0.021	0.017	0.013	0.011
	(5.495)	(6.825)	(5.244)	(4.503)	(3.871)
ROA	-0.019	0.010	0.015	0.012	0.013
	(-5.643)	(4.272)	(5.063)	(4.481)	(4.163)
MB	0.048	0.045	0.041	0.032	0.031
	(8.017)	(8.472)	(7.311)	(5.585)	(5.024)
Leverage	0.010	0.013	0.009	0.009	0.005
	(4.435)	(5.546)	(3.855)	(4.053)	(2.609)

Table IA.4: Financial Constraints Spillovers - Equal Weighting Scheme

This table presents network regression estimates of financial constraint spillovers via supply chain partners' investments, as specified in Equation (1). The dependent variable is firm investment *(CapEx/L.Assets)* in all models. The independent variable *FC* represents five measures of financial constraints: the *WW* index from Whited and Wu (2006), the size-age (SA) index from Hadlock and Pierce (2010), the proportion of long-term debt due *(LTD due)* from Almeida et al. (2012), a text-based measure *(Delay Inv)* from Hoberg and Maksimovic (2015), and the sum of the first four (standardized) financial constraint measures *(FC combo)*. Panel A reports estimates for ρ, which quantifies supply chain partners' investment complementarity. Panel B reports estimates of the average direct effect of own-firm financial constraints and other covariates on own-firm investment. Panel C reports estimates of the average indirect effect of financial constraints and other covariates on partners' investments. All non-dummy variables are standardized, and all models include year fixed effects. In parentheses, we report t-statistics based on standard errors calculated directly from the posterior distribution of MCMC parameter estimates.

	CapEx/L.Assets				
	WW	SA	LTD due	Delay Inv	FC combo
	Panel A: Investment Complementarity				
ρ	0.344	0.373	0.377	0.441	0.400
	(35.028)	(40.905)	(34.131)	(27.511)	(20.679)
	Panel B: Own-firm Effects				
FC	-0.305	-0.031	-0.032	-0.005	-0.095
	(-31.621)	(-4.162)	(-6.59)	(-0.899)	(-11.944)
ln(Sale)	-0.268	-0.107	-0.091	-0.064	-0.128
	(-36.772)	(-15.582)	(-14.953)	(-9.477)	(-13.955)
Cash	-0.195	-0.177	-0.131	-0.175	-0.146
	(-39.98)	(-38.048)	(-23.706)	(-26.021)	(-21.022)
Z-score	0.079	0.087	0.091	0.085	0.099
	(16.297)	(16.983)	(14.717)	(13.397)	(12.505)
ROA	-0.151	-0.012	-0.016	0.003	-0.037
	(-22.477)	(-2.268)	(-2.653)	(0.473)	(-4.629)
MB	0.111	0.094	0.073	0.098	0.093
	(23.69)	(17.816)	(12.256)	(15.561)	(12.209)
Leverage	0.004	0.005	-0.006	0.011	0.004
	(0.904)	(1.145)	(-1.234)	(1.73)	(0.644)
	Panel C: Indirect Effects				
FC	-0.158	-0.018	-0.019	-0.004	-0.063
	(-19.525)	(-4.11)	(-6.226)	(-0.894)	(-8.608)
ln(Sale)	-0.139	-0.062	-0.054	-0.050	-0.085
	(-19.983)	(-13.5)	(-11.871)	(-8.085)	(-9.573)
Cash	-0.101	-0.104	-0.078	-0.137	-0.097
	(-20.028)	(-21.865)	(-15.794)	(-13.372)	(-11.029)
Z-score	0.041	0.051	0.054	0.067	0.066
	(13.464)	(13.902)	(11.582)	(9.685)	(8.716)
ROA	-0.078	-0.007	-0.010	0.002	-0.024
	(-17.072)	(-2.258)	(-2.62)	(0.465)	(-4.302)
MB	0.057	0.055	0.044	0.077	0.061
	(15.977)	(14.587)	(10.317)	(10.896)	(8.788)
Leverage	0.002	0.003	-0.004	0.008	0.003
	(0.903)	(1.143)	(-1.23)	(1.717)	(0.638)

Table IA.5: Network Correlations of CapEx

This table presents pairwise network correlations of capital expenditures.

