Shock Spillover and Financial Response in Supply Chain Networks: Evidence from Firm-Level Data

Di (Andrew) Wu*

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ABSTRACT

Using machine learning methods on firm-level textual disclosures, I construct a large-scale dataset featuring firm-specific shocks to production. I map these shocks into a unique, hand-built network of firm-level supply chain connections to empirically quantify how these localized shocks affect remote firms along the chains. Surprisingly, contrary to prediction by typical network theories, these firm-specific shocks impact the revenue of firms even up to 4 connections away from the origins. This pronounced spillover effect is explained by three features--uneven distribution of monopolistic power, variations in supplier substitutability, and different inventory levels--that are salient in the data but usually not present in existing models. In addition, firms seem to respond to these spillovers by increasing their working capital and financial leverage. Moreover, the stock market reacts to shock spillovers from distant connections with slower speeds: post-shock abnormal returns are persistently negative for up to 40 days.

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1. Introduction

The most prevalent type of inter-firm relationships is the physical network of supply chains. Its large scale and complex, changing structure is evident from Figure 1, which plots a slice of the network between the 400 largest firms in the tech industry in 2002 and 2015. With globalization, supply chains have become even longer, denser, and more clustered. The additional verticalities introduced by these deeper firm-level interconnections remains unexplored, as typical studies on spillovers and externalities in finance focus on the existence of externalities and their effects on firms’ direct connections. By contrast, we have limited information on the extent of these externalities, measured by how deep they penetrate along the linkages to remote connections beyond the direct linkages.

This paper directly quantifies the extent of these externality spillovers: I hand-build two firm-level datasets to empirically examine the economic effect of firm-specific production shocks on the origin firms’ remote customers along the supply chain, beyond their direct, tier-1 connections. I then explore the implications of this remote spillover for the stock prices and corporate policies of firms further down the chains.

While there are many recent theoretical papers on the aggregation of shocks through production interconnections such as Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012), Gabaix (2011), and Kelly, Lustig, and Van Nieuwerburgh (2013), little empirical evidence exists on their firm-to-firm implications due to the lack of well identified data on firm-specific shocks, and the lack of granular data on firm-level networks of supply relationships.¹ This paper contributes two new datasets to address these limitations in identification and measurement. Specifically, I first build a 20-year database of over 8,000 firm-specific production shocks of a large variety of types and firms. I identify these shocks through a topic-based textual anal-

¹Existing data is either sector level, such as the make-use tables aggregated by the Bureau of Economic Analysis (BEA), or only capture a small fraction of relationships between small suppliers and very large customers, such as the Compustat Segments database.
ysis of over 5 million individual firm disclosures. This allows for well-identified, firm-level empirical examinations. I then map these shocks into a 20-year network of over 1 million supply chain relationships between publicly traded firms globally. I construct this firm-level supply chain network from the disclosure data and three other public and proprietary data sources. Tracing the exact origin of each shock to the network, I directly examine if these firm-specific, idiosyncratic shocks spill over along the linkages. I measure their impact on the economic outcomes, corporate policies, and stock prices of origin firms, their closest connections, and remote firms beyond the first-tier connections.

I find several new results. First, although typical theories on production networks predict that firm-specific shocks quickly decay after the first link, I document that, surprisingly, these shocks cause substantial impact to firms even up to 4 connections away from the origin: on average, an idiosyncratic shock that causes 1% decline in revenue growth for the origin firms causes 0.82% decline for their closest connections, but also causes 1.03%, 0.87%, and 0.40% decline for 2nd, 3rd, and 4th-tier connections.

I then demonstrate that the data exhibit three salient features, which are absent from typical theories, yet are particularly conducive to such prolonged and pronounced shock spillovers. First, (monopolistic) market powers are unevenly distributed along the supply chains. Firms located further away from origins tend to have lower market power, thus are less able to change prices to their customers, and at the same time face higher-powered suppliers who are more able to raise prices and pass more impact onto them. This dual price-quantity effect causes larger impact and longer spillovers than predicted by models with perfectly competitive firms. Second, the substitutability of suppliers and third, the level of inventories, also vary along the supply chains. These factors can also significantly affect the magnitude of spillovers. I first establish the validity of these channels through firm-level tests, where I show that they are indeed significantly related to the impact of spilled-over shocks. I then provide the network-level evidence for the market power channel by documenting that firms further down the supply
chains have lower average market power.

Next, I develop a series of robustness checks to solidify the results’ internal and external validities. First, although the distinguishing feature of the shock data is that they are derived from firm-specific disclosures, one still needs to verify that they do not have systematic causes (i.e. caused by macroeconomic fluctuations), nor systematic effects (i.e. their initial impact hits only the origin firm). During data construction, the shock disclosures are classified by a Bayesian topic model called Latent Dirichlet Analysis (LDA). This results in multiple, distinct types of causes, from natural disasters (earthquakes, floods), to production glitches (machine breakdowns), etc. I examine the impact of each category at a time, as well as a sub-category consisting of only localized plant fires, and find similar results across categories. This confirms that the sample is not contaminated by shocks with potentially systematic effects and that most shocks from my data are indeed localized. Second, firms might only report the largest shocks, leading to overstatement in coefficient estimates. I use the exogenous enactment of a much stricter SOX-Act provision to rule this case out. Third, I conduct a series of falsification tests to ensure that the shocks are indeed correctly mapped to the network data. A host of tests for other issues such as strategic reporting, the role of private firms, etc are discussed in the text.

Having documented the main economic facts, I then explore the stock market implications of these long spillovers. I first document that prices are quickly adjusted for firms with their own shocks or shocks from a directly connected supplier, with a two-day abnormal return of -3.98%. However, if the shock is originated from further up the supply chains, then the market response, while still big in magnitude, is much slower in speed: there is a persistent drift in returns for up to 40 days. Exploiting variations of my shock data where some shocks are disclosed by firms themselves while others are disclosed by their indirect connections, I demonstrate that information processing constraints, perhaps similar to those uncovered by Cohen and Lou (2012), are likely responsible for this slow reaction, giving rise to potentially profitable trading opportunities for investors more adept at analyzing the complex structure of
supply chains.

My final set of tests explores the responses from corporate policies and capital structure to shock spillovers. To do so, I first examine the languages of 10-K/Qs from the same firms that disclose shocks and uncover a series of policies that firms say they would adjust. I then empirically test whether firms actually do adjust these policies and the intensity of such adjustments. My evidence suggests that, after shock spillovers, firms increase their inventories, cash holdings and capital expenditures. I then show that this response is much larger to shocks originated from more closely connected sources, than from more remote firms up the supply chains.

This paper contributes to the literature on four fronts. First, a burgeoning literature in finance explores spillovers and externalities along various types of interconnections related to personnel (Shue (2013), Cohen, Frazzini, and Malloy (2008), Cohen, Frazzini, and Malloy (2010), Maturana and Nickerson (2015)), geography (Poll, Stoffman, and Yonker (2015)), trading, financing and insurance (Cohen-Cole, Kirilenko, and Patacchini (2014), Bajo, Chemmaunr, Simonyan, and Tehranian (2015), Billio, Getmansky, Lo, and Pelizzon (2012), Afonso, Kovner, and Schoar (2015)), product (Hoberg and Phillips (2015), Rauh and Sufi (2012), Foucault and Fresard (2014)), supply chain (Barrot and Sauvagnat (2014), Titman and Wessels (1988), Banerjee, Dasgupta, and Kim (2008), Fee, Hadlock, and Thomas (2006), Hennessy and Livdan (2009)), or internal connections within conglomerates (Schoar (2002)), and the effect of these externalities on firm behaviors. A large body of literature in operation management, such as Anupindi and Akella (1993), Tomlin (2006), and Ang, Iancu, Swinney, et al. (2014), focus on how to mitigate these externalities operationally. However, little is known about the extent of these externalities in terms of how deep their effect can penetrate along connections. This paper builds upon this literature by directly quantifying the extent of these externalities according to how far they propagate vertically down the supply chain linkages. I demonstrate that, at the micro level, these externalities spill over much deeper beyond just
one firm, with their effect reaching up to the 4th connection in some cases. Therefore, at the macro level, the aggregate effects are potentially even larger than existing studies suggest.

This paper also contributes to the literature on the identification and measurement of firm-specific shocks and their propagation. Existing studies in finance and operations management have examined shocks in the context of bankruptcies (Hertzel, Li, Officer, and Rodgers (2008), Kolay and Lemmon (2011)), financial distress (Hortaçsu, Matvos, Syverson, and Venkataraman (2013)), natural disasters and temperature variations (Barrot and Sauvagnat (2014), Boehm, Flaaen, and Pandalai-Nayar (2014), and Bergman, Iyer, and Thakor (2015)), and supply disruptions (Hendricks and Singhal (2005)). Moreover, Leary and Roberts (2014) identify shocks by extracting the idiosyncratic components of equity returns using asset pricing models. Giovanni, Levchenko, and Méjean (2014) employ a similar approach in extracting the idiosyncratic component of firm sales. Other papers, such as Strebulaev and Whited (2011) and Gourio (2008), recover such shocks with structural models on firm production and investment. However, so far we have limited information on the exact nature of those shocks. This paper builds upon this literature with a different source of data. With the actual texts of firm disclosures and news, I directly observe the actual events behind the shocks. This direct way of capturing the source of idiosyncratic production shocks results in additional granularities that are helpful not only for identification, but also for the precise measurement of economic magnitudes of a wide variety of shocks in other contexts as well (e.g. financing shocks or systematic shocks).

Moreover, this paper complements existing work on asset pricing and shock aggregation in production networks. Compared to sector-level studies on aggregate volatilities and production networks such as Ahern (2012) and Foerster, Sarte, and Watson (2011), this paper directly captures firm-specific production shocks, thus enriches the firm-level microfoundations of shock aggregation. This paper complements the work on correlated supplier-customer stock returns, such as Cohen and Frazzini (2008) and Menzly and Ozbas (2010), by measuring
the response of stock returns directly to firm-specific production shocks.

Finally, the empirical results on the link between market power and shock spillovers provide motivation for future theory developments on production networks that incorporate richer sets of frictions such as monopolistic competition, and the asset pricing relationship between the spillover effects and network-related systematic risks and expected stock returns. I explore some of these issues in related works.

The rest of the paper is organized as follows. Section 2 describes my sample and data sources. Section 3 reports the empirical results on shock spillover in the supply chain network, and their effect on firms’ revenue, cash flows, and gross margins. It also isolates several factors that could give rise to, and affect the magnitude of, these spillovers. A series of key robustness tests immediately follow in Section 4 to ensure the validity of these spillover results. Then, Section 5 discusses the responses, from both managers and the stock market, to these spillovers. Section 6 concludes.

2. Data and Identification

I derive the main empirical inferences in this paper by mapping a hand-collected, 20-year dataset of firm-specific idiosyncratic shocks into a hand-built dataset of firm-to-firm supply relations between publicly traded firms globally. This section describes my methodology to construct these datasets. A more in-depth review of the data construction methodology can be found in Appendix B.²

2.1. Firm-Specific Idiosyncratic Shocks

2.1.1. Data Sources and Initial Sample Selection

Using a two-step textual analysis technique, I extract data on firm-level idiosyncratic shocks from the language of corporate disclosures and news. The first step extracts the list of supply

²Please contact the author if interested in using the described data for research purposes.
shocks from these texts, and the second step isolates the firm specific, idiosyncratic ones from the first list. For the first step, I download and process the texts produced between 1994 and 2015 from the following sources:

1. SEC Form 8-Ks filed in the EDGAR system: In addition to regularly scheduled disclosures such as 10-K/Qs, public companies in the United States are required to report a wide variety of material corporate events on a more timely basis, in the form of 8-K filings, or “current reports.” Such disclosures were optional but became mandatory following the passage of the Sarbanes-Oxley Act. Correspondingly, many firms disclose a wide variety of supply chain-related events and disruptions in their 8-Ks. Additionally, exact event dates are included in HTML headers accompanying the main filings. I parse these data from the headers and merge them with the main texts to create one unique date-stamped, item-coded text string per 8-K filing. The filing firm’s identity is included in the SEC’s Central Index Key (CIK), which I merge with GVKEY from Compustat.
2. Press releases filed through the Dow Jones Newswire: I obtain the main texts of each release and match the name of the disclosing firm back to Compustat.
3. Company-specific news from Capital IQ: this includes most firm-related news in a time-stamped, machine readable format.

For each text document in the above list, Step 1 of the textual analysis uses a set of keyword filters that captures events containing keywords from the following groups:

- Supply chains: supplier, supply chain, shipment, raw material, etc;
- Events: disruption, shortage, delay, etc;
- Shocks: unexpected, sudden, shocks, etc;

Specific keyword filters can be found in Appendix B. This step results in a set of 24,838 events corresponding to supply-related shocks. For 19,771 of such shocks, I can identify the exact origin of the shock by iteratively searching the texts for the list of all known firm names extracted from Bloomberg. Of these shocks, 14,043 (71.03%) are shocks to the disclosing firm.
itself and 5,728 (28.97%) are disclosed as a supply shock from a named supplier firm. In the former case, the origin of the shock is identified as the disclosing firm itself. This distinction proves useful for a key robustness check in Section 4.1.3.

2.1.2. Classification of Shocks by Type

The second step of the textual analysis represents a key innovation of my data construction: I fit a Bayesian topic model from the Latent Dirichlet Allocation (LDA) family on the output disclosure collection from the previous step. The topic model is designed to infer the type, or nature, of each disclosed event. This paper is the first in finance to employ the LDA model to classify the nature of firm-level shocks from disclosures.\(^3\) In this subsection, I briefly review the reasoning for the model, while deferring the exact model specification and computation steps to Appendix B for interested readers.

In short, the LDA model assumes a simple, two-distribution data generating process where each disclosure is generated from a (latent) distribution over a collection of topics (i.e. shock types), each of which is, in turn, a distribution over the words in the English vocabulary. For example, a document that discusses the impact of a plant fire of its supplier should be represented by a topic distribution that places high weight on a topic that places high weight on words such as fire and flame. By contrast, a topic that places high weight on earthquake and flood should receive a low weight in this distribution.

However, the two distributions are unobservable from the point of the researcher. The advantage of probabilistic topic models is that, using Bayesian techniques, such models efficiently infer the hidden distributional properties from the observable data (i.e. the collection of documents). LDA represents one particular parameterization of the model: I first assume that these two latent distributions belong to the Dirichlet family. Then, armed with this functional form and the observed words in each disclosure, I compute the posterior (i.e. empirical) topic and

\(^3\)For a list of LDA applications and an evaluation of their effectiveness, see Blei, Ng, and Jordan (2003).
word distributions using the standard Bayes Theorem. These empirical distributions are the main outputs of the model. The only inputs in LDA are the document texts and the number of topics. As such, compared to a manual classification approach, researcher-induced subjectivity and bias are minimized, and a much larger number of disclosures can be classified within a short period of time. Intuitively, the model would achieve a satisfactory performance if the top words representing each topic are distinct from each other.

I fit the LDA algorithm with 20 topics on the collection of 19,771 disclosures. The first outputs are the word distributions that identify the topics, and the top 5 keywords for each topic are reported in Table A1 from Appendix B. Here the top words are very distinct while intuitively and clearly identifying each topic. From these top keywords alone, an average human reader would not have any confusion about the nature of each topic. The second output is the topic mixture for each disclosure, i.e. the proportion of each disclosure devoted to each topic. I keep the disclosure only if it exhibits more than 95% of a single topic. This results in a collection of 12,337 documents, each classified into one of the 20 topics.

2.1.3. Identifying Idiosyncratic Shocks

From the 20 types, I then isolate the firm-specific, idiosyncratic ones. First however, note that the meaning of “idiosyncratic shocks” differs in different research contexts in finance. In my setting of shock spillovers, the following definition applies:

**Definition 1** A shock is firm-specific and idiosyncratic if it is 1) not caused by exposure to common, systematic factors, and 2) its immediate effect is clearly limited to the origin firm only.

