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, Industry excess returns, Contagion, Natural disasters, Tacit collusion, Treatment externality.
JEL: G32, G33, L11, L14.

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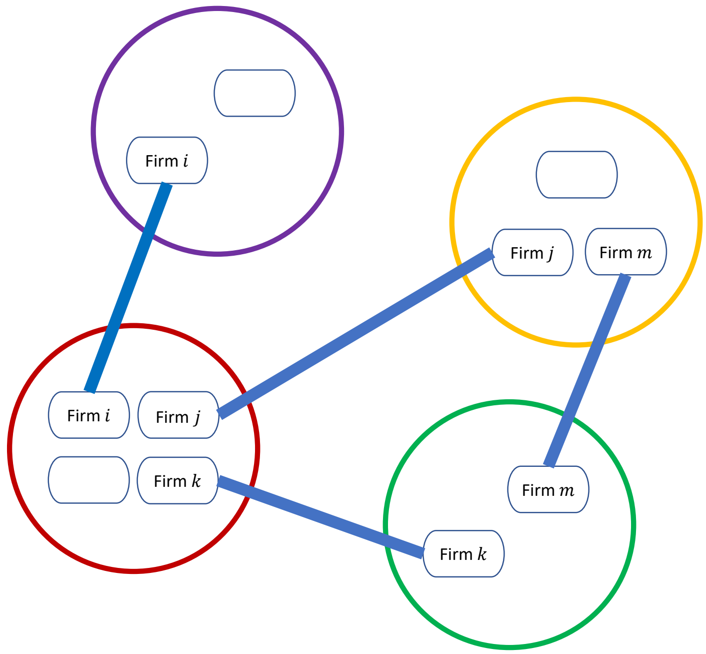
1 Introduction

Strategic competition among market leaders in product markets plays a vital role in determining firms' cash flows, because product markets are often highly concentrated in the hands of a few market leaders, even "superstar firms".[1] Strategic competition and distress risk create a positive feedback loop between imperfect product and credit markets (Chen et al., 2020). Also, there is a fast-growing literature empirically showing the strong relation between firms' financial condition and their product market behavior (e.g., Phillips, 1995; Chevalier, 1995; Kovenock and Phillips, 1995, 1997; Busse, 2002; Matsa, 2011*a*,*b*; Hadlock and Sonti, 2012; Hortaçsu et al., 2013; Phillips and Sertsios, 2013, 2017; Cookson, 2017). Existing theories and evidence suggest that strategic competition of peers in a given industry (i.e., horizontal competition) matters for propagation of shocks in the economy. Although there has been extensive discussions on the propagation of shocks through the production network (i.e., the vertical competition network), there is limited evidence on the causal impact of distress risk on firms' competitive behavior in product markets,[2] and the extant literature is also silent on how shocks are propagated through the competition network. We show that the competition network is an "elephant in the room," which has been overlooked, and the competition network has important asset pricing implications.

This paper provides the first elements to fill the gap in the literature along the following dimensions. First, we introduce and build a novel form of network connecting different industries through common market leaders in product markets. More precisely, each industry is a node on the competition network, and two industries are linked if and only if they share common market leaders which are multi-industry firms (see Figure 1). We compare the competition network with the production network of industries, and show that they have distinctive network structures and are not overlapped. We document many multi-industry market leaders that connect the related industries on the competition network in the data, consistent with the key insight of Hoberg and Phillips (2020). Second, we use an analytical intuitive model of the competition network, as a variant of the full-fledged quantitative dynamic model of Chen et al. (2020) to illustrate the core economic mechanism. In the model, market leaders compete intertemporally so that

[1]See, e.g., Grullon, Larkin and Michaely (2019), Gutiérrez, Jones and Philippon (2019), Autor et al. (2020), De Loecker, Eeckhout and Unger (2020), Corhay, Kung and Schmid (2020*b*). 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). Further, the strategic pricing competition is prevalent since the market leading position is highly persistent (e.g., Sutton, 2007; Bronnenberg, Dhar and Dubé, 2009).

[2]One notable exception is Phillips and Sertsios (2013), who focus primarily on the impact of firm distress and bankruptcy on product quality in the airline industry.



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.

they can tacitly collude, and thus the competition intensity is endogenously determined by conclusion capacity, which is in turn affected by the distress risk they face. Third, we show 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. This is because industries with higher competition centrality are more exposed to the spillover of distress shocks, which can lead to aggregate fluctuations due to the failure of the central limit theorem (CLT) in the aggregation (Gabaix, 2011). Last but not least, we identify idiosyncratic shocks to firms' distress using the occurrence of natural disasters and enforcement actions against financial frauds. We find that firms hit by disasters or enforcement actions exhibit an increased distress and then reduce their profit margins significantly, which triggers their industry peers to engage in more aggressive price competition, especially in industries with high entry barriers. As a consequence, the industry peers also exhibit increases in their own distress risk, and more importantly, we show that idiosyncratic distress shocks can further propagate to other connected industries on the competition network through the competition behavior of the common market leaders.

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 affected 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 because our goal is to identify and estimate the spillover effect. It is challenging because of the violation of 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 affected firms and the spillover effect to non-affected 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).[3] We match affected firms (i.e., firms hit by the natural disasters and violating firms prosecuted by legal enforcement actions) with non-affected industry peer firms in the same industry that have similar asset size, tangibility, and firm age. The affected 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 affected firms compete more aggressively as evidenced by significantly reduced gross profit margins. Importantly, consistent with our model, 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 reduce their profit margins significantly and exhibit

[3]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), and Grieser et al. (2021).

an increased distress.

To examine the impact of affected firms on their industry peers in more detail, we conduct panel regressions using pairs of focal firms and their industry peers in each year. This approach allows us to study changes in the likelihood of distress and the profit margin of a focal firm in response to natural disaster shocks of an industry peer. Consistent with the DID analysis, we find that the focal firm reduces its profit margin significantly when its industry peers experience major natural disaster shocks. The reduction in gross profit margin is about 1.2 percentage points, which is economically significant given a median gross profit margin of 34 percentage points. Given that Barrot and Sauvagnat (2016) find that shocks to suppliers propagate down negatively to their customers, a natural question is whether the effects on industry peers we find occur through common customers shared by the shocked firm and its industry peer; we rule out this channel, indeed, finding that gross profit margins are weakly positively related to customer distress.[4] The focal firm also exhibits a significant increase in the distress risk and a significant decrease in its distance to default when its industry peers experience major natural disaster shocks. This finding is again consistent with the DID analysis.

We further explore the heterogeneity in the firm-peer pairs. We find that the focal firm reduce its gross profit margin more in response to natural disaster shocks of its industry peers 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. In addition, we find that the within-industry spillover effect is stronger when firms (both non-affected focal firms and affected peer firms) have higher levels of financial leverage prior to the natural disaster shocks. This result is intuitive since the competition incentive should be stronger if firms are more distressed ex ante.

Finally, we examine the distress contagion effects across industries. As we discuss above, a focal firm will compete more aggressively against a natural disaster-shocked peer in its industry. If the focal firm is a market leader in another industry, the more aggressive competition extends to that other industry so that it exhibits 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.

[4]For firms that sell products or services on credit to customers (i.e., extend accounts receivable), it is natural to expect that product prices must include a default premium much like a bank charges a default premium in loan interest rates. This potentially explains the weakly positive relation between gross profit margin and customer default probability.

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.