	(1)			(2)			(3)			(4)			(5)		
Network polynomial order	**1st**	**2nd**	**3rd**	**1st**	**2nd**	**3rd**	**1st**	**2nd**	**3rd**	**1st**	**2nd**	**3rd**	**1st**	**2nd**	**3rd**
(1) Main Network	1.00														
(Random Corr.)	1.00	1.00	1.00												
(2) Suppliers Network	0.90			1.00											
(Random Corr.)	0.77	0.80	0.81	1.00	1.00	1.00									
(3) Customers Network	0.86			0.76			1.00								
(Random Corr.)	0.66	0.74	0.75	0.44	0.60	0.64	1.00	1.00	1.00						
(4) Compustat Network	0.79			0.81			0.76			1.00					
(Random Corr.)	0.57	0.67	0.61	0.59	0.62	0.63	0.49	0.58	0.58	1.00	1.00	1.00			
(5) Factset Network	0.88			0.82			0.82			0.76			1.00		
(Random Corr.)	0.73	0.77	0.73	0.64	0.68	0.69	0.60	0.65	0.66	0.47	0.67	0.57	1.00	1.00	1.00
(6) VTNIC	0.78			0.83			0.85			0.79			0.75		
(Random Corr.)	0.49	0.71	0.65	0.57	0.69	0.71	0.66	0.75	0.78	0.54	0.69	0.62	0.52	0.68	0.64

Table IA.6: Homophily in Production Networks

This table presents exponential random graph model (ERGM) estimates for the effect of financial constraints on supply chain network formation. The dependent variable in all models is a binary variable indicating a supply chain tie (partnership) between two firms in a given year. Supply chain ties are derived from the Compustat, FactSet, and VTNIC relationships from 2003 to 2020. The coefficients are the contribution of financial constraints (covariates) on the conditional log-odds that a firm-pair will engage in a new tie (i.e., supply chain partnership). The conditional log-odds coefficients represent the effect on the formation of an individual tie holding all other ties fixed. The intercept estimate (*edges*) indicates the homogeneous probability of forming a marginal tie (partnership) if a random *edge* (firm) is added to the network. The ERGM is estimated via MCMC maximum likelihood. The t-statistics (reported in parentheses) are calculated using the standard deviations of the posterior distribution of the corresponding parameter estimates.

	New connection		
	(1)	(2)	(3)
edges	-5.331	-5.321	-5.357
	(-1332.75)	(-1064.20)	(-892.83)
$\lvert I_i - I_j \rvert$	0.615		0.617
	(15.77)		(15.82)
$\lvert FC_i - FC_j \rvert$		0.012	0.012
		(6.01)	(6.00)

Table IA.7: Financial Constraints and Upstream vs. Downstream Network Formation

This table presents exponential random graph model (ERGM) estimates for the effect of financial constraints on supply chain network formation. The dependent variable in all models is a binary variable indicating a supply chain tie (partnership) between two firms in a given year. Supply chain ties are derived from the Compustat, FactSet, and VTNIC relationships from 2003 to 2020. In columns (1)–(8), the independent variable of interest is one of the eight measures of firms' financial constraints (*FC*) from Table 2. The coefficients are the contribution of financial constraints (covariates) on the conditional log-odds that a firm-pair will engage in a new tie (i.e., supply chain partnership). The conditional log-odds coefficients represent the effect on the formation of an individual tie holding all other ties fixed. The intercept estimate (*edges*) indicates the homogeneous probability of forming a marginal tie (partnership) if a random *edge* (firm) is added to the network. The coefficients of *FC (upstream)* and *FC (downstream)* estimate the effect of financial constraints on the conditional log-odds of creating a new connection with a supplier and a customer, respectively. The ERGM is estimated via MCMC maximum likelihood. The t-statistics (reported in parentheses) are calculated using the standard deviations of the posterior distribution of the corresponding parameter estimates.

	New connection							
	WW	SA	LTD due	Delay Inv	FC combo	C.viol	C.CapEx	C.strict
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
edges	-7.471	-8.185	-5.552	-5.397	-5.282	-7.176	-7.240	-7.192
	(-49.082)	(-30.875)	(-132.317)	(-90.228)	(-89.401)	(-50.938)	(-45.437)	(-46.837)
FC (upstream)	-2.072	-0.470	-0.062	-0.381	-0.019	-0.165	-0.184	-0.089
	(-28.464)	(-11.617)	(-2.406)	(-4.250)	(-5.473)	(-8.016)	(-3.655)	(-2.672)
FC (downstream)	2.005	0.234	0.037	-0.014	0.004	0.191	0.167	0.063
	(13.531)	(11.030)	(3.183)	(-0.305)	(1.869)	(2.863)	(8.981)	(2.795)
ln(Sales)	0.157	0.148	0.014	0.009	0.011	0.172	0.164	0.162
	(10.618)	(19.259)	(8.197)	(4.417)	(4.025)	(11.791)	(11.185)	(11.265)
Cash	-0.097	-0.087	-0.055	-0.078	-0.054	-0.247	-0.227	-0.230
	(-1.409)	(-1.296)	(-2.405)	(-3.953)	(-2.697)	(-4.724)	(-6.672)	(-6.663)
Z-score	0.006	0.006	0.000	0.000	0.000	0.009	0.007	0.007
	(8.094)	(6.014)	(0.043)	(0.822)	(0.294)	(3.776)	(3.980)	(3.814)
ROA	0.130	-0.016	-0.002	0.011	-0.002	-0.188	-0.083	-0.084
	(5.783)	(-1.839)	(-0.214)	(1.437)	(-0.135)	(-1.244)	(-1.259)	(-1.278)
MB	-0.011	-0.007	-0.002	0.001	-0.001	-0.018	-0.012	-0.013
	(-5.444)	(-3.974)	(-1.569)	(0.667)	(-0.697)	(-4.027)	(-2.365)	(-2.511)
Leverage	-0.044	-0.058	-0.040	-0.008	-0.033	-0.127	-0.088	-0.081
	(-1.615)	(-1.770)	(-2.010)	(-0.421)	(-1.328)	(-2.514)	(-2.207)	(-2.132)

