Competition Network, Distress Propagation, and Industry Returns

Winston Wei Dou Shane A. Johnson Mingming Ao Shao

Wei Wu *

Abstract

We build a competition network that links two industries through their common market leaders. Industries with higher centrality on the competition network have higher expected stock returns because of higher exposure to the cross-industry spillover of distress shocks. The competition intensity on the network is endogenously determined by the major players' economic and financial distress. We examine the core mechanism — the causal effects of firms' distress risk on their product market behavior and the propagation of these firm-specific distress shocks through the competition network — by exploiting the occurrence of local natural disasters to identify idiosyncratic distress shocks. Firms hit by natural disasters exhibit increased distress and then compete more aggressively by cutting profit margins. In response, their industry peers also cut profit margins and then become more distressed, especially in industries with high entry barriers. Crucially, distress shocks can propagate to other industries through common market leaders operating in multiple industries. These results cannot be explained by demand commonality or other network externality.

Keywords: Competition network centrality, Economic and financial distress, Tacit collusion, Natural disasters, Spillover and treatment externality.
JEL: G32, G33, L11, L14.

---

*Dou (Corresponding Author) is at University of Pennsylvania (Wharton). Johnson and Wu are at Texas A&M University (Mays). Shao is at San Diego State University. Emails: wdou@wharton.upenn.edu, shane@tamu.edu, mao@sdsu.edu, and wwu@mays.tamu.edu. We thank Andy Abel, Rui Albuquerque, Torben Andersen, Scott Baker, Simcha Barkai, Michael Barnett, Effi Benmelech, Jonathan Berk, Bo Bian, Gideon Bornstein, Cecilia Bustamante, Murray Carlson, Hui Chen, Lauren Cohen, Alex Corhay, Nicolas Crouzet, Jesse Davis, Miguel De Jesus, Ian Dew-Becker, Jack Favilukis, Christian Riis Flor, Carola Frydman, Lorenzo Garlappi, Ron Giammarino, Vincent Glode, Itay Goldstein, Joao Gomes, Marius Guenzel, Qiang Guo, Jarrad Harford, Gerard Hoberg, Claire Hong, Lawrence Hsiao, Qiushi Huang, Ravi Jagannathan, Yeejin Jang, Zhengyang Jiang, Yawen Jiao, William Johnson, Chad Jones, Richard Kihlstrom, Pete Klenow, Adam Kolasinski, Bob Korajczyk, Camielia Kuhnen, Howard Kung, Tim Landvoigt, Jun Li, Kai Li, Wenhao Li, Dmitry Livdan, Gregor Matvos, Timothy McQuade, Filippo Mezzanotti, Steffen Meyer, Alan Moreira, Erwan Morellec, David Musto, Marcus Opp, Jun Pan, Mitchell A. Petersen, Gordon Phillips, Jacopo Ponticelli, Julio Riutort, Hervé Roche, Sergio Salgado, Alexander Schandlbauer, Lukas Schmid, Andrei Shleifer, Harbir Singh, Rob Stambaugh, Luke Taylor, Alberto Teguia, Viktor Todorov, Yuri Tserlukevich, Rodrigo Wagner, Chaojun Wang, Jessie Wang, Wei Xiong, Hong Yan, David Zeke, Ben Zhang, Mo Zhang, Chao Zi, and seminar and conference participants at Adolfo Ibáñez University, ASU (W. P. Carey), AsianFA, EFA, FMA, Financial Markets and Corporate Governance Conference, Mack Institute for Innovation Management, Northwestern (Kellogg), SDSU (Fowler), SFS Cavalcade, Shanghai Advanced Institute of Finance (SAIF), Suffolk (Sawyer), Texas A&M (Mays), The 5th Annual Virtual QES Global Quant and Macro Investing Conference, The 28th Finance Forum, University of British Columbia (Sauder), USC (Marshall), University of Southern Denmark, UTSA, Wharton, Wharton MLG seminar, and Workshop of the Discussion Group on Macro-Finance Trends for their comments. We thank Scott Baker for sharing firms' retail consumer data. We thank Yao Han, Joseph Janko, and Xinyi Xia for excellent research assistance. All errors are our own. First draft is on August 7, 2020, and this draft is on December 1st, 2021.

1 Introduction

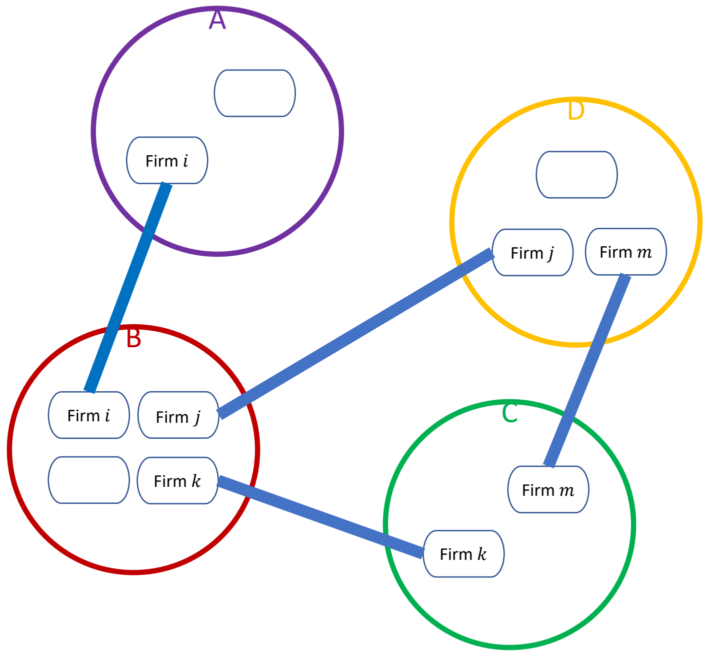
Strategic competition among market leaders in product markets plays a vital role in determining firms' cash flows and financial distress, because product markets are often highly concentrated in the hands of a few market leaders, some of which are considered "superstar firms."[1] Naturally, strategic competition and distress risk create a positive feedback loop between imperfect product and credit markets (Chen et al., 2020). Since the pioneering works by Phillips (1995), Chevalier (1995), and Kovenock and Phillips (1995), there has been a fast-growing literature empirically showing the strong relation between firms' financial conditions and their product market behaviors.[2] These theories and empirical evidence suggest that strategic competition among peers in a given industry (i.e., horizontal competition) could be an important channel through which distress shocks propagate. However, there is still little evidence on the causal effect of a firm's distress risk on the competitive behavior of itself and its peers in the product market, not to mention the exact mechanisms through which shocks are propagated within an industry and cross different industries on the competition network. This paper provides the first elements to fill the gap in the literature. Importantly, our model and empirical findings together support the hypothesis that industry competition in the form of tacit collusion is prevalent in the economy, consistent with extensive evidence documented in the economic and legal literature, as well as real-life practices such as antitrust enforcements, accusations, and announcements.[3] Further, this paper emphasizes that how shocks are propagated on the competition network is an "elephant in the room" that has been overlooked so far, although shock propagation on the production network has been extensively studied in the literature. Our results show that the competition network has first-order implications for both corporate finance and asset pricing.

We first introduce a novel form of network that connects industries through common market leaders (i.e., conglomerates) in product markets. Each industry is a node on the competition network, and two industries as two nodes are linked if and only if they share common market leaders which are multi-industry firms (see Figure 1). We compare

[1]See, e.g., Gutiérrez and Philippon (2017), Grullon, Larkin and Michaely (2019), Autor et al. (2020), De Loecker, Eeckhout and Unger (2020). Recently, Gutiérrez, Jones and Philippon (2019) and Corhay, Kung and Schmid (2020*b*) argue that high industry concentration due to high entry costs has been a fundamental driver of high markup and low investment levels in the United States (US) for the past a few decades. According to the US Census data, the top four firms within each four-digit Standard Industrial Classification (SIC) industry account for about 48% of the industry's total revenue (see Dou, Ji and Wu, 2021*a*, Online Appendix B).

[2]See, e.g., Kovenock and Phillips (1997), Busse (2002), Matsa (2011*a*,*b*), Hadlock and Sonti (2012), Hortaçsu et al. (2013), Phillips and Sertsios (2013, 2017), Cookson (2017), and Chen et al. (2020).

[3]"Tacit collusion" need not involve any collusion with explicit agreements in the legal sense, and an interchangeable term is "tacit coordination" (e.g., Ivaldi et al., 2007; Green, Marshall and Marx, 2014).



Note: This figure illustrates how the competition network is defined and constructed. Each big circle represents an industry, and the small blocks within a given circle represent the market leaders in the industry. Two industries are connected if and only if they share common market leaders.

Figure 1: Competition Network over Industries.

the competition network with the production network of industries, and find that they have distinctive network structures and are not overlapped. We show that there are indeed many multi-industry market leaders that connect the related industries on the competition network in the data, consistent with the findings of Hoberg and Phillips (2020).

We then build the idea of competition network into a simple theoretical framework that allows us to derive closed-form model solutions and illustrate the core economic mechanism in a transparent manner. Our illustrative model of competition network is a simplified variant of the full-fledged quantitative dynamic model of Chen et al. (2020). Although the main contributions of this paper are the empirical findings, the model serves as a coherent conceptual framework to formally set forth the hypotheses, guide the empirical tests, and make sense of the data patterns that we find. In the model, market leaders compete intertemporally in repeated games so that they can tacitly collude, trading off the benefits of future cooperation against those of reaping higher short-run profits by undercutting their rivals. Higher distress effectively makes firms more impatient and care less about future cooperation, leading to lower collusion capacity and profit margins. Thus, the competition intensity is endogenously determined by collusion capacity, which is in turn affected by the distress level of the market leaders.

Alternatively, market leaders can also compete non-collusively in which case the outcome of the economy is characterized by the non-collusive Nash equilibrium. Different from tacit collusion, higher distress of a market leader makes its production effectively more costly, which reduces its own market power but increases its rival's in a standard Cournot competition. Consequently, higher distress of a market leader reduces its own profit margin but increases its rival's, making the rival less distressed.

Despite an extensive set of direct micro-level evidence showing that firms compete in the form of tacit collusion in various specific industries, it is still controversial whether tacit collusion exerts a dominating force on the aggregate economy and capital market. Importantly, our model, as well as that of Chen et al. (2020), sharply contrasts the collusive Nash equilibrium with the non-collusive one by showing that they generate the opposite within-industry spillover effect, which leads to substantially different asset pricing implications. Such widely diverging predictions between the collusive and non-collusive equilibria allow for strong inference and enable us to test the hypothesis of tacit collusion as a prevalent form of industry competition by exploiting the econometric tools for analyzing spillover effects and asset pricing mechanisms. Specifically, our model predicts that, in the collusive Nash equilibrium, an adverse idiosyncratic distress shock (e.g., local natural disaster shocks) on a market leader lowers its rivals' profit margins, making them more distressed, because all firms become effectively more impatient. By contrast, in the non-collusive Nash equilibrium, an adverse idiosyncratic distress shock (e.g., local natural disaster shocks) on a market leader weakening its market power, enabling its rivals to increase their profit margins. Moreover, if some rivals are common market leaders that connect this industry to others, the initial adverse idiosyncratic distress shock can be propagated to the connected industries. But, the cross-industry spillover is very different in the collusive and non-collusive equilibrium — the direct effect and the within- and cross-industry spillover effects of distress shocks have the same direction in the collusive Nash equilibrium, whereas the direct and spillover effects have opposite directions in the non-collusive Nash equilibrium.

Intuitively, the cross-industry spillover effect implies that industries with higher competition network centrality on the competition network (i.e., industries that are more connected to others through common market leaders) have higher risk-adjusted expected stock returns in the collusive Nash equilibrium, after excluding the common market leaders. Industries with higher competition network centrality are more exposed to an economy-wide distress shock because the cross-industry spillover effect amplifies the direct loading on the economy-wide distress shock. By contrast, the cross-industry spillover effect tends to generate no clear (if not the opposite) asset pricing pattern in the non-collusive Nash equilibrium. In fact, industries with higher competition network centrality can be less exposed to an economy-wide distress shock because the cross-industry spillover effect can offset the direct loading on the economy-wide distress shock. We provide a comprehensive set of asset pricing tests and find that higher competition network centrality on the competition network is associated with higher risk-adjusted expected stock returns, supporting the hypothesis tacit collusion prevails.

Providing empirical evidence on the propagation of distress shocks via the competition network is a challenging task. The first main empirical challenge in studying the causal impact of distress risk on product market competition is endogeneity. Omitted variables such as new entrants can simultaneously drive both the likelihood of firms' distress risk and their product market behaviors. In addition, distress risk can be driven by industry-level factors that also affect industry peers directly, making it difficult to identify the impact of a firm's distress risk on its industry peers. To address the endogeneity problem, we use major natural disasters from the past 25 years in the US as idiosyncratic distress shocks. Following Barrot and Sauvagnat (2016) who study the propagation of idiosyncratic shocks on the production network, we focus on a set of major US natural disasters that caused substantial property losses. We show that these local natural disasters increase distress for the treated firms, consistent with the empirical findings of Aretz, Banerjee and Pryshchepa (2019).

The second challenge is to deal with treatment externality (i.e., interference) in the difference-in-differences (DID) setting. The existence of the spillover effect violates the stable unit treatment value assumption (SUTVA), which has served as the basis of causal effect estimation (e.g., Rubin, 1980; Manski, 1993, 2013). To tackle this challenge, we adopt the approach of two-stage quasi-natural experiments with partial interference to simultaneously identify the total treatment effect of the treated firms and the spillover effect to non-treated industry peer firms using the DID approach with the group-level spillover effects well controlled for. Similar empirical problem and methods have been studied in the statistical and econometric literature (e.g., Rubin, 1978, 1990; Sobel, 2006; Rosenbaum, 2007; Hudgens and Halloran, 2008; Liu and Hudgens, 2014; Basse and Feller, 2018).[4] We match treated firms (i.e., firms hit by natural disasters) with non-treated industry peer firms in the same industry having similar asset size, tangibility, and age. We find that the treated firms experience significant increases in distress risk and significant decreases in distance to default, indicating that these firms see increased distress following major natural disasters. Following increases in distress, the treated firms compete more

[4] Applications of causal inference with interference include Miguel and Kremer (2004), Athey, Eckles and Imbens (2018), Boehmer, Jones and Zhang (2020), Berg, Reisinger and Streitz (2021), Bustamante and Frésard (2021), and Grieser et al. (2021).

aggressively, as evidenced by significantly reduced gross profit margins. Importantly, consistent with the prediction of our model in the collusive Nash equilibrium, the DID analysis indicates the existence of a strong within-industry spillover effect. Specifically, we find that industry peers that are unaffected directly by natural disasters also exhibit a significant increase in their distress levels.

We explore the heterogeneity of the within-industry spillover effects and test a list of alternative explanations using the natural disaster setting. We find that the spillover effects are stronger in industries with higher entry barriers. This finding is consistent with the theory work of Chen et al. (2020), who show that firms will compete more aggressively with their distressed peers in industries with higher entry barriers because the winners of a price war in these industries enjoy larger economic rents after pushing out their competitors who are unlikely to be replaced by new entrants. The spillover effects are also stronger in industries with worse economic conditions and higher levels of financial constraints, which is intuitive because firms in these industries are effectively less patient and thus have more incentives to compete after the arrival of negative shocks. We then show that the within-industry spillover effects are unlikely rationalized by a list of alternative explanations including demand commonality, production network externality, lender commonality, and institutional blockholder commonality.

We further exploit two one-time economy-wide shocks to identify the spillover effects of changes in firms' financial distress risk: the American Jobs Creation Act of 2004 (AJCA) (see Faulkender and Petersen, 2012) and the Lehman crisis (see Chodorow-Reich, 2014; Chodorow-Reich and Falato, 2021), which lead to a reduction and an increase in the distress levels of the treated firms, respectively. Consistent with the prediction of our model in the collusive Nash equilibrium, we find that firms compete less aggressively in the product market after the passage of AJCA while they compete more aggressively after the Lehman crisis. Moreover, the distress levels of the non-treated industry peers reduce significantly after AJCA and while they increase significantly after the Lehman crisis.

Finally, we examine the distress contagion effects across industries. As discussed above, a focal firm will reduce its profit margin together with a peer that is negatively affected by idiosyncratic distress shocks due to lower collusion capacity in the collusive Nash equilibrium. If the focal firm is a market leader in another industry, the reduced collusion capacity extends to the other industry so that firms in that industry exhibit reduced profit margins as well. Thus, the propagation of a distress shock can transmitted from one industry to others via the competition network. This is indeed what we find in the data. Moreover, consistent with the prediction of our model in the collusive Nash equilibrium, we find that the cross-industry spillover effects are stronger in industries with higher efficiency of internal capital market of common leaders.

Related Literature. Our paper contributes to the literature that studies the propagation of idiosyncratic shocks in the economy. The extant literature has primarily focused on how shocks propagate across industries or sectors through input-output linkages (e.g., Horvath, 1998, 2000; Cohen and Frazzini, 2008; Acemoglu et al., 2012; Di Giovanni, Levchenko and Mejean, 2014; Barrot and Sauvagnat, 2016; Dew-Becker, Tahbaz-Salehi and Vedolin, 2020; Dew-Becker, 2021). Recently, a growing body of research has suggested that production network externality has important asset pricing implications (e.g., Cohen and Frazzini, 2008; Ahern, 2013; Herskovic, 2018; Herskovic et al., 2020; Gofman, Segal and Wu, 2020; Grigoris, Hu and Segal, 2021). We differ from the literature by examining distress propagation through the competition network that connects different product markets. Our analysis is similar to that of Chen et al. (2020) in this regard, but we differ from their paper by being the first to study such distress propagation in a causal framework and to document the asset pricing implications of competition network centrality.

Our paper also contributes to the literature studying the impact of financial characteristics on firms' competitive behaviors in the product market (e.g., Titman, 1984; Bolton and Scharfstein, 1990; Maksimovic and Titman, 1991; Phillips, 1995; Chevalier, 1995; Kovenock and Phillips, 1995; Chevalier and Scharfstein, 1996; Kovenock and Phillips, 1997; Zingales, 1998; Allen and Phillips, 2000; Busse, 2002; Campello, 2006; Matsa, 2011*a*,*b*; Hadlock and Sonti, 2012; Hortaçsu et al., 2013; Phillips and Sertsios, 2013; Cookson, 2017; Phillips and Sertsios, 2017; Banerjee et al., 2019; Grieser and Liu, 2019; Chen et al., 2020; Bustamante and Frésard, 2021). Matsa (2011*b*) shows that excessive leverage undermines firms' incentive to provide product quality. Phillips and Sertsios (2013) examine the interaction of product quality and pricing decisions with financial conditions in the airline industry. We contribute to the literature in several ways. First, we exploit the natural disaster setting to study the causal impact of distress risk on firms' product market behaviors. By addressing endogeneity concerns, our paper differs from previous studies on the product market implications of firms' (voluntary) decisions on financial structure (e.g., Phillips, 1995; Chevalier, 1995; Kovenock and Phillips, 1997). Second, we systematically examine changes in the profit margins of distressed firms and their industry peers in a broad sample of industries, which differentiates our paper from previous studies that have focused primarily on product market behaviors in one specific industry (e.g., Zingales, 1998; Busse, 2002; Matsa, 2011*a*,*b*; Hadlock and Sonti, 2012; Hortaçsu et al., 2013; Phillips and Sertsios, 2013; Cookson, 2017, 2018). Third, we document a cross-industry distress contagion effect through the competition network. Such a contagion effect is different economically from the contagion effect through the production network.

Our paper adds to the literature on distress risk's asset pricing implications (e.g., Campbell, Hilscher and Szilagyi, 2008; Gomes and Schmid, 2010; Garlappi and Yan, 2011; Gomes and Schmid, 2021) and real effects (e.g., Andrade and Kaplan, 1998; Campello, Graham and Harvey, 2010; Giroud et al., 2012; Phillips and Sertsios, 2013; Brown and Matsa, 2016; Giroud and Mueller, 2017; Baghai et al., 2020). Giroud et al. (2012) show that debt overhang in highly leveraged firms hurts operating performance. Brown and Matsa (2016) show that distress risk makes it more difficult for firms to attract high quality job applicants. Giroud and Mueller (2017) find that more highly leveraged firms experience significantly larger employment losses in response to declines in local consumer demand. Our evidence complements and extends these studies by focusing on the product market implications of distress risk. We show that firms and their industry peers engage in more aggressive price competition when firms face increased distress risk.

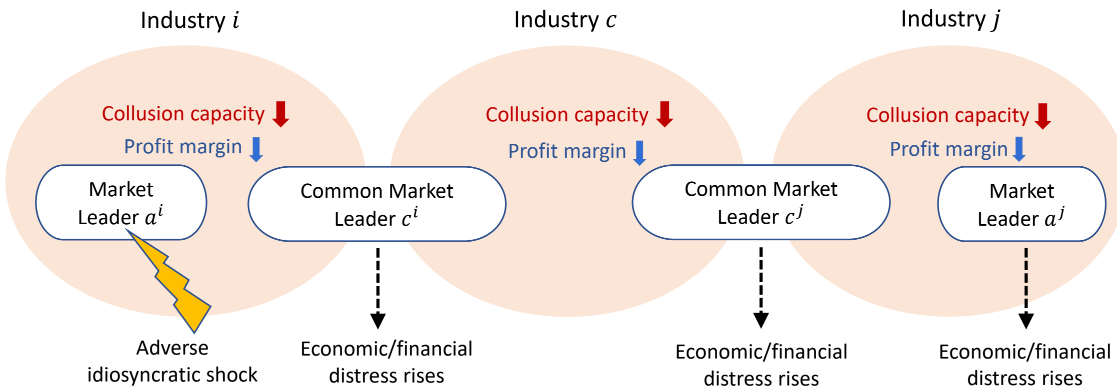
Our paper also contributes to the growing literature on financial contagion. As nicely summarized by Goldstein (2013), financial contagion takes place through two major classes of channels — fundamental- and information-based. The fundamental-based channel is through real linkages between economic entities, such as common (levered) investors (e.g., Kyle and Xiong, 2001; Kodres and Pritsker, 2002; Kaminsky, Reinhart and Végh, 2003; Martin, 2013; Gârleanu, Panageas and Yu, 2015) , financial-network linkages (e.g., Allen and Gale, 2000; Acemoglu, Ozdaglar and Tahbaz-Salehi, 2015), and supply-chain linkages (e.g., Barrot and Sauvagnat, 2016). Contagion can also work through the information-based channel such as self-fulfilling beliefs (e.g., Goldstein and Pauzner, 2004). Our paper proposes a novel channel of strategic dynamic competition through which distress risk is contagious among product-market peers.

Finally, our paper provides additional empirical evidence on tacit collusion. There has been extensive empirical evidence showing that tacit collusion can arise and be sustained for various reasons. The most direct real-life evidence is the observed antitrust enforcements, accusations, and government announcements over explicit collusion (e.g., Clark and Houde, 2013; Connor, 2016; Dasgupta and Zaldokas, 2018). Moreover, Wang (2009) shows high-frequency evidence highlighting the importance of short-run price commitment in tacit collusion as predicted by Maskin and Tirole (1988). More recently, there has been fast-growing real-life and experimental evidence on the hypothesis that AI pricing algorithms may raise their prices above the competitive level in a coordinated fashion, even if they have not been specifically instructed to do so and even if they do not communicate with one another (e.g., Beneke and Mackenrodt, 2020; Calvano et al., 2020). Furthermore, regulations such as price ceilings provide a focal-point mechanism to facilitate the tacit collusion of peers (e.g. Rey and Tirole, 2019), and many studies find strong evidence of tacit collusion that supported by the focal point mechanism (e.g., Knittel and Stango, 2003; Lewis, 2015). In addition, price experiments can also act as a testing and signaling device to facilitate tacit profit margin coordination (e.g., Byrne and de Roos, 2019). Last but not least, many studies find that (public) communication even cheap talk can help sustain tacit collusion because it can facilitate information revelation and monitoring. The tacit collusion can be sustained via firms' public announcements (e.g., Borenstein, 2004; Miller, 2010; Bourveau, She and Zaldokas, 2020; Aryal, Ciliberto and Leyden, 2021; Foros and Nguyen-Ones, 2021; Bertomeu et al., 2021). The communication can also be conducted via industry conferences and trade organization events, physical monitoring (e.g., Gan and Hernandez, 2013), and common ownership (e.g., Gutiérrez and Philippon, 2017). Importantly, high common ownership can facilitate tacit collusion in the long run via the communication channel, not necessarily reduce competition immediately in the short run via the merger and combined control channel (e.g., O'Brien and Salop, 2000; José, Schmalz and Tecu, 2018). In other words, the comovement between common ownership and industry competition should be at a low frequency or a long-run co-trend, like Gutiérrez and Philippon (2017) suggest, rather than at a high frequency, consistent with the recent findings by Dennis, Gerardi and Schenone (2021), Koch, Panayides and Thomas (2021), and Lewellen and Lowry (2021), among others. This is intuitive because the exact mechanism through which common ownership facilitates tacit collusion is likely to be the communication channel for tacit coordination, which usually takes the investors and managers quite some time to develop. As an example, He and Huang (2017) provide supporting evidence on the communication and monitoring channel through which institutional cross-ownership facilitates tacit collusion and collaboration among firms in product markets.

The rest of the paper proceeds as follows. In Section 2, we present an illustrative model for the core mechanism. In Section 3, we explain the data sources. In Section 4, we present our empirical findings. Finally, Section 5 concludes the paper.

2 An Illustrative Model for the Core Mechanism

The model in this section serves three main purposes. First, it helps illustrate the spillover effect of distress shocks through the competition network. Second, it shows that industries with higher centrality on the competition network are more exposed to systematic shocks that make all firms more distressed and carry negative market prices of risk, and thus the industries with higher centrality have higher expected stock returns. Third, although



Note: This figure illustrates a setting with three industries and four firms, where firms c^i and c^j operate in two industries as common market leaders connecting different industries. When market leader a^i in industry i becomes more distressed, economically or financially, caused by a firm-specific shock, the tacit collusion capacity decreases because of its shorter cash flow horizon, and thus the competition intensity rises in industry i, thereby making firm c^i more distressed. Market leader c^i responds by competing more aggressively in both industries i and c, which hurts the profitability of market leader c^j in industry c and makes it more distressed. Consequently, the tacit collusion capacity of industry j decreases, making market leader c^j compete more aggressively in both industries c and j. The increasingly competitive environment of industry j eventually hurts the profitability of market leader j, making the firm more distressed.

Figure 2: Distress contagion through endogenous competition of collusive equilibria in product markets.

the main contributions of this paper are the empirical findings, the model serves as a coherent conceptual framework to formally present the hypotheses and guide the empirical tests. We intentionally illustrate the core mechanism using a simple repeated game. A full-fledged, quantitative, continuous-time model is developed by Chen et al. (2020); we do not repeat the same model, but rather use a parsimonious yet generic model as the theoretical device to qualitatively illustrate the key ideas.

Each industry is atomistic in the economy. We consider four firms and three industries. The industries are connected through common market leaders that simultaneously compete in two industries, as demonstrated in Figure 2. For simplicity, we assume that the three industries are isolated from others on the competition network. We index the three industries by i, c, and j, and the four firms by a^i, c^i, c^j, and a^j, where a represents stand-*alone* market leaders and c *common* market leaders. As shown in Figure 2, firms i and c^i compete in industry i, firms j and c^j compete in industry j, and the two common market leaders c^i and c^j also compete with each other in industry c. We define the index sets of industries and firms by $\mathcal{K} \equiv \{i, c, j\}$ and $\mathcal{F} \equiv \{a^i, c^i, c^j, a^j\}$, respectively.

Distress Risk. We consider an infinite-horizon model with time periods $t = 1, 2, \cdots$ and the game starts at $t = 1$. In each period, firm $f \in \mathcal{F}$ survives with a risk-neutral probability $\lambda(x_f, \pi_f)$ where x_f captures the degree of financial constraints and π_f is the profit of firm $f \in \mathcal{F}$ in this period. Distress risk is measured by the risk-neutral probability of exit, $1-\lambda(x_f,\pi_f)$. For simplicity, we assume that an identical new market leader enters the industry immediately upon a firm's exit. We exogenously specify the logistic function of the risk-neutral survival probability as a function of x_f and π_f:

$$\frac{\lambda(x_f,\pi_f)}{1-\lambda(x_f,\pi_f)} \equiv e^{-x_f+\gamma\pi_f}, \tag{2.1}$$

where the degree of financial constraints x_f can be decomposed into economy-wide and idiosyncratic components, and the firm-level profit π_f is the aggregation of firm f's profits generated from different industries as follows:

$$x_f = \beta x + \varepsilon_f, \tag{2.2}$$

$$\pi_f = \sum_{k\in\mathcal{K}} \pi_{f,k}, \tag{2.3}$$

where ε_f captures firm f's idiosyncratic degree of financial constraints, x captures the economy-wide financial condition, and $\pi_{f,k}$ is the profit of firm f generated from industry k. The logistic specification follows Campbell, Hilscher and Szilagyi (2008) to parsimoniously connect the probability of bankruptcy or failure over the next period with the degree of financial constraints and cash flows.

Intuitively, equation (2.1) highlights that a higher degree of financial constraints x_f leads to a higher risk-neutral probability of exit (i.e., a higher distress level). And, γ in equation (2.1) captures the sensitivity of the risk-neutral survival probability to fluctuations of firm-level profits π_f, and we assume that $\gamma > 0$ to emphasize that higher profits lead to a lower risk-neutral probability of exit (i.e., a lower distress level). The coefficient β in equation (2.2) captures the loading of firm f's degree of financial constraints x_f on the aggregate financial condition x. We emphasize that the loadings of stock returns on x are endogenously different, depending on the centrality of an industry, although we assume that all firms' degrees of financial constraints x_f load homogeneously on x in our model to highlight the network effect. A variation in x can be interpreted as the financial constraints shock (e.g., Whited and Wu, 2006; Buehlmaier and Whited, 2018; Dou et al., 2021).[5]

Market Structure and Firm Profits. In industry $k\in\mathcal{K}$, the two market leaders can maintain a duopoly market structure by incurring a proportional cost of $\phi q_{f,k}$ with $f=1,2$. The quantities $q_{1,k}$, and $q_{2,k}$ are firm 1's and firm 2's output in each period. The

[5]One prominent example of financial constraints shocks is the unexpected variation in external financing costs (e.g., Bolton, Chen and Wang, 2013; Gilchrist et al., 2017; Belo, Lin and Yang, 2019).

fixed cost can be interpreted as a lobbying cost or a research and development expense to prevent many small followers from entering the market, turning it into a perfect competitive market. Under the duopoly market structure, the two market leaders face a downward-sloping demand curve:

$$p_k = a - bq_k, \quad \text{with } q_k = q_{1,k} + q_{2,k}, \tag{2.4}$$

where q_k is the total output of industry k in each period, and p_k is the price of goods in industry k. Firm f incurs a proportional cost to produce the goods, and its marginal cost is $\omega(x_f)$, which includes the cost ϕ to maintain the duopoly market structure. We assume that $\omega(x_f)$ increases in financial constraints x_t. That is, $\omega(\cdot) > 0$ and $\omega'(\cdot) > 0$, which captures the important idea that higher distress or financial constraints leads to higher marginal monetary costs to retain customer bases and suppliers. Thus, the profit of firm f from industry k is

$$\pi_{f,k} = \left[a - b(q_{1,k} + q_{2,k}) - \omega(x_f)\right] q_{f,k}. \tag{2.5}$$

There are two states for the industry competition – non-collusive and collusive. In the state of non-collusive competition, firms maximize their own values and thus profit levels conditioning on their competitors' behaviors. The non-collusive Nash equilibrium exists and is unique. In the state of collusive competition, firms tacitly coordinate to reach possibly higher profit levels. Although the agreed total market size q_k and thus the equilibrium price p_k cannot be freely changed by any firm in the state of collusive competition, a firm can deviate from the agreed supply scheme by "stealing" part of the demand from its competitor. In response to the deviation behavior, the competitor will start a "mad" price war. Specifically, in a mad price war, the competitor will never tacitly coordinate or maintain the duopoly market structure starting from the next period, and consequently, the market will become perfectly competitive with zero profits for every firm.

Suppose the collusive profits $\pi^C_{1,k}$ and $\pi^C_{2,k}$ are sustained by the collusive outputs $q^C_{1,k}$ and $q^C_{2,k}$ in the following way:

$$\pi^C_{f,k} = \left[a - b(q^C_{1,k} + q^C_{2,k}) - \omega(x_f)\right] q^C_{f,k}. \tag{2.6}$$

As demonstrated in Table 1, if firm 1 deviates from the tacit coordination, it will "steal" demand $q^C_{1,k}\delta e^{\eta\pi^C_{2,k}}$ from firm 2 without changing the agreed total market size $q^C_k = q^C_{1,k} + q^C_{2,k}$, thereby keeping the price p^C_k unaffected. Thus, the profit of firm 1 after its deviation becomes $\pi^C_{1,k}\left(1 + \delta e^{\eta\pi^C_{2,k}}\right)$, while the profit of firm 2 gets hurt because it loses

Table 1: Profits of firms 1 and 2 in industry $k \in \mathcal{K}$.

		Firm 2	
		Collude	Not collude
Firm 1	Collude	$\pi_{1,k}^C,\ \pi_{2,k}^C$	$\pi_{1,k}^C\left(1-\delta e^{\eta\pi_{1,k}^C} q_{2,k}^C/q_{1,k}^C\right),\ \pi_{2,k}^C\left(1+\delta e^{\eta\pi_{1,k}^C}\right)$
	Not collude	$\pi_{1,k}^C\left(1+\delta e^{\eta\pi_{2,k}^C}\right),\ \pi_{2,k}^C\left(1-\delta e^{\eta\pi_{2,k}^C} q_{1,k}^C/q_{2,k}^C\right)$	$\pi_{1,k}^N,\ \pi_{2,k}^N$

the amount of demand $q_{1,k}^C\delta e^{\eta\pi_{2,k}^C}$. Importantly, the amount of demand can be "stolen" increases with the rival's profit level $\pi_{2,k}^C$, which is quite intuitive since an excessively high profit level tends to compromise the customers' brand loyalty. The sensitivity coefficient η captures the within-industry elasticity. Larger η makes it easier for a firm to attract its rival's customers by deviating from the tacit coordination. Similarly, if firm 2 deviates from the tacit coordination, it will "steal" demand $q_{2,k}^C\delta e^{\eta\pi_{1,k}^C}$ from firm 1 without changing the agreed total market size q_k^C or the price p_k^C. We assume that the within-industry elasticity is sufficiently high in the sense that $\eta^{-1}\gamma$ is sufficiently small.

Again, we emphasize that the goal here is not to develop a stochastic dynamic game-theoretic models for asset pricing. For a full-fledged model, the reader is referred to Chen et al. (2020). Here, we use comparative static analysis to illustrate the endogenous responses of competition intensity, profit margin, and distress level to changes in economic conditions.

Within-Industry Spillover. The profit margin is defined as

$$\theta_{f,k} \equiv \frac{\pi_{f,k}}{p_k q_{f,k}}, \tag{2.7}$$

where $\pi_{f,k}$ is the profit of market leader f in industry k, p_k is the price of goods sold in industry k, and $q_{f,k}$ is the output of market leader f in industry k. And, firm f's total profit margin is

$$\theta_f \equiv \frac{\pi_f}{\sum_{k\in\mathcal{K}} p_k q_{f,k}}. \tag{2.8}$$

Proposition 2.1. *Consider an industry $k \in \mathcal{K}$ in which there are two market leaders, denoted by f and p. The direct and spillover effects of idiosyncratic changes in distress levels on firms' profit margins can be summarized as follows:*

(i) In the non-collusive Nash equilibrium, a firm's profit margin θ_f^N decreases with the idiosyncratic distress level ε_f, yet in contrast, peer firm p's profit margin θ_p^N increases with firm

f's idiosyncratic distress level ε_f as a spillover effect; i.e.,

$$\frac{\partial \theta_f^N}{\partial \varepsilon_f} < 0 \quad and \quad \frac{\partial \theta_p^N}{\partial \varepsilon_f} > 0.$$

(ii) In the collusive Nash equilibrium, firm f's profit margin θ_f^C decreases with its idiosyncratic distress level ε_f, and peer firm p's profit margin θ_p^C also decreases with firm f's idiosyncratic distress level ε_f as a spillover effect; i.e.,

$$\frac{\partial \theta_f^C}{\partial \varepsilon_f} \leq 0 \quad and \quad \frac{\partial \theta_p^C}{\partial \varepsilon_f} \leq 0.$$

Proposition 2.1 implies two important results. The proposition first implies that an increase in a firm's distress level has direct negative impact on its profit margin in both the non-collusive and collusive equilibrium. However, the profit level of a firm endogenously decreases in response to heightened distress for different reasons. On the one hand, in the non-collusive equilibrium, a firm's profit margin decreases with its distress level because higher distress makes the production more costly and thus the market power lower. On the other hand, in the collusive equilibrium, a firm's profit margin decreases with its distress level because higher distress of the firm makes the value of future cooperation lower for itself and suppresses the tacit collusion capacity of the industry.

Further, the proposition shows how the within-industry spillover effect works through the distressed competition mechanism, which is first proposed by Chen et al. (2020). The profit level of a firm increases with the idiosyncratic distress level of its rival firm in the non-collusive equilibrium, whereas its profit level decreases with the idiosyncratic distress level of its rival firm in the collusive equilibrium. At first glance, it seems striking that the spillover effect can have opposite signs in the non-collusive and collusive equilibrium. In fact, these theoretical results are quite intuitive and generic. In the non-collusive equilibrium, a firm's profit margin increases with its rival's distress level because the rival's market power is compromised by a higher distress level. On the contrary, in the collusive equilibrium, a firm's profit margin decreases with its rival's distress level because higher distress of the rival makes the value of future cooperation lower for these firms and suppresses the tacit collusion capacity of the industry.

These results lead to the following corollary on distress spillover. The intuitions of Proposition 2.1 and Corollary 2.1 are nicely illustrated in Figure 2.

Corollary 2.1. *Consider an industry $k \in \mathcal{K}$ in which there are two market leaders, denoted by f and p. The spillover effect of idiosyncratic changes in distress levels on the risk-neutral* *probability of exit can be summarized as follows:*

(i) In the non-collusive Nash equilibrium, peer firm p's risk-neutral probability of survival $\lambda(x_p, \pi_p^N)$ increases with firm f's idiosyncratic distress level ε_f as a spillover effect; i.e.,

$$\frac{\partial \lambda(x_p, \pi_p^N)}{\partial \varepsilon_f} \geq 0.$$

(ii) In the collusive Nash equilibrium, peer firm p's risk-neutral probability of survival $\lambda(x_p, \pi_p^C)$ decreases with firm f's idiosyncratic distress level ε_f as a spillover effect; i.e.,

$$\frac{\partial \lambda(x_p, \pi_p^C)}{\partial \varepsilon_f} \leq 0.$$

Cross-Industry Spillover. The following proposition shows that the profit level of an industry endogenously decreases in response to an adverse idiosyncratic change in the distress level of a market leader in a different industry as long as these two industries are connected on the competition network. The proof of Proposition 2.2 is in Online Appendix A.2.

Proposition 2.2. *Consider two connected industries k and k' with $k \neq k' \in \mathcal{K}$ and a market leader f in industry k. In the collusive Nash equilibrium, the profit margin $\theta_{f'}^C$ of firm f' in industry k' decreases with the idiosyncratic distress level ε_f of firm f in the other industry k:*

$$\frac{\partial \theta_{f'}^C}{\partial \varepsilon_f} \leq 0.$$

The cross-industry spillover effect relies on the positive complementarity between two connected industries' profit levels through their common market leader in the collusive equilibrium. More precisely, the two industries share a common market leader whose risk-neutral survival probability depends positively on both the industries' profit levels (i.e., $\gamma > 0$). This result leads to the following corollary on cross-industry distress spillover. The intuitions of Proposition 2.2 and Corollary 2.2 are clearly illustrated in Figure 2.

Corollary 2.2. *Consider two connected industries k and k' with $k \neq k' \in \mathcal{K}$ and a market leader f in industry k. In the collusive equilibrium, the risk-neutral probability of survival $\lambda(x_{f'}, \pi_{f'}^C)$ of firm f' in industry k' decreases with the idiosyncratic distress level ε_f of firm f in the other industry k:*

$$\frac{\partial \lambda(x_{f'}, \theta_{f'}^C)}{\partial \varepsilon_f} \leq 0.$$

Systematic Risk Exposure and Competition Network Centrality. The following proposition shows that the profit levels of industries with higher centrality on the competition network are more sensitive to fluctuations in the aggregate distress level x in equation (2.2), which captures the economy-wide degree of financial constraints. A higher x corresponds to a higher marginal utility of investors. Thus, industries with higher centrality on the competition network have higher expected stock returns. The proof of Proposition 2.3 is in Online Appendix A.3.

Proposition 2.3. *In the collusive Nash equilibrium, for the three industries i, c, and $j \in \mathcal{K}$ where all four market leaders have the same distress level, it holds that*

$$\frac{\partial \theta_c^C}{\partial x} < \frac{\partial \theta_i^C}{\partial x} < 0 \quad \textit{and} \quad \frac{\partial \theta_c^C}{\partial x} < \frac{\partial \theta_j^C}{\partial x} < 0, \tag{2.9}$$

where θ_k^C is the profit margin of industry k in the collusive Nash equilibrium for any $k \in \mathcal{K}$.

