The Epidemiology of Financial Constraints and Corporate Investment*

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Abstract

We show that a single firm's financial constraints trigger a series of investment disruptions that propagate through direct and indirect customer-supplier relationships. Quantitatively, propagation effects are responsible for roughly half of the total reduction in investment spending stemming from constraints. Firms with higher input specificity generate larger spillovers and rely more on trade credit. We employ a Network-RDD that accounts for investment spillovers to bolster identification. Our estimates are robust to network measurement error, endogenous selection effects, and various constraint measures. Our results demonstrate that interdependent investments amplify the consequences of capital market frictions in production networks.

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

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We show that a single firm's financial constraints trigger a series of investment disruptions that propagate through direct and indirect customer-supplier relationships. Quantitatively, propagation effects are responsible for roughly half of the total reduction in investment spending stemming from constraints. Firms with higher input specificity generate larger spillovers and rely more on trade credit. We employ a Network-RDD that accounts for investment spillovers to bolster identification. Our estimates are robust to network measurement error, endogenous selection effects, and various constraint measures. Our results demonstrate that interdependent investments amplify the consequences of capital market frictions in production networks.

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> *"Perhaps the most pervasive and important factors influencing the efficiency of corporate investment are those that arise from informational asymmetries and agency problems." — Stein (2003)*

Firms facing limited access to external financing often scale back investments, thus reducing their production capacity (Rajan and Zingales, 1998). An extensive literature, beginning with Fazzari and Petersen (1988), documents significant direct effects of a firm's financial constraints on its own investment behavior. However, the implications of constraints when investment decisions extend beyond the boundaries of a single firm remain relatively underexplored. Our study helps bridge this gap by showing that financial constraints trigger a domino effect of reduced investments through supply chain networks, where investment opportunities are deeply intertwined. Quantitatively, we find that the indirect effects of constraints on investment spending are comparable to the direct, own-firm effects. Our findings indicate that network effects amplify the consequences of capital market frictions, suggesting a firm-centric view only captures the tip of the iceberg.

Given recent global economic events, 89% of firms cite supply chain disruptions as their primary concern, with 43% allocating investments to mitigate these risks (Grux, 2023). Understanding the resilience of supply chains to withstand transitory restrictions in access to finance is critical yet challenging. Supply chains consist of intricate webs of input-output linkages where firms not only supply immediate customers but also serve as indirect suppliers further downstream. Acemoglu et al. (2012) show that frictions can allow propagation effects and accumulate over many indirect links to affect aggregate economic activity. Consequently, quantifying spillover effects requires empirically modeling equilibrium outcomes that depend on the entire production network.

To quantify network spillover effects, we adapt spatial econometrics for non-spatial network contexts—henceforth, network regressions—following Ozdagli and Weber (2023); Grieser, LeSage, and Zekhnini (2022b). Our baseline findings reveal strong constraint-driven network effects on supply chain investment according to common financial constraint proxies. Specifically, tightening a firm's constraints by one standard deviation results in a 13% decline in its own investment, relative to average investment levels. Moreover, the indirect (network) effects contribute to a further reduction in total supply chain investment by an additional 12%. Notably, half of the network effects we document originate from higher-order connections beyond direct partnerships. In our setting, sparsely connected supply chains exhibit "small-world" properties whereby firms become densely connected through indirect linkages. Thus, the evidence underscores the importance of modeling network dynamics that enhance identification and reveal new economic insights.[1]

While we defer technical details to the main text, network regressions utilize variation in the number of partners in firm-specific supply chains, as well as the strength of relationships a firm has with each partner. Network regressions provide strong identification, assuming both the supply chain network and financial constraints proxies are exogenous (LeSage and Pace, 2009; Grieser et al., 2022a). Recognizing the potential limitations of these assumptions, we adapt our empirical design to account for the possible confounding effects of endogenous network formation, measurement error in financial constraints or supply chain networks, and shared lender networks. To address these challenges, we leverage the strengths of network regressions by systematically integrating advancements from recent empirical studies.

One concern is that endogenous network formation could bias our results if partner selection depends on unobservable attributes linked to similarities in investment and financial constraint levels. However, formal tests reveal that firms with similar investment and constraint levels are *less* likely to form partnerships, reducing concerns related to homophily in network formation. Moreover, changes in financial constraints do not predict supply chain turnover, which exhibits a low annual rate of 4.5%. We also find quantitatively similar estimates to our baseline results when restricting our analysis to customer-supplier relationships established for at least five years. These long-standing partnerships are intuitively less likely to have formed in anticipation of changes in current constraints and investment decisions.

[1]See: Morris (2000); Bramoullé, Djebbari, and Fortin (2009); Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012); Elliott, Golub, and Jackson (2014); Barrot and Sauvagnat (2016); Acemoglu, Akcigit, and Kerr (2016a); Carvalho, Nirei, Saito, and Tahbaz-Salehi (2021); Ozdagli and Weber (2023).

These patterns collectively increase confidence that the spillover effects we document reflect strategic interactions rather than biases from short-term partner selection effects.

Our second challenge involves establishing a clear link between investment behavior and financial constraints—a longstanding challenge in the literature due to issues such as measurement error in constraint proxies (Farre-Mensa and Ljungqvist, 2016) and investment opportunities (Alti, 2003). In an influential study, Chava and Roberts (2008) address these concerns by exploiting discrete jumps in constraints surrounding covenant violations in a regression discontinuity design (RDD). Covenant violations improve objectivity in measuring constraints compared to indirect proxies and highlight a specific channel—i.e., the transfer of control rights–through which financing constraints affect investment.[2] The RDD also reduces the confounding effects of unobservable factors by comparing firms near violation thresholds.

We integrate the covenant RDD within a network framework that accounts for investment interdependence and examine if covenant violations trigger ripple effects in supply chain investment spending. The network RDD relaxes the conventional RDD assumption that one firm's treatment cannot influence other firms' outcomes (Cox, 1958; Berg, Reisinger, and Streitz, 2021). We find that covenant violations result in a 1.7 percentage point relative decrease in own-firm investment, and network effects contribute an additional 1.2 percentage point relative reduction in total supply chain investment. Thus, the indirect effects of covenant violations—those felt by supply chain partners—account for approximately 40% of the total impact of covenant violations, with roughly half of the indirect effects originating from higher-order connections.

By analyzing a *partners* of covenant-violating firms, our network RDD mitigates concerns that firms near the cutoff are systematically different between the treatment and control groups. For instance, while a firm may manipulate its own financial reporting to avoid a

[2]The appealing features of the covenant RDD have led to its widespread adoption in the literature. A non-exhaustive list includes: 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).

violation or renegotiate its own loans, it has limited control over its partners' covenant status. This holds particularly in our analysis of behaviors observed five years post-partnership formation using the long-term partner network. To further enhance identification, we use entropy balancing to impose exact covariate matching between treatment and control groups (Hainmueller, 2012). Our findings are robust across specifications, reducing concerns that latent differences among firms near the thresholds systematically affect *partners* outcomes.

Another empirical challenge comes from the potential mismeasurement of the supply chain network. Our findings remain consistent across diverse specifications of the supply chain network, including different databases, weighting schemes, and sample periods. Moreover, we use simulations to demonstrate that measurement error in identifying supply chain linkages only gradually attenuates the estimates when we randomly omit existing partner links or introduce false linkages. The stability in these results provides confidence in the robustness of our conclusions against reasonable variations in supply chain construction and moderate measurement errors in identifying links.

Finally, the unique structure of supply chain networks also helps mitigate concerns about unobservable industry effects or common lending networks driving the results. Notably, supply chains are firm-specific, sparse, and exhibit substantial intransitivity—only 7% of partners share an additional customer or supplier. Thus, the supply chain structure provides a unique context for each firm, limiting the scope for latent economic shocks, such as regulatory changes or technological advancements, that affect many firms simultaneously. Moreover, our inferences remain unaltered when we control for the direct and indirect effects of a comprehensive set of industry controls and financial distress measures, or when we employ a framework that explicitly models the diffusion of latent shocks through the supply chain network. Our findings are also robust to controlling for potential propagation effects through shared lender networks and the direct transmission of financial health.

The low partner turnover and short-run investment ripple effects we document are consistent with frictions impeding firms' ability to quickly change partners (Barrot and Sauvagnat, 2016). Consistent with this notion, we find a strong positive relation between input specificity, partner duration, and the magnitude of investment disruptions. Firms also extend trade credit provision to partners that generate larger disruptions. Thus, while firms appear to employ trade credit to buffer against the impact of partners' constraints, such measures do not fully mitigate the adverse effects of immediate supply chain disruptions.

We contribute to an extensive literature examining the impact of financial constraints on firm investment (Fazzari and Petersen, 1988; Kaplan and Zingales, 1997; Whited and Wu, 2006; Bodnaruk, Loughran, and McDonald, 2015). While prior research has primarily focused on the direct effects of a firm's financial constraints on its own investment decisions, our analysis reveals that supply chain networks substantially amplify the initial, own-firm impact of financial constraints. We provide robust evidence that this amplification occurs through intertwined investment opportunities, aligning with mounting evidence in recent studies on interdependent investment behavior (Dougal, Parsons, and Titman, 2015; Bustamante and Frésard, 2021; Grieser, LeSage, and Zekhnini, 2022b).

Our study also contributes to the literature on propagation effects in production networks due to various shocks, including natural disasters. (Barrot and Sauvagnat, 2016; Wu, 2016; Carvalho, Nirei, Saito, and Tahbaz-Salehi, 2021), import financing taxes (Demir, Javorcik, Michalski, and Ors, 2024), and tariff changes (Martin and Otto, 2023). Similar to Costello (2020); Alfaro, García-Santana, and Moral-Benito (2021); Lenzu, Rivers, and Tielens (2022), we investigate supply chain shocks originating from financing frictions. A related literature investigates the spillover effects of financial distress on a firm's competitors, supply chain partners, and joint ventures (Hertzel, Li, Officer, and Rodgers, 2008; Boone and Ivanov, 2012; Hertzel and Officer, 2012; Yang, Birge, and Parker, 2015; Kolay, Lemmon, and Tashjian, 2016; Bernstein, Colonnelli, Giroud, and Iverson, 2019). These studies often emphasize the direct transmission of financial health, whereas we find no evidence that a firm's financial constraints affect its partners' constraints. Moreover, financial constraints affect a much broader sample of firms and highlight a distinct economic channel—i.e., investment opportunities. Unlike financially constrained firms that have profitable investment opportunities, firms in distress may or may not have good investment options and likely face broader operational and financial challenges. While the goal of our paper is not to rule out that financial distress would also generate spillovers, we provide evidence that our results are primarily driven by constrained firms, not necessarily those in financial distress.

These literatures provide important insights into financial health transmission and supply chain interactions, as well as the economic mechanisms underlying these effects. However, these studies do not attempt to quantify spillover effects, which is a main focus of this study. We build on recent work showing that exogenous variation alone is inadequate for this objective (Angrist, 2014; Berg, Reisinger, and Streitz, 2021). Our empirical approach explicitly models feedback and higher-order network effects, highlighting the critical role of network structure in magnifying or dampening economic shocks.[3] In our setting, sparse supply chains become densely connected through indirect linkages. We demonstrate that these higher-order connections account for roughly 50% of the total network effects, aligning with documented in recent studies (Acemoglu, Akcigit, and Kerr, 2016a; Barrot and Sauvagnat, 2016; Bernstein, Colonnelli, Giroud, and Iverson, 2019; Carvalho, Nirei, Saito, and Tahbaz-Salehi, 2021).

While we do not claim to quantify all supply chain spillovers from financial constraints, our analysis underscores the critical role of production networks in amplifying the effects of financial constraints. Our findings indicate that these consequences reach well beyond own-firm effects, highlighting the limitations of traditional firm-centric models and promoting a more integrated approach to understanding economic dynamics. These insights on network dynamics can inform corporate finance strategies and policymaking to enhance supply chain resilience and mitigate economic fallout from capital market frictions. The network approach we employ likely has many useful applications in finance settings.

[3]See: Morris (2000); Jackson (2016); Acemoglu, Ozdaglar, and Tahbaz-Salehi (2017); Elliott and Golub (2022).

1. Data

1.1. Firm financial information, financial constraints, and debt covenants

We derive firm-level financial variables from the CRSP-Compustat merged database. We calculate the variables investment (*CapEx/lagged assets*), firm sales (*Ln(Sales)*), market-to-book ratio (Q), return on assets (ROA), cash holdings (*cash*), *Z-score*, and *Leverage*. We exclude utilities (SIC 4900–4999), financial firms (SIC 6000–6999), non-U.S. firms, and firms with missing data. We winsorize all variables at the 1% level. Appendix A details our variable construction.

We employ four common financial constraint proxies to facilitate comparison of our study to a broad literature. The Whited and Wu (WW) index, developed by Whited and Wu (2006), estimates the shadow cost of equity, using variables such as leverage and sales growth.[4] The size-age (SA) index from Hadlock and Pierce (2010) reflects the likely degree of financial constraints as a function of firm size and age. The fraction of long-term debt due within one year ($LTDD$) highlights near-term debt obligations stemming from financing decisions made several years in the past (Almeida, Campello, Laranjeira, and Weisbenner, 2012; Carvalho, 2015). The *Delay* variable from Hoberg and Maksimovic (2015) infers investment delays due to liquidity issues based on firm 10-K discussions. Lastly, we create a composite measure (*Combo*), summing the standardized values of the first four measures.