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4 The main algorithm and the Gibbs sampling programs are implemented in the C++ programming language. The classification remains robust from as few as 15 topics to as many as 45 topics, after which overlapping redundancies appear. See Appendix B for details. For research purposes, interested readers can also contact the author for programs used in the analyses.

5 Jegadeesh and Wu (2015) ask a team of human readers to manually classify a list of FOMC meeting minutes. They agree with the LDA model for the vast majority of cases.
In other words, a firm-specific shock is clearly identified from a disclosure if the disclosed event does not have systematic causes (i.e. caused by macroeconomic fluctuations), nor does it have systematic effects of its own (i.e. its initial impact hits only the origin firm). Both statements serve as exclusion conditions to insure the validity of the central identifying assumption of this paper: any effect that a shock might cause to other firms is attributable to the spillover effect through inter-firm linkages, and not due to original effect of the shock itself. The first condition (idiosyncratic cause) is easier to verify, and I discuss that below. The second, more nuanced condition (idiosyncratic effect) requires more extensive tests and is thus devoted its own Section 4.1.

I first focus on the causes of these shocks. Because the LDA provides an intuitive classification of shock types, the first condition, that the shocks are not caused by systematic factors, can be validated by examining the nature of these types. Specifically, the 20 types can be grouped into three levels of “idiosyncrasy”: First, 6 types of events are related to macroeconomic conditions and industry-wide factors, e.g. parts shortages caused by unexpectedly high demand from other firms or consumers. Second, 6 types are related to events with more granular causes, but it might still be possible to relate these types to industry-wide issues. For example, events related to labor strikes might well be caused by firm-specific factors, but one still cannot completely rule out the influence of industry-wide labor unions that can possibly coordinate these strikes with both origin firms and their connected customers. Finally, the last level contains 8 shock types, each one of which can be attributed to idiosyncratic causes with little ambiguity. Such events include various natural disasters, manmade disasters such as fire or crime, production glitches such as power outages and unexpected machinery breakdowns, and technology adoption failures such as IT glitches and attacks, etc. I include several concrete textual examples for each category in Appendix C.

Because events in the last group are clearly not caused by systematic factors, they are the best candidates for well-identified firm-specific shocks. I therefore keep only these events in my
sample and group these 8 types into five major groups.\textsuperscript{6} The resulting sample is summarized in Table 1 below. Overall, I identify 11,191 idiosyncratic shock events, covering 2,193 unique firms or 20.06\% of the sample firms. At the firm level, they are clearly of very low frequency, with each firm on average having 5 shocks.

[Insert Table 1 and Figure 2 here]

Figure 2 plots the total number of these idiosyncratic shocks over time, and the distribution by major types. Except for the first three years in the sample, the number of shocks does not exhibit any particular trend or correlation with systematic factors such as business cycles, further confirming that the shocks are indeed caused by idiosyncratic issues. A potential concern is that the number of natural disaster-related shocks seems to increase during the years of 2005 and 2011, the years when hurricane Katrina and the Japan earthquake took place. I address this and other concerns related to the shocks’ effects in Section 4.1.

2.2. Firm-Level Supply Chain Network

In order to empirically examine the spillover effect of the firm-specific shocks described in the previous subsection, I construct a comprehensive, firm-level network of supplier-customer relations between publicly traded firms globally, with historical coverage beginning at 1994. Each shock in the previous dataset can then be mapped precisely to this network. Specifically, for each year $t$, I capture the list of all supply relations between each supplier $j$ and customer $i$, inferred from the following sources:

1. The same collection of firm disclosures described in the previous subsection. In addition to operations-related disclosures, the SEC also requires firms to disclose the formation and termination of important business relationships, a large portion of which are supply chain relations. I use a robust name-matching algorithm to extract the identities of both

\textsuperscript{6}In untabulated results, I also include the second group e.g. labor strikes. The results are slightly stronger both economically and statistically.
parties and record formation and termination dates from the collection of 8-K filings, press releases, and firm-specific news. This procedure produces 414,355 supply relations among firms.

2. The Supply Chain Analytics databases from Bloomberg and Revere Data Systems, both of which conduct public and proprietary research that identifies supply chain relationships between publicly traded firms globally. I extract these data with proprietary APIs provided by these sources and identify 1,190,474 relations.

3. Shipment-level data from US Customs Bill of Lading and a leading business casualty insurance company. Both datasets provide a comprehensive account of all import/export goods that clear the US Customs at the ports of departure/arrival. Detailed identities of both supplier(shipper) and customer(consignee) are also recorded. I extract these information using a similar name-matching algorithm that results in 652,932 relations.

The resulting dataset contains 2,257,761 relations covering 23,059 publicly traded firms. I use the following criteria to construct my final sample of firms:

- My dataset identifies firms using the International Securities Identification Number (ISIN). I match the ISIN with GVKEY from the Compustat Global database to retrieve accounting data. I exclude all firms for which I am either 1) not able to match ISIN to GVKEY’s or 2) otherwise not able to obtain accounting data from Bloomberg.

- At minimum, my tests also use market capitalization and return on total assets as control variables. I exclude all firms for which these data are unavailable.

- The production process for financial and other services are likely to be different from that of other goods. I exclude all financial and personal services firms (SIC code 6000-7999) from the sample.

Overall, the final sample captures 10,930 unique firms and 1,007,998 relationships from 1994 to 2015. Table 2 provides summary statistics of sample firms and supply relationships
captured by this sample. The mean market value is $2.045 billion and the book-to-market ratio has a mean value of 0.715. The network data identifies over 90 links per firm over the 1994-2015 period, and each link on average persists for 7 years. In addition, Panel C of Table 2 reports the average statistics for firms located on the path of the shocks (i.e. connected at a distance of $n = 1, \ldots, 4$ from the firms where the shocks originate). On average, firms located further downstream (higher number of connections) from the shocks are slightly smaller and younger in age. Except for that, firms located at different network positions are similar in most other aspects such as book-to-market ratio, P/E ratio, leverage, etc.

[Insert Table 2 here]

For a smaller set of relationships (473,759), I am also able to capture the value of the relationship as a fraction of the customers' cost of goods sold (COGS). The summary statistics for these firms are very similar to the overall sample and are reported in Table 2 above. For this sample, the average total COGS explained by the supply shares is 34.04%. I use this smaller sample in a series of robustness tests, discussed in Section 4.

2.3. Other Relevant Data

All quarterly accounting data are from Compustat Global and Bloomberg. I obtain daily stock return data primarily from CRSP and compute the same for international firms using daily closing prices from Compustat, manually adjusted for stock splits and dividends. I use these data to construct firm-level outcome and control variables, which are discussed as they appear in subsequent texts. For interested readers, I also summarize the list of variables used in this paper and their construction methodology in Appendix A.

3. Spillover of Firm-Specific Idiosyncratic Shocks in Network

This section provides empirical evidence on the substantial spillover of firm-specific shocks along the firm-to-firm interconnections in the supply chain network, and the effect of such
spillover on the revenue and cash flows of firms that are 1) initially hit by the shocks, 2) closely connected to the shocks’ origins, and 3) remotely connected to the origin beyond the first-tier connections.

3.1. Hypothesis Development

Conceptually, the shocks captured by my disclosure data represent firm-specific innovations in their respective productivity processes. First, in models without networks, such shocks do not impact any firm beyond the origin. Second, in most theoretical models with production networks, such innovations are interlinked by the network connections (represented by the network’s adjacency matrix). In the aggregate, these interlinkages introduce additional co-variances among firms’ outputs, thus changing aggregate output and consumption volatilities. However, it is easy to derive that along each chain of links, e.g. $S \rightarrow C_1 \rightarrow C_2 \rightarrow \ldots$, the effect of a shock quickly decays after each link.\(^7\) This scenario, which serves as the null hypothesis, is that a shock to $S$ would not significantly affect $C_1$ and other firms beyond it.

So far, there is no empirical evidence on how far these shocks travel after $C_1$ and whether they do quickly dissipate. However, a large amount of disclosures from my text sample do suggest that the effect of these shocks might persist beyond $C_2$-type firms and even significantly affect more remotely connected firms. Figure 3 plots the exact timeline of such an example. Here, the factory of a hard drive component supplier (S:Nidec) was damaged during a flood in 2011, causing production disruption and leading to lower revenue growth. Its immediately connected customer (C1:Seagate) disclosed this disruption almost immediately, and verified that its own production facilities were not affected. However, due to input shortages, its output was also lower, while at the same time, due to its large market share in the hard drive industry,

\(^7\)To see this, consider the Cobb-Douglas production setting in Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) with output $Y_i$, labor input $L_i$ and intermediate good inputs $X_{ji}$: $Y_i = A_i L_i^{1-\alpha} \left( \prod_{j=1}^{N} X_{ji}^{\gamma_{ij}} \right)^{\alpha}$. Without an asymmetric network (e.g. if we only have a single chain), if $\alpha < 1$, i.e. labor has a non-zero share in total factor inputs, then at each subsequent connection $k$, the impact of a shock to firm $j$ would decrease by a factor of $\alpha^{\gamma_{kj}}$ as it travels downstream along the chain. With average $\alpha = 0.60$ and $\gamma_{kj} = 0.30$, the effect of the shock is 82% lower after each link.
it was able to charge a higher price for these outputs, partially offsetting the quantity drop and leading to a more moderate decline in revenue growth.

Surprisingly, C2 firms on the supply chain, Dell and HP, both experienced larger revenue declines, and both attributed them to supply chain disruptions caused by the flood. Particularly, they mention “significant and immediate” increases in supplier prices, coupled with their inability to pass this increase to customers (due to the more competitive nature of the computer manufacturing business compared to hard drive manufacturers), as the reason for these lowered revenue and earnings numbers.

This example suggests that, contrary to predictions by existing theories, which assume smooth production functions and competitive firms, significant spillover of firm-specific shocks to remote connections can occur if firms along the chains are not perfectly competitive and differ in characteristics such as market power. Consider a supply chain consisting of three firms, S→C1→C2, where S experiences a shock causing lower outputs to both itself and C1. Existing network models predict that the shock would not significantly effect C2 if C1 is perfectly competitive. However, suppose both C1 and C2 have monopolistic competitive powers. In this case, because C2’s input is now more scarce, C1 would raise its price above the competitive level in order to recoup some losses and pass some effect to C2. This behavior is extensively discussed in firm disclosures and illustrated in Figure 3. If C1 has a high market power, it would be able to raise prices significantly (Seagate, the C1 firm in the previous example, raised prices by 20% shortly after the flood). If C2 has a low market power, it cannot raise prices as effectively while simultaneously facing a high-powered supplier. In this case, C2’s output will be even further below the competitive level predicted by existing models, thereby further extending the spillover effect of the original shock.

In essence, at a granular level, significant deviations from perfect competition could lead to significant shock spillover effects beyond the prediction of existing models that assume perfect competition at all positions. In addition, Section 3.3 empirically examines two auxiliary factors
that might also contribute to shock spillovers: input substitutability and inventories. Given the above framework, I test the following alternative hypothesis against the theory-predicted null of no spillovers:

**Hypothesis 1** Given additional frictions such market power, input substitutability and inventory, firm-specific idiosyncratic shocks could spill over significantly beyond both the origin and its closest connections, and significantly impact the economic outcome of a larger number of distant connections.

I test the this hypothesis first using the following regression, which measures average outcomes across all shocks:

\[
Y_{it,t+k} = a + \sum_{n=0}^{10} b_n D_{i,t}^n + cX_{i,t} + F_{i,t} + \epsilon_{i,t},
\]

where \(D_{i,t}^n\) is a dummy variable that equals to 1 if one of firm \(i\)'s suppliers from a distance of \(n\) connections (up to 10) experiences an idiosyncratic shock in quarter \(t\). \(Y_{it,t+k}\) is the \(k\)-quarter growth rate in revenue, operating cash flow, or change in gross margins. \(X_{i,t-1}\) is a vector of lagged controls including market capitalization (\(Size\)), book-to-market ratio (\(BM\)), P/E ratio (\(PE\)), leverage ratio (\(Lev\)), return on assets (\(ROA\)), and inventory (\(INV\)), all defined in Appendix A. \(F_{i,t}\) is the set of fixed effects including: industry×year, fiscal quarter, and state/country fixed effects. The coefficients of interest is \(b_n\), which measures the average difference in revenue and other growth rates between firms hit with a shock spilled over from a distance of \(n\) connections, and firms never hit with any shocks. Hypothesis 1 predicts that the estimates for \(b_n\) will be significantly negative, not only for \(n > 0\), but also for many of \(n > 1\) as well.
3.2. Spillover Results

I first fit Regression (1) using 4-quarter revenue and operating cash flow growth rates,\(^8\) as well as changes in gross margin, and report the coefficient estimates for \(n = 0, \ldots, 4\) in Table 3. The coefficient \(b_0\) measures the effect of the shock on the originating firm itself, and none of the coefficients \(b_n\) are statistically significant at the 10% level when \(n \geq 5\).

[Insert Table 3 here]

The first column of this table reports the impact of the shocks on originating firms themselves. The coefficient estimate for \(b_0\) is -0.0258, compared to a sample mean revenue growth rate of 0.1061 with a standard deviation of 0.2885. Therefore, on average, the shocks captured by my disclosure data indeed have significant impact on the firms that are directly hit by them, causing revenue growth to be about 24.3% lower than average or 8.9% standard deviation lower.

The next four columns document the significant spillover of shocks to as far as 4 connections away from origin. Starting from the closest connection (\(n=1\)), these firm-specific shocks cause substantial impacts to the revenue growth of customer firms in the next 4 tiers of connections. Following the shock, revenue growth for the closest customers is about 21.6% below the mean. This is smaller in magnitude, but similar in statistical significance, to Barrot and Sauvagnat (2014), who, using hurricane and Compustat segments data, find that the largest customers (> 10% revenue) of firms whose headquarters are located in the disaster area subsequently experience revenue growth up to 35% lower.

Surprisingly, the effect of my firm-specific shocks continues to spill over to the customers of these customers (\(n=2\)), and their customers (\(n=3\)), and again to their customers (\(n=4\)). The average effect ranges between 11.7% to 35.5% lower than the mean. While the difference

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\(^8\)I also use revenue growth rates from \(t\) to \(t + 1\), \(t + 2\), and \(t + 3\) quarters. For most distances, the impact is concentrated around the first quarter i.e \((t, t + 1)\).
between these coefficients are not statistically significant at the 10% level, the coefficients themselves are all significantly negative, with \( t \)-statistics below -3.00. This provides strong evidence of the existence of frictions e.g. market power, that are not present in existing theoretical models. This results in the significant spillover of firm-specific, idiosyncratic shocks, not only beyond the origins of these shocks, but also beyond their closest connections as well. Section 3.3 tests these factors in detail at the firm level.

In addition, Panels B and C of this table report similar estimates using the 4-quarter growth rate of operating cash flows (Compustat variable OIBDPQ) and change in gross margin (SALEQ-COGSQA/SALEQ) on the left hand side. The estimates are consistent with the revenue results. In particular, gross margin declines are particularly acute for firms more remote from the origins, potentially indicating that they have lower market power than their suppliers, thus are not as free to adjust prices and consequently are hit with both quantity and price impacts, thereby further contributing to the spillover of shocks.

Finally, note that the previous results are reported as average percentage impacts across all types of shocks. Because different shocks likely have different impact magnitudes, some additional results are in order to provide further clarity on the magnitudes of coefficient estimates. In particular, for each tier of connections (i.e. where \( D_{i,t}^n = 1 \)), I first replace the dummy with the shock’s impact on the origin in Regression (1), resulting in the following specification:

\[
Y_{i,t+4} = a + \sum_{n=0}^{10} b_n Y_{0,i,t}^n + cX_{i,t} + F_{i,t} + \epsilon_{i,t} \tag{2}
\]

where \( Y_{0,i,t}^n \) is the 4-quarter revenue growth rate of the firm from which the distance-\( n \) shock impacting firm \( i \) originates. In this setting, the coefficient estimates can be interpreted as “elasticities”: \( b_n \) measure the impact of the spillover on subsequent connections \( n = 1, \ldots, 4 \) in units of the percentage impact on the origin firm. The results are reported in Table 4.