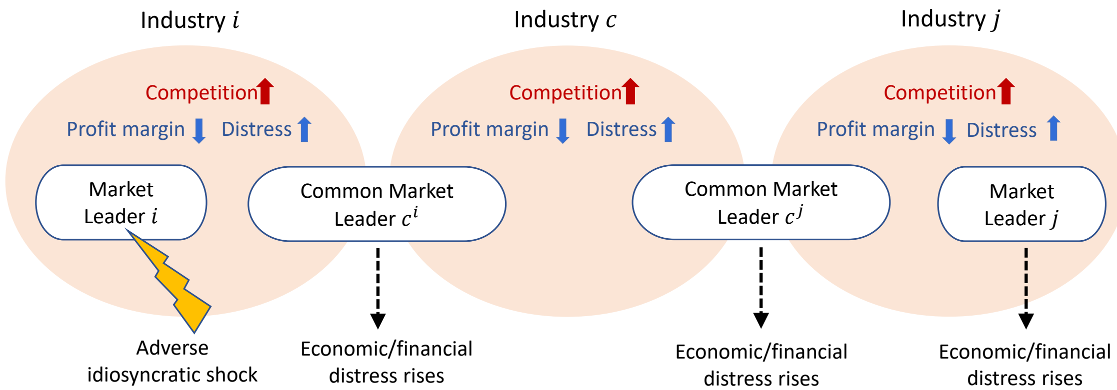
Our paper also contributes to the literature that studies the impact of financial characteristics on firms' competitive behavior in the product market. On the theory side, Titman (1984) and Maksimovic and Titman (1991) show how capital structure can affect a firm's choice of product quality. Bolton and Scharfstein (1990) presents a model showing that financial constraints give rise to rational predation behavior. Chen et al. (2020) models the dynamic interaction between strategic competition and distress risk. Empirical advances on the product-market implications of financial frictions include 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*), Matsa (2011*b*), Hadlock and Sonti (2012), Hortaçsu et al. (2013), Phillips and Sertsios (2013), Cookson (2017), Phillips and Sertsios (2017), Banerjee et al. (2019), and Grieser and Liu (2019). Phillips (1995) examines the changes in firms' production and pricing decisions after they undertake leveraged buyouts. Busse (2002) shows that airline firms are more likely to start price wars when they have worse financial conditions. Matsa (2011*b*) shows that excessive leverage undermines firms' incentive to provide product quality. Hadlock and Sonti (2012) find that exogenous increases in litigation liabilities are interpreted by the market as negative news for a firm's close competitors, consistent with the general hypothesis that increases in fixed liabilities lead to more aggressive product market interactions. Phillips and Sertsios (2013) examine the interaction of product quality and pricing decisions with financial conditions in the airline industry. Cookson (2017) shows that high leverage prevents incumbents from responding to entry threats.

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 also contributes 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.

Finally, our paper 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.

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.



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. When market leader i in industry i becomes economically or financially distressed due to a firm-specific shock, the competition intensity rises in industry i, and thus the level of economic or financial distress for firm c^i endogenously increases. 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 economically or financially distressed. In response, market leader c^j compete more aggressively in both industries c and j, which eventually hurts the profitability of market leader j in industry j and increases its economic or financial distress.

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

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 the aggregate financial constraints risk, thus have higher expected stock returns. Third, although the main contributions of this paper are the empirical findings, it serves as a theoretical device to formally present the hypotheses and guide the empirical tests. We intentionally illustrate the core mechanism using the simplest supergame — an i.i.d. repeated game, as the full-fledged quantitative continuous-time model is developed by Chen et al. (2020). We will not repeat the same model; rather, we use the simplest game-theoretic model 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 i, c^i, c^j, and j. 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 $\mathcal{F} \equiv \{i, c^i, c^j, j\}$, respectively.

We denote by $M_{f,k}$ the customer base of firm $f \in \mathcal{F}$ in industry $k \in \mathcal{K}$. For example, firm i only operates in industry i, and thus its customer base is $M_{i,i} > 0$ in industry i

and 0 in the other two industries. Consider another example. Firm c^i operates in both industry i and c. Its customer base is $M_{c^i,i} > 0$ in industry i, $M_{c^i,c} > 0$ in industry c, and 0 in industry j. To make the illustration more transparent, without loss of generality, we assume that each firm's customer base in a given industry is unity.

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 risk-neutral probability $\lambda(x_f, \theta_f)$ where x_f is the financial slack and θ_f is the profit of firm $f \in \mathcal{F}$. Upon a firm's exit, an identical new market leader enters the industry immediately. We exogenously specify the logistic function of the risk-neutral survival probability as a linear function of x_f and θ_f:

$$\ln\left[\frac{\lambda(x_f, \theta_f)}{1 - \lambda(x_f, \theta_f)}\right] = x_f + \gamma\theta_f, \tag{2.1}$$

where the financial slack x_f can be decomposed into an aggregate and an idiosyncratic component, and the firm-level profit θ_f is the aggregation of firm f's profits generated from different industries as follows:

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

$$\theta_f = \sum_{k \in \mathcal{K}} \theta_{f,k}, \tag{2.3}$$

where ε_f is the idiosyncratic financial slack of firm f, x captures the economy-wide financial condition, and $\theta_{f,k}$ is the profit per unit of customer base of firm f generated from industry k.

Here, γ in equation (2.1) captures the sensitivity of the risk-neutral survival probability to fluctuations in the profit level θ_f, and we assume that $\gamma > 0$ to capture the relation that higher profits and thus higher cash flows lead to lower risk-neutral probability of exit (i.e., lower distress). The coefficient β in equation (2.2) captures the loading of firm f's financial slack x_f on the aggregate financial condition x. We emphasize that stock returns loadings on x are endogenous different, depending the centrality of an industry, although all firms' financial slacks x_f load homogeneously on x in our model. 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]

In the repeated game, the two firms can choose to tacitly collude on their profit margins to ensure a profit level θ in a given industry. We assume that the payoff table of the firms in industry $k \in \mathcal{K}$ is summarized in Table 1. Not only the industry rivalries

[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).

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

		Firm 2	
		Collude	Not collude
Firm 1	Collude	$\theta,\ \theta$	$\theta(1-e^{\eta\theta}),\ \theta(1+e^{\eta\theta})$
	Not collude	$\theta(1+e^{\eta\theta}),\ \theta(1-e^{\eta\theta})$	$0,\ 0$

choose whether collude or not, but also choose the collusive profit level θ.

If the two firms do not collude, both would gain a zero profit. If the two firms collude to a positive profit level $\theta > 0$, the profits are θ for both firms. However, firms are free to choose to deviate from the collusion agreement and "steal" customers from their rivals by setting lower profit margins. Specifically, when one of the firms deviates from the collusion agreement by lowering its profit margin by an infinitesimal amount, the deviating firm would "steal" $e^{\eta\theta}$ units of customers from its rival. It is intuitive to assume that $\eta > 0$ as the collusion is harder to sustain with a higher collusive profit level θ. As the punishment for deviation, the rival will not collude again in the future if a firm deviates.

Equilibrium. Let's first consider industry i. For firm i in industry i with the collusive profit level θ, 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:

$$\text{Benefits of deviation of firm } i = \theta e^{\eta\theta}, \quad \text{and} \tag{2.4}$$

$$\text{Costs of deviation of firm } i = \sum_{t=1}^{\infty} \lambda(x_i,\theta_i)^t \left[1-\lambda(x_i,\theta_i)\right] t\theta \tag{2.5}$$

$$= \theta \frac{\lambda(x_i,\theta_i)}{1-\lambda(x_i,\theta_i)}, \quad \text{respectively.} \tag{2.6}$$

Because firm i only operates in industry i, it holds that $\theta_i = \theta$, which leads to

$$\text{Costs of deviation of firm } i = \theta \frac{\lambda(x_i,\theta)}{1-\lambda(x_i,\theta)}. \tag{2.7}$$

To ensure that firm i will not deviate from the collusive profit level θ, it must hold that

$$\theta e^{\eta\theta} \leq \theta \frac{\lambda(x_i,\theta)}{1-\lambda(x_i,\theta)}. \tag{2.8}$$

Plugging (2.1) into (2.8) and rearranging terms lead to the IC constraint for firm i in industry i as follows:

$$\theta \leq \frac{x_i}{\eta - \gamma} \tag{2.9}$$

For firm c^i in industry i with the collusive profit level θ, 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:

$$\text{Benefits of deviation of firm } c^i = \theta e^{\eta \theta_{c^i}}, \quad \text{and} \tag{2.10}$$

$$\text{Costs of deviation of firm } c^i = \sum_{t=1}^{\infty} \lambda(x_{c^i}, \theta_{c^i})^t \left[1 - \lambda(x_{c^i}, \theta_{c^i})\right] t\theta \tag{2.11}$$

$$= \theta \frac{\lambda(x_{c^i}, \theta_{c^i})}{1 - \lambda(x_{c^i}, \theta_{c^i})}, \quad \text{respectively.} \tag{2.12}$$

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

$$\text{Costs of deviation of firm } c^i = \theta \frac{\lambda(x_{c^i}, \theta + \theta_{c^i,c})}{1 - \lambda(x_{c^i}, \theta + \theta_{c^i,c})}. \tag{2.13}$$

To ensure that firm c^i will not deviate from the collusive profit level θ, it must hold that

$$\theta e^{\eta \theta} \leq \theta \frac{\lambda(x_{c^i}, \theta + \theta_{c^i,c})}{1 - \lambda(x_{c^i}, \theta + \theta_{c^i,c})}. \tag{2.14}$$

Plugging (2.1) into (2.14) and rearranging terms lead to the IC constraint for firm c^i in industry i as follows:

$$\theta \leq \frac{x_{c^i} + \gamma \theta_{c^i,c}}{\eta - \gamma} \tag{2.15}$$

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:

$$\theta^{(i)} = \frac{\min\left\{x_i, x_{c^i} + \gamma \theta_{c^i,c}\right\}}{\eta - \gamma}. \tag{2.16}$$

where $\theta^{(i)}$ denotes the equilibrium profit level of industry i.

