Competition Network, Distress Propagation, and Stock Returns

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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 and enforcement actions against financial frauds to identify idiosyncratic distress shocks. Firms hit by natural disasters or enforcement actions exhibit increased distress, then compete more aggressively by cutting profit margins. In response, their industry peers also cut profit margins, 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 centrality, Economic and financial distress, Tacit collusion, Natural disasters, Spillover and treatment externality.
JEL: G32, G33, L11, L14.

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1 Introduction

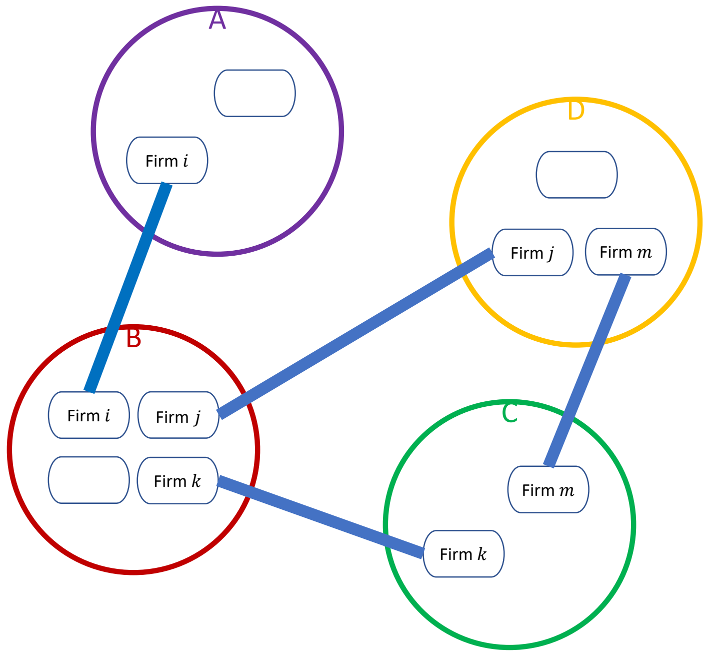
Strategic competition among market leaders in product markets plays a vital role in determining firms' cash flows and financial distress, because product markets are often highly concentrated in the hands of a few market leaders, even "superstar firms".[1] Naturally, strategic competition and distress 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 condition and their product market behavior.[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," which 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 US for the past a few decades. According to the US Census data, the top four firms within each four-digit 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 key insight and 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 conclusion 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 centrality on the competition network (i.e., industries which are more connected to others through the 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 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 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 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 in the past twenty-five years in the US and the enforcement actions against financial frauds 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 use the precise and detailed financial fraud data first constructed by Karpoff et al. (2017). We show that these local natural disasters and enforcement actions increase the distress for the treated firms, consistent with the empirical findings of Aretz, Banerjee and Pryshchepa (2019) and Graham, Li and Qiu (2008).

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 been serving 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) randomized experiments 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 the natural disasters and violating firms prosecuted by legal enforcement actions) with non-treated industry peer firms in the same industry that have similar asset size, tangibility, and firm age. We find that the

[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).

treated firms experience significant increases in distress risk and significant decreases in their distance to default, indicating that these firms see an increased distress following major natural disasters or enforcement actions. Following the increases in the distress, the treated firms compete more 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 the industry peers, which are unaffected directly by natural disasters or enforcement actions, 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 by with 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 the negative shocks. We then show the within-industry spillover effects are unlikely explained by a list of alternative explanations including demand commonality, production network externality, credit lending channel, and institutional blockholder commonality.

We further exploit the passage of the American Jobs Creation Act of 2004 (AJCA) (see Faulkender and Petersen, 2012) to study the impact of reduction in financial distress on firms' product market behaviors and the distress level of their peer firms. 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. This result is stronger for firms financially constrained prior to the passage of the act. Moreover, the distress level of the non-treated industry peers that are financially constrained prior to the passage of AJCA reduces significantly after the passage of the act.

Finally, we examine the distress contagion effects across industries. As we discuss 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 that other industry so that firms in that industry exhibit reduced profit margins as well. Thus, the propagation of a shock to distress risk can occur to other industries via networks of competitors. 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 how shocks propagate across industries or sectors through input-output linkages (e.g., Horvath, 1998, 2000; Acemoglu et al., 2012; Di Giovanni, Levchenko and Mejean, 2014; Barrot and Sauvagnat, 2016). Recently, a growing body of research has been suggesting that the production network externality has important asset pricing implications (e.g., Herskovic, 2018; Herskovic et al., 2020; Gofman, Segal and Wu, 2020; Grigoris, Hu and Segal, 2021). We differ from the literature by examining the distress propagation through product market competition networks. Our analysis is similar to 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 centrality.

Our paper also contributes to the literature that studies 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 behavior. By addressing the endogeneity concerns, our paper differs from previous papers that study the product market implications of firms' (voluntary) decisions about financial structure (e.g., Phillips, 1995; Chevalier, 1995; Kovenock and Phillips, 1997). Second, we systematically examine changes in profit margin of distressed firms and their industry peers in a broad sample of industries, which differentiates our paper from previous studies that primarily focus on product market behavior 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 cross-industry distress contagion through the competition network. Such contagion effects are different economically from the contagion effects 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.

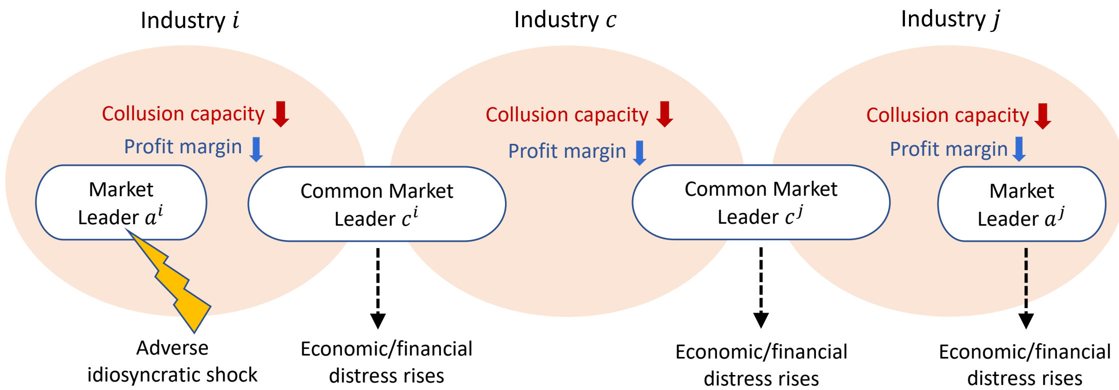
Our paper also contributes to the growing literature on financial contagion. As nicely summarized by Goldstein (2013), financial contagion takes place through two major classes of channels — the fundamental- and information-based channels. The fundamental-based channel is through real linkages between 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.

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



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, due to 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.

that make all firms more financially constrained and carry a negative market price of risk to investors, and thus the industries with higher centrality have higher expected stock returns. Third, although 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 will not repeat the same model; rather, we 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 stands for stand-*alone* market leaders and c for *common* ones. As shown in Figure 2, firm i and c^i compete in industry i, firm 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 an economy-wide and an idiosyncratic component, 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. The 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]

[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).

Market Structure and Firm Profits. In an 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 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, respectively, and p_k is the price of the 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 constraint x_t. That is, $\omega(\cdot) > 0$ and $\omega'(\cdot) > 0$. Thus, the profit of firm f from the 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 duopoly industry competition – non-collusive competition and collusive competition. In the state of non-collusive competition, firms maximize their own firm value and thus profit level given 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 firms 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 the mad price war. Specifically, in the mad price war, the competitor will never tacitly coordinate or maintain the duopoly market structure any more 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

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

		Firm 2	
		Collude	Not collude
Firm 1	Collude	$\pi^C_{1,k},\ \pi^C_{2,k}$	$\pi^C_{1,k}\left(1-\delta e^{\eta\pi^C_{1,k}} q^C_{2,k}/q^C_{1,k}\right),\ \pi^C_{2,k}\left(1+\delta e^{\eta\pi^C_{1,k}}\right)$
	Not collude	$\pi^C_{1,k}\left(1+\delta e^{\eta\pi^C_{2,k}}\right),\ \pi^C_{2,k}\left(1-\delta e^{\eta\pi^C_{2,k}} q^C_{1,k}/q^C_{2,k}\right)$	$\pi^N_{1,k},\ \pi^N_{2,k}$

$q^C_k = q^C_{1,k} + q^C_{2,k}$, 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 the amount of demand $q^C_{1,k}\delta e^{\eta\pi^C_{2,k}}$. Importantly, the amount of demand can be "stolen" increases with the rival's profit level $\pi^C_{2,k}$, 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 $q^C_{2,k}\delta e^{\eta\pi^C_{1,k}}$ from firm 1 without changing the agreed total market size q^C_k or the price p^C_k. 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 readers are referred to Chen et al. (2020). Here, we use the comparative static analysis to illustrate the endogenous responses of competition intensity, profit margins, and distress levels to changes in the 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^N_f decreases with the idiosyn-

cratic 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.

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

(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.

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

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. But, the profit level of a firm endogenously decreases in response to its 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 itself 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 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:*

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

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:*

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

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 lower marginal utility of marginal investors. Thus, industries with higher centrality on the competition network have higher expected stock returns. The proof of Proposition 2.3 is in 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*

$$\frac{\partial \theta^C_c}{\partial x} < \frac{\partial \theta^C_i}{\partial x} < 0 \quad \textit{and} \quad \frac{\partial \theta^C_c}{\partial x} < \frac{\partial \theta^C_j}{\partial x} < 0, \tag{2.9}$$

where θ^C_k 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 levels. First, the model predicts that the direction toward which a firm's profit margin and distress level 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 between 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 Standard Industrial Classification (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 stock returns of the individual firms in the industries value-weighted by their one-month lagged market capitalization. We use CRSP delisting returns to adjust for stock delists and we exclude financial and utility industries from the analysis.

Measures for Distress Risk and Gross Profitability. We use two empirical measures for distress risk. In Appendix B, we explain the construction method of these two measures in detail. Briefly, 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). We note that the distance to default measure negatively captures the distress risk: lower distance to default measure means higher risk of distress.

We use two empirical measures for gross profitability. The first measure is the gross profit margin computed as the difference between sales and cost of goods sold divided by sales. The second measure is the markup of the firms computed as the natural log of the ratio between sales and cost of goods sold. Sales and cost of goods sold are from Compustat.

Natural Disaster Data. We obtain information on the property losses caused by natural disasters hitting the US territory from Spatial Hazard Events and Loss Databases for the United States (SHELDUS). SHELDUS 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*), and it covers natural hazards such as thunderstorms, hurricanes, floods, wildfires, and tornados, as well as perils such as flash floods and heavy rainfall. For each event, the database provides information on the start date, the end date, and the Federal

[6]We follow Bustamante and Donangelo (2017) to 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.

Information Processing Standards (FIPS) code 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.[7] 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 the Fan and Lang (2000), which are computed based on the input-output accounts data. We identify firm-level supplier-customer links based on the Compustat customer segment data and the 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 the vertical relatedness data from Frésard, Hoberg and Phillips (2020).

Lender Exposure Data. We use Thomson Reuters LPC DealScan syndicated loan data to capture lenders' exposure to natural disasters. 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 SEC filings and other internal resources. According to Carey and Hrycray (1999), Dealscan database covers between 50% and 75% commercial loans in the US by 1992. 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). When there is more than one lender funding a loan, we follow the literature to focus on the lead lenders, who are designated by DealScan as the lead arrangers in the table of lender shares.

Financial Fraud Data. We assemble the financial fraud data following Karpoff et al. (2017). First, we collect all enforcement actions brought by the US Securities and Exchange Commission (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 pubic announcement which reveals to investors that a future enforcement

[7]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 the number of employees at the establishment level. We merge Infogroup to Compustat-CRSP based on stock tickers and the firm names.

action is possible (i.e., trigger dates) 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.

AJCA Data. We examine the impact of the American Jobs Creation Act of 2004 (AJCA), in which firms are allowed to repatriate foreign profits to the United States at a 5.25% tax rate, rather than the existing 35% corporate tax rate. We defined the firms shocked by the passage of AJCA as those with more than 33% pre-tax income from abroad during the three-year period prior to AJCA (i.e., 2001−2003). Firms' foreign pre-tax income and the total pre-tax income are from Compustat. We follow Grieser and Liu (2019) to use the 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 competition network through common market leaders and how we construct the competition centrality measure. Section 4.2 shows that industries with higher competition 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 enforcement actions against financial frauds and the AJCA tax holiday.

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. 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 the two industries share some common market leaders. We provide details on the construction of the competition network and empirical design below.