[Insert Table 4 here]
The results in this table suggest that the spillover effect is not driven only by shocks of large impact. Even after controlling for the impact of the shock on origin firms, the coefficient estimates are still close to 1 at the first three connections and remain statistically significant at distance 4, indicating that shocks that cause a one-unit impact at the origin firm continue to spillover downstream and cause impacts between 40% to 100% of the original impact even to remote, 4th-tier firms.

In summary, these results provide strong evidence that when firms are interconnected in the network of supply chains, shocks previously thought as purely localized are not limited within traditional firm boundaries. Instead, they can transmit along the supply linkages and cause widespread impacts at points remote from origin. I discuss the responses from corporate policies and stock prices in Section 5.

3.3. Determinants of Spillover Magnitude

Having documented the surprisingly large and far-reaching spillover results, this subsection examines in detail the economic story behind these spillovers. Because existing theories predict that shocks quickly die down after each connection, there must be additional frictions present in the data that give rise to such spillovers. One of them is the departure from perfect competitiveness, which has been discussed in Section 3.1 above: if firms located further downstream on average have lower market power than their suppliers, then the revenue impact of the shock could be bigger than predictions made with the assumption of perfect competitiveness. This section empirically examines the existence of these frictions from the data. I first conduct a firm-level test on whether market power is significantly related to the impact of transmitted shock on each individual firm. I then conduct a network-level test: I examine the average market power at each position of the network, i.e. at each distance from the shocks’ origins. In addition, conditional on the occurrence of spillover, input substitutability and inventory levels can further modify its magnitude. I conduct similar firm-level tests for these auxiliary frictions.
3.3.1. Main Channel: Market Power Along the Supply Chain

As discussed in Section 3.1 and corroborated by the anecdotal evidence in Figure 3, with monopolistic competition, firms’ ability to change prices following the spilled over shock beyond perfectly competitive levels can give rise to significant revenue impacts beyond levels predicted by models with perfect competition. At the firm level, this ability is captured by the monopolistic market power of the firm. The spillover effect is particularly acute for competitive firms with less competitive suppliers, which limits their ability to change prices and pass some of the shocks’ effects to customers (or final consumers), while enabling their suppliers to pass a larger portion of the impact to them via price increases. I summarize this channel in the following hypothesis:

**Hypothesis 2** Given a shock spilled over from a supplier, the revenue growth rates of firms with lower monopolistic power than their suppliers will be more severely impacted.

I directly compute the absolute market power of each firm as its size relative to the total size of its most granular industry classification (at the 4-digit SIC level):\[ MP_{i,t} = \frac{\text{Size}_{i,t-1}}{\sum_{k} \text{Size}_{k,t-1}}. \] I also compute its relative market power to its suppliers as the ratio of its own \( MP \) to the average \( MP \) of its connected suppliers: \[ MPR_{i,t} = \frac{MP_{i,t}}{E_{j} [MP_{j,t}]} \].

I then test Hypothesis 2 at the firm level using the following regression with \( MP \) and \( MPR \) measures as interaction variables:

\[
Y_{it,t+s} = a + \sum_{n=0}^{4} b_{n} D_{i,t}^{n} \cdot MP_{i,t} + \sum_{n=0}^{4} c_{n} D_{i,t}^{n} \cdot dMP_{i,t} + \tau X_{i,t-1} + F_{i,t} + \epsilon_{i,t}, \tag{3}
\]

where \( D^{n} \) are the same shock dummies. To facilitate interpretation, I demean the values of \( MP \) and \( MPR \) and scale them by the sample standard deviations. The coefficients of interest are \( b_{n} \) and \( c_{n} \). Here \( c_{n} \) measures the average spillover impact given average values of market power.

---

\( \)\( ^{9} \)The results are not changed when \( MP \) is computed at the 3-digit SIC level and are moderately weaker when computed at the 2-digit SIC level.
\(b_n\) assesses the validity of Hypothesis 2: it measures the incremental effect of one-standard-deviation change in market power (or market power ratio) on revenue growth rate differences between firms with distance-\(n\) shocks and firms without shocks.

[Insert Table 5 here]

Table 5 reports the results. First, the \(c_n\) estimates are still significantly negative, albeit smaller in magnitude, in both panels. Therefore, at average levels of market power, shocks can still cause impacts to close and remote firms. Second, the estimates for the interaction term, \(D \times MP\), are significantly positive. For example, a one-standard-deviation decrease in the market power of a firm closely connected to the shock origin (\(n=1\)) would further decrease the revenue growth by another 25% below average. This is consistent with Hypothesis 2 that market power is indeed significantly related to shock spillover at the firm level. Moreover, the estimates for relative market power, reported as \(D \times MPR\) in Panel B, are all significantly negative, indicating that firms with lower market power than their suppliers are indeed most exposed to the effect of shock spillovers.

Next I perform the network-level test. Recall that the average spillover effect is significantly negative up to 4 connections away from origin. If this effect arises because of market power, then market power should on average decline as shocks travel downstream from the origin toward final consumers. In other words, on average firms located “more downstream,” or close to final consumers, should be more competitive than “upstream firms” located more closely to raw materials. Because the notion of network positions is a relative one, the precise classification of “upstream” versus “downstream” is difficult without individual-good-level data. However, because my data captures the exact origins of each shock, I can proxy the firms’ network positions with their distances from the shocks’ origins: firms located further away from the shock should on average be more “downstream” and located closer to final consumers.\(^{10}\) I can therefore conduct a network-level test of the market power channel by comparing the

\(^{10}\)In the example from Figure 3, distance-2 firms, Dell and HP, indeed disclose that they produce IT products
average market power of firms located at each distance from the shock origins.

Starting from the origin of the shock $i$, I compute the average market power for each distance of connections:

$$\overline{MP}_n = \mathbb{E}\left[ MP_j | j \text{ on path of } i \text{ shock } \& \text{Dist}(j,i) = n \right], n = 1, \ldots, 10. \quad (4)$$

Even though $\overline{MP}_n$ is a relatively crude proxy, if it uniformly declines as $n$ increases, this would provide consistent evidence on the network level that market powers can indeed facilitate shocks spillovers to remote firms. Table 6 reports the $\overline{MP}_n$ levels.

This table provide confirmatory evidence that, on average, firms located further down the supply chain from shock origins have lower market power. Because the shocks are distributed across many positions in the network, this measure is relative in nature: origin and distance-1 firms tend to be located more “upstream” in the supply chains and are closer to raw materials, and on average, their market power is significantly higher than distance-3 or -4 firms, which are located closer to the final consumers. The standard deviations are high for all distances, as such, the results cannot statistically establish this pattern for all links. However, they are consistent with the intuition that the more remote, “downstream” firms producing more consumer-oriented goods are on average more competitive than firms producing business-oriented, intermediate goods. Therefore, through the market power channel, spillover to these more remote firms is possible.

3.3.2. Auxiliary Channels: Input Substitutability and Inventories Along the Supply Chain

This subsection links the degree of shock spillover to the degree of substitutability between inputs, which measures the ease of alternative sourcing, and inventories, which serve as a primarily for the consumer market, while the distance-1 firm, Seagate, primarily sells its hard drives to distance-2 firms rather than directly to consumers.
strategic buffer against production interruptions. Consider the same two-tier supply chain (S→C1→C2) mentioned before: first, if individual inputs are perfectly substitutable, then as long as there is more than one supplier at each link, a shock from S would never be able to transmit beyond S, because both C1 and C2 would costlessly switch to alternative sources. At the opposite, suppose that the inputs are perfect complements (i.e. the production functions are Leontief). Here alternative sourcing is impossible, and the shocks would “perfectly” transmit along the chain, with infinite marginal impact to both C1 and C2. Real-world production probably falls somewhere between the two extremes, while Boehm et al. (2014) find evidence that the relation is close to Leontief between imported and domestic inputs. Therefore, while not enough to generate spillover on their own, variations in input substitutability can further modify the magnitude of spillovers, conditional on their occurrence: if the first-tier (S→C1) connection has higher substitutability than higher-tier (C1→C2) connections, the effect on C2 could be bigger than predictions made using, say, Cobb-Douglas production functions.

Similarly, when hit with a supply shock, firms with more input inventories already have more redundant inputs at hand, so they are less subject to the impact of the shock. Firms with infinite inventories, similar to those with perfectly substitutable inputs, are never subject to any spilled over shocks. Firms with zero inventories are the most sensitive to the impact of any shock. Inventories are costly to hold, so most real-world firms hold some minimum “safety level” computed using common operations models. If the average level of inventories differ at different distances from the origin of supply shocks, then ceteris paribus, this would result in different levels of shock impact on average. I summarize these channels in the following hypothesis:

**Hypothesis 3** Given a shock spilled over from a supplier, the revenue growth rates of firms whose suppliers are less substitutable, and firms with lower inventory levels, will be more severely impacted.

A firm-level proxy for input substitutability is needed for the empirical tests. For a smaller
sample of firms, my data capture exact value of the supply relationships as a fraction of the customer’s inputs, i.e. \( \gamma_{ji,t} = \frac{V_{ji,t}}{COGS_{i,t}} \). If supplier \( j \) constitutes an important part of customer \( i \)’s production, as indicated by a high \( \gamma_{ji} \), then \( j \) is likely harder for \( i \) to substitute. In this setting, the \( \gamma_{ji} \)s measures the “switching cost” of finding alternative suppliers in the event of a disruptive supply shock. As such, they directly proxy for the substitutability of each supplier. For each customer \( i \), I compute its average supplier substitutability as \( \bar{\gamma}_{i,t} = \frac{1}{n} \sum \gamma_{ji,t} \). To ensure robustness, I use several industry-based alternative measures of substitutability and report their results in Appendix D. Firm-level inventories are defined as the ratio of total inventory to total assets: \( INVR_{i,t} = \frac{INV_{i,t-1}}{AT_{i,t-1}} \).

I then test Hypothesis 3 with the following regressions:

\[
Y_{it,t+4} = a + \sum_{n=0}^{4} b_n D_{i,t}^n \cdot \bar{\gamma}_{i,t} + \sum_{n=0}^{4} c_n D_{i,t}^n + d \bar{\gamma}_{i,t} + \tau X_{i,t-1} + F_{i,t} + \epsilon_{i,t}, \quad (5a)
\]

\[
Y_{it,t+4} = a + \sum_{n=0}^{4} b_n D_{i,t}^n \cdot INV_{i,t} + \sum_{n=0}^{4} c_n D_{i,t}^n + d INV_{i,t} + \tau X_{i,t-1} + F_{i,t} + \epsilon_{i,t}. \quad (5b)
\]

where I demean the values of \( \bar{\gamma} \) and \( INV \) and scale them by the sample standard deviations. The interpretation of these regressions is the same as Regression (3): \( b_n \) assesses the incremental effect of one-standard-deviation change in supplier substitutability (or inventories) on revenue growth rate differences between firms with distance-\( n \) shocks and firms without them. The coefficient estimates are reported in Table 7.

The roles of inventories and supplier substitutability are evident from this table. The estimates for both \( D \times INVR \) and \( D \times \bar{\gamma} \) are significantly positive and economically large. They can be interpreted as follows: when a firm experiences a shock, possibly from a remote source along its supply chain, if its inventory level, or supplier’s substitutability, is one standard deviation higher/lower, then the spillover effect would be mitigated/exacerbated by 11% and 37%
of the average revenue growth rates, respectively. Therefore, conditional on a shock occurring from somewhere in the supply chain, both inventories and supplier substitutability can indeed further affect its impact on the firm.

A word of caution is that, when put in the same regression, only $MP$ (or $MPR$) remains statistically significant. This is because market power leads to impacts on both prices and quantities, while inventories and substitutability likely affect quantities only. Therefore, these two channels are likely auxiliary to the market power channel.

4. Key Robustness Tests

The surprisingly pronounced spillover effects documented in the previous two sections demand careful checks and examinations in order to firmly establish their internal and external validity. The unique, granular nature of the data facilitates a series of direct robustness tests. In this section I discuss several tests that are most helpful in solidifying the paper’s results. A host of additional robustness checks can be found in Appendix D.

4.1. Are the Shocks Well-Identified?

Recall that the shocks captured by my data have to meet two hurdles to be considered well-identified idiosyncratic shocks: they have to have both idiosyncratic causes and localized, firm-specific effects. The construction and summary statistics presented in Section 2.1.3 have provided evidence on the first condition. This subsection specifically discusses tests needed to confirm the second condition.

4.1.1. Some Large Shocks Might Have Systematic Effects

The first concern is perhaps the most salient: some shocks, such as large natural disasters, although idiosyncratic in nature, might have wide-ranging impacts on not only the origin firms that report these shocks, but also their connected customers, either directly (i.e. the disaster
hits both the disclosing firm and their customers) or indirectly (i.e. the disaster creates a region-wide demand shock that feeds back to the revenue of both origin firms and their customers). In both cases, the shock’s spillover effect through linkages is contaminated by the “systematic effect” of the shocks and the coefficient estimates in my empirical framework would be amplified. Therefore, if on average my sample is populated by these large shocks, then the empirical results cannot be ascribed solely to shock spillover through supply chain linkages.

Fortunately, because LDA classifies shocks into distinct categories, I can perform three tests to rule out this case. First, I replicate the spillover results from Regression (1) while deleting from the sample one shock type at a time. I then redo the tests using only one category at a time. Finally, I keep only one category of shocks that are unequivocally idiosyncratic in both cause and effect: fires, which are extracted from the manmade disaster category of my sample by a simple keyword search for fire-related words. This results in a collection of 174 shocks, and I redo the spillover analysis using only this reduced sample. The results for these tests are reported in Panels A to C of Table 8.

[Insert Table 8 here]

In all three cases the results are not significantly changed, which confirms that on average, my sample is not contaminated by shocks with potentially systematic effects. Their initial impacts are localized to the origin firm only, thus their subsequent impact on connected customers are indeed due to the spillover induced by the supply chain linkages.

4.1.2. Prior Growth Trends

Next, for the disclosure-based shocks to be well-identified idiosyncratic shocks, before their onset, a firm’s revenue growth should be similar to those that are never hit with any shocks. This implies that there must not be a statistically significant difference in prior-period growth rates between these two groups. To test this prior trends assumption, I fit Regression (1), replacing the left hand variable with lagged one quarter \((t-1, t)\) to 8 quarters \((t-8, t)\) revenue.
growth rates, for both the origin firms \((n = 0)\) and their subsequent connections \((n = 1, \ldots 4)\). I tabulate these results in Table 9.

This table clearly demonstrates that none of the estimates for \((t − 1, t)\) to \((t − 8, t)\) are statistically significant. This indicates no significant difference in prior-to-shock revenue growth rates between treated (hit with shock) and control firms in the previous two years. As such, the significant difference in growth rates shown in Table 3 are likely due to the spillover effect through supply chain linkages rather than any existing trends in the data.

4.1.3. Strategic Disclosure of Shocks by Firms

A key feature of my shock data is that they are extracted from voluntary firm disclosures, such as 8-Ks and press releases. Therefore, one might worry whether firms are completely truthful in their disclosures, or if there are systematic differences in the reporting standards of these events.

This concern is legitimate and important, because strategic disclosure of these events can introduce amplifying biases to the estimates from the spillover regressions, for three reasons: First, firms might disclose a shock only if its impact is too large to strategically hide from public view. In this case, the shocks that I capture would be overrepresented by large idiosyncratic shocks, thereby artificially inflating the true spillover effect from the interconnections.