Table IA.8: Financial Constraints and Trade Credit

This table presents estimates for OLS regressions of firms' account payable days (Panel A) and account receivable days (Panel B) on measures of financial constraints. the independent variable of interest is one of the eight measures of firms' financial constraints (*FC*) from Table 2. All models include lagged controls for firm *sales, cash holdings, Z-score, ROA, Market-to-book, and book leverage*, as well as firm and year fixed effects. Regression estimates are standardized and thus the coefficients represent standard deviation changes in the dependent variable per one standard deviation change in financing constraints. In parentheses, we report t-statistics based on standard errors clustered at the firm and year level. All variables are defined in detail in the Appendix.

	Panel A: Buyer Payable Days							
FC Measure	WW	SA	LTD Due	Delay Inv.	FC Combo	C.viol	CapEx Cov.	C.Strictness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FC Variable	0.073***	0.126***	-0.001	0.007	0.035***	-0.004	-0.013	-0.005
	(5.290)	(3.921)	(-0.312)	(0.907)	(3.810)	(-1.716)	(-1.620)	(-0.529)
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	145113	145676	119678	58486	46369	73029	33271	33271
Adjusted R^2	0.467	0.465	0.493	0.475	0.500	0.479	0.604	0.604

	Panel B: Supplier Receivable Days							
FC Measure	WW	SA	LTD Due	Delay Inv.	FC Combo	C.viol	CapEx Cov.	C.Strictness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FC Variable	-0.035***	-0.396***	-0.010***	-0.012**	-0.045***	-0.001	-0.024***	-0.008
	(-3.712)	(-21.568)	(-2.771)	(-2.468)	(-6.537)	(-0.332)	(-3.544)	(-0.935)
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143335	143879	118718	58025	46063	72476	33164	33164
Adjusted R^2	0.547	0.556	0.581	0.549	0.584	0.533	0.781	0.781

Table IA.9: Network Regressions of Investment with Industry (TNIC) Contextual Effects

This table presents network regression estimates of financial constraint spillovers via supply chain partners' investments, as specified in Equation (1). The dependent variable is firm investment *(CapEx/L.Assets)* in all models. In columns (1)-(5), the independent variable *FC* represents five measures of financial constraints: the *WW* index from Whited and Wu (2006), the size-age (SA) index from Hadlock and Pierce (2010), the proportion of long-term debt due *(LTD due)* from Almeida et al. (2012), a text-based measure *(Delay Inv)* from Hoberg and Maksimovic (2015), and the sum of the first four (standardized) financial constraint measures *(FC combo)*. In columns (6)-(8), *FC* represents three measures of covenant-induced financial constraints: *C.viol* is an indicator variable equal to one if a firm reports a covenant violation in its 10-K or 10-Q; *C.CapEx* is an indicator variable equal to one if a firm has a capital expenditure covenant; *C.strict* is the probability that a firm violates at least one covenant in the next quarter. All regressions include industry-peer annual averages of the control variables of a firm's industry peer group (-i), as defined by firm i's Network Industry Classification (TNIC-3) in year t. Panel A reports estimates for ρ, which quantifies supply chain partners' investment complementarity. Panel B reports estimates of the average own-firm effect of own-firm financial constraints and other covariates on own-firm investment. Panel C reports estimates of the average indirect effect of financial constraints and other covariates on partners' investments. All non-dummy variables are standardized, and all models include year fixed effects. In parentheses, we report t-statistics based on standard errors calculated directly from the posterior distribution of MCMC parameter estimates.