We now use Figure 2 to recap the key mechanism. Suppose three industries i, c, and j are connected through two common market leaders. Specifically, industries i and c are connected by the common market leader c^i, while c and j are connected by the common market leader c^j. Our model predicts that an adverse idiosyncratic shock (e.g., local natural disaster shocks) to market leader a^i in industry i will cause common market leader c^i to significantly lower its profit margin in response to the more aggressive competition of market leader a^i, making market leader c^i more distressed. Because market leader c^i also competes with market leader c^j in industry c, when c^i becomes more distressed, market leader c^j will also lower its profit margin and become more distressed. Lastly, market leader c^j also competes with market leader a^j in industry j, when c^j becomes more distressed, market leader a^j will also lower its profit margin and become more distressed. Taken together, the initial adverse idiosyncratic shock to market leader a^i would result in a lower profit margin of market leader a^j through the lower profit margin set by the common market leaders c^i and c^j.

Hypotheses to Test. It is not surprising that the distress conditions of competitors are interdependent within an industry. Our paper pushes one step further by investigating the exact economic mechanism of the distress shock propagation from one firm to its rivals in a given industry and even from one industry to others through the common market leaders. Importantly, our simple model suggests a set of general hypotheses regarding the within- and cross-industry spillover effects of distress shocks on profit margins and distress level. First, the model predicts that the direction toward which a firm's profit margin and distress level move depends on the form of industry competition — non-collusive competition or tacit collusion. Specifically, we show that a firm will have a lower profit margin and a higher distress level in response to an increase in its rivals' distress level because of reduced collusion capacity if they compete in the form of tacit collusion. By contrast, a firm will have a higher profit margin and a lower distress level in response to an increase in its rivals' distress level if they compete non-collusively, the opposite to what would happen if they compete in the form of tacit collusion.

Second, we show that a firm will have a lower profit margin and a higher distress level when its rival' rival is hit by adverse distress shocks in a different industry because of reduced collusion capacity in both industries if they compete in the form of tacit collusion. By contrast, there is no clear prediction on the cross-industry spillover if firms compete non-collusively, because whether a common market leader gains market power or the opposite depends on whether itself gets the hit by an adverse distress shock or its rival gets it, which in turn leads to different impact on the common market leader's rivals in another industry.

Third, we show that industries with high centrality on the competition network have higher systematic risk exposures because of cross-industry spillover effects, thereby compensating the investors with higher expected returns, if firms compete in the form of tacit collusion. In a sharp contrast, the relation between competition network centrality and systematic risk exposure is unclear if firms compete non-collusively, because the cross-industry spillover effect may amplify or cancel off the direct effect of aggregate shocks.

Such opposite predictions for the non-collusive and collusive equilibrium enable us to infer whether market leaders compete under a cooperative framework by directly testing the existence and direction of the within- and cross-industry spillover effects, as well as the asset pricing implications of the cross-industry spillover effects.

3 Data

We assemble the data from various sources. In this section, we explain them in detail.

Industry Classification and Portfolio Returns. We obtain stock returns from the Center for Research in Security Prices (CRSP). Our model focuses on strategic competition among a few oligopolistic firms whose products are close substitutes. We therefore use four-digit SIC codes to define industries, following the literature (e.g., Hou and Robinson, 2006; Gomes, Kogan and Yogo, 2009; Frésard, 2010; Giroud and Mueller, 2010, 2011; Bustamante and Donangelo, 2017).[6]

We compute the industry-level stock returns as the value-weighted average of the firm-level stock returns in a given industry weighted by their 1-month lagged market capitalization. We use CRSP delisting returns to adjust for stock delists and we exclude utility and financial industries (i.e., industries with four-digit SIC codes 4900 – 4999 and 6000 – 6999, respectively) from the analysis.

Measures for Distress Risk. We use several empirical measures for distress risk. The first measure is the distress risk measure constructed as in Campbell, Hilscher and Szilagyi (2008, see the third column in Table IV of their paper). The second measure is the distance to default measure constructed using the naive Merton default probability as in Bharath and Shumway (2008, see equation 12 of their paper). The distance to default measure negatively captures the distress risk; namely, lower distance to default measure means higher distress risk. The two empirical measures for distress risk are yearly and depend on market price, which enables them to better capture potential spillover effects quickly. In Online Appendix B, we explain the construction method of the above two measures in detail.

We use bond yield spread and CDS spread as two additional measures for distress risk. Bond yield spread is the average yield spread of all bonds issued by a firm. As in Chen et al. (2018) and Chen et al. (2020), our bond yield spread data combine the Mergent Fixed Income Securities Database (FISD) from 1973 to 2004 and the TRACE database from 2005 to 2018. We clean the Mergent FISD and TRACE data following Collin-Dufresn, Goldstein and Martin (2001) and Dick-Nielsen (2009). For each transaction, we calculate the bond yield spread by taking the difference between the bond yield and the Treasury yield with corresponding maturity. We obtain CDS spread from Markit. Following previous studies (e.g., Klingler and Lando, 2018; Collin-Dufresne, Junge and Trolle, 2020), we focus on CDS contracts with "XR" (no restructuring) as restructuring clause and we examine the par-equivalent CDS spread. The bond yield spread and CDS spread are market-based measures for distress risk, and thus arguably more directly capture distress risk than the measure of Campbell, Hilscher and Szilagyi (2008) and the distance to default measure. The disadvantage of these two measures is that their coverage is relatively small in the

[6] Like Bustamante and Donangelo (2017), we use four-digit SIC codes in Compustat instead of historical SIC codes from CRSP to define industries, because previous studies have concluded that Compustat-based SIC codes are, in general, more accurate (e.g., Guenther and Rosman, 1994; Kahle and Walkling, 1996; Bhojraj, Lee and Oler, 2003). Earlier studies have also pointed out that the four-digit SIC codes in Compustat often end with a 0 or 9, which could represent a broader three-digit industry definition. To address this problem, we follow Bustamante and Donangelo (2017) and replace the SIC code of firms whose SIC code ends with a 0 or 9 with the SIC code of the main segment in the Compustat segment data. We further remove those firms whose four-digit SIC code still ends with a 0 or 9 after this adjustment.

cross section. The bond yield spread dataset spans the period from 1973 to 2018 and covers a cross section of 421 to 746 firms in the CRSP-Compustat merged sample (i.e., on average around 11.2% of firms in the cross section of CRSP-Compustat). The CDS dataset spans the period from 2001 to 2018, and it covers 90 firms in the CRSP-Compustat merged sample in 2001 and a cross section of 310 to 584 firms from 2002 to 2018 (i.e., on average around 7.5% of firms in the cross section of CRSP-Compustat).

Measures for Profit Margins and Markups. Following the recent literature (e.g., Antras, Fort and Tintelnot, 2017; Anderson, Rebelo and Wong, 2020; Autor et al., 2020; De Loecker, Eeckhout and Unger, 2020), we use the wedge between sales and variable costs of production to measure gross profit margins and markups in our main empirical analyses, and use cost of goods sold (COGS) from the financial statement of the firm as an empirical proxy for the variable cost of production. The item COGS bundles all expenses directly attributable to the production of the goods sold by the firm and includes materials and intermediate inputs, ordinary labor cost, energy, and so on. Specifically, gross profit margins are computed as the difference between sales and cost of goods sold divided by sales, and markups are computed as the natural log of the ratio between sales and cost of goods sold. The data of sales and cost of goods sold are from Compustat.

For robustness analysis, we use the wedge between sales and total costs of operating the firm to measure net profit margins and operating markups, similar to those empirical measures in the literature (e.g., Karabarbounis and Neiman, 2018; Baqaee and Farhi, 2019; Anderson, Rebelo and Wong, 2020), and use selling, general and administrative expenses (SG&A) as an operating expenses from the financial statement of the firm to gauge fixed costs of operating the firm, interest expenses (XINT) to gauge fixed costs of working capital for running the firm (e.g., Bolton, Chen and Wang, 2011, 2014; Jermann and Quadrini, 2012), and capital depreciation (DP) to gauge additional variable costs of production (e.g., Greenwood, Hercowitz and Huffman, 1988). The total cost of operating the business is the sum of COGS, SG&A, DP, and XINT. The item SG&A includes selling expenses (salaries of sales personnel, advertising, rent), general operating expenses, and administration (executive salaries, general support related to the overall administration). Specifically, net profit margins are computed as the difference between sales and total costs of operating the firm (i.e., COGS + SG&A + DP + XINT) divided by sales. The data are from Compustat.

Our measures are based on the so-called "accounting profits approach" to estimate profit margins and markups (e.g., Baqaee and Farhi, 2019; Autor et al., 2020).[7] We

[7] To differentiate the profit margin and markup measures based on the accounting profits approach

consider gross profit margins and markups to focus on production profits of firms, while we consider net profit margins and operating markups to capture the operating profits of firms. As emphasized by Baqaee and Farhi (2019), the accounting profits approach has the virtue of requiring very little manipulation of the raw data and being robust to potential mis-specification in the user-cost estimation approach and the production function estimation approach.

Natural Disaster Data. We obtain information on the property losses caused by natural disasters hitting the US territory from the Spatial Hazard Events and Loss Databases for the United States (SHELDUS). The dataset has been widely used in the recent finance literature (e.g., Morse, 2011; Barrot and Sauvagnat, 2016; Bernile, Bhagwat and Rau, 2017; Cortés and Strahan, 2017; Alok, Kumar and Wermers, 2020; Dou, Ji and Wu, 2021*b*; Dou, Kogan and Wu, 2021), and it covers natural hazards such as thunderstorms, hurricanes, floods, wildfires, and tornados, as well as perils such as flash floods and heavy rainfalls. For each event, the database provides information on the start date, end date, and the identifiers of all affected counties. We map public firms in Compustat-CRSP to SHELDUS based on the locations of their headquarters and establishments. We collect the locations of firms' headquarters from their 10-K filings downloaded from the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system. We collect the locations of firms' establishments from the Infogroup Historical Business Database.[8] The merged location data span the period from 1994 to 2018.

Production Network Data. We measure industry-level production network connectedness using the forward and backward connectedness measures of Fan and Lang (2000), which are computed based on input-output accounts data. We identify firm-level supplier-customer links based on Compustat customer segment data and Factset Revere data following Barrot and Sauvagnat (2016) and Gofman, Segal and Wu (2020). We identify firm pairs that have a high potential for vertical relatedness based on vertical relatedness data from Frésard, Hoberg and Phillips (2020).

Firms' Individual Consumer Data. We identify the geographic locations of firms' individual consumers using a detailed dataset from Baker, Baugh and Sammon (2020),

from the conceptual "marginal" profit margin and markup, Baqaee and Farhi (2019) use the term "average" markup when referring to the accounting-based measures.

[8]Infogroup gathers geographic location-related business and residential data from various public data sources, such as local yellow pages, credit card billing data, etc. The data contain addresses, sales, and number of employees at the establishment level. We merge Infogroup to Compustat-CRSP based on stock tickers and firm names.

which provides firms' sales to individual consumers at the city level from 2010 to 2015. The individual consumer dataset is constructed based on a transaction-level database that covers debit and credit card spending across around two million American users to gain insights about the firms that they patronize, and it mainly covers firms in the consumer-facing industries (i.e., airlines, grocery stores, hotels, retailers, restaurants, utilities, and many online services). We thank Scott Baker for generously allowing us to access this dataset.

Credit Lending Data. We use Thomson Reuters LPC DealScan syndicated loan data to capture lenders' exposure to natural disasters and to construct the firm-specific credit supply shocks during the Lehman crisis. The DealScan database contains comprehensive historical information on loan characteristics, such as borrower names, lender names, pricing, start dates, end dates, and loan purposes. The loan characteristics are compiled from filings of the US Securities and Exchange Commission (SEC) and other internal resources. According to Carey and Hrycray (1999), the DealScan database covers between 50% and 75% of commercial loans in the US. We merge borrowers in DealScan to Compustat-CRSP based on the link table built by Chava and Roberts (2008). We merge lenders in DealScan to Compustat-CRSP based on the link table built by Schwert (2018).

AJCA Data. We examine the impact of AJCA, in which firms are allowed to repatriate foreign profits to the US at a 5.25% tax rate, rather than the existing 35% corporate tax rate. We define the firms shocked by the passage of AJCA as those with more than 33% pre-tax income from abroad during the 3-year period prior to AJCA (i.e., 2001 to 2003). Firms' foreign pre-tax income and the total pre-tax income are from Compustat. We follow Grieser and Liu (2019) in using a cutoff value of 33%. Our results are robust to alternative cutoff values such as 10%, 25%, and 50%.

4 Empirical Results

We describe our empirical findings in this section. Section 4.1 illustrates how we build the competition network through common market leaders and how we construct the competition network centrality measure. Section 4.2 shows that industries with higher competition network centrality are associated with higher expected returns. Sections 4.3 and 4.4 exploit the natural disaster setting to examine the within-industry spillover effects and the cross-industry contagion effects, respectively. Section 4.5 presents evidence from the AJCA tax holiday and the Lehman crisis.

Table 2: Connected four-digit SIC pairs of the competition and production networks.

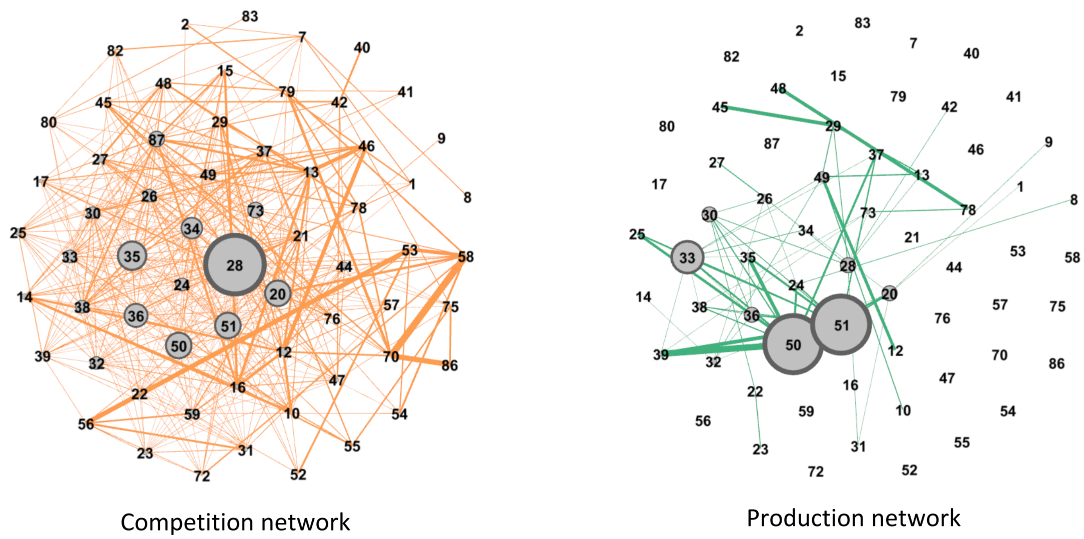
		Competition network		
		0	1	Total
Production network	0	531,791	1,129	532,920
	1	1,129	12	1,141
	Total	532,920	1,141	534,061

4.1 Competition Network and Centrality Measures

Construction of Competition Network. Motivated by our model, we construct the competition network of industries linked by common market leaders (i.e., conglomerates). Based on the competition network, we test whether the natural disaster shocks hitting market leaders in one industry can influence the profit margins of market leaders in another industry if these two industries share some common market leaders. We provide details on the construction of the competition network and describe the empirical design of our study below.

When constructing the competition network, we use Compustat historical segment data that provide information on the SIC codes for all the segments in which firms operate. Compustat historical segment data are widely used in the literature to identify the segments in which firms operate (e.g., Lamont, 1997; Rajan, Servaes and Zingales, 2000). The coverage of the data starts in 1976. We define a firm as a common market leader for a pair of four-digit SIC industries i and j if the firm is ranked among the top 10 based on the segment-level sales in both industries. The competition network at any point in time t is a collection of industries linked by common leaders. The network is updated dynamically every year according to our definition of common market leaders.

We construct the competition network at the four-digit SIC industry level. We drop financial industries (SIC codes from 6000 to 6999) in constructing the network. Two industries are connected on the competition network if they share at least one common market leader. To illustrate the difference between competition network and production network, we use the network structure in 1994 (i.e., the first year of our data in the natural disaster analysis) as an example. There are 1,141 pairs of connected industries out of 534,061 possible industry pairs in the competition network of 1994. We construct the production network based on the connectedness measures of Fan and Lang (2000). Specifically, we average the forward-connectedness and backward-connectedness measures between two four-digit SIC industries to get an average connectedness measure. We then define whether two four-digit SIC industries are connected or not in the production network. Two industries are connected on the production network if their connectedness



Note: This figure shows the competition and production networks at the two-digit SIC industry level in 1994, which is the first year of our data in the natural disaster analysis. The numbers in the graph represent the two-digit SIC industries. The size of the circles represents the magnitude of node degree (i.e., the number of other two-digit SIC industries to which a given industry connects). The thickness of the line represents the strength of connection between the two-digit SIC industries.

Figure 3: Competition network versus production network.

measure is above a cutoff value. We choose a cutoff value such that the total number of connections matches with that of the competition network in the 1994 snapshot. By doing this, we effectively normalize the total number of connections, which enables us to focus on the difference in the distribution of connections among industry pairs (i.e., the extent to which the competition network is overlapped with the production network).

Table 2 compares the connected four-digit SIC pairs of the competition network with those of the production network. These two networks share only 1.0% of connections, and the vast majority of the connected industry pairs are different between the two networks. Figure 3 further visualizes the structure of the two networks. We aggregate the industry connections to the two-digit SIC level in this plot to make the number of nodes manageable. The plot clearly shows that the competition network we construct and examine in this paper is distinct from the production network emphasized in the extant literature. Such a clear distinction between the two networks is evident in every year of our data sample. Consistently, in Section 4.2, we show that the asset pricing implications of the competition network centrality cannot be explained by other industry characteristics such as product network centrality. In Sections 4.3 and 4.4, we show that the within-industry and cross-industry spillover effects of distress risk cannot be explained by production network externality.

Common Market Leaders. Common market leaders operate in more than one industries. Although they are larger than an average firm, common market leaders are not mecessarily the largest firms in the economy. As shown in Table 3, there are around 496 common market leaders each year. Only 6.43% of the common market leaders are "superstar" firms (i.e., top 50 firms ranked by sales). The majority of the common market leaders are actually not the largest firms. For example, more than 87% of common market leaders are ranked outside of top 100 firms in terms of sales, while more than 55% of common market leaders are ranked outside of top 500 firms. Within the subset of the largest firms ranked by sales, about half or more are stand-alone firms that are not common market leaders. For example, in the top 100 firms, on average 59 of them are common market leaders and the rest are stand-alone firms. In the top 500 firms, on average 220 of them are common market leaders and the rest are stand-alone firms.

One may think that common market leaders are unlikely to experience distress risk because they are large enough to weather negative shocks. We find that this conjecture is not true in the data. Figure 4 shows the distress risk (Panel A) and financial constraint (Panel B) of the common market leaders. We also plot the two measures for the superstar firms (i.e., top 50 firms ranked by sales) and all firms in the economy. The distress risk measure is constructed as in the work of Campbell, Hilscher and Szilagyi (2008), while the financial constraint measure is the delay investment score from Hoberg and Maksimovic (2015). From these two plots, we can see that the distribution of the distress risk and financial constraint are quite wide for common market leaders. As shown in Panel A of Figure 4, we find that although the level of the distress risk for the common market leaders is lower than an average firm in the economy, common market leaders exhibit a wide distribution of distress risk. The distribution of the financial constraint measure looks even more similar among the three groups of firms (see Panel B). This pattern suggests that common market leaders, and even superstar firms seems to have fairly similar chances to become financially constrained to other firms in the economy. This finding is consistent with Hoberg and Maksimovic (2015), who show that financial constraint captured by the delay investment score cannot be simply explained by firm size.

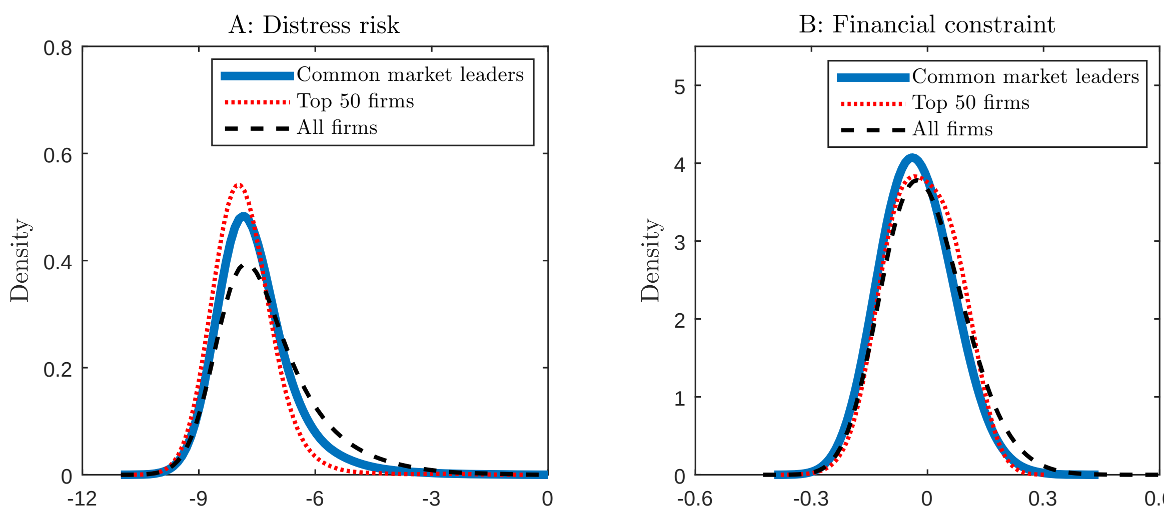
Panel C of Table 3 shows the distribution of the number of industries in which industry market leaders operate. We find that common market leaders mostly operate in two or three industries and this pattern is stable over time. The distribution pattern suggests that it is unlikely for common market leaders to fully eliminate their distress risk through diversification, which is consistent with what we see in Figure 4.

Table 3: Common market leaders.

	Panel A: number of common market leaders in the largest firms								
	Mean	Median	SD	Min	p10th	p25th	p75th	p90th	Max
Top 50 firms	30.7	31	3.8	20	26	28	34	35	37
Top 100 firms	58.5	59	7.0	34	51	54	63	68	71
Top 200 firms	108.7	106	14.5	73	95	99	119	133	140
Top 500 firms	219.6	211	35.9	150	186	190	232	284	295
All firms	495.8	448	107.6	317	399	415	560	687	726
	Panel B: # of common market leaders in the largest firms normalized by the total # of common market leaders (%)								
	Mean	Median	SD	Min	p10th	p25th	p75th	p90th	Max
Top 50 firms	6.43	6.53	1.36	3.31	4.31	5.54	7.42	8.15	8.52
Top 100 firms	12.11	12.43	1.82	8.26	9.80	10.45	13.36	14.36	14.84
Top 200 firms	22.31	22.56	2.19	17.63	19.22	20.43	23.81	25.06	25.97
Top 500 firms	44.78	45.20	3.04	39.14	40.30	42.02	47.15	48.61	49.55

	Panel C: distribution of the number of industries in which industry market leaders operate (%)							
# of industries	1	2	3	4	5	6	7	8
Year 1990	77.76	14.85	4.66	1.89	0.61	0.19	0.04	0
Year 2000	75.94	16.40	5.03	1.80	0.59	0.17	0.07	0
Year 2010	74.55	17.98	5.25	1.51	0.47	0.14	0	0.09
Year 2018	75.48	17.87	5.68	0.65	0.13	0.13	0.06	0

Note: For each year from 1976 to 2018, we count the number of common market leaders contained in the largest 50, 100, 200, and 500 firms (ranked by firm sales) and in the full sample. Panel A shows the summary statistics (i.e., mean, median standard deviation, min, 10th percentile, 25th percentile, 75th percentile, 90th percentile, max) for the corresponding yearly time series. Panel B shows the summary statistics for the number of common market leaders contained in the largest 50, 100, 200, and 500 firms normalized by the total number of common market leaders in the full sample. Panel C shows the distribution of the number of industries in which industry market leaders operate (%). Note that common market leaders are industry market leaders operate in two or more industries. We show the distributions in four snapshots: 1990, 2000, 2010, and 2018.



Note: This figure shows the distress risk (Panel A) and financial constraint (Panel B) of the common market leaders (solid blue lines), top 50 firms ranked by sales (dotted red lines), and all firms (dashed black lines).The distress risk measure is constructed as in the work of Campbell, Hilscher and Szilagyi (2008). The financial constraint measure is the delay investment score from Hoberg and Maksimovic (2015).

Figure 4: Distress risk and financial constraint of the common market leaders.

Table 4: Competition network centrality measures.

Panel A: Correlation among centrality measures				
	Degree	*Closeness*	*Betweenness*	*Eigenvector*
Degree	1			
Closeness	0.59***	1		
Betweenness	0.80***	0.42***	1	
Eigenvector	0.66***	0.27***	0.58***	1
Panel B: Variance explained by the principal components				
	*PC*1	*PC*2	*PC*3	*PC*4
Variance explained (%)	67.28	18.72	10.05	3.95

Note: Panel A shows the correlation among the four centrality measures (degree, closeness, betweenness, and eigenvector) computed from the competition networks. The sample period of the data is from 1977 to 2018. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. We perform principal component analysis based on the time series of the four centrality measures. Panel B shows the amount of variance explained by the four individual principal components.

Construction of Competition Network Centrality Measures. We consider four centrality measures for all industries connected on the competition network – *closeness, degree, betweenness*, and *eigenvector* – following the literature (e.g., Sabidussi, 1966; Bonacich, 1972; Freeman, 1977; El-Khatib, Fogel and Jandik, 2015). Closeness is the inverse of the sum of the (shortest) weighted distances between a node and all other nodes in a given network. It indicates how easily a node can be affected by disturbances to other nodes in the network. Degree is the number of direct links a node has with other nodes in the network. The more links the node has, the more central this node is in the network. Betweenness gauges how often a node lies on the shortest path between any other two nodes of the network. Hence, it indicates how much control a node could have on the spillover effect on the network, because a node located between two other nodes can either dampen or amplify the spillover effects between those two nodes through the network links. Finally, eigenvector centrality is a measure of the importance of a node in the network. It takes into account the extent to which a node is connected with other highly connected nodes. In Online Appendix D, we provide mathematical formulas and a simple example to demonstrate the calculations.

We construct all four measures and find that they are all highly correlated (see Table 4). Given the fact that they comove significantly and positively with each other over time and each of them only captures some, but by no means all, aspects of the centrality of nodes on the competition network, we consider the first principal component of the four centrality measures as our major measure in the paper. As a robustness check, we also show that the asset pricing results hold for each one of the four proxies as the centrality measure on the competition network. The eigen-decomposition of the covariance matrix of four different measures of network centrality exhibits a dominant highest eigenvalue and fast decay for the rest of the eigenvalues. Panel B of Table 4 shows that there is one

Table 5: Excess industry returns sorted on competition network centrality.

Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5 − Q1
		Panel A: Single sort on PC1 of the four centrality measures			
5.33	6.67*	5.46	7.82**	9.67***	4.34**
[1.59]	[1.95]	[1.59]	[2.56]	[2.96]	[2.54]
		Panel B: Single sort on degree centrality			
5.99*	5.06	6.42*	8.52***	9.40***	3.41**
[1.80]	[1.47]	[1.94]	[2.67]	[2.88]	[1.99]
		Panel C: Single sort on closeness centrality			
5.65*	6.01*	7.12**	7.39**	9.42***	3.77**
[1.70]	[1.79]	[2.07]	[2.34]	[2.91]	[2.23]
		Panel D: Single sort on betweenness centrality			
6.00*	5.69*	7.68**	7.13**	9.10***	3.10*
[1.72]	[1.80]	[2.36]	[2.28]	[2.80]	[1.83]
		Panel E: Single sort on eigenvector centrality			
5.58*	4.97	7.41**	7.97**	9.52***	3.94**
[1.68]	[1.54]	[2.18]	[2.43]	[2.89]	[2.43]

Note: This table shows the average excess industry returns for the industry quintile portfolios sorted on various measures of competition network centrality. In June of each year t, we sort industries into quintiles based on the centrality measure in year $t-1$. Once the portfolios are formed, the industry monthly returns are tracked from July of year t to June of year $t+1$. Because common leaders and conglomerates operate in more than one industry, we exclude them in computing industry returns. Industry returns are value-weighted from stock returns of the stand-alone firms in the industries based on firms' 1-month lagged market capitalization. We exclude from the analysis financial and utility industries and very small industries that contain fewer than three firms. Newey-West standard errors are estimated with one lag. We annualize average excess returns by multiplying them by 12. The sample period of the data is from July 1977 to June 2018. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

dominant common factor that drives much of the covariances of four different centrality measures on the competition network — the first principal component (PC1).

4.2 Asset Pricing Results

In this section, we use both portfolio sorting analyses and Fama-MacBeth regressions to test one of the main predictions of our model summarized in Proposition 2.3. Specifically, we test the hypothesis that industries with higher competition network centrality tend to have higher exposures to the systematic distress shock that carries a negative market price, thereby compensating the investors with higher expected stock returns.

Portfolio Sorting Analysis. In June of each year t, we sort industries into quintiles based on their competition network centrality measure in year $t-1$. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. We apply several filters in the construction of industry-level returns that are defined as the value-weighted average of firm-level returns in a given industry. First, we exclude common leaders from the sample in computing industry-level returns because they operate in more than one industry. Similar to Bustamante and Donangelo (2017), we further exclude firms that operate in more than three segments according to the Compustat segment data. By focusing on industry returns constructed from non-conglomerate firms in each industry, we address the concern of the double counting issue of market leaders' stock returns in different industries and the concern that the asset pricing results may be driven by the diversification effect of conglomerates (e.g., Lamont and Polk, 2001; Hann, Ogneva and Ozbas, 2013). Finally, we exclude financial and utility industries, as well as very small industries that contain fewer than three firms.

Table 5 shows the average excess returns of the industry portfolios sorted on the competition network centrality measure. Following previous asset pricing studies that examine the returns of industry portfolios (e.g., Hou and Robinson, 2006; Bustamante and Donangelo, 2017), we compute the returns of an industry quintile portfolio as the equal-weighted returns across industries in this industry quintile portfolio. We find that industries with higher competition network centrality are associated with higher excess returns, consistent with the prediction of Proposition 2.3. The magnitudes of return spread are economically large. The spread in average excess returns between the industries with the highest competition network centrality (Q5) and the industries with the lowest competition network centrality (Q1) is 4.34%. These spreads are comparable to the equity premium and value premium. We find similar patterns when we form industry portfolios using each one of the four single centrality measures. We also show that industries with higher competition network centrality are associated with higher alphas (i.e., risk-adjusted excess returns) after adjusting for the market return, Fama-French three factors, Pástor-Stambaugh liquidity factor, Stambaugh-Yuan mispricing factor, Hou-Xue-Zhang q factors, and Fama-French five factors (see Table 6). The result on the risk-adjusted excess returns based on various influential multi-factor asset pricing models suggests that the systematic distress shock that generates the dispersion of stock returns on the competition network is generically a consequence of the joint work of various primitive economic shocks.

As shown in Table OA.5 of the Online Appendix, competition network centrality seems to be largely unrelated to other industry characteristics including production network centrality, industry size, industry-level book-to-market ratio, industry-level gross profitability, and Herfindahl-Hirschman index (HHI). To formally control for these industry characteristics in our asset pricing tests, we perform a double sort analysis in which we first sort on these industry characteristics and then sort on competition network centrality. We find that the return spreads of competition network centrality remain robust after controlling for these industry characteristics (see Tables OA.6 and OA.7 of

Table 6: Risk-adjusted excess industry returns sorted on competition network centrality.

CAPM model	Fama-French three-factor model	Pástor-Stambaugh liquidity-factor model	Stambaugh-Yuan mispricing-factor model	Hou-Xue-Zhang q-factor model	Fama-French five-factor model
Panel A: Long-short quintile portfolio sorted on PC1 of the four centrality measures					
4.13**	4.18**	4.05**	4.58***	5.24**	4.80**
[2.37]	[2.29]	[2.18]	[2.24]	[2.23]	[2.52]
Panel B: Long-short quintile portfolio sorted on degree centrality					
3.59***	3.60**	3.35*	3.86**	4.17*	3.87**
[2.11]	[2.09]	[1.86]	[1.99]	[1.83]	[2.12]
Panel C: Long-short quintile portfolio sorted on closeness centrality					
3.68**	3.60**	3.75**	4.23**	5.37**	4.87***
[2.17]	[2.02]	[2.06]	[2.13]	[2.32]	[2.62]
Panel D: Long-short quintile portfolio sorted on betweenness centrality					
3.48**	3.41**	3.08*	3.22*	3.61*	3.73**
[2.03]	[1.97]	[1.71]	[1.70]	[1.66]	[2.11]
Panel E: Long-short quintile portfolio sorted on eigenvector centrality					
3.53**	4.09**	4.11**	4.83***	5.71***	5.85***
[2.16]	[2.47]	[2.42]	[2.69]	[2.76]	[3.39]

This table shows the alphas of the long-short industry quintile portfolio sorted on various measures of competition network centrality. The factor models include the capital asset pricing model (CAPM), Fama-French three-factor model (Fama and French, 1993), Pástor-Stambaugh liquidity-factor model (Pástor and Stambaugh, 2003), Stambaugh-Yuan mispricing-factor model (Stambaugh and Yuan, 2017), Hou-Xue-Zhang q-factor model (Hou, Xue and Zhang, 2015), and Fama-French five-factor model (Fama and French, 2015). In June of each year t, we sort industries into quintiles based on the centrality measure in year $t-1$. Once the portfolios are formed, the industry monthly returns are tracked from July of year t to June of year $t+1$. Because common leaders and conglomerates operate in more than one industry, we exclude them in computing industry returns. Industry returns are value-weighted from stock returns of the stand-alone firms in the industries based on firms' 1-month lagged market capitalization. We exclude from the analysis financial and utility industries and very small industries that contain fewer than three firms. Newey-West standard errors are estimated with one lag. We annualize alphas by multiplying them by 12. The sample period of the data is from July 1977 to June 2018. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

the Online Appendix).

Excluding Network Links Connected by the Largest Firms. We have shown that a subset of common market leaders are largest firms in the economy (see Table 3), which raises a possibility that the asset pricing implications of the competition network centrality may be driven by the largest firms that are also common market leaders. In Table 8, we compute the centrality measures by excluding network links connected by common market leaders that are also largest firms. We show that the return spread for industries sorted on the competition network centrality remains significantly positive after we exclude network links connected by common market leaders in the top 50, 100, and 200 firms ranked by sales. These findings suggest that the asset pricing implications of the competition network centrality are not driven by a handful of largest firms.

Table 7: Fama-MacBeth regressions.

	(1)	(2)	(3)	(4)	(5)	(6)
			$Ret_{i,t}$ (%)			
$Competition\_Centrality_{i,t-1}$	0.142***	0.145***	0.096***	0.080**	0.083**	0.162***
	[2.752]	[2.748]	[2.760]	[2.334]	[2.535]	[3.287]
$Production\_Centrality_{i,t-1}$		0.081	−0.013	−0.025	−0.024	−0.008
		[1.401]	[−0.221]	[−0.465]	[−0.444]	[−0.106]
$LnSales_{i,t-1}$			0.272***	0.303***	0.286***	0.350***
			[3.860]	[4.278]	[4.126]	[3.463]
$LnBEME_{i,t-1}$				0.071	0.092	0.220**
				[1.009]	[1.306]	[2.213]
$GP_{i,t-1}$					0.122**	0.276***
					[2.152]	[3.144]
$HHI_{i,t-1}$						−0.011
						[−0.180]
Constant	0.984***	0.963***	0.874***	0.844***	0.845***	0.651**
	[3.755]	[3.389]	[2.985]	[2.869]	[2.878]	[2.245]
Average obs/month	203	203	199	198	198	97
Average R-squared	0.006	0.010	0.026	0.042	0.053	0.096

Note: This table reports the slope coefficients and test statistics from Fama-MacBeth regressions that regress monthly industry returns ($Ret_{i,t}$) on the competition network centrality measure ($Competition\_Centrality_{i,t-1}$) and a set of control variables, which include production centrality ($Production\_Centrality_{i,t-1}$), natural log of industry revenue ($LnSales_{i,t-1}$), natural log of industry book-to-market ratio ($LnBEME_{i,t-1}$), industry gross profitability ($GP_{i,t-1}$), and industry concentration ratio ($HHI_{i,t-1}$). The competition network centrality measure is the PC1 of the four centrality measures of the competition network (i.e., degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality). The production network centrality is the PC1 of the same four centrality measures of the production network. Industry book-to-market ratio is the ratio between the book equity and the market equity of an industry. Industry gross profitability is constructed as gross profits (revenue minus cost of goods sold) scaled by assets, following the definition of Novy-Marx (2013). Industry-level revenue, cost of goods sold, book assets, book equity, and market equity are the sum of the corresponding firm-level measures for firms in the same industry. Industry concentration ratio is the HHI index of the top 50 firms. The concentration ratio data come from the US Census which covers manufacturing industries. All the independent variables are standardized to have means of 0 and standard deviations of 1. Because common leaders and conglomerates operate in more than one industry, we exclude them in computing industry returns and characteristics. Industry returns are value-weighted from stock returns of the stand-alone firms in the industries based on firms' 1-month lagged market capitalization. We exclude from the analysis financial and utility industries and very small industries that contain fewer than three firms. The sample period of the data is from 1977 to 2018. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Fama-MacBeth Regressions. We perform Fama-MacBeth tests by regressing monthly stock returns on the PC1 of the competition network centrality measures. As Table 7 shows, the slope coefficient for competition network centrality is positive and statistically significant. The slope coefficient is also economically significant. According to column (6) of Table 7, a one-standard-deviation increase in competition network centrality is associated with a 0.162- (1.94-) percentage-point increase in the monthly (annualized) stock returns. The relation between competition network centrality measures and returns is not subsumed by the industry characteristics. In other words, under the Fama-MacBeth regression setting, we strengthen the results by showing that higher competition network centrality predicts higher excess returns in the cross section not likely because of the association between competition network centrality and some other industry characteristics, such as production network centrality, industry-level sales, industry-level book-to-market ratios, and industry-level gross profitability. We also control for the HHI

Table 8: Return spreads after excluding network links connected by the largest firms.

Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5 − Q1
Panel A: Keep all network links connected by common market leaders					
5.33	6.67*	5.46	7.82**	9.67***	4.34**
[1.59]	[1.95]	[1.59]	[2.56]	[2.96]	[2.54]
Panel B: Exclude network links connected by common market leaders in the top 50 firms					
5.69*	6.10*	6.17*	6.99**	10.36***	4.67***
[1.75]	[1.74]	[1.88]	[2.21]	[3.15]	[2.76]
Panel C: Exclude network links connected by common market leaders in top 100 firms					
5.73*	5.45	7.77**	6.49**	9.91***	4.18**
[1.76]	[1.54]	[2.43]	[2.04]	[2.98]	[2.42]
Panel D: Exclude network links connected by common market leaders in top 200 firms					
6.05*	6.41*	6.76**	7.35**	8.98***	2.92*
[1.88]	[1.84]	[2.10]	[2.32]	[2.64]	[1.74]
Panel E: Exclude network links connected by common market leaders in top 500 firms					
7.45**	6.81**	6.60**	6.05*	8.63**	1.18
[2.26]	[2.03]	[2.02]	[1.94]	[2.47]	[0.68]

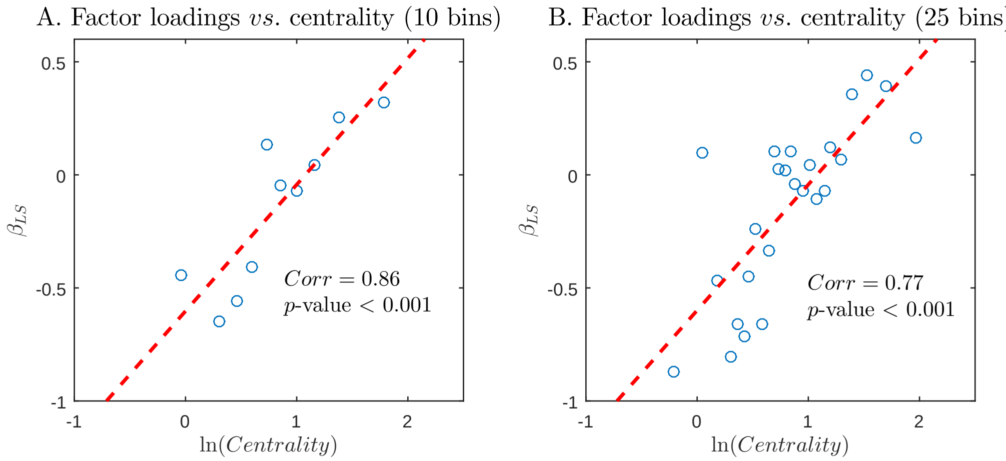
Note: This table shows the average excess industry returns for the industry quintile portfolios sorted on the PC1 of the four centrality measures. The method that we use to construct portfolio returns is explained in Table 5. In panel A, we keep all network links connected by common market leaders. This panel is the same as panel A of Table 5. In panels B to E, we compute the centrality measures by excluding network links connected by common market leaders in the top 50, 100, 200, and 500 firms ranked by sales each year, respectively. The sample period of the data is from July 1977 to June 2018. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

because industry returns have been shown to be priced in the cross section of industries (e.g., Hou and Robinson, 2006; Ali, Klasa and Yeung, 2009; Giroud and Mueller, 2011; Bustamante and Donangelo, 2017; Corhay, Kung and Schmid, 2020*a*).