When constructing the competition network, we use Compustat historical segment data which provide information on the SIC codes for all the segments that firms operate in. The coverage of the data starts from 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

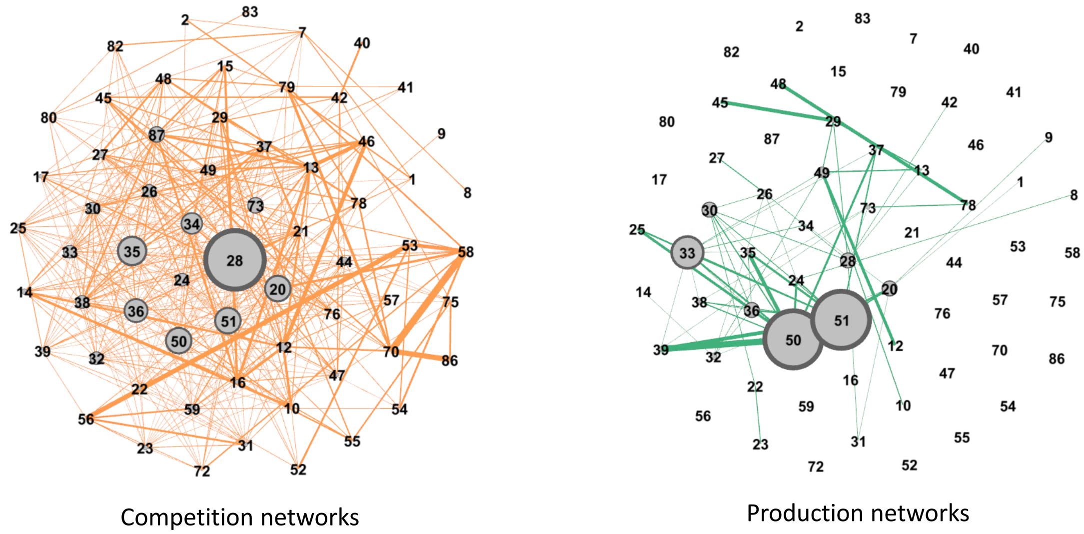
Table 2: Connected four-digit SIC pairs of the competition and production networks.

		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

ten 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 code from 5000 to 5999) in constructing the network. Two industries are connected 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 the Fan and Lang (2000). Specifically, we average the forward connectedness and backward connectedness measures between two four-digit SIC industry to get an average connectedness measure. We then define whether two four-digit SIC industries are connected or not in the production network by choosing a cutoff value such that the number of connected industries matches with those in the 1994 snapshot of the competition network. By doing this, we effectively normalize the number of total connections and focus on the difference in the distribution of the connections among industry pairs.

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 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 will 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 will show



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 that a given industry connects to). The thickness of the line represents the strength of connection between the two-digit SIC industries.

Figure 3: Competition networks and production networks.

that the within-industry and cross-industry spillover effects of distress risk cannot be explained by production network externality.

Construction of Competition Centrality Measures. We consider four centrality measures for all industries connected in the competition network – *closeness*, *degree*, *betweenness*, and *eigenvector* centrality measures – 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 other 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 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 the Appendix D, we provide the mathematical formulas and a simple example to demonstrate the calculations.

Table 3: Competition 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 principle components				
	*PC*1	*PC*2	*PC*3	*PC*4
Variance explained (%)	67.28	18.72	10.05	3.95

Note: Panel A of this table shows the correlation among the four centrality measures (degree, closeness, betweenness, and eigenvector centrality) 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 principle component analysis based on the time series of the four centrality measures. Panel B of this table shows the amount of variance explained by the four individual principle components.

We construct all four measures and find that they are all highly correlated (see Table 3). Given the fact that they comove significantly and positively with each other over time and each of them only captures some aspects (but by no means all) of the centrality of nodes on the competition network, we consider the first principle component of the four centrality measures as our major measure in the paper. But, as robustness checks, 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 3 and Figure 4 show that there is one 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: the centrality of the competition network is priced in the cross-section of industry stock returns as a primitive industry characteristic.

Portfolio Sorting Analyses. In June of each year t, we sort industries into quintiles based on their competition 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 constructing the industry returns, which are value-weighted from firm-level returns. First, we exclude common leaders from the sample in computing industry returns because they operate in more than one industry. Similarly, we also exclude

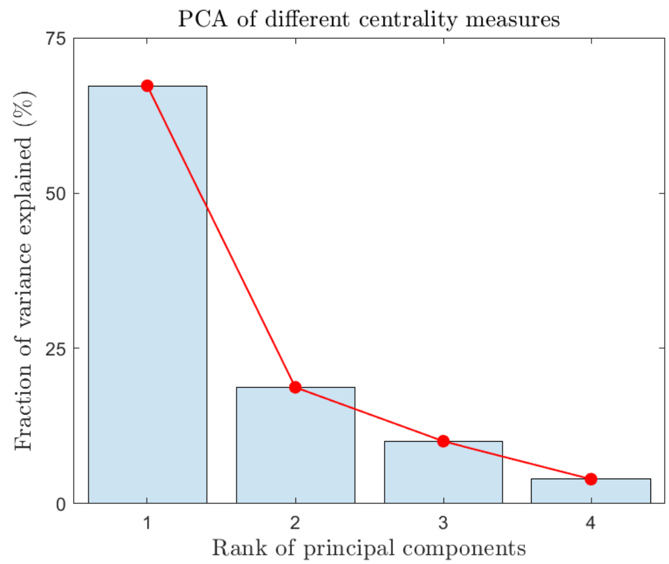


Figure 4: Eigen-decomposition of the covariance of four different centrality measures.

conglomerate firms which operate in multiple industries. To accomplish this, we follow Gopalan and Xie (2011) and Bustamante and Donangelo (2017) to define conglomerates as 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, our paper differs from the studies that examine the asset pricing implications of corporate diversifications (e.g., Lamont and Polk, 2001; Hann, Ogneva and Ozbas, 2013). Finally, we exclude financial and utility industries and very small industries that contain fewer than three firms from the analysis.

Table 4 shows the average excess returns of the long-short portfolios sorted on the competition centrality measure. We find that industries with higher competition centrality are associated with higher excess returns. The magnitudes of the return spreads are economically large. The spread in average excess returns between the industries with the highest competition centrality (Q5) and the industries with the lowest competition centrality (Q1) is 4.34%. These spreads are comparable to the equity premium and the 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 centrality are associated with higher alphas after adjusting for the market return, the Fama-French three factors, the Pástor-Stambaugh liquidity factor, the Stambaugh-Yuan mispricing-factor, the Hou-Xue-Zhang q factors, and the Fama-French five factors (see Table 5).

As shown in Table A.4 of the Appendix, competition centrality seems to be largely unrelated to other industry characteristics including production network centrality, in-

Table 4: Excess industry returns sorted on competition 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 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 industries, 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' one-month lagged market capitalization. We exclude financial and utility industries and very small industries that contain fewer than three firms from the analysis. 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.

dustry 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 the competition centrality. We find that the return spreads of the competition centrality remain robust after controlling for these industry characteristics (see Tables A.5 and A.6 of the Appendix).

Fama-MacBeth Regressions. We perform Fama-MacBeth tests by regressing monthly stock returns on the PC1 of the competition centrality measures. As Table 6 shows, the slope coefficient for competition centrality is positive and statistically significant. The slope coefficient is also economically significant. According to column (6) of Table 6, a one-standard-deviation increase in the competition centrality is associated with a 0.162- (1.94-) percentage-point increase in the monthly (annualized) stock returns. The relation between competition centrality measures and returns is not subsumed by the stock characteristics. In other words, under the Fama-MacBeth regression setting, we strengthen the double-sorting results above by showing that higher competition centrality

Table 5: Alphas of the long-short industry portfolio sorted on competition 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 centrality. The factor models include 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 industries, 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' one-month lagged market capitalization. We exclude financial and utility industries and very small industries that contain fewer than three firms from the analysis. 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.

predicts higher excess returns in the cross section after controlling for production network centrality, industry-level sales, industry-level book-to-market ratios, and industry-level gross profitability. We also control for the HHI because industry returns are 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 Centrality and Industry Risk Exposure. If the returns of the long-short industry portfolio sorted on competition centrality compensate for risk exposure, we expect the betas of industry stock returns to the returns of the long-short industry portfolio (denoted by β_{LS}) to be correlated with the sorting characteristic (i.e., competition centrality).[8]

[8] For example, in their seminal paper, Fama and French (1993) show that small stocks have higher loadings on the SMB factor while value stocks have higher loadings on the HML factor.

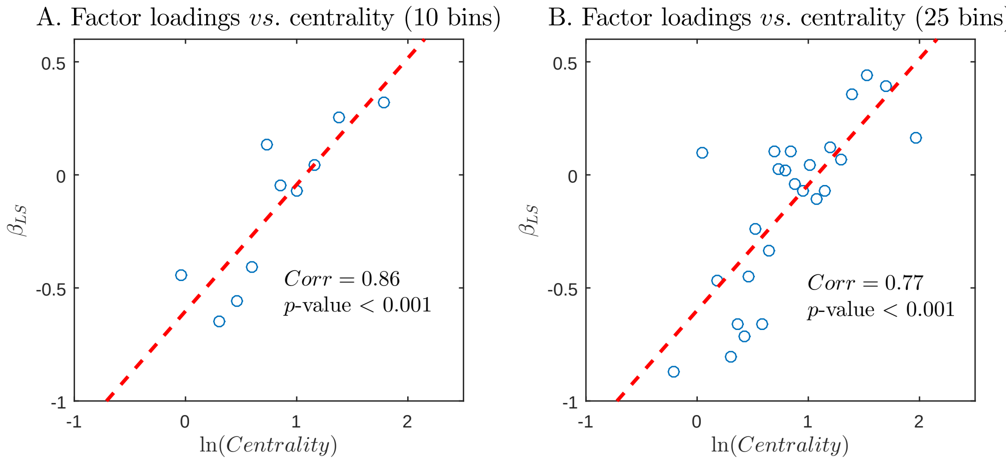
Table 6: Fama-MacBeth regressions.

	(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 centrality ($Competition\_Centrality_{i,t-1}$) 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 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.

We estimate the β_{LS} at industry level based on monthly returns of individual industries and the monthly returns of the long-short porfolio sorted on competition centrality. We find that the correlation coefficient between $\beta_{LS,i}$ and the natural log of the time-series average of the competition centrality (i.e., $\ln(Centrality_i)$) is 0.33, with p-value smaller than 0.001. Figure 5 shows the relation between competition centrality and β_{LS} using binned scatter plots. It is obvious that β_{LS} is strongly positively correlated with competition centrality.

Discount Rate and Cash Flow Channels. Our model predicts that the earnings of the industries with higher competition network centrality are more sensitive to fluctuations in the 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.



Note: This figure shows the relation between competition 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 the competition 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 centrality and industry factor loadings.

In panel A of Table 7, we tabulate the sensitivity of industry earnings to discount rate for industry quintile portfolios sorted on competition 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 centrality comove more negatively with discount rate shocks. In panel B of Table 7, we tabulate the sensitivity of industry earnings to aggregate cash flow for industry quintile portfolios sorted on competition centrality. We measure the aggregate cash flow using the average ROE across all industries. We show that the earnings of industries with higher competition 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 centrality are associated with higher expected returns.

4.3 Within-Industry Spillover Effects with Natural Disaster Shocks

After documenting the asset pricing implications of competition 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.

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,

Table 7: Discount rate and cash flow exposures for industry portfolios sorted on competition 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]

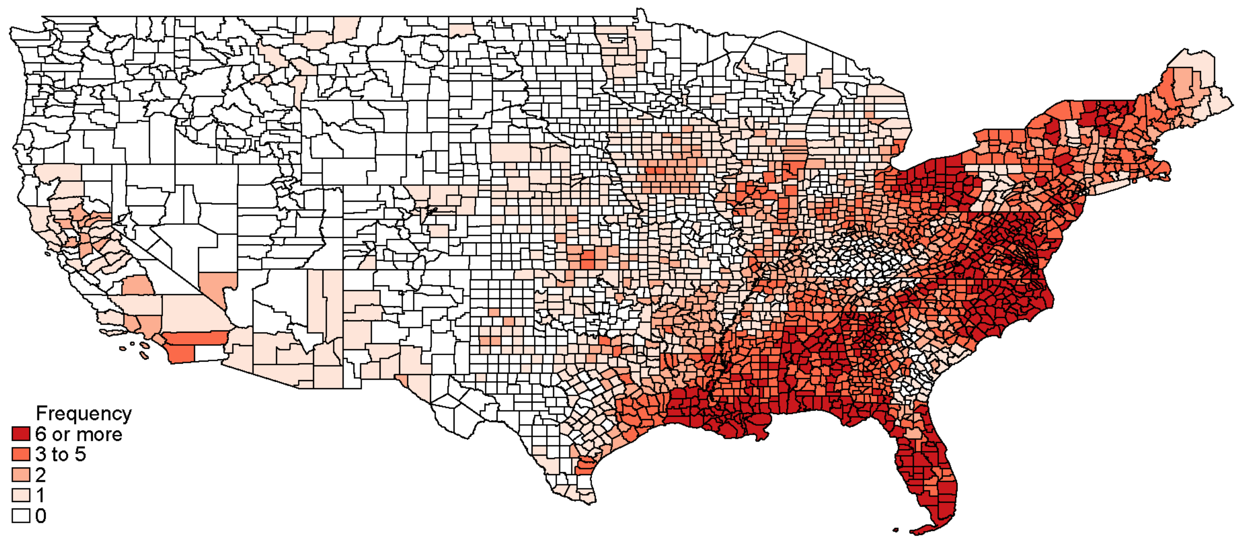
Note: This table examine the discount rate and cash flow exposures for industry portfolios sorted on competition centrality. In panel A, we tabulate the sensitivity of industry earnings to discount rate for industry quintile portfolios sorted on competition centrality. The regression specification is: $ROE\_shock_{p,t} = \beta_1 SmoothEP\_shock_t + \varepsilon_{p,t}$. $ROE\_shock_{p,t}$ is the yearly shock to the average return on equity (ROE) across industries in portfolio p in year t. Following the definition of ROE in 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 cyclically adjusted price-earnings ratio (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 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 the 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.