Table IA.9 continued

	CapEx/L.Assets							
	WW	SA	LTD due	Delay Inv	FC combo	C.viol	C.CapEx	C.strict
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Investment Complementarity							
ρ	0.465	0.528	0.500	0.440	0.416	0.410	0.404	0.417
	(43.652)	(50.748)	(41.57)	(39.545)	(32.691)	(30.499)	(33.592)	(36.267)
	Panel B: Own-firm effects							
FC	-0.125	0.054	-0.017	-0.006	-0.045	-0.050	-0.058	-0.001
	(-12.245)	(6.517)	(-3.041)	(-0.961)	(-5.88)	(-6.64)	(-8.183)	(-0.067)
ln(Sale)	-0.118	0.015	-0.039	-0.025	-0.057	-0.090	-0.096	-0.083
	(-11.801)	(1.657)	(-5.557)	(-3.251)	(-5.857)	(-10.059)	(-11.397)	(-10.395)
Cash	-0.096	-0.080	-0.055	-0.088	-0.067	-0.057	-0.059	-0.057
	(-13.688)	(-11.655)	(-7.538)	(-11.051)	(-7.596)	(-6.189)	(-7.329)	(-6.977)
Z-score	0.012	0.028	0.016	0.018	0.011	-0.064	-0.062	-0.062
	(2.174)	(5.125)	(2.423)	(2.853)	(1.355)	(-7.021)	(-8.123)	(-7.914)
ROA	-0.017	0.018	0.038	0.029	0.044	0.049	0.053	0.051
	(-2.651)	(3.605)	(5.806)	(4.623)	(6.013)	(5.037)	(6.804)	(6.384)
MB	0.125	0.115	0.129	0.123	0.136	0.145	0.146	0.148
	(25.211)	(24.223)	(21.309)	(20.818)	(18.324)	(17.351)	(18.508)	(19.284)
Leverage	-0.022	-0.014	-0.017	-0.021	-0.028	-0.046	-0.043	-0.052
	(-4.473)	(-2.754)	(-2.7)	(-3.133)	(-4.062)	(-5.14)	(-5.896)	(-6.205)
FC$_{-i}$	-0.278	-0.074	-0.057	-0.014	-0.106	-0.023	-0.088	0.033
	(-24.6)	(-7.433)	(-9.051)	(-2.137)	(-14.676)	(-3.223)	(-12.597)	(4.042)
ln(Sale)$_{-i}$	-0.506	-0.331	-0.299	-0.292	-0.371	-0.279	-0.287	-0.272
	(-38.804)	(-27.167)	(-31.462)	(-28.114)	(-30.48)	(-25.854)	(-27.145)	(-27.365)
Cash$_{-i}$	-0.308	-0.287	-0.267	-0.334	-0.350	-0.231	-0.242	-0.241
	(-30.72)	(-30.126)	(-23.294)	(-27.693)	(-26.152)	(-17.967)	(-22.041)	(-20.834)
Z-score$_{-i}$	0.000	0.001	0.005	0.011	-0.003	-0.032	-0.015	-0.018
	(-0.013)	(0.155)	(0.687)	(1.445)	(-0.395)	(-3.171)	(-1.62)	(-2.005)
ROA$_{-i}$	0.039	0.055	0.060	0.060	0.065	0.069	0.057	0.060
	(4.529)	(7.535)	(6.589)	(6.636)	(6.547)	(6.887)	(6.027)	(6.606)
MB$_{-i}$	0.013	0.019	0.012	0.034	0.037	-0.025	-0.033	-0.026
	(2.072)	(2.946)	(1.645)	(4.449)	(4.145)	(-2.638)	(-3.725)	(-3.003)
Leverage$_{-i}$	0.065	0.097	0.084	0.112	0.081	0.090	0.098	0.080
	(10.968)	(15.636)	(12.593)	(15.633)	(10.388)	(9.048)	(10.712)	(8.064)
	Panel C: Indirect effects							
FC	-0.106	0.059	-0.017	-0.004	-0.031	-0.033	-0.038	0.000
	(-11.256)	(6.273)	(-3.017)	(-0.958)	(-5.644)	(-6.238)	(-7.588)	(-0.067)
ln(Sale)	-0.100	0.017	-0.038	-0.019	-0.039	-0.060	-0.063	-0.058
	(-10.763)	(1.652)	(-5.337)	(-3.226)	(-5.586)	(-8.996)	(-9.938)	(-9.193)
Cash	-0.082	-0.087	-0.053	-0.067	-0.046	-0.038	-0.039	-0.039
	(-11.529)	(-10.251)	(-7.085)	(-9.877)	(-6.996)	(-5.949)	(-6.823)	(-6.539)
Z-score	0.010	0.030	0.016	0.014	0.008	-0.043	-0.041	-0.043
	(2.153)	(4.943)	(2.398)	(2.809)	(1.346)	(-6.55)	(-7.561)	(-7.447)
ROA	-0.015	0.020	0.037	0.022	0.031	0.033	0.034	0.035
	(-2.639)	(3.552)	(5.545)	(4.547)	(5.65)	(4.903)	(6.388)	(6.233)
MB	0.106	0.125	0.126	0.094	0.094	0.097	0.096	0.102
	(17.211)	(17.192)	(14.761)	(15.046)	(13.221)	(12.955)	(13.727)	(14.243)
Leverage	-0.019	-0.016	-0.017	-0.016	-0.019	-0.031	-0.028	-0.036
	(-4.404)	(-2.741)	(-2.691)	(-3.071)	(-3.964)	(-4.94)	(-5.657)	(-6.058)
FC$_{-i}$	-0.236	-0.081	-0.055	-0.011	-0.073	-0.016	-0.058	0.023
	(-16.84)	(-7.171)	(-8.49)	(-2.116)	(-11.666)	(-3.173)	(-10.619)	(3.948)
ln(Sale)$_{-i}$	-0.429	-0.361	-0.291	-0.223	-0.257	-0.187	-0.189	-0.188
	(-20.152)	(-18.224)	(-17.842)	(-17.799)	(-16.324)	(-14.57)	(-16.178)	(-17.735)
Cash$_{-i}$	-0.261	-0.313	-0.260	-0.254	-0.242	-0.155	-0.159	-0.166
	(-19.873)	(-19.308)	(-15.495)	(-17.468)	(-15.302)	(-12.47)	(-15.112)	(-15.186)
Z-score$_{-i}$	0.000	0.001	0.005	0.008	-0.002	-0.021	-0.010	-0.012
	(-0.012)	(0.155)	(0.686)	(1.442)	(-0.393)	(-3.148)	(-1.616)	(-1.989)
ROA$_{-i}$	0.033	0.060	0.059	0.045	0.045	0.046	0.038	0.042
	(4.45)	(7.023)	(6.491)	(6.509)	(6.154)	(6.403)	(5.845)	(6.407)
MB$_{-i}$	0.011	0.021	0.012	0.026	0.025	-0.017	-0.022	-0.018
	(2.075)	(2.919)	(1.642)	(4.385)	(4.01)	(-2.628)	(-3.624)	(-2.966)
Leverage$_{-i}$	0.055	0.106	0.082	0.086	0.056	0.060	0.065	0.055
	(9.481)	(13.155)	(10.825)	(12.551)	(9.203)	(7.986)	(9.483)	(7.627)