We obtain covenant information from Loan Pricing Corporation's DealScan, matching records to Compustat as per Chava and Roberts (2008). We calculate the distance from covenant violations using thresholds defined in DealScan and the relevant financial information from Compustat. We use the earliest loan origination date and the latest maturity date to identify covenant threshold applicability. We focus on covenants with consistent, relatively uniform definitions across firms, aligning closely with established empirical standards (Demerjian and Owens, 2016). We measure contract strictness (*C.strict*) as the probability

[4] Note that Whited and Wu (2006) caution against extrapolating their model estimates out of sample. However, we include the WW index, given its prevalent usage in the literature.

of violating at least one covenant according to Murfin (2012). Notably, DealScan only provides covenant information at the initiation of a loan facility, which may become stale if firms retire, refinance, or renegotiate their debt (e.g., Gopalakrishnan and Parkash, 1995; Denis and Wang, 2014). Accordingly, we identify firms that report realized covenant violations (*Confirmed. viol*) in their 10-K or 10-Q filings using the data from Nini, Smith, and Sufi (2012).

Table 1 presents summary statistics for covenant variables defined at annual and quarterly frequencies. As prior studies indicate, our financial constraint proxies and covenant-based measures indicate that constraints are distinct from financial distress Whited and Wu (2006); Campello et al. (2010). Roughly 24% of firms face capital investment restrictions ($C.CapEx$). Nearly 10% of firms report covenant violations, on average, in a given year, and roughly one-third of firms report violations during some point in the sample Nini, Smith, and Sufi (2012). However, only 60 covenant violations result in subsequent defaults.

1.2. Supply chain network

Customer-supplier information comes from Compustat Segment data for public firms reporting customers who account for at least 10% of a firm's sales. We also use FactSet Revere LiveData (2003-2019), which compiles information from primary source documents, such as annual reports, investor presentations, and company websites. To further reduce network sparsity, we use the *vertical text-based network industry classification* (VTNIC) from Frésard, Hoberg, and Phillips (2020). The authors use 10-Ks and BEA input-output tables to calculate *directed vertical similarity scores*, which indicate two firms' potential to form a supply chain link. We merge these datasets into a single *directed* network $S \equiv [s_{ij}]$, where s_{ij} indicates the portion of supplier i's sales to customer j, and s_{ji} denotes the share of customer j's purchases from supplier i. We prioritize known relationships by emphasizing Compustat and FactSet relationships, re-scaling values so that the maximum VTNIC score to the lowest observed Compustat and Factset score. We explore the sensitivity of results to supply chain network measurement error in Section 3.1, and to networks constructed with alternative weighting schemes and each data source separately in the Internet Appendix.

Table 1 presents summary statistics for the supply chain network.[5] First, we calculate average *degree centrality*, which measures the number of observed partnerships as a fraction of the total number of possible partnerships in the network. On average, firms partner directly with 0.78% of other firms (32 partners). The *clustering coefficient* quantifies the proportion of firm pairs (i, j) who share common supply-chain partners (k) that are themselves direct partners (i.e., $s_{ij} > 0$). The average coefficient suggests the network is highly intransitive: merely 7.8% of partners also partner with a common third firm. For reference, a fully transitive network has a clustering coefficient of 100. The average *shortest path length* reflects that the minimal number of links separating firm pairs is only 2.92. Over 99% of firms are connected via at least one path within the supply-chain network. In sum, the network is sparse and strongly intransitive, yet densely connected through higher-order links, emphasizing the need for a network-based approach to model propagation effects.

2. Quantifying supply chain network effects

2.1. A simple model with investment interdependence

We provide a simple framework to formalize the notion that supply chains can enhance productivity by aligning and mutually reinforcing investments (Holmstrom and Milgrom, 1994; Galeotti et al., 2020). Let the output Q of firm i depend on its own investment Y_i and the investment of its supply chain partner Y_j, and that a firm's profit function Π_i includes quadratic costs:

$$Q_i = \alpha_i Y_i + \Gamma Y_j Y_i \qquad \Pi_i = \alpha_i Y_i + \Gamma Y_j Y_i - \frac{1}{2} k Y_i^2. \tag{1}$$

Solving for the first order conditions, we obtain:

$$\frac{\partial \Pi_i}{\partial Y_i} = \alpha_i + \Gamma Y_j - k Y_i = 0. \tag{2}$$

[5] To simplify the analysis, we derive network statistics from the adjacency matrix $S^A \equiv [s_{ij}^A]$, with $s_{ij}^A = 1$ for $s_{ij} > 0$ and $s_{ij}^A = 0$ otherwise. See the Appendix or Jackson (2010) for details on network statistics.

This model leads to a simple linear relation between Y_i and Y_j:

$$Y_i = a + \rho Y_j + x_i \beta \qquad\qquad Y_j = a + \rho Y_i + x_j \beta, \tag{3}$$

where $\rho = \Gamma/k$ captures interdependence between firms i and j, and $\alpha_i/k = a + x_i\beta$ denotes firm i's characteristics.

Now consider a scenario where firm i faces external financing constraints, due to highly specific or intangible assets with low pledgeability in the spirit of (Hart and Moore, 1994; Almeida and Campello, 2007). Let fc_i represent the degree to which the constraints are binding $Y_i^c \leq F(fc_i) < Y_i^*$, resulting in $Y_i^{c*} = F(fc_i)$. From Equation (3), noting $Y_j^{c*} = a + bF(fc_i) + x_j\beta$, the partial derivative of firm (j)'s investment Y_j^{c*} with respect to firm (i)'s constraint F(fc_i) is:

$$\frac{\partial Y_j^{c*}}{\partial F(fc_i)} = \frac{\partial}{\partial F(fc_i)}(a + bF(fc_i) + x_j\beta) = b. \tag{4}$$

If $F(fc_i)$ is a decreasing function of financial constraints, then an increase in firm i's constraints reduces its financing capacity, thereby reducing firm j's optimal investment level.

2.2. Network regressions

We generalize the investment function for firm i from the two-firm case to a network with N firms. We represent a firm's investment as a function of its own constraints and policy choices, as well as its partners' investments in scalar and matrix notation:

$$\begin{aligned} y_{i,t} &= \rho \sum_{j=1}^{N} s_{ij,t-1} y_{j,t} + fc_{i,t-1}\delta + X_{i,t-1}\beta + \epsilon_{i,t}, \\ Y &= \rho SY + F\delta + X\beta + \epsilon, \end{aligned} \tag{5}$$

and solve the simultaneous equations as we did for the two-firm case to obtain the data-generating process:

$$Y = (I_N - \rho S)^{-1}(FC\delta + X\beta + \epsilon), \tag{6}$$

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 $S \equiv [s_{ij}]$ denotes the supply chain network that we define in Section 1.2. We row-normalize S and preclude firms from being their own partner ($s_{ii} \equiv 0$). As in the two-firm example, the parameter ρ in the network model captures interdependence in investments. Equation (5) reduces to a conventional firm-centric model (i.e., $y_{it} = fc_{i,t-1}\delta + X_{i,t-1}\beta + \epsilon_{it}$) when $\rho = 0$. The inverse term $(I - \rho W)^{-1}$ captures the cumulative effect of investment interdependence across the entire network.

Equation (6) indicates that the partial derivatives are a function of supply chain partner covariates, as in the two-firm example in Equation (4). In general, the partial derivative effects can depend on many firms in the supply chain. We separate the total partial derivative effects of changing firm i's constraints into the *direct effects* on its own investments (Y_i), and the cumulative *indirect effects* on other firms' investments (Y_j for $j \neq i$) throughout the rest of the supply chain:

$$E[\partial y_i/\partial fc_i] = (I_N - \rho S)^{-1}_{ii}\,\delta, \tag{7}$$

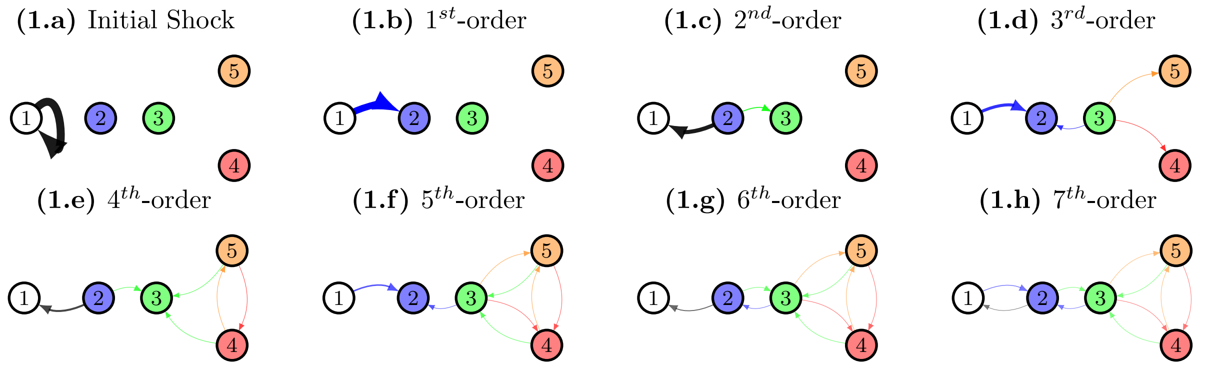
$$\sum_{j\neq i} E[\partial y_j/\partial fc_i] = \sum_{j\neq i} (I_N - \rho S)^{-1}_{ji}\,\delta. \tag{8}$$

The cross-partial derivatives $\partial y_j/\partial fc_i$ in Equation (8) are potentially non-zero, even though y_j does not depend directly on fc_i for $i \neq j$ in Equation (5). To illustrate how the direct and indirect effects of investment decisions can propagate through many connected firms, including indirect linkages, we write the infinite series expansion of the term $(I_N - \rho S)^{-1}$:

$$Y = (I_N + \rho S + \rho^2 S^2 + \rho^3 S^3 + \ldots)(FC\delta + X\beta + \epsilon), \tag{9}$$

where S^K represents k^{th}-order links. Figure I illustrates propagation effects originating from a shock to firm 1 through a simple network S. A change in firm 1's constraints (∂fc_1) initially affects its own investment y_1, which then influences partner 2's investments y_2 through ρS_{12}. Although firm 1 only partners with firm 2, firm 2's response influences firm 3's investment y_3 through 2^{nd}-order effects ($\rho^2 s_{12} \times s_{23}$), and so on. Firm 1 eventually influences all five firms through this chain reaction, including itself through feedback loops as in figure (1.c). The *direct effects* in Equation (7) summarize the cumulative own-firm impact, including feedback effects, and the *indirect effects* in Equation (8) describe the *cumulative* effects of ∂fc_1 on firms 2-5. The network multiplier $(1/(1-\rho))$ summarizes the cumulative network effects, which intuitively increases with stronger investment interactions (i.e., larger ρ).

Figure I



Equation (5) is analogous to an SEM, where each equation corresponds to a single firm's investment outcome as a function of its partners' investments. Thus, estimating Equation (5) directly induces a simultaneity bias. The most severe case, often referred to as the Manski (1993) reflection problem, occurs when firms are equally connected within perfectly transitive peer groups. We use numerical maximum likelihood to estimate the reduced form Equation (6), which is nonlinear in the structural parameters (ρ, β, δ). Identification comes from firm-level variation in f_{it}, X_{it} and s_{ij}, akin to SEM exclusion restrictions (Lee and Liu, 2010). We bootstrap standard errors assuming $\epsilon_{it} \sim N(0, \sigma^2 I_N)$.

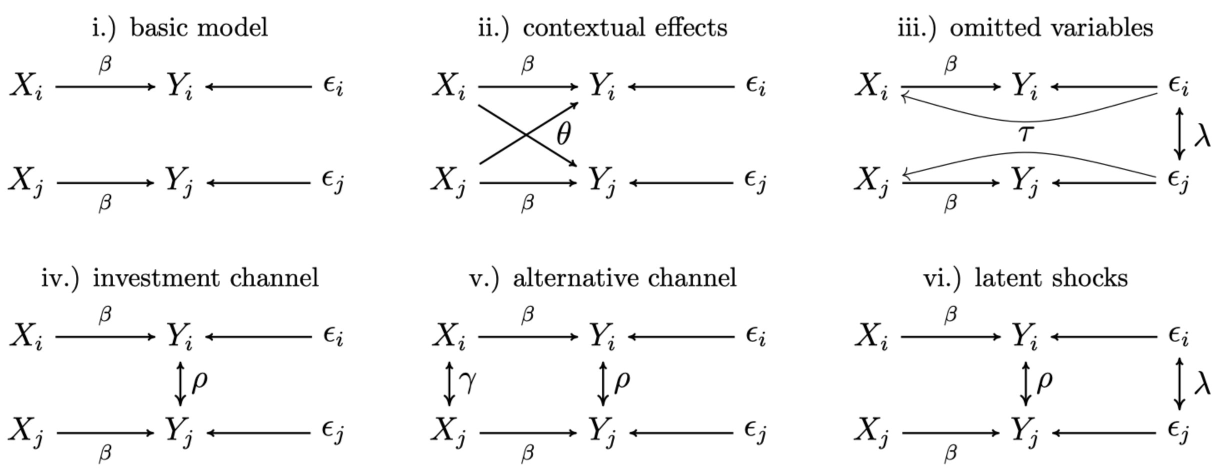
This contemporaneous relationship aligns with the economic intuition and assumptions established in recent studies (e.g., Dougal, Parsons, and Titman, 2015; Bustamante and Frésard, 2021; Berg, Reisinger, and Streitz, 2021). Intuitively, this framework models firms interacting through a series of actions, reactions, reactions to reactions, etc., over the course of a year. Best practices in supply chain management recommend concurrent investment coordination rather than sequential processes. This approach accelerates recovery after disruptions and enhances the ability to monitor market responses and quickly assess each operational area in emergencies (Fernie and Sparks, 2004; Slone, Mentzer, and Dittmann, 2007). We provide anecdotal evidence in the Internet Appendix consistent with this behavior.