A closely related concern is reverse causality: A manager facing low future revenue growth rates might attempt to “explain away” this bad performance by pointing to “idiosyncratic shocks to the supply chain” that are out of their control. Zhou (2014) documents the usage of such “external blame” language in earnings conference call transcripts. If such strategic blame is prevalent in the shock disclosures, then the true spillover effects measured in Regression (1) could also be contaminated upwards.
I first address the concern of unbalanced reporting of only large shocks, via an exogenous change in the disclosure reporting standards. In particular, an extension to the Sarbanes-Oxley Act (SOX Act) mandates additional “real time” disclosures of information on material changes in firms’ operations, which include supply chain-related activities, beyond the original SOX Act requirements. The SEC began to strictly enforce the provision on August 23, 2004.\textsuperscript{11} This enforcement thus serves as an exogenous policy shock after which firms would presumably disclose more supply disruptions, which is confirmed by Schmidt and Raman (2013). I therefore cut the sample into two halves corresponding to before and after this enforcement date, and replicate Regression (1) on each subsample. If unbalanced reporting is a problem, then the results would be weaker in the post-2004 subsample. Panel A of Table 11 presents the results. Results before and after 2004 are very similar in both economic magnitudes and statistical significance, indicating that firms are not intentionally disclosing only major shocks.\textsuperscript{12}

[Insert Table 11 here]

Next, the reverse causality concern is addressed with subsample analysis. Recall that my sample shocks are extracted from two types of disclosures: 71.03% are shocks to the disclosing firm itself and 28.97% are disclosed shocks from external suppliers. Because strategic blaming of external suppliers is not an issue for the former sample, I replicate Regression (1) using only this restricted sample of shocks and report the coefficients in Panel B of Table 11. Here again, the coefficients are not significantly different between the restricted and unrestricted samples, suggesting that reserve causality related to the strategic blaming of external parties in disclosures is not significantly present in my shock data.

Finally, recall Table 1 before: it also shows that the firms disclosing shocks are not statistically different in size, book-to-market ratios, and other dimensions, from those without disclosures. This indicates that the disclosure decision of a shock is not related to any par-

\textsuperscript{11}https://www.sec.gov/rules/final/33-8400.htm
\textsuperscript{12}Inserting the post-enforcement period as a dummy variable produces similar results.
ticular firm characteristics, alleviating potential concerns of some firms strategically reporting these shocks more than others.

Overall, the tests in this subsection further confirm that my sample of LDA-classified firm disclosures capture well-identified idiosyncratic shocks at the firm level. The versatility of my methodology enables its use to identify shocks in more general contexts as well (e.g. shocks outside supply chains such as financing shocks), as a robust identification tool for empirical finance researchers.

4.2. Are Shocks Correctly Mapped to the Network?

Having established that the shock data are well-identified and idiosyncratic, one still needs to make sure that these shocks are correctly mapped to the network, and that the spillover results are indeed caused by these mapped shocks and not by 1) spurious statistical factors and 2) the mathematical operation of taking averages on network links that are unevenly distributed at different positions. The first concern is easily addressed through a falsification test discussed below. I defer the technical details of the second test to Appendix D for interested readers.

Because my data record the date of occurrence for each shock, I conduct the following falsification test to rule out spurious relations. Specifically, for each shock date $t$ and firm $i$, I first reset all $D_{0i,t} = 0$. I then randomly assign falsified “shocks” to firms on each occurrence date, i.e. $\exists \hat{D}_{0i,t} = 1$ for some random $i$. I then trace out the customers of these firms, recreate similar tiered dummies $\hat{D}_{i,t}^n$, $n = 1, \ldots, 4$, and repeat Regression (1). Table 10 reports the coefficient estimates.

[Insert Table 10 here]

This table demonstrates that, while using real data, the spillover effect is significantly negative for the first 5 distances; none of the estimates are statistically significant using randomly assigned shock data. Therefore one can be more confident that the spillover impacts are indeed
caused by the mapped shocks to the network linkages, and not by spurious relations.

4.3. External Validity: Private Firms

A valid concern about the spillover results from the previous sections is their generalizability: crucially, my data contain only publicly-traded firms. This leads to two potential concerns, first, would network data be general and complete enough even with the lack of private firms? Second, would omitting private firms lead to amplifying biases on coefficient estimates? If both can be ruled out, then the spillover result, even though derived using public-firm data, can be readily generalized to all firms.

Recall that a subset of my network data contains valued relationships. This enables me to empirically examine the first concern. The intuition is as follows: first, the make-use table between sectors (defined by NAICS codes) constructed by the BEA contains data from both public and private firms with more than 50 employees. Second, if I aggregate the relationship values flowing from all firms in one sector to all firms in another, I can reproduce a similar table and compare the sectoral-level input shares $V/\text{COGS}$ with the shares in the BEA table. Therefore, if the shares are comparable, then adding or removing private firms probably would not fundamentally change the shape of the overall network.

I aggregate the smaller sample of 7,054 domestic firms with valued supplier relationship data into 41 industry groups according to BEA's definition. I then compute the within- and between-group trade shares by summing up the values at the end of 2013 for all firms within and between each group, then scale by the sum of COGS. This results in 1,681 sectoral shares, which I then correlate with the same shares computed from the 2013 use table from the BEA. Appendix B details the construction steps. The Spearman's rank correlation between these shares is 0.815. This indicates that, at least on the sectoral level, my public-firm data produce

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13 The actual BEA table has 71 industries. I remove industries that are not present in my dataset such as financial services, resulting in 41 groups.

14 Available at http://www.bea.gov/industry/xls/io-annual/IOUse_Before_Redefinitions_PRO_1997-2013_Summary.xlsx
a network of similar shape to the combined data of both public and private firms.

Second, because my shocks are all originated from publicly traded firms, to the extent that private firms serve as alternative suppliers to other public firms along the shocks’ paths, this would produce an attenuation bias to the estimates, making it more difficult to find a significant result. One would also raise other concerns related to external validity, e.g. the generalizability of results to positive shocks. I address these additional concerns in Appendix D.

5. Financial Response from Firm and Market to Spillovers

The results in the previous sections document a pronounced and robust spillover effect in the network of supply chains: localized, firm-specific shocks can cause substantial impact to the revenue of firms located up to 4 connections away. Given both the broad reach and the large magnitude, one would intuitively expect significant responses, from both corporate financial policies and firm valuations, to these significant spillovers.

However, existing theories and empirical research have not explored these responses. Specifically, first, do firms even recognize this spillover and adjust anything in response? Second, what policies would firms adjust? Third, how much would they adjust? Do they simply make up shortfalls after these spillovers, or would they respond more pro-actively and aggressively? Finally, is there any heterogeneity in the response to close vs. remote spillovers?

By examining firms’ post-shock discussions from their 10-K/Qs, this section first uncovers a series of policies that the firms say they would adjust, then empirically tests whether firms actually do adjust these policies and the intensity of such adjustments. I then examine the adjustment in firm values by documenting the stock price response to these shocks, and uncover heterogeneities in responses from shocks spilled over from close vs. remote sources.
5.1. **Hypothesis Development**

Because previous research has not provided empirical evidence or theoretical insights on corporate responses to supply chain shocks, one needs to be careful in the analysis to avoid data snooping bias. Fortunately, the same firms that disclose these shocks often discuss their response to these shocks in subsequent disclosures such as 10-K/Qs. Therefore, from these disclosures, I can directly extract the list of variables that are most often talked about.

I proceed with a simple three-step keyword search: First, similar to Jegadeesh and Wu (2013), for each firm that discloses a shock, I obtain their 10-K/Qs filed in the next four quarters, and isolate the Management Discussion & Analysis (MD&A) section. Second, from these discussions, I use the same keyword filters discussed in Section 2.1 to look for sentences related to these shocks. Third, from each keyword within the sentences, I tabulate the frequency of the words closest to the keyword and manually isolate the most frequent occurrences related to corporate policies. This results in three groups of top keywords related to:

1. **Strategic buffers and reserves**: *cash, working capital, inventory, buffer, excess, etc*
2. **Production adjustments and alternative sourcing**: *redesign, accommodate, alternative supplies, redundant sourcing, etc*
3. **Financing motives**: *strong balance sheet, funding source, etc*

These words directly give a starting point for the empirical analysis. First, they relate to buildups in working capital such as cash and inventories, possibly beyond the levels before the shocks’ impact. Second, they relate to adjusting production or redesign some aspects of products to accommodate a wider selection of alternative suppliers, which suggest changes in capital expenditures and possibly R&D investments into these adjustment costs and technologies. Third, firms seem to be concerned about how to finance these buildups, indicating that they might tap into external funding sources such as debt or equity issuances. I summarize these insights in the following hypothesis:
Hypothesis 4 Following a spilled over shock, firms enter an active buildup phase in their working capital and longer-term investments, possibly beyond simple recovery levels. Such activities require financing beyond internal funds.

I test this hypothesis using the following regressions:

\[ CF_{it+k} = a + b_n D^n_{it} + c X_{i,t-1} + d F_{i,t} + \epsilon_{i,t}, \quad (n = 0, 1, 2, k = -1, \ldots, 8), \]  

where \( D^n \) is the same shock dummy from previous specifications, except that I now group all firms beyond the closest connection into the “remote connections” group and set \( D^n=2 = 1 \) \( \forall n \geq 2 \). \( CF \) is the change in corporate investment and financing policies including:

- Working capital: (1) Cash, (2) Inventories
- Capital expenditures: (3) CAPEX, (4) R&D expense
- Financing “pecking order”: (5) Retained earnings, (6-7) net equity and debt issuances, and (8) trade credits (account payables)

All \( CF \) variables are changes scaled by lagged total assets. The exact construction for each variable can be found in Appendix A. Here the \( b_n \) coefficient measures the incremental change in corporate policies for firms hit with shocks compared to those that are not.

5.2. Proactive Cash and Capital Buildups

I first fit Regression (6) with the first four variables related to working capital and capital expenditures on the left hand side. To rule out prior trends, I first use changes from the \((t-1, t)\) period. I then use changes from \((t, t + 1), (t, t + 4), \) and \((t, t + 8)\) quarters. Table 12 reports the results.

[Insert Table 12 here]
Three observations are immediate from this table. First, contemporaneously, the shocks have negative impacts on the working capital of both origin firms and their customers: in the second row of this table both inventories and cash holding changes are from 2.0% to 8.3% standard deviation lower than comparable firms. In the quarters after the shock, however, firms hit with shocks (either directly or through spillovers) in turn accumulate significantly more cash and inventories than those not hit with shocks: rows 3 and 4 of the table indicate that cash and inventory growth are 4.7% to 14.8% standard deviation higher. This result strongly suggests a significant buildup in working capital after the shocks. Perhaps in a similar mechanism as Dessaint and Matray (2015), firms hit with supply shocks become more salient, causing managers to engage in more precautionary behaviors.

Second, the buildup behavior is also evident in longer-term capital expenditures: CAPEX growth ranges between 2.6% and 5.8% standard deviation higher during the next 8 quarters, while R&D expense is mildly higher but not as statistically significant. This is consistent with firms’ own disclosures that they pro-actively seek to accommodate alternative supply sources after the shocks, by reconfiguring their production systems or redesigning some aspects of their products. These efforts would, and indeed have, translated into higher capital expenditures.

Third, interestingly, the buildup is much more muted for firms experiencing shocks spilled over from more remote sources (distance $n>1$). For these firms, only CAPEX is significantly higher than comparable firms, and the buildup in working capital from closer connections is absent. This suggests the existence of information acquisition frictions within the deeper structures of supply chains: as the supply chains become longer, it would be exponentially more costly for firms to accurately monitor and trace the source of shocks from the more remote tiers of connections. As such, their response to remote shocks is more muted and slower. Anecdotally, this “limited visibility” has been extensively discussed in firms’ disclosures, and the empirical results from this section can motivate a class of information-theoretic models where the network structure of inter-firm relations can be explicitly accounted for, and thus
generate heterogeneous responses to shocks from different network positions.

5.3. Changes in Capital Structure and Financial Leverage

The capital buildup documented in the previous subsection is substantial in magnitude. Therefore, both the researcher, and indeed the firms themselves, would be concerned whether the firms have enough internal resources to finance these endeavors, or need to tap into external sources of financing. I therefore use the last four variables in the list from Section 5.1 on the left hand side of Regression (6). These are related to the “pecking-order” of financing, and the coefficient $b_n$ measures the incremental change of these financing policies after the shock spillover, compared to firms not hit with any shocks.

[Insert Table 13 here]

I report the results in Table 13 above. Similar to the previous table, three observations are evident from Table 13: first, the buildup documented in the previous subsection does not seem to be financed by internal funds. This is perhaps expected because the shocks captured by the disclosure data are mostly negative, leading to lower operating cash flow growth (from Table 3) and, ceteris paribus, lower retained earnings, which is confirmed in this table as changes in retained earnings range between 2.4% to 6.5% standard deviation lower. Similarly, because these shocks are shocks from suppliers, it is not surprising that trade credits are also slightly lower.

This leaves external sources of funding such as debt or equity issuances. The last three columns of the top panel show little change in equity issuances post-shock. However, debt issuance is significantly higher for both origin firms and their close, and remote, connections, ranging from 1.4% to 4.7% standard deviation higher. This translates into market leverage that is between 2.2% and 9.4% standard deviation higher. These results suggest an interesting trade-off: firms are taking on higher debt levels to build up their working capital reserves, which is itself a costly endeavor. As such, shock spillovers through the supply chains lead
to firms trading off higher default risk (as a consequence of becoming more levered) with lower operating risk (mitigated effect of spillovers). This again leaves room for future theory development in financing policies.

Third, similar to the previous table, the increase in debt issuance and leverage is also more subdued for firms facing more remote shocks. This again suggests the existence of information frictions that are severe and costly enough to prevent firms from engaging in potentially costly increases in financial leverage without clear visibility into the exact sources of spillovers.

5.4. Changes in Firm Valuation

This subsection examines the effect of shock spillovers on firm value. I form my hypothesis as follows: First assume that the market is not aware that shocks have hit the firm before they are disclosed (my tests also check for pre-announcement leaks). Then, when a firm discloses these shocks, an efficient market should immediately deduce the magnitude of the effects, and discount the stock prices accordingly to reflect the updated firm valuation. Because my shock sample consists of disclosures of both firms’ own shocks and shocks from their tier-1 suppliers, I form the first equal-weighted stock portfolio consisting of all origin firms and their immediate customers i.e. the S and C1 firms in the $S \rightarrow C1 \rightarrow C2 \rightarrow \ldots$ chain.

The effect on the remote connections, i.e. $C2, C3\ldots$’s price, however, is uncertain. In the extreme case, the market might not even know that $C1$ and $C2$ are linked. A more likely scenario is that the market is aware of the linkage, but takes some time to fully ascertain the effect as $C2$ is further away from the shock source. This can either be due to investor inattention as suggested by Cohen and Frazzini (2008), or due to information processing constraints that prevent investors from processing complex network structures in a timely fashion. Therefore, the abnormal market return for remote connections, if any, might persist for a longer period than that of the origins and their immediate connections. I summarize this intuition in the following hypothesis:
**Hypothesis 5** Firms that experience a supply disruption should experience negative abnormal returns around the event’s reporting date. If customers linked to the firm also experience negative abnormal returns, then these returns should persist for a longer period after the reporting date.

For a window of \([-10, 40]\) trading days around the report date \(t\), I define the report period cumulative abnormal return (CAR) and abnormal turnover (AT) as follows:

\[
\begin{align*}
\text{CAR}_{i,t+s} &= \prod_{k=-10}^{s} \text{Ret}_{i,k} - \prod_{k=-10}^{s} \text{Ret}_{vw,k}, \\
\text{AT}_{i,s} &= \frac{60\text{Vol}_s - 1}{\sum_{k=40}^{100} \text{Vol}_{s-k}}, \quad s \in [-10, 40],
\end{align*}
\]

where \(\text{Ret}_{i,t}\) and \(\text{Ret}_{vw,t}\) are gross returns on stock \(i\) and on the CRSP value-weighted index on date \(t\). \(\text{Vol}_t\) is the trading turnover on date \(t\). CAR measures market-adjusted returns while AT measures the extra trading volume as a fraction of the previous 60 trading days from \(t-100\) to \(t-40\). Figure 4 plots the average CAR and AT for the three equal-weighted portfolios consisting of (1: S+C1), (2: select C1), and (3: C2,C3...) firms, respectively.