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). Insurance coverage and public disaster assistance can only partially offset firms' losses from natural disasters (see Appendix C for detailed discussion). As a result, natural disaster shocks 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, credit lending channel, and institutional blockholder commonality.

4.3.1 DID Analysis

Treated and Matched Peer Firms. We follow Barrot and Sauvagnat (2016) in defining a firm as been 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 major natural disasters during that year.[9] We list the major natural

[9] We follow Barrot and Sauvagnat (2016) to define major natural disasters as those that cause at least $1 billion total estimated property damages and last less 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).



Note: This figure presents the frequency of major natural disaster for each county in the US mainland over the period from 1994 to 2018. The list of counties affected by each major natural disaster is obtained from the SHELDUS database. Table A.7 describes the major natural disasters included in the sample.

Figure 6: Frequency of major natural disasters by the US counties.

disasters included in our sample in Table A.7 of the Appendix, and we plot the frequency of major natural disasters for each county in the US mainland from 1994 to 2018 in Figure 6. Panel A of Table 8 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 located in experience on average (weighted by the number of the firms in the counties) \$1.9 billion 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) of the firms.

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 five non-treated peer firms in the same four-digit SIC industries with similar asset size, tangibility, and firm age.[10] 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

[10] 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.

damage during the major natural disasters. To make sure 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 and these matched peer firms do not share any common customers with the treated firms.

Regression Specifications of the DID Analyses. To clearly identify and dissect out the within-industry spillover effects, it is important to recognize that the cross-industry spillover effects also exist simultaneously in the background. For example, suppose we want 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 competition networks. This is because although natural disasters are idiosyncratic shocks, the same set of natural disasters can simultaneously affect firms in industries A and B and thus can lead to biased estimates of the within-industry spillover effects. To control for the strength of cross-industry spillover, we construct the variable $Ln(1 + n(\mathcal{C}_{i,t}))$, which is the natural log of one plus the number of industries that are connected to firm i's industry through competition networks and are shocked by the 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:

$$Y_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1 + n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}. \quad (4.1)$$

The 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. The independent variable $Treat_{i,t}$ is an indicator variable that equals one if firm i is negatively affected by major natural disasters in year t. $Post_{i,t}$ is an indicator variable that equals one for observations after major natural disasters. $Ln(1 + n(\mathcal{C}_{i,t}))$ captures the strength of cross-industry spillover. 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., two years before and two years after the 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 the coefficient β_1 and the coefficient β_3 captures the total treatment effect for the treated firms (see, e.g, Boehmer, Jones and Zhang, 2020), while the coefficient β_3 alone captures the within-industry spillover effects to the peer firms. Finally, the coefficient β_4 captures the cross-industry spillover effects

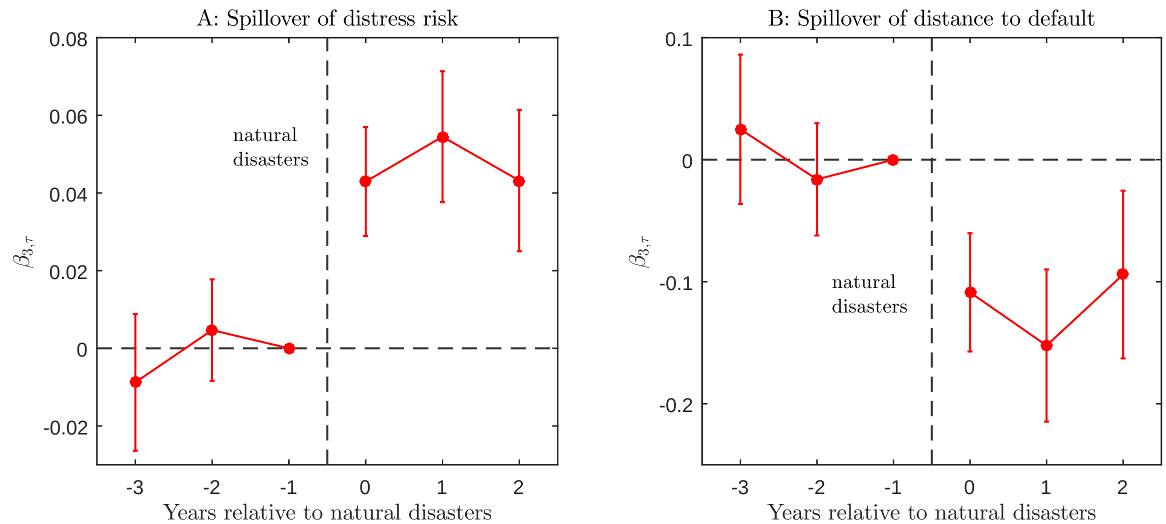
Table 8: Identifying within-industry spillover effects using the DID analysis.

	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 the 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	−0.083	−0.084*	−0.001	−0.001	−0.002	−0.002
	[1.513]	[1.529]	[−1.637]	[−1.663]	[−0.256]	[−0.275]	[−0.317]	[−0.338]
$Treat_{i,t}$	−0.015	−0.015	0.093*	0.094*	0.001	0.001	0.001	0.001
	[−1.284]	[−1.292]	[1.896]	[1.910]	[0.150]	[0.158]	[0.181]	[0.190]
$Post_{i,t}$	0.053***	0.052***	−0.129***	−0.121***	−0.007**	−0.006**	−0.010**	−0.009**
	[6.419]	[6.333]	[−4.125]	[−3.909]	[−2.090]	[−1.970]	[−2.481]	[−2.342]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.018**		−0.095***		−0.006**		−0.009**
		[1.972]		[−2.602]		[−2.101]		[−2.356]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	128406	128406	108996	108996	133350	133350	133237	133237
R-squared	0.564	0.564	0.666	0.666	0.746	0.746	0.772	0.772
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.006	0.009	0.001	0.002

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 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 one 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, and it is the natural log of one plus the number of industries that are connected to firm i's industry through competition networks and are shocked by the 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 firm 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 also require that the matched peer firms do not share any common customers with the treated firms. We identify the supplier-customer links using the Compustat customer segment data and the Factset Revere data. For each major natural disaster, we include four yearly observations (i.e., two years before and two years after the major natural disaster) for the treated firms and their matched non-treated peers in the analysis. The regression specification is: $Y_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1+n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}$. $Treat_{i,t}$ is an indicator variable that equals one if firm i is a treated firm. $Post_{i,t}$ is an indicator variable that equals one 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.

through competition network. It is important to point out that natural disasters are not a one-time shock, and 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 the time fixed effect δ_t.



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. We also require that the matched peer firms do not share any common customers with the treated firms. For each major natural disaster shock, we include six yearly observations (i.e., three years before and three 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 dependend 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 one if firm i is a treated firm. $ND_{i,t-\tau}$ is an indicator variable that equals one 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 one plus the number of industries that are connected to firm i's industry through competition networks and are shocked by the 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. Vertical dashed lines represent the occurrence of major natural disasters.

Figure 7: Within-industry spillover effects of distress risk.

Findings of the DID Analyses. We tabulate the results of the DID regressions for firm distress in columns (1) to (4) of panel B in Table 8. 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 zero (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.

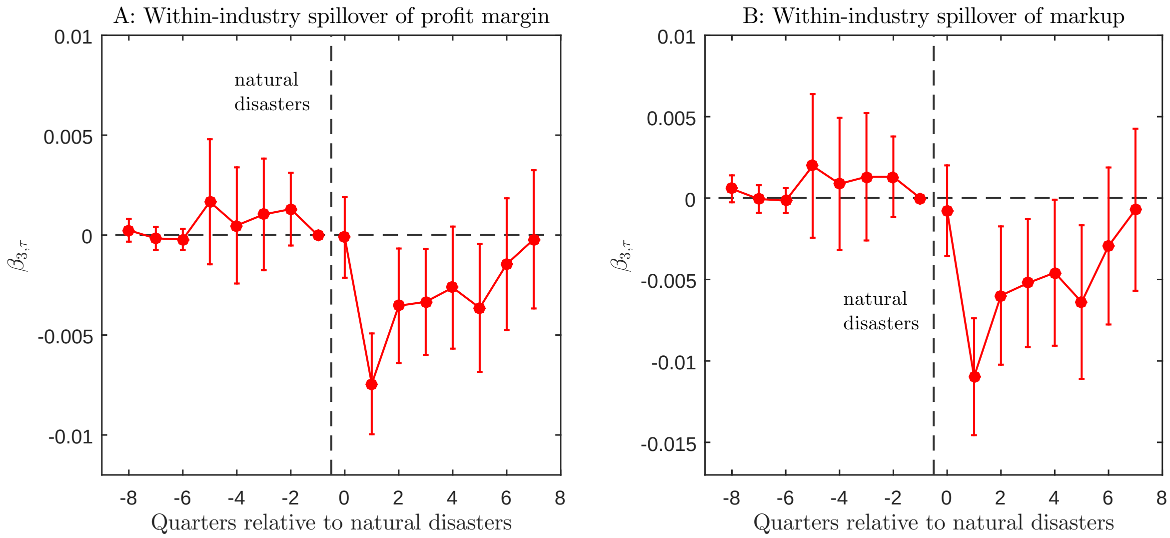
We then examine the impact of distress risk on the treated firms' gross profit margin. We focus on profit margin rather than the product price in this paper for the following reasons. First, we are concerned with the real impact of product market competition, and thus it is the profit margin, rather 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 of product costs which can be affected by idiosyncratic shocks such as natural disasters. An increase of product prices does not necessarily mean a reduction of competition intensity.[11] 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, the implicit discounts, coupons, rebates, and gifts are not easily observable to economists. Last but not the least, price levels cannot be meaningfully compared across industries, but profit margins can.

To quantify the changes in treated firms' gross profit margin, we again use the regression specification (4.1), with the 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 8, we find that the treated firms significantly reduce their gross profit margin and markup, suggesting that these firms decide to reduce profitability and compete more aggressively in the product market after the increase of their 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 themselves more distressed. We find strong supporting evidence for this prediction. The coefficient β_3 in columns (5) to (8) of panel B in Table 8 is negative and statistically significant, suggesting that the industry peers that are unaffected directly by natural disasters also reduce their profit margin significantly. The intensified product market competition makes the non-treated industry peers also suffer from a significant increase in distress risk. The coefficient β_3 in columns (1) and (2) of panel B in Table 8 is positive and statistically significant, while the coefficient β_3 in columns (3) and (4) of panel B in Table 8 is negative and statistically significant. These findings indicate the existence of the within-industry spillover effect: industry peers become more distressed and they compete more aggressively with the firms that affected by natural disaster shocks.

Panel B of Table 8 also reports the coefficients for the 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 that are linked to

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



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 ten non-treated peer firms in the same four-digit SIC industry. Because the quarterly data are noiser 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. We also require that the matched peer firms do not share any common customers with the treated firms. For each firm, we include 16 quarterly observations (i.e., eight quarters before and eight quarters after the major natural disasters) 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 dependend 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 one if firm i is a treated firm. $ND_{i,t-\tau}$ is an indicator variable that equals one 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, and it is the natural log of one plus the number of industries that are connected to firm i's industry through competition networks and are shocked by the 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. Vertical dashed lines represent the occurrence of major natural disasters.

Figure 8: Within-industry spillover effects of profit margin.

the focal industry through competition networks are shocked by the 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 will study the cross-industry spillover effects in greater detail and highlight the role of common leaders as the key players that transmit shocks across industries through the competition networks.

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

$$Y_{i,t} = \sum_{\tau=-3}^{2} \beta_{1,\tau} \times Treat_{i,t} \times ND_{i,t-\tau} + \beta_2 \times Treat_{i,t} + \sum_{\tau=-3}^{2} \beta_{3,\tau} \times ND_{i,t-\tau}$$
$$+ \beta_4 \times Ln(1 + n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}. \tag{4.2}$$

The dependend variable ($Y_{i,t}$) is the distress risk ($Distress_{i,t}$) and the distance to default ($DD_{i,t}$). $Treat_{i,t}$ is an indicator variable that equals one if firm i is a treated firm. $ND_{i,t-\tau}$ is an indicator variable that equals one 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. In Figure 7, 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 the natural disaster shocks. There is no significant change in the distress risk or distance to default prior to the 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 two years, which justifies the choice of time window in the DID analysis presented in Table 8.