Now, we turn to industries c and j. Similarly, the collusive equilibrium profit level in industries c and j are

$$\theta^{(c)} = \frac{\min\left\{x_{c^i} + \gamma \theta_{c^i,i}, x_{c^j} + \gamma \theta_{c^j,j}\right\}}{\eta - \gamma}, \text{ and } \theta^{(j)} = \frac{\min\left\{x_j, x_{c^j} + \gamma \theta_{c^j,c}\right\}}{\eta - \gamma}, \text{ respectively.}$$

Taken together, the equilibrium $(\theta^{(i)}, \theta^{(c)}, \theta^{(j)})$ is characterized by the following three equations:

$$\theta^{(i)} = \frac{\min\left\{x_i, x_{c^i} + \gamma\theta^{(c)}\right\}}{\eta - \gamma}, \tag{2.17}$$

$$\theta^{(c)} = \frac{\min\left\{x_{c^i} + \gamma\theta^{(i)}, x_{c^j} + \gamma\theta^{(j)}\right\}}{\eta - \gamma}, \tag{2.18}$$

$$\theta^{(j)} = \frac{\min\left\{x_j, x_{c^j} + \gamma\theta^{(c)}\right\}}{\eta - \gamma}. \tag{2.19}$$

Main Results and Hypotheses. To ensure the existence of the collusive equilibrium, we assume that $\eta > 2\gamma$, which requires that the elasticity of short-run demand is sufficiently large relative to the sensitivity of risk-neutral survival probability to short-run cash flows. Otherwise, firms wouldn't have incentives to deviate from the collusion with a profit level θ, no matter how large it is, which would be very counterintuitive and unrealistic.

The following proposition shows that the profit levels of both the focal firm and its rival endogenously decrease in response to an adverse idiosyncratic distress shock to the financial slack of the focal firm. The proof of Proposition 2.1 is in Appendix A.1.

Proposition 2.1. *For an industry $k \in \mathcal{K}$ and any market leader f in the industry, the equilibrium profit level $\theta^{(k)}$ decreases with the idiosyncratic financial slack ε_f:*

$$\frac{\partial\theta^{(k)}}{\partial\varepsilon_f} \geq 0.$$

Proposition 2.1 implies two important results. We denote the two market leaders in industry $k \in \mathcal{K}$ by f and f'. In equilibrium, it holds that $\theta^{(k)} = \theta_{f,k} = \theta_{f',k}$ in our simple model. Thus, the proposition first implies the endogenous competition result: $\frac{\partial\theta_{f,k}}{\partial\varepsilon_f} \geq 0$; that is, the profit level of firm f endogenously decreases as a result of an adverse idiosyncratic distress shock to firm f. The proposition further implies the within-industry spillover effect through the distressed competition mechanism first proposed by Chen et al. (2020): $\frac{\partial\theta_{f',k}}{\partial\varepsilon_f} \geq 0$; that is, the profit level of firm f' endogenously decreases as a result of an adverse idiosyncratic distress shock to its rival firm f. These results lead to the following corollary on financial distress spillover. The intuitions of Proposition 2.1 and Corollary 2.1 are nicely illustrated in Figure 2.

Corollary 2.1. *For an industry $k \in \mathcal{K}$ and two market leaders f and f' in the industry with $f \neq f' \in \mathcal{F}$, the equilibrium risk-neutral survival probability $\lambda(x_{f'}, \theta_{f'})$ of firm f' decreases with* *the idiosyncratic financial slack ε_f:*

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

The following proposition shows that the profit level of an industry endogenously decreases in response to an adverse idiosyncratic distress shock to the financial slack 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. *For two connected industries k and k' with $k \neq k' \in \mathcal{K}$ and any market leader f in industry k, the equilibrium profit level $\theta^{(k')}$ of industry k' decreases with the idiosyncratic financial slack ε_f of firm f in the other industry k:*

$$\frac{\partial \theta^{(k')}}{\partial \varepsilon_f} \geq 0.$$

The cross-industry spillover effect relies on the positive complementarity between two connected industries' profit levels $\theta^{(k)}$ and $\theta^{(k')}$ through the their common market leader. 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 financial distress spillover. The intuitions of Proposition 2.2 and Corollary 2.2 are clearly illustrated in Figure 2.

Corollary 2.2. *For two connected industries k and k' with $k \neq k' \in \mathcal{K}$ and two market leaders f and f', firm f is in industry k and firm f' in industry k'. The equilibrium risk-neutral survival probability $\lambda(x_{f'}, \theta_{f'})$ of firm f' decreases with the idiosyncratic financial slack ε_f of firm f in the other industry:*

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

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 financial condition x in equation (2.2). A higher x should correspond 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. *Among the three industries i, c, and $j \in \mathcal{K}$, it holds that*

$$\frac{\partial \theta^{(c)}}{\partial x} \geq \max\left\{\frac{\partial \theta^{(i)}}{\partial x}, \frac{\partial \theta^{(j)}}{\partial x}\right\}. \tag{2.20}$$

We 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 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 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 j in industry j, when c^j becomes more distressed, market leader j will also lower its profit margin and become more distressed. Taken together, the initial adverse idiosyncratic shock to market leader i would result in a lower profit margin of market leader j through the lower profit margin set by the common market leaders c^i and c^j.

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]

[6]We follow Bustamante and Donangelo (2017) to use four-digit SIC codes in Compustat to define industries. We do not use historical SIC codes from CRSP 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.

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 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.

[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.

Production Network Data. We measure industry-level production network connectedness using the forward and backward connectedness measure 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 name, lender name, pricing, start date, end date, loan purpose, 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 U.S. 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). We first collect all enforcement actions brought by the U.S. Securities and Exchange Commission (SEC) and the U.S. 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 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 and Financial Constraint Measures. 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%. We follow Faulkender and Petersen (2012) to focus on the impact of the passage of AJCA on the financially constrained firms. 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 the year prior to the passage of the AJCA (i.e., 2003).

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

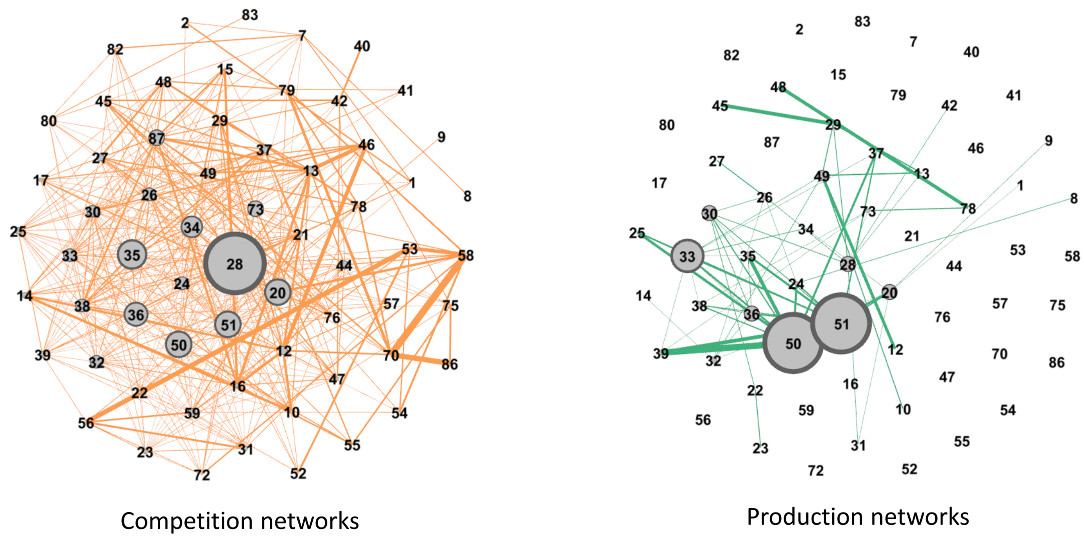
Construction of The Competition Network. Motivated by our model, we construct the competition network of industries linked by common market leaders. Based on the competition network, we test whether the natural disaster shocks hitting market leaders in one industry can influence the profit margins of 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 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

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



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.

industries are connected if they share at least one common market leader. There are 1,141 pairs of connected industries out of 534,061 possible industry pairs in 1994, which is the first year of our data in the natural disaster analysis. To examine the difference between competition network and production network, we construct the production network of the 1994 snapshot based on the connectedness measure of the Fan and Lang (2000). Specifically, we average the forward connectedness and backward connectedness measure 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. In Section 4.2, we will show 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 that the within-industry and cross-industry spillover effects of distress risk cannot be explained by production network externality.