Three observations are evident from this figure. First, the reported events captured by my dataset are not leaked in advance. Both abnormal returns and abnormal turnover prior to the events’ disclosure dates are not significantly different from zero. The events therefore are likely reported on a timely basis consistent with SEC-mandated disclosure standards, and do not represent stale news either.

Second, the solid black line of this figure (left axis) plots the cumulative abnormal returns (CAR) for the equal-weighted portfolio consisting of all origin firms and their tier-1 customers. Here, consistent with the hypothesis, the market reacts promptly to supply shocks on the origin firms and their immediate customers: For the three days \([t,t+2]\) after the event, the cumulative
abnormal return is -3.98%. The return does not revert in the following days, indicating that the market is indeed cognizant of the first-tier spillover effect of the shock on real outcomes such as revenue.

Third, the dotted black line plots the CAR for the equal-weighted portfolio of all remote connections of the origin firms beyond the tier-1 connections. The market does not seem to immediately price in these remote, spilled-over shocks, and the CAR declines more slowly, and persistently drifts downwards for up to 40 trading days. This indicates that the market is slower to realize the impact of shock spillovers from more remote sources. In addition, the gray line plots the CAR for the equal-weighted portfolio of all tier-1 customers that did not directly report any supplier shocks. That is, for these firms, the impact has to be inferred from someone else’s disclosure, either the supplier’s or from another customer that is also connected to the supplier. Here the market reaction is also slower than the case of direct disclosures, consistent with the information processing constraint channel: inferring these indirect network linkages takes time, and the market is thus slower in fully adjusting the stock prices for firms located more remotely from the origins.

These results suggest the existence of possible profitable arbitrage opportunities for investors who are more adept at analyzing the complex structure of supply chains, and also establishes the linkage of the spillover effects to network-related systematic risks and expected stock returns. I explore these asset pricing related issues in a related paper.

6. Concluding Remarks

This paper is the first in finance to empirically quantify how firms’ localized, idiosyncratic shocks spill over along the supply chain interconnections and affect both close and remote firms along the chain. This is achieved via precisely mapping 1) a hand-built database of over 8,000 firm-level idiosyncratic supply shocks of diverse types, extracted from the texts of over 5 million firm disclosures, to 2) a hand-built network of over 1 million supply chain connections
between publicly traded firms globally.

The results suggest that when firms are interconnected in the complex web of supply chains, localized shocks are not that local: they cause substantial impact to firms even up to 4 connections away from the origin, through frictions such as the uneven distribution of market power along the supply chains. Facing such significant risk propagation, managers respond with significant buildups in capital financed by debt issuances, leading to higher financial leverages. The stock market reacts to shock spillovers from distant connections with slower speeds: post-shock abnormal returns are persistently negative for up to 40 days. The empirical results in this paper provides the economic foundation for future theory developments on production networks and asset pricing. I explore some of these issues in related works.
References


Appendices

For interested readers, this section provides additional information on data construction, extra examples, and additional empirical extensions and robustness tests. All tables in this section are provided in-text for easy reference. Tables referenced in the main text are listed at the end.

Appendix A  List of Variables and Their Construction

- **Size**: Market capitalization of firms as of December of the previous calendar year. Computed as (PRC × SHROUT) with both variables obtained from CRSP (domestic firms) and Compustat Daily Price data (international firms).

- **BM**: Ratio of book equity to market capitalization as of December of the previous calendar year.

- **PE**: Price adjusted for splits (PRC/CFACPR) divided by adjusted earnings per share (EPSPX/AJEX).

- **ROA**: Net profits after taxes (NI) plus interest expenses (XINT) divided by total assets (AT) as of December of the previous calendar year.

- **Lev**: Long-term liabilities (DLTT) plus short-term liabilities (DLC) divided by market capitalization as of December of the previous calendar year.

- **INVt**: Total inventory (INVTQ) divided by total assets (ATQ) in quarter $t - 1$.

- **GM**: Gross margin, computed as revenue (SALEQ) minus cost of goods sold (COGSQ) divided by revenue in quarter $t$.

- **CAPEX**: Capital expenditure (CAPXQ) divided by total assets (ATQ) in quarter $t - 1$.

- **RD**: Research and development expenditure (XRDQ) divided by total assets (ATQ) in quarter $t - 1$.

- **Cash**: Cash and short-term investments (CHEQ) divided by total assets (ATQ) in quarter $t - 1$. 
• **RE**: Retained earnings (REQ) divided by total assets (ATQ) in quarter $t - 1$.

• **NEI**: Net equity issuance, computed as sale of common and preferred stock (SSTKQ) minus purchase of common and preferred stock (PRSTKCQ), divided by total assets (ATQ) in quarter $t - 1$.

• **NDI**: Net debt issuance, computed as long-term debt issuance (DLTISQ) minus long-term debt reduction (DLTRQ), divided by total assets (ATQ) in quarter $t - 1$.

• **$D^n$**: Dummy variable that equals to 1 if one of the firm’s supplier at a distance of $n$ connections experiences a shock.

• **$\gamma$**: Supply relationship share, computed as $\gamma_{ji,t} = \frac{V_{ji,t}}{COGS_{i,t}}$.

• **MP**: Market power measure computed as $MP_{i,t} = \frac{Size_{i,t-1}}{\sum_k^N Size_{k,t-1}}$, where $Size$ is defined above.

### Appendix B  Data Construction Methodologies

#### B.1  The LDA Algorithm

Prior to the advent of probabilistic topic models, the classification of textual documents and the inference of their contexts are done either manually or in a static fashion using word-based approaches such as keyword searches or latent semantic analysis. Probabilistic topic models such as the Latent Dirichlet Allocation (LDA) algorithm remove this limitation and allow for automated and accurate classification of documents on a large, “big data” scale. First developed by Blei et al. (2003), the LDA belongs to a broader class of probabilistic topic models that use hierarchical Bayesian analysis to uncover the underlying semantic structure of textual documents. The advantage of this approach is discussed in the main text. Here I first illustrate the approach with a simple example. Suppose that the full vocabulary used in firm disclosures consists of only $V = 4$ words (ignore common words such as *I, the*, etc): \{*earthquake, demolish, economy, consumption*\}. Suppose there are $D = 3$ disclosures:

1. *An earthquake demolished our factory.*
2. We are unable to meet consumer demand due to strong economy.

3. An earthquake demolished our factory. In addition consumer demand is very strong due to the economy, so we are unable to meet the demands.

A human reader would intuitively recognize that the first document is primarily in the context of natural disasters and the second is about an economy-driven demand shock. The third document is a mixture of both. Suppose I fit the LDA model with \( N = 2 \) topics. If the model performs satisfactorily, then first, the posterior topic distributions should clearly and intuitively identify the topics and thus be something similar to:

- \( \hat{\beta}_1 \equiv \{ \hat{P}_{\text{topic } 1}(\text{earthquake}), \hat{P}_{\text{topic } 1}(\text{demolish}), \hat{P}_{\text{topic } 1}(\text{economy}), \hat{P}_{\text{topic } 1}(\text{consumer}) \} \)
  \[ = \{0.55, 0.43, 0.01, 0.01\} \]

- \( \hat{\beta}_2 \equiv \{ \hat{P}_{\text{topic } 2}(\text{earthquake}), \hat{P}_{\text{topic } 1}(\text{demolish}), \hat{P}_{\text{topic } 1}(\text{economy}), \hat{P}_{\text{topic } 1}(\text{consumer}) \} \)
  \[ = \{0.01, 0.01, 0.60, 0.48\} \]

Next, the posterior topic mixture in each document should correspond to the human reader's intuition:

- \( \hat{\theta}_1 \equiv \{ \hat{P}_{\text{document } 1}(\text{Topic } 1), \hat{P}_{\text{document } 1}(\text{Topic } 2) \} = \{0.99, 0.01\} \)

- \( \hat{\theta}_2 \equiv \{ \hat{P}_{\text{document } 2}(\text{Topic } 1), \hat{P}_{\text{document } 2}(\text{Topic } 2) \} = \{0.01, 0.99\} \)

- \( \hat{\theta}_3 \equiv \{ \hat{P}_{\text{document } 3}(\text{Topic } 1), \hat{P}_{\text{document } 3}(\text{Topic } 2) \} = \{0.51, 0.49\} \)

I proceed with my LDA classification of firm disclosures by generalizing this example to the sample of \( D = 19,771 \) disclosures. Stop words, location and industry-specific terms, and other commonly appearing words, such as a, the, etc., are removed prior to processing. This results in a collection of \( V = 53,971 \) English words.\textsuperscript{15}

\textsuperscript{15}I do not stem the words before processing i.e. each inflection of a word is treated as a new word.
I hypothesize that there are \( N = 20 \) unique topics in the document. Here, each of the \( N \) topics represents a distribution over the \( V \) words in the disclosure vocabulary, and each document is a mixture of the \( N \) topics. I assume that the observable data, i.e. words in each document, is generated from a probabilistic data generating process parameterized as follows:

1. Each of document \( d = 1, \ldots, D \) contains a mixture of \( N \) topics. Let the proportion of topic \( n \) in document \( d \) be \( \theta_{d,n} \) and let the vector \( \theta_d = [\theta_{d,1}, \ldots, \theta_{d,N}]' \) represent the true topic mixture of document \( d \). For each \( d \), I assume that this mixture follows an order-\( N \) Dirichlet distribution over the \( N \) topics, governed by the latent, parameter vector \( \mu \) of size \( N \):

   \[
   \theta_d \sim \text{Dirichlet}_N(\mu)
   \]

2. Given document \( d \)'s topic mixture \( \theta_d \), let the assignment of each word \( i \) in document \( d \) into topics be \( Z_{d,i} \), where \( Z_{d,i} \in \{1, \ldots, N\} \). I assume that this assignment follows the multinomial distribution governed by the document-specific topic vector \( \theta_d \) described in the previous step:

   \[
   Z_{d,i} | \theta_d \sim \text{Multinomial}(\theta_d) \tag{8}
   \]

   Suppose there are \( I_d \) unique words in document \( d \). Let the vector \( Z_d \) denote the collection of the topic assignment of all words within \( d \), i.e. \( Z_d = \{Z_{d,i}\}_{i=1}^{I_d} \)

3. The \( N \) topic distributions (applied universally to all documents) are in the collection \( \beta = \{\beta_1, \ldots, \beta_N\} \). Each topic \( \beta_n \) also follows an order-\( V \) Dirichlet distribution over the \( V \) words, governed by the latent scalar parameter \( \phi \):

   \[
   \beta_n \sim \text{Dirichlet}_V(\phi) \tag{9}
   \]

4. For each word \( i \) in document \( d \), there are \( V \) choices to choose from the disclosure vocabulary. Conditional on the chosen topic for word \( i \) in Step 2 above (i.e. a draw from Distribution (8)), and on the structure of the topic distribution from Step 3 (i.e. a draw from Distribution (9)), I
assume that actual choice of the word, \( W_{d,i} \), follows a multinomial distribution governed by the resulting word-topic assignment \( \beta_{Z_{d,i}} \):

\[
W_{d,i} | (\{\beta_n\}_{n=1}^N, Z_{d,i}) \sim \text{Multinomial}(\beta_{Z_{d,i}})
\]

Similarly, let the \( W_d \) denote the collection of the vocabulary choice of all words within document \( d \):

\[
W_d = \{W_{d,i}\}_{i=1}^{I_d}
\]

The above four distributions constitute the latent data generating process that results in my observable document collection \( \{W_d\}_{d=1}^D \). Recall that they are not directly observable to the researcher. Instead, the only observable data is the occurrence of the actual words \( i \) in each document \( d \), i.e. \( W_d \). I can then write the overall data generating process as the joint distribution of latent variables \( \{\beta_n\}_{n=1}^N, \{\theta_d\}_{d=1}^D, \{Z_d\}_{d=1}^D \) and the observable variable \( \{W_d\}_{d=1}^D \):

\[
P(\{\beta_n\}_{n=1}^N, \{\theta_d\}_{d=1}^D, \{Z_d\}_{d=1}^D, \{W_d\}_{d=1}^D) = \prod_{n=1}^N P(\beta_n) \prod_{d=1}^D P(\theta_d) \prod_{i=1}^{I_d} P(Z_{d,i} | \theta_d) P(W_{d,i} | \{\beta_n\}_{n=1}^N, Z_{d,i})
\]

where \( P(\cdot) \) are the respective (Dirichlet or multinomial) density functions specified above.

Now that I observe my firm disclosure collection \( \{W_d\}_{d=1}^D \), I can compute the posterior distribution of the document-topic structure given the observed documents using Bayes' Rule:

\[
P(\{\beta_n\}_{n=1}^N, \{\theta_d\}_{d=1}^D, \{Z_d\}_{d=1}^D | \{W_d\}_{d=1}^D) = \frac{P(\{\beta_n\}_{n=1}^N, \{\theta_d\}_{d=1}^D, \{Z_d\}_{d=1}^D, \{W_d\}_{d=1}^D)}{P(\{W_d\}_{d=1}^D)}.
\]

(10)

Similar to other Bayesian inference methods, the numerator in Equation (10) can be easily computed. The denominator is by construction a double integral and therefore cannot be feasibly computed. However, it can be efficiently approximated using a Gibbs sampler. I use a customized Gibbs sampler written in C++ for fast implementation.
Once the posterior probabilities are computed, I compute the posterior expectations of two key latent variables, which represent the main output from the LDA algorithm:

1. Posterior vocabulary distribution for each topic: \( \{\hat{\beta}_1, \ldots, \hat{\beta}_N\} \)

2. Posterior topic mixture for each document in my collection: \( \{\hat{\theta}_1, \ldots, \hat{\theta}_D\} \)

The first set of output from my LDA procedure identifies the topics. For each topic \( k \), \( \hat{\beta}_k = [\hat{\beta}_{k,1}, \ldots, \hat{\beta}_{k,V}]' \), and each entry \( \hat{\beta}_{k,j} \) represents the probability that the word \( j \) characterizes topic \( k \). My whole collection of 8-K and other disclosures has \( V = 72,442 \) unique terms. As a result, each \( \hat{\beta}_k \) contains 72,442 entries, the majority of which receives a weight close to zero. The top 5 keywords for each topic are reported in the table below. The main text interprets these topics.