Table IA.10: Complementarity in Financial Constraint Measures

This table presents network regression estimates for partners' financial constraints complementarity using measure of financial constraints as the dependent variable (i.e., $FC = \rho SFC + X\beta + \epsilon$). The dependent variable is the firm's financial constraint FC in all models. FC represents the following measures of financial constraints: the financial constraints index from Whited and Wu (2006) (WW); the size-age index (SA) from Hadlock and Pierce (2010); the proportion of long-term debt due (*LTD due*) from Almeida et al. (2012); the text-based measure (*Delay Inv*) from Hoberg and Maksimovic (2015); the sum of the first four (standardized) financial constraint measures (*FC combo*); an indicator variable equal to one if a firm reports a covenant violation in its 10-K or 10-Q (*C.viol*); an indicator variable equal to one if a firm has a capital expenditure covenant (*CapexCov*) from Nini et al. (2009); and the probability that a firm violates at least one covenant in the next quarter (*C.strict*) from Murfin (2012). Panel A reports estimates for ρ, which quantifies the complementarity in supply chain partners' financial constraints. Panels B and C report estimates of the average own-firm effect and indirect effects of firm attributes on financial constraints. All non-dummy variables are standardized, and all models include year fixed effects. In parentheses, we report t-statistics based on standard errors calculated directly from the posterior distribution of MCMC parameter estimates.