Construction of The Competition Centrality Measure. 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.

We construct all four measures and found 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

Table 3: Competition centrality measures

Panel A: Correlation among centrality measures				
	Degree	*Closeness*	*Betweenness*	*Eigenvector*
Degree	1			
Closeness	0.70***	1		
Betweenness	0.79***	0.50***	1	
Eigenvector	0.70***	0.41***	0.62***	1
Panel B: Variance explained by the principle components				
	*PC*1	*PC*2	*PC*3	*PC*4
Variance explained (%)	72.00	15.16	9.32	3.51

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. Two industries are linked in the competition networks if there is at least one firm that is common leaders in both industries. 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.

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 test one of the main predictions of our model: the competition centrality of industries on the competition network is priced in the cross-section of stock returns as a primitive industry characteristic.

We first perform portfolio sorting analyses. For each industry on the competition network, we look at the competition centrality measure constructed in Section 4.1. In the June of each year t, we sort firms 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 $t+1$. Because common leaders operate in more than one industry, we exclude them from the sample in computing industry returns. Similarly, we also exclude conglomerate firms because they operate in multiple industries. To accomplish this, we follow Gopalan and Xie (2011) and Bustamante and Donangelo (2017) and define conglomerates as those firms operating in more than three segments according to the Compustat segment data. By focusing on stand-alone firms in each industry that are not conglomerates, 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 industries that contain fewer than three firms from the analysis.

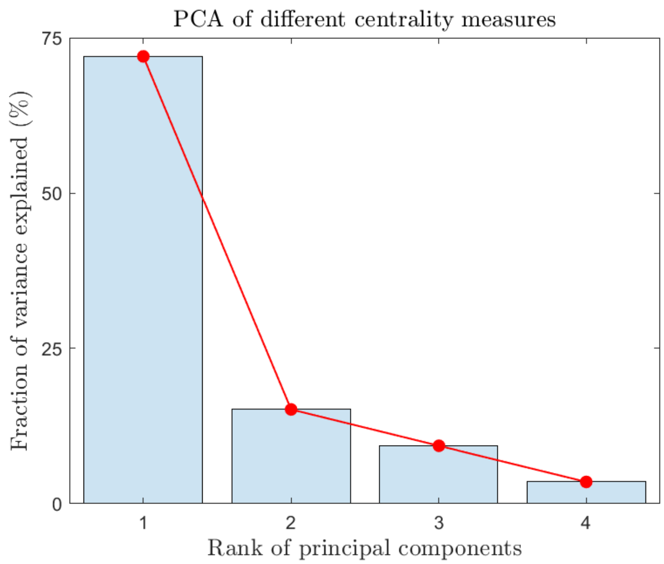


Figure 4: Eigen-decomposition of the covariance of four different centrality measures.

Table 4 shows 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 3.96%. 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 Carhart four factors, the Fama-French five factors, and the Hou-Xue-Zhang q 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, industry size, industry-level book-to-market ratio, industry-level gross profitability, and Herfindahl-Hirschman index (HHI). To formally control for these industry characteristics in our asset pricing tests, we perform a double sort analysis on these industry characteristics and 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,

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					
5.55*	6.46*	5.96*	8.03***	9.51***	3.96**
[1.73]	[1.91]	[1.66]	[2.63]	[2.91]	[2.44]
Panel B: single sort on degree centrality					
5.61	7.04**	5.46*	8.40***	9.28***	3.67**
[1.61]	[2.16]	[1.65]	[2.64]	[2.84]	[2.18]
Panel C: single sort on closeness centrality					
5.35	6.61**	6.04*	7.80**	9.42***	4.07**
[1.48]	[2.09]	[1.80]	[2.46]	[2.92]	[2.30]
Panel D: single sort on betweenness centrality					
6.21*	5.21*	7.47**	7.03**	9.14***	2.93*
[1.76]	[1.69]	[2.29]	[2.25]	[2.81]	[1.75]
Panel E: single sort on eigenvector centrality					
5.83*	6.27*	5.53*	8.27**	9.33***	3.50**
[1.67]	[1.95]	[1.67]	[2.57]	[2.84]	[2.14]

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, their monthly returns are tracked from July of year t to June of year $t+1$. The sample period of the data is from July 1977 to June 2018. Because common leaders operate in more than one industries, we exclude them in computing industry returns. We exclude financial and utility industries and 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. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

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 0.158- (1.90-) 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 predicts higher excess returns in the cross section after controlling for production network centrality, industry-level market capital size, industry-level book-to-market ratios, and industry-level gross profitability in Table 6. 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*).

4.3 Within-Industry Spillover Effects with Natural Disaster Shocks

We exploit the occurrences of natural disasters as exogenous shocks to firms' distress risk to examine the within-industry distress spillover effects. The negative impact of

Table 5: Alphas of the long-short industry portfolio sorted on competition centrality

CAPM α (%)	Fama-French three-factor α (%)	Carhart four-factor α (%)	Fama-French five-factor α (%)	Hou-Xue-Zhang q-factor α (%)
Panel A: long-short quintile portfolio sorted on PC1 of the four centrality measures				
3.69**	3.68**	4.05**	4.78***	5.44**
[2.22]	[2.13]	[2.10]	[2.72]	[2.58]
Panel B: long-short quintile portfolio sorted on degree centrality				
4.34***	4.27**	3.85*	4.61**	4.88**
[2.59]	[2.43]	[1.96]	[2.54]	[2.19]
Panel C: long-short quintile portfolio sorted on closeness centrality				
4.57**	4.85***	3.95*	5.84***	5.38**
[2.57]	[2.61]	[1.90]	[2.96]	[2.18]
Panel D: long-short quintile portfolio sorted on betweenness centrality				
3.48**	3.39**	3.05	4.00**	3.99*
[2.07]	[2.00]	[1.62]	[2.32]	[1.87]
Panel E: long-short quintile portfolio sorted on eigenvector centrality				
3.63**	3.95**	3.23*	5.34***	4.90**
[2.21]	[2.35]	[1.68]	[2.93]	[2.08]

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), Carhart four-factor model (Carhart, 1997), Fama-French five-factor model (Fama and French, 2015), and Hou-Xue-Zhang q-factor model (Hou, Xue and Zhang, 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, their monthly returns are tracked from July of year t to June of year $t+1$. The sample period of the data is from July 1977 to June 2018. Because common leaders operate in more than one industries, we exclude them in computing industry returns. We exclude financial and utility industries and 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. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

natural disasters on economic activities has been widely studied in the literature (e.g., Garmaise and Moskowitz, 2009; Strobl, 2011; Baker and Bloom, 2013; Cavallo et al., 2013; Hsiang and Jina, 2014; Barrot and Sauvagnat, 2016; Dessaint and Matray, 2017; Seetharam, 2018; Aretz, Banerjee and Pryshchepa, 2019; Boustan et al., 2020). Insurance coverage and public disaster assistance can only partially offset firms' losses in natural disasters (see Appendix C for detailed discussions). 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 the natural disasters within industries. We further use pairwise panel regressions to provide collaborative evidence and examine the heterogeneity of the treatment effects. Finally, we show that the within-industry spillover effects cannot be explained by demand commonality, production network externality, or credit lending channel.