Competition Network Centrality and Industry Risk Exposure. If the excess return of the long-short industry portfolio sorted on competition network centrality is the compensation for risk exposures, we expect that the long-short return spreads should capture the fundamental systematic distress shocks, and that the betas of industry stock returns to the long-short return spreads, denoted by β_{LS}, be correlated with the sorting industry characteristic (i.e., competition network centrality).[9]

We estimate the β_{LS} at industry level based on monthly returns of individual industries and the monthly returns of the long-short portfolio sorted on competition network centrality. We find that the cross-industry correlation coefficient between $\beta_{LS,i}$ and the natural log of the time-series average of the competition network centrality, denoted by $\ln(Centrality_i)$, is 0.33, with a p-value smaller than 0.001. Figure 5 shows the relation

[9]For example, in their seminal paper, Fama and French (1993) show that small stocks have higher loadings on the small-minus-big (SMB) factor while value stocks have higher loadings on the high-minus-low (HML) factor. Similar tests are also conducted in Fama and French (2015).



Note: This figure shows the relation between competition network centrality and industry factor loadings. Factor loadings are measured by the betas of industry stock returns to the returns of the long-short industry portfolio sorted on competition network centrality (i.e., β_{LS}). ln($Centrality$) is the natural log of the PC1 of the four centrality measures of the competition network. Panel A presents the binned scatter plot between ln($Centrality$) and β_{LS}, in which we sort ln($Centrality$) into 10 bins. Panel B presents the binned scatter plot between ln($Centrality$) and β_{LS}, in which we sort ln($Centrality$) into 25 bins.

Figure 5: Relation between competition network centrality and industry factor loadings.

between competition network centrality measures and factor loadings β_{LS} using binned scatter plots. It is evident that β_{LS} is strongly positively correlated with competition network centrality.

Our model predicts that the earnings of the industries with higher competition network centrality are more sensitive to fluctuations in aggregate financial condition. Consistent with our model, we show that the return on equity (ROE) of industries with higher competition network centrality comoves more negatively with discount rate shocks and more positively with aggregate cash flow shocks.

In panel A of Table 9, we tabulate the sensitivity of industry earnings to discount rate for industry quintile portfolios sorted on competition network centrality. We measure the discount rate using the smoothed earnings-price ratio, which is the reciprocal of the cyclically adjusted price-earnings ratio (CAPE) proposed by Campbell and Shiller (1988, 1998). We show that the earnings of industries with higher competition net centrality comove more negatively with discount-rate shocks. In panel B of Table 9, we tabulate the sensitivity of industry earnings to aggregate cash flow for industry quintile portfolios sorted on competition network centrality. We measure the aggregate cash flow using the average ROE across all industries. We show that the earnings of industries with higher competition network centrality comove more positively with aggregate cash-flow shocks. The heterogeneous discount-rate and cash-flow loadings across industries are consistent with the finding that industries with higher competition network centrality are associated with higher expected returns.

Table 9: Discount-rate and cash-flow exposures and competition network centrality.

Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5 − Q1
Panel A: Sensitivity of industry earnings to discount rate					
-0.27	-0.90	-1.85^{*}	-1.63^{*}	-2.50^{**}	-2.23^{**}
[−0.32]	[−1.23]	[−1.95]	[−1.99]	[−2.43]	[−2.21]
Panel B: Sensitivity of industry earnings to aggregate cash flow					
0.65^{***}	0.52^{***}	1.08^{***}	0.91^{***}	1.24^{***}	0.58^{***}
[4.46]	[5.06]	[9.24]	[8.36]	[10.37]	[2.87]

Note: This table examine the discount rate and cash flow exposures for industry portfolios sorted on competition network centrality. In panel A, we tabulate the sensitivity of industry earnings to discount rate for industry quintile portfolios sorted on competition network centrality. The regression specification is: $ROE\_shock_{p,t} = \beta_1 SmoothEP\_shock_t + \varepsilon_{p,t}$. $ROE\_shock_{p,t}$ is the yearly shock to the average ROE across industries in portfolio p in year t. Following the definition of ROE by Santos and Veronesi (2010), we calculate industry-level ROE in year t as the ratio of industry-level clean-surplus earnings in year t and industry-level book equity in year $t-1$, where clean-surplus earnings in year t are the changes in book equity from year $t-1$ to year t plus dividends in year t. $SmoothEP\_shock_t$ is the yearly shock to the smoothed earnings-price ratio, which is the reciprocal of the CAPE (e.g., Campbell and Shiller, 1988, 1998). In panel B, we tabulate the sensitivity of industry earnings to aggregate cash flow for industry quintile portfolios sorted on competition network centrality. The regression specification is: $ROE\_shock_{p,t} = \beta_1 Agg\_ROE\_shock_t + \varepsilon_{p,t}$. $Agg\_ROE\_shock_t$ is the yearly shock to the average ROE across all industries in year t. We extract the yearly shock to the portfolio ROE, aggregate ROE, and smoothed earnings-price ratio using the Hodrick-Prescott (HP) filter with a smoothing parameter of 6.25 (Ravn and Uhlig, 2002). The sample period of the data is from 1977 to 2018. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Cross Sectional Asset Pricing Tests. We perform the cross sectional asset pricing tests to examine whether our competition network centrality (CNC) measure is a factor that is significantly priced in the cross section of asset returns. The test portfolios include 15 industry portfolios double sorted on size (3 groups) and book-to-market ratio (5 groups), 5 Fama French industry portfolios, and 6 maturity-sorted Treasury bond portfolios.[10] We focus on industry returns in the test portfolios because exposures to the CNC factor mainly capture the risk exposure of industries.

For each industry portfolio $i = 1, 2, ..., N$, we estimate betas from time-series regressions of portfolio excess returns, $R^e_{i,t}$, on the vector of risk factors, fac_t:

$$R^e_{i,t} = a_i + \beta'_{i,fac} fac_t + \varepsilon_{i,t}. \tag{4.1}$$

We then run a cross-sectional regression of average excess portfolio returns on the

[10] To construct the 15 industry portfolios double sorted on size and book-to-market ratio, in each June of year t, we independently sort industries into three groups based on their market cap in year $t-1$ and sort industries into five groups based on their book-to-market ratio in year $t-1$. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. Because common leaders and conglomerates operate in more than one industry, we exclude them in computing industry returns and characteristics. The returns of a given industry are value-weighted from stock returns of the stand-alone firms in the industries based on firms' 1-month lagged market capitalization. We exclude financial and utility industries and very small industries that contain fewer than three firms in constructing the industry portfolios. Following previous asset pricing studies that examine the returns of industry portfolios (e.g., Hou and Robinson, 2006; Bustamante and Donangelo, 2017), we compute the returns of an industry portfolio as the equal-weighted returns across industries in this industry portfolio.

Table 10: Cross sectional asset pricing tests.

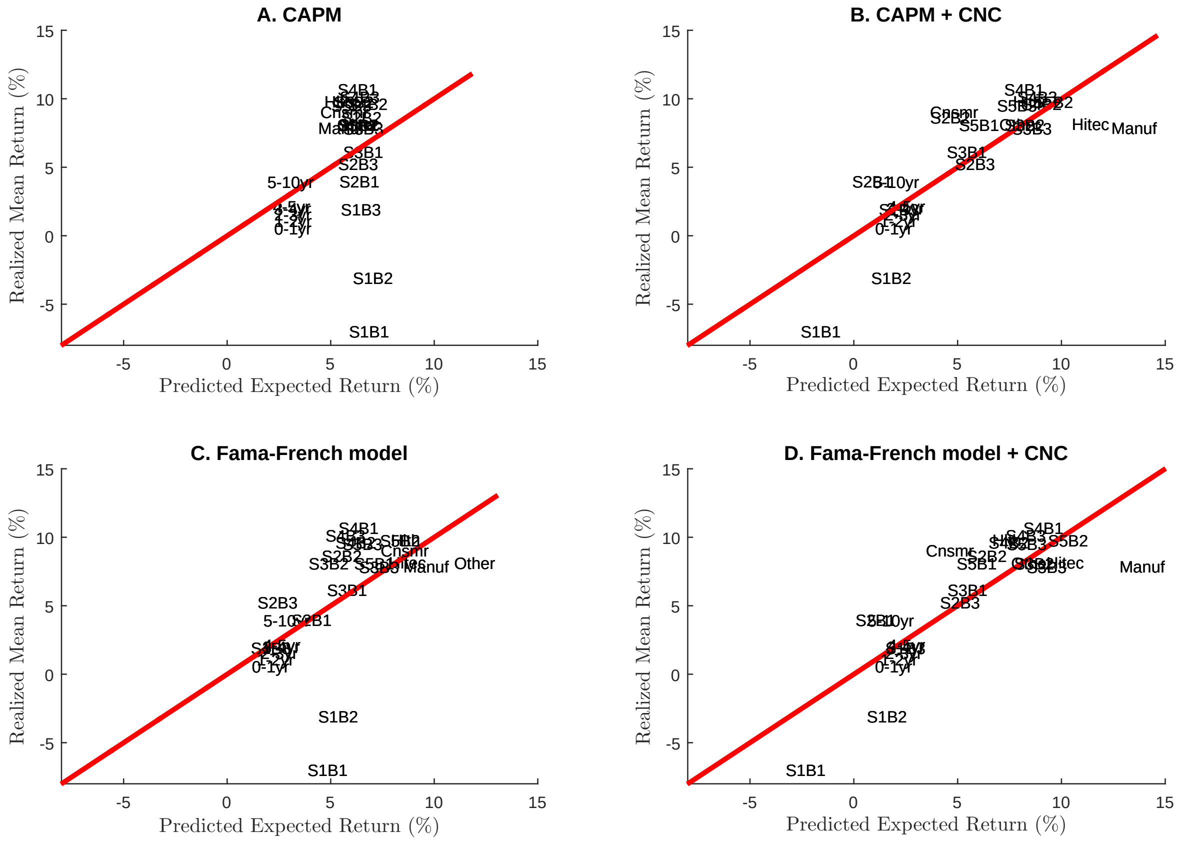
	(1) MKT	(2) MKT, CNC	(3) FF	(4) FF, CNC
		Panel A: Price of risk		
Intercept	3.18	1.90	2.00	1.87
t-FM	3.93	2.56	2.72	2.55
t-Shanken	3.92	1.65	2.40	1.60
MKT	0.71	2.01	1.90	1.93
t-FM	0.98	2.95	2.87	2.92
t-Shanken	0.74	1.64	1.94	1.57
CNC		6.50		6.84
t-FM		4.36		4.08
t-Shanken		2.76		2.52
SMB			−1.41	−0.21
t-FM			−2.72	−0.45
t-Shanken			−2.03	−0.25
HML			0.93	−0.25
t-FM			1.55	−0.43
t-Shanken			1.13	−0.24
		Panel B: Test diagnostics		
Total MAPE	3.10	1.87	2.39	1.89
Adjusted R-squared	0.228	0.311	0.338	0.387
χ^2_{N-K}	55.99	20.60	42.69	19.30
p-value	<0.001	0.606	0.005	0.566

Note: This table presents pricing results for the 15 industry portfolios double sorted on size (3 groups) and book-to-market ratio (5 groups), Fama French 5 industry portfolios, and 6 Treasury bond portfolios sorted by maturity. Each model is estimated as $E[R^e] = \lambda_0 + \beta_{fac}\lambda_{fac}$. MKT denotes the market excess returns, FF denotes the Fama-French three factors, CNC denotes the competition network centrality factor, which the the returns of the long-short quintile industry portfolio sorted on competition network centrality. Panel A reports the prices of risk with Fama-MacBeth (t-FM) and Shanken t-statistics (t-Shanken). Panel B reports test diagnostics, including mean absolute pricing errors (MAPEs), adjusted R-squared, and a χ^2 statistic that tests whether the pricing errors are jointly zero. χ^2_{N-K} represents the χ^2 statistic with $N-K$ degrees of freedom, where N denotes the number of test portfolios and K denotes the number of risk factors in the asset pricing model. Data are quarterly, 1977Q3 to 2018Q2. Returns and risk premia are reported in percent per year (quarterly percentages multiplied by four).

estimated betas:

$$E[R^e_{i,t}] = \lambda_0 + \beta'_{i,fac}\lambda_{fac} + v_i. \tag{4.2}$$

Following previous studies (e.g., Adrian, Etula and Muir, 2014; He, Kelly and Manela, 2017), we include the intercept (i.e., λ_0) in the cross-sectional regression. The results of the cross sectional asset pricing tests are shown in Table 10. Panel A presents the cross-sectional prices of risk, while panel B presents a few test diagnostics for each model. The CAPM model (column 1) is not able to account for the spread in average returns across portfolios. The cross-sectional intercept is economically large at 3.18% per annum and statistically significant (t-FM = 3.93 and t-Shanken = 3.92). The factor price of the market factor is statistically insignificant (t-FM = 0.98 and t-Shanken = 0.74), and the pricing errors are large as seen by the χ^2 test which measures the sum of the squared pricing errors (χ^2 = 55.99 with p-value $<$0.001). The Fama-French three-factor model (column 3)



Note: We plot the realized mean excess returns of 20 industry equity portfolios (15 industry portfolios double sorted on size and book-to-market ratio and 5 Fama French industry portfolios) and 6 maturity-sorted Treasury bond portfolios against the mean excess returns predicted by various linear factor asset pricing models. Following The sample period is 1977Q3 to 2018Q2. Data are quarterly, but returns are expressed in percent per year.

Figure 6: Realized versus predicted mean excess returns with the CNC factor.

does a better job in reducing the cross-sectional intercept. The economic magnitude of the intercept decreases to 2.00% per annum with Fama-MacBeth and Shanken t-statistics to be 2.72 and 2.40, respectively. However, the pricing errors are still large and statistically significant (χ^2 = 42.69 with p-value = 0.005). In addition, the price of risk for the SMB factor is in fact significantly negative (t-FM = -2.72 and t-Shanken = -2.03), suggesting that the SMB factor struggles to price the industry returns. The relative poor performance of the CAPM model and the Fama-French three-factor model is perhaps not surprising, because it has been shown that traditional factor models have difficulties explaining industry returns (e.g., Lewellen, Nagel and Shanken, 2010).

Adding the CNC factor to the CAPM model (column 2) and the Fama-French three-factor model (column 4) improves the performance of the asset pricing models. The factor price of CNC is statistically significant (t-Shanken = 2.76 in column 2, t-Shanken = 2.52 in column 4). The economic magnitude of the intercept decreases to 1.90% and 1.87%

per annum in columns (2) and (4), respectively (t-Shanken = 1.65 in column 2, t-Shanken = 1.60 in column 4). The pricing errors also reduce significantly after adding the CNC factor. The χ^2 reduces to 20.60 and 19.30 in columns (2) and (4), and both of them are statistically insignificant (p-value = 0.606 in column 2 and p-value = 0.566 in column 4). We also plot the realized mean excess returns of test portfolios against their predicted mean excess returns based on various factor models in Figure 6. Again, we can see that CAPM fails to price the test portfolios, while the two-factor model with market returns and CNC produces a cross-sectional fit comparable with the Fama-French three-factor model. Taken together, the above findings suggest that CNC is indeed a factor that is significantly priced in the cross section of asset returns, especially in the cross section of industry returns.

4.3 Within-Industry Spillover Effects with Natural Disaster Shocks

After documenting the asset pricing implications of competition network centrality, we move on to test the underlying economic mechanisms. Specifically, we exploit the occurrences of natural disasters as exogenous shocks to firms' distress risk to examine the within-industry distress spillover effects in Section 4.3 and the cross-industry spillover effects in Section 4.4.[11]

The negative impact of natural disasters on economic activities has been widely studied in the literature (e.g., Garmaise and Moskowitz, 2009; Strobl, 2011; Baker and Bloom, 2013; Cavallo et al., 2013; Hsiang and Jina, 2014; Barrot and Sauvagnat, 2016; Dessaint and Matray, 2017; Seetharam, 2018; Aretz, Banerjee and Pryshchepa, 2019; Boustan et al., 2020; Brown, Gustafson and Ivanov, 2021). Insurance coverage and public disaster assistance can only partially offset firms' losses from natural disasters (see Online Appendix C for detailed discussion). As a result, natural disaster shocks negatively affect firms' cash flow (e.g., Brown, Gustafson and Ivanov, 2021) and increase firms' distress risk exogenously (e.g., Aretz, Banerjee and Pryshchepa, 2019). In this section, we first use DID analysis to identify the spillover effects of natural disasters within industries. We then show that the spillover effects are stronger for industries with higher levels of entry barrier and financial constraint. Finally, we show that the within-industry spillover effects cannot be rationalized by a list of alternative explanations including demand commonality, production network externality, lender commonality, and institutional blockholder commonality.

[11] Besides the natural disaster shocks, in Online Appendix G, we also exploit the setting where firms suffer from distress due to firm-specific enforcement actions against financial frauds and use the DID econometric specification with partial interference to examine the spillover impact of firms' idiosyncratic adverse distress shocks on their industry peers.

4.3.1 DID Analysis

Treated and Matched Peer Firms. We follow Barrot and Sauvagnat (2016) in defining a firm as being negatively affected by a natural disaster in a given year if the county in which the firm's headquarter or one of its major establishments is located experiences property losses due to a major natural disaster during that year.[12] We list the major natural disasters included in our sample in Table OA.8 of the Online Appendix, and we plot the frequency of major natural disasters for each county in the US mainland from 1994 to 2018 in Figure OA.7 of the Online Appendix. Panel A of Table 12 presents the summary statistics for the key variables in our analysis. As shown in this panel, major natural disasters affect around 10% of firms in the Compustat firm-year panel. Major natural disasters cause substantial economic losses. Based on the SHELDUS data, we find that the counties in which the treated firms are located experience on average (weighted by the number of the firms in the counties) \$1.9 billion in property losses in the disaster years. This amount represents the lower bound of the negative economic impact caused by major natural disasters, because it only includes direct property damage and does not include other economic losses (e.g., reduction in revenue and growth) of the firms.

Firm Losses Following Major Natural Disasters. Firms report their natural disaster losses in special items (Compustat item SPI) of the income statement, which contain large, one-time expenses or source of income that firms do not expect to recur in future years (e.g., Johnson, Lopez and Sanchez, 2011). To quantify the amount of firm losses following major natural disasters, we use the following DID regression specification:

$$Special\_items_{i,t}/Sales_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}. \quad (4.3)$$

Dependent variable $Special\_items_{i,t}/Sales_{i,t}$ is the special items scaled by firm sales. Negative amount of special items represents firm losses. Independent variable $Treat_{i,t}$ is an indicator variable that equals 1 if firm i is negatively affected by a major natural disaster in year t. $Post_{i,t}$ is an indicator variable that equals 1 for observations after major natural disasters. The term θ_i represents firm fixed effects, and the term δ_t represents year fixed effects. For each treated firm or matched non-treated peer firm, we include four yearly observations (i.e., 2 years before and 2 years after major natural disasters) in the analysis. The coefficient β_1 is the coefficient of interest and it captures the amount of

[12]We follow Barrot and Sauvagnat (2016) to define major natural disasters as those that cause at least \$1 billion in total estimated property damages and that last fewer than 30 days. A major establishment is defined as an establishment that has 75% of firm-level sales. Our results are robust to other cutoffs such as 25% and 50%. We exclude financial firms from our sample following Barrot and Sauvagnat (2016).

Table 11: Firm losses following major natural disasters.

	(1)	(2)	(3)	(4)
	$Special\_items_{i,t}/Sales_{i,t}$			
$Treat_{i,t} \times Post_{i,t}$	-0.013^{**}	-0.013^{**}	-0.012^{**}	-0.012^{**}
	[−2.187]	[−2.145]	[−2.171]	[−2.131]
$Treat_{i,t}$	0.012^{**}	0.012^{**}	0.005	0.005
	[2.426]	[2.445]	[1.171]	[1.036]
$Post_{i,t}$	0.001	0.007^{*}	0.002	0.004
	[0.186]	[1.851]	[0.472]	[1.241]
Firm FE	No	No	Yes	Yes
Year FE	No	Yes	No	Yes
Observations	135320	135320	135290	135290
R-squared	0.001	0.004	0.274	0.276

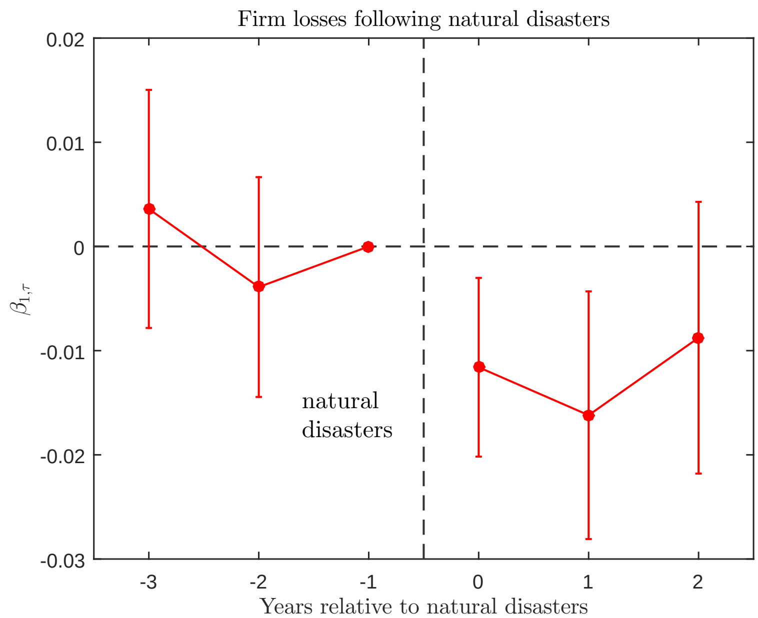
Note: This table examines the amount of firm losses following major natural disasters using a DID analysis. For each treated firm (i.e., the firm whose headquarter or any of its major establishments is located in a county that is negatively affected by major natural disasters), we match it with up to five non-treated peer firms in the same four-digit SIC industry. We perform the matching based on the values of three matching variables (i.e., firm asset size, tangibility, and age) prior to natural disaster shocks using the shortest distance method. We require that the matched peer firms are not suppliers or customers of the treated firms. We identify the supplier-customer links using Compustat customer segment data and Factset Revere data. For each major natural disaster, we include in the analysis four yearly observations (i.e., 2 years before and 2 years after the major natural disaster) for the treated firms and their matched non-treated peers. The regression specification is: $Special\_items_{i,t}/Sales_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}$. The outcome variable is the special items scaled by firm sales. Negative amount of special items represents firm losses. $Treat_{i,t}$ is an indicator variable that equals 1 if firm i is a treated firm. $Post_{i,t}$ is an indicator variable that equals 1 for observations after major natural disasters. The term θ_i represents firm fixed effects, and the term δ_t represents year fixed effects. The sample of this table spans from 1994 to 2018. Standard errors are clustered at the firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

firm losses following major natural disasters. As shown in Table 11, a firm on average reports losses that amount to more than 1.2% of its sales when the county in which it is located is hit by a major natural disaster.

Because special items contain other items besides natural disaster losses. One concern is that the β_1 coefficient may pick up changes of gains or losses other than those from natural disasters. This concern is unlikely to be the driver of our results because there is no good reason to believe firms on average experience significant losses from other channels around idiosyncratic natural disaster shocks. To further alleviate the concern, we examine the dynamics of firm losses around major natural disasters. We include six yearly observations (i.e., 3 years before and 3 years after a major natural disaster) in the DID analysis to better illustrate the dynamics. Specifically, we consider the yearly regression specification as follows:

$$\begin{aligned} Special\_items_{i,t}/Sales_{i,t} = & \sum_{\tau=-3}^{2} \beta_{1,\tau} \times Treat_{i,t} \times ND_{i,t-\tau} + \beta_2 \times Treat_{i,t} \\ & + \sum_{\tau=-3}^{2} \beta_{3,\tau} \times ND_{i,t-\tau} + \theta_i + \delta_t + \varepsilon_{i,t}. \end{aligned} \tag{4.4}$$

$Treat_{i,t}$ is an indicator variable that equals 1 if firm i is a treated firm. $ND_{i,t-\tau}$ is an



Note: This figure plots firm losses around major natural disasters. For each treated firm (i.e., the firm whose headquarter or any of its major establishments is located in a county that is negatively affected by major natural disasters), we match it with up to five non-treated peer firms in the same four-digit SIC industry. We require that the matched peer firms are not suppliers or customers of the treated firms. For each major natural disaster shock, we include six yearly observations (i.e., 3 years before and 3 years after a major natural disaster) for the treated firms and their matched non-treated peers in the analysis. To estimate the dynamics of the firm losses, we consider the yearly regression specification as follows: $Special\_items_{i,t}/Sales_{i,t} = \sum_{\tau=-3}^{2} \beta_{1,\tau} \times Treat_{i,t} \times ND_{i,t-\tau} + \beta_2 \times Treat_{i,t} + \sum_{\tau=-3}^{2} \beta_{3,\tau} \times ND_{i,t-\tau} + \theta_i + \delta_t + \varepsilon_{i,t}$. The dependent variable is the special items scaled by firm sales. Negative amount of special items represents firm losses. $Treat_{i,t}$ is an indicator variable that equals 1 if firm i is a treated firm. $ND_{i,t-\tau}$ is an indicator variable that equals 1 if firm i (when firm i is a treated firm) or the treated firm to which firm i is matched (when firm i is a matched non-treated firm) experiences natural disaster shocks in year $t-\tau$. The term θ_i represents firm fixed effects, and the term δ_t represents year fixed effects. When running the regression, we impose $\beta_{1,-1} = \beta_{3,-1} = 0$ to avoid collinearity in categorical regressions, and by doing this, we set the years immediately preceding the disaster years as the benchmark. The sample of this figure spans from 1994 to 2018. We plot estimated coefficients $\beta_{1,\tau}$ with $\tau = -3, -2, \cdots, 2$, as well as their 90% confidence intervals with standard errors clustered at the firm level. The vertical dashed line represents the occurrence of major natural disasters.

Figure 7: Firm losses following major natural disasters.

indicator variable that equals 1 if firm i (when firm i is a treated firm) or the treated firm to which firm i is matched (when firm i is a matched non-treated firm) experiences natural disaster shocks in year $t-\tau$. The term θ_i represents firm fixed effects, and the term δ_t represents year fixed effects. When running the regression, we impose $\beta_{1,-1} = \beta_{3,-1} = 0$ to avoid collinearity in categorical regressions, and by doing this, we set the years immediately preceding the disaster years as the benchmark. In Figure 7, we plot estimated coefficients $\beta_{1,\tau}$ with $\tau = -3, -2, \cdots, 2$, as well as their 90% confidence intervals with standard errors clustered at the firm level. We find that the increase in the reported firm losses takes place only after the occurrence of natural disaster shocks. There is no significant change in the reporting of special items prior to natural disaster shocks. This pattern further confirms that the estimates in Table 11 reflect natural disaster losses of the affected firms.

Regression Specifications to Identify Within-Industry Spillover Effects. To clearly identify and dissect out within-industry spillover effects, it is important to recognize that cross-industry spillover effects also exist simultaneously in the background. For example, to test whether firm j affected by natural disasters can generate a within-industry spillover effect to a non-treated peer firm i in the same industry (denote this industry as industry A), it is important to control for the cross-industry spillover effects caused by natural disaster shocks in other industries (say industry B) that are connected to industry A via the competition network. This is because although natural disasters are idiosyncratic shocks, the concurrent natural disasters can simultaneously affect firms in industries A and B and thus can lead to biased estimates of within-industry spillover effects. To control for the strength of cross-industry spillover effects, we construct variable $Ln(1 + n(\mathcal{C}_{i,t}))$, which is the natural log of 1 plus the number of industries connected to firm i's industry through the competition network and shocked by natural disasters in year t.

We formally test whether natural disasters lead to an increased likelihood of distress of the treated firms and their industry peers using the following regression specification:

$$Y_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1 + n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}. \quad (4.5)$$

Dependent variable $Y_{i,t}$ represents the distress risk ($Distress_{i,t}$) and the distance-to-default measure ($DD_{i,t}$) of firm i in year t. Independent variable $Treat_{i,t}$ is an indicator variable that equals 1 if firm i is negatively affected by a major natural disaster in year t. $Post_{i,t}$ is an indicator variable that equals 1 for observations after major natural disasters. $Ln(1 + n(\mathcal{C}_{i,t}))$ captures the strength of cross-industry spillover effects. The term θ_i represents firm fixed effects, and the term δ_t represents year fixed effects. For each treated firm or matched non-treated peer firm, we include four yearly observations (i.e., 2 years before and 2 years after major natural disasters) in the analysis. In the presence of potential spillover effects between the treated firms and the corresponding non-treated peer firms, the summation between coefficient β_1 and coefficient β_3 captures the total treatment effect for the treated firms (e.g., Boehmer, Jones and Zhang, 2020), while coefficient β_3 alone captures the within-industry spillover effects to the peer firms. Finally, coefficient β_4 captures the cross-industry spillover effects through the competition network. It is important to point out that natural disasters are not a one-time shock; instead, they are shocks taking place throughout our sample period, which allows us to separate the within-industry spillover effects captured by β_3 from the aggregate time-series variation captured by time fixed effect δ_t.

DID Analysis Findings. We tabulate the results of the DID regressions for firm distress in columns (1) to (4) of panel B in Table 12. We find that the distress risk of the treated firms increases substantially, while the distance-to-default measure of the treated firms decreases substantially following the natural disaster shocks. The p-value for the null hypothesis that the total treatment effect is 0 (i.e., $\beta_1 + \beta_3 = 0$) is lower than 0.001. These findings suggest that the treated firms become more distressed following major natural disasters. Our results are consistent with those of Aretz, Banerjee and Pryshchepa (2019), who show that hurricane strikes substantially increase firms' distress risk.

We then examine the impact of distress risk on the treated firms' gross profit margin. We focus on profit margin rather than product price in this paper for the following reasons. First, we are concerned with the real impact of product market competition, and thus, it is the profit margin rather than the nominal price tag that matters here. Second, the purpose of competition, and even price wars, is not to reduce competitors' prices, but to destroy their profit margins. Third, product market price may simply reflect changes in product costs that can be affected by idiosyncratic shocks such as natural disasters. An increase in product price does not necessarily mean a reduction in competition intensity.[13] Fourth, accurate and detailed data of retail prices and firms' marginal costs for a broad set of industries are not available. Even if they were available, implicit discounts, coupons, rebates, and gifts are not easily observable to economists. Last but not least, price levels cannot be meaningfully compared across industries, but profit margins can.

To quantify the changes in treated firms' gross profit margins, we again use the regression specification (4.5), with dependent variable $Y_{i,t}$ representing the gross profit margin and markup of firm i in year t. As shown in columns (5) to (8) of panel B in Table 12, we find that the treated firms significantly reduce their gross profit margins and markups, suggesting that these firms decide to reduce profitability and compete more aggressively in the product market after increased distress risk. This finding is consistent with the prediction of our model in the collusive Nash equilibrium.

Next, we test our model's predictions on the within-industry spillover effects. Specifically, our model predicts that industry peers will compete more aggressively with the distressed firms, which in turn will make the peers themselves more distressed. We find strong supporting evidence for this prediction. Coefficient β_3 in columns (5) to (8) of

[13] In Section C.2 of the Online Appendix, we show that both gasoline price and crude oil price increased sharply in response to damage to the refinery industry caused by Hurricanes Harvey and Irma. However, the amount of increase in gasoline price (in percentage term) was much lower than that of crude oil. As a result, the profit margin of the oil refinery industry reduced significantly after the hurricanes, suggesting that refinery firms did not simply pass the increased input costs to their customers; instead, they internalized some of the increased costs. This finding is consistent with our model in the collusive Nash equilibrium that predicts intensified product market competition in response to firms' increased distress risk.

Table 12: Identifying within-industry spillover effects using DID analysis.

	Panel A: Summary statistics of the firm-year panel							
	Obs. #	Mean	Median	SD	p10th	p25th	p75th	p90th
$ND_{i,t}$	88297	0.100	0	0.301	0	0	0	1
$Distress_{i,t}$	92185	-7.228	-7.489	1.005	-8.317	-7.986	-6.701	-5.618
$DD_{i,t}$	80858	5.321	4.506	4.254	0.292	2.070	7.833	11.884
$PM_{i,t}$	96269	0.346	0.338	0.264	0.092	0.206	0.519	0.703
$Markup_{i,t}$	96140	0.515	0.412	0.451	0.097	0.230	0.731	1.208
$Ln(1+n(\mathcal{C}_{i,t}))$	98562	0.747	0.693	0.739	0	0	1.386	1.792

	Panel B: Identifying within-industry spillover effects using DID analysis							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.019	0.019	-0.087^{*}	-0.088^{*}	-0.001	-0.001	-0.001	-0.001
	[1.538]	[1.556]	[-1.717]	[-1.743]	[-0.196]	[-0.218]	[-0.267]	[-0.291]
$Treat_{i,t}$	-0.014	-0.014	0.096^{*}	0.097^{*}	-0.001	-0.001	-0.001	-0.001
	[-1.250]	[-1.257]	[1.940]	[1.953]	[-0.189]	[-0.181]	[-0.151]	[-0.143]
$Post_{i,t}$	0.053^{***}	0.052^{***}	-0.122^{***}	-0.115^{***}	-0.007^{**}	-0.007^{**}	-0.010^{***}	-0.010^{**}
	[6.498]	[6.411]	[-3.882]	[-3.695]	[-2.283]	[-2.149]	[-2.649]	[-2.496]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.018^{*}		-0.083^{**}		-0.006^{**}		-0.009^{**}
		[1.952]		[-2.295]		[-2.227]		[-2.449]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130099	130099	110581	110581	135037	135037	134924	134924
R-squared	0.565	0.565	0.667	0.667	0.745	0.746	0.773	0.773
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.004	0.006	$<10^{-3}$	0.001

Note: This table examines within-industry spillover effects following major natural disasters. Panel A of this table shows the summary statistics for the firm-year panel from 1994 to 2018. $Distress_{i,t}$ is the distress risk constructed as in the work of Campbell, Hilscher and Szilagyi (2008). $DD_{i,t}$ is the distance to default constructed following the naive approach illustrated in Bharath and Shumway (2008). $PM_{i,t}$ is the gross profit margin defined as the difference between sales and cost of goods sold divided by sales. $Markup_{i,t}$ is the markup, defined as the natural log of the ratio between sales and cost of goods sold. $ND_{i,t}$ is an indicator variable that equals 1 if firm i is negatively affected by major natural disasters in year t. $Ln(1+n(\mathcal{C}_{i,t}))$ captures the strength of cross-industry spillover effects, and it is the natural log of 1 plus the number of industries connected to firm i's industry through competition networks and shocked by natural disasters in year t. Panel B of this table reports the results from the DID analysis. For each treated firm (i.e., the firm whose headquarter or any of its major establishments is located in a county that is negatively affected by major natural disasters), we match it with up to five non-treated peer firms in the same four-digit SIC industry. We perform the matching based on the values of three matching variables (i.e., firm asset size, tangibility, and age) prior to natural disaster shocks using the shortest distance method. We require that the matched peer firms are not suppliers or customers of the treated firms. We identify the supplier-customer links using Compustat customer segment data and Factset Revere data. For each major natural disaster, we include in the analysis four yearly observations (i.e., 2 years before and 2 years after the major natural disaster) for the treated firms and their matched non-treated peers. The regression specification is: $Y_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1+n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}$. $Treat_{i,t}$ is an indicator variable that equals 1 if firm i is a treated firm. $Post_{i,t}$ is an indicator variable that equals 1 for observations after major natural disasters. The term θ_i represents firm fixed effects, and the term δ_t represents year fixed effects. In the last row of the table, we present the p-value for the null hypothesis that the total treatment effect for the treated firms is zero (i.e., $\beta_1 + \beta_3 = 0$). The sample of this table spans from 1994 to 2018. Standard errors are clustered at the firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

panel B in Table 12 is negative and statistically significant, suggesting that the industry peers that are unaffected directly by natural disasters also reduce their profit margins significantly. The intensified product market competition makes the non-treated industry peers also suffer from a significant increase in distress risk. Coefficient β_3 in columns (1) and (2) of panel B in Table 12 is positive and statistically significant, while coefficient β_3 in columns (3) and (4) of panel B in Table 12 is negative and statistically significant. These findings indicate the existence of the within-industry spillover effect: industry peers

Table 13: Within-industry spillover effects in bond yield spread and CDS spread.

	Panel A: Summary statistics of the firm-year panel							
	Obs. #	Mean	Median	SD	p10th	p25th	p75th	p90th
$Bond\_yield\_spread_{i,t}$(%)	13624	2.981	1.898	3.014	0.698	1.062	3.827	6.284
$CDS\_spread_{i,t}$(%)	7588	1.082	0.290	2.452	0.070	0.121	0.863	2.521

	Panel B: Identifying within-industry spillover effects using DID analysis			
	(1)	(2)	(3)	(4)
	$Bond\_yield\_spread_{i,t}$(%)		$CDS\_spread_{i,t}$(%)	
$Treat_{i,t} \times Post_{i,t}$	0.022	0.021	-0.103	-0.104
	[0.198]	[0.193]	[-0.638]	[-0.641]
$Treat_{i,t}$	0.030	0.031	0.083	0.084
	[0.353]	[0.365]	[0.607]	[0.610]
$Post_{i,t}$	0.176**	0.180**	0.340**	0.347**
	[2.115]	[2.174]	[2.090]	[2.052]
$Ln(1 + n(\mathcal{C}_{i,t}))$		-0.052		-0.107
		[-0.869]		[-0.734]
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	15731	15731	7467	7467
R-squared	0.721	0.721	0.628	0.628
Test p-value: $\beta_1 + \beta_3 = 0$	0.016	0.015	0.094	0.094

Note: This table examines within-industry spillover effects in bond yield spread and CDS spread following major natural disasters. Panel A of this table shows the summary statistics for the firm-year panel from 1994 to 2018. $Bond\_yield\_spread_{i,t}$ is the bond yield spread, which is the average bond yield spread of all bonds issued by a firm. For each transaction, we calculate the bond yield spread by taking the difference between the bond yield and the Treasury yield with corresponding maturity. $CDS\_spread_{i,t}$ is the par-equivalent spread of CDS with 1-year maturity. Both the bond yield spread and CDS spread in year t are the spread in the last quarter so the spreads capture credit risk at the year end. Panel B of this table reports the results from the DID analysis. The regression specification is: $Y_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1 + n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}$. Definition for the independent variables are given in Table 12. The sample of bond yield spread spans from 1994 to 2018, while the sample of CDS spread spans from 2001 to 2018. Standard errors are clustered at the firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

become more distressed, and they compete more aggressively with the firms affected by natural disaster shocks.

Panel B of Table 12 also reports the coefficients for cross-industry spillover effects (i.e., β_4). These coefficients are statistically significant and the sign of these coefficients is consistent with the prediction of our model. When more industries linked to the focal industry through competition networks are shocked by natural disasters, the firms in the focal industry experience a larger increase in distress and compete more aggressively in the product market. In Section 4.4, we study cross-industry spillover effects in greater detail and highlight the role of common leaders as the key players that transmit shocks across industries through competition networks.

Besides using the distress measure of Campbell, Hilscher and Szilagyi (2008) and the distance to default measure, we also examine the spillover effect of distress risk using bond yield spread and CDS spread. Table 13 presents the findings. The within-industry spillover effect captured by the coefficient β_3 is positive and statistically significant for both bond yield spread and CDS spread. Following the natural disaster shocks to the focal firms, the bond yield spread and CDS spread of the unaffected industry peer firms increase by 18 and 34 basis points, respectively, which are large economically compared to the means and medians of the spreads. We should note that the coverage of the spread data is relatively small in the cross section, which is around 10% of the CRSP-Compustat merged sample. In addition, the CDS spread sample is only avaible after 2001. The limitation in sample coverage likely accounts for the insignificant coefficients for cross-industry spillover effects (i.e., β_4) in Table 13.