We also examine the dynamics of the spillover effects for profit margin. Because the data for the measures of profit margin and markup can be computed from Compustat at quarterly frequency, we follow Barrot and Sauvagnat (2016) to show the quarterly dynamic effects. As shown in Figure 8, the reduction in profit margin and markup takes place within two quarters after the occurrence of the natural disasters. There is no significant change in the profit margin or markup prior to the natural disaster shocks, which again provides evidence supporting the parallel trend assumption for the DID analysis. The spillover effects in profitability last for around two years, a time window that is roughly consistent with other impact of natural disasters documented in the literature.[12]

[12] For example, Barrot and Sauvagnat (2016) show that natural disaster shocks dampen the sales growth for the customers of the treated firms for about two years. In Section 4.3.3, we will 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 9: 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
$Treat_{i,t} \times Post_{i,t}$	0.013	0.032*	−0.039	−0.123*	−0.001	−0.003	−0.002	−0.003
	[0.724]	[1.950]	[−0.551]	[−1.815]	[−0.110]	[−0.691]	[−0.239]	[−0.634]
$Treat_{i,t}$	0.003	−0.024	−0.022	0.142**	−0.002	0.001	−0.000	0.001
	[0.172]	[−1.512]	[−0.311]	[2.113]	[−0.337]	[0.320]	[−0.047]	[0.233]
$Post_{i,t}$	0.090***	0.017*	−0.178***	−0.059	−0.015**	0.001	−0.021***	0.001
	[6.963]	[1.680]	[−3.654]	[−1.495]	[−2.456]	[0.492]	[−2.868]	[0.447]
$Ln(1 + n(\mathcal{C}_{i,t}))$	0.067***	−0.021*	−0.146***	−0.052	−0.022***	0.003	−0.029***	0.005
	[4.535]	[−1.802]	[−2.669]	[−1.019]	[−4.224]	[1.070]	[−4.494]	[1.274]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61665	66694	52759	56157	64778	68547	64737	68475
R-squared	0.596	0.575	0.699	0.676	0.731	0.804	0.769	0.816
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.002	0.652	$<10^{-3}$	0.689

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: $Y_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1 + n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}$. The definition of the dependent and independent variables are explained in Table 8. We present results from the DID analysis in industries with high entry barriers (top tertile) and low entry barriers (middle and bottom tertiles). 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 one year prior to the natural disaster shocks. The number of firm-year observations in the subsample of low entry barriers is not exactly twice of that in the subsample of high entry barriers because the number of treated firms are 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.

Robustness Checks. We perform a battery of robustness checks. In Table A.8 of the Appendix, we show 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 A.9 of the 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) (see, Hoberg and Phillips, 2010, 2016), and we show that the within-industry spillover effects remain robust. In Table A.10 of the Appendix, we show that the within-industry spillover effects remain robust when we use an alternative measure (i.e., $ln(1 + \overline{Damage(\mathcal{C}_{i,t})})$) to capture the cross-industry spillover, which is the natural log of one plus the average amount of property damage (in million dollars) caused by major natural disasters in year t across industries that are connected to firm i's industry through competition networks.

4.3.2 Heterogeneity of the Spillover Effects

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 one year prior to the 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 analyses. Table 9 tabulates the results. Consistent with our prediction, we find that the within-industry spillover effects captured by the 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 the total treatment effects (captured by the sum of β_1 and β_3) offers additional insights for the heterogeneous spillover effects. The total treatment effects are significant for all industries when we examine the distress level of treated firms (see last row of columns 1 to 4 in Table 9). This is because natural disasters make the treated firms more distressed in all industries. However, the total treatment effects for profit margin is only significant in industries with high entry barriers (see last row of columns 5 to 8 in Table 9), 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 level of the industry peers. Consistent with our model, we observe the 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 with worse economic and financial conditions prior to natural disasters. This is because in these industries firms are effectively less patient and thus have more incentives to compete after the arrival of the 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 this industry from the previous year. We then sort industries into two groups based on the industry-level economic conditions one year prior to the natural disaster shocks and then examine the within-industry spillover effects in the industries with high financial constraints (top half) and low financial constraints (bottom half) using DID analyses. Panel A of Table 10 tabulates the results. Consistent with our prediction, we find that the within-industry spillover effects captured by the 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 level of treated firms (see 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 margin of the treated firms (see last row of columns 5 to 8 in panel

Table 10: 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
$Treat_{i,t} \times Post_{i,t}$	0.026	0.021	-0.068	-0.134^{**}	-0.002	-0.002	-0.008	0.002
	[1.461]	[1.190]	[−0.989]	[−1.967]	[−0.306]	[−0.424]	[−0.972]	[0.233]
$Treat_{i,t}$	-0.032^{*}	-0.021	0.133^{*}	0.153^{**}	0.002	0.001	0.003	0.001
	[−1.817]	[−1.240]	[1.737]	[2.047]	[0.366]	[0.211]	[0.342]	[0.171]
$Post_{i,t}$	0.078^{***}	0.022^{*}	-0.209^{***}	-0.006	-0.017^{***}	0.006	-0.019^{***}	0.003
	[6.026]	[1.800]	[−4.374]	[−0.134]	[−3.110]	[1.525]	[−2.820]	[0.639]
$Ln(1+n(\mathcal{C}_{i,t}))$	0.037^{***}	0.003	-0.127^{***}	-0.104^{**}	-0.014^{***}	-0.002	-0.018^{***}	-0.004
	[3.187]	[0.217]	[−2.751]	[−2.280]	[−3.428]	[−0.586]	[−3.667]	[−0.987]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63488	61146	53779	51520	65537	64012	65460	63974
R-squared	0.606	0.583	0.694	0.698	0.767	0.772	0.788	0.804
Test p-value: β_1 + β_3 = 0	$<10^{-3}$	0.003	$<10^{-3}$	0.013	$<10^{-3}$	0.368	$<10^{-3}$	0.382

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
$Treat_{i,t} \times Post_{i,t}$	0.009	0.039^{**}	0.041	-0.096	0.002	-0.001	-0.001	-0.001
	[0.353]	[2.183]	[0.412]	[−1.265]	[0.184]	[−0.117]	[−0.071]	[−0.113]
$Treat_{i,t}$	-0.028	-0.030^{*}	0.107	0.146^{*}	0.002	0.009^{*}	0.010	0.013^{**}
	[−1.074]	[−1.755]	[1.009]	[1.843]	[0.287]	[1.860]	[0.869]	[2.072]
$Post_{i,t}$	0.111^{***}	0.004	-0.291^{***}	-0.080^{*}	-0.031^{***}	0.004	-0.038^{***}	0.005
	[5.295]	[0.326]	[−3.908]	[−1.698]	[−3.073]	[1.361]	[−3.096]	[1.286]
$Ln(1+n(\mathcal{C}_{i,t}))$	0.034^{*}	-0.000	-0.141^{**}	-0.099^{*}	-0.021^{***}	-0.006^{*}	-0.025^{***}	-0.007
	[1.886]	[−0.013]	[−2.342]	[−1.868]	[−3.393]	[−1.806]	[−3.270]	[−1.581]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31161	58143	27339	47605	32813	60649	32794	60597
R-squared	0.626	0.604	0.736	0.704	0.730	0.805	0.787	0.826
Test p-value: β_1 + β_3 = 0	$<10^{-3}$	0.003	0.002	0.005	$<10^{-3}$	0.329	$<10^{-3}$	0.385

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: $Y_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1+n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}$. The definition of the dependent and independent variables are explained in Table 8. 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 this industry from the previous year. We sort industries into two groups based on the industry-level economic conditions one 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. Financial constraint of a four-digit SIC industry is measured by the sales-weighted average of the delay investment score in this industry (Hoberg and Maksimovic, 2015). We sort industries into tertiles based on the industry-level financial constraints one year prior to the 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.

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 in these industries.

We measure the financial constraint of a four-digit SIC industry using the sales-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 one year prior to the 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 analyses. Panel B of Table 10 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 level of treated firms (see 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 margin of the treated firms (see 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 it is unlikely to be the case.[13]

We first exclude matched peer firms that are geographically close to natural disaster areas in the DID analysis. Specifically, we remove the matched peer firms with headquarter or any major establishment that locate within 100 miles from any zip code negatively affected by the major natural disasters in a given year. By doing this, we remove a set

[13] 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 that natural disasters can lead to economic and financial distress of the treated firms. The alternative explanation we aim to rule out here is that the demand shocks caused by the 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.

of firms that are more susceptible to the negative demand shocks caused by the natural disasters. As shown in panel A of Table A.11 in the Appendix, our findings of the within-industry spillover effects remain robust.

Although a matched peer firm is geographically far from the natural disaster areas, 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 remove matched peer firms with customers negatively affected by the natural disasters. We identify the supplier-customer links using the Compustat customer segment data and the Factset Revere data, which mainly capture business relationship among firms and provide limited coverage on individual consumers.[14] Because of the limitation of the supplier-customer data, it is possible that individual consumers negatively affected by the natural disasters may be the common customers for the treated firms and their industry peers, and such type of demand commonality can drive the within-industry spillover effects. To rule out this possibility, we further remove treated firms and their matched peers in the consumer-facing industries (i.e., airlines, grocery stores, hotels, retailers, restaurants, utilities, and many online services). In other words, we focus on matched peer firms that i) operate in the non consumer-facing industries, ii) far away from the natural disaster areas, and iii) with no business customers affected by the natural disasters. As shown in panel B of Table A.11, 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 the supply chains. We present a set of evidence suggesting it is unlikely to be the case.

First, we note that in the baseline DID test shown in Table 8, we have already removed matched peer firms that are suppliers or customers of the treated firms. The fact that we find strong within-industry spillover effects in Table 8 suggests that these effects are unlikely caused by suppliers or customers of the treated firms. Second, in the baseline DID test, we also require that the matched peer firms do not share any common customers with the treated firms. By doing so, we rule out the alternative explanation that the within-industry spillover effects are caused by common customers of both the treated

[14] We are not aware of any dataset that provides comprehensive coverage of individual consumers. One exception is the pairwise customer similarity measure constructed by Baker, Baugh and Sammon (2020) based on household-level financial transaction data. However, their dataset is relatively short in time series (from 2010 to 2015) and has limited overlap with our sample in the cross section.

firms and their industry peers.[15] Finally, to strengthen our results, we further remove matched peer firms that are related to the treated firms vertically in the DID analysis. By doing so, we further drop firms that are potential customers or suppliers of the treated firms from the pool of the matched firms. We define two firms as connected vertically if their vertical relatedness scores are ranked top 10% among the scores of all firm pairs (see, Frésard, Hoberg and Phillips, 2020). As shown in Table A.12, the within-industry spillover effects remain robust.

Credit Lending Channel. The third alternative explanation that we test is the credit lending channel. This alternative explanation argues that non-treated industry peers may borrow from lenders that have heavy exposures to disaster firms, and as a result these firms suffer from financial distress when their lenders are negatively affected.

To test this possibility, we remove the matched peer firms that share any common lender 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 proceeding five-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. As shown in Table A.13 of the 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 the credit lending channel unlikely explains the within-industry spillover effects.[16]

Institutional Blockholder Commonality. The last alternative explanation that we test is institutional blockholder commonality. This alternative explanation argues that when

[15] 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. If the firms shocked by natural disasters and their peer firms share common customers, 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.

[16] Because DealScan data are mainly collected from commitment letters and credit agreements drawn from SEC filings, the database mainly covers medium-size to large loans (e.g., Carey, Post and Sharpe, 1998). We limit our analysis in Tables A.13 of the Appendix to the firms covered by the DealScan data because we cannot accurately measure the lender exposure for the firms outside of the DealScan universe.

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 term may cause economic and financial distress of these firms.

To test this possibility, we remove the matched peer firms that share any common institutional blockholders with the treated firms in the DID analysis based on the 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 A.14 of the Appendix, the within-industry spillover effects remain robust, suggesting that institutional blockholder commonality unlikely explains our findings.

4.4 Cross-Industry Contagion Effects with Natural Disaster Shocks

In Section 4.3.1 above, we have already provided some evidence for the cross-industry spillover effects. In particular, panel B of Table 8 shows that the coefficient for the cross-industry spillover term (i.e., β_4 in equation 4.1) is statistically significant with the signs consistent with the predictions of our model in the collusive Nash equilibrium. In this section, we further study the cross-industry spillover effects by highlighting the role of the common market leaders in transmitting shocks across industries.

Regression Specifications. We examine the 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 margin of common market leaders in the same industry. The data set 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:

$$Y_t^{(c_{i,j})} = \sum_{m=1}^{3} \beta_m ND\_mild_{j,t}^{(m)} + \sum_{s=1}^{3} \beta_s ND\_severe_{j,t}^{(s)} + \varepsilon_t^{(c_{i,j})}. \tag{4.3}$$

The dependent variable $Y_t^{(c_{i,j})}$ is the distress risk and profit margin of the 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 one if the m^{th} $(m = 1, 2, 3)$ largest firm (ranked by sales) in industry j in year t experiences mild damage during the natural disaster shocks. Similarly, $ND\_severe_{j,t}^{(s)}$, are indicator variables that equal one if the s^{th} $(s = 1, 2, 3)$ largest firm (ranked by sales) in industry j in year t experiences severe damage during the natural disaster shocks.[17] 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 by natural disasters.