2.3. Identification of network effects

Leary and Roberts (2014) highlight the difficulties in distinguishing whether firm decisions are influenced by peer decisions, peer characteristics, or peer selection effects within a linear-in-means peer effects model. While network regressions improve upon linear models by exploiting intransitive relationships and capturing non-linear network dynamics, Leary and Roberts (2014) provide a useful framework to outline endogeneity issues commonly encountered in studies of financial constraints and firm interactions.

Figure II provides a visual comparison of different models to aid in the discussion of these issues. Model (i) provides a baseline without endogeneity, Model (ii) includes contextual peer effects, and Model (iii) adds a form of omitted variable bias with $\tau \neq 0$ (i.e., $corr(X, \epsilon) \neq 0$). Linear methods such as ordinary least squares are valid for estimating the firm-centric Models (i)–(iii), which exclude interactions in the outcome variable. Notably, even if the contextual effects θ are not of direct interest, estimating Model (ii) may help mitigate omitted variable bias if measurement errors in own-firm covariates are correlated with partners' covariates. Model (iv) introduces investment interactions among firms, where the direct effects of constraints (β) trigger indirect effects on partner investments via ρ, yielding the network dynamics discussed in Section 2. Model (v) links constraints directly between firms (γ), and Model (vi) adds latent common influences (λ).

Figure II: Channels of influence



We use Models (ii), (iii), (v), and (vi) to illustrate potential sources of spurious correlations in investment behaviors. We identify four key challenges in our study: (a) endogenous network formation, (b) inaccurate or missing supply chain links, (c) measurement errors in financial constraints, and (d) alternative channels. To address these issues, we leverage the strengths of network regressions by integrating recent empirical innovations.

3. Baseline results

Table 2 presents estimates for models explaining corporate investment for each of the eight financial constraints (FC) measures outlined in Section 1. We report estimates for the structural coefficient ρ, as well as the partial derivative of the direct and indirect effects defined in Equations (7) and (8). Notably, the direct and indirect effects differ from the structural coefficients (i.e., δ, β), which do not convey economic effects in isolation. We standardize all non-dummy variables to facilitate the comparison of magnitudes across models and include time fixed effects in all specifications.

The first row of Table 2 reports ρ coefficients, providing strong evidence of supply chain investment interactions across all eight models. The average ρ estimate of 0.485 implies that an initial shift in investment leads direct partners to adjust investment, collectively, by roughly half of that change, leading second-order connections to adjust by roughly one quarter of the initial amount (0.485^2), and so forth. The direct effects estimates suggest that tightening a firm's constraints by one standard deviation curtails own-firm investment by 0.08 standard deviations, or 0.83 percentage points ($0.08 \times 0.097 = 0.83\%$). This economic effect is consistent with those reported in recent studies focusing on own-firm effects of constraints on investment (e.g., Almeida and Campello, 2007; Hoberg and Maksimovic, 2015). Our estimates of the average indirect effects suggest that propagation through supply chain networks leads to an additional cumulative drop of 0.7 percentage points in total investment spending. This economically significant spillover effect is nearly as large as the direct effect of financial constraints, amounting to approximately 84% of the direct impact on investment.

While Columns (1)-(5) provide a useful starting point for our analysis, indirect constraint proxies may exhibit measurement error, such as inadvertently reflecting unmodeled aspects of a firm's investment opportunities or life cycle (Alti, 2003; Farre-Mensa and Ljungqvist, 2016). Model (iii) of Figure II illustrates this scenario when $\tau \neq 0$. To partially address this concern, we use covenant-based measures of constraints. Debt covenants explicitly define binding legal agreements in which a violation can restrict a firm's autonomy over investment and financing decisions via the transfer of control rights (Baird and Rasmussen, 2006). Thus, covenant stringency enhances measurement objectivity compared to indirect proxies and establishes a direct mechanism linking financing to investment behavior.

Columns (6)-(8) report results for covenant-based measures of constraints. Notably, the results for capital expenditure-specific covenants in Column (7) provide evidence of economically meaningful effects directly linking constraints to investment spending. The consistency of results across all eight models in Table 2 indicates that our conclusions are not overly sensitive to the choice of financial constraint proxy. These findings are robust to alternative sample periods, network constructions, measures of investment, and variations in control variables.[6] We also obtain quantitatively similar estimates when controlling for several financial distress measures such as rating downgrades, firms exiting the sample, bankruptcy, and distance to default estimates.[7] Our goal is not to rule out that financial distress generates spillovers, but to ensure that our findings are primarily due to constraints of firms that are not near insolvency, aligning with the emphasis of recent studies (Dichev and Skinner, 2002; Whited and Wu, 2006; Campello et al., 2010; Nini et al., 2012).

Our study emphasizes the indirect effects estimates, which represent the *cumulative* external impact of tightening a firm's financial constraints on partners' investment spending. Section 2 demonstrates that these indirect effects depend on the structure of the entire production network, including indirect supply chain linkages. Table 1 highlights that the production network exhibits the pervasive small-world property common to many economic networks (Jackson, 2010). While only 0.78% of firm pairs are direct partners, most firms

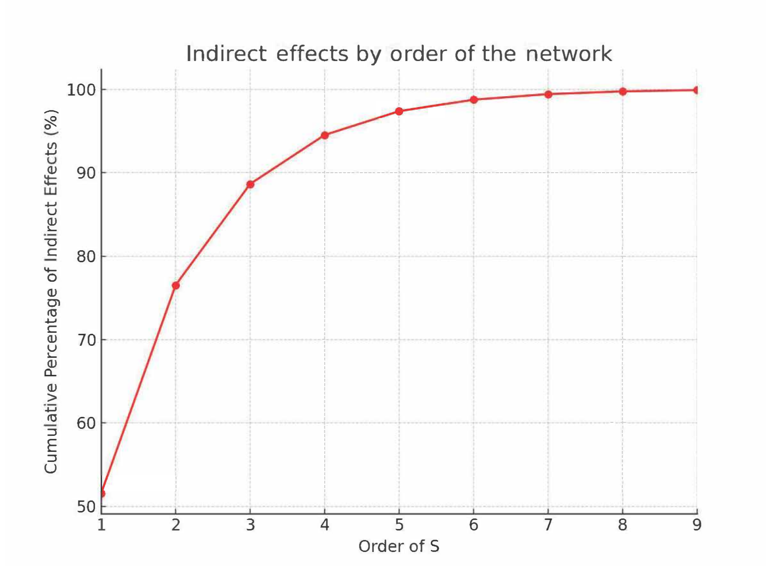
[6] See the Internet Appendix for these results. We note that the covenant-based proxies in Column (6)-(8) employ quarterly data to maintain consistency with later analysis. We also report quantitatively similar estimates for analogous specifications using annual data in the Internet Appendix.

[7] We do not include these variables in our primary analysis because they reduce the sample size considerably. We also exclude firms with less than eight consecutive quarters of data or more than two quarters of negative sales growth, as in Whited and Wu (2006), and firms with Tobin's Q less than one.

are separated by just a few intermediary links, and nearly all firms are connected through at least one chain.

To illustrate the impact of the small-world property, Figure III displays the percentage of cumulative indirect effects attributed to each order of network connections. Strikingly, only half of the network effects originate from direct partners, with the remaining effects stemming from higher-order connections. This distribution underscores the considerable role of indirect network linkages in amplifying the effects of financial constraints. According to the network multiplier that we calculate from the average ρ coefficient in Table 2 ($\frac{1}{1-\bar{\rho}} = 1.94$), total network effects nearly double the impact of an initial investment disturbance. This magnitude aligns with the network multiplier effects reported in recent studies.[8]

Figure III: Cumulative effects and higher order links



3.1. Endogeneity and supply chain network structure

Endogenous network formation can lead to selection biases if firms are more likely to form partnerships when they exhibit similar unobservable characteristics that are correlated with investment—i.e., they exhibit homophily. This scenario may introduce challenges in distinguishing between interdependent investment behavior and inherent firm similarities or

[8]See: (Elliott, Golub, and Jackson, 2014; Acemoglu, Akcigit, and Kerr, 2016a; Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2016b, 2017; Boehm, Flaaen, and Pandalai-Nayar, 2019; Di Giovanni and Hale, 2022; Ozdagli and Weber, 2023).

shared environmental factors, such as natural disasters, market shifts, or regulatory changes. In Models (iii) or (vi) of Figure II, the parameters λ and τ represent the potential influence of the unmodeled partner selection process or latent common factors.

3.1.1. Supply chain stability and heterophily

Several features of our study limit the potential influence of endogenous network formation. Intransitivity in supply chain relationships implies firms are less likely to be connected simply because they share similar characteristics, reducing the risk of homophily bias. For a more formal examination, we use Exponential Random Graph Models (ERGMs) to analyze partner selection as a function of similarities in constraint and investment levels among firms. ERGMs extend logistic regressions to account for interdependence within the entire network, aiding in the prediction of supply chain formation (e.g., Robins, Pattison, Kalish, and Lusher, 2007; Ahern and Harford, 2014; Kim, Howard, Cox Pahnke, and Boeker, 2016). For example, Apple simultaneously decides to purchase processors from Intel and not to purchase from AMD.

The ERGM estimates reveal *heterophily* in our variables of interest; firms with similar investment and constraint levels are *less likely* to form partnerships. A one standard deviation decrease in the differences in two firms' investment or constraint levels leads to, respectively, a 0.62 and 0.09 percentage point *reduction* in the likelihood of forming a partnership. Although this evidence does not definitively resolve concerns, it suggests that homophily is unlikely to be the primary factor influencing our findings. We provide additional ERGM estimates and detailed discussions in the Internet Appendix.

3.1.2. Long-term partner network

To further address potential selection effects, we focus on long-standing supply chain relationships that are less likely to be influenced by current financial constraints and investment opportunities. To this end, we replicate our analysis in Table 2, restricting the supply chain network to include only long-term partnerships that are at least five years old at time $t-1$ (i.e., $s_{i,j,t-1} > 0 \wedge s_{i,j,t-6} > 0$). We posit that partner selection decisions made at time $t-6$

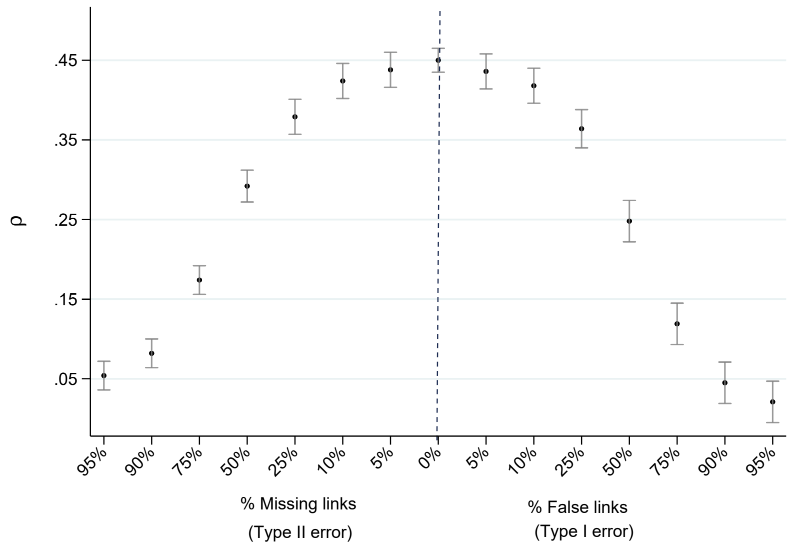
or earlier are less likely to conflate with financial constraints at time $t-1$ and investment decisions at time t. Table 3 presents results for the restricted, long-term partner network. The ρ, direct, and indirect effects estimates for indirect proxies of financial constraints in Columns (1)-(5) are only 8% lower than the corresponding estimates in Table 2, on average. The estimates using covenant-based measures in models (6)-(8) show a stronger attenuation of about 25%, yet they remain economically meaningful. The estimates are all within 5% of each other across all eight columns, demonstrating strong consistency across several financial constraint measures.

3.1.3. Measurement error in the supply chain network

To evaluate the robustness of our estimates to measurement errors in identifying partnerships, we conduct robustness analyses using simulations, alternative weighting schemes, and various data sources. First, we generate simulated data using Equation (6) as the data generating process and the real data for independent variables. To generate investment outcomes, we fix the true coefficient $\rho^* = 0.450$ to match the average estimate from Tables 2 and 3, and we fix the true network $S^* = S$ to match our primary supply chain network defined in Section 1.

We systematically introduce error from *false links* by *replacing* 5%, 10%, 25%, 50%, 75%, 90%, and 95% of a firm's *known* partnerships with links drawn randomly from the full sample of non-partner firms. Similarly, we introduce error from *missing links* by randomly *removing* the same percentages of a firm's *true* supply chain connections *without replacement*. Figure IV reports the average ρ estimates from 100 simulations for each level of false and missing links. The baseline case, altering 0% of firm links (using S^*), yields an average ρ estimate of 0.448, closely matching the set parameter ($\rho^* = 0.45$). The ρ estimates gradually attenuate as we increase the error rate, dropping modestly from 0.45 to 0.36 (0.38) even after removing (replacing) 25% of the links. The estimates decline precipitously only after removing or replacing 75% of a firm's known links.

Figure IV: Measurement error in supply chain networks



The attenuation effect in Figure IV is marginally more pronounced for false links than omitted links at each level, but the effect is nearly symmetric. Notably, introducing false links preserves the density of the fixed network by *replacing* existing links. Thus, estimations with false links serve as falsification tests by allowing firms to maintain a constant number of connections, which might include other important economic relationships such as geographic proximity, product market competition, and common lenders. Thus, the relatively low ρ estimates for high percentages of false links are reassuring that the supply chain network captures economic features distinct from other types of connections.