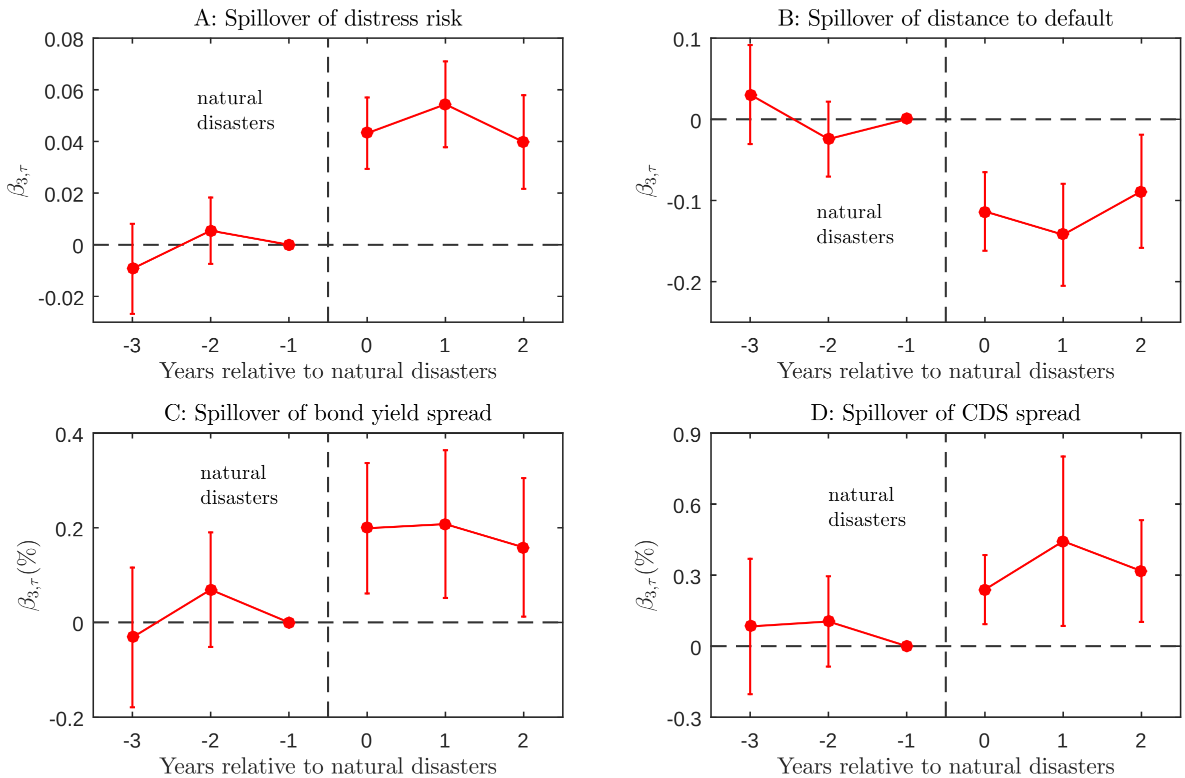
Evidence Supporting the Parallel Trend Assumption. We further examine the dynamics of within-industry spillover effects. Because the data for the measures of distress risk and distance to default are at a yearly frequency, we include six yearly observations (i.e., 3 years before and 3 years after a major natural disaster) in the DID analysis to better illustrate the dynamics of the spillover effects. Specifically, we consider the yearly regression specification as follows:

$$\begin{aligned} Y_{i,t} = & \sum_{\tau=-3}^{2} \beta_{1,\tau} \times Treat_{i,t} \times ND_{i,t-\tau} + \beta_2 \times Treat_{i,t} + \sum_{\tau=-3}^{2} \beta_{3,\tau} \times ND_{i,t-\tau} \\ & + \beta_4 \times Ln(1 + n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}. \end{aligned} \tag{4.6}$$

The dependent variables ($Y_{i,t}$) include the distress risk, the distance to default, the bond yield spread (in percent), and the CDS spread (in percent). $Treat_{i,t}$ is an indicator variable that equals 1 if firm i is a treated firm. $ND_{i,t-\tau}$ is an indicator variable that equals 1 if firm i (when firm i is a treated firm) or the treated firm to which firm i is matched (when firm i is a matched non-treated firm) experiences natural disaster shocks in year $t - \tau$. The term θ_i represents firm fixed effects, and the term δ_t represents year fixed effects. When running the regression, we impose $\beta_{1,-1} = \beta_{3,-1} = 0$ to avoid collinearity in categorical regressions, and by doing this, we set the years immediately preceding the disaster years as the benchmark. In Figure 8, we plot estimated coefficients $\beta_{3,\tau}$ with $\tau = -3, -2, \cdots, 2$, as well as their 90% confidence intervals with standard errors clustered at the firm level.

We find that the spillover effect emerges only after the occurrence of natural disaster shocks. There is no significant change in the distress risk or distance to default prior to natural disaster shocks, which provides evidence supporting the parallel trend assumption for the DID analysis. We also find that within-industry spillover effects last for more than 2 years, which justifies the choice of time window in the DID analysis presented in Table 12.

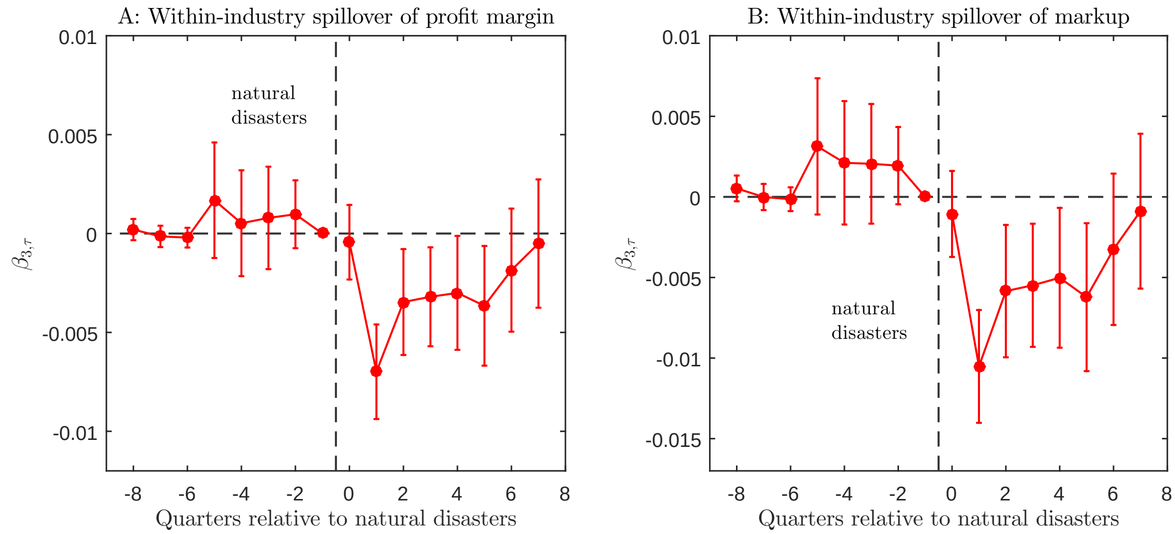
We also examine the dynamics of the spillover effects for profit margin. Because data



Note: This figure plots the within-industry spillover effects of distress risk around major natural disasters. For each treated firm (i.e., the firm whose headquarter or any of its major establishments is located in a county that is negatively affected by major natural disasters), we match it with up to five non-treated peer firms in the same four-digit SIC industry. We require that the matched peer firms are not suppliers or customers of the treated firms. For each major natural disaster shock, we include six yearly observations (i.e., 3 years before and 3 years after a major natural disaster) for the treated firms and their matched non-treated peers in the analysis. To estimate the dynamics of the spillover effect, we consider the yearly regression specification as follows: $Y_{i,t} = \sum_{\tau=-3}^{2} \beta_{1,\tau} \times Treat_{i,t} \times ND_{i,t-\tau} + \beta_2 \times Treat_{i,t} + \sum_{\tau=-3}^{2} \beta_{3,\tau} \times ND_{i,t-\tau} + \beta_4 Ln(1+n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}$. The dependent variables ($Y_{i,t}$) in panels A to D are the distress risk, the distance to default, the bond yield spread (in percent), and the CDS spread (in percent), respectively. $Treat_{i,t}$ is an indicator variable that equals 1 if firm i is a treated firm. $ND_{i,t-\tau}$ is an indicator variable that equals 1 if firm i (when firm i is a treated firm) or the treated firm to which firm i is matched (when firm i is a matched non-treated firm) experiences natural disaster shocks in year $t-\tau$. $Ln(1+n(\mathcal{C}_{i,t}))$ captures the strength of cross-industry spillover, and it is the natural log of 1 plus the number of industries that are connected to firm i's industry through competition networks and are shocked by natural disasters in year t. The term θ_i represents firm fixed effects, and the term δ_t represents year fixed effects. When running the regression, we impose $\beta_{1,-1} = \beta_{3,-1} = 0$ to avoid collinearity in categorical regressions, and by doing this, we set the years immediately preceding the disaster years as the benchmark. The sample of this figure spans from 1994 to 2018. We plot estimated coefficients $\beta_{3,\tau}$ with $\tau = -3, -2, \cdots, 2$, as well as their 90% confidence intervals with standard errors clustered at the firm level. The vertical dashed lines represent the occurrence of major natural disasters.

Figure 8: Within-industry spillover effects of distress risk.

for the measures of profit margin and markup can be computed from Compustat at a quarterly frequency, we follow Barrot and Sauvagnat (2016) in showing the quarterly dynamic effects. As shown in Figure 9, a reduction in profit margin and markup takes place within two quarters after the occurrence of natural disasters. There is no significant change in profit margin or markup prior to natural disaster shocks, which again provides evidence supporting the parallel trend assumption for the DID analysis. The spillover effects in profitability last for around 2 years, a time window that is roughly consistent



Note: This figure plots the within-industry spillover effects of profit margin around major natural disasters. For each treated firm (i.e., the firm whose headquarter or any of its major establishments is located in a county that is negatively affected by major natural disasters), we match it with up to 10 non-treated peer firms in the same four-digit SIC industry. Because the quarterly data are noisier than the yearly data, we use a larger matching ratio between the matched peer firms and treated firms. We require that the matched peer firms are not suppliers or customers of the treated firms. For each firm, we include 16 quarterly observations (i.e., 8 quarters before and 8 quarters after a major natural disaster) in the analysis. To estimate the dynamics of the spillover effect, we consider the quarterly regression specification as follows: $Y_{i,t} = \sum_{\tau=-8}^{7} \beta_{1,\tau} \times Treat_{i,t} \times ND_{i,t-\tau} + \beta_2 \times Treat_{i,t} + \sum_{\tau=-8}^{7} \beta_{3,\tau} \times ND_{i,t-\tau} + \beta_4 Ln(1 + n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}$. The dependent variable ($Y_{i,t}$) is the gross profit margin ($PM_{i,t}$) and markup ($Markup_{i,t}$) in panels A and B, respectively. $Treat_{i,t}$ is an indicator variable that equals 1 if firm i is a treated firm. $ND_{i,t-\tau}$ is an indicator variable that equals 1 if firm i (when firm i is a treated firm) or the treated firm to which firm i is matched (when firm i is a matched non-treated firm) experiences natural disaster shocks in quarter $t-\tau$. $Ln(1+n(\mathcal{C}_{i,t}))$ captures the strength of cross-industry spillover effect, and it is the natural log of 1 plus the number of industries connected to firm i's industry through competition networks and shocked by natural disasters in year t. The term θ_i represents firm fixed effects, and the term δ_t represents quarter fixed effects. When running the regression, we impose $\beta_{1,-1} = \beta_{3,-1} = 0$ to avoid collinearity in categorical regressions, and by doing this, we set the quarters immediately preceding the disaster quarters as the benchmark. The sample of this figure spans from 1994 to 2018. We plot estimated coefficients $\beta_{3,\tau}$ with $\tau = -8, -7, \cdots, 7$, as well as their 90% confidence intervals with standard errors clustered at the firm level. The vertical dashed lines represent the occurrence of major natural disasters.

Figure 9: Within-industry spillover effects of profit margin.

with other natural disaster impacts documented in the literature.[14]

Robustness Checks. We perform a battery of robustness checks. In Table OA.9 of the Online Appendix, we show that our findings are robust to alternative matching ratios between the treated firms and non-treated peer firms (i.e., one to ten and one to three). In Table OA.10 of the Online Appendix, we show that our findings are robust to alternative industry classifications. Specifically, we choose peer firms based on the text-based network industry classifications (TNIC) developed by Hoberg and Phillips (2010, 2016), and we show that the within-industry spillover effects remain robust. In Table OA.11 of the Online Appendix, we show that the within-industry spillover effects remain robust when

[14]For example, Barrot and Sauvagnat (2016) show that natural disaster shocks dampen sales growth for the customers of treated firms for about 2 years. In Section 4.3.3, we show that the within-industry spillover effect we document here cannot be explained by the production network externality, a channel that is the main focus of Barrot and Sauvagnat (2016).

Table 14: Heterogeneity across industries with different levels of entry barriers.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
Industry entry barriers	High	Low	High	Low	High	Low	High	Low
$Treat_{i,t} \times Post_{i,t}$	0.017	0.027*	−0.047	−0.120*	0.000	−0.003	−0.001	−0.004
	[0.955]	[1.682]	[−0.667]	[−1.776]	[0.061]	[−0.825]	[−0.066]	[−0.779]
$Treat_{i,t}$	0.003	−0.025	−0.036	0.170**	−0.004	0.004	−0.003	0.002
	[0.161]	[−1.584]	[−0.507]	[2.526]	[−0.713]	[0.876]	[−0.346]	[0.376]
$Post_{i,t}$	0.087***	0.020**	−0.178***	−0.051	−0.016***	0.002	−0.023***	0.002
	[6.821]	[1.962]	[−3.647]	[−1.295]	[−2.863]	[0.792]	[−3.225]	[0.664]
$Ln(1+n(\mathcal{C}_{i,t}))$	0.068***	−0.021*	−0.138**	−0.041	−0.021***	0.002	−0.027***	0.003
	[4.653]	[−1.795]	[−2.562]	[−0.812]	[−4.039]	[0.678]	[−4.262]	[0.907]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61456	68595	52995	57509	64598	70413	64558	70340
R-squared	0.598	0.573	0.701	0.674	0.720	0.798	0.765	0.809
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.002	$<10^{-3}$	0.727	$<10^{-3}$	0.706

Note: This table examines the within-industry spillover effects following major natural disasters across industries with different levels of entry barriers. The regression specification is: $Y_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1 + n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}$. Definition for the dependent and independent variables are given in Table 12. We present results from DID analysis in industries with high entry barriers (top tertile) and low entry barriers (middle and bottom tertiles). The entry barrier of a four-digit SIC industry is measured by the sales-weighted average of fixed assets across firms in this industry. We sort industries into tertiles based on the industry-level entry barriers 1 year prior to natural disaster shocks. The number of firm-year observations in the subsample of low entry barriers is not exactly twice that in the subsample of high entry barriers because the number of treated firms is not uniformly distributed across industries. The sample spans from 1994 to 2018. Standard errors are clustered at the firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

we use an alternative measure, $ln(1 + \mathcal{D}_{i,t})$, to capture the cross-industry spillover effects, which is the natural log of 1 plus the average amount of property damage (in millions of dollars) caused by major natural disasters in year t across industries that are connected to firm i's industry through competition networks, denoted by $\mathcal{D}_{i,t}$. In Table OA.12 of the Online Appendix, we show that the within-industry spillover effects remain robust when we use net profit margin to measure profitability.

Because we have focused on the major natural disasters in the US, it is helpful to check whether our findings of the spillover effects are indeed driven by industries whose profits mainly come from the domestic market. This is because firms primarily compete in the foreign markets should be less likely affected by shocks in the US. In Table OA.13 of the Online Appendix, we exclude from the DID analysis the industries with the highest fraction of foreign profits (i.e., top quintile), and we show that the spillover effects remain robust. In fact, the economic magnitudes of the spillover effects become larger compared to those in Table 12. These findings further validate our identification strategy.

4.3.2 Heterogeneity in Spillover Effects within An Industry

We expect the within-industry spillover effects to be stronger in industries with higher entry barriers. As shown by Chen et al. (2020), firms will compete more aggressively with their distressed peers in these industries because the winners of a price war in these industries enjoy larger economic rents after pushing out their competitors who are unlikely to be replaced by new entrants. To test this prediction, we measure the entry barrier of a four-digit SIC industry using the sales-weighted average fixed assets, following previous studies (e.g., Li, 2010). We then sort industries into tertiles based on the industry-level entry barriers 1 year prior to natural disaster shocks and then examine the within-industry spillover effects in the industries with high entry barriers (top tertile) and low entry barriers (middle and bottom tertiles) using DID analysis. Table 14 tabulates the results. Consistent with our prediction, we find that the within-industry spillover effects captured by coefficient β_3 mostly concentrate in industries with high entry barriers, while they are almost absent in industries with low entry barriers. Examining the patterns of total treatment effects (captured by the sum of β_1 and β_3) offers additional insights on the heterogeneity of spillover effects. The total treatment effects are significant for all industries when we examine the distress levels of treated firms (see the last row of columns 1 to 4 in Table 14). This is because natural disasters make the treated firms more distressed in all industries. However, the total treatment effects for profit margin are only significant in industries with high entry barriers (see the last row of columns 5 to 8 in Table 14), suggesting that the distressed treated firms engage in price competition only in industries with high entry barriers. As illustrated by our model in the collusive Nash equilibrium, it is the intensified product market competition that increases the distress levels of the industry peers. Consistent with our model, we observe strong within-industry spillover effects of distress only in industries with high entry barriers.

We also expect the within-industry spillover effects to be stronger in industries whose market leaders are more likely to tacitly collude with each other. To test this prediction, we proxy the prevalence of tacit collusion by the levels profitability comovement, which is the average pairwise correlation of the net profitability for top four firms ranked by sales in this industry. The pairwise correlation between two firms is calculated as the correlation coefficient of their net profitability in the previous ten years. We then sort industries into two groups based on the industry-level profitability comovement 1 year prior to natural disaster shocks and then examine the within-industry spillover effects in the industries with high profitability comovement (above median) and low profitability comovement (below median) using DID analysis. Table 15 tabulates the results. Consistent with our prediction, we find that the within-industry spillover effects captured by coefficient β_3 mostly concentrate in industries with high profitability comovement, while they are much weaker in industries with low profitability comovement.

Finally, we expect the within-industry spillover effects to be stronger in industries with

Table 15: Heterogeneity across industries with different levels of profitability comovement.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
Profitability comovement	High	Low	High	Low	High	Low	High	Low
$Treat_{i,t} \times Post_{i,t}$	0.013	0.028	−0.085	−0.087	−0.006	0.004	−0.007	0.004
	[0.755]	[1.565]	[−1.249]	[−1.190]	[−0.877]	[0.755]	[−0.875]	[0.681]
$Treat_{i,t}$	−0.015	−0.023	0.065	0.171**	−0.004	0.002	−0.001	0.001
	[−0.864]	[−1.294]	[0.880]	[2.089]	[−0.726]	[0.399]	[−0.100]	[0.083]
$Post_{i,t}$	0.071***	0.039***	−0.181***	−0.034	−0.011**	−0.003	−0.017**	−0.004
	[5.557]	[3.381]	[−3.694]	[−0.744]	[−2.116]	[−0.965]	[−2.443]	[−1.089]
$Ln(1+n(\mathcal{C}_{i,t}))$	0.038***	0.001	−0.067	−0.067	−0.016***	0.002	−0.022***	0.002
	[2.860]	[0.075]	[−1.353]	[−1.383]	[−3.738]	[0.481]	[−3.877]	[0.555]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	60279	60576	52734	49305	63231	62122	63180	62062
R-squared	0.590	0.606	0.704	0.696	0.706	0.803	0.769	0.814
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.043	$<10^{-3}$	0.867	$<10^{-3}$	0.976

Note: This table examines the within-industry spillover effects following major natural disasters across industries with different levels of profitability comovement. The regression specification is: $Y_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1 + n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}$. Definition for the dependent and independent variables are given in Table 12. We present results from DID analysis in industries with high profitability comovement (above median) and low profitability comovement (below median). The profitability comovement of a four-digit SIC industry is measured as the average pairwise correlation of the net profitability for top four firms ranked by sales in this industry. The pairwise correlation between two firms is calculated as the correlation coefficient of their net profitability in the previous ten years. The sample spans from 1994 to 2018. Standard errors are clustered at the firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

worse economic and financial conditions prior to natural disasters. This is because firms in these industries are effectively less patient and thus have more incentive to compete after the arrival of negative shocks. To test this prediction, we measure the economic condition of a four-digit SIC industry using the change of the return on assets (ROA) in the industry from the previous year. We then sort industries into two groups based on the industry-level economic conditions 1 year prior to the natural disaster shocks and then examine the within-industry spillover effects in the industries with good economic conditions (top half) and bad economic conditions (bottom half) using DID analysis. Panel A of Table 16 tabulates the results. Consistent with our prediction, we find that the within-industry spillover effects captured by coefficient β_3 mostly concentrate in industries with bad economic conditions, while they are almost absent in industries with good economic conditions. The total treatment effects are significant in all industries when we examine the distress levels of treated firms (see the last row of columns 1 to 4 in panel A), but they are only significant in industries with bad economic conditions when we examine the profit margins of the treated firms (see the last row of columns 5 to 8 in panel A). These findings are consistent with the prediction of our model, and they suggest that distressed treated firms engage in price competition only in industries with bad economic conditions, which leads to distress propagation to their industry peers.

We measure the financial constraint of a four-digit SIC industry using the sales-

Table 16: Heterogeneity across industries with different economic and financial conditions.

	Panel A: Heterogeneity across industry economic conditions							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
Industry economic conditions	Bad	Good	Bad	Good	Bad	Good	Bad	Good
$Treat_{i,t} \times Post_{i,t}$	0.027	0.021	−0.070	−0.146**	−0.002	−0.002	−0.008	0.002
	[1.500]	[1.207]	[−1.013]	[−2.142]	[−0.340]	[−0.279]	[−0.985]	[0.357]
$Treat_{i,t}$	−0.035**	−0.020	0.129*	0.165**	0.001	0.001	0.001	0.001
	[−1.971]	[−1.186]	[1.685]	[2.200]	[0.112]	[0.123]	[0.106]	[0.071]
$Post_{i,t}$	0.078***	0.023*	−0.209***	0.004	−0.017***	0.005	−0.019***	0.002
	[6.115]	[1.864]	[−4.374]	[0.087]	[−3.192]	[1.564]	[−2.866]	[0.494]
$Ln(1 + n(\mathcal{C}_{i,t}))$	0.034***	0.004	−0.120***	−0.092**	−0.014***	−0.002	−0.018***	−0.004
	[2.966]	[0.370]	[−2.635]	[−2.034]	[−3.543]	[−0.584]	[−3.784]	[−0.904]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	64345	61829	54606	52132	66381	64702	66304	64664
R-squared	0.607	0.583	0.695	0.698	0.768	0.773	0.789	0.805
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	0.002	$<10^{-3}$	0.012	$<10^{-3}$	0.340	$<10^{-3}$	0.365

	Panel B: Heterogeneity across industry financial constraints							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
Industry financial constraints	High	Low	High	Low	High	Low	High	Low
$Treat_{i,t} \times Post_{i,t}$	0.012	0.037**	0.046	−0.096	0.000	0.000	−0.001	−0.000
	[0.470]	[2.103]	[0.458]	[−1.281]	[0.039]	[0.092]	[−0.099]	[−0.011]
$Treat_{i,t}$	−0.024	−0.033**	0.084	0.152*	0.005	0.008*	0.012	0.011*
	[−0.962]	[−1.987]	[0.809]	[1.929]	[0.706]	[1.658]	[1.158]	[1.894]
$Post_{i,t}$	0.115***	0.002	−0.302***	−0.063	−0.029***	0.004	−0.036***	0.004
	[5.526]	[0.166]	[−4.034]	[−1.352]	[−2.934]	[1.208]	[−3.003]	[1.218]
$Ln(1 + n(\mathcal{C}_{i,t}))$	0.035**	−0.001	−0.120**	−0.087*	−0.019***	−0.006*	−0.022***	−0.007*
	[1.984]	[−0.070]	[−2.026]	[−1.674]	[−3.045]	[−1.916]	[−2.783]	[−1.648]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31326	59310	27545	48609	32923	61851	32911	61792
R-squared	0.625	0.608	0.735	0.707	0.730	0.805	0.787	0.827
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	0.007	0.002	0.009	$<10^{-3}$	0.277	$<10^{-3}$	0.354

Note: This table examines the within-industry spillover effects following major natural disasters across industries with different economic and financial conditions prior to the natural disasters. The regression specification is: $Y_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1 + n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}$. Definitions for the dependent and independent variables are given in Table 12. Panel A presents the results in industries with good economic conditions (top half) and bad economic conditions (bottom half) prior to the natural disasters. The economic condition of a four-digit SIC industry is measured by the change of the return on assets (ROA) in the industry from the previous year. We sort industries into two groups based on the industry-level economic conditions 1 year prior to the natural disaster shocks. Panel B presents the results in industries with high financial constraint (top tertile) and low financial constraint (middle and bottom tertiles) prior to the natural disasters. The financial constraint of a four-digit SIC industry is measured by the sales-weighted average of the delay investment score in the industry (Hoberg and Maksimovic, 2015). We sort industries into tertiles based on the industry-level financial constraints 1 year prior to natural disaster shocks. The sample spans from 1994 to 2018 in panel A, while it spans from 1998 to 2016 in panel B due to shorter sample period of the delay investment score. Standard errors are clustered at the firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

weighted average of the delay investment score (Hoberg and Maksimovic, 2015). This measure is constructed based on textual analysis of firms' 10-K filings and thus captures the degree of financial constraints directly. We sort industries into tertiles based on the industry-level financial constraints 1 year prior to natural disaster shocks and then examine the within-industry spillover effects in the industries with high financial constraints (top tertile) and low financial constraints (middle and bottom tertiles) using DID analysis. Panel B of Table 16 tabulates the results. Again, consistent with our prediction, we find that the within-industry spillover effects mostly concentrate in industries with high financial constraints. The total treatment effects are significant in all industries when we examine the distress levels of treated firms (see the last row of columns 1 to 4 in panel B) but they are only significant in industries with high financial constraints when we examine the profit margins of the treated firms (see the last row of columns 5 to 8 in panel B). These findings suggest that distressed treated firms engage in price competition only in industries with high levels of financial constraints.

4.3.3 Testing Alternative Explanations

In this section, we test a list of alternative explanations. We show that the within-industry spillover effects we have documented above are unlikely explained by demand commonality, production network externality, credit lending channel, or blockholder commonality.

Demand Commonality. The first alternative explanation that we test is demand commonality. This alternative explanation argues that natural disasters lead to negative demand shocks directly hurting both the treated firms and their industry peers, and thus the within-industry spillover effects can be potentially explained by demand commonality. We present a set of evidence suggesting that this is unlikely to be the case.[15]

We first require the matched peer firms to be geographically far from the natural disaster areas in the DID analysis. Specifically, we require the matched peer firms to have headquarters and major establishments located more than 100 miles from any zip code negatively affected by major natural disasters in a given year. By doing this, we exclude a set of peer firms that are more susceptible to the negative demand shocks caused by natural disasters. As shown in panel A of Table OA.14 in the Online Appendix, our findings of the within-industry spillover effects remain robust.

Although a matched peer firm is geographically far from the natural disaster areas,

[15]Note that we do not aim to rule out the possibility that negative demand shocks make firms directly affected by natural disasters more distressed. In fact, demand shock is one of the channels through which natural disasters can lead to economic and financial distress of treated firms. The alternative explanation we aim to rule out here is that the demand shocks caused by natural disasters also make the non-treated industry peers more distressed. In other words, demand commonality drives the within-industry spillover effects in the alternative explanation.

its customers may mainly come from these areas, and thus, this peer firm may still be directly affected by the demand shocks. To rule out this possibility, we further require the matched peer firms to have no customers negatively affected by natural disasters. We consider both business customers and individual consumers in our analysis. We identify firms' business customers and their geographic locations using Compustat customer segment data and Factset Revere data. We identify firms' individual consumers and their geographic locations using a detailed dataset from Baker, Baugh and Sammon (2020), which provides firms' sales to individual consumers at the city level.[16] In panel B of Table OA.14, we require that the matched peer firms to (i) be far away from natural disaster areas, (ii) have no business customers affected by natural disasters, and (iii) have no individual customers from areas affected by natural disasters. The within-industry spillover effects are still robust, suggesting that demand commonality is unlikely to be the main driver for the within-industry spillover effects.

Production Network Externality. The second alternative explanation that we test is production network externality. This alternative explanation argues that the within-industry spillover effects are driven by spillovers along supply chains. We present a set of evidence suggesting that this is unlikely to be the case.

First, we note that in the baseline DID test shown in Table 12, we have already required the matched peer firms not to be either suppliers or customers of the treated firms. The fact that we find strong within-industry spillover effects in Table 12 suggests that these effects are unlikely caused by suppliers or customers of the treated firms. Second, to strengthen our results, in Table OA.15 of the Online Appendix, we further require that the matched peer firms do not share any common customers or any common suppliers with treated firms. By doing so, we rule out the alternative explanation that the within-industry spillover effects are caused by common customers or suppliers of both treated firms and their industry peers.[17] Moreover, we also remove the matched peer firms that are related to the treated firms vertically in the DID analysis. By doing so, we drop firms that are potential customers or suppliers of the treated firms from the pool of matched firms. We

[16] The full dataset contains more than two million users from 2010 to 2015. We make the assumption that firms with sales to individual consumers in a city in 2010 (2015) have sales to individual consumers in this city before 2010 (after 2015).

[17] In this alternative explanation, natural disaster shocks make the customers of the treated firms more distressed, which in turn increases the distress risk of other suppliers of these customer firms. Similarly, natural disaster shocks can make the suppliers of the treated firms more distressed, which in turn increases the distress risk of other customers of these supplier firms. If the firms shocked by natural disasters and their peer firms share common customers or suppliers, it is possible that the observed within-industry spillover effects are driven by product network externality rather than by the competition mechanism illustrated by our model.

define two firms as connected vertically if their vertical relatedness scores are ranked in the top 10% among the scores of all firm pairs (see, Frésard, Hoberg and Phillips, 2020). As shown in Table OA.15, the within-industry spillover effects remain robust.

Lender Commonality. The third alternative explanation that we test is the channel of lender commonality. This alternative explanation argues that non-treated industry peers may borrow from lenders that have heavy exposure to disaster firms, and as a result these firms suffer from financial distress when their lenders are negatively affected.

To test this possibility, we require the matched peer firms to share no common lenders with the treated firms in the DID analysis. We also control for firms' exposure to natural disasters through lenders ($Lender\_Exposure_{i,t-1}$). We identify the borrower-lender relationship and construct $Lender\_Exposure_{i,t-1}$ using the LPC DealScan database in two steps. First, we find out each lender l's exposure to natural disasters in year t, which is the outstanding loans issued by lender l from $t-5$ to $t-1$ to firms that experience natural disasters in year t normalized by the total amount of outstanding loans issued by lender l from $t-5$ to $t-1$.[18] Second, for each firm i, we compute $Lender\_Exposure_{i,t-1}$ by averaging the lender-level exposure across all lenders of the firm. The average is weighted based on the amount of outstanding loans borrowed from different lenders. As shown in Table OA.16 of the Online Appendix, our findings remain robust after controlling for $Lender\_Exposure_{i,t-1}$ and removing the matched peer firms that share any common lender with the treated firms, suggesting that lender commonality unlikely explains the within-industry spillover effects.[19]

Institutional Blockholder Commonality. The last alternative explanation that we test is institutional blockholder commonality. This alternative explanation argues that when firms are hit by natural disasters, their institutional blockholders such as mutual funds may experience fire sales (e.g., Coval and Stafford, 2007). If these institutional blockholders also hold a large number of shares of firms' industry peers, the stock prices of the peer firms may be negatively affected during the fire sales, which in turn may cause economic and financial distress for these firms.

To test this possibility, we require the matched peer firms to share no common

[18]We focus on loans issued in the preceding 5-year window following the literature (e.g., Bharath et al., 2007). When there is more than one lender funding a loan, we focus on the lead lenders following previous studies (e.g., Schwert, 2018; Chodorow-Reich and Falato, 2021).

[19]Because DealScan data are mainly collected from commitment letters and credit agreements drawn from SEC filings, the database mainly covers medium to large-size loans (e.g., Carey, Post and Sharpe, 1998). We limit our analysis in Table OA.16 of the Online Appendix to the firms covered by the DealScan data because we cannot accurately measure lender exposure for the firms outside of the DealScan universe.

institutional blockholders with the treated firms in the DID analysis based on 13F institutional holdings data. Following previous studies (e.g., Hadlock and Schwartz-Ziv, 2019), we define blockholders of a firm as the owners that hold 5% of the firm's market cap or above. As shown in Table OA.17 of the Online Appendix, the within-industry spillover effects remain robust, suggesting that institutional blockholder commonality unlikely explains our findings.

Controlling for All Alternative Channels Simultaneously. In Table OA.18 of the Online Appendix, we examine the within-industry spillover effects by controlling for multiple alternative channels simultaneously. For each treated firm, we match it with up to five non-treated peer firms in the same four-digit SIC industry. We construct a set dummy variables to label the matched peer firms that share common demand with the treated firms ($Common\_Demand_{i,t}$), that are connected to the treated firms through the production networks ($Production\_Network_{i,t}$), that share common lenders with the treated firms ($Common\_Lender_{i,t}$), and that share common institutional blockholders with the treated firms ($Common\_Lender_{i,t}$). We then add these dummies and their interactions with the $Post_{i,t}$ term to regression specification (4.5). We find that within-industry spillover effects captured by the coefficient for $Post_{i,t}$ remain robust after controlling for all four alternative channels simultaneously.

4.4 Cross-Industry Contagion Effects with Natural Disaster Shocks

In Section 4.3.1 above, we provide some evidence for cross-industry spillover effects. In particular, panel B of Table 12 shows that the coefficient for the cross-industry spillover term (i.e., β_4 in equation 4.5) is statistically significant, with the signs consistent with the predictions of our model in the collusive Nash equilibrium. In this section, we further study cross-industry spillover effects by highlighting the role of the common market leaders in transmitting shocks across industries.

Regression Specifications. We examine cross-industry contagion effects in two steps. In the first step, we estimate the impact of natural disaster shocks of market leaders on the profit margins of common market leaders in the same industry. The dataset is a panel with each cross section containing the industry pairs in which the common market leaders operate. We run the following panel regression using industry pair-year observations:

$$Y_t^{(c_{i,j})} = \sum_{m=1}^{3} \beta_m ND\_mild_{j,t}^{(m)} + \sum_{s=1}^{3} \beta_s ND\_severe_{j,t}^{(s)} + \varepsilon_t^{(c_{i,j})}. \tag{4.7}$$

Dependent variable $Y_t^{(c_{i,j})}$ is the distress risk and profit margin of common market leader $c_{i,j}$, which is a market leader in both industry i and industry j. The independent variables, $ND\_mild_{j,t}^{(m)}$, are indicator variables that equal 1 if the m^{th} $(m = 1, 2, 3)$ largest firm (ranked by sales) in industry j in year t experiences mild damage during natural disaster shocks. Similarly, $ND\_severe_{j,t}^{(s)}$, are indicator variables that equal 1 if the s^{th} $(s = 1, 2, 3)$ largest firm (ranked by sales) in industry j in year t experiences severe damage during natural disaster shocks.[20] We include both the $ND\_mild_{j,t}^{(m)}$ and $ND\_severe_{j,t}^{(s)}$ dummies to reflect the fact that the impact of natural disasters depends on the magnitude of damage caused.

Our regression specification (4.7) essentially estimates the impact of idiosyncratic natural disaster shocks to the top three market leaders in industry j on the distress risk and profit margin of the common market leader (i.e., $c_{i,j}$) in year t. We compute fitted value $\widehat{IdShock}_{j,t}^{(c_{i,j})}$ as follows:

$$\widehat{IdShock}_{j,t}^{(c_{i,j})} = \widehat{Y}_t^{(c_{i,j})} = \sum_{m=1}^{3} \hat{\beta}_m ND\_mild_{j,t}^{(m)} + \sum_{s=1}^{3} \hat{\beta}_s ND\_severe_{j,t}^{(s)}. \tag{4.8}$$

Fitted value $\widehat{IdShock}_{j,t}^{(c_{i,j})}$ intuitively captures changes in the distress risk and profit margin of common market leader $c_{i,j}$ attributed to idiosyncratic shocks of the top three market leaders in industry j.

In the second step, we estimate the cross-industry distress contagion effect based on the first-step estimates. In particular, for each industry i in year t, we identify all industries $j \in \mathcal{I}_{i,t}$ that are connected to industry i through common market leaders. After that, we construct the changes in distress risk or profit margin of common market leaders in industry i, attributed to idiosyncratic shocks to market leaders in other industries as follows:

$$\widehat{IdShock}_{-i,t} = \frac{1}{n(\mathcal{I}_{i,t})} \sum_{j \in \mathcal{I}_{i,t}} \widehat{IdShock}_{j,t}^{(c_{j,i})}, \tag{4.9}$$

where variable $n(\mathcal{I}_{i,t})$ is the number of industries in set $\mathcal{I}_{i,t}$.

We then run the following panel regression using all industry-year observations in the

[20]We define $ND\_mild_{j,t}^{(m)}$ as 1 if the county in which the m^{th} $(m = 1, 2, 3)$ largest firm is located experiences more than \$0.25 million but less than \$50 million in property losses. We define $ND\_severe_{j,t}^{(s)}$ as 1 if the county in which the s^{th} $(s = 1, 2, 3)$ largest firm is located experiences more than \$50 million in property losses.

Table 17: Distress spillover effects across industries

	Panel A: Construction of $\widehat{IdShock}_{j,t}^{(c_{i,j})}$ (first step)			
	(1) $Distress_t^{c_{i,j}}$	(2) $DD_t^{c_{i,j}}$	(3) $PM_t^{c_{i,j}}$	(4) $Markup_t^{c_{i,j}}$
$ND\_mild_{j,t}^{(1)}$	−0.038	0.258	−0.012*	−0.020*
	[−1.191]	[1.100]	[−1.694]	[−1.798]
$ND\_severe_{j,t}^{(1)}$	0.149**	−1.277***	−0.032***	−0.047***
	[2.480]	[−3.189]	[−2.792]	[−2.691]
$ND\_mild_{j,t}^{(2)}$	0.051	−0.135	−0.007	−0.010
	[1.635]	[−0.636]	[−1.054]	[−1.038]
$ND\_severe_{j,t}^{(2)}$	0.057*	−0.200	−0.030***	−0.047***
	[1.943]	[−1.449]	[−2.749]	[−2.881]
$ND\_mild_{j,t}^{(3)}$	0.028	0.040	0.004	0.008
	[0.905]	[0.193]	[0.651]	[0.750]
$ND\_severe_{j,t}^{(3)}$	0.122**	−0.927***	−0.030***	−0.049***
	[2.156]	[−2.706]	[−2.999]	[−3.299]
Observations	7058	6882	7166	7166
R-squared	0.003	0.004	0.006	0.006

	Panel B: Cross-industry contagion (second step)							
	(1) $Distress_{i,t}^{(-c)}$	(2)	(3) $DD_{i,t}^{(-c)}$	(4)	(5) $PM_{i,t}^{(-c)}$	(6)	(7) $Markup_{i,t}^{(-c)}$	(8)
$\widehat{IdShock}_{-i,t}$	0.798**	0.765**	0.519**	0.483**	0.547**	0.548**	0.540**	0.544**
	[2.305]	[2.232]	[2.537]	[2.244]	[2.392]	[2.355]	[2.243]	[2.249]
$\widehat{IdShock}_{-i,t} \times Forward\_Con_{-i,i,t}$		−14.069		3.746		−23.335		−32.280
		[−0.265]		[0.199]		[−1.098]		[−1.287]
$\widehat{IdShock}_{-i,t} \times Backward\_Con_{-i,i,t}$		56.248		18.988		20.027		22.222
		[0.808]		[0.729]		[0.949]		[1.099]
$Forward\_Con_{-i,i,t}$		−100.239		−17.781		7.840		14.219
		[−0.250]		[−0.148]		[1.171]		[1.408]
$Backward\_Con_{-i,i,t}$		425.600		−120.534		−6.318		−8.858
		[0.808]		[−0.739]		[−0.979]		[−1.140]
Observations	5152	5148	5020	5016	5264	5260	5264	5260
R-squared	0.001	0.005	0.001	0.002	0.001	0.003	0.001	0.005

Note: This table reports the results of the two-step estimation of the cross-industry distress spillover effects. In panel A, we estimate the first-step specification: $Y_t^{(c_{i,j})} = \sum_{m=1}^{3} \beta_m ND\_mild_{j,t}^{(m)} + \sum_{s=1}^{3} \beta_s ND\_severe_{j,t}^{(s)} + \varepsilon_t^{(c_{i,j})}$ and denote the fitted value by $\widehat{IdShock}_{i,t}^{(c_{i,j})}$. The dependent variables $Distress_t^{(c_{i,j})}$, $DD_t^{(c_{i,j})}$, $PM_t^{(c_{i,j})}$, and $Markup_t^{(c_{i,j})}$ are the distress risk, distance to default, profit margin, and markup of common market leader $c_{i,j}$, respectively. The independent variables, $ND\_mild_{j,t}^{(m)}$, are indicator variables that equal 1 if the m^{th} $(m = 1, 2, 3)$ largest firm (ranked by sales) in industry j in year t experiences mild damage during natural disaster shocks. Similarly, $ND\_severe_{j,t}^{(s)}$, are indicator variables that equal 1 if the s^{th} $(s = 1, 2, 3)$ largest firm (ranked by sales) in industry j in year t experiences severe damage during natural disaster shocks. In panel B, we use the fitted value of the first step to construct independent variable $\widehat{IdShock}_{-i,t}$ as the simple average of $\widehat{IdShock}_{j,t}^{(c_{j,i})}$ over all industries connected to industry i through competition networks. The regression specification is: $Y_{i,t}^{(-c)} = \beta_1 \widehat{IdShock}_{-i,t} + \beta_2 \widehat{IdShock}_{-i,t} \times Forward\_Con_{-i,i,t} + \beta_3 \widehat{IdShock}_{-i,t} \times Backward\_Con_{-i,i,t} + \beta_4 Forward\_Con_{-i,i,t} + \beta_5 Backward\_Con_{-i,i,t} + \varepsilon_{i,t}$. The industry-level dependent variables $Y_{i,t}^{(-c)}$ are sales weighted across all firms excluding the common market leaders in year t. Variables $Forward\_Con_{-i,i,t}$ and $Backward\_Con_{-i,i,t}$ are the simple average of $Forward\_Con_{j,t}^{(c_{j,i})}$ and $Backward\_Con_{j,t}^{(c_{j,i})}$ over all industries (indexed by j) connected to industry i through competition networks, respectively. $Forward\_Con_{j,t}^{(c_{j,i})}$ and $Backward\_Con_{j,t}^{(c_{j,i})}$ are the forward- and backward- connectedness measures between industry j and industry i (Fan and Lang, 2000). $Forward\_Con_{-i,i,t}$ captures the value of industry i's output used to produce \$1 of output for the industries connected through competition networks. $Backward\_Con_{-i,i,t}$ captures the output value of the connected industries used to produce \$1 of industry i's output. The sample spans the period from 1994 to 2018. Standard errors are clustered at the industry level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

competition network:

$$Y_{i,t}^{(-c)} = \beta_1 \widehat{IdShock}_{-i,t} + \varepsilon_{i,t}, \tag{4.10}$$

where $Y_{i,t}^{(-c)}$ is the distress risk or profit margin of industry i sales-weighted across firms in industry i excluding the common market leaders in year t. Coefficient β_1 is the coefficient of interest, and it intuitively captures how industry i's profit margin responds to other industries' idiosyncratic shocks that propagate to industry i through some common market leaders.