Our regression specification (4.3) essentially estimates the impact of the idiosyncratic natural disaster shocks to the top three market leaders in industry j on the distress risk and the profit margin of the common market leader (i.e., $c_{i,j}$) in year t. We compute the fitted value $\widehat{IdShock}_{j,t}^{(c_{i,j})}$ as follows:

$$\widehat{IdShock}_{j,t}^{(c_{i,j})} = \widehat{Y}_t^{(c_{i,j})} = \sum_{m=1}^{3} \hat{\beta}_m ND\_mild_{j,t}^{(m)} + \sum_{s=1}^{3} \hat{\beta}_s ND\_severe_{j,t}^{(s)}. \tag{4.4}$$

The fitted value $\widehat{IdShock}_{j,t}^{(c_{i,j})}$ intuitively captures the changes of the distress risk and the profit margin of the common market leader $c_{i,j}$ attributed to the 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 of distress risk or profit margin of common market leaders in industry i, attributed to idiosyncratic shocks to market leaders in other industries as follows:

$$\widehat{IdShock}_{-i,t} = \frac{1}{n(\mathcal{I}_{i,t})} \sum_{j \in \mathcal{I}_{i,t}} \widehat{IdShock}_{j,t}^{(c_{j,i})}, \tag{4.5}$$

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

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

$$Y_{i,t}^{(-c)} = \beta_1 \widehat{IdShock}_{-i,t} + \varepsilon_{i,t}, \tag{4.6}$$

where $Y_{i,t}^{(-c)}$ is the distress risk or profit margin of industry i sales-weighted across firms in the 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.

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

Table 11: Distress contagion 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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}^{(-c)}$		$DD_{i,t}^{(-c)}$		$PM_{i,t}^{(-c)}$		$Markup_{i,t}^{(-c)}$	
$\widehat{IdShock}_{-i,t}$	0.798^{**}	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 contagion 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 the common market leader $c_{i,j}$, respectively. The independent variables, $ND\_mild_{j,t}^{(m)}$, are indicator variables that equal one if the m^{th} $(m = 1, 2, 3)$ largest firm (ranked by sales) in industry j in year t experiences mild damage during the natural disaster shocks. Similarly, $ND\_severe_{j,t}^{(s)}$, are indicator variables that equal one if the s^{th} $(s = 1, 2, 3)$ largest firm (ranked by sales) in industry j in year t experiences severe damage during the natural disaster shocks. In panel B, we use the fitted value of the first step to construct the independent variable $\widehat{IdShock}_{-i,t}$ as the simple average of $\widehat{IdShock}_{j,t}^{(c_{j,i})}$ over all industries connected to the industry i through the 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. The 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 the 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 output of 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.

Cross-Industry Contagion Effects. We present the estimation results for the cross-industry contagion analysis in Table 11 and the corresponding summary statistics in Table A.15 of the Appendix. Panel A of Table 11 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 the industry-level connectedness and the 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 11, 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.

Heterogeneity Across the Efficiency of Internal Capital Market. In our model with the collusive Nash equilibrium, the cross-industry spillover effects rely critically on proper functioning of the internal capital market of common leaders. When 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 this common leader, because different segments do not coordinate to maximize the value of the entire firm. Therefore, we expect the cross-industry spillover 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. We sort industries into tertiles based on the industry-level efficiency one year prior to the natural disaster shocks and then examine the cross-industry spillover

Table 12: Heterogeneous cross-industry spillover effects across efficiency of the internal capital markets of common leaders.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}^{(-c)}$		$DD_{i,t}^{(-c)}$		$PM_{i,t}^{(-c)}$		$Markup_{i,t}^{(-c)}$	
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

Note: This table reports the heterogeneous cross-industry spillover effects across efficiency of the internal capital markets of common leaders. The regression specification is: $Y_{i,t}^{(-c)} = \beta_1 \widehat{IdShock}_{-i,t} + \varepsilon_{i,t}$. The definition of the dependent and independent variables are explained in Table 11. 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 one year prior to the 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.

effects in the industries with high efficiency (top tertile and middle tertile) and low efficiency (bottom tertile). Table 12 tabulates the results. Consistent with the prediction of our model in the collusive Nash equilibrium, we find that the cross-industry spillover 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.

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 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. Importantly, in Section 4.5.2, we exploit the setting of AJCA tax holiday and use the econometric specification of heterogenous average spillover effects across different industries to investigate the impact of the reduction of financial distress (i.e., the positive distress shock) on industry peers.

4.5.1 Evidence from Enforcement Against Financial Frauds

We follow Karpoff et al. (2017) and examine firms that are 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

Table 13: Evidence from legal enforcement actions against financial frauds.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.355***	0.355***	−1.052***	−1.053***	−0.008	−0.008	−0.020	−0.020
	[4.804]	[4.803]	[−3.715]	[−3.717]	[−1.169]	[−1.170]	[−1.554]	[−1.556]
$Treat_{i,t}$	−0.002	−0.001	−0.304	−0.305	0.003	0.003	0.011	0.011
	[−0.021]	[−0020]	[−0.796]	[−0.800]	[0.350]	[0.350]	[0.580]	[0.578]
$Post_{i,t}$	0.074***	0.071***	−0.290***	−0.261***	−0.009***	−0.009***	−0.016***	−0.015**
	[3.805]	[3.603]	[−3.370]	[−3.052]	[−2.848]	[−2.778]	[−2.650]	[−2.476]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.018		−0.153		−0.000		−0.004
		[0.581]		[−1.296]		[−0.091]		[−0.454]
$ROA_{i,t-3:t-1}$	0.237***	0.236***	0.556*	0.562*	−0.012	−0.012	−0.033	−0.033
	[2.622]	[2.616]	[1.923]	[1.942]	[−0.520]	[−0.520]	[−0.805]	[−0.803]
$StockRet_{i,t-3:t-1}$	−0.100**	−0.100**	0.421***	0.418***	0.004	0.004	0.009	0.009
	[−1.999]	[−1.995]	[2.684]	[2.671]	[0.603]	[0.602]	[0.698]	[0.691]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9188	9188	7918	7918	9721	9721	9717	9717
R-squared	0.653	0.654	0.775	0.775	0.874	0.874	0.890	0.890
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.013	0.015	0.004	0.005

Note: This table presents the results of the DID analysis that examines the response of the distress risk and gross profit margin to legal enforcement actions against financial frauds of peer firms. For each violating firm, we match it with up to ten non-violating peer firms in the same four-digit SIC industry based on firm asset size, tangibility, and firm age. We use a relative high matching ratio to reduce noise because there are on average less 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. We also require that the matched peer firms do not share any common customers with the violating firms. For each firm, we include four yearly observations in the analysis. Specifically, for each firm, we include two years before and two years after the trigger dates, which are the dates of the first pubic 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) – (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 one if firm i is a firm that commits financial fraud. $Post_{i,t}$ is an indicator variable that equals one for observations after the trigger dates. $Ln(1+n(\mathcal{C}_{i,t}))$ captures the strength of cross-industry spillover, and it is the natural log of one plus the number of industries that are connected to firm i's industry through competition networks and contain 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 the 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.

the reaction of their industry peers.[18]

Similar to the natural disaster setting, we use the DID analysis to study the spillover effects from distress firms to their industry peers. For each violating firm, we match it with up to ten non-violating peer firms in the same four-digit SIC industry based on firm asset size, tangibility, and firm age. We require that the matched peer firms are not suppliers or customers of the violating firms. We also require that the matched peer firms do not share any common customers with the violating firms. For each firm, we include four yearly observations (i.e., two years before and two years after the year of fraud revelation) in the analysis. Different from natural disasters, financial frauds do

[18]We limit our analysis to fraud cases in which firms receive at least \$0.25 millions dollars of monetary fine from the US government to ensure the violating firms face sizable legal penalties. Our findings are robust to other cutoffs.

not occur exogenously. In particular, it has been shown that financial frauds tend to peak towards the end of a boom and are 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:

$$\begin{aligned} Y_{i,t} = &\beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1 + n(\mathcal{C}_{i,t})) \\ &+ \beta_5 ROA_{i,t-3:t-1} + \beta_6 StockRet_{i,t-3:t-1} + \theta_i + \delta_t + \varepsilon_{i,t}, \end{aligned} \tag{4.7}$$

where $Treat_{i,t}$ is an indicator variable that equals one if firm i is a firm that commits financial fraud. $Post_{i,t}$ is an indicator variable that equals one for observations after the trigger date, which are the dates of the first pubic announcements revealing to investors that future enforcement actions are 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 13 presents the findings from the DID analysis. Consistent with the natural disaster setting, we find that the 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. The 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 the frauds. In Figures A.5 and A.6 of the Appendix, we examine the dynamics of the spillover effects. We find that the spillover effect emerges only after the revelation of the frauds. There is no significant change in the distress risk or distance to default prior to the trigger dates, which provides evidence supporting the parallel trend assumption for the DID analysis. Finally, we should point out that the fraud setting has a caveat because there are on average less 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 13.

4.5.2 Evidence from the AJCA Tax Holiday

In this section, we study the impact of reduction in financial distress on firms' product market behaviors and the distress level of their peer firms. Specifically, we examine the

Table 14: Spillover effects in the AJCA tax holiday setting.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
Financial constraint (FC) measure	WW	HP	WW	HP	WW	HP	WW	HP
$AJCA_i \times FC_i$	-0.092	-0.318^{***}	0.970	0.772	0.038	0.083^{**}	0.078	0.185^{**}
	[-0.761]	[-3.224]	[1.307]	[1.080]	[0.871]	[2.072]	[0.869]	[2.122]
$ITI_{i,t} \times FC_i$	-0.836^{***}	-0.765^{***}	2.366^{**}	2.798^{**}	0.270^{***}	0.339^{***}	0.290^{**}	0.456^{***}
	[-4.204]	[-4.088]	[1.990]	[2.546]	[4.302]	[5.118]	[2.552]	[3.677]
$AJCA_i \times NonFC_i$	-0.111^{***}	-0.097^{***}	0.880^{***}	0.945^{***}	0.037^{***}	0.039^{***}	0.068^{***}	0.071^{***}
	[-3.024]	[-2.652]	[3.048]	[3.350]	[2.781]	[2.996]	[2.618]	[2.802]
$ITI_{i,t} \times NonFC_i$	0.051	0.009	-0.947^{**}	-0.735^{*}	-0.044^{**}	-0.039^{**}	-0.180^{***}	-0.174^{***}
	[0.633]	[0.115]	[-2.139]	[-1.690]	[-2.293]	[-2.050]	[-4.978]	[-4.887]
FC_i	0.609^{***}	0.571^{***}	-2.070^{***}	-1.614^{***}	-0.032^{**}	-0.019	-0.012	0.007
	[14.457]	[15.520]	[-9.050]	[-7.211]	[-2.110]	[-1.346]	[-0.456]	[0.290]
$Ln(1+n(\mathcal{C}_{i,t}))$	-0.057^{***}	-0.048^{***}	0.407^{***}	0.315^{***}	0.045^{***}	0.040^{***}	0.110^{***}	0.101^{***}
	[-3.263]	[-2.846]	[3.611]	[2.879]	[8.526]	[7.967]	[11.012]	[10.561]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13509	14649	11609	12539	14134	15291	14118	15270
R-squared	0.193	0.190	0.160	0.151	0.029	0.032	0.039	0.044

Note: This table examines the spillover effects in the AJCA tax holiday setting. The data are firm-year panel data that span five years after the passage of the AJCA (i.e., 2004 to 2008). The regression specification is: $Y_{i,t} = \beta_1 AJCA_i \times FC_i + \beta_2 ITI_{i,t} \times FC_i + \beta_3 AJCA_i \times NonFC_i + \beta_4 ITI_{i,t} \times NonFC_i + \beta_5 FC_i + \beta_6 Ln(1+n(\mathcal{C}_{i,t})) + \delta_t + \varepsilon_{i,t}$. The dependent variables are the distress risk ($Distress_{i,t}$), distance to default ($DD_{i,t}$), gross profit margin ($PM_{i,t}$), and markup ($Markup_{i,t}$). $AJCA_i$ is an indicator variable that equals one if firm i has more than 33% pre-tax income from abroad during the period from 2001 to 2003. $ITI_{i,t}$ stands for industry treatment intensity and it is the fraction of firms in firm i's industry with $AJCA_i$ indicator that equals one. FC_i is an indicator variable that equals one if firm i are financially constrained in the year prior to the passage of the AJCA (i.e., 2003). We measure financial constraint using the WW index and the HP index. A firm is financially constrained if its WW index or HP index is ranked in the top quintile across all firms in 2003. $NonFC_i$ is an indicator variable that equals one if firm i is not financially constrained. $Ln(1+n(\mathcal{C}_{i,t}))$ captures the strength of cross-industry spillover via the competition network, and it is the natural log of one plus the number of industries that are connected to firm i's industry through competition networks and have at least one firm shocked by the passage of AJCA 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.

impact of the American Jobs Creation Act of 2004 (AJCA), in which firms are allowed to repatriate foreign profits to the United States at a 5.25% tax rate, rather than the existing 35% corporate tax rate. The passage of the AJCA reduces the distress level of the treated firms (i.e., those with significant amount of pre-tax income from abroad), especially for those that are financially constrained prior to the AJCA (see Faulkender and Petersen, 2012). Consistent with the prediction of our model, we find that: i) firms compete less aggressively in the product market after the passage of AJCA, especially for those that are financially constrained prior to AJCA, and ii) the distress level of the non-treated industry peers that are financially constrained prior to AJCA reduces significantly after the passage of AJCA.