<table>
<thead>
<tr>
<th>Group 1: Systematic Types</th>
<th>Topic 1</th>
<th>Topic 2</th>
<th>Topic 3</th>
<th>Topic 4</th>
<th>Topic 5</th>
<th>Topic 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>global uncertainty</td>
<td>economy</td>
<td>consumer</td>
<td>sector</td>
<td>retail</td>
<td></td>
<td></td>
</tr>
<tr>
<td>systematic</td>
<td>global</td>
<td>condition</td>
<td>economic</td>
<td>industry</td>
<td></td>
<td></td>
</tr>
<tr>
<td>markets</td>
<td>risk</td>
<td>recession</td>
<td>demand</td>
<td>competitive</td>
<td>sales</td>
<td></td>
</tr>
<tr>
<td>widespread</td>
<td>terrorism</td>
<td>condition</td>
<td>capacity</td>
<td>cost</td>
<td>seller</td>
<td></td>
</tr>
<tr>
<td>countries</td>
<td>property</td>
<td>growth</td>
<td>consumption</td>
<td>price</td>
<td>third-party</td>
<td></td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Group 2: Middle Types</th>
<th>Topic 1</th>
<th>Topic 2</th>
<th>Topic 3</th>
<th>Topic 4</th>
<th>Topic 5</th>
<th>Topic 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>worker</td>
<td>union</td>
<td>government</td>
<td>research</td>
<td>transportation</td>
<td>quality</td>
<td></td>
</tr>
<tr>
<td>labor</td>
<td>strike</td>
<td>legal</td>
<td>intellectual</td>
<td>channel</td>
<td>design</td>
<td></td>
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<td>organization</td>
<td>regulation</td>
<td>property</td>
<td>logistical</td>
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<td>wage</td>
<td>licence</td>
<td>dispute</td>
<td>development</td>
<td>flaw</td>
<td></td>
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<tr>
<td>employee</td>
<td>relation</td>
<td>regional</td>
<td>restriction</td>
<td>outsourcing</td>
<td>recall</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Group 3: Idiosyncratic Types</th>
<th>Topic 1</th>
<th>Topic 2</th>
<th>Topic 3</th>
<th>Topic 4</th>
<th>Topic 5</th>
<th>Topic 6</th>
<th>Topic 7</th>
<th>Topic 8</th>
</tr>
</thead>
<tbody>
<tr>
<td>disaster</td>
<td>flood</td>
<td>fire</td>
<td>hurricane</td>
<td>machinery</td>
<td>breakdown</td>
<td>IT</td>
<td>failure</td>
<td></td>
</tr>
<tr>
<td>destruction</td>
<td>water</td>
<td>damage</td>
<td>weather</td>
<td>equipment</td>
<td>equipment</td>
<td>breach</td>
<td>install</td>
<td></td>
</tr>
<tr>
<td>earthquake</td>
<td>recovery</td>
<td>accident</td>
<td>tornado</td>
<td>production</td>
<td>assembly</td>
<td>equipment</td>
<td>manufacturer</td>
<td></td>
</tr>
<tr>
<td>damage</td>
<td>power</td>
<td>storm</td>
<td>suspend</td>
<td>factory</td>
<td>outage</td>
<td>sensitive</td>
<td>intrus</td>
<td></td>
</tr>
<tr>
<td>catastrophe</td>
<td>disaster</td>
<td>electricity</td>
<td>sustain</td>
<td>shutdown</td>
<td>manufacture</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The second set of output is the collection of document-level topic mixture vectors, \( \{\hat{\theta}_1, \ldots, \hat{\theta}_D\} \). From this collection, each document \( d \) has one mixture, \( \hat{\theta}_d = [\hat{\theta}_{d,1}, \ldots, \hat{\theta}_{d,N}]' \). Because there are 20 topics, each vector \( \hat{\theta}_d \) has 20 entries, where each \( \hat{\theta}_{d,n} \) corresponds to the proportion of document \( d \) that
is devoted to topic $n$. The 20 entries sum up to one for each document. I keep the disclosure only if it contains more than 95% of a single topic. The main text then discusses the contexts of these topics and that these topics help identify shocks that are idiosyncratic in causes.

B.2 Network Data

I start at the year 1994, when computerized filing records become available in SEC’s EDGAR system. For each firm pair $ji$, I identify them as in a supply relationship if either firm discloses the relationship in a filing, or either firm is identified in the other sources. The relationship is removed if either party discloses its termination. Note that in this setting, I do not capture the value of the relationships. Therefore, if supplier $j$ and customer $i$ are in a relationship at $t$, I set the relationship dummy $\gamma_{ji,t} = 1$ and 0 otherwise. A smaller portion of my sample (e.g. those identified by Bloomberg or the import-export data) does report relations with specific dollar values. In this case where firm $j$ supplies $V_{ji,t}$ worth of goods to firm $i$ in year $t$, I set $\gamma_{ji,t} = \frac{V_{ji,t}}{\text{COGS}_{i,t-1}}$. This restricted sample is useful in several robustness checks.

In essence, the existence (and for a smaller sample, the magnitude) of supply chain linkages between firms are captured by the relationship indicator $\gamma_{ji}$. For my sample of $N = 10,930$ firms, I organize all $\gamma_{ij}$ parameters in the following N-by-N matrix:

$$
\Gamma_t = \begin{bmatrix}
\gamma_{11,t} & \cdots & \gamma_{1N,t} \\
\vdots & \ddots & \vdots \\
\gamma_{N1,t} & \cdots & \gamma_{NN,t}
\end{bmatrix}
$$

(11)

In this matrix, if firms $i$ and $j$ have no direct customer-supplier relationship, $\gamma_{ij} = \gamma_{ji} = 0$. Otherwise, the non-zero entries in $\Gamma$ represent direct customer-supplier relationships, or supply chain linkages. Note that $\Gamma$ needs not be symmetric. For example, if firm $j$ is a supplier of $i$, but does not purchase any input from $i$, then $\gamma_{ji}$ is nonzero while $\gamma_{ij}$ is zero. In the smaller sample where $\gamma_{ji} < 1$, the sum of the $i$th row conveys the significance of firm $i$ to the economy, while the sum of $i$th column measures firm $i$’s degree of reliance on external intermediate goods. In this case each column sums to less than one.
by construction.$^{16}$

The relationships in this economy, summarized in $\Gamma$, constitute a directed network where each firm $i$ is a node and each relationship $\gamma_{ij}$, if nonzero, is a link that points from firm $i$ (supplier) to firm $j$ (customer). Equivalently, the supply chain network can be visualized as a directed graph where $\Gamma$ represents the adjacency matrix of this graph. The main text then discusses the summary statistics of this network.

Finally, an important reason to represent the linkages in a network structure is to gauge the effect of supply chain linkages beyond the immediate connections. To illustrate this, Figure 1 presents a visualization of a portion of the network: 400 select US firms from technology-related industries (Fama-French industry codes 35 to 37) in the years of 2002 and 2015, respectively. There are few isolated nodes within the network. For many firms, the supply chain can be quite long, even extending to fourth- and fifth-tier suppliers. These firms will be subject to additional shocks if shocks can spill over beyond the closest connections into customers further downstream. I empirically document these spillovers in Section 3.

### Appendix C Additional Event Text Examples

This section lists several examples for each category of shocks characterized by the LDA algorithm. Category 1 consists of events caused by economy- or industry-wide systematic factors. Category 2 consists of events caused by potentially idiosyncratic factors but could also caused by industry-wide issues. Category 3 consists of events caused by idiosyncratic factors.

- **Example 1A, Economic Issues:** [The firm] announced its plan to cancel the development of...power plant that it had planned to construct...because of...reduced customer demand for electricity due to the recession and slow economic recovery, surplus generating capacity in the Midwest market, and lower natural gas prices linked to expanded shale gas supplies. (CMS Energy Corp 8-K)

- **Example 1B, Industry Issues:** Ford Motor Co. is scrambling to find enough steel frames to keep up with demand...frame’s main supplier...was having trouble building enough of the parts to keep pace with production needs...Ford has had to cancel planned overtime at the plants and has temporarily halted assembly lines during regular shifts as workers waited for more frames to arrive. (Wall Street Journal)

---

$^{16}$This ensures that $\Gamma'$ has positive eigenvalues and the inverse, $(I - \Gamma')^{-1}$, is not singular. I use this inverse extensively in a related paper to compute the centrality of each firm.

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• **Example 2A, Labor Issues:** Yue Yuen Industrial Holdings Ltd., which makes shoes for Adidas AG and Nike Inc., said production...was disrupted as workers upset with organizational changes went on strike. About 2,000 employees...were affected...The strike cost the company $27 million in direct costs, including lost profits and additional air freight costs. (Reuters)

• **Example 2B, QC Issues:** As part of ongoing quality assurance, Intel Corporation has discovered a design issue in a recently released support chip..Intel has stopped shipment of the affected support chip from its factories..and expects full volume recovery in April..Intel expects this issue to reduce revenue by approximately $300 million as the company discontinues production. (Intel 8-K)

• **Example 3B, Natural Disasters Hitting Supplier:** As a result of the earthquake...supplier suspended manufacuring operations at the factory where these materials are produced...We currently have inventory of these materials...through May 24, 2011...However, many of the factors in this situation are beyond our control, and an unfavorable development relating to any of these factors could have a material adverse effect on our results of operations. (A123 Systems 8-K)

• **Example 3C, Mannmade Disasters:** [A] blaze occurred Sept. 4 during the installation of equipment at a factory...for SK Hynix...It will take at least half a year before SK Hynix's damaged clean room is fully re-built...if...production is halted for more than a week, substantial shortages could lead to higher prices, benefiting all memory-chip manufacturers...customers include Apple, Samsung, Lenovo Group Ltd., Dell Inc. and Sony Corp. (Bloomberg)

• **Example 3D, Production Disruptions:** Rio Tinto Alcan’s Laterriere Works aluminium smelter in Quebec suffered a significant power outage yesterday...leaving the plant without the adequate energy required to continue operating at full capacity...one of two production lines has been suspended...in the coming weeks, Rio Tinto Alcan will mobilise the necessary resources to restore the suspended line. (Rio Tinto Press Release)

• **Example 3E, Adoption Failures:** [The] Company has experienced a backlog of orders with a significant contract manufacturer in China...while the Company had thought such manufacturing delays would be temporary, the Company learned recently that this supplier had ceased manufacturing products for the Company due to difficulties the supplier is experiencing...The timing for resuming production of the products previously manufactured by this supplier is uncertain, and will depend to a significant extent on whether the Company is able to obtain certain custom tooling used by the supplier to manufacture the Company’s products. (Loud Technologies 8-K)

### Appendix D  Additional Extensions and Robustness Tests

See the Online Appendix for the complete list of additional robustness checks. The first issue is to check whether firms endogenous decisions to enter into their network positions (and inventory) introduce any bias on the interaction regressions such as Regression (5a) and (5b). To do so, I exploit exogeneous variations in inventory determined by the length of lead time, which is in turn determined crucially by 1) distance to the supplier and 2) mode of transportation (land vs. sea). I also use two alternative measures
of supplier substitutability derived from Giannetti, Burkart, and Ellingsen (2011) and also used by Barrot and Sauvagnat (2014). These measures are based on industry rather than firm characteristics. I find similar results with these alternative measures.

Next, because the distribution of network linkages is uneven, linear regressions could result in the observation of “spillover effects” purely due to taking averages on uneven links. This is ruled out by computing the average degree of asymmetry at each distance from the shock, then showing that links with high values are not necessarily followed by more links with high values. The linearity issue is further ruled out with similar results from a matching approach. In another test, I use only natural disasters reported by US National Oceanic & Atmospheric Administration (NOAA) in the suppliers’ geographical locations as an alternative source of shocks, and find broadly similar results.
Tables and Figures

Figure 1: Visualization of Sample Supply Chain Network Shape, 2002 and 2015

This figure presents a visualization of a portion of the network: 400 select US firms from technology-related industries (Fama-French industry codes 35 to 37) in the years of 2002 and 2015. The network data is constructed from a combination of firm disclosures and proprietary data sources described in detail in Section 2.2.
Figure 2: Distribution of Shocks Across Time and Types

The top panel of this figure plots the number of total shocks captured by the disclosure data over time. The bottom panel of this figure plots the number of each type of idiosyncratic shocks, as classified by the LDA, over time from 1994 to 2015. The shock classification procedure is described in Section 2.1.3 of the text.
Figure 3: Example Timeline of A Shock Spillover

Shock Origin: NIDEC Inc

10 Aug  8 Sep  28 Sep  18 Oct  7 Nov  27 Nov  17 Dec  6 Jan  26 Jan  15 Feb  6 Mar  26 Mar

First disclosure of flood impact

Multiple status updates

Lowered revenue guidance

Lowered guidance again
Actual revenue drops 7%

Net revenue further decreases to -14%

Physical damage assessment
Minor damages

YoY revenue growth 25% lower

Multiple status updates
Mentioned raising prices

New bond issuance

Disclosure of flood impact on suppliers

Cautions supply problems
Forecasts lower revenue growth,
higher margins

Raised revenue guidance

Revenue growth back on track

CEO discussed inventory problems

Mentioned raising prices to pass shocks on customers

Actual output lower but significantly higher prices;
revenue growth lower but beat expectations

Verified no damage to itself
7 out of 10 suppliers hit

Tier-1 Connection: Seagate

8 Sep  28 Sep  18 Oct  7 Nov  27 Nov  17 Dec  6 Jan  26 Jan  15 Feb  6 Mar  26 Mar

First warning of supply problems from flood

Discussed supplier price increases due to flood

Raised earnings guidance

Revenue missed forecast

Mentioned strategic purchase of inventories

Revenue missed forecast

Tier-2 Connection: Dell

19 Aug  8 Sep  28 Sep  18 Oct  7 Nov  27 Nov  17 Dec  6 Jan  26 Jan  15 Feb  6 Mar  26 Mar

Revenue missed forecast

Continued warning of supply chain problems;
mentioned inability to raise prices in consumer segment

First warning of supply problems
Anticipate severe impact
Anticipate supplier price increase

Mentioned strategic purchase of inventories

Revenue decline by 7%
Earnings missed forecast;
Attribute 50% of drop to flooding

Now net debt issuance

Tier-2 Connection: HP

CEOs discusses supply constraints
Anticipates disruption up to 6 months

Mentioned significant and immediate increases in supplier prices (+20%)
Figure 4: **Stock Price Reactions Following Close vs. Remote Shocks**

The solid black line of this figure (left axis) plots the cumulative abnormal returns (CAR) for the equal-weighted portfolio consisting of all origin firms and their tier-1 customers, around the date when a supply shock is first disclosed. The gray line plots the CAR for the equal-weighted portfolio of all tier-1 customers that did not directly report any supplier shocks. The dotted black line plots the CAR for the equal-weighted portfolio of all remote connections of the origin firms beyond the tier-1 connections. The light gray bars (right axis) plot the daily abnormal turnovers (AT) for the equal-weighted portfolio consisting of all origin firms and their tier-1 customers, and the dark gray bars plot the average AT for all remote connections of the origin firms beyond the tier-1 connections. The CAR and AT measures are computed according to Equation (7) of the text from 10 trading days prior to 40 days after the shock's disclosure date. The negative abnormal turnovers are truncated at -1% to save display space.
Table 1: **Summary Statistics of Idiosyncratic Shock Data**

This table presents summary statistics of supply chain shock events extracted from firm disclosures from 1994 to 2015. The top panel reports sample sizes and number of firms. The middle panel reports the breakdown of captured shocks by major type as classified by the LDA algorithm, discussed in Section 2.1 of the text and Appendix B.1. The bottom panel compares characteristics such as firm size, book-to-market P/E ratio, return on assets, leverage ratio, and inventory level, between disclosing vs. non-disclosing firms. The numbers in brackets are t-statistics for the quarterly average difference in quarterly levels of these measures between disclosing firms and the overall sample. The definition and construction of all variables can be found in Appendix A.