Cross-Industry Contagion Effects. We present the estimation results for the cross-industry contagion analysis in Table 17 and the corresponding summary statistics in Table OA.19 of the Online Appendix. Panel A of Table 17 presents the results from the first-step regressions. We find that the common leaders' distress risk (profit margin) is positively (negatively) associated with the natural disaster shocks to the top market leaders in the same industries. This pattern is more pronounced for severe natural disaster shocks. Panel B presents the second-step estimates on the cross-industry contagion effect. The coefficient of $\widehat{IdShock}_{-i,t}$ is positive and statistically significant, indicating that the distress risk and profit margin of industry i are positively associated with other industries' idiosyncratic shocks that propagate to industry i through common market leaders. In summary, our results suggest that adverse idiosyncratic shocks in one industry can be transmitted to another industry through the common leaders that operate in both industries. These findings are consistent with the predictions of our model in the collusive Nash equilibrium.

We further show that the cross-industry contagion results cannot be explained away by production network externality. Specifically, we control for the interaction between industry-level connectedness and predicted idiosyncratic shocks. The industry-level connectedness measures are constructed following Fan and Lang (2000), and they capture the production network connectedness between two industries. As shown by panel B of Table 17, the coefficient for the predicted idiosyncratic shocks remains positive and statistically significant when the production network connectedness measure is zero, suggesting that the cross-industry contagion effect cannot be explained away by production network externality.

In addition, we show that the cross-industry spillover effects remain robust after excluding industries whose common market leaders are mainly superstar firms (i.e., top 50 firms ranked by sales). Specifically, we exclude an industry from our analysis if half or more than half of the links between this industry and other industries in the competition network are connected through superstar firms. As shown in Table OA.20 of the Online Appendix, the coefficient of $\widehat{IdShock}_{-i,t}$ remains positive and statistically significant after dropping these industries, suggesting that the cross-industry spillover effects are not simply driven by superstar firms.

Heterogeneity in Contagion Effects across Industries. In our model with the collusive Nash equilibrium, cross-industry contagion effects rely critically on proper functioning of the internal capital market of common leaders. When the internal capital market breaks down, the distress of one segment of a given common leader will not lead to changes of product market behaviors in other segments of the common leader, because different segments do not share the balance sheet as a whole. Therefore, we expect cross-industry contagion effects to be stronger in industries with higher efficiency of the internal capital markets of common leaders. To test this prediction, we measure the efficiency of internal capital market of a four-digit SIC industry using the absolute value added by allocation in Rajan, Servaes and Zingales (2000) averaged across all common leaders in this industry. We sort industries into tertiles based on the industry-level efficiency 1 year prior to natural disaster shocks and then examine cross-industry contagion effects in the industries with high efficiency (top and middle tertile) and low efficiency (bottom tertile) of internal capital market. Table 18 tabulates the results. Consistent with the prediction of our model in the collusive Nash equilibrium, we find that cross-industry contagion effects captured by the coefficient of $\widehat{IdShock}_{-i,t}$ mostly concentrate in industries with high efficiency of internal capital market of common leaders, while they are almost absent in industries with low efficiency of internal capital market of common leaders. These findings are robust both with and without controlling for production network connectedness.

4.5 Evidence from Two Additional Quasi-Natural Experiments

We provide collaborative evidence from two additional quasi-natural experiment settings in this section. In Section 4.5.1, we exploit the setting of the AJCA tax holiday to investigate the impact of a reduction in financial distress (i.e., positive distress shock) on industry peers. In Section 4.5.2, we exploit the setting of the Lehman crisis and examine the impact of an increase in financial distress (i.e., negative distress shock) on industry peers. Different from natural disasters, both the AJCA tax holiday and the Lehman crisis are one-time economy-wide shocks. Therefore, we use the econometric specification of heterogeneous average spillover effects across different industries to identify the spillover effects.

Table 18: Heterogeneous cross-industry spillover effects across efficiency of the internal capital markets of common leaders.

	Panel A: Without controlling for production network connectedness							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress^{(-c)}_{i,t}$		$DD^{(-c)}_{i,t}$		$PM^{(-c)}_{i,t}$		$Markup^{(-c)}_{i,t}$	
Internal capital market efficiency	High	Low	High	Low	High	Low	High	Low
$\widehat{IdShock}_{-i,t}$	0.898**	0.498	0.680***	0.073	0.772***	0.195	0.733**	0.215
	[2.339]	[0.701]	[2.630]	[0.208]	[2.831]	[0.545]	[2.536]	[0.587]
Observations	3335	1609	3266	1554	3406	1640	3406	1640
R-squared	0.001	0.001	0.002	0.001	0.003	0.001	0.002	0.001
	Panel B: Controlling for production network connectedness							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress^{(-c)}_{i,t}$		$DD^{(-c)}_{i,t}$		$PM^{(-c)}_{i,t}$		$Markup^{(-c)}_{i,t}$	
Internal capital market efficiency	High	Low	High	Low	High	Low	High	Low
$\widehat{IdShock}_{-i,t}$	0.839**	0.458	0.635**	−0.003	0.780***	0.168	0.715**	0.241
	[2.072]	[0.606]	[2.342]	[−0.007]	[2.812]	[0.447]	[2.447]	[0.644]
$\widehat{IdShock}_{-i,t} \times Forward\_Con_{-i,i,t}$	3.819	2.869	9.212	17.267	−22.076	−30.671	−24.986	−40.425
	[0.039]	[0.064]	[0.257]	[0.643]	[−0.774]	[−1.371]	[−0.873]	[−1.587]
$\widehat{IdShock}_{-i,t} \times Backward\_Con_{-i,i,t}$	108.290	−44.596	27.342	14.047	−0.222	50.533*	10.602	41.902
	[1.145]	[−0.488]	[0.852]	[0.323]	[−0.006]	[1.758]	[0.299]	[1.624]
$Forward\_Con_{-i,i,t}$	35.895	26.031	−57.268	−92.880	7.456	10.059	11.285	17.374*
	[0.049]	[0.078]	[−0.247]	[−0.563]	[0.830]	[1.418]	[0.982]	[1.667]
$Backward\_Con_{-i,i,t}$	815.981	−328.059	−169.438	−103.431	−0.016	−15.668*	−4.242	−16.551
	[1.138]	[−0.473]	[−0.816]	[−0.389]	[−0.001]	[−1.772]	[−0.306]	[−1.631]
Observations	3331	1609	3262	1554	3402	1640	3402	1640
R-squared	0.007	0.007	0.003	0.003	0.004	0.003	0.006	0.005

Note: This table reports the heterogeneous cross-industry spillover effects across efficiency of the internal capital markets of common leaders. The regression specification of panel A is: $Y^{(-c)}_{i,t} = \beta_1 \widehat{IdShock}_{-i,t} + \varepsilon_{i,t}$. The regression specification of panel B is: $Y^{(-c)}_{i,t} = \beta_1 \widehat{IdShock}_{-i,t} + \beta_2 \widehat{IdShock}_{-i,t} \times Forward\_Con_{-i,i,t} + \beta_3 \widehat{IdShock}_{-i,t} \times Backward\_Con_{-i,i,t} + \beta_4 Forward\_Con_{-i,i,t} + \beta_5 Backward\_Con_{-i,i,t} + \varepsilon_{i,t}$. Definitions of the dependent and independent variables are given in Table 17. We present results in industries with high efficiency of internal capital market of common leaders (top tertile and middle tertile) and low efficiency of internal capital market of common leaders (bottom tertile). The efficiency of internal capital market is measured by the absolute value added by allocation in Rajan, Servaes and Zingales (2000). We sort industries into tertiles based on the average efficiency across all common leaders in the industry 1 year prior to natural disaster shocks. The sample spans the period from 1994 to 2018. Standard errors are clustered at the industry level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

4.5.1 Evidence from the AJCA Tax Holiday

In this section, we study the impact of reduced financial distress on firms' product market behaviors and the distress levels of their peer firms. Specifically, we examine the impact of AJCA, in which firms are allowed to repatriate foreign profits to the US at a 5.25% tax rate, rather than the existing 35% corporate tax rate. The passage of AJCA reduces the distress levels of treated firms (i.e., those with a significant amount of pretax income from abroad), especially for those that were financially constrained prior to AJCA (see Faulkender and Petersen, 2012). Consistent with the prediction of our model, we find that (i) firms that were financially constrained prior to AJCA compete less aggressively in the product market after the passage of AJCA, and (ii) the distress levels of the non-treated

Table 19: Spillover effects in the AJCA tax holiday setting.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$AJCA_i$	-0.267^{***}	-0.261^{***}	0.433	0.387	0.053	0.050	0.024	0.017
	[−2.963]	[−2.872]	[0.699]	[0.618]	[1.325]	[1.252]	[0.312]	[0.222]
$\overline{AJCA}_{i,t}$	-0.525^{***}	-0.382^{**}	2.969^{***}	2.209^{*}	0.316^{***}	0.213^{**}	0.466^{***}	0.254^{*}
	[−2.809]	[−1.993]	[3.084]	[1.942]	[3.720]	[2.453]	[3.124]	[1.712]
$High\_Cross\_Ind\_Shocks_{i,t}$		−0.110		0.742^{*}		0.076^{**}		0.158^{***}
		[−1.511]		[1.916]		[2.497]		[2.987]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2166	2166	1806	1806	2303	2303	2292	2292
R-squared	0.127	0.129	0.143	0.147	0.029	0.038	0.016	0.028

Note: This table examines the spillover effects in the AJCA tax holiday setting. The data sample is a firm-year panel that spans 5 years after the passage of AJCA (i.e., 2004 to 2008). We focus our analysis on the financially constrained firms (i.e., those with financial constraint ranked in the top quintile) prior to the passage of AJCA. Financially constraint is measured as the average delay investment score of Hoberg and Maksimovic (2015) in the 5-year window prior to the the passage of AJCA (i.e., 1999 to 2003). The regression specification is: $Y_{i,t} = \beta_1 AJCA_i + \beta_2 \overline{AJCA}_{i,t} + \beta_3 High\_Cross\_Ind\_Shocks_{i,t} + \delta_t + \varepsilon_{i,t}$. The dependent variables are the distress risk ($Distress_{i,t}$), distance to default ($DD_{i,t}$), gross profit margin ($PM_{i,t}$), and markup ($Markup_{i,t}$). We follow Grieser and Liu (2019) to define $AJCA_i$ is an indicator variable that equals 1 if firm i has more than 33% pretax income from abroad during the period from 2001 to 2003. $\overline{AJCA}_{i,t}$ is the industry treatment intensity which is the fraction of firms in firm i's industry with an $AJCA_i$ indicator that equals 1. $High\_Cross\_Ind\_Shocks_{i,t}$ captures the strength of cross-industry spillover effects via the competition network, and it is a dummy variable that equals one if the average industry treatment intensity for the industries connected to firm i's industry through competition networks is higher than 20% in year t. The term δ_t represents year fixed effects. Standard errors are clustered at the firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

industry peers that were financially constrained prior to AJCA reduce significantly after the passage of AJCA.

Different from natural disasters, the AJCA tax holiday is a one-time shock. Therefore, we cannot use the DID specification (4.5) to identify the spillover effect because we will not be able to separate the spillover effects caused by AJCA from unrelated aggregate time-series changes. To overcome this empirical challenge, we use the method highlighted by Berg, Reisinger and Streitz (2021) and identify spillover effects by exploiting the variation in the fraction of treated firms across industries. Specifically, we run the following regression:

$$Y_{i,t} = \beta_1 AJCA_i + \beta_2 \overline{AJCA}_{i,t} + \beta_3 High\_Cross\_Ind\_Shocks_{i,t} + \delta_t + \varepsilon_{i,t}, \tag{4.11}$$

where $AJCA_i$ is an indicator variable that equals 1 if firm i has more than 33% pretax income from abroad during the period from 2001 to 2003 following the definition in Grieser and Liu (2019). $\overline{AJCA}_{i,t}$ is the industry treatment intensity which is the fraction of firms in firm i's industry with an $AJCA_i$ indicator that equals 1. $High\_Cross\_Ind\_Shocks_{i,t}$ captures the strength of cross-industry spillover effects via the competition network, and it is a dummy variable that equals one if the average industry treatment intensity for the industries connected to firm i's industry through competition networks is higher than 20% in year t. Our data sample is a firm-year panel that spans 5 years after the passage of AJCA (i.e., 2004 to 2008). Because AJCA mainly altered the operating behaviors (e.g., investment) of the most constrained firms (e.g., Faulkender and Petersen, 2012; Grieser and Liu, 2019), we focus our analysis on the firms that are most financially constrained prior to the passage of AJCA. Specifically, we measure financial constraint using the delay investment score of Hoberg and Maksimovic (2015) averaged across the 5-year period prior to the the passage of AJCA (i.e., 1999 to 2003) and focus on the firms ranked in the top quintile based on the average constraint scores.

Table 19 tabulates the results from the regressions. Coefficient β_2 represents the within-industry spillover effects. It is positive and statistically significant for profit margin (see columns 5 and 6), and markup (see columns 7 and 8), suggesting that firms that are financially distressed prior to AJCA compete less aggressively in the product market when a larger fraction of firms in the industry are shocked by the passage of AJCA. Coefficient β_2 is negative and statistically significant for distress (see columns 1 and 2), and it is positive and statistically significant for distance to default (see columns 3 and 4), suggesting that firms that are financially distressed prior to AJCA become less distressed when a larger fraction of firms in the industry are shocked by the passage of AJCA. These results are consistent with the predictions of our model in the collusive equilibrium and demonstrate the existence of the within-industry spillover effects. In Table OA.21 of the Online Appendix, we further examine the within-industry spillover effects by allowing the treated firms and non-treated firms to have heterogenous spillover effects (see Berg, Reisinger and Streitz, 2021). We find that the spillover effects mainly exist from treated firms to non-treated firms, rather than from treated firms to other treated firms. We examine distress risk using bond yield spread and CDS spread as two additional measures. Because the limited coverage of the spread data in the cross section, we do not limit our analysis to financially constrained firms and instead use the full sample. As shown in Table OA.22 of the Online Appendix, we again find that the within-industry spillover effects are robust in both bond yield spread and CDS spread.

Table 19 also speaks to the cross-industry spillover effects. Coefficient β_3 is positive for profit margin (see columns 5 and 6), and markup (see columns 7 and 8), suggesting that when more industries connected to the focal industry via the competition network are shocked by the passage of AJCA, the firms in the focal industries compete less aggressively in the product market. Coefficient β_3 is negative for distress (see columns 1 and 2), and it is positive for distance to default (see columns 3 and 4), suggesting that when more industries connected to the focal industry via the competition network are shocked by the passage of AJCA, the distress levels of the firms in the focal industries are reduced more. These results are also consistent with the predictions of our model and demonstrate the existence of the cross-industry spillover effects.

4.5.2 Evidence from the Lehman Crisis

For both idiosyncratic shocks and systematic shocks, our model has the same predictions for the spillover effects. In this subsection, we exploit the Lehman crisis as a quasi-experiment for systematic shocks (Chodorow-Reich, 2014; Chodorow-Reich and Falato, 2021) and examine the spillover effects via competition network.

Kim (2021) exploits the same setting and studies the output price dynamics around the Lehman crisis. Using cross-sectional regressions, he finds that firms experiencing more negative credit supply shocks decrease their output prices more after the Lehman crisis, a finding that is consistent with our model. Here, we go one step beyond and further examine the existence of spillover effects. Specifically, we run the following cross-sectional regression:

$$\Delta Y_i = \beta_1 Lehman_i + \beta_2 \overline{Lehman}_i + \beta_3 High\_Cross\_Ind\_Shocks_i + \varepsilon_i, \tag{4.12}$$

where ΔY_i represents the the changes of the dependent variables of firm i after the Lehman crisis. $Lehman_i$ is an indicator variable that equals 1 if firm i experiences a below-median credit supply shock during the Lehman crisis. The method we use to construct the measure of firm-specific credit supply shock is the same as that of Chodorow-Reich (2014), and it is explained in Online Appendix F. A lower level of credit supply shock implies that the lender health of the firm deteriorated more during the Lehman crisis. $\overline{Lehman}_{i,t}$ is the industry treatment intensity which is the fraction of firms in firm i's industry with an $Lehman_i$ indicator that equals 1. $High\_Cross\_Ind\_Shocks_{i,t}$ captures the strength of cross-industry spillover effects via the competition network, and it is a dummy variable that equals one if the average industry treatment intensity for the industries connected to firm i's industry through competition networks is higher than 20% in year t.

Table 20 tabulates the results from the regressions. Coefficient β_2 represents the within-industry spillover effects. It is negative and statistically significant for profit margin (see columns 5 and 6), and markup (see columns 7 and 8), suggesting that firms compete more aggressively in the product market when a larger fraction of firms in the industry experience adverse credit-supply shocks during the Lehman crisis. Coefficient β_2 is positive and statistically significant for distress (see columns 1 and 2), and it is negative and statistically significant for distance to default (see columns 3 and 4), suggesting that firms become more distressed when a larger fraction of firms in the industry experience adverse credit-supply shocks during the Lehman crisis. These results are consistent with

Table 20: Spillover effects in the Lehman crisis setting.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta Distress_i$		ΔDD_i		ΔPM_i		$\Delta Markup_i$	
$Lehman_i$	0.009	0.008	-0.356	-0.353	0.019	0.020	0.021	0.021
	[0.187]	[0.174]	[-1.298]	[-1.287]	[0.590]	[0.612]	[1.102]	[1.122]
$\overline{Lehman}_i$	0.509^{***}	0.456^{***}	-1.173^{***}	-0.947^{**}	-0.321^{***}	-0.221^{***}	-0.113^{***}	-0.068^{**}
	[5.345]	[4.656]	[-2.597]	[-2.012]	[-4.621]	[-4.170]	[-3.123]	[-2.153]
$High\_Cross\_Ind\_Shocks_i$		0.057		-0.188		-0.101^{***}		-0.046^{**}
		[1.520]		[-0.804]		[-2.662]		[-2.354]
Observations	2401	2401	1920	1920	2583	2583	2580	2580
R-squared	0.017	0.018	0.008	0.009	0.005	0.008	0.002	0.004

Note: This table examines the spillover effects in the Lehman crisis setting. The regression specification is: $\Delta Y_i = \beta_1 Lehman_i + \beta_2 \overline{Lehman}_i + \beta_3 High\_Cross\_Ind\_Shocks_i + \varepsilon_i$. The dependent variables are the changes of distress risk ($\Delta Distress_{i,t}$), changes of distance to default ($\Delta DD_{i,t}$), changes of gross profit margin ($\Delta PM_{i,t}$), and changes of markup ($\Delta Markup_{i,t}$) from 2005 to 2009. $Lehman_i$ is an indicator variable that equals 1 if firm i experiences a below-median credit supply shock during the Lehman crisis. The method we use to construct the measure of firm-specific credit supply shock is the same as that of Chodorow-Reich (2014), and it is explained in Online Appendix F. A lower level of credit supply shock implies that the lender health of the firm deteriorated more during the Lehman crisis. $\overline{Lehman}_{i,t}$ is the industry treatment intensity which is the fraction of firms in firm i's industry with an $Lehman_i$ indicator that equals 1. $High\_Cross\_Ind\_Shocks_{i,t}$ captures the strength of cross-industry spillover effects via the competition network, and it is a dummy variable that equals one if the average industry treatment intensity for the industries connected to firm i's industry through competition networks is higher than 20% in year t. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

the predictions of our model in the collusive equilibrium and demonstrate the existence of the within-industry spillover effects.

5 Conclusion

In this paper, we build a competition network that links industries through common major players in horizontal competition of product markets. Using the network structure, we show that industries with higher competition network centrality are more exposed to cross-industry spillover effects of distress shocks, which can lead to aggregate fluctuations, thereby have higher expected stock returns. To test the core mechanism, we examine the causal effects of firms' distress risk on their product market behaviors and the propagation of these firm-specific distress shocks through the competition network. We identify idiosyncratic distress risk by exploiting the occurrence of local natural disasters. We find that firms hit by disasters exhibit increased distress and then compete more aggressively in product markets by cutting their profit margins. In response, their industry peers also engage in more aggressive competition and exhibit their own increased distress, especially in industries with high entry barriers. Importantly, distress risk can propagate to other industries through common market leaders operating in multiple industries. These results cannot be explained by demand commonality or other network externality. We also find consistent results by examining the impact of the passage of AJCA in 2004 and the Lehman crisis in 2008, which lead to a reduction and an increase in the distress levels of the treated firms, respectively.

References

Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. 2015. "Systemic risk and stability in financial networks." *American Economic Review*, 105(2): 564–608.

Acemoglu, Daron, Vasco M Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. 2012. "The network origins of aggregate fluctuations." *Econometrica*, 80(5): 1977–2016.

Adrian, Tobias, Erkko Etula, and Tyler Muir. 2014. "Financial intermediaries and the cross-section of asset returns." *Journal of Finance*, 69(6): 2557–2596.

Ahern, Kenneth R. 2013. "Network centrality and the cross section of stock returns." Working Paper.

Ali, Ashiq, Sandy Klasa, and Eric Yeung. 2009. "The limitations of industry concentration measures constructed with Compustat data: Implications for finance research." *Review of Financial Studies*, 22(10): 3839–3871.

Allen, Franklin, and Douglas Gale. 2000. "Financial contagion." *Journal of Political Economy*, 108(1): 1–33.

Allen, Jeffrey W, and Gordon M Phillips. 2000. "Corporate equity ownership, strategic alliances, and product market relationships." *Journal of Finance*, 55(6): 2791–2815.

Alok, Shashwat, Nitin Kumar, and Russ Wermers. 2020. "Do fund managers misestimate climatic disaster risk?" *Review of Financial Studies*, 33(3): 1146–1183.

Anderson, Eric, Sergio Rebelo, and Arlene Wong. 2020. "Markups Across Space and Time." National Bureau of Economic Research, Inc NBER Working Papers 24434.

Andrade, Gregor, and Steven N Kaplan. 1998. "How costly is financial (not economic) distress? Evidence from highly leveraged transactions that became distressed." *Journal of Finance*, 53(5): 1443–1493.

Antras, Pol, Teresa C Fort, and Felix Tintelnot. 2017. "The margins of global sourcing: Theory and evidence from us firms." *American Economic Review*, 107(9): 2514–64.

Aretz, Kevin, Shantanu Banerjee, and Oksana Pryshchepa. 2019. "In the path of the storm: does distress risk cause industrial firms to risk-shift?" *Review of Finance*, 23(6): 1115–1154.

Aryal, Gaurab, Federico Ciliberto, and Benjamin T. Leyden. 2021. "Coordinated capacity reductions and public communication in the airline industry." *Review of Economic Studies*, forthcoming.

Athey, Susan, Dean Eckles, and Guido W. Imbens. 2018. "Exact p-values for network interference." *Journal of the American Statistical Association*, 113(521): 230–240.

Autor, David, David Dorn, Lawrence F. Katz, Christina Patterson, and John Van Reenen. 2020. "The fall of the labor share and the rise of superstar firms." *Quarterly Journal of Economics*, 135(2): 645–709.

Baghai, Ramin, Rui Silva, Viktor Thell, and Vikrant Vig. 2020. "Talent in distressed firms: Investigating the labor costs of financial distress." *Journal of Finance*, forthcoming.

Baker, Scott R, and Nicholas Bloom. 2013. "Does uncertainty reduce growth? Using disasters as natural experiments." NBER Working Paper.

Baker, Scott R, Brian Baugh, and Marco C Sammon. 2020. "Measuring customer churn and interconnectedness." NBER working paper.

Banerjee, Shantanu, Sudipto Dasgupta, Rui Shi, and Jiali Yan. 2019. "Predatory advertising, financial fraud, and leverage." Working Paper.

Baqaee, David Rezza, and Emmanuel Farhi. 2019. "Productivity and Misallocation in General Equilibrium*." *The Quarterly Journal of Economics*, 135(1): 105–163.

Barrot, Jean-Noël, and Julien Sauvagnat. 2016. "Input specificity and the propagation of idiosyncratic shocks in production networks." *Quarterly Journal of Economics*, 131(3): 1543–1592.

Basse, Guillaume, and Avi Feller. 2018. "Analyzing two-stage experiments in the presence of interference." *Journal of the American Statistical Association*, 113(521): 41–55.

Belo, Frederico, Xiaoji Lin, and Fan Yang. 2019. "External equity financing shocks, financial flows, and asset prices." *Review of Financial Studies*, 32(9): 3500–3543.

Beneke, Francisco, and Mark-Oliver Mackenrodt. 2020. "Remedies for algorithmic tacit collusion." *Journal of Antitrust Enforcement*, 9(1): 152–176.

Berg, Tobias, Markus Reisinger, and Daniel Streitz. 2021. "Handling spillover effects in empirical research." *Journal of Financial Economics*, forthcoming.

Bernile, Gennaro, Vineet Bhagwat, and P Raghavendra Rau. 2017. "What doesn't kill you will only make you more risk-loving: Early-life disasters and CEO behavior." *Journal of Finance*, 72(1): 167–206.

Bertomeu, Jeremy, John Harry Evans, Mei Feng, and Ayung Tseng. 2021. "Tacit collusion and voluntary disclosure: Theory and evidence from the U.S. automotive industry." *Management Science*, 67(3): 1851–1875.

Bharath, Sreedhar, Sandeep Dahiya, Anthony Saunders, and Anand Srinivasan. 2007. "So what do I get? The bank's view of lending relationships." *Journal of Financial Economics*, 85(2): 368–419.

Bharath, Sreedhar T, and Tyler Shumway. 2008. "Forecasting default with the Merton distance to default model." *Review of Financial Studies*, 21(3): 1339–1369.

Bhojraj, Sanjeev, Charles MC Lee, and Derek K Oler. 2003. "What's my line? A comparison of industry classification schemes for capital market research." *Journal of Accounting Research*, 41(5): 745–774.

Boehmer, Ekkehart, Charles M Jones, and Xiaoyan Zhang. 2020. "Potential pilot problems: Treatment spillovers in financial regulatory experiments." *Journal of Financial Economics*, 135(1): 68–87.

Bolton, Patrick, and David S. Scharfstein. 1990. "A theory of predation based on agency problems in financial contracting." *American Economic Review*, 80(1): 93–106.

Bolton, Patrick, Hui Chen, and Neng Wang. 2011. "A unified theory of Tobin's q, corporate investment, financing, and risk management." *Journal of Finance*, 66(5): 1545–1578.

Bolton, Patrick, Hui Chen, and Neng Wang. 2013. "Market timing, investment, and risk management." *Journal of Financial Economics*, 109(1): 40–62.

Bolton, Patrick, Hui Chen, and Neng Wang. 2014. "Debt, Taxes, and Liquidity." Working paper.

Bonacich, Phillip. 1972. "Factoring and weighting approaches to status scores and clique identification." *Journal of Mathematical Sociology*, 2(1): 113–120.

Borenstein, Severin. 2004. "Case 9 Rapid price communication and coordination: The airline tariff publishing case." In . , ed. John Kwoka Jr. and Lawrence White. Oxford University Press.

Bourveau, Thomas, Guoman She, and Alminas Zaldokas. 2020. "Corporate disclosure as a tacit coordination mechanism: Evidence from Cartel enforcement regulations." *Journal of Accounting Research*, 58(2): 295–332.

Boustan, Leah Platt, Matthew E Kahn, Paul W Rhode, and Maria Lucia Yanguas. 2020. "The effect of natural disasters on economic activity in US counties: A century of data." *Journal of Urban Economics*, 118: 103257.

Brown, James R, Matthew T Gustafson, and Ivan T Ivanov. 2021. "Weathering cash flow shocks." *Journal of Finance*, 76(4): 1731–1772.

Brown, Jennifer, and David A Matsa. 2016. "Boarding a sinking ship? An investigation of job applications to distressed firms." *Journal of Finance*, 71(2): 507–550.

Buehlmaier, Matthias, and Toni Whited. 2018. "Are financial constraints priced? Evidence from textual analysis." *Review of Financial Studies*, 31(7): 2693–2728.

Busse, Meghan. 2002. "Firm financial condition and airline price wars." *RAND Journal of Economics*, 33(2): 298–318.

Bustamante, M. Cecilia, and Andres Donangelo. 2017. "Product market competition and industry returns." *Review of Financial Studies*, 30(12): 4216–4266.

Bustamante, M Cecilia, and Laurent Frésard. 2021. "Does firm investment respond to peers' investment?" *Management Science*, 67(8): 4703–4724.

Byrne, David P., and Nicolas de Roos. 2019. "Learning to coordinate: A study in retail gasoline." *American Economic Review*, 109(2): 591–619.

Calvano, Emilio, Giacomo Calzolari, Vincenzo Denicolò, and Sergio Pastorello. 2020. "Artificial intelligence, algorithmic pricing, and collusion." *American Economic Review*, 110(10): 3267–97.

Campbell, John, Jens Hilscher, and Jan Szilagyi. 2008. "In search of distress risk." *Journal of Finance*, 63(6): 2899–2939.

Campbell, John Y, and Robert J Shiller. 1988. "Stock prices, earnings, and expected dividends." *Journal of Finance*, 43(3): 661–676.

Campbell, John Y., and Robert J. Shiller. 1998. "Valuation ratios and the long-run stock market outlook." *Journal of Portfolio Management*, 24(2): 11–26.

Campello, Murillo. 2006. "Debt financing: Does it boost or hurt firm performance in product markets?" *Journal of Financial Economics*, 82(1): 135–172.

Campello, Murillo, John R Graham, and Campbell R Harvey. 2010. "The real effects of financial constraints: Evidence from a financial crisis." *Journal of Financial Economics*, 97(3): 470–487.

Carey, Mark, and Mark Hrycray. 1999. "Credit flow, risk, and the role of private debt in capital structure." Working Paper.

Carey, Mark, Mitch Post, and Steven A Sharpe. 1998. "Does corporate lending by banks and finance companies differ? Evidence on specialization in private debt contracting." *Journal of Finance*, 53(3): 845–878.

Cavallo, Eduardo, Sebastian Galiani, Ilan Noy, and Juan Pantano. 2013. "Catastrophic natural disasters and economic growth." *Review of Economics and Statistics*, 95(5): 1549–1561.

Chava, Sudheer, and Michael R Roberts. 2008. "How does financing impact investment? The role of debt covenants." *Journal of Finance*, 63(5): 2085–2121.

Chen, Hui, Rui Cui, Zhiguo He, and Konstantin Milbradt. 2018. "Quantifying liquidity and default risks of corporate bonds over the business cycle." *Review of Financial Studies*, 31(3): 852–897.

Chen, Hui, Winston Wei Dou, Hongye Guo, and Yan Ji. 2020. "Feedback and contagion through distressed competition." Working paper.

Chevalier, Judith A. 1995. "Do LBO supermarkets charge more? An empirical analysis of the effects of LBOs on supermarket pricing." *Journal of Finance*, 50(4): 1095–1112.

Chevalier, Judith A., and David S. Scharfstein. 1996. "Capital-market imperfections and countercyclical markups: Theory and evidence." *American Economic Review*, 86(4): 703–725.

Chodorow-Reich, Gabriel. 2014. "The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis." *The Quarterly Journal of Economics*, 129(1): 1–59.

Chodorow-Reich, Gabriel, and Antonio Falato. 2021. "The loan covenant channel: How bank health transmits to the real economy."

Clark, Robert, and Jean-Francois Houde. 2013. "Collusion with asymmetric retailers: Evidence from a gasoline price-fixing case." *American Economic Journal: Microeconomics*, 5(3): 97–123.

Cohen, Lauren, and Andrea Frazzini. 2008. "Economic links and predictable returns." *Journal of Finance*, 63(4): 1977–2011.

Collin-Dufresne, Pierre, Benjamin Junge, and Anders B Trolle. 2020. "Market structure and transaction costs of index CDSs." *Journal of Finance*, 75(5): 2719–2763.

Collin-Dufresn, Pierre, Robert S Goldstein, and J Spencer Martin. 2001. "The determinants of credit spread changes." *Journal of Finance*, 56(6): 2177–2207.

Connor, John M. 2016. "The private international cartels (PIC) data set: guide and summary statistics, 1990-July 2016 (Revised 2nd Edition)." Working Paper.

Cookson, J. Anthony. 2017. "Leverage and strategic preemption: Lessons from entry plans and incumbent investments." *Journal of Financial Economics*, 123(2): 292 – 312.

Cookson, J Anthony. 2018. "Anticipated entry and entry deterrence: Evidence from the American casino industry." *Management Science*, 64(5): 2325–2344.

Corhay, Alexandre, Howard Kung, and Lukas Schmid. 2020*a*. "Competition, markups, and predictable returns." *Review of Financial Studies*, 33(12): 5906–5939.

Corhay, Alexandre, Howard Kung, and Lukas Schmid. 2020*b*. "Q: Risk, rents, or growth?" Working Papers.

Cortés, Kristle Romero, and Philip E Strahan. 2017. "Tracing out capital flows: How financially integrated banks respond to natural disasters." *Journal of Financial Economics*, 125(1): 182–199.

Coval, Joshua, and Erik Stafford. 2007. "Asset fire sales (and purchases) in equity markets." *Journal of*

Financial Economics, 86(2): 479–512.

Dasgupta, Sudipto, and Alminas Zaldokas. 2018. "Anticollusion enforcement: Justice for consumers and equity for firms." *Review of Financial Studies*, 32(7): 2587–2624.

De Loecker, Jan, Jan Eeckhout, and Gabriel Unger. 2020. "The rise of market power and the macroeconomic implications." *Quarterly Journal of Economics*, 135(2): 561–644.

Dennis, Patrick, Kristopher Gerardi, and Carola Schenone. 2021. "Common ownership does not have anti-competitive effects in the airline industry." *Journal of Finance*, forthcoming.

Dessaint, Olivier, and Adrien Matray. 2017. "Do managers overreact to salient risks? Evidence from hurricane strikes." *Journal of Financial Economics*, 126(1): 97–121.

Dew-Becker, Ian. 2021. "Tail risk in production networks." Working Paper.

Dew-Becker, Ian, Alireza Tahbaz-Salehi, and Andrea Vedolin. 2020. "Skewness and time-varying second moments in a nonlinear production network: theory and evidence." Working Paper.

Dick-Nielsen, Jens. 2009. "Liquidity biases in TRACE." *Journal of Fixed Income*, 19(2): 43–55.

Di Giovanni, Julian, Andrei A Levchenko, and Isabelle Mejean. 2014. "Firms, destinations, and aggregate fluctuations." *Econometrica*, 82(4): 1303–1340.

Dou, Winston Wei, Leonid Kogan, and Wei Wu. 2021. "Common Fund Flows: Flow Hedging and Factor Pricing." Working Paper.

Dou, Winston Wei, Yan Ji, and Wei Wu. 2021*a*. "Competition, profitability, and discount rates." *Journal of Financial Economics*, 140(2): 582–620.

Dou, Winston Wei, Yan Ji, and Wei Wu. 2021*b*. "The oligopoly Lucas tree." *Review of Financial Studies*, forthcoming.

Dou, Winston Wei, Yan Ji, David Reibstein, and Wei Wu. 2021. "Inalienable Customer capital, corporate liquidity, and stock returns." *Journal of Finance*, 76(1): 211–265.

El-Khatib, Rwan, Kathy Fogel, and Tomas Jandik. 2015. "CEO network centrality and merger performance." *Journal of Financial Economics*, 116(2): 349 – 382.

Fama, Eugene F., and Kenneth R. French. 1993. "Common risk factors in the returns on stocks and bonds." *Journal of Financial Economics*, 33(1): 3–56.

Fama, Eugene F., and Kenneth R. French. 2015. "A five-factor asset pricing model." *Journal of Financial Economics*, 116(1): 1–22.

Fan, Joseph PH, and Larry HP Lang. 2000. "The measurement of relatedness: An application to corporate diversification." *Journal of Business*, 73(4): 629–660.

Faulkender, Michael, and Mitchell Petersen. 2012. "Investment and capital constraints: Repatriations under the American Jobs Creation Act." *Review of Financial Studies*, 25(11): 3351–3388.

Foros, Øystein, and Mai Nguyen-Ones. 2021. "Coordinate to obfuscate? The role of prior announcements of recommended prices." *Economics Letters*, 198: 109680.

Freeman, Linton C. 1977. "A set of measures of centrality based on betweenness." *Sociometry*, 40(1): 35–41.

Frésard, Laurent. 2010. "Financial strength and product market behavior: The real effects of corporate cash holdings." *Journal of Finance*, 65(3): 1097–1122.

Frésard, Laurent, Gerard Hoberg, and Gordon M Phillips. 2020. "Innovation activities and integration through vertical acquisitions." *Review of Financial Studies*, 33(7): 2937–2976.

Froot, Kenneth A. 2001. "The market for catastrophe risk: a clinical examination." *Journal of Financial Economics*, 60(2-3): 529–571.

Gan, Li, and Manuel A. Hernandez. 2013. "Making friends with your neighbors? Agglomeration and tacit collusion in the lodging industry." *Review of Economics and Statistics*, 95(3): 1002–1017.

Garlappi, Lorenzo, and Hong Yan. 2011. "Financial distress and the cross-section of equity returns." *Journal of Finance*, 66(3): 789–822.

Gârleanu, Nicolae, Stavros Panageas, and Jianfeng Yu. 2015. "Financial entanglement: A theory of incomplete integration, leverage, crashes, and contagion." *American Economic Review*, 105(7): 1979–2010.

Garmaise, Mark J, and Tobias J Moskowitz. 2009. "Catastrophic risk and credit markets." *Journal of Finance*, 64(2): 657–707.

Gilchrist, Simon, Jae Sim, Raphael Schoenle, and Egon Zakrajsek. 2017. "Inflation dynamics during the financial crisis." *American Economic Review*, 107(3): 785–823.

Giroud, Xavier, and Holger M. Mueller. 2010. "Does corporate governance matter in competitive industries?" *Journal of Financial Economics*, 95(3): 312 – 331.

Giroud, Xavier, and Holger M. Mueller. 2011. "Corporate governance, product market competition, and equity prices." *Journal of Finance*, 66(2): 563–600.

Giroud, Xavier, and Holger M Mueller. 2017. "Firm leverage, consumer demand, and employment losses during the Great Recession." *Quarterly Journal of Economics*, 132(1): 271–316.

Giroud, Xavier, Holger M Mueller, Alex Stomper, and Arne Westerkamp. 2012. "Snow and leverage." *Review of Financial Studies*, 25(3): 680–710.

Gofman, Michael, Gill Segal, and Youchang Wu. 2020. "Production networks and stock returns: The role of vertical creative destruction." *Review of Financial Studies*, 33(12): 5856–5905.

Goldstein, Itay. 2013. "Chapter 36 Empirical literature on financial crises: Fundamentals vs. panic." In *The Evidence and Impact of Financial Globalization*. 523 – 534.

Goldstein, Itay, and Ady Pauzner. 2004. "Contagion of self-fulfilling financial crises due to diversification of investment portfolios." *Journal of Economic Theory*, 119(1): 151 – 183.

Gomes, Joao F., and Lukas Schmid. 2010. "Levered returns." *Journal of Finance*, 65(2): 467–494.

Gomes, Joao F, and Lukas Schmid. 2021. "Equilibrium asset pricing with leverage and default." *Journal of Finance*, 76(2): 977–1018.

Gomes, Joao F., Leonid Kogan, and Motohiro Yogo. 2009. "Durability of output and expected stock returns." *Journal of Political Economy*, 117(5): 941–986.

Graham, John R., Si Li, and Jiaping Qiu. 2008. "Corporate misreporting and bank loan contracting." *Journal of Financial Economics*, 89(1): 44–61.

Green, Edward J., Robert C. Marshall, and Leslie M. Marx. 2014. "Tacit collusion in oligopoly." In *The Oxford Handbook of International Antitrust Economics*. Vol. 2 of *Antitrust Economics*, , ed. Roger D. Blair and D. Daniel Sokol, 217–239. Oxford University Press.

Greenwood, Jeremy, Zvi Hercowitz, and Gregory W. Huffman. 1988. "Investment, Capacity Utilization, and the Real Business Cycle." *The American Economic Review*, 78(3): 402–417.

Grieser, William, and Zack Liu. 2019. "Corporate investment and innovation in the presence of competitor constraints." *Review of Financial Studies*, 32(11): 4271–4303.

Grieser, William, Charles Hadlock, James LeSage, and Morad Zekhnini. 2021. "Network effects in corporate financial policies." *Journal of Financial Economics*, forthcoming.

Grigoris, Fotis, Yunzhi Hu, and Gill Segal. 2021. "Counterparty risk: Implications for network linkages and asset prices." Working Paper.

Grullon, Gustavo, Yelena Larkin, and Roni Michaely. 2019. "Are US industries becoming more concentrated?" *Review of Finance*, 23(4): 697–743.