Different from natural disasters or the enforcement of corporate fraud, AJCA tax holiday is a one-time shock. Therefore, we cannot use the DID specification (4.1) 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:

$$\begin{aligned} Y_{i,t} =& \beta_1 AJCA_i \times FC_i + \beta_2 ITI_{i,t} \times FC_i + \beta_3 AJCA_i \times NonFC_i \\ &+ \beta_4 ITI_{i,t} \times NonFC_i + \beta_5 FC_i + \beta_6 Ln(1 + n(\mathcal{C}_{i,t})) + \delta_t + \varepsilon_{i,t}, \end{aligned} \tag{4.8}$$

where $AJCA_i$ is an indicator variable that equals one if firm i has more than 33% pre-tax income from abroad during the three-year period prior to AJCA (i.e., 2001−2003). $ITI_{i,t}$ stands for industry treatment intensity and it is the fraction of firms in firm i's industry with $AJCA_i$ indicator that equals one. FC_i is an indicator variable that equals one if firm i are financially constrained in the year prior to the passage of the AJCA (i.e., 2003). We measure financial constraint using the WW index (Whited and Wu, 2006) and the HP index (Hadlock and Pierce, 2010). A firm is financially constrained if its WW index or HP index is ranked in the top quintile across all firms in 2003. $NonFC_i$ is an indicator variable that equals one if firm i is not financially constrained. $Ln(1 + n(\mathcal{C}_{i,t}))$ captures the strength of cross-industry spillover via the competition network, and it is the natural log of one plus the number of industries that are connected to firm i's industry through competition networks and have at least one firm shocked by the passage of AJCA in year t. The term δ_t represents year fixed effects. Our sample is the firm-year panel from CRSP-Compustat and we focus on the five-year sample period after the passage of the AJCA (i.e., from 2004 to 2008). The average value of $ITI_{i,t}$ is the 0.13 and the standard deviation of $ITI_{i,t}$ is 0.18 with the variation primarily from the cross section.

Table 14 tabulates the results from the regressions. The 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. The 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 and demonstrate the existence of the within-industry spillover effects. In Table A.16 of the 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 the treated firms to the non-treated firms, rather than from the treated firms to other treated firms.

Table 14 also speaks to the cross-industry spillover effects. The coefficient β_6 is positive and statistically significant 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. The coefficient β_6 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 when more industries connected to the focal industry via the competition network are shocked by the passage of AJCA, the distress level of the firms in the focal industries reduced more. These results are also consistent with the predictions of our model and demonstrate the existence of the cross-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 centrality are more exposed to the cross-industry spillover 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 behavior 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 enforcement actions against financial frauds and the passage of the American Jobs Creation Act of 2004, which lead to an increase and a reduction of the distress levels of the treated firms, respectively.

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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:

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

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

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

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

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

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

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

which further leads to

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

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:

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

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

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

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

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

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

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

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.

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

and thus

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

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 has actually been proved above in the proof of Proposition 2.1. Take industries i and c as an example. The solution in (A.26) implies that

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

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) to measure 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 the following:

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

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 to the returns of the S&P 500 index. $SIGMA$ is the annualized standard deviation of daily returns over the past three 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) to construct the distance to default measure using the naive Merton default probability ($DD_{i,t}$). Specifically, we define the distance to default with one-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. The variable $r_{i,t}$ represents the firm's stock return over the year. The variable $\sigma_{i,t}$ represents the total volatility of the firm, which is approximated by:

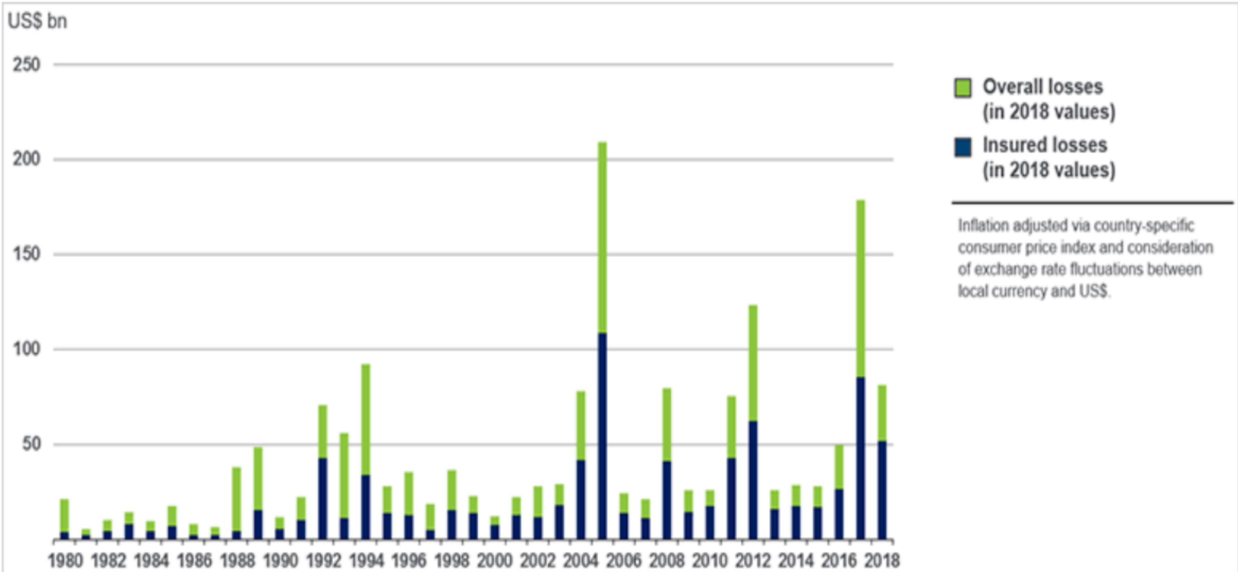
$$\sigma_{i,t} = \frac{E_{i,t}}{E_{i,t} + F_{i,t}}\sigma_{i,t}^E + \frac{E_{i,t}}{E_{i,t} + F_{i,t}}\sigma_{i,t}^D,$$

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 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 a 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 - 2018 period are not insured (see Figure A.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 compensations. Similarly, public disaster assistance will take 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 six years from the date the presidential disaster declaration is announced (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 A.1: Overall and insured losses from US natural disasters from 1980 to 2018.

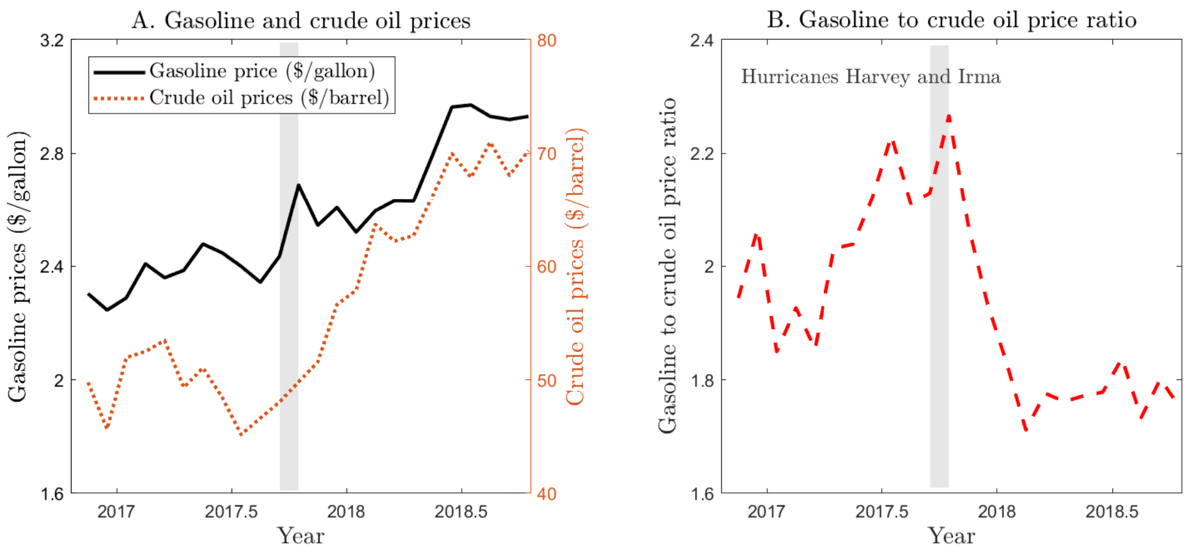
C.2 Hurricanes Harvey and Irma: An Anecdote Example

Hurricanes Harvey and Irma caused huge amount of damage to the US oil refinery industry. More than a dozen of major oil refineries that locate in Gulf Coast suffered great losses from the two hurricanes. In responses to the damage caused by the natural disasters, both gasoline price and the crude oil price increased sharply (see panel A of Figure A.2). However, the amount of increase in the gasoline price (in percentage term) was much lower than that of the crude oil. As a result, the profit margin of oil refinery industry reduced significantly after the hurricanes (see panel B of Figure A.2), suggesting that the refinery firms do not simply pass the increased input costs to their customers, and instead they internalize some of the increased costs. This finding is consistent with our theory which 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 A.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 A.2: Profitability in the oil refinery industry around Hurricanes Harvey and Irma.

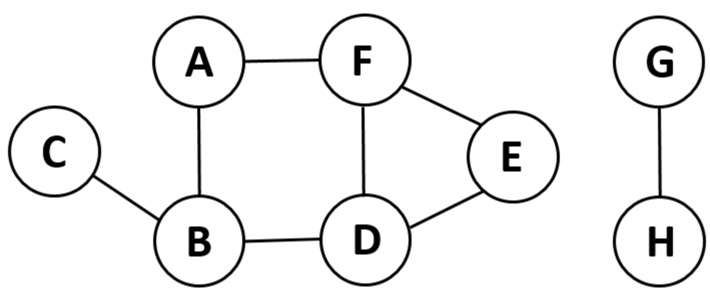


Figure A.3: An example network.

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 one if node i and node j are connected. For the network shown in Figure A.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. The variable n is the size of the component i belongs to, and the variable N is the size of the entire network. In the network example shown in Figure A.3, there are two components in the network: one with size of 6 nodes (nodes A to F) and the other with size of 2 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 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. The variable n is the size of the component i belongs to, and the variable N is the size of the entire network. For the network shown in Figure A.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 the connection matrix $\mathbf{A}$, and λ is its corresponding eigenvector. The eigenvector centrality for node i is thus the elements of the eigenvector E^* associated with $\mathbf{A}$'s principal eigenvalue λ^*. For the network shown in Figure A.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 A.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 the Compustat historical segment data. Because Compustat only covers public firms, it is possible that the competition network we have constructed is not an accurate representation of the competition network in the economy. In this section, we incorporate privates 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 centrality measure remain robust after taking private firms into consideration.

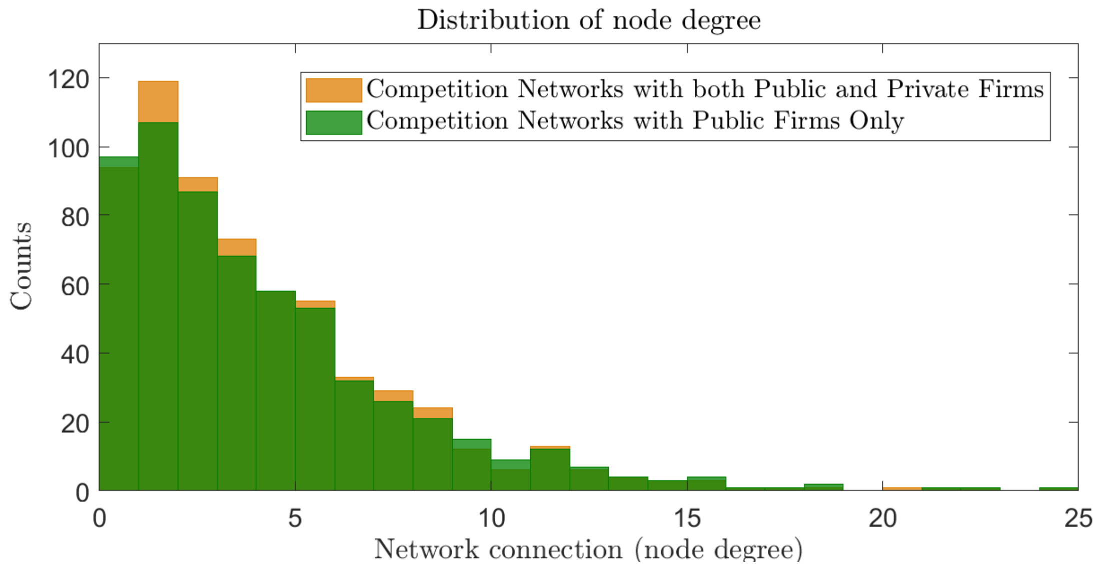


Figure A.4: Node degree of the competition networks with and without private firms at the four-digit SIC industry level in 1994.