	FC							
FC:	WW	SA	LTD due	Delay Inv	FC combo	C.viol	C.CapEx	C.strict
				Panel A: FC Complementarity				
ρ	-0.018	0.017	0.020	0.064	-0.010	-0.002	0.045	0.048
	(-6.951)	(6.562)	(2.488)	(6.662)	(-1.52)	(-0.437)	(10.64)	(8.907)
				Panel B: Own-firm Effects				
ln(Sale)	-0.635	-0.668	-0.148	0.080	-0.523	-0.128	0.083	-0.078
	(-239.455)	(-275.231)	(-27.722)	(12.986)	(-92.583)	(-44.218)	(38.449)	(-24.389)
Cash	-0.074	-0.032	0.124	-0.279	-0.120	-0.128	-0.081	-0.110
	(-28.692)	(-13.19)	(29.733)	(-48.093)	(-24.48)	(-41.8)	(-44.828)	(-33.966)
Z-score	-0.139	-0.213	-0.120	0.051	-0.143	-0.012	0.015	0.023
	(-51.971)	(-79.46)	(-18.954)	(8.132)	(-22.772)	(-4.524)	(7.328)	(5.705)
ROA	-0.093	-0.031	0.034	-0.022	-0.043	0.015	0.016	-0.071
	(-33.277)	(-10.502)	(6.638)	(-3.298)	(-6.913)	(4.072)	(6.054)	(-25.068)
MB	0.252	0.154	0.005	-0.056	0.129	-0.047	-0.012	-0.156
	(103.797)	(55.509)	(1.068)	(-8.076)	(22.676)	(-13.645)	(-4.43)	(-43.791)
Leverage	0.010	-0.013	-0.237	0.120	-0.091	0.031	0.039	0.409
	(4.566)	(-5.351)	(-48.852)	(22.49)	(-17.159)	(10.964)	(18.438)	(128.124)
				Panel C: Indirect Effects				
ln(Sale)	0.011	-0.011	-0.003	0.005	0.005	0.000	0.004	-0.004
	(7.05)	(-6.453)	(-2.481)	(5.665)	(1.531)	(0.435)	(9.662)	(-7.93)
Cash	0.001	-0.001	0.003	-0.019	0.001	0.000	-0.004	-0.006
	(6.889)	(-5.957)	(2.434)	(-6.195)	(1.549)	(0.431)	(-9.749)	(-8.422)
Z-score	0.002	-0.004	-0.002	0.003	0.001	0.000	0.001	0.001
	(7.052)	(-6.403)	(-2.395)	(5.291)	(1.543)	(0.391)	(5.883)	(4.779)
ROA	0.002	-0.001	0.001	-0.001	0.000	0.000	0.001	-0.004
	(6.772)	(-5.641)	(2.303)	(-2.799)	(1.46)	(-0.376)	(5.248)	(-8.039)
MB	-0.004	0.003	0.000	-0.004	-0.001	0.000	-0.001	-0.008
	(-7.095)	(6.458)	(0.932)	(-4.357)	(-1.525)	(0.448)	(-4.136)	(-8.231)
Leverage	0.000	0.000	-0.005	0.008	0.001	0.000	0.002	0.021
	(-3.728)	(-4.228)	(-2.447)	(6.139)	(1.523)	(-0.443)	(9.056)	(8.499)

Table IA.11: Input Specificity and Supply Chain Relationship Length

This table presents OLS regressions of supply-chain partners' length of relationship on measures of input specificity. The dependent variable in all models is the total number of years (until year t) that two firms have been supply chain partners. In columns (2), (4), (6), and (8), we assign firms into high-input-specificity groups if their respective measure is above the sample median. All models include lagged controls for firm *sales, cash holdings, Z-score, ROA, Market-to-book, and book leverage.* We cluster standard errors at the industry and year levels and report t-statistics in parentheses. All non-dummy variables are standardized, and all models include year fixed effects. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	SC-relationship length							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R&D/Sales	-0.011							
	(-1.482)							
R&D/Sales high		0.200***						
		(5.656)						
Product diff.			0.100***					
			(21.551)					
Product diff. high				0.436***				
				(3.742)				
TNIC-3 HHI					0.036***			
					(4.480)			
TNIC-3 HHI high						0.224***		
						(4.414)		
Patents/Sales							0.002	
							(1.352)	
Patents/Sales high								0.177***
								(8.115)
ln(Sales)	0.168***	0.166***	0.201***	0.206***	0.202***	0.199***	0.157***	0.159***
	(5.784)	(5.696)	(5.962)	(5.835)	(5.807)	(5.797)	(5.501)	(5.640)
Cash	-0.003	-0.010*	0.018***	-0.000	0.000	-0.002	-0.014**	-0.018***
	(-0.938)	(-1.933)	(4.279)	(-0.060)	(0.054)	(-0.339)	(-2.682)	(-3.321)
Altman-Z	-0.035***	-0.032***	-0.033***	-0.034***	-0.032***	-0.031***	-0.016*	-0.015*
	(-4.579)	(-4.704)	(-5.654)	(-4.916)	(-4.827)	(-4.760)	(-2.105)	(-2.028)
ROA	0.011***	0.013***	0.028***	0.033***	0.030***	0.030***	0.020***	0.020***
	(3.340)	(3.033)	(4.869)	(4.973)	(4.489)	(4.507)	(4.153)	(4.261)
MB	-0.005	-0.007*	-0.016***	-0.013**	-0.014**	-0.014**	-0.023***	-0.024***
	(-1.478)	(-1.788)	(-3.315)	(-2.589)	(-2.863)	(-2.831)	(-3.532)	(-3.669)
Leverage	-0.019***	-0.018***	-0.017**	-0.021***	-0.023***	-0.023***	-0.000	0.000
	(-3.109)	(-3.064)	(-2.754)	(-3.221)	(-3.628)	(-3.680)	(-0.134)	(0.005)
Observations	2119694	2119694	2078333	2078333	2058681	2058681	917117	917117
Adjusted R^2	0.451	0.451	0.432	0.428	0.430	0.430	0.511	0.511