Missing links simulate scenarios where the available data fails to capture all supply chain links. Databases like Compustat and Factset identify important supply chain connections among a broad sample of large, publicly traded firms, likely representing more influential relationships. Consequently, deleting these documented links in our simulations likely distorts inferences more severely than the links missing in our databases. False links occur when a documented supply chain link is either erroneous or inactive. The VTNIC reduces missing links but introduces false links, as it captures the *propensity* for firms to engage in supply chain relationships rather than observed relationships. We obtain quantitatively similar estimates to our baseline analysis for several variations in network definitions—using Compustat, Factset, and VTNIC individually and alternative weighting schemes.

In summary, both simulations and robustness analyses yield highly consistent network multiplier effects stemming from investment interdependence. The stability of ρ coefficient estimates across moderate variations in network construction is consistent with the analytical framework of LeSage and Pace (2014). Overall, this analysis strengthens confidence that our conclusions are robust to a reasonable degree of network measurement error, including issues related to false or missing links.

3.2. Network regression discontinuity design

As highlighted in Section 3, using covenant-based measures to gauge financial constraints helps mitigate concerns over measurement error. However, unobservable factors, such as management quality, firm life cycle stages, or market conditions, may continue to pose significant challenges if they relate to both financial constraints and investment levels. Model (iii) of Figure II illustrates this issue when $\tau \neq 0$.

Chava and Roberts (2008) develop a covenant-violation RDD that offers several advantages over common financial constraint proxies, inspiring its adoption in several influential studies.[9] Covenant violations are determined by definite criteria and mandatory reporting, and they create a discrete jump in financial constraints by restricting a firm's autonomy over investment and financing decisions (Nini, Smith, and Sufi, 2009). Moreover, firms within a narrow bandwidth of violation arguably share similar attributes apart from their treatment status, reducing the potential influence of unobserved characteristics.

While an RDD provides an appealing alternative identification strategy, it also relies on the stable unit treatment value assumption (SUTVA) (Cox, 1958; Roberts and Whited, 2012; Berg, Reisinger, and Streitz, 2021). SUTVA assumes that one firm's treatment does not affect

[9] See: Roberts and Sufi (2009); Hadlock and Pierce (2010); 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).

the outcomes of other firms. Interdependent investment clearly violates this assumption, introducing the potential for firms to receive indirect treatment. To model indirect treatment effects, we integrate the covenant violation RDD within a network framework, starting with the following structural equation:

$$Y = \rho SY + \Phi D + X\beta + f(Z) + \epsilon, \tag{10}$$

where D is a vector of treatment indicators for each firm, and Z is the running variable for current ratio, net worth, and tangible net worth covenants as in Chava and Roberts (2008). Equation (10) violates SUTVA and estimates of own-firm treatment effects in a classical RDD framework are ill-identified. Drawing an epidemiological parallel, vaccination of an individual reduces health risks for others. Comparing the health outcomes of vaccinated and unvaccinated individuals would yield biased estimates of vaccine efficiency. Similarly, a firm's adjustments to investments post-covenant violation could influence the investment decisions of its partners. Thus, a network framework can improve own-firm treatment effect estimates.

By focusing on the *partners* of covenant-violators, our study mitigates potential concerns that firms near the cutoff systematically differ by more than their proximity to the threshold. For instance, one concern in the conventional RDD framework is that firms might manipulate their financial reporting to avoid covenant violations. However, firms typically have limited control over their supply chain partners' actions, reducing this concern in our setting.

3.2.1. Network RDD: Local linear approach

Critical choices in estimating an RDD include making assumptions on how to assign treatment status (i.e., sharp vs. fuzzy design) and how to model the functional form of the running variable $f(Z)$. We first consider a *sharp* RDD, where treatment assignment is deterministic: $D = [d_{it}]$, $s.t.$ $d_{it} = 1$ if $z_{it} - z_0 < 0$ and $d_{it} = 0$, otherwise. Here, z_0 denotes the covenant violation threshold. Common approaches to modeling $f(Z)$ include local linear regressions and polynomial regressions, each offering distinct trade-offs.

We start with the local linear regression approach, which involves estimating a linear model within a narrow bandwidth around the threshold z_0. By focusing on the most informative data points near the cutoff and using a simple, functional form, the local linear model reduces bias by avoiding extrapolation from less relevant observations far from the cutoff. Despite these appealing features, the firm-centric local linear regression omits a large portion of the sample from the analysis, which can lead to an omitted variable bias. To overcome this limitation, we adapt the method proposed by Cornwall and Sauley (2021). Specifically, we estimate the reduced form Equation (11) for the full sample, and subsequently filter the residuals to remove the effects of investment interdependence.

$$Y = (I_N - \hat{\rho}S)^{-1}(X\hat{\beta} + f(Z) + \hat{\Phi}D + \epsilon), \tag{11}$$

$$\tilde{\epsilon} = [I_N - \hat{\rho}S][Y - (I_N - \hat{\rho}S)^{-1}X\hat{\beta}]. \tag{12}$$

The residuals in Equation (12) are filtered in the sense that $(I_N - \hat{\rho}S)^{-1}X\hat{\beta}$ removes investment spillovers in Y, *not due to 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 treatment and control groups:

$$\begin{aligned} \underline{\tilde{\epsilon}} &= \underline{\phi} + \underline{\lambda}Z + \underline{u} \quad \text{if } d_{it} = 1 \\ \bar{\tilde{\epsilon}} &= \bar{\phi} + \bar{\lambda}Z + \bar{u} \quad \text{if } d_{it} = 0. \end{aligned} \tag{13}$$

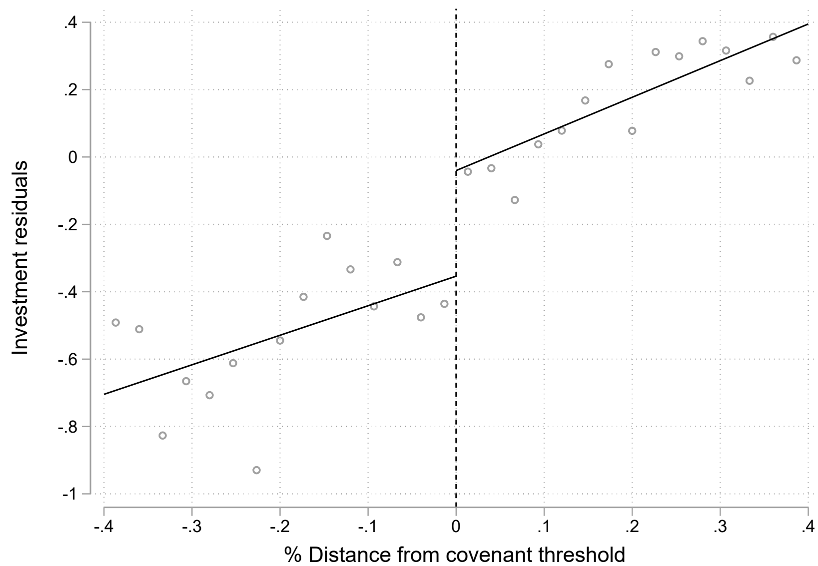
where $\hat{\phi} = \underline{\phi} - \bar{\phi}$ is the local average treatment effect (LATE) estimate. The local linear network RDD employs an iterative MCMC process of estimating Equations (11)-(13), using $\hat{\phi}$, $\bar{\lambda}$, $\underline{\lambda}$ in the last step as a proxy for $\hat{\Phi}$ and $f(Z)$ in the following iteration.[10]

Figure V plots the network RDD residuals and regression lines for Equations (13) and (13), indicating a clear discontinuity at the threshold. Column (1) of Table 4 presents ρ estimates, which are consistent with the magnitudes reported in Table 2. The direct local average treatment effects estimates indicate that a technical covenant violation ($Technicalviol.$) curtails own-firm investment by 1.8 percentage points. The indirect treatment effects suggest

[10] Estimates from 4000 draws approximate the joint parameter distribution with an initial Φ and *f(Z)* each set to 0, where $f(Z) = \bar{\lambda}Z + \underline{\lambda}(Z \times D)$. We calculate the optimal bandwidths (14,182 firm-quarters) according to Imbens and Kalyanaraman (2012). In untabulated analysis, we also explore bandwidths where the absolute value of the relative distance from a covenant threshold is less than 0.20, following Falato and Liang (2016).

a violation further reduces total supply chain investment, relatively, by an additional 1.95 percentage points, or roughly 109% of the own-firm treatment effects.

Figure V: RDD residual plot and treatment effects



3.2.2. Network RDD: Hybrid covenant violation classifications

The analysis in Column (1) of Table 2 assigns treatment status $d_{it} = 1$ based on technical violations we infer from DealScan and Compustat, as per Chava and Roberts (2008). In this approach, some firms are misclassified due to waived violations or debt renegotiations. Consequently, we adopt the approach of Roberts and Sufi (2009) and Nini et al. (2012), defining $Confirmedviol.$ to represent *actual* treatment, where $d_{it} = 1$ if a firm reports a covenant violation in their financial statements, and 0 otherwise. While confirmed violations ensure compliance with treatment status, firms often fail to report the specific covenants they breach. Consequently, we can not assign treatment status as a deterministic function of Z.

To address these limitations, we combine the advantages of both technical and confirmed violations within a fuzzy local linear network RDD framework. We define a hybrid violation $Hybridviol. = 1$ only when a firm meets both criteria: it is in technical violation

($Technicalviol. = 1$) and officially reports the violation ($Confirmedviol. = 1$). This dual condition creates a subset of the data where treatment is almost deterministic, approximating a sharp RDD. We estimate a specification using $Hybridviol.$ to assign treatment status via the local linear network method, the running variable Z, and control variables X as in Column (1).[11] The results reported in Columns (1) and (2) reveal that, for similar ρ values, the direct and indirect effects estimates for $Hybridviol.$ are approximately twice as large as those for $Technicalviol.$. This finding is reassuring since hybrid violations are more likely to capture consequential violations that are not waived or renegotiated, thus generating larger supply chain disruptions.

3.2.3. Network RDD: Polynomial approach

While the local linear regression minimizes extrapolation errors by focusing on a narrow bandwidth of firms around a violation threshold, it may not capture broader patterns across the entire sample or non-linear relationships. This limitation makes the polynomial approach particularly appealing for the study of confirmed covenant violations, where we do not observe which exact covenant thresholds are breached, and the relationships between the running variables and outcomes are potentially complex.

A major advantage of the polynomial approach is that the analysis uses the full sample (Angrist and Pischke, 2008) with covenant violations confirmed from firms' 10-K and 10-Q filings. Thus, adapting the approach to a network framework only requires modifying our initial setup in Equation (5). Following the methodology of Roberts and Sufi (2009) and Nini et al. (2012), we specify a 3^{rd}-degree polynomial of the running variables

$$Y = \rho SY + \Phi D + Z\psi_1 + Z^2\psi_2 + Z^3\psi_3 + X\beta + \epsilon, \tag{14}$$

where we assign treatment according to confirmed violations $D = Confirmedviol.$. The network polynomial RDD achieves identification by controlling for a flexible, functional form of the running variable Z. Thus, we add financial ratios for *operating cash flow to lagged*

[11] We also estimate a fuzzy RDD IV approach using technical violations as an instrument for confirmed violations, and we experiment with mechanically reassigning potentially falsely treated firms to the control group and kicking them out of the sample altogether.

assets, total debt to assets, interest expense to lagged assets, net worth to assets, current assets to current liabilities, and *market-to-book* values to the set of control variables to help isolate the discontinuity Φ that occurs at the violation threshold.[12]

Column (3) of Table 4 presents the network polynomial RDD results. Column (4) uses *Hybridviol.* to assign treatment status, more closely approximating a sharp design. Estimates for investment interdependence (ρ) remain consistent with prior analysis. The estimates suggest the direct treatment effects of covenant violations decrease own-firm investment by 1.5 percentage points, and the indirect treatment effects reduce total supply chain investments by an additional 1.7 percentage points.

3.2.4. Network RDD: Entropy balancing

The local linear and polynomial methods are techniques to strengthen the validity of the core RDD assumption by improving covariate balance between the treatment and control groups. To enhance this objective, we employ entropy balancing in our network RDD framework. Entropy balancing, introduced by Hainmueller (2012), optimizes a weighted least squares regression to achieve an exact match in covariate moments (e.g., means and variances) between treatment and control groups, while minimizing differences from equally weighted observations. By minimizing pre-treatment differences, entropy balancing strengthens the chances that variations in outcomes are mostly attributable to *partners'* treatment effects, thereby mitigating potential biases from financial manipulations or latent shocks common to the *partners* of firms' near the threshold.

We estimate Equation (14) with entropy balancing for the first two moments (mean and variance) of the control variables and running variable polynomials in Column (5), adding ratio variable polynomials in Column (6). While the direct effects remain consistent with estimates from specifications without entropy balancing, the indirect effects are moderately attenuated relative to the results reported in Columns (3) and (4). Overall, our findings

[12] We adapt Equation (14) according to Nini, Smith, and Sufi (2012), excluding first-differencing and including only time fixed effects. Nini, Smith, and Sufi (2012) note that the fuzzy polynomial RDD aligns closely with a sharp RDD if covenants are uniformly written. While actual uniformity is rare, the approach provides a useful approximation.

remain stable with exact matching on pre-treatment covariate moments for an extensive set of controls. This stability increases our confidence that our conclusions are not overly sensitive to confounding variation in common shocks or financial manipulations around covenant violation thresholds.