We obtain information about private firms from Capital IQ, which is one of the most comprehensive datasets that cover private firms. Capital IQ provides the total sales of the private firms and the list of four-digit SIC industries that firms operate in 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 assign 9% of the 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 A.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 remained the same after we take private firms into consideration in forming the network. Figure A.4 shows the distribution of node degree of the competition networks with and without private firms in 1994. Again, we find 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 set of competition networks are highly similar throughout our sample period.

Table A.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 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 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 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 industries, 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' one-month lagged market capitalization. We exclude financial and utility industries and very small industries that contain fewer than three firms from the analysis. 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.

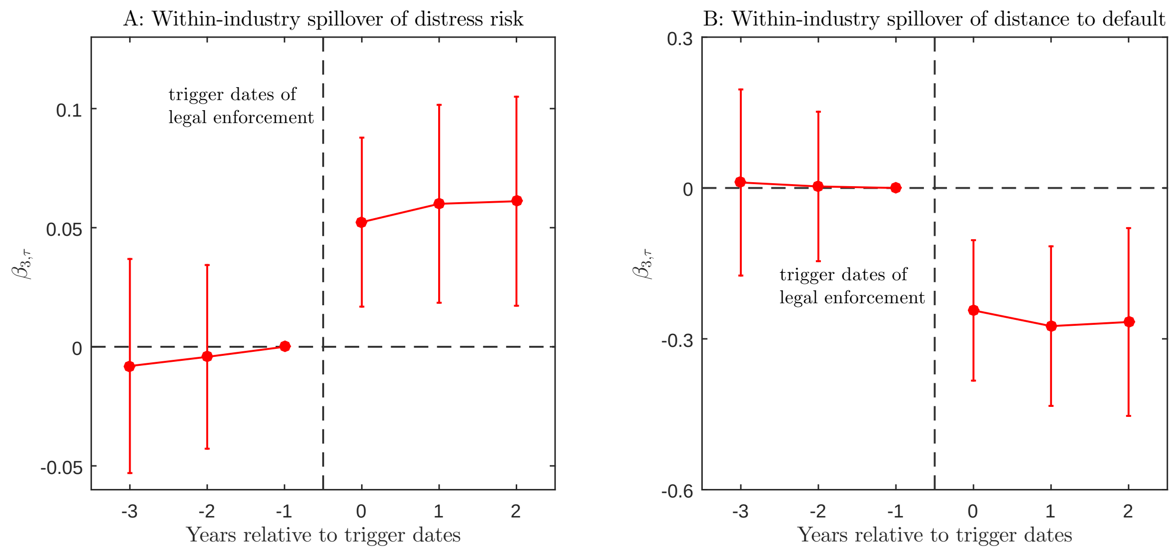
We next study the asset pricing implications of the centrality of the competition network constructed using both public and private firms. Table A.2 shows that the excess returns and alphas are higher for industries with higher centrality in the competition network. Table A.3 presents the results from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

F Supplementary Empirical Results

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

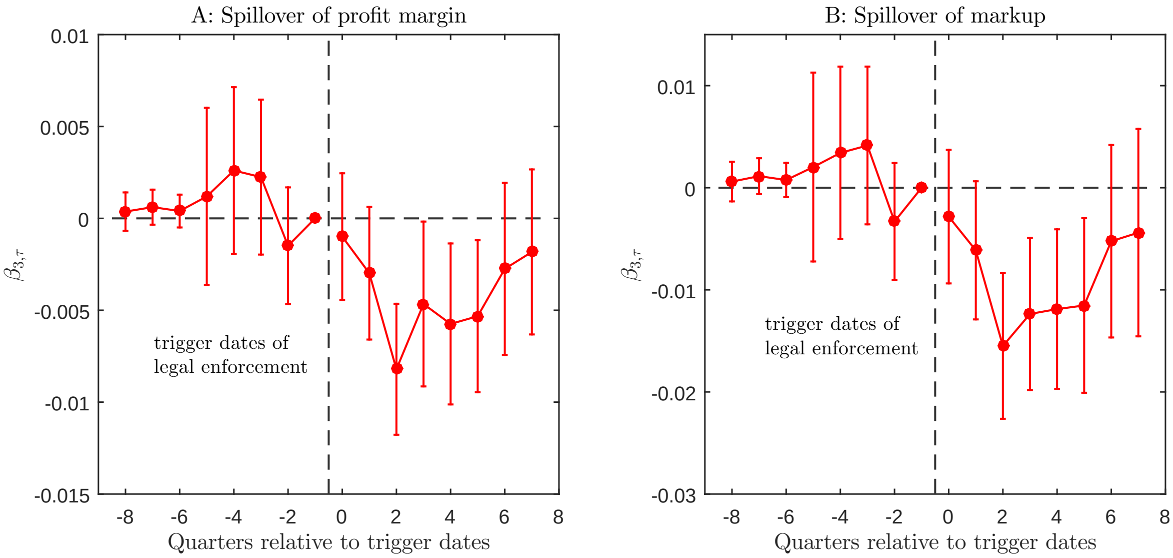
	(1)	(2)	(3)	(4)	(5)	(6)
			$Ret_{i,t}$ (%)			
$Competition\_Centrality_{i,t-1}$	0.149***	0.151***	0.102***	0.089***	0.092***	0.156***
	[2.908]	[2.905]	[3.067]	[2.721]	[2.905]	[3.423]
$Production\_Centrality_{i,t-1}$		0.082	−0.014	−0.028	−0.027	−0.017
		[1.428]	[−0.243]	[−0.513]	[−0.491]	[−0.221]
$LnSales_{i,t-1}$			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 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.



Note: This figure plots the within-industry spillover effects of distress risk around legal enforcement actions against financial frauds. For each violating firm, we match it with up to ten non-violating peer firms in the same four-digit SIC industry based on firm asset size, tangibility, and firm age. 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 with the treated firms. For each firm, we include six yearly observations in the analysis. Specifically, for each firm, we include three years before and three years after the trigger dates, which are the dates of the first pubic 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 dependend 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 one if firm i is a firm that commits financial fraud. $Fraud_{i,t-\tau}$ is an indicator variable that equals one 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 year $t-\tau$. $Ln(1 + n(\mathcal{C}_{i,t}))$ captures the strength of cross-industry spillover, and it is the natural log of one plus the number of industries that are connected to firm i's industry through competition networks and contain 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 dates 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 $\tau = -3, -2, \cdots, 2$, as well as their 90% confidence intervals with standard errors clustered at the firm level. Vertical dashed lines represent the trigger dates of the legal enforcement actions against financial frauds.

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



Note: This figure plots the within-industry spillover effects of profit margin around legal enforcement actions against financial frauds. For each violating firm, we match it with up to ten non-violating peer firms in the same four-digit SIC industry based on firm asset size, tangibility, and firm age. 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 with the treated firms. For each firm, we include 16 quarterly observations observations in the analysis. Specifically, for each firm, we include eight quarters before and eight quarters after the trigger dates, which are the dates of the first pubic 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 dependend 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 one if firm i is a firm that commits financial fraud. $Fraud_{i,t-\tau}$ is an indicator variable that equals one 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, and it is the natural log of one plus the number of industries that are connected to firm i's industry through competition networks and contain 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 dates 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. Vertical dashed lines represent the trigger dates of the legal enforcement actions against financial frauds.

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

Table A.4: Relation between competition 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 centrality and industry characteristics. $Competition\_Centrality_{i,t}$ is the competition 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). $Production\_Centrality_{i,t}$ 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. Industry concentration ratio is the HHI index of the top 50 firms. The concentration ratio data come from US Census which covers manufacturing industries. 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 industries, 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' 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.

Table A.5: 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 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 one-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 one-year lagged competition 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 centrality quintiles together across the industry groups. Thus, in each June, we effectively sort industries into competition 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 industries, 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' 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 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 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 A.6: 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 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 one-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 one-year lagged competition 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 centrality quintiles together across the industry groups. Thus, in each June, we effectively sort industries into competition 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 industries, 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' 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 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 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 A.7: 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 major natural disasters as the disasters that cause at least $1 billion dollars total estimated property damages and last less than 30 days. The property damages are from Spatial Hazard Events and Loss Databases for the United States (SHELDUS).

Table A.8: Alternative matching ratios between treated firms and non-treated peer firms.

	Panel A: Matching one treated firm with up to ten 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**	0.028**	−0.087*	−0.088*	−0.006	−0.006	−0.006	−0.006
	[2.173]	[2.201]	[−1.723]	[−1.748]	[−1.013]	[−1.043]	[−0.977]	[−1.013]
$Treat_{i,t}$	−0.015	−0.015	0.086*	0.087*	0.001	0.001	−0.001	−0.001
	[−1.318]	[−1.332]	[1.836]	[1.848]	[0.196]	[0.210]	[−0.192]	[−0.175]
$Post_{i,t}$	0.048***	0.046***	−0.129***	−0.124***	−0.008*	−0.007*	−0.012***	−0.011**
	[5.856]	[5.774]	[−4.331]	[−4.208]	[−1.864]	[−1.740]	[−2.626]	[−2.484]
$Ln(1 + n(\mathcal{C}_{i,t}))$		0.022**		−0.060		−0.010**		−0.012**
		[2.105]		[−1.591]		[−2.045]		[−2.502]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	194736	194736	161877	161877	202605	202605	202431	202431
R-squared	0.554	0.554	0.656	0.656	0.738	0.738	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 one treated firm with up to three non-treated peer firms							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.018	0.019	−0.076	−0.077	−0.000	−0.000	−0.000	−0.000
	[1.424]	[1.434]	[−1.455]	[−1.473]	[−0.021]	[−0.033]	[−0.038]	[−0.048]
$Treat_{i,t}$	−0.017	−0.017	0.091*	0.092*	0.001	0.001	0.002	0.002
	[−1.413]	[−1.417]	[1.707]	[1.718]	[0.487]	[0.491]	[0.379]	[0.383]
$Post_{i,t}$	0.056***	0.055***	−0.140***	−0.133***	−0.006**	−0.006**	−0.010***	−0.010***
	[6.146]	[6.061]	[−4.079]	[−3.911]	[−2.551]	[−2.463]	[−2.898]	[−2.812]
$Ln(1 + n(\mathcal{C}_{i,t}))$		0.017*		−0.078**		−0.004		−0.005
		[1.859]		[−2.136]		[−1.595]		[−1.541]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	94618	94618	81530	81530	98298	98298	98215	98215
R-squared	0.568	0.569	0.672	0.673	0.758	0.758	0.785	0.785
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 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 ten non-treated peer firms in the same four-digit SIC industry based on firm asset size, tangibility, and firm age. In panel B, we match each treated firm with up to three non-treated peer firms. The regression specification and the definition of the dependent and independent variables are explained in Table 8 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 A.9: Matching industry peers with text-based network industry classifications.

	(1)	(2)	(3)	(4)
	$Distress_{i,t}$	$DD_{i,t}$	$PM_{i,t}$	$Markup_{i,t}$
$Treat_{i,t} \times Post_{i,t}$	0.012	−0.028	−0.005	−0.007
	[1.011]	[−0.592]	[−1.023]	[−1.263]
$Treat_{i,t}$	−0.010	0.030	0.008*	0.012**
	[−0.930]	[0.622]	[1.893]	[2.347]
$Post_{i,t}$	0.044***	−0.154***	−0.007*	−0.009**
	[5.550]	[−5.119]	[−1.945]	[−2.405]
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	208919	174174	216242	216085
R-squared	0.543	0.640	0.742	0.765
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	0.001	$<10^{-3}$

Note: This table examines the within-industry spillover effects of the major natural disasters based on text-based network industry classifications (TNIC) (see, Hoberg and Phillips, 2010, 2016). We perform a DID analysis. Specifically, we match each treated firm with up to ten non-treated peer firms in its TNIC industry based on firm asset size, tangibility, and firm age. 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 with the treated firms. For each firm, we include four yearly observations (i.e., two years before and two years after the major natural disasters) 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 one if firm i is a treated firm. $Post_{i,t}$ is an indicator variable that equals one 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 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.

Table A.10: Alternative measure to control for cross-industry spillovers.