Guenther, David A., and Andrew J. Rosman. 1994. "Differences between COMPUSTAT and CRSP SIC codes and related effects on research." *Journal of Accounting and Economics*, 18(1): 115–128.

Gutiérrez, Germán, and Thomas Philippon. 2017. "Investmentless growth: An empirical investigation." *Brookings Papers on Economic Activity*, 89–169.

Gutiérrez, Germán, Callum Jones, and Thomas Philippon. 2019. "Entry costs and the macroeconomy." NBER Working Paper.

Hadlock, Charles, and Miriam Schwartz-Ziv. 2019. "Blockholder heterogeneity, multiple blocks, and the dance between blockholders." *Review of Financial Studies*, 32(11): 4196–4227.

Hadlock, Charles, and Ramana Sonti. 2012. "Financial strength and product market competition: Evidence from asbestos litigation." *Journal of Financial and Quantitative Analysis*, 47: 179–211.

Hann, Rebecca N, Maria Ogneva, and Oguzhan Ozbas. 2013. "Corporate diversification and the cost of capital." *Journal of Finance*, 68(5): 1961–1999.

He, Jie (Jack), and Jiekun Huang. 2017. "Product market competition in a world of cross-ownership: Evidence from institutional blockholdings." *Review of Financial Studies*, 30(8): 2674–2718.

Henry, David K, Sandra Cooke-Hull, Jacqueline Savukinas, Fenwick Yu, Nicholas Elo, and B Vac Arnum. 2013. "Economic impact of Hurriane Sandy: potential economic activity lost and gained in New Jersey and New York." US Department of Commerce Report.

Herskovic, Bernard. 2018. "Networks in production: Asset pricing implications." *Journal of Finance*, 73(4): 1785–1818.

Herskovic, Bernard, Bryan Kelly, Hanno Lustig, and Stijn Van Nieuwerburgh. 2020. "Firm volatility in granular networks." *Journal of Political Economy*, 128(11): 4097–4162.

He, Zhiguo, Bryan Kelly, and Asaf Manela. 2017. "Intermediary asset pricing: New evidence from many asset classes." *Journal of Financial Economics*, 126(1): 1–35.

Hoberg, Gerard, and Gordon M. Phillips. 2020. "Scope, scale and competition: The 21st century firm." Working Paper.

Hoberg, Gerard, and Gordon Phillips. 2010. "Product market synergies and competition in mergers and acquisitions: A text-based analysis." *Review of Financial Studies*, 23(10): 3773–3811.

Hoberg, Gerard, and Gordon Phillips. 2016. "Text-based network industries and endogenous product differentiation." *Journal of Political Economy*, 124(5): 1423–1465.

Hoberg, Gerard, and Vojislav Maksimovic. 2015. "Redefining financial constraints: A text-based analysis." *Review of Financial Studies*, 28(5): 1312–1352.

Hortaçsu, Ali, Gregor Matvos, Chad Syverson, and Sriram Venkataraman. 2013. "Indirect costs of financial distress in durable goods industries: The case of auto manufacturers." *Review of Financial Studies*, 26(5): 1248–1290.

Horvath, Michael. 1998. "Cyclicality and sectoral linkages: Aggregate fluctuations from independent sectoral shocks." *Review of Economic Dynamics*, 1(4): 781–808.

Horvath, Michael. 2000. "Sectoral shocks and aggregate fluctuations." *Journal of Monetary Economics*, 45(1): 69–106.

Hou, Kewei, and David T. Robinson. 2006. "Industry concentration and average stock returns." *Journal of Finance*, 61(4): 1927–1956.

Hou, Kewei, Chen Xue, and Lu Zhang. 2015. "Digesting anomalies: An investment approach." *Review of Financial Studies*, 28(3): 650–705.

Hsiang, Solomon M, and Amir S Jina. 2014. "The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones." Working Paper.

Hudgens, Michael G., and M. Elizabeth Halloran. 2008. "Toward causal inference with interference." *Journal of the American Statistical Association*, 103: 832–842.

Ivaldi, Marc, Bruno Jullien, Patrick Rey, Paul Seabright, and Jean Tirole. 2007. "Chapter 8 The Economics of Tacit Collusion: Implications for Merger Control." In *The Political Economy of Antitrust*. Vol. 282 of *Contributions to Economic Analysis*, , ed. V. Ghosal and J. Stennek, 217–239. Elsevier.

Jermann, Urban, and Vincenzo Quadrini. 2012. "Macroeconomic effects of financial shocks." *American Economic Review*, 102(1): 238–271.

Johnson, Peter M, Thomas J Lopez, and Juan Manuel Sanchez. 2011. "Special items: A descriptive analysis." *Accounting Horizons*, 25(3): 511–536.

José, Azar, Martin C. Schmalz, and Isabel Tecu. 2018. "Anticompetitive effects of common ownership." *Journal of Finance*, 73(4): 1513–1565.

Kahle, Kathleen M., and Ralph A. Walkling. 1996. "The impact of industry classifications on financial research." *Journal of Financial and Quantitative Analysis*, 31(3): 309–335.

Kaminsky, Graciela L., Carmen M. Reinhart, and Carlos A. Végh. 2003. "The unholy trinity of financial contagion." *Journal of Economic Perspectives*, 17(4): 51–74.

Karabarbounis, Loukas, and Brent Neiman. 2018. "Accounting for Factorless Income." In *NBER Macroeconomics Annual 2018, volume 33. NBER Chapters*, 167–228. National Bureau of Economic Research, Inc.

Karpoff, Jonathan M, Allison Koester, D Scott Lee, and Gerald S Martin. 2017. "Proxies and databases in financial misconduct research." *The Accounting Review*, 92(6).

Karpoff, Jonathan M, D Scott Lee, and Gerald S Martin. 2008. "The cost to firms of cooking the books."

Journal of Financial and Quantitative Analysis, 43(3): 581–611.

Kim, Ryan. 2021. "The effect of the credit crunch on output price dynamics: The corporate inventory and liquidity management channel." *Quarterly Journal of Economics*, 136(1): 563–619.

Klingler, Sven, and David Lando. 2018. "Safe haven CDS premiums." *Review of Financial Studies*, 31(5): 1856–1895.

Knittel, Christopher R., and Victor Stango. 2003. "Price ceilings as focal points for tacit collusion: Evidence from credit cards." *American Economic Review*, 93(5): 1703–1729.

Koch, Andrew, Marios Panayides, and Shawn Thomas. 2021. "Common ownership and competition in product markets." *Journal of Financial Economics*, 139(1): 109–137.

Kodres, Laura E., and Matthew Pritsker. 2002. "A rational expectations model of financial contagion." *Journal of Finance*, 57(2): 769–799.

Kovenock, Dan, and Gordon Phillips. 1995. "Capital structure and product-market rivalry: How do we reconcile theory and evidence?" *American Economic Review*, 85(2): 403–408.

Kovenock, Dan, and Gordon Phillips. 1997. "Capital structure and product market behavior: An examination of plant exit and investment decisions." *Review of Financial Studies*, 10(3): 767–803.

Kyle, Albert S., and Wei Xiong. 2001. "Contagion as a wealth effect." *Journal of Finance*, 56(4): 1401–1440.

Lamont, Owen. 1997. "Cash flow and investment: Evidence from internal capital markets." *Journal of Finance*, 52(1): 83–109.

Lamont, Owen A, and Christopher Polk. 2001. "The diversification discount: Cash flows versus returns." *Journal of Finance*, 56(5): 1693–1721.

Lewellen, Jonathan, Stefan Nagel, and Jay Shanken. 2010. "A skeptical appraisal of asset pricing tests." *Journal of Financial Economics*, 96(2): 175–194.

Lewellen, Katharina, and Michelle Lowry. 2021. "Does common ownership really increase firm coordination?" *Journal of Financial Economics*, 141(1): 322–344.

Lewis, Matthew S. 2015. "Odd prices at retail gasoline stations: Focal point pricing and tacit collusion." *Journal of Economics & Management Strategy*, 24(3): 664–685.

Liu, Lan, and Michael G. Hudgens. 2014. "Large sample randomization inference of causal effects in the presence of interference." *Journal of the American Statistical Association*, 109(505): 288–301.

Li, Xi. 2010. "The impacts of product market competition on the quantity and quality of voluntary disclosures." *Review of Accounting Studies*, 15(3): 663–711.

Maksimovic, Vojislav, and Sheridan Titman. 1991. "Financial policy and reputation for product quality." *Review of Financial Studies*, 4(1): 175–200.

Manski, Charles F. 1993. "Identification of endogenous social effects: The reflection problem." *Review of Economic Studies*, 60(3): 531–542.

Manski, Charles F. 2013. "Identification of treatment response with social interactions." *Econometrics Journal*, 16(1): S1–S23.

Martin, Ian. 2013. "The Lucas orchard." *Econometrica*, 81(1): 55–111.

Maskin, Eric, and Jean Tirole. 1988. "A theory of dynamic oligopoly, II: Price competition, kinked demand curves, and edgeworth cycles." *Econometrica*, 56(3): 571–599.

Matsa, David A. 2011*a*. "Competition and product quality in the supermarket industry." *Quarterly Journal of Economics*, 126(3): 1539–1591.

Matsa, David A. 2011*b*. "Running on empty? Financial leverage and product quality in the supermarket industry." *American Economic Journal: Microeconomics*, 3(1): 137–73.

Miguel, Edward, and Michael Kremer. 2004. "Worms: Identifying impacts on education and health in the presence of treatment externalities." *Econometrica*, 72(1): 159–217.

Miller, Amalia R. 2010. "Did the Airline Tariff Publishing Case Reduce Collusion?" *Journal of Law and Economics*, 53(3): 569–586.

Morse, Adair. 2011. "Payday lenders: Heroes or villains?" *Journal of Financial Economics*, 102(1): 28–44.

Novy-Marx, Robert. 2013. "The other side of value: the gross profitability premium." *Journal of Financial Economics*, 108(1): 1–28.

O'Brien, Daniel P., and Steven C. Salop. 2000. "Competitive efffects of partial ownership: Financial interest and corporate control." *Antitrust Law Journal*, 67(3): 559–614.

Opp, Marcus M., Christine A. Parlour, and Johan Walden. 2014. "Markup cycles, dynamic misallocation, and amplification." *Journal of Economic Theory*, 154: 126–161.

Pástor, Ľuboš, and Robert F. Stambaugh. 2003. "Liquidity risk and expected stock returns." *Journal of Political Economy*, 111(3): 642–685.

Phillips, Gordon. 1995. "Increased debt and industry product markets an empirical analysis." *Journal of Financial Economics*, 37(2): 189–238.

Phillips, Gordon, and Giorgo Sertsios. 2013. "How do firm financial conditions affect product quality and pricing?" *Management Science*, 59(8): 1764–1782.

Phillips, Gordon, and Giorgo Sertsios. 2017. "Financing and new product decisions of private and publicly traded firms." *Review of Financial Studies*, 30(5): 1744–1789.

Povel, Paul, Rajdeep Singh, and Andrew Winton. 2007. "Booms, busts, and fraud." *Review of Financial Studies*, 20(4): 1219–1254.

Rajan, Raghuram, Henri Servaes, and Luigi Zingales. 2000. "The cost of diversity: The diversification discount and inefficient investment." *Journal of Finance*, 55(1): 35–80.

Ravn, Morten O., and Harald Uhlig. 2002. "On adjusting the Hodrick-Prescott filter for the frequency of observations." *Review of Economics and Statistics*, 84(2): 371–376.

Rey, Patrick, and Jean Tirole. 2019. "Price caps as welfare-enhancing coopetition." *Journal of Political Economy*, 127(6): 3018–3069.

Rosenbaum, Paul R. 2007. "Interference between units in randomized experiments." *Journal of the American Statistical Association*, 102(477): 191–200.

Rubin, Donald B. 1978. "Bayesian inference for causal effects: The role of randomization." *Annals of Statistics*, 6(1): 34–58.

Rubin, Donald B. 1980. "Comment on randomization analysis of experimental data: The Fisher randomization test." *Journal of the American Statistical Association*, 75(371): 591–593.

Rubin, Donald B. 1990. "[On the application of probability theory to agricultural experiments. Essay on principles. Section 9.] Comment: Neyman (1923) and causal inference in experiments and observational studies." *Statistical Science*, 5(4): 472–480.

Sabidussi, G. 1966. "The centrality index of a graph." *Psychometrika*, 31: 581–603.

Santos, Tano, and Pietro Veronesi. 2010. "Habit formation, the cross section of stock returns and the cash-flow risk puzzle." *Journal of Financial Economics*, 98(2): 385–413.

Schwert, Michael. 2018. "Bank capital and lending relationships." *Journal of Finance*, 73(2): 787–830.

Seetharam, Ishuwar. 2018. "The indirect effects of hurricanes: Evidence from firm internal networks." Working Paper.

Sobel, Michael E. 2006. "What do randomized studies of housing mobility demonstrate?" *Journal of the American Statistical Association*, 101(476): 1398–1407.

Stambaugh, Robert F, and Yu Yuan. 2017. "Mispricing factors." *Review of Financial Studies*, 30(4): 1270–1315.

Strobl, Eric. 2011. "The economic growth impact of hurricanes: Evidence from US coastal counties." *Review of Economics and Statistics*, 93(2): 575–589.

Titman, Sheridan. 1984. "The effect of capital structure on a firm's liquidation decision." *Journal of Financial Economics*, 13(1): 137–151.

Wang, Zhongmin. 2009. "(Mixed) strategy in oligopoly pricing: Evidence from gasoline price cycles before and under a timing regulation." *Journal of Political Economy*, 117(6): 987–1030.

Whited, Toni M, and Guojun Wu. 2006. "Financial constraints risk." *Review of Financial Studies*, 19(2): 531–559.

Zingales, Luigi. 1998. "Survival of the fittest or the fattest? Exit and financing in the trucking industry." *Journal of Finance*, 53(3): 905–938.

Online Appendix

A Proofs

A.1 Proof for Proposition 2.1

To fix ideas, we consider industry i with market leaders a^i and c^i. We first describe the equilibrium in the state of non-collusive Nash equilibrium as follows:

$$q^N_{a^i,i} = \frac{a - 2\omega(x_{a^i}) + \omega(x_{c^i})}{3b} \quad \text{and} \quad q^N_{c^i,i} = \frac{a - 2\omega(x_{c^i}) + \omega(x_{a^i})}{3b}, \tag{A.1}$$

and

$$\pi^N_{a^i,i} = \frac{[a - 2\omega(x_{a^i}) + \omega(x_{c^i})]^2}{9b} \quad \text{and} \quad \pi^N_{c^i,i} = \frac{[a - 2\omega(x_{c^i}) + \omega(x_{a^i})]^2}{9b}. \tag{A.2}$$

The profit margins of market leader a^i and c^i from industry i are

$$\theta^N_{a^i,i} = \frac{\pi^N_{a^i,i}}{p^N_i q^N_{a^i,i}} = \frac{a - 2\omega(x_{a^i}) + \omega(x_{c^i})}{a + \omega(x_{a^i}) + \omega(x_{c^i})} \text{ and } \theta^N_{c^i,i} = \frac{\pi^N_{c^i,i}}{p^N_i q^N_{c^i,i}} = \frac{a - 2\omega(x_{c^i}) + \omega(x_{a^i})}{a + \omega(x_{a^i}) + \omega(x_{c^i})}. \tag{A.3}$$

Thus, it holds that

$$\frac{\partial \theta^N_{a^i,i}}{\partial \varepsilon_{a^i}} = \frac{\partial \theta^N_{a^i,i}}{\partial x_{a^i}} \frac{\partial x_{a^i}}{\partial \varepsilon_{a^i}} < 0 \quad \text{and} \quad \frac{\partial \theta^N_{c^i,i}}{\partial \varepsilon_{a^i}} = \frac{\partial \theta^N_{c^i,i}}{\partial x_{a^i}} \frac{\partial x_{a^i}}{\partial \varepsilon_{a^i}} > 0. \tag{A.4}$$

Now, we consider the collusive Nash equilibrium. For firm a^i and c^i in industry i with the collusive profit levels $\pi^C_{a^i,i}$ and $\pi^C_{c^i,i}$, the gain of deviation to reap more profits in the current period and the loss of deviation to lose the benefits of future cooperation for firm a^i are characterized as follows:

$$\text{Benefits of deviation for firm } a^i = \pi^C_{c^i,i} \delta e^{\eta \pi^C_{c^i,i}}, \text{ and} \tag{A.5}$$

$$\text{Costs of deviation for firm } a^i = \sum_{t=1}^{\infty} \lambda(x_{a^i}, \pi^C_{a^i,i})^t \left[1 - \lambda(x_{a^i}, \pi^C_{a^i,i})\right] t \pi^C_{a^i,i} \tag{A.6}$$

$$= \pi^C_{a^i,i} \frac{\lambda(x_{a^i}, \pi^C_{a^i,i})}{1 - \lambda(x_{a^i}, \pi^C_{a^i,i})}, \text{ respectively.} \tag{A.7}$$

To ensure that firm a^i will not deviate from the collusive profit level $\pi^C_{a^i,i}$, it must hold that

$$\pi^C_{a^i,i} \delta e^{\eta \pi^C_{c^i,i}} \leq \pi^C_{a^i,i} \frac{\lambda(x_{a^i}, \pi^C_{a^i,i})}{1 - \lambda(x_{a^i}, \pi^C_{a^i,i})}. \tag{A.8}$$

Plugging (2.1) into (A.8) and rearranging terms lead to the IC constraint for firm i in industry i as follows:

$$\pi^C_{a^i,i} \delta e^{\eta \pi^C_{c^i,i}} \leq \pi^C_{a^i,i} e^{-x_{a^i} + \gamma \pi^C_{a^i,i}} \tag{A.9}$$

which further leads to

$$\pi^C_{c^i,i} \leq \eta^{-1} \left[-\ln(\delta) - x_{a^i} + \gamma \pi^C_{a^i,i} \right]. \tag{A.10}$$

On the other hand, for firm c^i in industry i with the collusive profit level $\pi^C_{c^i,i}$, the gain of deviation to reap more profits in the current period and the loss of deviation to lose the benefits of future cooperation are characterized as follows:

$$\text{Benefits of deviation for firm } c^i = \pi^C_{c^i,i}\delta e^{\eta\pi^C_{a^i,i}}, \quad \text{and} \tag{A.11}$$

$$\text{Costs of deviation for firm } c^i = \sum_{t=1}^{\infty}\lambda(x_{c^i},\pi^C_{c^i})^t\left[1-\lambda(x_{c^i},\pi^C_{c^i})\right]t\pi^C_{c^i,i} \tag{A.12}$$

$$= \pi^C_{c^i,i}\frac{\lambda(x_{c^i},\pi^C_{c^i})}{1-\lambda(x_{c^i},\pi^C_{c^i})}, \quad \text{respectively.} \tag{A.13}$$

Because firm c^i operates in both industries i and c, it holds that $\pi^C_{c^i} = \pi^C_{c^i,i} + \pi^C_{c^i,c}$, which leads to

$$\text{Costs of deviation of firm } c^i = \pi^C_{c^i,i}\frac{\lambda(x_{c^i},\pi^C_{c^i,i}+\pi^C_{c^i,c})}{1-\lambda(x_{c^i},\pi^C_{c^i,i}+\pi^C_{c^i,c})}. \tag{A.14}$$

To ensure that firm c^i will not deviate from the collusive profit level $\pi^C_{c^i,i}$, it must hold that

$$\pi^C_{c^i,i}\delta e^{\eta\pi^C_{a^i,i}} \leq \pi^C_{c^i,i}\frac{\lambda(x_{c^i},\pi^C_{c^i,i}+\pi^C_{c^i,c})}{1-\lambda(x_{c^i},\pi^C_{c^i,i}+\pi^C_{c^i,c})}. \tag{A.15}$$

Plugging (2.1) into (A.15) and rearranging terms lead to the IC constraint for firm c^i in industry i as follows:

$$\pi^C_{c^i,i}\delta e^{\eta\pi^C_{a^i,i}} \leq \pi^C_{c^i,i}e^{-x_{c^i}+\gamma(\pi^C_{c^i,i}+\pi^C_{c^i,c})}, \tag{A.16}$$

which further leads to

$$\pi^C_{a^i,i} \leq \eta^{-1}\left[-\ln(\delta)-x_{c^i}+\gamma(\pi^C_{c^i,i}+\pi^C_{c^i,c})\right]. \tag{A.17}$$

Similar to Opp, Parlour and Walden (2014), Dou, Ji and Wu (2021*a*,*b*), and Chen et al. (2020), we assume that the firms collude on the highest profit level in the sense that the IC constraint is binding:

$$\pi^C_{c^i,i} = \eta^{-1}\left[-\ln(\delta)-x_{a^i}+\gamma\pi^C_{a^i,i}\right], \tag{A.18}$$

$$\pi^C_{a^i,i} = \eta^{-1}\left[-\ln(\delta)-x_{c^i}+\gamma(\pi^C_{c^i,i}+\pi^C_{c^i,c})\right]. \tag{A.19}$$

Similarly, the following equilibrium conditions can be derived:

$$\pi^C_{c^i,c} = \eta^{-1}\left[-\ln(\delta)-x_{c^j}+\gamma(\pi^C_{c^j,c}+\pi^C_{c^j,j})\right], \tag{A.20}$$

$$\pi^C_{c^j,c} = \eta^{-1}\left[-\ln(\delta)-x_{c^i}+\gamma(\pi^C_{c^i,c}+\pi^C_{c^i,i})\right], \tag{A.21}$$

$$\pi^C_{a^j,j} = \eta^{-1}\left[-\ln(\delta)-x_{c^j}+\gamma(\pi^C_{c^j,j}+\pi^C_{c^j,c})\right], \tag{A.22}$$

$$\pi^C_{c^j,j} = \eta^{-1}\left[-\ln(\delta)-x_{a^j}+\gamma\pi^C_{a^j,j}\right]. \tag{A.23}$$

Let $\overrightarrow{\pi}^C = (\pi^C_{c^i,i},\pi^C_{a^i,i},\pi^C_{c^i,c},\pi^C_{c^j,c},\pi^C_{a^j,j},\pi^C_{c^j,j})^T$ and $\overrightarrow{x} \equiv (x_{a^i},x_{c^i},x_{c^j},x_{a^j})^T$. Then, equations (A.18) – (A.23) can be rewritten as

$$H(\overrightarrow{x}) = \Gamma\overrightarrow{\pi}^C, \tag{A.24}$$

where

$$H(\overrightarrow{x}) \equiv \eta^{-1} \begin{bmatrix} \ln(\delta) + x_{a^i} \\ \ln(\delta) + x_{c^i} \\ \ln(\delta) + x_{c^j} \\ \ln(\delta) + x_{c^i} \\ \ln(\delta) + x_{c^j} \\ \ln(\delta) + x_{a^j} \end{bmatrix} \quad \text{and} \quad \Gamma \equiv \begin{bmatrix} -1 & \mu & 0 & 0 & 0 & 0 \\ \mu & -1 & \mu & 0 & 0 & 0 \\ 0 & \mu & -1 & \mu & 0 & 0 \\ 0 & 0 & \mu & -1 & \mu & 0 \\ 0 & 0 & 0 & \mu & -1 & \mu \\ 0 & 0 & 0 & 0 & \mu & -1 \end{bmatrix}, \text{ with } \mu \equiv \eta^{-1}\gamma. \tag{A.25}$$

Therefore, the profit levels of all firms in the collusive Nash equilibrium is

$$\overrightarrow{\pi}^C = \Gamma^{-1} H(\overrightarrow{x}), \tag{A.26}$$

where

$$\Gamma^{-1} = \frac{-1}{\det \Gamma} \begin{bmatrix} 3\mu^4 - 4\mu^2 + 1 & \mu^5 - 3\mu^3 + \mu & -2\mu^4 + \mu^2 & -\mu^5 + \mu^3 & \mu^4 & \mu^5 \\ \mu^5 - 3\mu^3 + \mu & \mu^4 - 3\mu^2 + 1 & -2\mu^3 + \mu & -\mu^4 + \mu^2 & \mu^3 & \mu^4 \\ -2\mu^4 + \mu^2 & -2\mu^3 + \mu & (\mu^2 - 1)(2\mu^2 - 1) & \mu(\mu^2 - 1)^2 & -\mu^4 + \mu^2 & -\mu^5 + \mu^3 \\ -\mu^5 + \mu^3 & -\mu^4 + \mu^2 & \mu(\mu^2 - 1)^2 & (\mu^2 - 1)(2\mu^2 - 1) & -2\mu^3 + \mu & -2\mu^4 + \mu^2 \\ \mu^4 & \mu^3 & -\mu^4 + \mu^2 & -2\mu^3 + \mu & \mu^4 - 3\mu^2 + 1 & \mu^5 - 3\mu^3 + \mu \\ \mu^5 & \mu^4 & -\mu^5 + \mu^3 & -2\mu^4 + \mu^2 & \mu^5 - 3\mu^3 + \mu & 3\mu^4 - 4\mu^2 + 1 \end{bmatrix}$$

and

$$\det \Gamma = -\mu^6 + 6\mu^4 - 5\mu^2 + 1.$$

It is obvious that all elements of $\partial \overrightarrow{\pi}^C / \partial \overrightarrow{x}$ are negative when μ is sufficiently small. Therefore, for any two market leaders f and p in industry $k \in \mathcal{K}$, firm f's profit level π_f^C decreases with its idiosyncratic distress level ε_f, and peer firm p's profit level π_p^C also decreases with firm f's idiosyncratic distress level ε_f as a spillover effect; i.e.

$$\frac{\partial \pi_{f,k}^C}{\partial x_f} \leq 0 \quad \text{and} \quad \frac{\partial \pi_{p,k}^C}{\partial x_f} \leq 0, \tag{A.27}$$

and thus

$$\frac{\partial \pi_{f,k}^C}{\partial \varepsilon_f} \leq 0 \quad \text{and} \quad \frac{\partial \pi_{p,k}^C}{\partial \varepsilon_f} \leq 0. \tag{A.28}$$

Higher ε_f leads to lower collusion capacity, thus causes lower price level p_k^C and higher outputs $(q_{f,k}^C, q_{p,k}^C)$ in the tacit collusion. Consequently, the profit margins $\theta_{f,k}^C \equiv \pi_{f,k}^C / [\pi_{f,k}^C + \omega(x_f) q_{f,k}^C]$ and $\theta_{p,k}^C \equiv \pi_{p,k}^C / [\pi_{p,k}^C + \omega(x_p) q_{p,k}^C]$ are both decreasing in ε_f.

A.2 Proof for Proposition 2.2

The cross-industry spillover effect is actually proved above in the proof of Proposition 2.1. Take industries i and c as an example. The solution in (A.26) implies that

$$\frac{\partial \pi_{a^i,i}^C}{\partial \varepsilon_{c^j}} = \frac{-\mu^3 + \mu}{\eta(\mu^6 - 6\mu^4 + 5\mu^2 - 1)}. \tag{A.29}$$

Clearly, $\partial\pi^C_{a^i,i}/\partial\varepsilon_{c^j} < 0$ as long as $\mu \leq 1/3$. Higher ε_{c^j} leads to lower collusion capacity of market leaders in industry i, thus causes lower price level p^C_i and higher outputs $(q^C_{a^i,i}, q^C_{c^i,i})$ in the tacit collusion. Consequently, the profit margins $\theta^C_{c^i,i} \equiv \pi^C_{a^i,i}/[\pi^C_{a^i,i} + \omega(x_{a^i})q^C_{a^i,i}]$ decreases in ε_{c^j}.

A.3 Proof for Proposition 2.3

According to (A.26), it follows that

$$\frac{\partial\vec{\pi}^C}{\partial x} = \frac{-1}{\eta\det\Gamma}\begin{bmatrix} \mu^5+2\mu^4-2\mu^3-3\mu^2+\mu+1 \\ \mu^5+\mu^4-4\mu^3-2\mu^2+2\mu+1 \\ -\mu^4-3\mu^3-\mu^2+2\mu+1 \\ -\mu^4-3\mu^3-\mu^2+2\mu+1 \\ \mu^5+\mu^4-4\mu^3-2\mu^2+2\mu+1 \\ \mu^5+2\mu^4-2\mu^3-3\mu^2+\mu+1 \end{bmatrix}, \quad \text{with } \mu\equiv\eta^{-1}\gamma. \tag{A.30}$$

Therefore, the industry-level profits in the collusive Nash equilibrium are

$$\frac{1}{\partial x}\begin{bmatrix} \partial\pi^C_i \\ \partial\pi^C_c \\ \partial\pi^C_j \end{bmatrix} = \frac{-\beta}{\eta\det\Gamma}\begin{bmatrix} 2\mu^5+3\mu^4-6\mu^3-5\mu^2+3\mu+2 \\ -2\mu^4-6\mu^3-2\mu^2+4\mu+2 \\ 2\mu^5+3\mu^4-6\mu^3-5\mu^2+3\mu+2 \end{bmatrix}. \tag{A.31}$$

Thus, the difference between industries' exposures to the economy-wide degree of financial constraints is

$$\frac{\partial\pi^C_c}{\partial x} - \frac{\partial\pi^C_i}{\partial x} = \frac{\beta(-2\mu^5-5\mu^4+3\mu^2+\mu)}{\eta(\mu^6-6\mu^4+5\mu^2-1)}. \tag{A.32}$$

When μ is sufficiently small, $\partial\pi^C_c/\partial x$ is more negative than $\partial\pi^C_i/\partial x$. Specifically, $\partial\pi^C_c/\partial x - \partial\pi^C_i/\partial x < 0$ as long as $\mu \leq 1/3$. Higher x leads to lower collusion capacity of market leaders in all industries, and it reduces π^C_c to a greater extent than π^C_i, thereby lowering p^C_c and pushing up q^C_c to a greater extent than p^C_i and q^C_i, respectively. Consequently, the profit margin $\theta^C_c \equiv \pi^C_c/[\pi^C_c + \omega(x_{c^i})q^C_{c^i,c} + \omega(x_{c^j})q^C_{c^j,c}]$ decreases in x faster than $\theta^C_i \equiv \pi^C_i/[\pi^C_i + \omega(x_{a^i})q^C_{a^i,i} + \omega(x_{c^i})q^C_{c^i,i}]$.

B Measures for Distress Risk

We use two empirical measures to examine firms' distress risk: the distress risk measure of Campbell, Hilscher and Szilagyi (2008) and the distance to default measure of Bharath and Shumway (2008).

Distress Risk. We follow Campbell, Hilscher and Szilagyi (2008) in measuring distress risk ($Distress_{i,t}$). Specifically, based on the third column in Table IV of Campbell, Hilscher and Szilagyi (2008), we define distress risk as follows:

$$\begin{aligned} Distress_{i,t} = &-9.164 - 20.264NIMTAAVG_{i,t} + 1.416TLMTA_{i,t} - 7.129EXRETAVG_{i,t} \\ &+ 1.411SIGMA_{i,t} - 0.045RSIZE_{i,t} - 2.132CASHMTA_{i,t} + 0.075MB_{i,t} - 0.058PRICE_{i,t}. \end{aligned} \tag{B.1}$$

Here, $NIMTAAVG$ is the moving average of the ratio between net income and market total assets. $TLMTA$ is the ratio between total liabilities and market value of total assets. $EXRETAVG$ is the moving average of stock returns in excess of the returns of the S&P 500 index. $SIGMA$ is the annualized standard deviation of daily returns over the past 3 months. $RSIZE$ is the relative size measured as the log ratio of a firm's market equity to that of the S&P 500 index. $CASHMTA$ is the ratio between cash and market value of total asset. MB is the ratio between market equity and book equity. $PRICE$ is the log of the stock price, truncated above at \$15. A higher level of $Distress_{i,t}$ implies a higher probability of bankruptcy or failure.

Distance to Default. We follow Bharath and Shumway (2008) in constructing the distance to default measure using the naive Merton default probability ($DD_{i,t}$). Specifically, we define the distance to default with a 1-year forecasting horizon following equation 12 of Bharath and Shumway (2008):

$$DD_{i,t} = \frac{\ln\left((E_{i,t} + F_{i,t})/F_{i,t}\right) + (r_{i,t} - 0.5\sigma_{i,t}^2)}{\sigma_{i,t}}.$$

where E is the market value of the firm's equity and F is the face value of the firm's debt. Variable $r_{i,t}$ represents the firm's stock return over the year. Variable $\sigma_{i,t}$ represents the total volatility of the firm, which is approximated by:

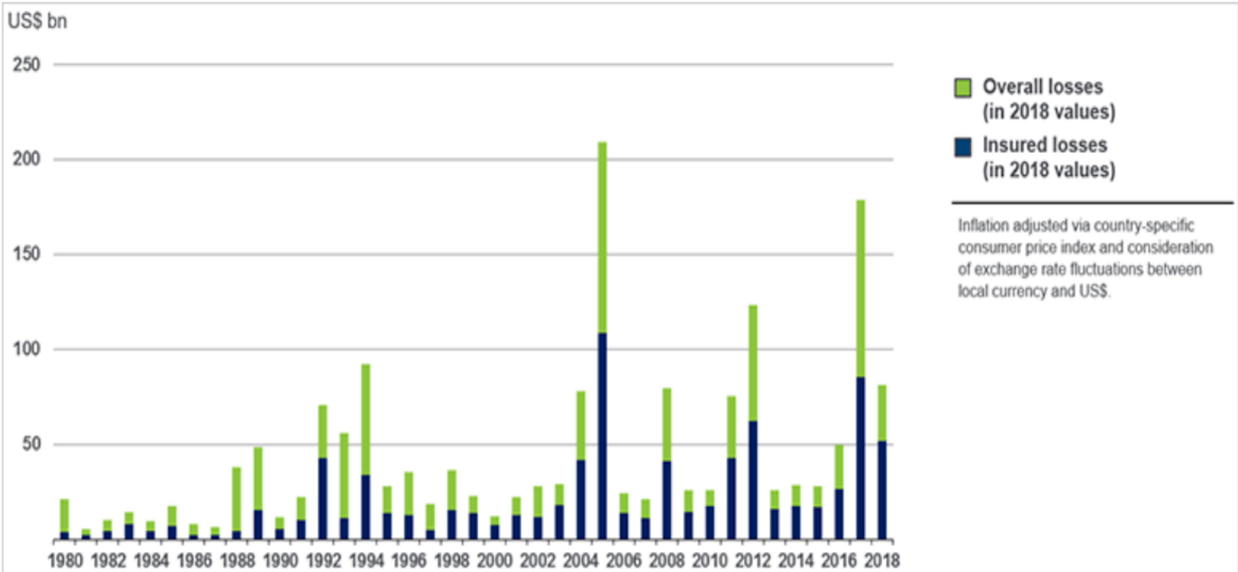
$$\sigma_{i,t} = \frac{E_{i,t}}{E_{i,t} + F_{i,t}}\sigma_{i,t}^E + \frac{E_{i,t}}{E_{i,t} + F_{i,t}}\sigma_{i,t}^D,$$

where $\sigma_{i,t}^E$ is the annualized stock volatility computed based on daily stock returns over the year, and $\sigma_{i,t}^D$ is approximated by $\sigma_{i,t}^D = 0.05 + 0.25\sigma_{i,t}^E$. The distance to default measure negatively captures the distress risk. A lower level of $DD_{i,t}$ implies a higher probability of bankruptcy or failure.

C Natural Disasters and Distress Risk

C.1 Disaster Losses Are Only Partially Offset by Insurance

Insurance coverage and public disaster assistance can only partially offset firms' losses in natural disasters. Froot (2001) documents that disaster insurance premiums are much higher than the value of expected losses, because the catastrophe insurance market is highly concentrated. Consistent with this finding, it is shown that (i) about half of the firms with significant exposure to natural disasters do not take out insurance policies (Henry et al., 2013), and (ii) about half of the natural disaster losses over the 1980 to 2018 period are not insured (see Figure OA.1). Even for insured firms, the coverage is far from complete. Garmaise and Moskowitz (2009) show that insured firms only partially cover risks, bringing disruptive effect to firms' investment activities. Aretz, Banerjee and Pryshchepa (2019) show that delays in the settlement of insurance claims imply that insured firms experience economic and financial distress until eventual compensation. Similarly, public disaster assistance takes time to arrive. According to the Federal Emergency Management Agency (FEMA) Disaster Declarations Database, the average duration of public disaster assistance may last up to 6 years from the announcement date of a presidential disaster declaration (e.g., Seetharam, 2018).



Source: © 2019 Munich Re, Geo Risks Research, NatCatSERVICE. As of March 2019.

Note: This figure plots the overall and insured losses from US natural disasters from 1980 to 2018. The figure is taken from the research report titled "Facts + Statistics: US catastrophes" by the Insurance Information Institution, available at `www.iii.org/fact-statistic/facts-statistics-us-catastrophes`.

Figure OA.1: Overall and insured losses from US natural disasters from 1980 to 2018.

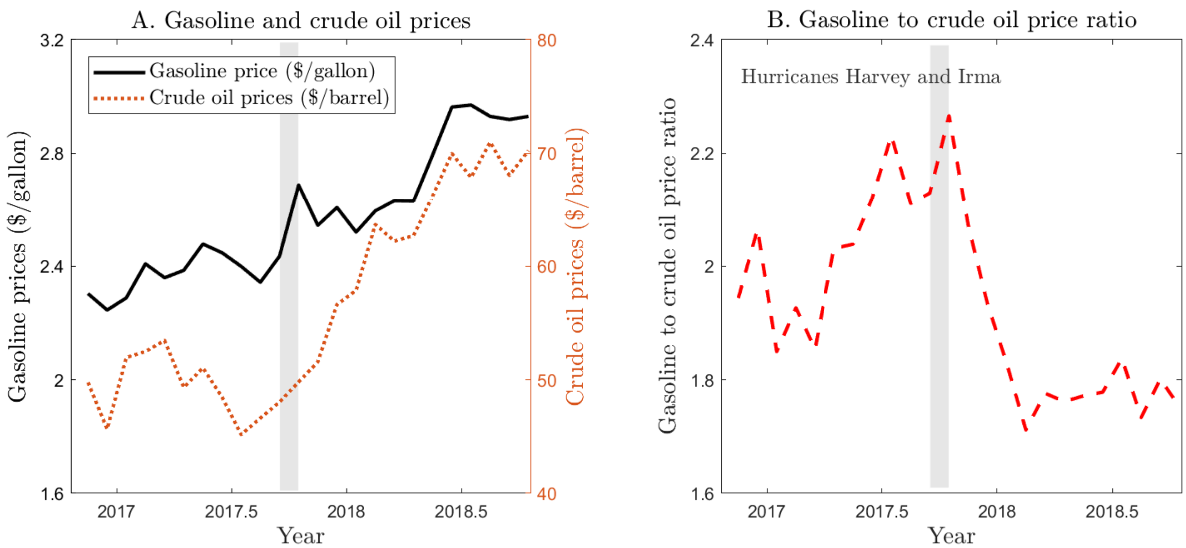
C.2 Hurricanes Harvey and Irma: An Anecdotal Example

Hurricanes Harvey and Irma caused huge amount of damage to the US oil refinery industry. More than a dozen major oil refineries located on the Gulf Coast suffered great losses from the two hurricanes. In responses to the damage caused by the natural disasters, both gasoline price and crude oil price increased sharply (see panel A of Figure OA.2). However, the amount of increase in gasoline price (in percentage terms) was much lower than that of crude oil. As a result, the profit margin of the oil refinery industry reduced significantly after the hurricanes (see panel B of Figure OA.2), suggesting that refinery firms did not simply pass the increased input costs to their customers; instead, they internalized some of the increased costs. This finding is consistent with our theory that predicts intensified product market competition in response to firms' increased distress risk.

D Measures for Network Centrality

We explain the mathematical definition of the four network centrality measures (degree, closeness, betweenness, and eigenvector centrality) in this section. We use an example network taken from El-Khatib, Fogel and Jandik (2015) to help with the illustration (see Figure OA.3).

Degree Centrality. Degree centrality is the number of direct links a node has with other nodes in the network. The more links the node has, the more central this node is in the network. The mathematical



Note: Panel A of this figure shows the gasoline price and crude oil price around Hurricanes Harvey and Irma. Both prices are obtained from the Federal Reserve Economic Data. Panel B of this figure plots the ratio between gasoline price and the crude oil price. The gray areas in both panels represent the period of Hurricanes Harvey and Irma.

Figure OA.2: Profitability in the oil refinery industry around Hurricanes Harvey and Irma.

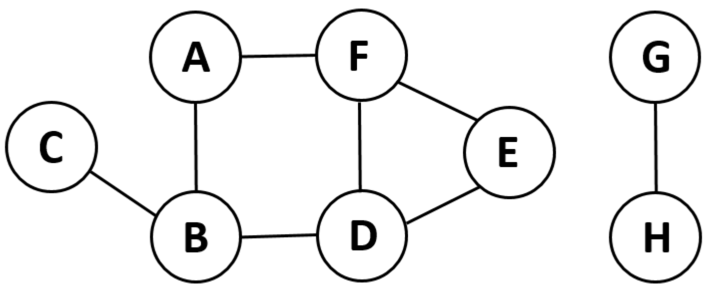


Figure OA.3: An example network.

definition for degree centrality is:

$$Degree_i = \sum_{j \neq i} x_{i,j}, \tag{D.1}$$

where $x_{i,j}$ is an indicator variable that equals 1 if node i and node j are connected. For the network shown in Figure OA.3, the degree centrality for nodes A to H is 2, 3, 1, 3, 2, 3, 1, and 1, respectively.