3.2.5. Network RDD: Long-term partners

Firms might strategically choose new supply chain partners to reduce the disruptions stemming from partners' financial constraints. Focusing on short-term spillover effects mitigates these concerns due to frictions in substituting partners (Barrot and Sauvagnat, 2016; Boehm, Flaaen, and Pandalai-Nayar, 2019). To further mitigate the potential influence of supply chain turnover, we estimate all network RDD specifications from Columns (1)-(6), using the long-term partner network from the analysis in Table 3. Although slightly weaker, the estimates we report in Columns (7)-(12) are stable across specifications, and they reinforce the pattern that the *cumulative* network effects are consistently comparable in magnitude to the own-firm effects. These findings confirm the presence of significant investment spillovers in supply chains, reducing concerns over potential biases from associations between covenant violations and short-term partner turnover.

3.2.6. Network RDD: Measuring market responses

If spillovers affect partners' investment prospects, they might also affect partners' stock returns, to the extent they are unanticipated. To explore this possibility, we employ the network RDD to compare the returns of firms whose partners are marginally above or below the covenant violation threshold. Table 5 presents analysis using abnormal quarterly stock returns as the dependent variable, adjusted according to Daniel, Grinblatt, Titman, and Wermers (1997). Columns (1)-(6) report results from specifications analogous to Columns (1)-(6) of Table 4. Columns (7)-(12) report estimates from analysis using the long-term partner network.

Consistent with prior literature, the own-firm effects of financial constraints on stock returns are negative on average (Cortes and H Rocha, 2021). While the impact on returns is less pronounced than for investment outcomes, this discrepancy may stem from inherent difficulties in pinpointing the exact timing of market reactions to financial constraints relative to corporate investment data. The indirect effects reveal a negative and significant impact on returns in nine of the twelve models, suggesting that covenant violations and the subsequent low returns reflecting fundamental market valuations transmit through the supply chain network.

3.3. Accounting for common shocks

Common shocks refer to external events, such as policy changes or technological advancements, that simultaneously affect multiple firms within the supply chain network, potentially confounding the analysis by introducing correlated errors among partners. As noted in Section 1.2, the supply chain network is sparse and highly intransitive, indicating little overlap in firm connections. These features dramatically limit the type of shock and the number of paths through which that shock can propagate, thus limiting the scope of any particular shock to influence several firms at once.

In sum, the structural aspects of the supply chain network and the advantages of network regressions facilitate the separation of influences of observed variables from unobserved common shocks. Enhancements to our initial framework, such as adopting a network RDD, applying entropy balancing, and adjusting stock returns according to Daniel et al. (1997), substantially mitigate concerns related to the effects of latent common shocks, depicted by $\lambda \neq 0$ in Models (ii) and (vi) of Figure II. Nonetheless, we employ additional strategies to address the potential distortions arising from common shocks.

3.3.1. Accounting for industry-wide shocks

We first address the potential that documented ripple effects are due to industry-wide shocks by directly accounting for several industry characteristics based on TNIC-3 industry definitions Hoberg and Phillips (2010a, 2016). This approach has distinct advantages over other methods, such as using industry fixed effects. TNIC classifications provide a more accurate representation of a firm's competitive environment than traditional industry classifications, such as SIC codes, by assigning to each firm a unique set of competitors. Secondly, the TNIC's dynamic definitions allow control of evolving industry trends and opportunities, surpassing the limitations of static industry characteristics.

Integrating industry controls into network regressions provides an important advantage. Rather than confining industry shocks to an equal, initial impact on all firms within a given industry, network regressions allow industry shocks to diffuse through the supply chain network, thereby enhancing flexibility and explanatory power over a simple fixed effects model. As shown in Table 6, the adjustment results in a modest decrease in the average ρ estimate from 0.48 to 0.45. However, the direct and indirect effects estimates remain strongly consistent with prior estimates, indicating strong network effects. Thus, accounting for the direct effects of industry-specific covariates and for the subsequent diffusion through the supply chain network does not fundamentally change our conclusions.

3.3.2. Controlling for common shocks with spatial methods

To further evaluate the potential confounding effects of latent common shocks, we estimate a Spatial Autocorrelation (SAC) model. Common shocks could result from unobserved influences in the independent variables that, in turn, influence the dependent variable, or they could directly arise from latent shocks to the dependent variable. The SAC model provides a framework to account for both possibilities:

$$Y = \rho SY + FC\delta + X\beta + \epsilon, \quad \epsilon = \lambda S\epsilon + u \tag{15}$$

The network lag of the dependent variable (ρSY) captures the direct influence of partners' investment outcomes on the firm's own investment, including the spillover effects of partners' characteristics (e.g., financial constraints). The $\epsilon = \lambda S\epsilon + u$ term implies that the error is a function of supply chain disturbances plus an i.i.d error term u. The $\lambda S\epsilon$ term captures latent common shocks that affect multiple firms in the supply chain in similar ways but are not included in the model. Given that $\epsilon = (I_N - \lambda S)^{-1}u$, we substitute ϵ back into the first equation and solve for the reduced form in terms of Y to get:

$$Y = (I_N - \rho S)^{-1}\left(FC\delta + X\beta + (I_N - \lambda S)^{-1}u\right) \tag{16}$$

Equation (16) models the diffusion of unobserved shocks $\lambda S\epsilon$ through the same supply-chain network driving investment interactions ρSY. Thus, the SAC model effectively addresses the influence of latent common shocks by providing a framework for network effects in both the dependent variable and the error terms. We estimate the SAC model for the eight analogous models presented in Table 2. The analysis reveals a slight decrease in the average ρ estimate from .485 in Table 2 to .447, while the average λ estimate is .084. Figure VI displays the average cumulative percentage of total effects estimates attributed to investment interactions (ρ) and common shocks (λ), calculated for different orders of connection in the supply chain network S.

Figure VI: Common shocks in supply chain networks

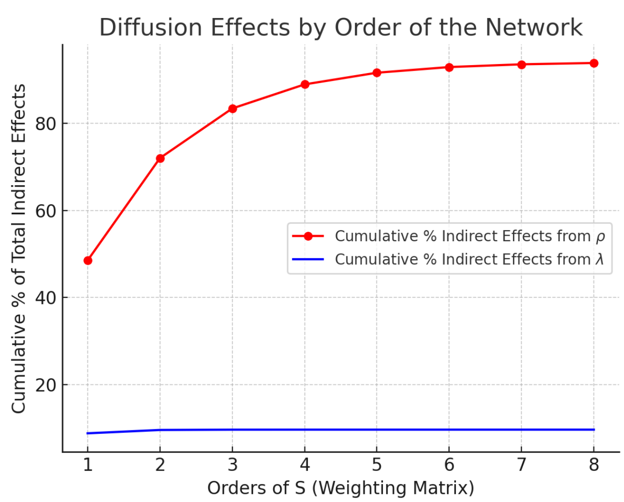


Figure VI reveals that network dependence in the outcome variable generates a very different process than common shocks in the error term. Network dependence in the outcome variable signifies that the total impact of a change in an independent variable is not only due to the direct effect (β), but also gets amplified through interactions in the network, captured by ρ. This multiplier effect means that changes in one unit can indirectly affect other units through the network structure, leading to a more widespread impact than just the direct effect. By contrast, network dependence in the error term does not directly affect the dependent variable itself but is confined to the error terms, represented as $\lambda S\epsilon$. Hence, there is no multiplier effect on the dependent variable itself. Here, λ measures the degree of autocorrelation in the errors across the supply chain.

3.4. Financial health transmission and lender networks

Three alternative channels related to a firm's access to finance could generate similar investment correlations to what we document. Firstly, credit supply shocks may affect multiple supply chain partners that use common lenders (Alfaro, García-Santana, and Moral-Benito, 2021). Secondly, an adverse shock to a firm's financial health may transmit directly to a partner's financial health rather than indirectly through interdependent investment opportunities. These two channels would lead to $\gamma \neq 0$ in Model (v) of Figure II. Finally, a firm's financial constraints might directly influence its partners' investments, often referred to as contextual effects, i.e., $\theta \neq 0$ in Model (ii) from Figure II.

To address the potential for the common lender channel, we define a banking network $B \equiv [b_{ij}]$, where $b_{ij} = 1$ if two firms share a common lender or investment bank, and $b_{ij} = 0$ otherwise. We define a firm's lenders as the syndicate banks on the firm's loans in the DealScan database. We define a firm's investment bank as the underwriter of the firm's most recent IPO/SEO according to the SDC platinum database, following Grullon et al. (2014). Using this network, we define an alternate supply chain network by excluding partners from our baseline network, S, with a common banking relationship. That is, $S^{'} \equiv s^{'}_{ij}$, where $s^{'}_{ij} = s_{ij}$ if $s_{ij} > 0 \wedge b_{ij} = 0$, and $s^{'}_{ij} = 0$ otherwise. The data reveal that only 6% of partners share a common lender at any point during the sample period.

Panel A of Table 7 reports network regression estimates of Equation (6) using the alternative supply chain network $S^{'}$ that excludes common banking relationships. We estimate eight specifications corresponding to those reported in Table 2. The ρ coefficients remain strongly consistent with those from Table 2, indicating that common lending relationships have a trivial effect on our baseline estimates. While these findings are reassuring, firms may be connected in the lending channel through higher-order connections, and our analysis demonstrates the potentially large influence of higher-order connections.

To separate the influence of the supply chain network from the banking channel, accounting for higher-order connections, we estimate the following specification:

$$Y = (I_N - \rho_1 S^{'} - \rho_2 B)^{-1}(FC\delta + X\beta + \epsilon), \tag{17}$$

where $\rho_{_{S'}}$ and $\rho_{_B}$ indicate the relative influence of the two networks S' and B, respectively, on investment outcomes. We estimate Equation (17) using the multiple network regression framework developed in Grieser et al. (2022b). In Panel B, we report the $\rho_{_{S'}}$ and $\rho_{_B}$ coefficients for each of the eight specifications corresponding to the analysis reported in Panel A. The average $\rho_{_B}$ estimate of 0.186 across all eight columns reveals moderate investment interdependence driven by the banking channel, yielding an average network multiplier of 1.23. The average $\rho_{_{S'}}$ coefficient of 0.445 is similar to the average estimate of 0.485 from our baseline analysis. Overall, the network multiplier effects of investment spending in the supply chain network demonstrate remarkable stability, even after accounting for higher-order banking connections.

It is also possible that ρ may not indicate interdependent investment but rather unmodeled direct transmission of financial health or financing opportunities. To test this alternative hypothesis, we first estimate a variation of Model (v) in Figure II:

$$\text{FC} = (I_N - \gamma S)^{-1}(X\beta + \epsilon), \tag{18}$$

using the main supply chain network S. Panel C of Table 7 reports γ estimates using each of the eight financial constraint proxies used in Table 2 as the outcome variable. The average γ estimate of 0.03 across the six statistically significant specifications is less than 10% of the ρ estimates for investment interdependence. In Panel D, we report estimates from analogous regressions using leverage, equity issuance, and debt issuance as the outcome variables (Y), respectively, in Columns (1)-(4). The intuition is that effects operating primarily through financing channels rather than investment interdependence should yield correlated financing outcomes. The γ estimate in all four cases is economically small relative to the investment interdependence we document in prior analysis. The ρ estimate for leverage of 0.067 is less than 14% of effect for investment, and the average network multiplier across the three specifications is only 1.038, which is much lower than the multiplier of 2 for investment spending.

Finally, we consider the potential that financial constraints directly influence partners' investments. This scenario is plausible if a firm's constraints provide signals of partners' financing or investment prospects or directly impact the collateral value of partners' assets (e.g., Boone and Ivanov, 2012). To evaluate this possibility, we estimate the following specification akin to Model (ii) in Figure II:

$$y_{it} = fc_{i,t-1}\delta + \theta \sum_{j\neq i}^{N} s_{ij,t-1} fc_{j,t-1} + X_{i,t-1}\beta + \epsilon_{i,t}. \tag{19}$$

We use OLS to estimate Equation (19), since the model does not include interdependent outcomes. The findings, shown in Table 8, indicate that a firm's investment is either positively associated with its partners' constraints or the relationship is statistically insignificant. This outcome supports the pattern of partner heterophily in constraint levels, highlighted in Section 3.1. Moreover, this evidence suggests that investment correlations do not arise from direct responses to a partner's constraints.

4. Cross-sectional variation and validating evidence

4.1. Input specificity, partnership duration, and investment disruptions

Input specificity in production networks can generate substantive switching costs that amplify propagation effects (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 might expect more substantial indirect effects of financial constraints from firms producing specialized inputs.

We create four indicators of input specificity. Following Barrot and Sauvagnat (2016), we measure the firm's R&D and patents relative to its sales, providing insights into innovation and intellectual property intensity. The implicit assumption is that firms producing unique goods invest more in R&D and obtain more patents, indicative of specialized input/output production. Next, we adopt the *Prod. similarity* metric from Hoberg and Phillips (2016), which gauges a firm's total product market overlap with rivals. For consistency with other measures, we introduce *Prod. differentiation* as the negative product of *Prod. similarity*. Greater product differentiation suggests that a firm has fewer rivals producing substitute goods the firm's partners could purchase. Lastly, we assess market concentration using the Herfindahl-Hirschmann Index (HHI), derived from firm-specific TNIC data, as indicated by Hoberg and Phillips (2010a, 2016). For each metric, we also employ indicator values if they surpass the annual median within the firm's specific industry (SIC-3) classification.

We first evaluate whether the association between input specificity and partnership duration is consistent with increased switching costs. Table 9, Panel A, presents OLS regression estimates for pairwise partnership lengths (in years) regressed against the eight measures of input specificity. The findings suggest that firms' input specificity is positively associated with partnership duration.