	(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**	−0.083	−0.099*	−0.001	0.000	−0.002	−0.000
	[1.513]	[2.087]	[−1.637]	[−1.876]	[−0.256]	[0.029]	[−0.317]	[−0.056]
$Treat_{i,t}$	−0.015	−0.018	0.093*	0.090*	0.001	0.001	0.001	0.002
	[−1.284]	[−1.518]	[1.896]	[1.755]	[0.150]	[0.180]	[0.181]	[0.332]
$Post_{i,t}$	0.053***	0.047***	−0.129***	−0.106***	−0.007**	−0.007**	−0.010**	−0.010**
	[6.419]	[5.543]	[−4.125]	[−3.353]	[−2.090]	[−2.184]	[−2.481]	[−2.515]
$Ln(1+\overline{Damage(\mathcal{C}_{i,t})})$		0.005*		−0.026**		−0.002*		−0.002*
		[1.929]		[−2.401]		[−1.697]		[−1.803]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	128406	117429	108996	99812	133350	122441	133237	122343
R-squared	0.564	0.578	0.666	0.676	0.746	0.748	0.772	0.776
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.006	0.016	0.001	0.004

Note: This table uses an alternative measure to control for cross-industry spillovers. Different from Table 8 of the main text, we capture the strength of cross-industry spillover using $Ln(1+\overline{Damage(\mathcal{C}_{i,t})})$, which is the natural log of one plus the average amount of property damage (in million 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: $Y_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1+\overline{Damage(\mathcal{C}_{i,t})}) + \theta_i + \delta_t + \varepsilon_{i,t}$. The definition of the dependent and other independent variables are explained in Table 8. 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 A.11: 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)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.009	0.009	-0.078	-0.079	0.004	0.004	0.009	0.009
	[0.530]	[0.534]	[-1.181]	[-1.197]	[0.781]	[0.772]	[0.885]	[0.880]
$Treat_{i,t}$	-0.015	-0.015	0.105	0.106	-0.003	-0.003	-0.004	-0.004
	[-0.953]	[-0.968]	[1.564]	[1.586]	[-0.756]	[-0.741]	[-0.423]	[-0.413]
$Post_{i,t}$	0.075***	0.072***	-0.167***	-0.157***	-0.013***	-0.012**	-0.029***	-0.028***
	[4.784]	[4.664]	[-3.442]	[-3.259]	[-2.596]	[-2.542]	[-2.922]	[-2.909]
$Ln(1 + n(\mathcal{C}_{i,t}))$		0.036**		-0.114**		-0.007*		-0.010
		[2.527]		[-2.500]		[-1.800]		[-1.289]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	98651	98651	83625	83625	102858	102858	102761	102761
R-squared	0.594	0.594	0.686	0.686	0.776	0.776	0.781	0.781
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.003	0.005	$<10^{-3}$	0.001

Panel B: Matched non-treated firms far from the disaster area + without affected customers + non-consumer facing industries								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.001	0.001	-0.070	-0.073	0.002	0.002	-0.006	-0.006
	[0.034]	[0.057]	[-0.819]	[-0.850]	[0.327]	[0.317]	[-0.360]	[-0.383]
$Treat_{i,t}$	-0.019	-0.020	0.084	0.086	-0.000	-0.000	0.006	0.006
	[-0.957]	[-0.976]	[0.972]	[0.997]	[-0.095]	[-0.079]	[0.457]	[0.476]
$Post_{i,t}$	0.082***	0.078***	-0.161**	-0.151**	-0.011**	-0.011**	-0.034**	-0.033**
	[3.897]	[3.748]	[-2.346]	[-2.221]	[-2.187]	[-2.158]	[-2.303]	[-2.278]
$Ln(1 + n(\mathcal{C}_{i,t}))$		0.047**		-0.099*		-0.007		-0.017
		[2.445]		[-1.684]		[-1.540]		[-1.457]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	60031	60031	51353	51353	99363	99363	62006	62006
R-squared	0.604	0.604	0.687	0.687	0.780	0.780	0.761	0.761
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.009	0.012	$<10^{-3}$	$<10^{-3}$

Note: This table tests the demand commonality channel. In panel A, we perform the DID analysis by removing matched peer firms that locate within 100 miles from any zip code negatively affected by the major natural disasters in a given year. In panel B, we further remove matched peer firms with customers negatively affected by the natural disasters. We also remove treated firms and the matched peer firms in the consumer-facing industries (i.e., airlines, grocery stores, hotels, retailers, restaurants, utilities, and many online services). We identify the supplier-customer links using the Compustat customer segment data and the Factset Revere data. The regression specification and the definition of the dependent and independent variables are explained in Table 8 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 A.12: Testing the production network externality channel.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.024^{*}	0.025^{*}	-0.111^{**}	-0.112^{**}	-0.002	-0.002	-0.001	-0.001
	[1.719]	[1.726]	[−1.980]	[−1.999]	[−0.257]	[−0.268]	[−0.116]	[−0.129]
$Treat_{i,t}$	-0.028^{**}	-0.028^{**}	0.147^{***}	0.148^{***}	0.002	0.002	0.000	0.000
	[−2.075]	[−2.079]	[2.650]	[2.661]	[0.304]	[0.309]	[0.044]	[0.049]
$Post_{i,t}$	0.051^{***}	0.050^{***}	-0.124^{***}	-0.117^{***}	-0.010^{**}	-0.009^{*}	-0.014^{***}	-0.013^{**}
	[5.315]	[5.268]	[−3.385]	[−3.229]	[−2.015]	[−1.933]	[−2.590]	[−2.484]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.018		-0.091^{**}		-0.008^{*}		-0.011^{**}
		[1.570]		[−2.121]		[−1.664]		[−2.154]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	108010	108010	89679	89679	112484	112484	112367	112367
R-squared	0.564	0.564	0.671	0.671	0.740	0.740	0.764	0.764
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. Same as in Table 8 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 with the treated firms. Different from Table 8, 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 8. 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 A.13: Testing the credit lending channel.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.032^{*}	0.033^{*}	-0.170^{**}	-0.172^{**}	0.001	0.001	-0.001	-0.001
	[1.690]	[1.711]	[−2.298]	[−2.328]	[0.143]	[0.139]	[−0.073]	[−0.079]
$Treat_{i,t}$	0.001	0.001	0.066	0.067	-0.003	-0.003	-0.003	-0.003
	[0.059]	[0.052]	[0.963]	[0.975]	[−0.665]	[−0.666]	[−0.590]	[−0.591]
$Post_{i,t}$	0.072^{***}	0.068^{***}	-0.154^{***}	-0.139^{***}	-0.013^{*}	-0.011^{*}	-0.015^{**}	-0.014^{**}
	[5.315]	[5.127]	[−3.263]	[−3.017]	[−1.911]	[−1.801]	[−2.225]	[−2.101]
$Lender\_Exposure_{i,t-1}$	0.170^{**}	0.167^{**}	0.078	0.081	-0.003	-0.002	0.000	0.001
	[2.053]	[2.018]	[0.254]	[0.264]	[−0.106]	[−0.082]	[0.017]	[0.047]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.052^{***}		-0.165^{***}		-0.015^{***}		-0.018^{***}
		[3.717]		[−3.239]		[−3.368]		[−3.334]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48636	48636	46035	46035	49905	49905	49889	49889
R-squared	0.591	0.591	0.704	0.704	0.748	0.749	0.837	0.837
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.007	0.017	0.002	0.004

Note: This table tests the credit lending channel. We remove the matched peer firms that share any common lender 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 proceeding five-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 8 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 A.14: Testing the common institutional blockholder channel.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.021	0.021	-0.096^{*}	-0.097^{*}	-0.002	-0.002	-0.001	-0.001
	[1.542]	[1.554]	[−1.842]	[−1.862]	[−0.356]	[−0.371]	[−0.244]	[−0.263]
$Treat_{i,t}$	-0.022^{*}	-0.023^{*}	0.136^{***}	0.136^{***}	0.002	0.002	0.001	0.002
	[−1.780]	[−1.786]	[2.641]	[2.654]	[0.445]	[0.451]	[0.276]	[0.284]
$Post_{i,t}$	0.054^{***}	0.053^{***}	-0.116^{***}	-0.109^{***}	-0.009^{**}	-0.008^{**}	-0.012^{***}	-0.011^{***}
	[5.928]	[5.888]	[−3.602]	[−3.429]	[−2.059]	[−1.980]	[−2.621]	[−2.505]
$Ln(1 + n(\mathcal{C}_{i,t}))$		0.016		-0.085^{**}		-0.007^{*}		-0.010^{**}
		[1.506]		[−2.279]		[−1.682]		[−2.198]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	117445	117445	99815	99815	123274	123274	123145	123145
R-squared	0.561	0.561	0.663	0.663	0.754	0.754	0.773	0.773
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.004	0.006	0.001	0.002

Note: This table tests the common institutional blockholder channel. We remove the matched peer firms that share any 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 8 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 A.15: 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 variables in Table 11 of the main text.

Table A.16: Heterogenous spillover effects in the AJCA tax holiday setting.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
Financial constraint (FC) measure	WW	HP	WW	HP	WW	HP	WW	HP
$AJCA_i \times FC_i$	-0.268^{*}	-0.424^{***}	1.045	0.814	0.099^{*}	0.196^{***}	0.179^{*}	0.413^{***}
	[−1.692]	[−3.375]	[1.075]	[0.902]	[1.739]	[3.691]	[1.692]	[3.959]
$ITI_{i,t} \times AJCA_i \times FC_i$	−0.001	−0.242	2.021	2.632	−0.022	-0.242^{*}	−0.190	-0.724^{***}
	[−0.002]	[−0.711]	[0.737]	[0.783]	[−0.140]	[−1.658]	[−0.676]	[−2.614]
$ITI_{i,t} \times NonAJCA_i \times FC_i$	-0.956^{***}	-0.855^{***}	2.433^{*}	2.875^{**}	0.310^{***}	0.407^{***}	0.357^{***}	0.591^{***}
	[−4.552]	[−4.212]	[1.950]	[2.519]	[4.662]	[5.831]	[2.960]	[4.554]
$AJCA_i \times NonFC_i$	-0.183^{***}	-0.181^{***}	0.986^{***}	1.100^{***}	0.064^{***}	0.064^{***}	0.115^{***}	0.111^{***}
	[−4.575]	[−4.550]	[3.239]	[3.682]	[4.277]	[4.338]	[3.833]	[3.775]
$ITI_{i,t} \times AJCA_i \times NonFC_i$	0.217^{**}	0.207^{**}	-1.185^{**}	-1.088^{**}	-0.109^{***}	-0.099^{***}	-0.288^{***}	-0.267^{***}
	[2.221]	[2.145]	[−2.284]	[−2.122]	[−5.033]	[−4.641]	[−6.651]	[−6.216]
$ITI_{i,t} \times NonAJCA_i \times NonFC_i$	−0.186	-0.262^{**}	−0.587	−0.213	0.046	0.043	−0.028	−0.046
	[−1.640]	[−2.363]	[−0.899]	[−0.334]	[1.525]	[1.486]	[−0.513]	[−0.890]
FC_i	0.595^{***}	0.551^{***}	-2.039^{***}	-1.568^{***}	-0.027^{*}	−0.018	−0.003	0.007
	[13.778]	[14.490]	[−8.781]	[−6.890]	[−1.717]	[−1.202]	[−0.098]	[0.284]
$Ln(1+n(\mathcal{C}_{i,t}))$	-0.043^{**}	-0.033^{*}	0.387^{***}	0.286^{***}	0.039^{***}	0.035^{***}	0.101^{***}	0.094^{***}
	[−2.431]	[−1.900]	[3.425]	[2.603]	[7.275]	[6.763]	[9.853]	[9.482]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13509	14649	11609	12539	14134	15291	14118	15270
R-squared	0.195	0.192	0.160	0.151	0.032	0.035	0.041	0.048

Note: This table examines the spillover effects in the AJCA tax holiday setting. The data are firm-year panel data that span five years after the passage of the AJCA (i.e., 2004 to 2008). The regression specification is: $Y_{i,t} = \beta_1 AJCA_i \times FC_i + \beta_2 ITI_{i,t} \times AJCA_i \times FC_i + \beta_3 ITI_{i,t} \times NonAJCA_i \times FC_i + \beta_4 AJCA_i \times NonFC_i + \beta_5 ITI_{i,t} \times AJCA_i \times NonFC_i + \beta_6 ITI_{i,t} \times NonAJCA_i \times NonFC_i + \beta_7 FC_i + \beta_8 Ln(1+n(\mathcal{C}_{i,t})) + \delta_t + \varepsilon_{i,t}$. The dependent variables are the distress risk ($Distress_{i,t}$), distance to default ($DD_{i,t}$), gross profit margin ($PM_{i,t}$), and markup ($Markup_{i,t}$). $AJCA_i$ is an indicator variable that equals one if firm i has more than 33% pre-tax income from abroad during the period from 2001 to 2003. $ITI_{i,t}$ stands for industry treatment intensity and it is the fraction of firms in firm i's industry with $AJCA_i$ indicator that equals one. FC_i is an indicator variable that equals one if firm i are financially constrained in the year prior to the passage of the AJCA (i.e., 2003). We measure financial constraint using the WW index and the HP index. A firm is financially constrained if its WW index or HP index is ranked in the top quintile across all firms in 2003. $NonFC_i$ is an indicator variable that equals one if firm i is not financially constrained. $Ln(1+n(\mathcal{C}_{i,t}))$ captures the strength of cross-industry spillover via the competition network, and it is the natural log of one plus the number of industries that are connected to firm i's industry through competition networks and have at least one firm shocked by the passage of AJCA 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.