Table IA.12: Supply-chain partner turnover

This table presents the annual share of firms' supply chain partners that do not extend a supply-chain relationship from the previous year.

Year	Supply-chain turnover
2004	0.062
2005	0.058
2006	0.049
2007	0.047
2008	0.054
2009	0.051
2010	0.043
2011	0.046
2012	0.031
2013	0.033
2014	0.026
2015	0.047
2016	0.033
2017	0.040
2018	0.063
2019	0.047
Total	0.045

Table IA.13: Summary Statistics (Quarterly Sample)

This table presents summary statistics for firm-level accounting information from Compustat Quarterly. Confirmed covenant violation data are based on an extended sample from Nini et al. (2012). All variables are defined in detail in the Variable Definitions Appendix.

	N	Mean	SD	P10	P50	P90
Capex/L.Assets	486,123	0.071	0.14	0.00	0.03	0.17
Assets	486,123	1668.510	5,539.86	3.68	108.63	3,124.00
Sales	486,123	383.635	1,290.94	0.00	21.62	724.51
Cash Hold.	486,123	0.219	0.26	0.01	0.11	0.64
ROA	486,123	-0.021	0.12	-0.16	0.02	0.06
Mkt-to-book	486,123	4.791	15.42	0.85	1.61	6.13
Book Leverage	486,123	0.329	0.78	0.00	0.16	0.58
Altman-Z	397,266	4.165	21.17	-6.39	1.73	11.73
Confirmed C. Violation	292,180	0.051	0.22	0.00	0.00	0.00
New Cov. Violation	292,180	0.016	0.13	0.00	0.00	0.00
Technical Violation	51,848	0.199	0.40	0.00	0.00	1.00
Technical Violation-Hybrid	52,205	0.066	0.25	0.00	0.00	0.00

Figure IA.2: Local Linear Network RDD

This figure plots the residuals from a local linear network RDD of investment on firms' distance from covenant thresholds as outlined in Section 4.2.1.

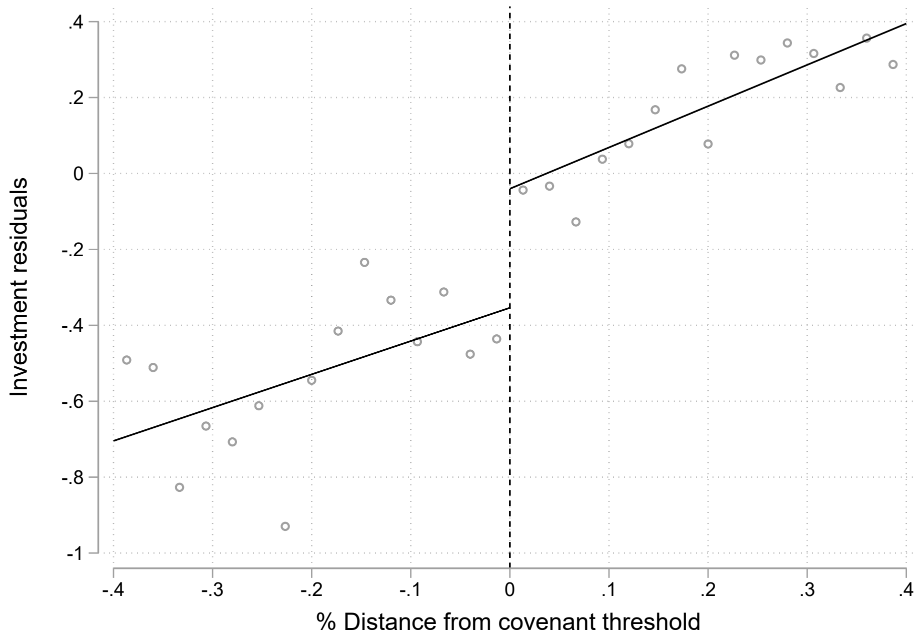
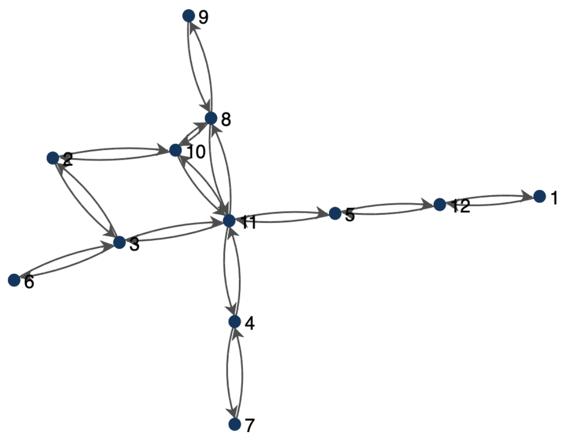