Next, we investigate the relation between input specificity and investment spillovers. The indirect effects from Equation (8) represent the *cumulative* impact of a change in firm j's constraints on the capital expenditures of all firms connected within the supply chain. Thus far, we have reported the average effects across all firm-years. We shift focus in this analysis to firm-specific indirect effects, represented via column sums of Equation (8): $\sum_{i \neq j}(I_N - \rho S)^{-1}_{ij}$. Panel B of Table 9 displays the estimates, indicating that a one standard deviation increase in input specificity, or being above the industry median, is associated with a 2.8 percentage point increase in firm-specific supply chain investment disruptions.

These findings provide strong corroborating evidence that our results operate through an investment channel. In particular, input specificity is positively associated with longer-term partnerships, where partners' business opportunities are likely more deeply intertwined. The findings indicate that input specificity amplifies investment propagation effects, aligning with the theory that firms with specialized assets have fewer alternatives for input substitution. These findings are also consistent with anecdotal evidence and numerous media references we present in the Internet Appendix highlighting the interdependence in partners' investment opportunities.

4.2. Supply chain investment disruptions and trade credit usage

If firms are unable to find substitutable inputs quickly, they may make alternative adjustments to their actions in response to productivity shocks. One strong possibility is for firms to extend trade credit to partners that cannot raise capital through more traditional channels (Petersen and Rajan, 1997). Extending trade credit may alleviate the effects of partners' constraints on own-firm investment opportunities by minimizing disruptions to the quality and quantity of intermediate inputs the partner produces or purchases. All else equal, we should anticipate more extensive use of trade credit in supply chains that exhibit stronger ex-ante spillover effects.

To explore the use of trade credit, we first calculate firm-specific indirect effects of Equation (8). These indirect effects describe the cumulative effects of a one percentage point decline in firm i's investment on all other firms in the supply chain. Following Murfin and Njoroge (2015), we define the average number of days for a firm to pay suppliers (*Payable days*), the average number of days it takes customers to collect funds (*Receivable days*), and *Net trade days* as the difference between *Payable days* and *Receivable days*.

Table 10 reports OLS regression results, suggesting firms that induce higher spillovers receive more trade credit by paying their suppliers later or receiving payments sooner. Quantitatively, supply-chain partners increase trade credit by 5% in response to a one standard deviation increase in a firm's investment spillover effects. Overall, the estimates suggest companies employ trade credit as a safeguard against disruptions stemming from their partners' limited access to finance. However, such strategies appear inadequate to completely shield against short-term supply chain disruptions. When viewed in conjunction with the analysis presented in Table 9, these findings provide strong validating cross-sectional evidence that investment interdependence, rather than unobservable common shocks, generate the investment disruptions we document.

4.3. Summary of findings and additional analyses

We dedicate much of the paper to validating the methods we employ and mapping technical details to economic intuition. We thus relegate several discussions to the Internet Appendix to keep this study at a reasonable length. Most notably, we provide several anecdotes highlighting supply-chain partners' intertwined investment opportunities. We also show that our findings are robust to variations in supply-chain network constructions, sample periods, winsorization schemes, and control variables, including specifications without controls. We discuss network regression standard error calculations and comparisons to linear methods, including fixed effects regressions. We also provide illustrations of network propagation and higher-order effects. Overall, the extra analyses lend strong support to this study's conclusions.

5. Conclusion

Our study investigates how limited access to external financing affects supply chain investments. We show that financing frictions trigger significant ripple effects in supply chains partners with interdependent investment opportunities. We quantify that these ripple effects are roughly as influential as the direct, own-firm effects of constraints. Notably, firms with specialized inputs, despite more extensive use of trade credit terms, are more central in propagating investment spillovers. Our findings, robust across various metrics and models, highlight that these investment distortions are recognized by equity markets and underscore the deep economic ramifications of network effects in investment spending.

Consequently, this study feeds into broader discourses on the systemic implications of capital market frictions, pointing to production networks as critical amplifiers that influence broader investment trends. The evidence presented calls for further investigation into supply-chain spillovers and their implications, particularly for the efficacy of monetary policy and in steering corporate investment strategies. More broadly, our work helps pave the way for a deeper understanding of their implications in a variety of settings in which firm interactions likely play a prominent role.

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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)
FC	A measure of the firm's financial constraints defined by one of the accounting or debt-based measures below.
FC (own-firm)	The financial constraints of the focal firm. It captures the level of financial constraints faced by the focal firm.
FC (partners')	The average financial constraints of all partners in the supply chain network. It represents the overall level of financial constraints in the supply chain network.
Clustering	A measure of the degree to which the focal firm's partners are connected to each other in the supply chain network. It captures the level of clustering or interconnectedness among the partners.
Shortest path	The shortest path length between the focal firm and each partner in the supply chain network. It represents the minimum number of intermediaries between the focal firm and its partners.
Partner length	The average length of the supply chain partners' relationships with the focal firm. It measures the duration of the relationships between the focal firm and its partners.
R&D/Sales	The ratio of R&D expenses over sales.
Prod similarity	The total similarity measure created by Hoberg and Phillips (2010a), measuring a firm's product market similarity with its rivals.
Prod differentiation	The negative value of *Prod similarity*.
TNIC-3 HHI	The HHI of the firm's industry concentration based on the Hoberg and Phillips (2010a) text-based industry classifications.
Patent/Sales	The ratio of firms' patents granted over their total sales.
Input specificity	The degree to which the focal firm's inputs are specialized or customized for its specific production process. We use four proxies of input specificity: R&D/Sales, product differentiation, TNIC-3 HHI, and Patents/Sales.
Indirect effects	The value of the cross-partial derivative in Equation (8), or $\sum_{j\neq i}\left(I_N-\rho S\right)^{-1}_{i,j}\delta$ 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 Tables report the average of the indirect effects from unit j to other firms (Kelejian and Piras, 2017).
Indirect effects (partners')	The average of the *Indirect effects* of a firm's supply chain partners.
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)

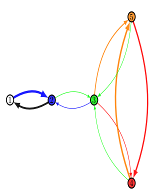
Long-term debt due (LTDD)	Long term debt due in one year/(Current + long-term debt)
Delay	Measure of financial constraints constructed by Hoberg and Maksimovic (2015), who provide the following definition: "higher values are more similar to a set of firms known to be at risk of delaying their investments due to issues with liquidity and indicate plans to issue debt"
FC combo (Combo)	Sum of standardized (demeaned and divided by standard deviation) of *WW, SA, LTDD* and *Delay*
Debt-based measures of financial constraints	
Confirmed viol. (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.
Technical 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 five-firm supply-chain network. We plot the first, second, and third orders of the network, S, and the cumulative network effects in sub-figures (a), (b), (c), and (d), respectively. The cumulative effects in sub-figure (d) are determined by the inverse term $(I_n - \rho S)^{-1}$. For this example, we set $\rho^* = 0.5$.

Figure B.1

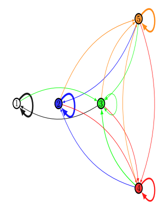
(a)



S

	1	2	3	4	5
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

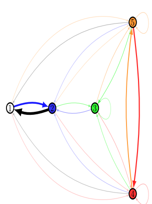
(b)



S^2

	1	2	3	4	5
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

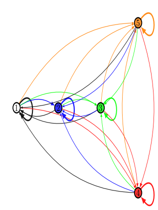
(c)



S^3

	1	2	3	4	5
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

(d)



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

	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
Total	1.88	2.14	1.65	2.08	2.25

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 $S_{2,3} = 0.18$, firm 3 is connected to firms 2, 4, and 5, and so on. Sub-figure (b) shows that firm 1 exhibits a second-order connection to firm 3, even though firm 1 is not directly connected to firm 3, and to itself through feedback effects (it is a peer to a peer). Similarly, firm 1 has third-order connections to firms 2, 4, and 5. The network becomes more densely connected for higher orders , and all firms are connected by the seventh-order (unreported).

Sub-figure (d) illustrates the final, cumulative propagation effects for the network S from sub-figure (a) when $\rho = 0.5$. The column sums illustrate the effects propagating from firm i to all other firms (out-degree effects). The row sums indicate the effects received by other firms (in-degree effects). The diagonal elements all equal 1 plus the feedback effects onto the respective firm. While each firm exhibits unique out-degree and in-degree effects, the average in-degree effect equals the average out-degree effect across all firms, by definition. The network multiplier $1/(1-\rho) = 1/(1-0.5) = 2$ summarizes the average effects.

Continuing with the example from Figure B.1, consider how an initial shock shock that causes firm 1 to curtail investment by \$1 transmits through network S. Sub-figure (a) illustrates that a shock to firm 1 will exhibit a first-order transmission to firm 2, causing firm 2 to cut investment by $\$\rho \times s_{2,1} = .5 \times .82 = \$.41$. Sub-figure (c) shows firm 1's second-order connections are equivalent to firm 2's first order connections times firm 1's relation with firm 2. That is $s^2_{1,1} = s_{1,2} \times s_{2,1} = 1 \times .82 = .82$. Similarly, $s^2_{1,3} = s_{2,1} \times s_{2,3} = 1 \times .18$. Thus, the second-order effect, operating through firm 2, feeds back to firm 1, which cuts investment by $\$\rho^2 \times s^2_{1,1} = .5^2 \times .82 = \$0.205$, and spills over to firm 3, which cuts investment by $\$\rho^2 \times s^2_{1,3} = .5^2 \times .18 = \$0.045$. In the third-order transmission firm 2 cuts investment by an additional $\$\rho^3 \times .82 \times 1 \times .82 + \$\rho^3 \times .18 \times .82 \times .18$. Firm 4 is now affected through the chain $s_{1,2} \rightarrow s^2_{1,1}, s^2_{1,3} \rightarrow s^3_{3,4}$, indicating a third-order connection propagating from firm 1 $s_{3,1} = 1 \times .18 \times .17 = .03$. Thus, firm 4 cuts investment by $\$\rho^3 \times s^3_{3,1} = .5^3 \times .03 = \$0.004$, and firm 5 cuts investment by $\$\rho^3 \times s_{5,1} = .5^3 \times .05 = 0.006$.

This process can describe a series of reactions, reactions to reactions, and so on, or 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 are \$0.62.

Table 1: Summary statistics

This table presents summary statistics for firm-level and network characteristics. Firm financial information comes from Compustat, and loan covenant information comes from LPC DealScan. Supply chain relationships come from Compustat Segment data, Factset Revere, and the VTNIC from Frésard et al. (2020). We report summary statistics for degree centrality for the entire supply chain network, and separately for each data source. We normalize degree centrality (in %) by the total number of firms in the network. Appendix A contains detailed definitions for all variables.

	N	Mean	SD	P10	P50	P90
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
WW	144,301	-0.142	0.225	-0.353	-0.164	0.038
SA	154,641	-2.707	1.030	-3.837	-2.871	-1.395
LTDD	117,211	0.163	0.243	0.000	0.059	0.500
Delay	60,251	-0.001	0.056	-0.068	-0.007	0.075
Combo	45,203	-0.005	2.310	-2.593	-0.309	2.909
Indirect 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
Prod similarity	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	0.251	1.155	0.001	0.017	0.255
Buyer payable days	147,610	102.009	249.790	14.821	44.180	158.721
Supplier receivable days	145,790	58.093	47.400	6.892	52.020	103.371
Firm characteristics						
Quarterly observations						
C.viol.	292,180	0.051	0.220	0.000	0.000	0.000
C.strict	52,178	0.275	0.264	0.000	0.236	0.672
C.CapEx	52,178	0.243	0.429	0.000	0.000	1.000
Technical viol.	52,178	0.198	0.400	0.000	0.000	1.000
Hybrid viol.	52,178	0.066	0.250	0.000	0.000	0.000
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
Partner length (yrs)	203,823	9.621	4.272	3.541	9.875	15.500

Table 2: Financial constraint-induced investment spillovers

This table presents network regression estimates for financial constraint spillovers on supply chain partners' investment, as specified in Equation (5). The dependent variable in all models is firm investment *(CapEx/L.Assets)*. The independent variable *FC* in columns (1)-(5) represents, respectively, 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 *(LTDD)* from Almeida et al. (2012), a text-based measure *(Delay)* from Hoberg and Maksimovic (2015), and the sum of the first four (standardized) financial constraint measures *(Combo)*. In columns (6)-(8), *FC* represents three quarterly covenant-based measures of 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 estimated probability that a firm violates at least one covenant in quarter $t+1$. The ρ coefficient quantifies the strength of investment interdependence in the supply chain network. The *Direct effects* estimates represent the average own-firm partial derivative effects of the corresponding covariate on own-firm investment. The *Indirect effects* estimates represent the average cross-firm partial derivative spillover effects of the corresponding covariate on other firms' investments. All models include year or quarter fixed effects and standardized non-dummy variables. In parentheses, we report t-statistics based on standard errors that come directly from the posterior distribution of the MLE parameter estimates.

	Investment (Annual)					*Investment (Qtr.)*		
	WW	SA	LTDD	Delay	Combo	C.viol	C.CapEx	C.strict
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Investment								
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)
Direct 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)
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 for financial constraint spillovers on supply chain partners' investment, as specified in Equation (5). The supply chain network is restricted to include only long-term partnerships that are at least five years old at time $t-1$ (i.e., $s_{i,j,t-1} > 0 \wedge s_{i,j,t-6} > 0$). The dependent variable in all models is firm investment *(CapEx/L.Assets)*. The independent variable *FC* in columns (1)-(5) represents, respectively, 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 *(LTDD)* from Almeida et al. (2012), a text-based measure *(Delay)* from Hoberg and Maksimovic (2015), and the sum of the first four (standardized) financial constraint measures *(Combo)*. In columns (6)-(8), *FC* represents three quarterly covenant-based measures of 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 estimated probability that a firm violates at least one covenant in quarter $t+1$. The ρ coefficient quantifies the strength of investment interdependence in the supply chain network. The *Direct effects* estimates represent the average own-firm partial derivative effects of the corresponding covariate on own-firm investment. The *Indirect effects* estimates represent the average cross-firm partial derivative spillover effects of the corresponding covariate on other firms' investments. All models include year or quarter fixed effects and standardized non-dummy variables. In parentheses, we report t-statistics based on standard errors that come directly from the posterior distribution of the MLE parameter estimates.