Closeness Centrality. Closeness centrality is the inverse of the sum of the (shortest) weighted distances between a node and all other nodes in a given network. It indicates how easily a node can be affected by other disturbances to other nodes in the network. The mathematical definition for closeness centrality is:

$$Closeness_i = \frac{n-1}{\sum_{j \neq i} d_{i,j}} \times \frac{n}{N}, \tag{D.2}$$

where $d_{i,j}$ is the shortest distance between nodes i and j. Variable n is the size of the component to which node i belongs, and variable N is the size of the entire network. In the network example shown in Figure OA.3, there are two components in the network: one with a size of six nodes (nodes A to F) and the other with a size of two nodes (nodes G and H). The closeness centrality for nodes A to H is 0.469, 0.536, 0.341, 0.536, 0.417, 0.469, 0.250, and 0.250, respectively.

Betweenness Centrality. Betweenness centrality gauges how often a node lies on the shortest path between any other two nodes of the network. Hence, it indicates how much control a node could have on the spillover effect on the network, because a node located between two other nodes can either dampen or amplify the spillover effect between those two nodes through the network links. The mathematical definition for betweenness centrality is:

$$Betweenness_i = \sum_{i<j\neq k\in N} \frac{g_{i,j,(k)}/g_{i,j}}{(n-1)(n-2)/2}, \tag{D.3}$$

where $g_{i,j}$ is 1 for any geodesic connecting nodes i and j, and $g_{i,j,(k)}$ is 1 if the geodesic between nodes i and j also passes through node k. Variable n is the size of the component to which node i belongs, and variable N is the size of the entire network. For the network shown in Figure OA.3, the betweenness centrality for nodes A to H is 0.1, 0.45, 0, 0.3, 0, 0.15, 0, and 0, respectively.

Eigenvector Centrality. Eigenvector centrality is a measure of the importance of a node in the network. It takes into account the extent to which a node is connected with other highly connected nodes. Eigenvector centrality is solved by satisfying the following equation:

$$\lambda E'E = E'\mathbf{A}E, \tag{D.4}$$

where E is an eigenvector of connection matrix $\mathbf{A}$, and λ is its corresponding eigenvector. The eigenvector centrality for node i is thus the elements of eigenvector E^* associated with $\mathbf{A}$'s principal eigenvalue λ^*. For the network shown in Figure OA.3, the eigenvector centrality for nodes A to H is 0.358, 0.408, 0.161, 0.516, 0.401, 0.502, 0, and 0, respectively.

E Competition Networks with Public and Private Firms

Table OA.1: Connected four-digit SIC pairs of the competition networks with and without private firms.

		Competition network with public firms only		
		0	1	Total
Competition network with both public and private firms	0	547,410	78	547,488
	1	77	1,063	1,140
	Total	547,487	1,141	548,628

In the main text, we construct the competition network based on Compustat historical segment data.

Because Compustat only covers public firms, it is possible that the competition network we construct is not an accurate representation of the competition network in the economy. In this section, we incorporate private firms in constructing the competition network. We show that the resulting competition network is very similar to the one constructed based on public firms only. We also show that the asset pricing implications of the competition network centrality measure remain robust after taking private firms into consideration.

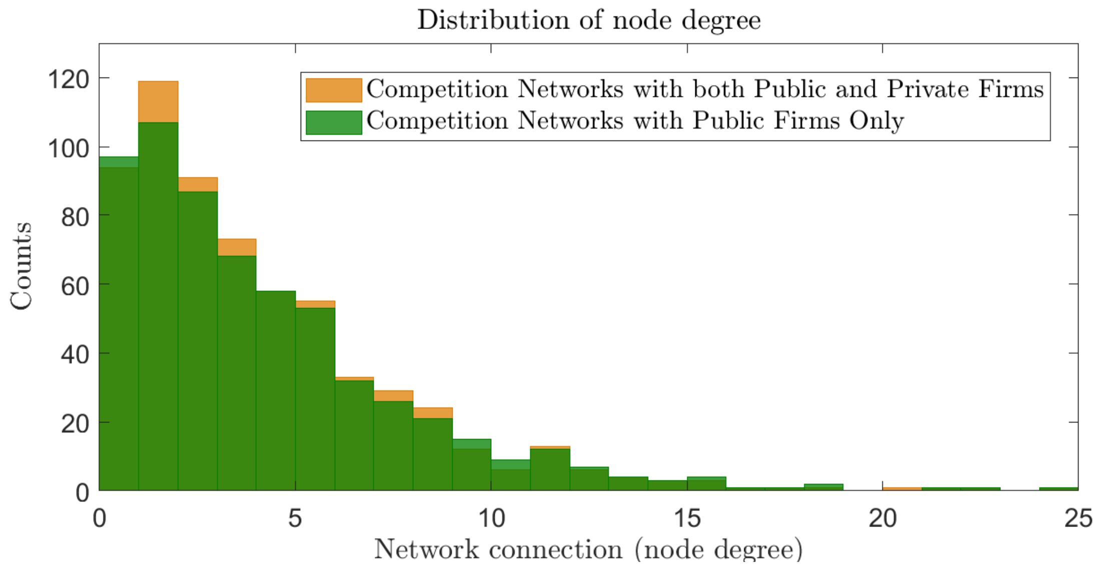


Figure OA.4: Node degree of the competition networks with and without private firms at the four-digit SIC industry level in 1994.

We obtain information about private firms from Capital IQ, which is one of the most comprehensive datasets covering private firms. Capital IQ provides the total sales of the private firms and the list of four-digit SIC industries in which firms operate ranked by the relative importance of these industries. The limitation of Capital IQ is that, unlike Compustat historical segment data, Capital IQ does not provide a breakdown of the industry-level sales within firms because the disclosure of private firms is in general less detailed. To overcome this limitation, we estimate the breakdown of the industry-level sales within firms using the weights computed based on public firms in the Compustat data. Specifically, for firms that operate in two industries, we assign 80% of sales to the primary industries and assign 20% of sales to the secondary industries. For firms that operate in three or more industries, we assign 68% of sales to the primary industries, 23% of sales to the secondary industries, and 9% of sales to the tertiary industries. Our findings remain robust if we assign sales to all industries in which the firms operate based on the weights estimated from public firms in the Compustat data.

Table OA.1 tabulates the connected four-digit SIC pairs of the competition networks with and without private firms in 1994. Adding private firms only causes a minor change to the competition network. More than 93% of the links remain the same after we take private firms into consideration in forming the network. Figure OA.4 shows the distribution of node degree of the competition networks with and without private firms in 1994. Again, we find that the distribution remains largely unchanged after adding private firms. We compare the competition networks with and without private firms in other snapshots and we find that the two sets of competition network are highly similar throughout our sample period.

Table OA.2: Excess industry returns and alphas sorted on the centrality of the competition network constructed using both public and private firms.

Panel A: Excess returns for the quintile portfolios sorted on competition network centrality					
Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5 − Q1
5.84*	4.53	7.75**	8.25***	9.17***	3.33**
[1.81]	[1.36]	[2.15]	[2.62]	[2.78]	[2.04]

Panel B: Alphas of the long-short portfolios sorted on competition network centrality					
CAPM model	Fama-French three-factor model	Pástor-Stambaugh liquidity-factor model	Stambaugh-Yuan mispricing-factor model	Hou-Xue-Zhang q-factor model	Fama-French five-factor model
2.75*	2.91*	3.01*	4.95***	4.79***	5.41***
[1.85]	[1.89]	[1.92]	[2.77]	[2.79]	[2.71]

Note: Panel A of this table shows the average excess returns for the industry quintile portfolios sorted on the centrality of the competition network constructed using both public and private firms. Panel B of this table shows the alphas of the long-short industry quintile portfolio sorted on the centrality of the competition network with both public and private firms. The competition network centrality is the PC1 of the four centrality measures of the competition network (i.e., degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality). In June of each year t, we sort industries into quintiles based on the centrality measure in year $t-1$. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. Because common leaders and conglomerates operate in more than one industry, we exclude them in computing industry returns. Industry returns are value-weighted from stock returns of the stand-alone firms in the industries based on firms' 1-month lagged market capitalization. We exclude from the analysis financial and utility industries and very small industries that contain fewer than three firms. Newey-West standard errors are estimated with one lag. We annualize average excess returns by multiplying them by 12. The sample period of the data is from July 1977 to June 2018. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

We next study the asset-pricing implications of the centrality of the competition networks constructed using both public and private firms. Table OA.2 shows that the excess returns and alphas are higher for industries with higher centrality in the competition network. Table OA.3 presents the results from Fama-MacBeth regressions and we again find that competition network centrality is positively priced in the cross section of industries.

F Credit Supply Shocks During the Lehman Crisis

We follow Chodorow-Reich (2014) to construct the measure of firm-specific credit supply shocks during the Lehman crisis. Specifically, we first define:

$$\Delta L_{-i,b} = \frac{\sum_{j\neq i} \alpha_{b,j,crisis} L_{b,j,crisis}}{0.5 \sum_{j\neq i} \alpha_{b,j,normal} L_{b,j,normal}}. \tag{F.1}$$

where $L_{b,j,t}$ is a dummy variable that equals to 1 if bank b lends to borrow j in period t, and $\alpha_{b,j,t}$ denotes bank b's share in each syndicated loan that is made to firm j in period t.[21] Because Dealscan only reports lender shares for about one-third of loans, we impute the missing lender shares using the same method of Chodorow-Reich (2014). The crisis period refers to the 9-month period from October 2008 to June 2009, and the pre-crisis normal period refers to the 18-month period containing October 2005 to June 2006 and October 2006 to June 2007. We multiply the denominator by 0.5 to account for the fact that the crisis period consists of 9 months while the pre-crisis normal period consists of 18 months. $\Delta L_{-i,b}$ captures the quantity

[21] The syndicated loan data come from Thomson Reuters LPC DealScan and we focus on loans with either primary or secondary purpose listed as "working capital" or "corporate purpose".

Table OA.3: Fama-MacBeth regressions on the centrality of the competition network constructed using both public and private firms.

	(1)	(2)	(3)	(4)	(5)	(6)
	$Ret_{i,t}$ (%)					
$Competition\_Centrality_{i,t-1}$	0.149***	0.151***	0.102***	0.089***	0.092***	0.156***
	[2.908]	[2.905]	[3.067]	[2.721]	[2.905]	[3.423]
$Production\_Centrality_{i,t-1}$		0.082	−0.014	−0.028	−0.027	−0.017
		[1.428]	[−0.243]	[−0.513]	[−0.491]	[−0.221]
$LnSales_{i,t-1}$			0.274***	0.303***	0.287***	0.358***
			[3.891]	[4.281]	[4.136]	[3.537]
$LnBEME_{i,t-1}$				0.064	0.083	0.201**
				[0.922]	[1.182]	[2.027]
$GP_{i,t-1}$					0.113**	0.259***
					[1.995]	[2.924]
$HHI_{i,t-1}$						−0.017
						[−0.282]
Constant	0.987***	0.963***	0.878***	0.849***	0.847***	0.658**
	[3.763]	[3.390]	[3.003]	[2.886]	[2.885]	[2.264]
Average obs/month	204	204	199	199	199	98
Average R-squared	0.005	0.010	0.026	0.041	0.052	0.096

Note: This table reports the slope coefficients and test statistics from Fama-MacBeth regressions that regress monthly industry returns ($Ret_{i,t}$) on the centrality of the competition network constructed using both public and private firms ($Competition\_Centrality_{i,t-1}$). Other control variables include production centrality ($Production\_Centrality_{i,t-1}$), natural log of industry revenue ($LnSales_{i,t-1}$), natural log of industry book-to-market ratio ($LnBEME_{i,t-1}$), industry gross profitability ($GP_{i,t-1}$), and industry concentration ratio ($HHI_{i,t-1}$). The competition network centrality is the PC1 of the four centrality measures of the competition network (i.e., degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality). The production network centrality is the PC1 of the same four centrality measures of the production network. Industry book-to-market ratio is the ratio between the book equity and the market equity of an industry. Industry gross profitability is constructed as gross profits (revenue minus cost of goods sold) scaled by assets, following the definition of Novy-Marx (2013). Industry-level revenue, cost of goods sold, book assets, book equity, and market equity are the sum of the corresponding firm-level measures for firms in the same industry. Industry concentration ratio is the HHI index of the top 50 firms. The concentration ratio data come from US Census which covers manufacturing industries. All the independent variables are standardized to have means of 0 and standard deviations of 1. Because common leaders and conglomerates operate in more than one industries, we exclude them in computing industry returns and characteristics. Industry returns are value-weighted from stock returns of the stand-alone firms in the industries based on firms' one-month lagged market capitalization. We exclude financial and utility industries and very small industries that contain fewer than three firms from the analysis. The sample period of the data is from 1977 to 2018. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

of loans made by bank b to all borrowers other than firm i relative to the pre-crisis normal period.

Next, we aggregate $\Delta L_{-i,b}$ across all lenders that lend to firm i for the last syndicated loan that firm i borrowed before the Lehman crisis:

$$\Delta\widetilde{L}_i = \sum_{b \in s_i} \alpha_{b,i,last} \Delta L_{-i,b}. \tag{F.2}$$

where $\alpha_{b,i,last}$ is bank b's share in the last syndicated loan taken by firm i before the Lehman crisis and s_i denotes the set of banks that lend to firm i in that syndicated loan. $\Delta\widetilde{L}_i$ captures the credit supply shocks to firm i during the Lehman crisis. A lower level of of $\Delta\widetilde{L}_i$ implies that the lender health of firm i deteriorated more during the Lehman crisis.

G Evidence from Enforcement Against Financial Fraud

We follow Karpoff et al. (2017) and examine firms that have been prosecuted by the SEC and DOJ for Section 13(b) violations. Because violating firms face legal punishment and penalties imposed by the market, their distress risk increases significantly (e.g., Graham, Li and Qiu, 2008; Karpoff, Lee and Martin, 2008), which provides us a nice setting to examine the reaction of their industry peers.[22]

We assemble financial fraud data following Karpoff et al. (2017). First, we collect all enforcement actions brought by the SEC and the US Department of Justice (DOJ) for violations of Section 13(b) of the Securities Exchange Act of 1934. We then match violating firms to the Compustat-CRSP based on firm names. For each financial fraud case, we hand-collect the date of the first public announcement revealing to investors that a future enforcement action is possible (i.e., trigger date) by examining firms' 8-K filings downloaded from the EDGAR system and other news releases covered by the Factiva database and the RavenPack database. Our merged sample spans the period from 1976 to 2018 and it covers 838 unique violating firms that operate in non-financial industries.

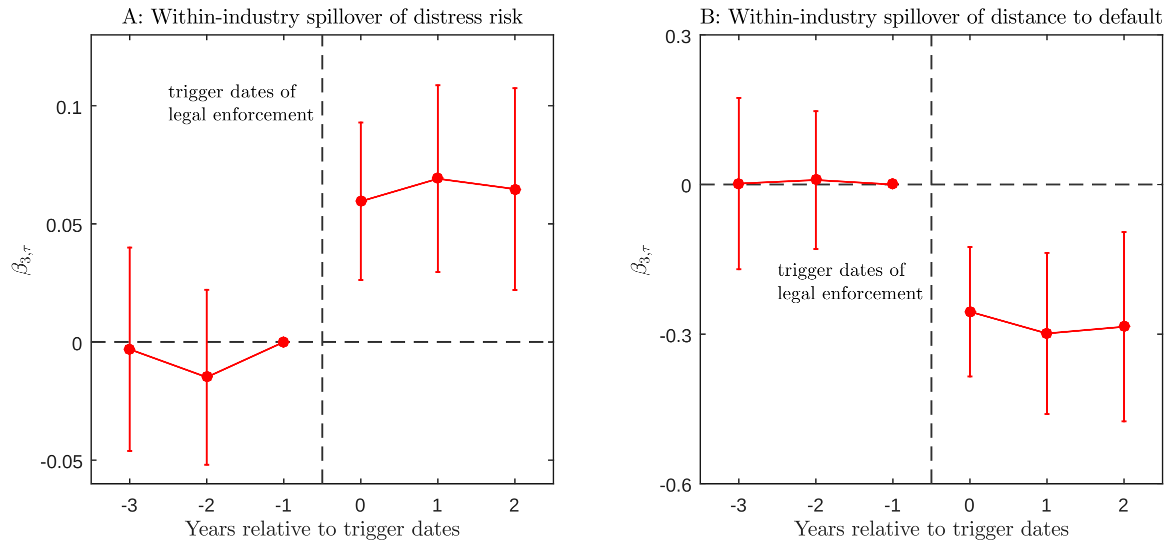
Similar to the natural disaster setting, we use DID analysis to study the spillover effects from distressed firms to their industry peers. For each violating firm, we match it with up to 10 non-violating peer firms in the same four-digit SIC industry based on firm asset size, tangibility, and age. We require that the matched peer firms are not suppliers or customers of the violating firms. For each firm, we include four yearly observations (i.e., 2 years before and 2 years after the year of fraud revelation) in the analysis. Different from natural disasters, financial fraud does not occur exogenously. In particular, it has been shown that financial fraud tends to peak toward the end of a boom and is then revealed in the ensuing bust (e.g., Povel, Singh and Winton, 2007). To control for business cyclicality, we add past average ROA and stock returns as additional control variables in the DID regressions. Our regression specification is:

$$\begin{aligned} Y_{i,t} =& \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1 + n(\mathcal{C}_{i,t})) \\ &+ \beta_5 ROA_{i,t-3:t-1} + \beta_6 StockRet_{i,t-3:t-1} + \theta_i + \delta_t + \varepsilon_{i,t}, \end{aligned} \tag{G.1}$$

where $Treat_{i,t}$ is an indicator variable that equals 1 if firm i is a firm that commits financial fraud. $Post_{i,t}$ is an indicator variable that equals 1 for observations after the trigger date, which is the date of the first public announcement revealing to investors that future enforcement action is possible. $Ln(1 + n(\mathcal{C}_{i,t}))$ captures the strength of cross-industry spillover via the competition network. $ROA_{i,t-3:t-1}$ is the average ROA of firm i from year $t-3$ to year $t-1$. $StockRet_{i,t-3:t-1}$ is the average stock returns of firm i from year $t-3$ to year $t-1$. The term θ_i represents firm fixed effects, and the term δ_t represents year fixed effects.

Table OA.4 in the Online Appendix presents the findings from the DID analysis. Consistent with the natural disaster setting, we find that coefficient β_3 is significantly positive for distress risk and significantly negative for distance to default, suggesting that industry peers of the violating firms become more distressed. Coefficient β_3 is significantly negative for gross profitability and markup, suggesting that industry peers of the violating firms engage in more aggressive product market competition after the revelation of fraud. In Figures OA.5 and OA.6 of the Online Appendix, we examine the dynamics of the spillover effects. We find that the spillover effect emerges only after the revelation of fraud. There is no significant change in the distress risk or distance to default prior to the trigger dates, which provides evidence supporting the

[22] We limit our analysis to fraud cases in which firms receive at least $0.25 million in monetary fines from the US government to ensure that the violating firms face sizable legal penalties. Our findings are robust to other cutoffs.



Note: This figure plots the within-industry spillover effects of distress risk around legal enforcement actions against financial fraud. For each violating firm, we match it with up to 10 non-violating peer firms in the same four-digit SIC industry based on firm asset size, tangibility, and age. We require that the matched peer firms are not suppliers or customers of the treated firms. For each firm, we include six yearly observations in the analysis. Specifically, for each firm, we include 3 years before and 3 years after the trigger date, which is the date of the first public announcement revealing to investors that a future enforcement action is possible. To estimate the dynamics of the spillover effect, we consider the yearly regression specification as follows: $Y_{i,t} = \sum_{\tau=-3}^{2} \beta_{1,\tau} \times Treat_{i,t} \times Fraud_{i,t-\tau} + \beta_2 \times Treat_{i,t} + \sum_{\tau=-3}^{2} \beta_{3,\tau} \times Fraud_{i,t-\tau} + \beta_4 Ln(1 + n(\mathcal{C}_{i,t})) + \beta_5 ROA_{i,t-3:t-1} + \beta_6 StockRet_{i,t-3:t-1} + \theta_i + \delta_t + \varepsilon_{i,t}$. The dependent variable ($Y_{i,t}$) is the distress risk ($Distress_{i,t}$) and the distance to default ($DD_{i,t}$) in panels A and B, respectively. $Treat_{i,t}$ is an indicator variable that equals 1 if firm i is a firm that commits financial fraud. $Fraud_{i,t-\tau}$ is an indicator variable that equals 1 if the trigger date of the legal enforcement action against firm i (when firm i is a treated firm) or the treated firm to which firm i is matched (when firm i is a matched non-treated firm) takes place in year $t - \tau$. $Ln(1 + n(\mathcal{C}_{i,t}))$ captures the strength of cross-industry spillover effect, and it is the natural log of 1 plus the number of industries connected to firm i's industry through competition networks and containing violating firms in year t. $ROA_{i,t-3:t-1}$ is the average ROA of firm i from year $t-3$ to year $t-1$. $StockRet_{i,t-3:t-1}$ is the average stock returns of firm i from year $t-3$ to year $t-1$. The term θ_i represents firm fixed effects, and the term δ_t represents year fixed effects. When running the regression, we impose $\beta_{1,-1} = \beta_{3,-1} = 0$ to avoid collinearity in categorical regressions, and by doing this, we set the years immediately preceding the years of the trigger date as the benchmark. The sample of this figure spans from 1976 to 2018. We exclude firms in financial industries from the analysis. We plot estimated coefficients $\beta_{3,\tau}$ with $\tau = -3, -2, \cdots, 2$, as well as their 90% confidence intervals with standard errors clustered at the firm level. The vertical dashed lines represent the trigger dates of the legal enforcement actions against financial fraud.

Figure OA.5: Within-industry spillover effects of distress risk in the financial fraud setting.

parallel trend assumption for the DID analysis. Finally, we should point out that the fraud setting has a caveat because there are on average fewer than 20 violating firms per year in our sample. The sparsity of the treated firms prevents us from studying the cross-industry spillover effects. Consistent with this caveat, the coefficient for the cross-industry spillover term (i.e., β_4) is statistically insignificant as shown in Table OA.4.

H Supplementary Empirical Results

Similar to Boehmer, Jones and Zhang (2020), we identify the total treatment effect of the treated firms and the spillover effect to the non-treated peer firms simultaneously using the DID approach. Specifically, we match each treated firm with up to 5 non-treated peer firms in the same four-digit SIC industry with similar

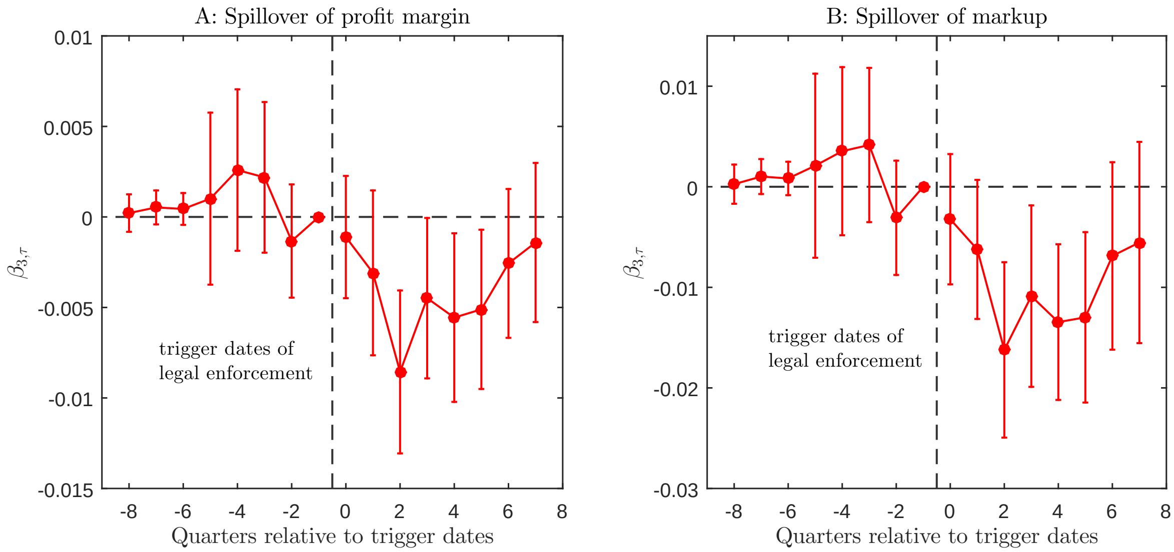
Table OA.4: Evidence from legal enforcement actions against financial frauds.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.358***	0.358***	−1.057***	−1.058***	−0.008	−0.008	−0.020	−0.020
	[4.856]	[4.855]	[−3.725]	[−3.730]	[−1.202]	[−1.204]	[−1.554]	[−1.558]
$Treat_{i,t}$	−0.030	−0.030	−0.260	−0.262	0.003	0.003	0.012	0.012
	[−0.455]	[−0.453]	[−0.699]	[−0.704]	[0.383]	[0.382]	[0.636]	[0.632]
$Post_{i,t}$	0.068***	0.065***	−0.283***	−0.256***	−0.008***	−0.008***	−0.015***	−0.014**
	[3.561]	[3.359]	[−3.341]	[−3.037]	[−2.631]	[−2.512]	[−2.488]	[−2.280]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.019		−0.142		−0.001		−0.005
		[0.588]		[−1.210]		[−0.324]		[−0.615]
$ROA_{i,t-3:t-1}$	0.223**	0.222**	0.578**	0.582**	−0.011	−0.011	−0.032	−0.032
	[2.452]	[2.447]	[1.975]	[1.989]	[−0.501]	[−0.500]	[−0.786]	[−0.784]
$StockRet_{i,t-3:t-1}$	−0.104**	−0.103**	0.462***	0.459***	0.006	0.006	0.011	0.011
	[−2.058]	[−2.053]	[2.902]	[2.894]	[0.954]	[0.947]	[0.884]	[0.872]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9284	9284	8009	8009	9817	9817	9813	9813
R-squared	0.653	0.653	0.775	0.775	0.878	0.878	0.892	0.892
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.016	0.018	0.004	0.006

Note: This table presents the results of a DID analysis examining the response of distress risk and gross profit margin to legal enforcement actions against financial fraud of peer firms. For each violating firm, we match it with up to 10 non-violating peer firms in the same four-digit SIC industry based on firm asset size, tangibility, and age. We use a relatively high matching ratio to reduce noise because there are on average fewer than 20 violating firms per year in our sample. We require that the matched peer firms are not suppliers or customers of the violating firms. For each firm, we include four yearly observations in the analysis. Specifically, for each firm, we include 2 years before and 2 years after the trigger date, which is the date of the first public announcement revealing to investors that a future enforcement action is possible. The regression specification is: $Y_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1+n(\mathcal{C}_{i,t})) + \beta_5 ROA_{i,t-3:t-1} + \beta_6 StockRet_{i,t-3:t-1} + \theta_i + \delta_t + \varepsilon_{i,t}$. The dependent variables in columns (1) to (4) are the distress risk ($Distress_{i,t}$), distance to default ($DD_{i,t}$), gross profit margin ($PM_{i,t}$), and markup ($Markup_{i,t}$), respectively. $Treat_{i,t}$ is an indicator variable that equals 1 if firm i is a firm that commits financial fraud. $Post_{i,t}$ is an indicator variable that equals 1 for observations after the trigger dates. $Ln(1+n(\mathcal{C}_{i,t}))$ captures the strength of cross-industry spillover effects, and it is the natural log of 1 plus the number of industries connected to firm i's industry through competition networks and containing violating firms in year t. $ROA_{i,t-3:t-1}$ is the average ROA of firm i from year $t-3$ to year $t-1$. $StockRet_{i,t-3:t-1}$ is the average stock returns of firm i from year $t-3$ to year $t-1$. The term θ_i represents firm fixed effects, and the term δ_t represents year fixed effects. In the last row of the table, we present the p-value for the null hypothesis that the total treatment effect for the treated firms is zero (i.e., $\beta_1 + \beta_3 = 0$). The sample of this table spans from 1976 to 2018. We exclude firms in financial industries from the analysis. Standard errors are clustered at the firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

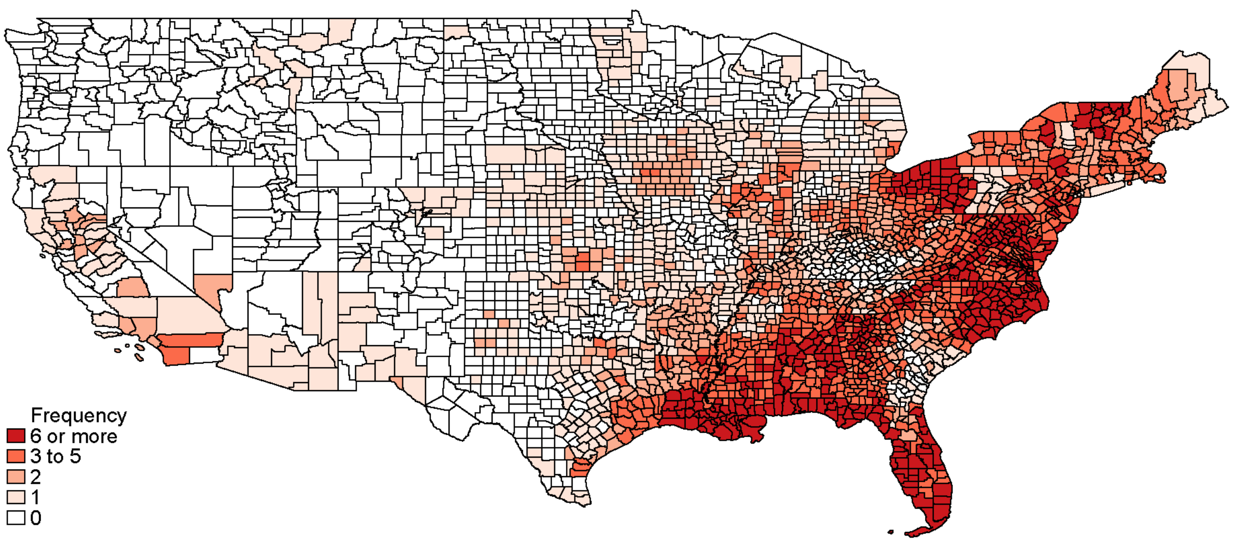
asset size, tangibility, and age.[23] Because we are interested in studying the spillover effect, it is important for us to make sure that the matched peer firms are not directly affected by major natural disaster shocks. In particular, we require the matched peer firms to have no establishment (including headquarters) in any county that experiences any positive amount of property damage during a major natural disaster. To make sure that the spillover effects we document are distinct from production network externality, we require that the matched peer firms are not suppliers or customers of the treated firms.

[23] If the treated firm is a common leader, we match it to non-treated peer firms in all four-digit SIC industries in which this treated firm is a common leader.



Note: This figure plots the within-industry spillover effects of profit margin around legal enforcement actions against financial fraud. For each violating firm, we match it with up to 10 non-violating peer firms in the same four-digit SIC industry based on firm asset size, tangibility, and age. We require that the matched peer firms are not suppliers or customers of the treated firms. For each firm, we include 16 quarterly observations in the analysis. Specifically, for each firm, we include eight quarters before and eight quarters after the trigger date, which is the date of the first public announcement revealing to investors that a future enforcement action is possible. To estimate the dynamics of the spillover effect, we consider the quarterly regression specification as follows: $Y_{i,t} = \sum_{\tau=-8}^{7} \beta_{1,\tau} \times Treat_{i,t} \times Fraud_{i,t-\tau} + \beta_2 \times Treat_{i,t} + \sum_{\tau=-8}^{7} \beta_{3,\tau} \times Fraud_{i,t-\tau} + \beta_4 Ln(1 + n(\mathcal{C}_{i,t})) + \beta_5 ROA_{i,t-12:t-1} + \beta_6 StockRet_{i,t-12:t-1} + \theta_i + \delta_t + \varepsilon_{i,t}$. The dependent variable ($Y_{i,t}$) is the gross profit margin ($PM_{i,t}$) and markup ($Markup_{i,t}$) in panels A and B, respectively. $Treat_{i,t}$ is an indicator variable that equals 1 if firm i is a firm that commits financial fraud. $Fraud_{i,t-\tau}$ is an indicator variable that equals 1 if the trigger date of the legal enforcement actions against firm i (when firm i is a treated firm) or the treated firm to which firm i is matched (when firm i is a matched non-treated firm) takes place in quarter $t - \tau$. $Ln(1 + n(\mathcal{C}_{i,t}))$ captures the strength of cross-industry spillover effect, and it is the natural log of 1 plus the number of industries connected to firm i's industry through competition networks and containing violating firms in year t. $ROA_{i,t-12:t-1}$ is the average ROA of firm i from quarter $t - 12$ to quarter $t - 1$. $StockRet_{i,t-12:t-1}$ is the average stock returns of firm i from quarter $t - 12$ to quarter $t - 1$. The term θ_i represents firm fixed effects, and the term δ_t represents quarter fixed effects. When running the regression, we impose $\beta_{1,-1} = \beta_{3,-1} = 0$ to avoid collinearity in categorical regressions, and by doing this, we set the quarters immediately preceding the quarters of the trigger date as the benchmark. The sample of this figure spans from 1976 to 2018. We exclude firms in the financial industries from the analysis. We plot estimated coefficients $\beta_{3,\tau}$ with $\tau = -8, -7, \cdots, 7$, as well as their 90% confidence intervals with standard errors clustered at the firm level. The vertical dashed lines represent the trigger dates of the legal enforcement actions against financial frauds.

Figure OA.6: Within-industry spillover effects of profit margin in the financial fraud setting.



Note: This figure presents the frequency of major natural disaster for each county in the US mainland from 1994 to 2018. The list of counties affected by each major natural disaster is obtained from the SHELDUS database. Table OA.8 describes the major natural disasters included in the sample.

Figure OA.7: Frequency of major natural disasters by US county.

Table OA.5: Relation between competition network centrality and industry characteristics

	Panel A: Summary statistics of the industry characteristics						
	Mean	Median	SD	p10	p25	p75	p90
$Centrality_{i,t}$	2.971	2.350	2.077	1.156	1.654	3.702	5.669
$Production\_Centrality_{i,t}$	1.731	1.543	0.958	0.889	1.416	1.893	2.344
$LnSales_{i,t}$	7.747	7.691	1.940	5.293	6.412	9.074	10.448
$LnBEME_{i,t}$	−0.531	−0.548	0.700	−1.336	−0.966	−0.105	0.298
$GP_{i,t}$	0.346	0.323	0.213	0.097	0.185	0.473	0.622
$HHI_{i,t}$	0.068	0.049	0.061	0.018	0.030	0.082	0.148

	Panel B: Industry characteristics across portfolios sorted on competition network centrality									
	Mean					Median				
$Centrality_{i,t}$ quintiles	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
$Centrality_{i,t}$	1.070	1.935	2.379	3.293	6.247	1.157	1.903	2.241	3.250	5.655
$Production\_Centrality_{i,t}$	1.680	1.734	1.766	1.702	1.777	1.534	1.624	1.523	1.524	1.543
$LnSales_{i,t}$	7.633	7.624	7.782	7.850	7.877	7.520	7.591	7.759	7.735	7.834
$LnBEME_{i,t}$	−0.601	−0.537	−0.513	−0.473	−0.527	−0.623	−0.543	−0.520	−0.496	−0.537
$GP_{i,t}$	0.402	0.314	0.308	0.354	0.352	0.378	0.284	0.277	0.335	0.326
$HHI_{i,t}$	0.066	0.064	0.068	0.066	0.073	0.048	0.044	0.054	0.049	0.051

	Panel C: Relation between competition network centrality and industry characteristics									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$Competition\_Centrality_{i,t}$									
$Production\_Centrality_{i,t}$	0.046	0.036	0.050*	0.024	0.052*	0.027	0.053*	0.028	0.040	0.006
	[1.566]	[1.021]	[1.689]	[0.683]	[1.743]	[0.777]	[1.759]	[0.781]	[0.665]	[0.088]
$LnSales_{i,t}$			−0.013	0.040	−0.008	0.042	−0.008	0.042	0.135	0.171
			[−0.373]	[0.929]	[−0.206]	[0.939]	[−0.223]	[0.946]	[1.315]	[1.525]
$LnBEME_{i,t}$					0.047*	0.024	0.045*	0.016	−0.001	−0.028
					[1.792]	[0.871]	[1.790]	[0.592]	[−0.013]	[−0.539]
$GP_{i,t}$							−0.009	−0.028	−0.163*	−0.174*
							[−0.250]	[−0.760]	[−1.809]	[−1.936]
$HHI_{i,t}$									0.091	0.096
									[0.961]	[1.009]
Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	9195	9195	9186	9186	8840	8840	8840	8840	3327	3327
R-squared	0.002	0.020	0.002	0.021	0.005	0.022	0.005	0.023	0.036	0.066

Note: This table shows the relation between competition network centrality and industry characteristics. $Competition\_Centrality_{i,t}$ is the competition network centrality measure, which is the PC1 of the four centrality measures of the competition networks (i.e., degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality). $Production\_Centrality_{i,t}$ is the production network centrality, which is the PC1 of four centrality measures of the production networks. $LnSales_{i,t}$ is the natural log of industry revenue. $LnBEME_{i,t}$ is the natural log of industry book-to-market ratio, which is the ratio between the book equity and the market equity of an industry. $GP_{i,t}$ is industry gross profitability, which is the gross profits (revenue minus cost of goods sold) scaled by assets, following the definition of Novy-Marx (2013). Industry-level revenue, cost of goods sold, book assets, book equity, and market equity are the sum of the corresponding firm-level measures for firms in the same industry. $HHI_{i,t}$ is the HHI of the top 50 firms. The concentration ratio data come from the US Census, which covers manufacturing industries. Panel A tabulates summary statistics of the industry characteristics. P10, p25, p75, and p90 are the 10^{th}, 25^{th}, 75^{th}, and 90^{th} percentiles. Panel B tabulates the mean and median values of the industry characteristics across industry quintile portfolios sorted on competition network centrality. The sorting is performed at yearly frequency. Panel C performs panel regressions which regress industry-level competition network centrality on various industry characteristics. The dependent variable and all the independent variables are standardized to have means of 0 and standard deviations of 1. Because common leaders and conglomerates operate in more than one industry, we exclude them in computing industry characteristics. We exclude from the analysis financial and utility industries and very small industries that contain fewer than three firms. The sample period of the data is from 1977 to 2018. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table OA.6: Excess returns of the double-sort analysis.

Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5 − Q1
Panel A: Double sort on production network centrality					
6.34^{*}	6.69^{*}	5.45	6.86^{**}	9.77^{***}	3.43^{**}
[1.93]	[1.93]	[1.62]	[2.20]	[2.97]	[2.20]
Panel B: Double sort on industry size					
5.90^{*}	6.46^{*}	5.56^{*}	7.62^{**}	9.65^{***}	3.75^{**}
[1.78]	[1.90]	[1.66]	[2.43]	[2.96]	[2.37]
Panel C: Double sort on industry book-to-market ratio					
5.73^{*}	6.93^{**}	5.73^{*}	7.22^{**}	9.54^{***}	3.80^{**}
[1.75]	[1.98]	[1.70]	[2.34]	[2.91]	[2.25]
Panel D: Double sort on industry gross profitability					
5.58	6.23^{*}	6.52^{*}	7.79^{**}	8.93^{***}	3.35^{**}
[1.63]	[1.83]	[1.95]	[2.52]	[2.75]	[2.04]
Panel E: Double sort on industry concentration ratio					
3.54	6.81^{*}	7.88^{**}	7.80^{**}	9.29^{***}	5.75^{***}
[1.06]	[1.93]	[2.47]	[2.38]	[2.93]	[3.46]

Note: This table shows the average excess returns for the industry portfolios sorted on competition network centrality after controlling for various industry characteristics using the double-sort analysis. In each June, we first sort industries into five groups based on their 1-year lagged characteristics including production centrality (panel A), size (panel B), book-to-market ratio (panel C), profitability (panel D), and concentration ratio (panel E). Next, we sort industries within each group into quintiles based on their 1-year lagged competition network centrality, which is the PC1 of the four centrality measures of the competition networks (i.e., degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality). We then pool the industries in the same competition network centrality quintiles together across the industry groups. Thus, in each June, we effectively sort industries into competition network centrality quintiles controlling for various industry characteristics. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. Because common leaders and conglomerates operate in more than one industry, we exclude them in computing industry returns. Industry returns are value-weighted from stock returns of the stand-alone firms in the industries based on firms' 1-month lagged market capitalization. We exclude from the analysis financial and utility industries and very small industries that contain fewer than three firms. The production network centrality is computed based on the PC1 of four centrality measures of the production networks. The industry size is the measured by the revenue of an industry. The industry book-to-market ratio is the ratio between the book equity and the market equity of an industry. The industry gross profitability is constructed as gross profits (revenue minus cost of goods sold) scaled by assets, following the definition of Novy-Marx (2013). The industry-level revenue, cost of goods sold, book assets, book equity, and market equity are the sum of the corresponding firm-level measures for firms in the same industry. Industry concentration ratio is the HHI index of the top 50 firms. The concentration ratio data come from the US Census, which covers manufacturing industries. Newey-West standard errors are estimated with one lag. We annualize average excess returns by multiplying them by 12. The sample period of the data is from July 1977 to June 2018. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table OA.7: Alphas of the double-sort analysis.