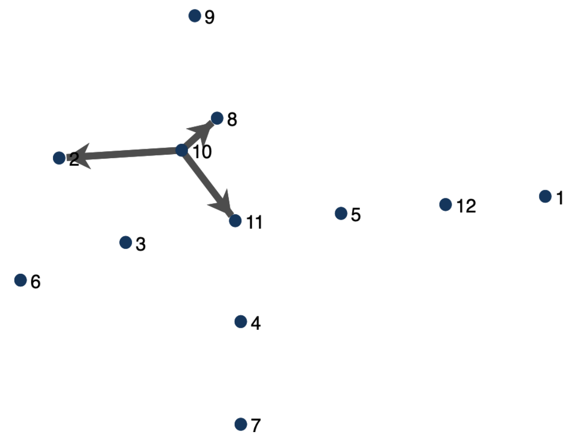
Figure IA.3: Example of Shock Propagation in Production Network

This figure plots the propagation of a shock through a simple supply-chain network. Panel (a) graphs the first-order network of direct partnerships. Panel (b) illustrates the first-order transmission of a shock initially occurring for node 10. Panel (c)-(f) plot the transmission of the initial shock occurring for node 10 for subsequent degrees of separation. The intensity of transmission is indicated by the width of the edges connecting each pair of nodes.

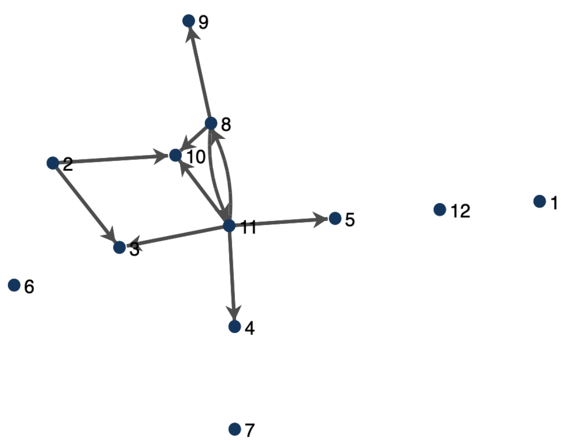
(3.a) SC network



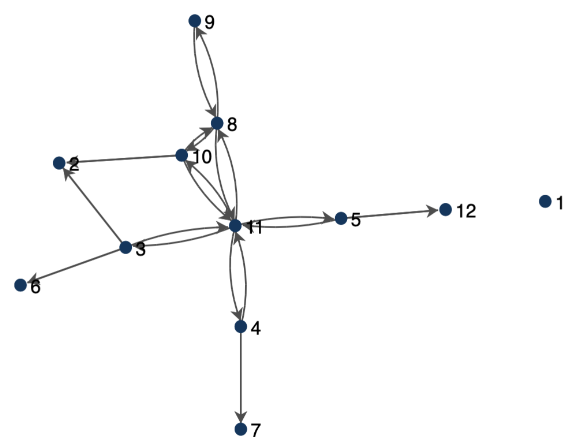
(3.b) 1^{st}-order



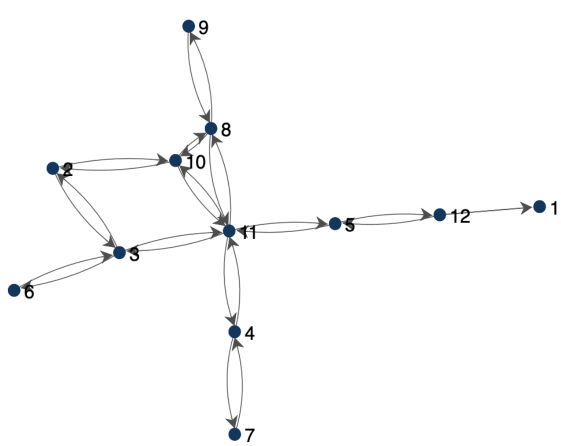
(3.c) 2^{nd}-order



(3.d) 3^{rd}-order



(3.e) 4^{th}-order



(3.f) 5^{th}-order