	Investment (Annual)					*Investment (Qtr.)*		
	WW	SA	LTDD	Delay	Combo	C.viol	C.CapEx	C.strict
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Investment								
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)
Direct 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)
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 (NRDD) estimates for the strength of financial constraint spillovers on supply chain investment. The dependent variable in all models is firm investment *(CapEx/L.Assets)*. Columns (1)–(2) employ a local-linear NRDD specification in Equation (11), and Columns (3)–(6) employ the polynomial NRDD specification in Equation (14). The key at the bottom of the table indicates whether treatment status is assigned via technical violations, confirmed violations, or hybrid violations. Technical violations indicate whether a firm has crossed a contractual threshold for *net worth*, *tangible net worth*, and *current ratio* covenants according to Compustat and Dealscan data only. Confirmed violations indicate that a firm reports a covenant violation in its 10-K or 10-Q. Hybrid Violations indicate that a firm is both in technical violation (*Technical viol.*=1) and report a confirmed violation (*Confirmed. viol.*=1), and is otherwise set to 0. The key also indicates whether polynomial NRDD specifications include polynomial terms for the running variables for *current ratio, net worth,* and *tangible net worth* covenants and polynomial terms for ratio variables: *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* values. Column (5)-(6) employs entropy balancing for the first two moments of all variables included in the model. Columns (7)–(12) report estimates for analogous specifications in Columns (1)–(6) using the long-term partner network restricted to only include partnerships that are at least five years old at time $t-1$ (i.e., $s_{i,j,t-1} > 0 \wedge s_{i,j,t-6} > 0$). The ρ coefficient quantifies the strength of investment interdependence in the supply chain network. The *Direct effects* estimates represent the average own-firm partial derivative treatment effects of violations on own-firm investment. The *Indirect effects* estimates represent the average cross-firm partial derivative treatment effects spillovers on other firms' investments. All models include control variables for the natural log of *Sales*, *ROA*, *Book leverage*, *Market-to-book ratio*, year or quarter fixed effects, and standardize non-dummy variables. We report t-statistics in parentheses based on standard errors that come directly from the posterior distribution of MLE parameter estimates.

	Network RDD: Complete partner network						Network RDD: Long-term partner network					
	Local linear		Polynomial				Local linear		Polynomial			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Investment												
ρ	0.526	0.537	0.534	0.514	0.326	0.284	0.466	0.465	0.465	0.401	0.263	0.231
	(107.722)	(112.01)	(98.343)	(96.624)	(61.891)	(56.485)	(101.343)	(98.116)	(100.435)	(87.087)	(56.005)	(50.861)
Direct effects												
Treatment	-0.186	-0.335	-0.153	-0.180	-0.183	-0.177	-0.270	-0.237	-0.170	-0.197	-0.195	-0.189
	(-2.982)	(-3.32)	(-15.551)	(-18.294)	(-47.782)	-(48.107)	(-3.713)	(-3.713)	(-16.165)	(-18.829)	(-43.246)	(-46.387)
Indirect effects												
Treatment	-0.202	-0.396	-0.174	-0.151	-0.088	-0.070	-0.258	-0.224	-0.145	-0.130	-0.069	-0.056
	(-2.983)	(-3.33)	(-14.417)	(-16.911)	(-31.810)	(-31.023)	(-2.071)	(-2.071)	(-15.451)	(-17.898)	(-29.517)	(-31.465)
Treatment variable												
Technical viol.	✓						✓					
Hybrid viol.		✓		✓				✓		✓		
Confirmed viol.			✓		✓	✓			✓		✓	✓
Running polynomial			✓	✓	✓	✓			✓	✓	✓	✓
Ratio polynomial			✓	✓		✓			✓	✓		✓
Entropy balancing					✓	✓					✓	✓

Table 5: Network RDD: Covenant violations and market valuations

This table presents network regression discontinuity design (NRDD) estimates for the strength of financial constraint spillovers on stock returns in supply chain networks. The dependent variable in all models is annual characteristic-adjusted stock returns according to Daniel et al. (1997). Columns (1)–(2) employ a local-linear NRDD specification in Equation (11), and Columns (3)–(6) employ the polynomial NRDD specification in Equation (14). The key at the bottom of the table indicates whether treatment status is assigned via technical violations, confirmed violations, or hybrid violations. Technical violations indicate whether a firm has crossed a contractual threshold for *net worth*, *tangible net worth*, and *current ratio* covenants according to Compustat and Dealscan data only. Confirmed violations indicate that a firm reports a covenant violation in its 10-K or 10-Q. Hybrid Violations indicate that a firm is both in technical violation (*Technical viol.*=1) and report a confirmed violation (*Confirmed. viol.*=1), and is otherwise set to 0. The key also indicates whether polynomial NRDD specifications include polynomial terms for the running variables for *current ratio, net worth,* and *tangible net worth* covenants and polynomial terms for ratio variables: *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* values. Column (5)-(6) employs entropy balancing for the first two moments of all variables included in the model. Columns (7)–(12) report estimates for analogous specifications in Columns (1)–(6) using the long-term partner network restricted to only include partnerships that are at least five years old at time $t-1$ (i.e., $s_{i,j,t-1} > 0 \wedge s_{i,j,t-6} > 0$). The ρ coefficient quantifies the strength of stock-return interdependence. in the supply chain network. The *Direct effect* estimates represent the average own-firm partial derivative treatment effects of violations on own-firm stock returns. The *Indirect effect* estimates represent the average cross-firm partial derivative treatment effects on partners' stock returns. All models include control variables for the natural log of *Sales*, *ROA*, *Book leverage*, *Market-to-book ratio*, year or quarter fixed effects, and standardized non-dummy variables. We report t-statistics in parentheses based on standard errors that come directly from the posterior distribution of MLE parameter estimates.

	Network RDD: Complete partner network						Network RDD: Long-term partner network					
	Local linear		Polynomial				Local linear		Polynomial			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Stock returns												
ρ	0.100	0.099	0.144	0.143	0.068	0.067	0.072	0.072	0.094	0.094	0.036	0.036
	(9.771)	(9.621)	(12.960)	(11.856)	(5.283)	(5.028)	(8.625)	(8.653)	(9.673)	(10.238)	(3.373)	(3.286)
Direct effects												
Treatment	-0.017	-0.221	-0.237	-0.236	-0.074	-0.071	-0.032	-0.029	-0.231	-0.231	-0.071	-0.070
	(-0.422)	(-3.855)	(-21.392)	(-22.088)	(-24.962)	(-23.534)	(-0.771)	(-0.702)	(-19.088)	(-19.173)	(-23.534)	(-22.784)
Indirect effects												
Treatment	-0.002	-0.023	-0.040	-0.039	-0.005	-0.003	-0.002	-0.002	-0.024	-0.024	-0.003	-0.003
	(-0.422)	(-3.855)	(-9.811)	(-8.856)	(-4.919)	(-3.192)	(-0.771)	(-0.702)	(-7.952)	(-8.628)	(-3.192)	(-3.117)
Treatment variable												
Technical viol.	✓						✓					
Hybrid viol.		✓		✓				✓		✓		
Confirmed viol.			✓		✓	✓			✓		✓	✓
Running Polynomial			✓	✓	✓	✓			✓	✓	✓	✓
Ratio Polynomial			✓	✓		✓			✓	✓		✓
Entropy balancing					✓	✓					✓	✓

Table 6: Accounting for industry shocks

This table presents network regression estimates for financial constraint spillovers on supply chain partners' investment, as specified in Equation (5). The dependent variable in all models is firm investment *(CapEx/L.Assets)*. The independent variable *FC* in columns (1)-(5) represents, respectively, 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 *(LTDD)* from Almeida et al. (2012), a text-based measure *(Delay)* from Hoberg and Maksimovic (2015), and the sum of the first four (standardized) financial constraint measures *(Combo)*. In columns (6)-(8), *FC* represents three quarterly covenant-based measures of 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 estimated probability that a firm violates at least one covenant in quarter $t+1$. The ρ coefficient quantifies the strength of investment interdependence in the supply chain network. The *Direct effects* estimates represent the average own-firm partial derivative effects of the corresponding covariate on own-firm investment. The *Indirect effects* estimates represent the average cross-firm partial derivative spillover effects of the corresponding covariate on other firms' investments. All models include year fixed effects and all non dummy variables are standardized. In parentheses, we report t-statistics based on standard errors that come directly from the posterior distribution of the MLE parameter estimates. All specifications include firm-level control variables: ln(Sales), Cash, Z-score, ROA, MB, Leverage, as well as the corresponding industry averages according to TNIC-3 industry peers defined in Hoberg and Phillips (2010b).

	Dependent variable: *Investment* – Complete partner network							
	WW	SA	LTDD	Delay	Combo	C.viol	C.CapEx	C.strict
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Investment								
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)
Direct 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)
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)
Own-firm controls	✓	✓	✓	✓	✓	✓	✓	✓
Industry controls	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓

	Dependent variable: *Investment* – Long-term partner network							
	WW	SA	LTDD	Delay	Combo	C.viol	C.CapEx	C.strict
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Investment								
ρ	0.397	0.427	0.427	0.370	0.368	0.337	0.320	0.332
	(43.241)	(48.105)	(44.156)	(38.718)	(31.907)	(28.764)	(29.735)	(29.875)
Direct effects								
FC	-0.104	0.021	-0.018	-0.005	-0.036	-0.052	-0.064	-0.005
	(-10.433)	(2.594)	(-3.047)	(-0.744)	(-4.401)	(-6.47)	(-8.973)	(-0.611)
Indirect effects								
FC	-0.066	0.015	-0.013	-0.003	-0.020	-0.025	-0.029	-0.002
	(-9.667)	(2.586)	(-2.999)	(-0.744)	(-4.301)	(-6.068)	(-8.222)	(-0.611)
Own-firm controls	✓	✓	✓	✓	✓	✓	✓	✓
Industry controls	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓

Table 7: Propagation through lender networks and financial health transmission

This table presents network regression estimates for investment interdependence operating through lender networks and for the direct transmission of financial health through supply chains. The banking network $B \equiv [b_{ij}]$, where $b_{ij} = 1$ if two firms share a common lender or investment bank, and $b_{ij} = 0$ otherwise. Panel A reports network regression estimates of Equation (6) using an alternative supply chain network $S^{'}$ that excludes these common banking relationships. The eight specifications correspond to the analysis in Table 2. Panel B reports estimates for multiple network regression specifications following Equation (17). The coefficient estimates for $\rho_{_{S'}}$ and $\rho_{_B}$ indicate, respectively, the relative strength of investment interdependence stemming from the supply chain network, $S^{'}$, and the common bank network, B. Panel C reports network regression estimates of Equation (18) for each of the eight constraint measures we employ in Tables 2 and 3. The coefficient γ summarizes the strength of interdependence when using the corresponding financial constraint as the dependent variable. Panel D reports estimates for interdependence in other financing outcomes: book leverage, equity issuance, and debt issuance. All models include year or quarter fixed effects and standardized non-dummy variables. In parentheses, we report t-statistics based on standard errors that come directly from the posterior distribution of the MLE parameter estimates.

Panel A: Supply chain links excluding common bank connections: $Y = \rho_{S'} S^{'} Y + X\beta + \epsilon$

	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)
$\rho_{_{S'}}$	0.395	0.423	0.428	0.468	0.441	0.547	0.480	0.482
	(53.319)	(57.355)	(47.535)	(45.823)	(41.094)	(108.922)	(128.456)	(115.623)

Panel B: Supply chain (S') vs. common bank connections (B): $Y = \rho_{S'} S^{'} Y + \rho_B B\, Y + X\beta + \epsilon$

	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)
$\rho_{_{S'}}$	0.471	0.535	0.488	0.457	0.418	0.390	0.398	0.405
	(27.771)	(31.85)	(26.663)	(26.182)	(22.851)	(20.289)	(20.841)	(21.183)
$\rho_{_B}$	0.188	0.171	0.195	0.183	0.206	0.172	0.185	0.187
	(9.295)	(8.949)	(9.666)	(8.313)	(9.313)	(5.743)	(6.751)	(7.017)

Panel C: Financial constraint interdependence: $FC = \gamma S\, FC + X\beta + \epsilon$

	WW	SA	LTD Due	Delay Inv	FC combo	C.viol	C.CapEx	C.strict
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
γ	-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 D: Interdependence in other financing outcomes: $Y = \gamma S\, Y + X\beta + \epsilon$

	Leverage	Equity issue	Debt issue
	(1)	(2)	(3)
γ	0.067	0.025	0.018
	(7.81)	(5.16)	(2.17)

Table 8: Investment spending and partners' financial constraints

This table presents OLS regression estimates of investment spending on own-firm financial constraints (*FC (own-firm)*) and the weighted average financial constraints of a firm's supply chain partners (*FC (partners'*.) The dependent variable is Firm investment *(CapEx/L.Assets)* in all models. The independent variable *FC* in columns (1)-(5) represents, respectively, 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 *(LTDD)* from Almeida et al. (2012), a text-based measure *(Delay)* from Hoberg and Maksimovic (2015), and the sum of the first four (standardized) financial constraint measures *(Combo)*. In columns (6)-(8), *FC* represents three quarterly covenant-based measures of 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 estimated probability that a firm violates at least one covenant in quarter $t+1$. All models include year or quarter fixed effects and standardized non-dummy variables.