Table 6: Fama-MacBeth regressions

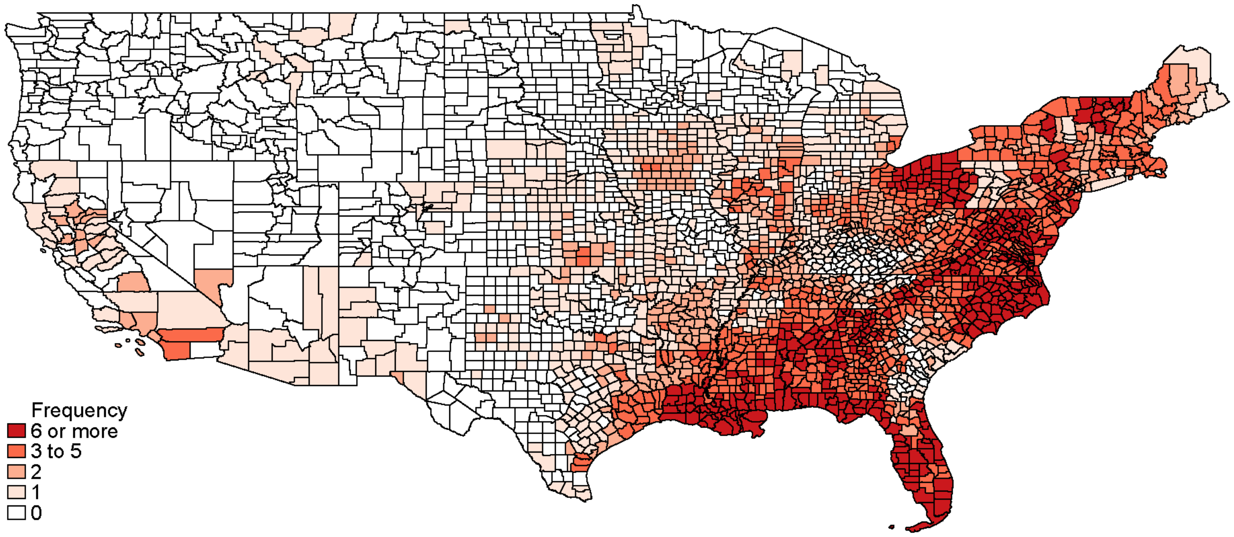
	(1)	(2)	(3)	(4)	(5)	(6)
			$Ret_{i,t}$ (%)			
$Competition\_Centrality_{i,t-1}$	0.142***	0.141***	0.087***	0.075**	0.079**	0.158***
	[2.794]	[2.731]	[2.615]	[2.307]	[2.502]	[3.353]
$Production\_Centrality_{i,t-1}$		0.078	−0.007	−0.025	−0.026	−0.112
		[1.533]	[−0.151]	[−0.557]	[−0.565]	[−1.441]
$Lnsize_{i,t-1}$			0.210**	0.292***	0.311***	0.500***
			[2.367]	[3.469]	[3.670]	[3.944]
$LnBEME_{i,t-1}$				0.159**	0.190***	0.334***
				[2.485]	[2.912]	[4.029]
$GP_{i,t-1}$					0.154***	0.285**
					[2.673]	[3.297]
$HHI_{i,t-1}$						−0.016
						[−0.252]
Constant	0.985***	0.972***	0.787***	0.777***	0.772***	0.528*
	[3.757]	[3.618]	[2.753]	[2.748]	[2.741]	[1.756]
Average obs/month	203	204	199	199	198	97
Average R-squared	0.005	0.010	0.031	0.045	0.057	0.103

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 size ($Lnsize_{i,t-1}$), 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 size is the market equity 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). 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 U.S. Census which covers manufacturing industries. All the independent variables are standardized to have means of 0 and standard deviations of 1. The sample period of the data is from 1977 to 2018. Because common leaders operate in more than one industries, we exclude them in computing industry returns and characteristics. We exclude financial and utility industries and industries that contain fewer than three firms from the analysis. . *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

4.3.1 Difference-in-Differences (DID) Analysis

We follow Barrot and Sauvagnat (2016) to define 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.[8] We list the major natural 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 5. Panel A of Table 7 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

[8]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 5: Frequency of major natural disasters by the US counties.

that the counties in which the affected 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 affected firms and the spillover effect to the non-affected peer firms simultaneously using the DID approach. Specifically, we match each firm affected by a natural disaster with up to ten non-affected peer firms in the same four-digit SIC industries with similar asset size, tangibility, and firm age.[9] Because we are interested in studying the spillover effect, it is important for us to make sure that the matched peer firms are not directly affected by major natural disaster shocks. In particular, we require the matched peer firms to have no establishment (including headquarters) in any county that experiences any positive amount of property damage during 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.

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

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

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-affected 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 affected 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-affected 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-affected peer firms, the summation between the coefficient β_1 and the coefficient β_3 captures the total treatment effect for the affected 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 through competition network.

We tabulate the results of the regressions in columns (1) to (4) of panel B in Table 7. We find that the distress risk of the affected firms increases substantially, while the distance-to-default measure of the affected 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 affected 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

Table 7: Identifying within-industry spillover effects using the DID analysis.

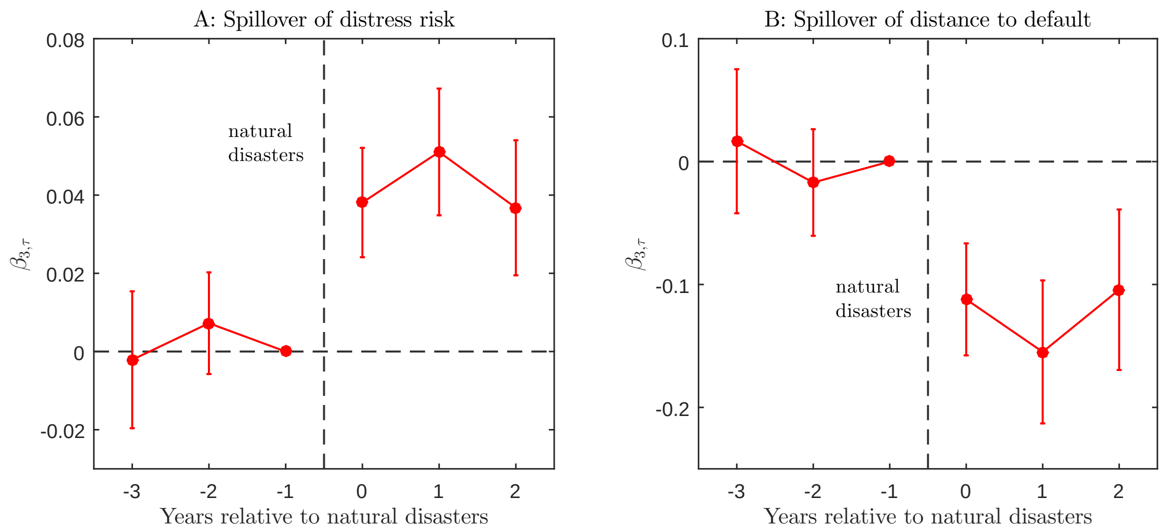
Panel A: Summary statistics of the firm-year panel								
	Obs. #	Mean	Median	SD	p10th	p25th	p75th	p90th
$ND_{i,t}$	88297	0.100	0	0.301	0	0	0	1
$Distress_{i,t}$	92185	−7.228	−7.489	1.005	−8.317	−7.986	−6.701	−5.618
$DD_{i,t}$	80858	5.321	4.506	4.254	0.292	2.070	7.833	11.884
$PM_{i,t}$	96269	0.346	0.338	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)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.028**	0.028**	−0.087*	−0.088*	−0.002	−0.003	−0.006	−0.006
	[2.173]	[2.201]	[−1.723]	[−1.749]	[−0.753]	[−0.799]	[−0.977]	[−1.013]
$Treat_{i,t}$	−0.015	−0.015	0.086*	0.086*	−0.002	−0.002	−0.001	−0.001
	[−1.318]	[−1.332]	[1.836]	[1.844]	[−0.596]	[−0.574]	[−0.192]	[−0.175]
$Post_{i,t}$	0.048***	0.046***	−0.129***	−0.122***	−0.006**	−0.005**	−0.012***	−0.011**
	[5.856]	[5.774]	[−4.331]	[−4.169]	[−2.504]	[−2.299]	[−2.626]	[−2.484]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.022**		−0.069*		−0.008***		−0.012**
		[2.105]		[−1.780]		[−3.154]		[−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	0.753	0.753	0.760	0.760
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$

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

substantially increase firms' distress risk.

We then examine the impact of distress risk on the affected 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 7, we find that the affected 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.