### Panel A: Overall Shock Statistics

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Number</td>
<td>11191</td>
</tr>
<tr>
<td>% of firms reporting at least one shock</td>
<td>20.06%</td>
</tr>
<tr>
<td>Avg no. of shocks per firm</td>
<td>5.104</td>
</tr>
<tr>
<td>No. of shocks with supplier identified</td>
<td>8295</td>
</tr>
<tr>
<td>No. of shocks matched to network data</td>
<td>8160</td>
</tr>
</tbody>
</table>

### Panel B: Distribution of Shock Types

<table>
<thead>
<tr>
<th>Types of Identified Shocks</th>
<th># of Events</th>
<th>Percent sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Natural disasters</td>
<td>2256</td>
<td>27.20%</td>
</tr>
<tr>
<td>Manmade disasters</td>
<td>2145</td>
<td>25.86%</td>
</tr>
<tr>
<td>Production glitches</td>
<td>2076</td>
<td>25.03%</td>
</tr>
<tr>
<td>IT issues</td>
<td>1032</td>
<td>12.44%</td>
</tr>
<tr>
<td>Adjustment failures</td>
<td>786</td>
<td>9.48%</td>
</tr>
<tr>
<td>Total</td>
<td>8295</td>
<td>100.00%</td>
</tr>
</tbody>
</table>

### Panel C: Summary Statistics of Disclosing Firms vs. Full Sample

<table>
<thead>
<tr>
<th>Average</th>
<th>Reporting</th>
<th>Diff</th>
<th>t-Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size</td>
<td>2.201</td>
<td>0.156</td>
<td>(1.94)</td>
</tr>
<tr>
<td>BM</td>
<td>0.687</td>
<td>-0.028</td>
<td>(-0.27)</td>
</tr>
<tr>
<td>PE</td>
<td>13.902</td>
<td>0.677</td>
<td>(0.68)</td>
</tr>
<tr>
<td>ROA</td>
<td>0.087</td>
<td>-0.023</td>
<td>(-0.56)</td>
</tr>
<tr>
<td>Leverage</td>
<td>0.411</td>
<td>0.039</td>
<td>(0.13)</td>
</tr>
<tr>
<td>Total Inventory</td>
<td>0.148</td>
<td>0.013</td>
<td>(1.20)</td>
</tr>
</tbody>
</table>

No. Obs (quarters) 82
Table 2: **Summary Statistics of Sample Firms and Network Connections**

Panels A and B of this table present the number of firms in the sample and overall sample characteristics such as firm size, book-to-market P/E ratio, return on assets, leverage ratio, and inventory level. The definition and construction of all variables can be found in Appendix A. Panel C reports the same characteristics for firms that are connected to the shocks’ originating firms at various distances. The shocks are described in Section 2.1 of the text and summarized in Table 1. Panel D presents summary characteristics of the network linkages.

<table>
<thead>
<tr>
<th>A: Number of Firms</th>
<th>Total</th>
<th>Domestic</th>
<th>Foreign</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total in Sample</td>
<td>10930</td>
<td>7089</td>
<td>3841</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>B: Overall Sample Statistics</th>
<th>Mean</th>
<th>Median</th>
<th>75p</th>
<th>25p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Revenue Growth</td>
<td>0.107</td>
<td>0.071</td>
<td>0.217</td>
<td>-0.044</td>
</tr>
<tr>
<td>Size</td>
<td>2.045</td>
<td>2.577</td>
<td>12.212</td>
<td>0.580</td>
</tr>
<tr>
<td>BM</td>
<td>0.715</td>
<td>0.552</td>
<td>0.909</td>
<td>0.314</td>
</tr>
<tr>
<td>ROA</td>
<td>0.110</td>
<td>0.106</td>
<td>0.139</td>
<td>-0.004</td>
</tr>
<tr>
<td>Leverage</td>
<td>0.372</td>
<td>0.138</td>
<td>0.457</td>
<td>0.009</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>C: Treated vs. Untreated</th>
<th>0 (Origin)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>&gt;4 or Never</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size</td>
<td>2.201</td>
<td>2.218</td>
<td>1.954</td>
<td>1.819</td>
<td>1.911</td>
<td>2.073</td>
</tr>
<tr>
<td>BM</td>
<td>0.687</td>
<td>0.682</td>
<td>0.802</td>
<td>0.779</td>
<td>0.570</td>
<td>0.703</td>
</tr>
<tr>
<td>ROA</td>
<td>0.087</td>
<td>0.108</td>
<td>0.130</td>
<td>0.105</td>
<td>0.109</td>
<td>0.112</td>
</tr>
<tr>
<td>Leverage</td>
<td>0.411</td>
<td>0.371</td>
<td>0.394</td>
<td>0.335</td>
<td>0.404</td>
<td>0.368</td>
</tr>
<tr>
<td>Inventory</td>
<td>0.148</td>
<td>0.139</td>
<td>0.101</td>
<td>0.082</td>
<td>0.148</td>
<td>0.153</td>
</tr>
<tr>
<td>No. Obs</td>
<td>8160</td>
<td>36477</td>
<td>40469</td>
<td>44290</td>
<td>45491</td>
<td>116044</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>D: Average Link Statistics</th>
<th>Total Sample</th>
<th>Quantified Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total # of Links</td>
<td>1007998</td>
<td># of Quantified Suppliers</td>
</tr>
<tr>
<td>Total # of Quantified Links</td>
<td>473759</td>
<td># of Quantified Customers</td>
</tr>
<tr>
<td>Total Links Per Firm</td>
<td>92.22</td>
<td>Mean Total Supplier share</td>
</tr>
<tr>
<td>Quantified Links Per Firm</td>
<td>43.34</td>
<td></td>
</tr>
</tbody>
</table>
Table 3: Spillover of Idiosyncratic Shocks in the Network: Average Results

This table reports the coefficient estimates of $b_n$, $n = 0, \ldots, 4$ from Regression (1) of the text. $b_n$ measures the average difference between firms hit with a shock spilled over from a distance of $n$ connections, and firms never hit with any shocks. The dependent variables in Panels A to C are growth rates in revenue, operating income, and gross margin, respectively. $D^n$ is a dummy variable that equals to 1 if one of firm $i$’s suppliers from a distance of $n$ connections experiences an idiosyncratic shock captured by the disclosure data. All control variables are defined in Appendix A. All standard errors are clustered at the firm level. All regressions include industry×year, fiscal quarter, and state/country fixed effects, and are in quarterly frequency from 1994 to 2015.

### Panel A: Four-Quarter Revenue Growth Rates

<table>
<thead>
<tr>
<th>Distance from Shock Origin (in # of Connections)</th>
<th>D</th>
<th>n=1</th>
<th>n=2</th>
<th>n=3</th>
<th>n=4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Origin</td>
<td>-0.0258***</td>
<td>-0.0229**</td>
<td>-0.0377***</td>
<td>-0.0325***</td>
<td>-0.0125**</td>
</tr>
<tr>
<td></td>
<td>(-3.32)</td>
<td>(-2.67)</td>
<td>(-4.22)</td>
<td>(-3.86)</td>
<td>(-2.44)</td>
</tr>
</tbody>
</table>

**Control Variables**

<table>
<thead>
<tr>
<th>Size</th>
<th>-0.0117***</th>
<th>PE</th>
<th>0.0034</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(-6.61)</td>
<td></td>
<td>(1.48)</td>
</tr>
<tr>
<td>BM</td>
<td>-0.0682***</td>
<td>ROA</td>
<td>-0.0290***</td>
</tr>
<tr>
<td></td>
<td>(-20.62)</td>
<td></td>
<td>(-11.28)</td>
</tr>
</tbody>
</table>

**Fixed Effects**

- ✓

**No. Obs**

- 335337

**AR2**

- 0.167

### Panel B: Four-Quarter Operating Income Growth Rates

<table>
<thead>
<tr>
<th>Distance from Shock Origin (in # of Connections)</th>
<th>D</th>
<th>n=1</th>
<th>n=2</th>
<th>n=3</th>
<th>n=4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Origin</td>
<td>-0.0543***</td>
<td>-0.0475**</td>
<td>-0.0598***</td>
<td>-0.0543***</td>
<td>-0.0219**</td>
</tr>
<tr>
<td></td>
<td>(-3.46)</td>
<td>(-2.89)</td>
<td>(-3.65)</td>
<td>(-3.18)</td>
<td>(-2.37)</td>
</tr>
</tbody>
</table>

**Control Variables**

- ✓

**Fixed Effects**

- ✓

**No. Obs**

- 254322

**AR2**

- 0.106

### Panel C: Four-Quarter Change in Gross Margin

<table>
<thead>
<tr>
<th>Distance from Shock Origin (in # of Connections)</th>
<th>D</th>
<th>n=1</th>
<th>n=2</th>
<th>n=3</th>
<th>n=4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Origin</td>
<td>-0.0192*</td>
<td>-0.0154*</td>
<td>-0.0207**</td>
<td>-0.0261**</td>
<td>-0.0108*</td>
</tr>
<tr>
<td></td>
<td>(-2.14)</td>
<td>(-2.05)</td>
<td>(-2.75)</td>
<td>(-2.94)</td>
<td>(-2.12)</td>
</tr>
</tbody>
</table>

**Control Variables**

- ✓

**Fixed Effects**

- ✓

**No. Obs**

- 280617

**AR2**

- 0.073
Table 4: Spillover of Idiosyncratic Shocks: Results Scaled by Shocks’ Original Impact

This table reports the coefficient estimates of $b_n$, $n = 0, \ldots, 4$ from Regression (2) of the text. $b_n$ measure the incremental impact of the spillover on subsequent connections $n = 1, \ldots, 4$ in units of the percentage impact on the origin firm. The dependent variable is growth rates in revenue. All control variables are defined in Appendix A. All standard errors are clustered at the firm level. All regressions include industry×year, fiscal quarter, and state/country fixed effects, and are in quarterly frequency from 1994 to 2015.

<table>
<thead>
<tr>
<th>Four-Quarter Revenue Growth Rates</th>
<th>Distance from Shock Origin (in # of Connections)</th>
<th>n=1</th>
<th>n=2</th>
<th>n=3</th>
<th>n=4</th>
<th>n=5</th>
</tr>
</thead>
<tbody>
<tr>
<td>D</td>
<td></td>
<td>0.8271***</td>
<td>1.0313***</td>
<td>0.8762***</td>
<td>0.4036**</td>
<td>0.1209</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(3.16)</td>
<td>(3.98)</td>
<td>(3.55)</td>
<td>(2.62)</td>
<td>(1.54)</td>
</tr>
</tbody>
</table>

**Control Variables**

<p>| | | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Size</td>
<td>-0.0143***</td>
<td>PE</td>
<td>0.0047</td>
<td>Lev</td>
<td>-0.0037</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-5.61)</td>
<td></td>
<td>(1.32)</td>
<td></td>
<td>(-0.32)</td>
<td></td>
</tr>
<tr>
<td>BM</td>
<td>-0.0667***</td>
<td>ROA</td>
<td>-0.0288***</td>
<td>Inv</td>
<td>-0.0129***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-18.41)</td>
<td></td>
<td>(-10.93)</td>
<td></td>
<td>(-4.50)</td>
<td></td>
</tr>
</tbody>
</table>

**Fixed Effects**

<table>
<thead>
<tr>
<th></th>
<th>√</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>No. Obs</td>
<td></td>
<td>335337</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AR2</td>
<td></td>
<td>0.134</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 5: Market Power and Shock Spillover, Firm-Level Evidence

This table reports the coefficient estimates of $c_n$ and $b_n$, $n = 0, \ldots, 4$ from Regression (3) of the text. $c_n$ is the first row of each panel and measures the average spillover impact given average values of market power. $b_n$ is the second row and measures the incremental effect of one-standard-deviation change in market power (or market power ratio) on revenue growth rate differences between firms with distance-$n$ shocks and firms without shocks. $D^n$ is a dummy variable that equals to 1 if one of firm $i$’s suppliers from a distance of $n$ connections experiences an idiosyncratic shock captured by the disclosure data. $MP$ is the firm’s own market power and $MPR$ is the ratio of the average market power of the firms’ suppliers to that of the firm, defined in Section 3.3.1 of the text. Both $MP$ and $MPR$ are standardized to mean of zero and standard deviation of one. All control variables are defined in Appendix A. All standard errors are clustered at the firm level. All regressions include industry×year, fiscal quarter, and state/country fixed effects, and are in quarterly frequency from 1994 to 2015.

<table>
<thead>
<tr>
<th>Panel A: Firms’ Own Market Power</th>
<th>Distance from Shock Origin</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>n=1</td>
</tr>
<tr>
<td>$D$</td>
<td>-0.022**</td>
</tr>
<tr>
<td></td>
<td>(-2.58)</td>
</tr>
<tr>
<td>$D \times MP$</td>
<td>0.026***</td>
</tr>
<tr>
<td></td>
<td>(4.73)</td>
</tr>
<tr>
<td>Firm Controls</td>
<td>✓</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>✓</td>
</tr>
</tbody>
</table>

| Panel B: Ratio of Own Power to Average Supplier Market Power |

<table>
<thead>
<tr>
<th>Distance from Shock Origin</th>
</tr>
</thead>
<tbody>
<tr>
<td>n=1</td>
</tr>
<tr>
<td>$D$</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>$D \times MPR$</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Firm Controls</td>
</tr>
<tr>
<td>Fixed Effects</td>
</tr>
</tbody>
</table>
Table 6: **Market Power and Shock Spillover, Network-Level Evidence**

This table reports the mean, median, and 75th- and 25th-percentile values of $MP$ and $MPR$ measures, defined in Section 3.3.1 of the text, at distances of $n = 0, \ldots, 4$ from the origin of the idiosyncratic shock captured by the disclosure data. The computation uses the lagged value of the $Size$ variable, which is the market capitalization of firms defined in Appendix A. The power measures are computed as a ratio of firm sizes to total industry sizes at the 4-digit SIC level. All measures are computed in quarterly frequency from 1994 to 2015.

<table>
<thead>
<tr>
<th>MP</th>
<th>Distance from Shock Origin (in # of Connections)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Overall</td>
</tr>
<tr>
<td>Mean</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.3476</td>
</tr>
<tr>
<td>Median</td>
<td>0.0866</td>
</tr>
<tr>
<td>75th Percentile</td>
<td>0.8834</td>
</tr>
<tr>
<td>25th Percentile</td>
<td>0.0249</td>
</tr>
</tbody>
</table>

| No. Obs | 33537 | 8160 | 40469 | 36477 | 45491 | 44290 |
Table 7: Input Substitutability, Inventories, and Shock Spillover

This table reports the coefficient estimates of $c_n$ and $b_n$, $n = 0, \ldots, 4$ from Regressions (5a) and (5b) of the text. $c_n$ is the first row of each panel and measures the average spillover impact given average values of market power. $b_n$ is the second row and measures the incremental effect of one-standard-deviation change in inventory (or supplier substitutability) on revenue growth rate differences between firms with distance-$n$ shocks and firms without shocks. $D^n$ is a dummy variable that equals to 1 if one of firm $i$’s suppliers from a distance of $n$ connections experiences an idiosyncratic shock captured by the disclosure data. $INVR$ is the inventory-to-total-assets level and $\bar{\gamma}$ is average supplier share, defined in Section 3.3.2 of the text. Both $INVR$ and $\bar{\gamma}$ are standardized to mean of zero and standard deviation of one. The supplier substitutability measure uses a reduced sample where the specific values are available for each link. All control variables are defined in Appendix A. All standard errors are clustered at the firm level. All regressions include industry×year, fiscal quarter, and state/country fixed effects, and are in quarterly frequency from 1994 to 2015.

<table>
<thead>
<tr>
<th>Panel A: Inventory Levels</th>
<th>Distance from Shock Origin (in # of Connections)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>n=1</td>
</tr>
<tr>
<td>D</td>
<td>-0.023**</td>
</tr>
<tr>
<td></td>
<td>(-2.82)</td>
</tr>
<tr>
<td>D×INVR</td>
<td>0.010***</td>
</tr>
<tr>
<td></td>
<td>(4.36)</td>
</tr>
<tr>
<td>Firm Controls</td>
<td>✓</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>✓</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Supplier Substitutability (Sample with $\gamma &lt; 1$ only)</th>
<th>Distance from Shock Origin</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>n=1</td>
</tr>
<tr>
<td>D</td>
<td>-0.020**</td>
</tr>
<tr>
<td></td>
<td>(-2.51)</td>
</tr>
<tr>
<td>D×$\bar{\gamma}$</td>
<td>0.035***</td>
</tr>
<tr>
<td></td>
<td>(4.80)</td>
</tr>
<tr>
<td>Firm Controls</td>
<td>✓</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>✓</td>
</tr>
</tbody>
</table>
Table 8: **Robustness: Ensuring Shocks Have Only Firm-Specific Effects**

This table reports the coefficient estimates of $b_n$, $n = 0, \ldots, 4$ from Regression (1) of the text, on 11 reduced samples where I either remove one shock category at a time (Panel A), or use one shock category at a time (Panel B). The shock categories are classified by the LDA algorithm and defined in Section 2.1 of the text. The “Fire Only” category is a subset of shocks from the “Manmade” category that pertains to localized fires only, and is constructed according to Section 4.1.1 of the text. $b_n$ measures the average difference between firms hit with a shock spilled over from a distance of $n$ connections, and firms never hit with any shocks. $D_n$ is a dummy variable that equals to 1 if one of firm $i$’s suppliers from a distance of $n$ connections experiences an idiosyncratic shock captured by the disclosure data. All control variables are defined in Appendix A. All standard errors are clustered at the firm level. All regressions include industry×year, fiscal quarter, and state/country fixed effects, and are in quarterly frequency from 1994 to 2015.