	CapEx / L.Assets							
	WW	SA	LTDD	Delay	Combo	C.viol	C.CapEx	C.strict
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FC (own-firm)	-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)
FC (partners')	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)
SIC-3, Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
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

Table 9: Input specificity, partner duration, and investment spillovers

This table presents estimates describing the relationships among input specificity, partner duration, and firm-specific spillover (indirect) effects. Panel A reports OLS estimates of firms' partnership duration on different measures of input specificity. We use four measures of a firms' *input specificity* as independent variables: The ratio of its R&D expenses to sales *R&D/Sales* (Column 1); *Prod differentiation*, which is 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), we designate high input specificity if a respective measure lies above the median industry (three digit SIC) value in year t. Panel B reports OLS estimates of firm-specific indirect effects on measures of input specificity. The dependent variable, *indirect effects*, represents the estimated cumulative impact of a change in firm i's financial constraints on the investment of all firms connected within its supply chain, calculated as the column sum of Equation (8): $\sum_{i \neq j}(I_N - \rho S)^{-1}_{ij}$. The independent variables are the same eight measures of input specificity used in Panel A. All models include control variables for the natural log of *Sales*, *ROA*, *Book leverage*, *Market-to-book ratio*, year and industry (SIC-3) fixed effects, and standardize non-dummy variables. We report t-statistics in parentheses from standard errors clustered at the industry and year levels.

Panel A: Supply chain partner length (years)

	Input specificity measure							
	R&D/Sales		Prod differentiation		TNIC-3 HHI		Patents/Sales	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Input specificity	-0.011	0.100	0.100	0.436	0.036	0.231	0.008	0.131
	(-1.578)	(3.530)	(27.389)	(9.066)	(11.171)	(9.395)	(1.409)	(5.029)
SIC-3, Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
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

Panel B: Indirect effects stemming from firm i

	Input specificity measure							
	R&D/Sales		Prod differentiation		TNIC-3 HHI		Patents/Sales	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Input specificity	0.035	0.115	0.019	0.064	0.019	0.033	0.017	0.445
	(15.717)	(8.392)	(2.465)	(5.008)	(3.643)	(2.717)	(3.587)	(14.277)
SIC-3, Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
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 10: Supply chain investment spillovers and trade credit utilization

This table presents OLS regressions of firms' trade credit on firm-specific spillover (indirect) effects. In columns (1)-(2), (3)-(4), and (5)-(6), the dependent variable is, respectively: the average number of days it takes a firm to pay its 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 independent variable *Indirect effects (own-firm)*, represents the estimated cumulative impact of a change in firm i's financial constraints on the investment of all firms connected within its supply chain, calculated as the column sum of Equation (8): $\sum_{i \neq j}(I_N - \rho S)^{-1}_{ij}$. *Indirect effects (partners')* denotes the weighted average *indirect effects* of a firm's supply chain partners. All models include control variables for the natural log of *Sales*, *ROA*, *Book leverage*, *Market-to-book ratio*, year and industry (SIC-3) fixed effects, and standardize non-dummy variables. We report t-statistics in parentheses from standard errors clustered at the industry and year levels.

	Payable days		Receivable days		Net trade days	
	(1)	(2)	(3)	(4)	(5)	(6)
Indirect effects (own-firm)	0.031	0.024	-0.014	-0.016	0.035	0.028
	(10.770)	(8.840)	(-4.484)	(-5.098)	(12.628)	(10.794)
Indirect effects (partners')		-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	✓	✓	✓	✓	✓	✓
Observations	61004	59473	61004	59473	61004	59473
Adjusted R^2	0.151	0.148	0.178	0.180	0.146	0.143

Internet Appendix

Table of Contents

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 1.2 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 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 (6) and (9) 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."[13]

[13] See https://www.wsj.com/articles/SB108491126556814808.

- 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."[14]

- 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."[15]

- 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.[16] At the same time, investment spending into expanding shipyard and other facilities also affected the suppliers of the crane rail clamps market.[17]

- 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"

[14] See https://on.wsj.com/35eiJDd

[15] See https://on.wsj.com/3G2oTmE.

[16] See https://on.wsj.com/349G6xa.

[17] See https://bit.ly/3IBKDaP.

but is worried about the effect of credit constraints on its suppliers, adding that he is looking at ways to address the issue."[18]

- 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."[19]

B. Discussion on fixed effects

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 characteristics 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.

[18]See https://reut.rs/3u33xTU.
[19]See https://on.wsj.com/3u3iaXu.

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, *C.CapEx* contains explicit restrictions on capital investment, which increases confidence that the effects we document operate through investment externalities. The variable *LTDD* 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 3.2. 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 × 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 *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 (IA.33.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 (IA.33.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

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

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

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

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.[20] 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

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

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 $\mu_j \overset{\text{i.i.d.}}{\sim} N(0,1)$, $j = 1, \ldots, N$. 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 $\tilde{S}_i\mu$ 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. 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).[21] 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). While this evidence may not be conclusive, it does offer some preliminary support in allaying concerns regarding homophily.

F. Upstream vs. downstream network formation

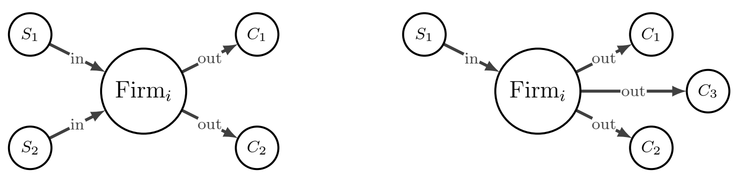
Our analysis provides robust evidence that financial constraints generate considerable spillovers for supply chain partners' investment decisions. Accordingly, firms plausibly consider potential

[21] 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: $\text{p(new tie)} = exp(\text{edges} + \beta|I_i - I_j|)/(1 + exp(\text{edges} + \beta|I_i - I_j|)$.

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:

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

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. 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.8: This table presents OLS regressions of supply-chain partners' length of relationship on measures of input specificity.

- Table IA.9: This table presents the complete set of estimates used for the plot in Figure IA.2 of the main text.

- Table IA.10: 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.11: This table shows summary statistics for Compustat's quarterly dataset.

- Figure V: This figure plots the residuals from a local linear network RDD of investment on firms' distance from covenant thresholds as outlined in Section 3.2.1.

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 (5). 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 *(LTDD)* from Almeida et al. (2012), a text-based measure *(Delay)* from Hoberg and Maksimovic (2015), and the sum of the first four (standardized) financial constraint measures *(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	LTDD	Delay	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 (5). 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 *(LTDD)* from Almeida et al. (2012), a text-based measure *(Delay)* from Hoberg and Maksimovic (2015), and the sum of the first four (standardized) financial constraint measures *(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	LTDD	Delay	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 (5). 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 *(LTDD)* from Almeida et al. (2012), a text-based measure *(Delay)* from Hoberg and Maksimovic (2015), and the sum of the first four (standardized) financial constraint measures *(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	LTDD	Delay	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 (5). 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 *(LTDD)* from Almeida et al. (2012), a text-based measure *(Delay)* from Hoberg and Maksimovic (2015), and the sum of the first four (standardized) financial constraint measures *(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	LTDD	Delay	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 investment

This table presents pairwise network correlations of investment (Capex/L.assets).

	(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	LTDD	Delay	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: 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 (5). 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 *(LTDD)* from Almeida et al. (2012), a text-based measure *(Delay)* from Hoberg and Maksimovic (2015), and the sum of the first four (standardized) financial constraint measures *(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.8 continued

	CapEx/L.Assets							
	WW	SA	LTDD	Delay	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.9: 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 ($LTDD$) from Almeida et al. (2012); the text-based measure (*Delay*) from Hoberg and Maksimovic (2015); the sum of the first four (standardized) financial constraint measures (*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 (*C.CapEx*) 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	LTDD	Delay	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.10: 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.11: 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: Financial constraints complementarity 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 $\text{FC} = \rho S\,\text{FC} + X\beta + \epsilon$. 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 ($LTDD$) from Almeida et al. (2012); the text-based measure ($Delay$) from Hoberg and Maksimovic (2015); the sum of the first four (standardized) financial constraint measures ($Combo$); 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 ($C.CapEx$) 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.

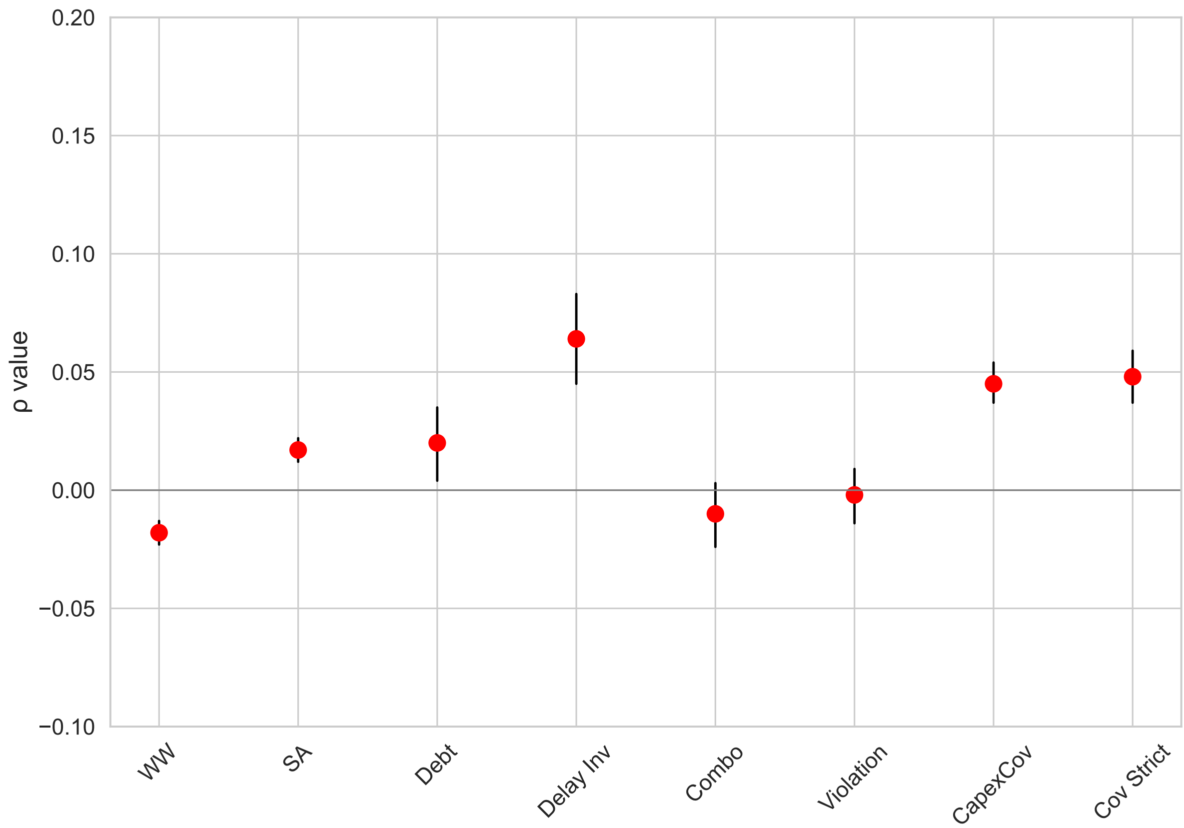
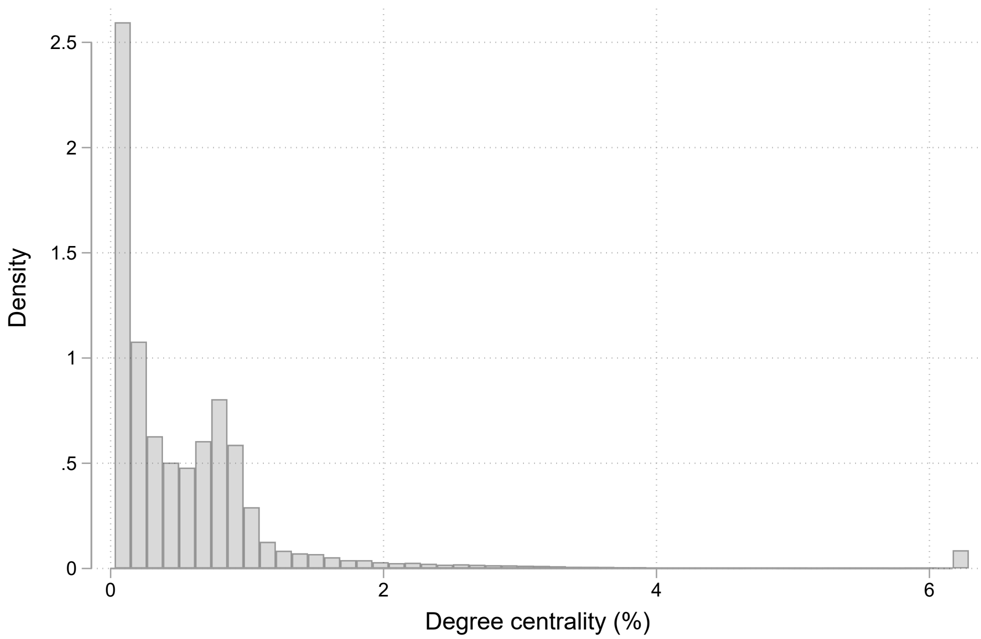


Figure IA.3

(3.a) This subfigure plots the distribution of firms' annual degree centrality, which measures the number of direct supply chain connections, according to our primary network that combines all three data sources for supply chain relationships (i.e., Compustat, FactSet Revere, and VTNIC).



(3.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.