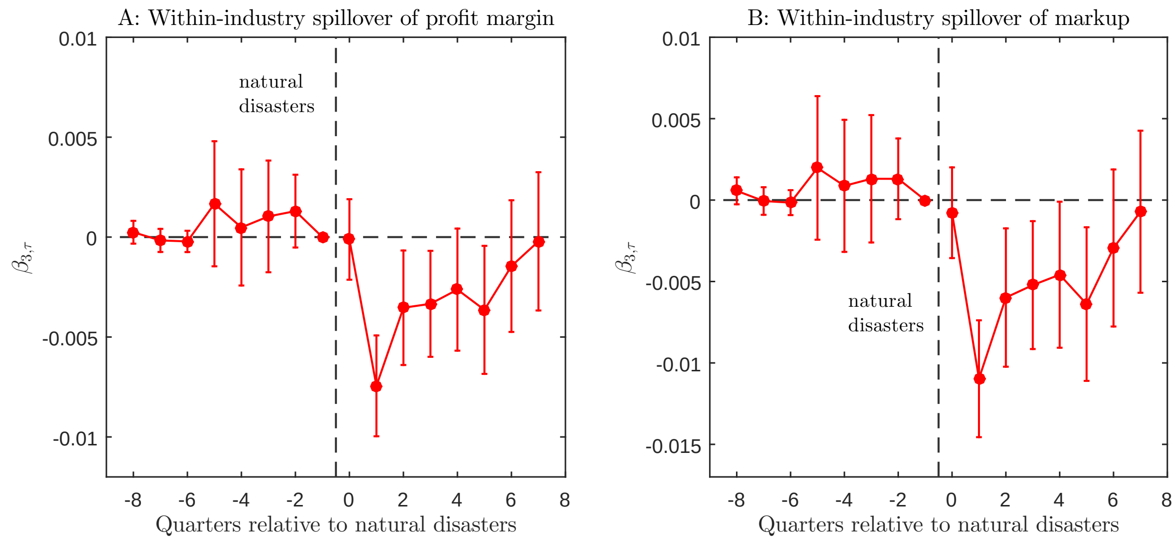


Note: This figure plots the within-industry spillover effects of distress risk around major natural disasters. For each treated firm (i.e., the firm whose headquarter or any of its major establishments is located in a county that is negatively affected by major natural disasters), we match it with up to ten non-affected 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 firm, we include six yearly observations (i.e., three years before and three years after the major natural disasters) 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 line represents the occurrence of major natural disasters.

Figure 6: Within-industry spillover effects of distress risk.

This finding is consistent with the prediction of our model.

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 7 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-affected 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 7 is positive and statistically significant, while the coefficient β_3 in columns (3) and (4) of panel B in Table 7 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



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-affected 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 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 line represents the occurrence of major natural disasters.

Figure 7: Within-industry spillover effects of profit margin.

by natural disaster shocks.

Panel B of Table 7 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 are consistent with the prediction of our model. When more industries that are linked to the focal industry through competition networks are shocked by the natural disasters, the firms in the focal industry experience larger magnitude of 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.

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:

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

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 6, 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 7.

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 7, 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.[10]

[10]For example, Barrot and Sauvagnat (2016) show that natural disaster shocks dampen the sales growth for the customers of the affected 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).

Finally, we perform a set 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-affected peer firms (i.e., one to five 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 are robust to alternative measures for the cross-industry spillover. Specifically, we measure the strength of cross-industry spillover using the variable $Ln(1+\overline{Damage(\mathcal{C}_{i,t})})$, 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.

4.3.2 Firm-Peer Pairwise Panel Regressions

To examine the impact of affected firms on their industry peers in more detail, we estimate panel regressions using a dataset containing the pairs of focal firms and their industry peers in each year. Specifically, we run the following regressions:

$$Y_{i,t} = \beta_1 ND\_Peer_{i,p,t} + \beta_2 Ln(1+n(\mathcal{C}_{i,t})) + \Gamma' Controls_{i,t-1} + \theta_{i,p} + \delta_t + \varepsilon_{i,p,t}. \tag{4.3}$$

The dependent variables $Y_{i,t}$ include the focal firms' distress risk ($Distress_{i,t}$), the distance to default ($DD_{i,t}$), the gross profit margin ($PM_{i,t}$), and the markup ($Markup_{i,t}$). $ND\_Peer_{i,p,t}$ is an indicator variable that equals one if the peer firm p's headquarter or one of its major establishments is negatively affected by a major natural disaster in year t. $Ln(1+n(\mathcal{C}_{i,t}))$ captures the strength of cross-industry spillover via the competition network. Control variables are the lagged focal firm characteristics including the natural log of lagged asset size, the natural log of the lagged fixed-asset-to-total-asset ratio, and the natural log of firm age. The term $\theta_{i,p}$ represents firm-peer pair fixed effects, and the term δ_t represents year fixed effects. Because we are interested in examining the within-industry spillover effects, it is important to make sure the focal firms do not experience natural disaster shocks themselves. Therefore, we require the focal firms to have no establishment (including headquarters) in any county that experiences any positive amount of property damage during the major natural disasters.

Panel A of Table 8 presents the results from the firm-peer pairwise panel regressions. Consistent with the DID analysis, we find that focal firms reduce their profit margin significantly when their industry peers experience major natural disaster shocks. The

Table 8: Firm-peer pairwise panel analysis

	Panel A: Firm-peer pairwise panel regression							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$ND\_Peer_{i,p,t}$	0.017***	0.012***	−0.054***	−0.040**	−0.014**	−0.012**	−0.016***	−0.014***
	[3.792]	[2.905]	[−3.261]	[−2.406]	[−2.564]	[−2.191]	[−4.643]	[−4.140]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.076***		−0.192***		−0.032**		−0.039***
		[5.051]		[−3.824]		[−1.988]		[−4.047]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-peer pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2834990	2834990	2110815	2110815	2998774	2998774	2990258	2990258
R-squared	0.626	0.627	0.726	0.726	0.793	0.793	0.821	0.821

	Panel B: Heterogeneity across industry entry cost							
	(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
$ND\_Peer_{i,p,t}$	0.016**	−0.003	−0.059**	−0.019	−0.026***	0.001	−0.026***	−0.001
	[2.288]	[−1.140]	[−2.049]	[−1.435]	[−2.859]	[0.241]	[−3.977]	[−0.515]
$Ln(1+n(\mathcal{C}_{i,t}))$	0.092***	0.080***	−0.219***	−0.183**	−0.049***	0.004	−0.073***	0.003
	[4.862]	[3.225]	[−3.592]	[−2.041]	[−3.101]	[0.126]	[−6.714]	[0.203]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-peer pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1114907	1621737	932314	1089987	1200299	1698059	1198001	1692172
R-squared	0.665	0.631	0.768	0.719	0.763	0.815	0.777	0.850

Note: Panel A of this table examines the response of the level of distress risk and gross profit margin to natural disaster shocks of peer firms. The data set of this table is a panel that contains pairwise observations between the focal firms and their four-digit SIC industry peers in each year. We exclude from our analysis the focal firms that experience natural disaster shocks themselves. The regression specification is: $Y_{i,t} = \beta_1 ND\_Peer_{i,p,t} + \beta_2 Ln(1+n(\mathcal{C}_{i,t})) + \Gamma' Controls_{i,t-1} + \theta_{i,p} + \delta_t + \varepsilon_{i,p,t}$. The dependent variables $Y_{i,t}$ are the distress risk ($Distress_{i,t}$), distance to default ($DD_{i,t}$), gross profit margin ($PM_{i,t}$), and markup ($Markup_{i,t}$). Distress risk is constructed as in Campbell, Hilscher and Szilagyi (2008). Distance to default ($DD_{i,t}$) is constructed following the naive approach illustrated in Bharath and Shumway (2008). Gross profit margin is defined as the difference between sales and cost of goods sold divided by sales. Markup is defined as the natural log of the ratio between sales and cost of goods sold. $ND\_Peer_{i,p,t}$ is an indicator variable that equals one if the peer firm p's headquarter or one of its major establishments 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. Control variables are the lagged focal firm characteristics including the natural log of lagged asset size, the natural log of the lagged fixed-asset-to-total-asset ratio, and the natural log of firm age. The term $\theta_{i,p}$ represents firm-peer pair fixed effects, and the term δ_t represents year fixed effects. Panel B of this table examines the impact of natural disasters shocks of the peer firms across industries with different levels of entry barriers. We split samples into two subgroups, one with high entry barriers (above median) and another with low entry barriers (below median). Entry barrier of a four-digit SIC industry is measured by the sales-weighted average of fixed assets across firms in this industry. 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.

reduction in gross profit margin is about 1.2 percentage points, which are economically significant given the median gross profit margin of 34 percentage points. Moreover, the distress risk of the focal firm increases significantly and the distance-to-default measure decreases significantly when the focal firm's industry peers experience major natural disaster shocks, providing direct evidence for the within-industry distress spillover.

We further explore the heterogeneity of the within-industry spillover effects. In panel B of Table 8, we show that the impact of affected firms on their industry peers is stronger in industries with higher entry barriers. We proxy the entry barrier of a four-digit SIC industry using the sales-weighted average fixed assets, following previous studies (e.g., Li, 2010). Our finding is consistent with the theory work by Chen et al. (2020), who show that peer firms are more likely to compete with the distressed firm in industries with higher entry barriers because the winners of the price competition in these industries enjoy larger economic rents after pushing out their competitors due to weaker entry threat; the high entry barriers make it less likely that new entrants will replace the competitors that were driven out. In Table A.11 of the Appendix, we also explore the heterogeneity across the level of financial leverage. We show that when affected peers or non-affected focal firms have higher financial leverage prior to disaster shocks, the within-industry spillover effect is stronger. This result is intuitive since the competition incentive should be stronger if firms are more distressed ex ante.