CAPM model	Fama-French three-factor model	Pástor-Stambaugh liquidity-factor model	Stambaugh-Yuan mispricing-factor model	Hou-Xue-Zhang q-factor model	Fama-French five-factor model
Panel A: Double sort on production network centrality					
3.35^{**}	3.05^{*}	2.98^{*}	3.92^{**}	4.21^{**}	3.42^{**}
[2.11]	[1.87]	[1.77]	[2.20]	[2.10]	[2.04]
Panel B: Double sort on industry size					
3.74^{**}	3.69^{**}	3.64^{**}	4.18^{**}	5.20^{**}	4.52^{***}
[2.33]	[2.19]	[2.11]	[2.27]	[2.49]	[2.60]
Panel C: Double sort on industry book-to-market ratio					
3.49^{**}	3.77^{**}	3.77^{**}	4.66^{**}	5.28^{**}	4.76^{**}
[2.04]	[2.11]	[2.06]	[2.35]	[2.38]	[2.58]
Panel D: Double sort on industry profitability					
3.47^{**}	3.74^{**}	3.84^{**}	3.96^{**}	4.45^{**}	4.16^{**}
[2.11]	[2.20]	[2.20]	[2.02]	[2.00]	[2.30]
Panel E: Double sort on industry concentration ratio					
5.93^{***}	5.94^{***}	5.84^{***}	6.46^{***}	6.84^{***}	6.45^{***}
[3.54]	[3.44]	[3.30]	[3.38]	[3.18]	[3.58]

Note: This table shows the alphas of the long-short industry quintile portfolio sorted on competition network centrality after controlling for various industry characteristics using the double-sort analysis. In each June, we first sort industries into five groups based on their 1-year lagged characteristics including production centrality (panel A), size (panel B), book-to-market ratio (panel C), profitability (panel D), and concentration ratio (panel E). Next, we sort industries within each group into quintiles based on their 1-year lagged competition network centrality, which is the PC1 of the four centrality measures of the competition networks (i.e., degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality). We then pool the industries in the same competition network centrality quintiles together across the industry groups. Thus, in each June, we effectively sort industries into competition network centrality quintiles controlling for various industry characteristics. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. Because common leaders and conglomerates operate in more than one industry, we exclude them in computing industry returns. Industry returns are value-weighted from stock returns of the stand-alone firms in the industries based on firms' 1-month lagged market capitalization. We exclude from the analysis financial and utility industries and very small industries that contain fewer than three firms. The production network centrality is computed based on the PC1 of four centrality measures of the production networks. Industry size is measured by the revenue of an industry. Industry book-to-market ratio is the ratio between the book equity and the market equity of an industry. Industry gross profitability is constructed as gross profits (revenue minus cost of goods sold) scaled by assets, following the definition of Novy-Marx (2013). The industry-level revenue, cost of goods sold, book assets, book equity, and market equity are the sum of the corresponding firm-level measures for firms in the same industry. Industry concentration ratio is the HHI index of the top 50 firms. The concentration ratio data come from the US Census which covers manufacturing industries. Newey-West standard errors are estimated with one lag. We annualize alphas by multiplying them by 12. The sample period of the data is from July 1977 to June 2018. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table OA.8: List of major natural disasters.

Disasters	Year	Affected States
Northridge Earthquake	1994	CA
Tropical Storm Alberto	1994	AL, FL, GA
Hurricane Opal	1995	AL, FL, GA, LA, MS, NC, SC
North American Blizzard of 1996	1996	CT, DE, IN, KY, MA, MD, NC, NJ, NY, PA, VA, WV
Hurricane Fran	1996	NC, SC, VA, WV
North American Ice Storm of 1998	1998	ME, NH, NY, VT
Hurricane Bonnie	1998	NC, VA
Tropical Storm Frances	1998	LA, TX
Hurricane Georges	1998	AL, FL, LA, MS
Hurricane Floyd	1999	CT, DC, DE, FL, MD, ME, NC, NH, NJ, NY, PA, SC, VA, VT
Tropical Storm Allison	2001	AL, FL, GA, LA, MS, PA, TX
Hurricane Isabel	2003	DE, MD, NC, NJ, NY, PA, RI, VA, VT, WV
Southern California Wildfires	2003	CA
Hurricane Charley	2004	FL, GA, NC, SC
Hurricane Frances	2004	AL, FL, GA, KY, MD, NC, NY, OH, PA, SC, VA, WV
Hurricane Ivan	2004	AL, FL, GA, KY, LA, MA, MD, MS, NC, NH, NJ, NY, PA, SC, TN, WV
Hurricane Jeanne	2004	DE, FL, GA, MD, NC, NJ, PA, SC, VA
Hurricane Dennis	2005	AL, FL, GA, MS, NC
Hurricane Katrina	2005	AL, AR, FL, GA, IN, KY, LA, MI, MS, OH, TN
Hurricane Rita	2005	AL, AR, FL, LA, MS, TX
Hurricane Wilma	2005	FL
Midwest Floods	2008	IA, IL, IN, MN, MO, NE, WI
Hurricane Gustav	2008	AR, LA, MS
Hurricane Ike	2008	AR, LA, MO, TN, TX
Groundhog Day Blizzard	2011	CT, IA, IL, IN, KS, MA, MO, NJ, NM, NY, OH, OK, PA, TX, WI
Hurricane Irene	2011	CT, MA, MD, NC, NJ, NY, VA, VT
Tropical Storm Lee	2011	AL, CT, GA, LA, MD, MS, NJ, NY, PA, TN, VA
Hurricane Isaac	2012	FL, LA, MS
Hurricane Sandy	2012	CT, DE, MA, MD, NC, NH, NJ, NY, OH, PA, RI, VA, WV
Illinois Flooding	2013	IL, IN, MO
Colorado Flooding	2013	CO
Louisiana Flooding	2016	LA
Hurricane Matthew	2016	FL, GA, NC, SC
Western California Wildfires	2017	CA
Hurricane Harvey	2017	TX
Hurricane Irma	2017	FL, PR
Hurricane Maria	2017	PR
Western California Wildfires	2018	CA
Hurricane Florence	2018	NC, SC
Hurricane Michael	2018	FL, GA, NC, SC, VA

Note: This table lists the major natural disasters from 1994 to 2018. Following Barrot and Sauvagnat (2016), we define a major natural disaster as one that causes at least $1 billion in total estimated property damage and that lasts fewer than 30 days. The property damage data are from SHELDUS.

Table OA.9: Alternative matching ratios between treated firms and non-treated peer firms.

	Panel A: Matching 1 treated firm with up to 10 non-treated peer firms							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.028**	0.029**	−0.086*	−0.087*	−0.005	−0.006	−0.005	−0.006
	[2.221]	[2.251]	[−1.715]	[−1.738]	[−0.957]	[−0.991]	[−0.925]	[−0.965]
$Treat_{i,t}$	−0.015	−0.015	0.090*	0.091*	0.001	0.001	−0.001	−0.001
	[−1.368]	[−1.382]	[1.903]	[1.914]	[0.119]	[0.135]	[−0.287]	[−0.270]
$Post_{i,t}$	0.047***	0.045***	−0.124***	−0.120***	−0.008**	−0.007*	−0.012***	−0.011**
	[5.723]	[5.643]	[−4.155]	[−4.056]	[−1.971]	[−1.831]	[−2.713]	[−2.553]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.020**		−0.050		−0.010**		−0.012***
		[2.005]		[−1.331]		[−2.206]		[−2.634]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	197257	197257	164136	164136	205140	205140	204972	204972
R-squared	0.554	0.554	0.657	0.657	0.737	0.737	0.760	0.760
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.001	0.002	$<10^{-3}$	$<10^{-3}$
	Panel B: Matching 1 treated firm with up to 3 non-treated peer firms							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.019	0.019	−0.087	−0.077	−0.000	−0.000	−0.000	−0.000
	[1.452]	[1.463]	[−1.662]	[−1.681]	[−0.060]	[−0.073]	[−0.080]	[−0.093]
$Treat_{i,t}$	−0.017	−0.017	0.093*	0.093*	0.001	0.001	0.001	0.001
	[−1.440]	[−1.443]	[1.718]	[1.726]	[0.315]	[0.318]	[0.163]	[0.166]
$Post_{i,t}$	0.056***	0.055***	−0.129***	−0.123***	−0.006***	−0.006**	−0.010***	−0.010***
	[6.153]	[6.077]	[−3.727]	[−3.581]	[−2.645]	[−2.544]	[−2.978]	[−2.879]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.015*		−0.070*		−0.004		−0.005
		[1.707]		[−1.913]		[−1.630]		[−1.581]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	95804	95804	82652	82652	99489	99489	99409	99409
R-squared	0.569	0.569	0.673	0.673	0.759	0.759	0.786	0.786
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.003	0.005	$<10^{-3}$	0.001

Note: This table examines the spillover effects of the major natural disasters with alternative matching ratios between treated firms and non-treated peer firms. In panel A, we match each treated firm with up to 10 non-treated peer firms in the same four-digit SIC industry based on firm asset size, tangibility, and age. In panel B, we match each treated firm with up to 3 non-treated peer firms. The regression specification and the definition of the dependent and independent variables are explained in Table 12 of the main text. The sample of this table spans from 1994 to 2018. Standard errors are clustered at the firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table OA.10: Matching industry peers with text-based network industry classifications.

	(1)	(2)	(3)	(4)
	$Distress_{i,t}$	$DD_{i,t}$	$PM_{i,t}$	$Markup_{i,t}$
$Treat_{i,t} \times Post_{i,t}$	0.013	−0.025	−0.005	−0.006
	[1.094]	[−0.541]	[−1.005]	[−1.231]
$Treat_{i,t}$	−0.012	0.027	0.007^{*}	0.011^{**}
	[−1.108]	[0.556]	[1.708]	[2.166]
$Post_{i,t}$	0.044^{***}	-0.154^{***}	-0.007^{**}	-0.010^{**}
	[5.597]	[−5.165]	[−2.051]	[−2.536]
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	211770	176763	219133	218988
R-squared	0.543	0.639	0.742	0.766
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	0.002	$<10^{-3}$

Note: This table examines the within-industry spillover effects of the major natural disasters based on TNIC (Hoberg and Phillips, 2010, 2016). We perform a DID analysis. Specifically, we match each treated firm with up to 10 non-treated peer firms in its TNIC industry based on firm asset size, tangibility, and age. We require that the matched peer firms are not suppliers or customers of the treated firms. For each firm, we include four yearly observations (i.e., 2 years before and 2 years after major natural disaster) in the analysis. The regression specification is: $Y_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}$. The dependent variables are the distress risk ($Distress_{i,t}$), distance to default ($DD_{i,t}$), gross profit margin ($PM_{i,t}$), and markup ($Markup_{i,t}$). $Treat_{i,t}$ is an indicator variable that equals 1 if firm i is a treated firm. $Post_{i,t}$ is an indicator variable that equals 1 for observations after major natural disasters. The term θ_i represents firm fixed effects, and the term δ_t represents year fixed effects. In the last row of the panel, we present the p-value for the null hypothesis that the total treatment effect for the treated firms is 0 (i.e., $\beta_1 + \beta_3 = 0$). The sample of this table spans from 1994 to 2018. Standard errors are clustered at the firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table OA.11: Alternative measure to control for cross-industry spillover effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.019	0.027^{**}	-0.087^{*}	-0.103^{*}	−0.001	0.000	−0.001	0.000
	[1.538]	[2.130]	[−1.717]	[−1.933]	[−0.196]	[0.098]	[−0.267]	[0.011]
$Treat_{i,t}$	−0.014	−0.017	0.096^{*}	0.092^{*}	−0.001	−0.001	−0.001	−0.000
	[−1.250]	[−1.436]	[1.940]	[1.775]	[−0.189]	[−0.162]	[−0.151]	[−0.023]
$Post_{i,t}$	0.053^{***}	0.046^{***}	-0.122^{***}	-0.098^{***}	-0.007^{**}	-0.007^{**}	-0.010^{***}	-0.011^{***}
	[6.498]	[5.597]	[−3.882]	[−3.063]	[−2.283]	[−2.370]	[−2.649]	[−2.673]
$Ln(1 + \mathcal{D}_{i,t})$		0.005^{**}		-0.025^{**}		-0.002^{*}		-0.002^{*}
		[1.960]		[−2.325]		[−1.821]		[−1.909]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130099	119053	110581	101308	135037	124047	134924	123949
R-squared	0.565	0.579	0.667	0.676	0.745	0.748	0.773	0.777
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.004	0.012	$<10^{-3}$	0.003

Note: This table uses an alternative measure to control for cross-industry spillover effects. Different from Table 12 of the main text, we capture the strength of cross-industry spillover effects using $Ln(1 + \mathcal{D}_{i,t})$, which is the natural log of 1 plus the average amount of property damage (in millions of dollars) caused by major natural disasters in year t across industries that are connected to firm i's industry through competition networks. The regression specification is: $Y_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1 + \mathcal{D}_{i,t}) + \theta_i + \delta_t + \varepsilon_{i,t}$. The definition of the dependent and other independent variables are explained in Table 12. The sample of this table spans from 1994 to 2018. Standard errors are clustered at the firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table OA.12: Net profit margin.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$NPM_{i,t}$		$NPM_{i,t}$		$NPM_{i,t}$		$NPM_{i,t}$	
Sample	Full sample		High entry barrier	Low entry barrier	Bad economic condition	Good economic condition	High financial constraint	Low financial constraint
$Treat_{i,t} \times Post_{i,t}$	-0.003	-0.003	-0.004	-0.005	0.001	-0.009	0.004	-0.000
	$[-0.717]$	$[-0.736]$	$[-0.478]$	$[-1.148]$	[0.082]	$[-1.495]$	[0.391]	$[-0.068]$
$Treat_{i,t}$	0.002	0.002	-0.000	0.006	0.004	0.003	-0.007	0.010^{*}
	[0.498]	[0.505]	$[-0.030]$	[1.233]	[0.512]	[0.474]	$[-0.765]$	[1.810]
$Post_{i,t}$	-0.007^{***}	-0.006^{**}	-0.017^{***}	0.005^{*}	-0.025^{***}	0.015^{***}	-0.034^{***}	0.007^{**}
	$[-2.119]$	$[-2.013]$	$[-3.052]$	[1.770]	$[-4.696]$	[3.966]	$[-3.709]$	[2.111]
$Ln(1 + n(\mathcal{C}_{i,t}))$		-0.006^{*}	-0.024^{***}	0.006	-0.012^{***}	-0.003	-0.020^{***}	-0.007^{*}
		$[-1.800]$	$[-3.910]$	[1.623]	$[-2.649]$	$[-1.049]$	$[-2.628]$	$[-1.811]$
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	135468	135468	64714	70729	66698	64811	32927	61835
R-squared	0.778	0.778	0.750	0.832	0.808	0.796	0.771	0.820
Test p-value: $\beta_1 + \beta_3 = 0$	0.002	0.003	$<10^{-3}$	0.935	$<10^{-3}$	0.188	$<10^{-3}$	0.117

Note: This table examines the within-industry spillover effects in net profit margin following major natural disasters. The regression specification is: $NPM_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1 + n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}$. Net profit margins ($NPM_{i,t}$) are computed as the difference between sales and total costs of operating the firm (i.e., sales − cost of goods sold − selling, general and administrative expenses − depreciation − interest expenses) divided by sales. Definition for the independent variables are given in Table 12. Columns (1) and (2) present results in the full sample. Columns (3) and (4) present results from DID analysis in industries with high entry barriers (top tertile) and low entry barriers (middle and bottom tertiles), respectively. The entry barrier of a four-digit SIC industry is measured by the sales-weighted average of fixed assets across firms in this industry. Columns (5) and (6) present results in industries with good economic conditions (top half) and bad economic conditions (bottom half) prior to the natural disasters, respectively. The economic condition of a four-digit SIC industry is measured by the change of the return on assets (ROA) in the industry from the previous year. Columns (7) and (8) present results in industries with high financial constraint (top tertile) and low financial constraint (middle and bottom tertiles) prior to the natural disasters. The financial constraint of a four-digit SIC industry is measured by the sales-weighted average of the delay investment score in the industry (Hoberg and Maksimovic, 2015). We sort industries into groups based on the industry-level entry barriers, economic conditions, and financial constraints 1 year prior to natural disaster shocks. The sample spans from 1994 to 2018 in Columns (1) to (6), while it spans from 1998 to 2016 in Columns (7) to (8) due to shorter sample period of the delay investment score. Standard errors are clustered at the firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table OA.13: Excluding industries with high fraction of profits from foreign countries.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.006	0.007	-0.044	-0.045	0.003	0.003	0.002	0.002
	[0.464]	[0.482]	[-0.787]	[-0.804]	[0.656]	[0.633]	[0.313]	[0.288]
$Treat_{i,t}$	-0.018	-0.019	0.122^{**}	0.122^{**}	0.001	0.001	0.001	0.001
	[-1.415]	[-1.425]	[2.118]	[2.127]	[0.173]	[0.188]	[0.237]	[0.250]
$Post_{i,t}$	0.068^{***}	0.066^{***}	-0.156^{***}	-0.151^{***}	-0.011^{***}	-0.010^{***}	-0.015^{***}	-0.015^{***}
	[7.165]	[7.087]	[-4.274]	[-4.198]	[-2.934]	[-2.822]	[-3.259]	[-3.130]
$Ln(1 + n(\mathcal{C}_{i,t}))$		0.021^{**}		-0.056		-0.007^{**}		-0.010^{**}
		[2.118]		[-1.412]		[-2.192]		[-2.341]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	102012	102012	87622	87622	105457	105457	105367	105367
R-squared	0.582	0.582	0.682	0.682	0.768	0.768	0.797	0.797
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.007	0.011	$<10^{-3}$	$<10^{-3}$

Note: This table examines the within-industry spillover effects of the major natural disasters by excluding industries with high fraction of profits from foreign countries. The fraction of foreign profits of an industry is the ratio between the industry-level foreign pre-taxable income and the industry-level total pre-tax income. The industry-level foreign (total) pre-taxable income is the sum of the firm-level foreign (total) pre-taxable income across firms in the industry, of which the data come from Compustat. We sort industries into quintiles based on the fraction of foreign profits each year. We control for the entry costs of the industry in the sorting to make sure the quintile assignment is orthogonal to entry costs. We exclude the industries in the top foreign profits quintile in the DID tests. The regression specification and the definition of the dependent and independent variables are explained in Table 12 of the main text. The merged sample of this table spans from 1994 to 2018. Standard errors are clustered at the focal firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table OA.14: Testing the demand commonality channel.

Panel A: Matched non-treated firms far from the disaster area (i.e., $\geq$ 100 miles)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.011	0.011	-0.089	-0.089	0.004	0.004	0.009	0.009
	[0.656]	[0.660]	[-1.346]	[-1.360]	[0.812]	[0.804]	[0.928]	[0.923]
$Treat_{i,t}$	-0.016	-0.016	0.113^{*}	0.114^{*}	-0.003	-0.003	-0.004	-0.004
	[-1.036]	[-1.052]	[1.681]	[1.703]	[-0.778]	[-0.762]	[-0.465]	[-0.454]
$Post_{i,t}$	0.073^{***}	0.070^{***}	-0.154^{***}	-0.145^{***}	-0.012^{**}	-0.012^{**}	-0.028^{***}	-0.027^{***}
	[4.720]	[4.596]	[-3.182]	[-3.015]	[-2.553]	[-2.480]	[-2.862]	[-2.830]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.034^{**}		-0.103^{**}		-0.007^{*}		-0.010
		[2.460]		[-2.297]		[-1.815]		[-1.288]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	99857	99857	84697	84697	104064	104064	103967	103967
R-squared	0.594	0.594	0.685	0.685	0.773	0.774	0.779	0.779
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.004	0.006	$<10^{-3}$	0.001

Panel B: Matched non-treated firms far from the disaster area + without affected business and retailed customers								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.013	0.013	-0.064	-0.065	0.001	0.001	0.004	0.004
	[0.709]	[0.724]	[-0.895]	[-0.911]	[0.217]	[0.202]	[0.343]	[0.332]
$Treat_{i,t}$	-0.023	-0.023	0.119^{*}	0.120^{*}	0.001	0.001	0.004	0.004
	[-1.383]	[-1.410]	[1.664]	[1.685]	[0.163]	[0.187]	[0.407]	[0.426]
$Post_{i,t}$	0.070^{***}	0.067^{***}	-0.164^{***}	-0.158^{***}	-0.012^{**}	-0.012^{**}	-0.027^{***}	-0.026^{***}
	[4.372]	[4.237]	[-3.006]	[-2.907]	[-2.166]	[-2.126]	[-2.594]	[-2.588]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.038^{**}		-0.075		-0.008^{*}		-0.012
		[2.512]		[-1.565]		[-1.662]		[-1.324]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	93108	93108	78781	78781	97199	97199	97097	97097
R-squared	0.605	0.605	0.692	0.692	0.778	0.778	0.783	0.783
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.005	0.007	0.001	0.002

Note: This table tests the demand commonality channel. In panel A, we perform DID analysis by requiring the headquarters and the major establishments of the matched peer firms to be more than 100 miles away from any zip code negatively affected by major natural disaster in a given year. In panel B, we further require the matched peer firms to have no customers negatively affected by natural disaster. We identify firms' business customers using Compustat customer segment data and Factset Revere data. We identify firms' retail customers based on the household-level financial transaction data constructed by Baker, Baugh and Sammon (2020). The regression specification and the definition of the dependent and independent variables are explained in Table 12 of the main text. The merged sample of this table spans from 1994 to 2018. Standard errors are clustered at the focal firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table OA.15: Testing the production network externality channel.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.025^{*}	0.025^{*}	-0.111^{**}	-0.112^{**}	-0.002	-0.002	-0.001	-0.001
	[1.771]	[1.778]	[−1.987]	[−2.004]	[−0.259]	[−0.269]	[−0.114]	[−0.127]
$Treat_{i,t}$	-0.028^{**}	-0.028^{**}	0.146^{***}	0.146^{***}	0.002	0.002	0.000	0.000
	[−2.068]	[−2.072]	[2.590]	[2.600]	[0.304]	[0.308]	[0.014]	[0.020]
$Post_{i,t}$	0.051^{***}	0.050^{***}	-0.123^{***}	-0.116^{***}	-0.010^{**}	-0.009^{*}	-0.014^{***}	-0.013^{**}
	[5.208]	[5.165]	[−3.327]	[−3.187]	[−2.019]	[−1.942]	[−2.599]	[−2.496]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.017		-0.085^{**}		-0.008		-0.011^{**}
		[1.487]		[−1.967]		[−1.598]		[−2.125]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	106886	106886	88542	88542	111387	111387	111270	111270
R-squared	0.562	0.562	0.668	0.669	0.740	0.740	0.763	0.763
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.009	0.013	0.001	0.002

Note: This table tests the production network externality channel. As in Table 12 of the main text, we require that the matched peer firms are not suppliers or customers of the treated firms. We also require that the matched peer firms do not share any common customers or any common suppliers with the treated firms. Different from Table 12, we further remove matched peer firms related to the treated firms vertically in the DID analysis. We define two firms as connected vertically if their vertical relatedness scores are within top 10% of all firm pairs (see, Frésard, Hoberg and Phillips, 2020). The regression specification and the definition of the dependent and independent variables are explained in Table 12. The merged sample of this table spans from 1994 to 2018. Standard errors are clustered at the focal firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table OA.16: Testing the lender commonality channel.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.034^{*}	0.034^{*}	-0.171^{**}	-0.172^{**}	0.001	0.001	-0.001	-0.001
	[1.750]	[1.769]	[−2.291]	[−2.317]	[0.115]	[0.111]	[−0.114]	[−0.120]
$Treat_{i,t}$	0.000	0.000	0.067	0.067	-0.003	-0.003	-0.004	-0.004
	[0.001]	[0.003]	[0.982]	[0.987]	[−0.683]	[−0.691]	[−0.695]	[−0.703]
$Post_{i,t}$	0.071^{***}	0.066^{***}	-0.143^{***}	-0.129^{***}	-0.012^{*}	-0.011^{*}	-0.015^{**}	-0.014^{**}
	[5.218]	[5.026]	[−3.032]	[−2.794]	[−1.925]	[−1.809]	[−2.257]	[−2.129]
$Lender\_Exposure_{i,t-1}$	0.163^{**}	0.160^{*}	0.085	0.088	-0.002	-0.002	0.002	0.003
	[1.979]	[1.942]	[0.278]	[0.287]	[−0.087]	[−0.058]	[0.065]	[0.100]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.051^{***}		-0.152^{***}		-0.014^{***}		-0.018^{***}
		[3.628]		[−2.988]		[−3.385]		[−3.322]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49517	49517	46842	46842	50788	50788	50772	50772
R-squared	0.590	0.590	0.704	0.704	0.752	0.752	0.839	0.840
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.007	0.017	0.001	0.004

Note: This table tests the lender commonality channel. We require the matched peer firms to share no common lenders with the treated firms in the DID analysis. We also control for firms' exposure to natural disasters through lenders ($Lender\_Exposure_{i,t-1}$). We identify the borrower-lender relationship and construct $Lender\_Exposure_{i,t-1}$ using the LPC DealScan database in two steps. First, we find out each lender l's exposure to natural disasters in year t, which is the outstanding loans issued by lender l from $t-5$ to $t-1$ to firms that experience natural disasters in year t normalized by the total amount of outstanding loans issued by lender l from $t-5$ to $t-1$. We focus on loans issued in the preceding 5-year window following the literature (e.g., Bharath et al., 2007). Second, for each firm i, we compute $Lender\_Exposure_{i,t-1}$ by averaging the lender-level exposure across all lenders of this firm. The average is weighted based on the amount of outstanding loans borrowed from different lenders. The regression specification and the definition of the dependent and independent variables are explained in Table 12 of the main text. The merged sample of this table spans from 1994 to 2018. Standard errors are clustered at the focal firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table OA.17: Testing the institutional blockholder commonality channel.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.022	0.022	-0.102^{**}	-0.103^{**}	-0.001	-0.001	-0.001	-0.001
	[1.615]	[1.628]	[−1.963]	[−1.984]	[−0.258]	[−0.275]	[−0.166]	[−0.188]
$Treat_{i,t}$	-0.024^{*}	-0.024^{*}	0.132^{***}	0.133^{***}	0.001	0.001	0.001	0.001
	[−1.884]	[−1.889]	[2.579]	[2.591]	[0.313]	[0.319]	[0.164]	[0.171]
$Post_{i,t}$	0.054^{***}	0.052^{***}	-0.111^{***}	-0.104^{***}	-0.009^{**}	-0.008^{**}	-0.012^{***}	-0.011^{***}
	[5.872]	[5.833]	[−3.427]	[−3.265]	[−2.138]	[−2.054]	[−2.696]	[−2.575]
$Ln(1 + n(\mathcal{C}_{i,t}))$		0.015		-0.079^{**}		-0.007^{*}		-0.010^{**}
		[1.455]		[−2.132]		[−1.751]		[−2.238]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	118636	118636	100840	100840	124472	124472	124344	124344
R-squared	0.561	0.561	0.663	0.663	0.755	0.755	0.773	0.773
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.005	0.007	0.001	0.003

Note: This table tests the institutional blockholder commonality channel. We require the matched peer firms to share no common institutional blockholders with the treated firms in the DID analysis. Institutional blockholders of a firm are 13F institutions that hold 5% of the firm's market cap or above. The regression specification and the definition of the dependent and independent variables are explained in Table 12 of the main text. The merged sample of this table spans from 1994 to 2018. Standard errors are clustered at the focal firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table OA.18: Controlling for all alternative channels simultaneously.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.016	0.017	−0.039	−0.041	0.001	0.001	0.003	0.003
	[1.008]	[1.020]	[−0.610]	[−0.629]	[0.471]	[0.446]	[0.558]	[0.536]
$Treat_{i,t}$	−0.023	−0.023	0.081	0.082	−0.004	−0.003	−0.005	−0.005
	[−1.481]	[−1.487]	[1.218]	[1.233]	[−1.174]	[−1.163]	[−0.918]	[−0.909]
$Post_{i,t}$	0.054***	0.053***	−0.165***	−0.158***	−0.006**	−0.006**	−0.011**	−0.011**
	[4.085]	[4.020]	[−3.191]	[−3.075]	[−2.150]	[−2.039]	[−2.234]	[−2.143]
$Post_{i,t} \times Common\_Demand_{i,t}$	−0.013	−0.013	0.065	0.065	0.004	0.004	0.007	0.007
	[−0.795]	[−0.798]	[1.030]	[1.035]	[1.142]	[1.142]	[1.283]	[1.282]
$Post_{i,t} \times Production\_Network_{i,t}$	0.014	0.014	−0.011	−0.011	−0.003	−0.003	−0.005	−0.005
	[1.021]	[1.017]	[−0.199]	[−0.202]	[−1.402]	[−1.402]	[−1.137]	[−1.137]
$Post_{i,t} \times Common\_Lender_{i,t}$	0.006	0.005	0.039	0.040	0.007	0.007	0.011	0.011
	[0.310]	[0.302]	[0.520]	[0.528]	[1.559]	[1.563]	[1.510]	[1.513]
$Post_{i,t} \times Common\_Blockholder_{i,t}$	0.014	0.014	0.022	0.020	0.001	0.001	0.000	0.000
	[0.882]	[0.898]	[0.359]	[0.340]	[0.188]	[0.169]	[0.063]	[0.047]
$Common\_Demand_{i,t}$	−0.015	−0.015	0.001	0.001	−0.003	−0.003	−0.006	−0.005
	[−0.940]	[−0.942]	[0.015]	[0.019]	[−0.901]	[−0.895]	[−0.912]	[−0.907]
$Production\_Network_{i,t}$	−0.002	−0.002	−0.010	−0.010	0.002	0.002	0.002	0.002
	[−0.190]	[−0.170]	[−0.172]	[−0.189]	[0.858]	[0.829]	[0.539]	[0.513]
$Common\_Lender_{i,t}$	0.051***	0.051***	−0.244***	−0.243***	−0.013***	−0.013***	−0.022***	−0.022***
	[3.081]	[3.073]	[−3.275]	[−3.263]	[−3.767]	[−3.754]	[−3.783]	[−3.772]
$Common\_Blockholder_{i,t}$	−0.023*	−0.024*	0.082	0.083	0.002	0.002	0.007	0.007
	[−1.874]	[−1.892]	[1.487]	[1.514]	[0.837]	[0.859]	[1.298]	[1.316]
$Lender\_Exposure_{i,t-1}$	0.157***	0.157***	−0.231	−0.233	−0.011	−0.011	−0.017	−0.017
	[2.776]	[2.783]	[−0.988]	[−0.997]	[−1.251]	[−1.268]	[−1.151]	[−1.166]
$Ln(1 + n(\mathcal{C}_{i,t}))$		0.017*		−0.081**		−0.005***		−0.008***
		[1.874]		[−2.226]		[−3.156]		[−2.827]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130387	130387	110883	110883	135322	135322	135209	135209
R-squared	0.565	0.565	0.667	0.667	0.793	0.793	0.805	0.805
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.002	0.003	0.001	0.003

Note: This table examine the within-industry spillover effects by controlling for all four alternative channels simultaneously. For each treated firm, we match it with up to five non-treated peer firms in the same four-digit SIC industry. We perform the matching based on the values of three matching variables (i.e., firm asset size, tangibility, and age) prior to natural disaster shocks using the shortest distance method. $Common\_Demand_{i,t}$ is a dummy variable that equals one for the matched peer firms that i) located within 100 miles from any zip code negatively affected by major natural disaster in a given year, 2) or have any business customers or individual consumers which are located in the areas affected by the natural disasters. We identify firms' business customers using Compustat customer segment data and Factset Revere data. We identify firms' retail customers based on the household-level financial transaction data constructed by Baker, Baugh and Sammon (2020). $Production\_Network_{i,t}$ is a dummy variable that equals one for the matched peer firms that i) are suppliers or customers of the treated firms, or ii) share common suppliers or customers with the treated firms, or iii) have high vertical relatedness scores (Frésard, Hoberg and Phillips, 2020) with the treated firms (i.e., within top 10% of all firm pairs). $Common\_Lender_{i,t}$ is a dummy variable that equals one for the matched peer firms that share common lenders with the treated firms. $Common\_Blockholder_{i,t}$ is a dummy variable that equals one for the matched peer firms that share common institutional blockholders with the treated firms. $Lender\_Exposure_{i,t-1}$ captures firms' exposure to natural disasters through lenders as explained in Table OA.16. The merged sample of this table spans from 1994 to 2018. Standard errors are clustered at the focal firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table OA.19: Summary statistics for the cross-industry contagion analysis.

	Obs. #	Mean	Median	SD	p10th	p25th	p75th	p90th
$Distress_t^{(c_{i,j})}$	7058	−7.567	−7.727	0.702	−8.325	−8.091	−7.203	−6.437
$DD_t^{(c_{i,j})}$	6882	6.405	5.666	4.630	0.629	2.748	9.560	14.109
$PM_t^{(c_{i,j})}$	7166	0.314	0.300	0.140	0.131	0.200	0.412	0.538
$Markup_t^{(c_{i,j})}$	7166	0.400	0.356	0.220	0.141	0.223	0.530	0.773
$ND\_mild_{i,t}^{(1)}$	8415	0.081	0	0.273	0	0	0	0
$ND\_severe_{i,t}^{(1)}$	8415	0.023	0	0.150	0	0	0	0
$ND\_mild_{i,t}^{(2)}$	8415	0.086	0	0.280	0	0	0	0
$ND\_severe_{i,t}^{(2)}$	8415	0.023	0	0.150	0	0	0	0
$ND\_mild_{i,t}^{(3)}$	8415	0.087	0	0.281	0	0	0	0
$ND\_severe_{i,t}^{(3)}$	8415	0.028	0	0.164	0	0	0	0
$Distress_{i,t}^{(-c)}$	5152	−7.193	−7.489	1.033	−8.215	−7.912	−6.793	−5.515
$DD_{i,t}^{(-c)}$	5020	5.966	5.484	3.635	1.480	3.240	8.225	11.462
$PM_{i,t}^{(-c)}$	5264	0.324	0.308	0.132	0.154	0.222	0.416	0.528
$Markup_{i,t}^{(-c)}$	5264	0.427	0.379	0.222	0.171	0.257	0.557	0.794
$\widehat{IdShock}_{-i,t}(Distress)$	5152	−7.566	−7.578	0.036	−7.578	−7.578	−7.571	−7.527
$\widehat{IdShock}_{-i,t}(DD)$	5020	6.407	6.453	0.249	6.318	6.453	6.453	6.515
$\widehat{IdShock}_{-i,t}(PM)$	5264	0.314	0.317	0.009	0.305	0.315	0.317	0.317
$\widehat{IdShock}_{-i,t}(Markup)$	5264	0.400	0.405	0.014	0.385	0.401	0.405	0.405
$Forward\_Con_{-i,i,t}$	5260	0.002	0	0.011	0	0	0	0
$Backward\_Con_{-i,i,t}$	5260	0.001	0	0.007	0	0	0	0

Note: This table reports the summary statistics for the variables in Table 17 of the main text.

Table OA.20: Cross-industry spillover effects after excluding industries whose common market leaders are mainly superstar firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}^{(-c)}$		$DD_{i,t}^{(-c)}$		$PM_{i,t}^{(-c)}$		$Markup_{i,t}^{(-c)}$	
$\widehat{IdShock}_{-i,t}$	0.698**	0.698**	0.467**	0.394**	0.484**	0.440**	0.491**	0.431*
	[2.198]	[2.140]	[2.279]	[2.070]	[2.157]	[2.061]	[2.192]	[1.856]
$\widehat{IdShock}_{-i,t} \times Forward\_Con_{-i,i,t}$		22.488		40.563		−9.660		−9.140
		[0.244]		[1.220]		[−0.224]		[−0.204]
$\widehat{IdShock}_{-i,t} \times Backward\_Con_{-i,i,t}$		10.431		40.566		41.000		47.559
		[0.124]		[1.225]		[1.102]		[1.364]
$Forward\_Con_{-i,i,t}$		175.560		−251.160		3.413		4.642
		[0.251]		[−1.172]		[0.249]		[0.255]
$Backward\_Con_{-i,i,t}$		77.652		−235.689		−12.399		−18.209
		[0.122]		[−1.112]		[−1.067]		[−1.318]
Observations	4849	4847	4717	4715	4950	4948	4950	4948
R-squared	0.001	0.003	0.001	0.004	0.001	0.002	0.001	0.003

Note: This table reports the cross-industry spillover effects after excluding industries whose common market leaders are mainly superstar firms (i.e., top 50 firms ranked by sales). Specifically, we exclude an industry from our analysis if half or more than half of the links between this industry and other industries in the competition network are connected through superstar firms. The regression specification of panel A is: $Y_{i,t}^{(-c)} = \beta_1 \widehat{IdShock}_{-i,t} + \varepsilon_{i,t}$. The regression specification of panel B is: $Y_{i,t}^{(-c)} = \beta_1 \widehat{IdShock}_{-i,t} + \beta_2 \widehat{IdShock}_{-i,t} \times Forward\_Con_{-i,i,t} + \beta_3 \widehat{IdShock}_{-i,t} \times Backward\_Con_{-i,i,t} + \beta_4 Forward\_Con_{-i,i,t} + \beta_5 Backward\_Con_{-i,i,t} + \varepsilon_{i,t}$. Definitions of the dependent and independent variables are given in Table 17. The sample spans the period from 1994 to 2018. Standard errors are clustered at the industry level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table OA.21: Heterogenous spillover effects in the AJCA tax holiday setting.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$AJCA_i$	-0.410^{***}	-0.391^{***}	1.052	0.909	0.175^{***}	0.164^{***}	0.241^{***}	0.215^{***}
	[−4.007]	[−3.811]	[1.546]	[1.330]	[4.148]	[3.829]	[2.994]	[2.630]
$\overline{AJCA}_{i,t} \times AJCA_i$	−0.148	−0.087	1.337	0.849	−0.016	−0.055	−0.124	-0.212^{**}
	[−0.907]	[−0.512]	[1.234]	[0.770]	[−0.357]	[−1.095]	[−1.378]	[−2.152]
$\overline{AJCA}_{i,t} \times (1 - AJCA_i)$	-1.095^{***}	-0.935^{***}	5.467^{***}	4.277^{**}	0.787^{***}	0.686^{***}	1.310^{***}	1.080^{***}
	[−3.327]	[−2.668]	[3.670]	[2.449]	[6.113]	[4.770]	[5.487]	[4.145]
$High\_Cross\_Ind\_Shocks_{i,t}$		−0.077		0.604		0.048		0.109^{**}
		[−1.047]		[1.489]		[1.550]		[2.016]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2166	2166	1806	1806	2303	2303	2292	2292
R-squared	0.131	0.132	0.148	0.150	0.056	0.059	0.044	0.050

Note: This table examines the heterogenous spillover effects in the AJCA tax holiday setting. The data sample is a firm-year panel that spans 5 years after the passage of AJCA (i.e., 2004 to 2008). We focus our analysis on the financially constrained firms (i.e., those with financial constraint ranked in the top quintile) prior to the passage of AJCA. Financially constraint is measured as the average delay investment score of Hoberg and Maksimovic (2015) in the 5-year window prior to the the passage of AJCA (i.e., 1999 to 2003). The regression specification is: $Y_{i,t} = \beta_1 AJCA_i + \beta_2 \overline{AJCA}_{i,t} \times AJCA_i + \beta_3 \overline{AJCA}_{i,t} \times (1 - AJCA_i) + \beta_4 High\_Cross\_Ind\_Shocks_{i,t} + \delta_t + \varepsilon_{i,t}$. The dependent variables are the distress risk ($Distress_{i,t}$), distance to default ($DD_{i,t}$), gross profit margin ($PM_{i,t}$), and markup ($Markup_{i,t}$). We follow Grieser and Liu (2019) to define $AJCA_i$ is an indicator variable that equals 1 if firm i has more than 33% pretax income from abroad during the period from 2001 to 2003. $\overline{AJCA}_{i,t}$ is the industry treatment intensity which is the fraction of firms in firm i's industry with an $AJCA_i$ indicator that equals 1. $High\_Cross\_Ind\_Shocks_{i,t}$ captures the strength of cross-industry spillover effects via the competition network, and it is a dummy variable that equals one if the average industry treatment intensity for the industries connected to firm i's industry through competition networks is higher than 20% in year t. The term δ_t represents year fixed effects. Standard errors are clustered at the firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table OA.22: Spillover effects of bond yield spread and CDS spread in the AJCA tax holiday setting.

	(1)	(2)	(3)	(4)
	$Bond\_yield\_spread_{i,t}(\%)$		$CDS\_spread_{i,t}(\%)$	
$AJCA_i$	−0.423	−0.389	−0.239	−0.227
	[−1.629]	[−1.506]	[−1.426]	[−1.363]
$\overline{AJCA}_{i,t}$	-0.926^{**}	-0.776^{**}	-0.753^{***}	-0.636^{**}
	[−2.476]	[−2.051]	[−3.179]	[−2.582]
$High\_Cross\_Ind\_Shocks_{i,t}$		-0.503^{**}		−0.254
		[−2.002]		[−1.329]
Year FE	Yes	Yes	Yes	Yes
Observations	2419	2419	2779	2779
R-squared	0.421	0.423	0.159	0.160

Note: This table examines the spillover effects of bond yield spread and CDS spread in the AJCA tax holiday setting. The data sample is a firm-year panel that spans 5 years after the passage of AJCA (i.e., 2004 to 2008). The regression specification is: $Y_{i,t} = \beta_1 AJCA_i + \beta_2 \overline{AJCA}_{i,t} + \beta_3 High\_Cross\_Ind\_Shocks_{i,t} + \delta_t + \varepsilon_{i,t}$. The dependent variables are the bond yield spread ($Bond\_yield\_spread_{i,t}$) and CDS spread ($CDS\_spread_{i,t}$). Because the limited coverage of the spread data in the cross section, unlike in Table 19 of the main text, we do not limit our analysis to financially constrained firms and instead use the full sample. Standard errors are clustered at the firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.