### Panel A: Remove Individual Shock Categories

<table>
<thead>
<tr>
<th>Category Removed</th>
<th>(0) None</th>
<th>(1) Disaster</th>
<th>(2) Manmade</th>
<th>(3) Breakdown</th>
<th>(4) IT</th>
<th>(5) Adjustment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Origin Firms</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>None</td>
<td>-0.0258***</td>
<td>-0.0252***</td>
<td>-0.0231***</td>
<td>-0.0225***</td>
<td>-0.0286***</td>
<td>-0.0292***</td>
</tr>
<tr>
<td></td>
<td>(-3.32)</td>
<td>(-3.18)</td>
<td>(-3.74)</td>
<td>(-3.22)</td>
<td>(-3.94)</td>
<td>(-3.47)</td>
</tr>
<tr>
<td>Distance 1 Firms</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>None</td>
<td>-0.0229**</td>
<td>-0.0241**</td>
<td>-0.0210**</td>
<td>-0.0204**</td>
<td>-0.0251**</td>
<td>-0.0224**</td>
</tr>
<tr>
<td></td>
<td>(-2.67)</td>
<td>(-2.96)</td>
<td>(-2.60)</td>
<td>(-2.62)</td>
<td>(-3.03)</td>
<td>(-2.71)</td>
</tr>
</tbody>
</table>

| Firm Controls   | ✓         | ✓           | ✓           | ✓            | ✓      | ✓             |
| Fixed Effects   | ✓         | ✓           | ✓           | ✓            | ✓      | ✓             |
| No. Obs         | 335337    | 335337      | 335337      | 335337       | 335337 | 335337        |
| AR2             | 0.167     | 0.153       | 0.162       | 0.155        | 0.166  | 0.159         |

### Panel B: Use Individual Shock Categories and Fire Only

<table>
<thead>
<tr>
<th>Category Used</th>
<th>(1) Fire Only</th>
<th>(2) Disaster</th>
<th>(3) Manmade</th>
<th>(4) Breakdown</th>
<th>(5) IT</th>
<th>(6) Adjustment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Origin Firms</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fire Only</td>
<td>-0.0174**</td>
<td>-0.0247***</td>
<td>-0.0275**</td>
<td>-0.0288***</td>
<td>-0.0191*</td>
<td>-0.0199**</td>
</tr>
<tr>
<td></td>
<td>(-2.87)</td>
<td>(-3.66)</td>
<td>(-2.73)</td>
<td>(-3.96)</td>
<td>(-2.03)</td>
<td>(-2.84)</td>
</tr>
</tbody>
</table>

| Firm Controls | ✓         | ✓           | ✓           | ✓            | ✓      | ✓             |
| Fixed Effects | ✓         | ✓           | ✓           | ✓            | ✓      | ✓             |
| No. Obs       | 335337     | 335337      | 335337      | 335337       | 335337 | 335337        |
| AR2           | 0.109      | 0.134       | 0.138       | 0.145        | 0.120  | 0.117         |
Table 9: Robustness: Prior Growth Trends

This table reports the coefficient estimates of $b_n$, $n = 0, \ldots, 4$ from Regression (1) of the text. $b_n$ measures the average difference between firms hit with a shock spilled over from a distance of $n$ connections, and firms never hit with any shocks. The dependent variables are lagged growth rates in revenue from the previous 1, 2, 4, and 8 quarters prior to the shocks’ quarter. $D^n$ is a dummy variable that equals to 1 if one of firm $i$’s suppliers from a distance of $n$ connections experiences an idiosyncratic shock captured by the disclosure data. All control variables are defined in Appendix A. All standard errors are clustered at the firm level. All regressions include industry×year, fiscal quarter, and state/country fixed effects, and are in quarterly frequency from 1994 to 2015.

<table>
<thead>
<tr>
<th>Prior revenue growth trends</th>
<th>Distance from Shock Origin (in # of Connections)</th>
<th>Origin</th>
<th>n=1</th>
<th>n=2</th>
<th>n=3</th>
<th>n=4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>t-1→t</td>
<td>0.0012</td>
<td>-0.0004</td>
<td>-0.0004</td>
<td>-0.0013</td>
<td>0.0003</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.72)</td>
<td>(-0.54)</td>
<td>(-0.83)</td>
<td>(-0.61)</td>
<td>(0.49)</td>
</tr>
<tr>
<td></td>
<td>t-2→t</td>
<td>-0.0030</td>
<td>-0.0033</td>
<td>0.0009</td>
<td>-0.0016</td>
<td>-0.0019</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-1.25)</td>
<td>(-0.89)</td>
<td>(1.43)</td>
<td>(-1.31)</td>
<td>(-0.62)</td>
</tr>
<tr>
<td></td>
<td>t-4→t</td>
<td>-0.0036*</td>
<td>0.0076</td>
<td>0.0039</td>
<td>0.0008</td>
<td>-0.0026</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-1.67)</td>
<td>(1.53)</td>
<td>(1.22)</td>
<td>(0.69)</td>
<td>(-1.08)</td>
</tr>
<tr>
<td></td>
<td>t-8→t</td>
<td>0.0106</td>
<td>-0.0056</td>
<td>0.0097</td>
<td>0.0103</td>
<td>-0.0034</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.75)</td>
<td>(-0.41)</td>
<td>(1.19)</td>
<td>(0.58)</td>
<td>(-0.87)</td>
</tr>
<tr>
<td>Firm Controls</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>
Table 10: **Robustness: Falsification Test with Random Shocks**

This table reports the coefficient estimates of $b_n$, $n = 0, \ldots, 4$ from Regression (1) of the text. $b_n$ measure the incremental impact of the spillover on subsequent connections $n = 1, \ldots, 4$ in units of the percentage impact on the origin firm. The dependent variable is growth rates in revenue. The first row of the independent variables is the real shocks: $D^n$ is a dummy variable that equals to 1 if one of firm $i$’s suppliers from a distance of $n$ connections experiences an idiosyncratic shock captured by the actual disclosure data. FAKED is the falsified shocks: they are shocks randomly given to other firms at the time of the real shocks, constructed according to Section 4.2 of the text. All control variables are defined in Appendix A. All standard errors are clustered at the firm level. All regressions include industry×year, fiscal quarter, and state/country fixed effects, and are in quarterly frequency from 1994 to 2015.

<table>
<thead>
<tr>
<th>Distance from Shock Origin (in # of Connections)</th>
<th>n=0</th>
<th>n=1</th>
<th>n=2</th>
<th>n=3</th>
<th>n=4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Origin</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Real Shocks</td>
<td>-0.0258***</td>
<td>-0.0229**</td>
<td>-0.0377***</td>
<td>-0.0325***</td>
<td>-0.0125**</td>
</tr>
<tr>
<td></td>
<td>(-3.32)</td>
<td>(-2.67)</td>
<td>(-4.22)</td>
<td>(-3.86)</td>
<td>(-2.44)</td>
</tr>
<tr>
<td>Fake Shocks</td>
<td>0.0057</td>
<td>0.0102</td>
<td>0.0024</td>
<td>-0.0058</td>
<td>0.0035</td>
</tr>
<tr>
<td></td>
<td>(1.02)</td>
<td>(0.79)</td>
<td>(1.23)</td>
<td>(-0.55)</td>
<td>(0.64)</td>
</tr>
<tr>
<td>Firm Controls</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

Four-Quarter Revenue Growth Rates
Table 11: **Robustness: Strategic Disclosures**

This table reports the coefficient estimates of $b_n$, $n = 0, \ldots, 4$ from Regression (1) of the text, on a series of subsamples. $b_n$ measures the average difference between firms hit with a shock spilled over from a distance of $n$ connections, and firms never hit with any shocks. Subsamples A and B includes all observations prior to, and after, August 23, 2004, respectively, corresponding to the enforcement date of Provision 209 of the Sarbanes-Oxley Act. Subsample C consists of internal shocks disclosed by the firm. See Section 4.1.3 of the text for details. $D_n$ is a dummy variable that equals to 1 if one of firm $i$’s suppliers from a distance of $n$ connections experiences an idiosyncratic shock captured by the disclosure data. All control variables are defined in Appendix A. All standard errors are clustered at the firm level. All regressions include industry×year, fiscal quarter, and state/country fixed effects, and are in quarterly frequency from 1994 to 2015.

<table>
<thead>
<tr>
<th>Coefficient for shock dummy using different subsamples</th>
<th>Distance from Shock Origin (in # of Connections)</th>
<th>Origin</th>
<th>n=1</th>
<th>n=2</th>
<th>n=3</th>
<th>n=4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full Sample</td>
<td>-0.0258***</td>
<td>-0.0229**</td>
<td>-0.0377***</td>
<td>-0.0325***</td>
<td>-0.0125**</td>
<td>(-3.32)</td>
</tr>
<tr>
<td>Subsamples</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A: Pre-SOX Sample</td>
<td>-0.0206***</td>
<td>-0.0249**</td>
<td>-0.0350***</td>
<td>-0.0338***</td>
<td>-0.0119**</td>
<td>(-3.28)</td>
</tr>
<tr>
<td>B: Post-SOX Sample</td>
<td>-0.0272***</td>
<td>-0.0215**</td>
<td>-0.0387***</td>
<td>-0.0324***</td>
<td>-0.0130**</td>
<td>(-3.36)</td>
</tr>
<tr>
<td>C: Excluded External Disclosures</td>
<td>-0.0279***</td>
<td>-0.0268**</td>
<td>-0.0372***</td>
<td>-0.0339***</td>
<td>-0.0117**</td>
<td>(-3.44)</td>
</tr>
<tr>
<td>Firm Controls</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
</tbody>
</table>
Table 12: Corporate Response to Shock Spillovers: Capital Buildup

This table reports the coefficient estimates of $b_n$, $n = 0, 1, > 1$, from Regression (6) of the text. $b_n$ measures the average difference in corporate policies between firms hit with a shock spilled over from a distance of $n$ connections, and firms never hit with any shocks. The dependent variables are changes in cash (CHEQ), inventory (INVTQ), capital expenditures (CAPXQ), and R&D expenditures (XRDQ), scaled by lagged total assets (ATQ), from the previous quarter to the quarter of shocks, and from the shock quarters to the subsequent 1, 4, and 8 quarters. $D_n$ is a dummy variable that equals to 1 if one of firm $i$'s suppliers from a distance of $n$ connections experiences an idiosyncratic shock captured by the disclosure data. All dependent variables are standardized to mean of zero and standard deviation of one. All control variables are defined in Appendix A. All standard errors are clustered at the firm level. All regressions include industry×year, fiscal quarter, and state/country fixed effects, and are in quarterly frequency from 1994 to 2015.

<table>
<thead>
<tr>
<th>Change in Capital Expenditures</th>
<th>Working Capital</th>
<th>Other Capital Expenditures</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Inventory</td>
<td>Cash</td>
</tr>
<tr>
<td></td>
<td>Origin n=1</td>
<td>Origin n=1</td>
</tr>
<tr>
<td>t-1,t</td>
<td>-0.001</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(-0.40)</td>
<td>(-1.01)</td>
</tr>
<tr>
<td>t,t+1</td>
<td>-0.083***</td>
<td>-0.020***</td>
</tr>
<tr>
<td></td>
<td>(-4.67)</td>
<td>(-2.04)</td>
</tr>
<tr>
<td>t,t+4</td>
<td>0.095***</td>
<td>-0.023*</td>
</tr>
<tr>
<td></td>
<td>(4.85)</td>
<td>(-2.20)</td>
</tr>
<tr>
<td>t,t+8</td>
<td>0.148**</td>
<td>0.047**</td>
</tr>
<tr>
<td></td>
<td>(3.03)</td>
<td>(2.56)</td>
</tr>
</tbody>
</table>

The table above shows the coefficient estimates for the change in capital expenditures. The estimates are provided for different time periods: t-1,t, t,t+1, t,t+4, and t,t+8. The table also includes the corresponding t-statistics in parentheses.
Table 13: Corporate Response to Shock Spillovers: Financing Policies

This table reports the coefficient estimates of $b_n$, $n = 0, 1, > 1$, from Regression (6) of the text. $b_n$ measures the average difference in corporate policies between firms hit with a shock spilled over from a distance of $n$ connections, and firms never hit with any shocks. The dependent variables are changes in leverage (DLTT-DLC divided by market capitalization), net debt issuance (DLTISQ-DLTRQ), net equity issuance (SSTKQ-PRSTKCQ), account payables (APQ), and retained earnings (REQ), scaled by lagged total assets (ATQ), from the previous quarter to the quarter of shocks, and from the shock quarters to the subsequent 1, 4, and 8 quarters. $D_n$ is a dummy variable that equals to 1 if one of firm $i$’s suppliers from a distance of $n$ connections experiences an idiosyncratic shock captured by the disclosure data. All dependent variables are standardized to mean of zero and standard deviation of one. All control variables are defined in Appendix A. All standard errors are clustered at the firm level. All regressions include industry×year, fiscal quarter, and state/country fixed effects, and are in quarterly frequency from 1994 to 2015.

<table>
<thead>
<tr>
<th>Change in Capital Structure</th>
<th>Leverage</th>
<th>Financing 1</th>
<th>Financing 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Market Leverage</td>
<td>Net Debt Issue</td>
<td>Net Equity Issue</td>
</tr>
<tr>
<td></td>
<td>Origin</td>
<td>n=1</td>
<td>n&gt;1</td>
</tr>
<tr>
<td>$t-1,t$</td>
<td>0.007</td>
<td>-0.002</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>(0.85)</td>
<td>(-0.14)</td>
<td>(0.97)</td>
</tr>
<tr>
<td>$t,t+1$</td>
<td>0.015</td>
<td>-0.023</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(1.34)</td>
<td>(-1.48)</td>
<td>(0.62)</td>
</tr>
<tr>
<td>$t,t+4$</td>
<td>0.086***</td>
<td>0.079*</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>(3.18)</td>
<td>(1.94)</td>
<td>(0.60)</td>
</tr>
<tr>
<td>$t,t+8$</td>
<td>0.085**</td>
<td>0.094***</td>
<td>0.022**</td>
</tr>
</tbody>
</table>

Financing 2

<table>
<thead>
<tr>
<th></th>
<th>Retained Earnings</th>
<th>Trade Credits (Payables)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Origin</td>
<td>n=1</td>
</tr>
<tr>
<td>$t-1,t$</td>
<td>-0.002</td>
<td>-0.011</td>
</tr>
<tr>
<td></td>
<td>(-0.62)</td>
<td>(-1.25)</td>
</tr>
<tr>
<td>$t,t+1$</td>
<td>-0.040*</td>
<td>-0.066*</td>
</tr>
<tr>
<td></td>
<td>(-2.21)</td>
<td>(-1.88)</td>
</tr>
<tr>
<td>$t,t+4$</td>
<td>-0.025**</td>
<td>-0.017</td>
</tr>
<tr>
<td></td>
<td>(-2.48)</td>
<td>(-1.49)</td>
</tr>
<tr>
<td>$t,t+8$</td>
<td>0.007</td>
<td>-0.013</td>
</tr>
<tr>
<td></td>
<td>(1.41)</td>
<td>(-1.50)</td>
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</tbody>
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