4.3.3 Testing Against Alternative Explanations

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

Demand Commonality. The first alternative explanation that we test against is demand commonality. This alternative explanation argues that natural disasters lead to negative demand shocks that hurt both the affected 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.[11]

We first exclude focal firms that are geographically close to natural disaster areas in the firm-peer pairwise analysis. Specifically, we remove focal firms (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 of firms that are more susceptible to the negative demand shocks caused by the natural disasters. As shown in panel A of Table A.12 in the Appendix, our findings of the within-industry spillover effects remain robust.

One may further argue that although a focal firm is geographically far from the natural

[11] 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 affected firms. The alternative explanation we aim to rule out here is that the demand shocks caused by the natural disasters also make the non-affected industry peers more distressed. In other words, demand commonality drives the within-industry spillover effects in the alternative explanation.

disaster areas, its customers may mainly come from these areas and thus this firm may still be directly affected by the demand shocks. To rule out this possibility, we further remove focal firms with customers negatively affected by the natural disasters from the sample of focal firms far from the natural disaster areas. As shown in panel B of Table A.12, our findings of the within-industry spillover effects remain robust.

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.[12] Because of the limitation of the supplier-customer data, one may argue that it is possible that individual consumers negatively affected by the natural disasters may be the common customers for the affected firms and their industry peers, and such type of demand commonality can drive the within-industry spillover effects. To test this hypothesis, we further remove focal firms in the consumer-facing industries (i.e., airlines, grocery stores, hotels, retailers, restaurants, utilities, and many online services) and focus on the focal 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 C of Table A.12, our findings of the within-industry spillover effects still remain robust. The above results collectively suggest 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 against 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.

In Table A.13 of the Appendix, we show that the within-industry spillover effect is robust after we remove firm-peer pairs linked through supply chains. Specifically, we remove the observations in which the focal firm is a supplier or a customer of the peer firm. We also remove the firm-pairs with top 10% of vertical relatedness scores (Frésard, Hoberg and Phillips, 2020). In Table A.14 of the Appendix, we show that when a firm's customers or suppliers experience natural disaster shocks, the firm does not change its gross profit margin significantly. This finding is in sharp contrast with the within-industry spillover effects that we document above. In Table A.15 of the Appendix, we use the vertical relatedness scores measure and show that when a firm's upstream

[12] We are not aware of any dataset that provides comprehensive coverage of individual consumers. One exception may be 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 overlaps little with our sample in the cross section (i.e., firm pairs within four-digit SIC industries).

firms or downstream firms experience natural disaster shocks, the firm also does not reduce its profit margin.

Finally, we test an alternative explanation in which the within-industry spillover effects are caused by common customers of both the firms affected by natural disasters and their industry peers. In this alternative explanation, natural disaster shocks make the customers of the affected firms more distressed, which in turn increase 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 still driven by product network externality rather than by the competition mechanism illustrated by our model. To test against this alternative explanation, we rerun the pairwise analysis by excluding the firm pairs that are connected through common customers. As shown in Table A.16 of the Appendix, the spillover effects remain robust, suggesting that common customers unlikely explain the within-industry spillover effects. In addition, we directly test the relation between the gross profit margin of a firm and the distress risk of its customers. As shown in Table A.17 of the Appendix, the suppliers actually do not reduce their gross profit margin when customers become more financially distressed. If anything, the results seem to suggest that the suppliers would increase their profit margin in response to distress of their customers. This finding further casts doubt to the alternative explanation based on common customers.

Credit Lending Channel. The third alternative explanation for the within-industry spillover effects is the credit lending channel. This alternative explanation argues that non-affected 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 construct firms' exposure to natural disasters through lenders. We first find out the exposure to natural disasters for each lender l in each year t. Specifically, we compute the dollar amount of loans that are issued by leader l from $t-5$ to $t-1$ and remain outstanding in year t to firms that experience natural disasters in year t. We then normalize this amount by the amount of loan outstanding. We focus on loans issued in the proceeding five-year window following the literature (e.g., Bharath et al., 2007). Next, for each firm i, we compute its exposure to natural disasters through lenders by aggregating the lender-level exposure across all lenders. The aggregation is value weighted based on the outstanding loan amount borrowed from different lenders. We add the focal firms' exposure to natural disasters through lenders as an additional control variable in the firm-peer pairwise regressions. As shown in Table A.18 of the

Appendix, our findings remain robust after adding this control variable, suggesting that the credit lending channel unlikely explains the within-industry spillover effects.[13]

4.4 Cross-Industry Contagion Effects with Natural Disaster Shocks

In Section 4.3.1, we provide preliminary evidence for the cross-industry spillover effects. In particular, panel B of Table 7 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 this section, we further study the cross-industry spillover effects by highlighting the role of the common market leaders in transmitting shocks across industries.

Our empirical test for cross-industry contagion effects has 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 in. We run the following panel regression using industry pair-year observations:

$$Y_t^{(c_{i,j})} = \sum_{m=1}^{3} \beta_m ND_{j,t}^{(m)} + \delta_t + \varepsilon_t^{(c_{i,j})}. \tag{4.4}$$

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, $ND_{j,t}^{(m)}$, 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 major natural disaster shocks, and the term δ_t represents year fixed effects. Our regression specification (4.4) essentially estimates the impact of the idiosyncratic natural disaster shocks to the top three market leaders in industry j on the distress risk or the profit margin of the common market leader (i.e., $c_{i,j}$) in year t. Once we obtain the estimates $\hat{\beta}_m$ $(m = 1, 2, 3)$ of specification (4.4), we compute the fitted value $\widehat{IdShock}_{j,t}^{(c_{i,j})}$, which intuitively captures the changes of the distress risk or 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

[13]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 Table A.18 of the Appendix to the focal firms covered by the DealScan data because we cannot accurately measure the lender exposure for the focal firms outside of the DealScan universe.

Table 9: Distress contagion across industries

Panel A: Construction of $\widehat{IdShock}_{j,t}^{(c_{i,j})}$ (first step)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_t^{c_{i,j}}$		$DD_t^{c_{i,j}}$		$PM_t^{c_{i,j}}$		$Markup_t^{c_{i,j}}$	
$ND_{j,t}^{(1)}$	0.068***	0.057**	−0.314*	−0.379**	−0.023***	−0.028***	−0.050***	−0.062***
	[2.626]	[2.360]	[−1.895]	[−2.392]	[−4.009]	[−4.495]	[−4.362]	[−4.773]
$ND_{j,t}^{(2)}$	0.032	0.046*	−0.143	−0.309**	−0.012**	−0.014***	−0.022**	−0.027***
	[1.258]	[1.918]	[−0.839]	[−1.974]	[−2.337]	[−2.766]	[−2.398]	[−2.861]
$ND_{j,t}^{(3)}$	0.004	0.017	0.050	−0.169	−0.000	−0.004	0.003	−0.007
	[0.137]	[0.653]	[0.275]	[−0.900]	[−0.011]	[−0.839]	[0.300]	[−0.656]
Observations	7058	7058	6882	6882	7166	7166	7166	7166
R-squared	0.002	0.121	0.001	0.153	0.005	0.011	0.006	0.016

Panel B: Cross-industry contagion (second step)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}^{(-c)}$		$DD_{i,t}^{(-c)}$		$PM_{i,t}^{(-c)}$		$Markup_{i,t}^{(-c)}$	
$\widehat{IdShock}_{-i,t}$	0.781***	0.705***	0.756***	0.740***	0.679***	0.626***	0.662***	0.596***
	[3.552]	[3.533]	[3.586]	[3.080]	[3.296]	[2.984]	[3.405]	[3.060]
$\widehat{IdShock}_{-i,t} \times Forward\_connectedness_{-i,i,t}$		14.251*		2.815		3.239		8.312
		[1.680]		[1.012]		[0.154]		[0.448]
$\widehat{IdShock}_{-i,t} \times Backward\_connectedness_{-i,i,t}$		36.688**		8.652*		34.896		33.619
		[2.234]		[1.763]		[1.010]		[1.193]
$Forward\_connectedness_{-i,i,t}$		103.365*		−11.866		−0.415		−1.773
		[1.649]		[−0.866]		[−0.062]		[−0.227]
$Backward\_connectedness_{-i,i,t}$		278.586**		−56.251**		−10.873		−13.837
		[2.268]		[−2.244]		[−1.039]		[−1.259]
Observations	5346	5346	5346	5346	5346	5346	5346	5346
R-squared	0.021	0.022	0.121	0.122	0.003	0.005	0.005	0.010

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: $Y_t^{(c_{i,j})} = \sum_{m=1}^{3} \beta_m ND_{j,t}^{(m)} + \delta_t + \varepsilon_t^{(c_{i,j})}$ 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, $ND_{j,t}^{(m)}$, are indicator variables that equal one if the m^{th} $(m = 1, 2, 3)$ largest stand-alone firm (ranked by sales) in industry j is affected by a major natural disaster in year t. 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 fitted value $\widehat{IdShock}_{j,t}^{(c_{j,i})}$ is estimated in the first step, and it captures the changes of outcome variables of the common leader $c_{j,i}$ attributed to natural disaster shocks to market leaders in industry j. The cross-industry contagion effect is estimated by the following specification: $Y_{i,t}^{(-c)} = \beta_1 \widehat{IdShock}_{-i,t} + \beta_2 \widehat{IdShock}_{-i,t} \times Forward\_connectedness_{-i,i,t} + \beta_3 \widehat{IdShock}_{-i,t} \times Backward\_connectedness_{-i,i,t} + \beta_4 Forward\_connectedness_{-i,i,t} + \beta_5 Backward\_connectedness_{-i,i,t} + \Gamma' Controls_{i,t-1} + \varepsilon_{i,t}$. 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 $Forward\_connectedness_{-i,i,t}$ and $Backward\_connectedness_{-i,i,t}$ are the simple average of $Forward\_connectedness_{j,t}^{(c_{j,i})}$ and $Backward\_connectedness_{j,t}^{(c_{j,i})}$ over all industries (indexed by j) connected to the industry i through competition networks, respectively. $Forward\_connectedness_{j,t}^{(c_{j,i})}$ and $Backward\_connectedness_{j,t}^{(c_{j,i})}$ are the forward and backward connectedness measures between industry j and industry i (Fan and Lang, 2000) . $Forward\_connectedness_{-i,i,t}$ captures the value of industry i's output used to produce \$1 output of the industries connected through competition networks. $Backward\_connectedness_{-i,i,t}$ 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.

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:

$$Y_{i,t}^{(-c)} = \beta_1 \widehat{IdShock}_{-i,t} + \Gamma' Controls_{i,t-1} + \varepsilon_{i,t}, \tag{4.6}$$

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. Control variables are the lagged focal firm characteristics including the natural log of lagged asset size, the natural log of the lagged fixed-asset-to-total-asset ratio, and the natural log of firm age. 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.

We present the estimation results for the cross-industry contagion analysis in Table 9 and the corresponding summary statistics in Table A.19 of the Appendix. Panel A of Table 9 presents the results from the first-step regressions. We find that the common leaders' distress risk (profit margins) are positively (negatively) associated with the natural disaster shocks to the top market leaders in the same industries. 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.

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 the measure captures the production network connectedness between two industries. As shown by panel B of Table 9, the coefficient for the predicted idiosyncratic shocks remain positive and statistically significant when the production network connectedness measure is zero, suggesting that the cross-industry contagion effect cannot be explained away by

Table 10: 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 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. $StockRet_{i,t-3:t-1}$ is the average stock returns of firm i from year $t-3$ to year t. 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.

production network externality.

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 examine the impact of distressed firms on their industry peers within a setting where firms suffer from distress due to enforcement actions against financial frauds. In Section 4.5.2, we exploit the AJCA tax holiday setting and study the impact of the reduction of financial distress 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 the reaction of their industry peers.[14]

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 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 return-on-assets (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 dates. $Ln(1 + n(\mathcal{C}_{i,t}))$ 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. $StockRet_{i,t-3:t-1}$ is the average stock returns of firm i from year $t-3$ to year t. The term θ_i represents firm fixed effects, and the term δ_t represents year fixed effects.

Table 10 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 the 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

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

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 of legal enforcement actions, 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 10.

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 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

Table 11: 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 using a homogenous spillover model. 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 (columns 1–4) and the HP index (columns 5–8). 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. 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.

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. 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 11 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.20 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 11 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

Here we only prove that $\frac{\partial\theta^{(i)}}{\partial\varepsilon_i} \geq 0$ and $\frac{\partial\theta^{(i)}}{\partial\varepsilon_{c^i}} \geq 0$. Other inequalities can be shown in the same way. We first show that $\frac{\partial\theta^{(i)}}{\partial\varepsilon_i} \geq 0$. If $x_i \leq x_{c^i} + \gamma\theta^{(c)}$, it holds that $\theta^{(i)} = \frac{x_i}{\eta-\gamma}$, and thus, $\frac{\partial\theta^{(i)}}{\partial\varepsilon_i} = \frac{1}{\eta-\gamma} > 0$. If $x_i > x_{c^i} + \gamma\theta^{(c)}$, then it holds that $\theta^{(i)} = \frac{x_{c^i}+\gamma\theta^{(c)}}{\eta-\gamma}$. From the equilibrium conditions (2.17) through (2.19), we know that $\theta^{(c)}$ is a function of x_{c^i}, x_{c^j}, and x_j in the equilibrium, so is $\theta^{(i)}$. Thus, $\frac{\partial\theta^{(i)}}{\partial\varepsilon_i} = 0$. Taken together, we have shown that $\frac{\partial\theta^{(i)}}{\partial\varepsilon_i} \geq 0$ in the equilibrium.

We now prove $\frac{\partial\theta^{(i)}}{\partial\varepsilon_{c^i}} \geq 0$. If $x_i \leq x_{c^i} + \gamma\theta^{(c)}$, it holds that $\theta^{(i)} = \frac{x_i}{\eta-\gamma}$, and thus, $\frac{\partial\theta^{(i)}}{\partial\varepsilon_{c^i}} = 0$. If $x_i > x_{c^i} + \gamma\theta^{(c)}$, then it holds that $\theta^{(i)} = \frac{x_{c^i}+\gamma\theta^{(c)}}{\eta-\gamma}$, and thus, $\frac{\partial\theta^{(i)}}{\partial\varepsilon_{c^i}} = \frac{1}{\eta-\gamma} + \frac{\gamma}{\eta-\gamma}\frac{\theta^{(c)}}{\partial\varepsilon_{c^i}}$. Further, if $x_{c^i} + \gamma\theta^{(i)} \leq x_{c^j} + \gamma\theta^{(j)}$, it follows from (2.17) – (2.19) that $\theta^{(c)} = \frac{x_{c^i}}{\eta-2\gamma}$ in the equilibrium. Therefore, $\frac{\partial\theta^{(i)}}{\partial\varepsilon_{c^i}} = \frac{1}{\eta-\gamma} + \frac{\gamma}{\eta-\gamma}\frac{1}{\eta-2\gamma} > 0$. If $x_{c^i} + \gamma\theta^{(i)} > x_{c^j} + \gamma\theta^{(j)}$, it follows from (2.17) – (2.19) that $\theta^{(c)}$ is a function of x_{c^j} and x_j in the equilibrium. Therefore, $\frac{\partial\theta^{(i)}}{\partial\varepsilon_{c^i}} = \frac{1}{\eta-\gamma} > 0$. Taken together, we have shown that $\frac{\partial\theta^{(i)}}{\partial\varepsilon_{c^i}} \geq 0$ in the equilibrium.

A.2 Proof for Proposition 2.2

Here we only prove that $\frac{\partial\theta^{(c)}}{\partial\varepsilon_i} \geq 0$. Other inequalities can be shown in the same way. If $x_i \leq x_{c^i} + \gamma\theta^{(c)}$ and $x_{c^i} + \gamma\theta^{(i)} \leq x_{c^j} + \gamma\theta^{(j)}$, it follows from (2.17) – (2.19) that $\theta^{(c)} = \frac{x_{c^i}}{\eta-\gamma} + \frac{\gamma}{(\eta-\gamma)^2}x_i$ in the equilibrium. Therefore, it holds that $\frac{\partial\theta^{(c)}}{\partial\varepsilon_i} = \frac{\gamma}{(\eta-\gamma)^2} > 0$. In other cases, it follows from (2.17) – (2.19) that $\theta^{(c)}$ is a function of x_{c^i}, x_{c^j}, and x_j. Therefore, $\frac{\partial\theta^{(c)}}{\partial\varepsilon_i} = 0$. Taken together, $\frac{\partial\theta^{(c)}}{\partial\varepsilon_i} \geq 0$ in the equilibrium.

A.3 Proof for Proposition 2.3

Here we only prove that $\frac{\partial\theta^{(c)}}{\partial x} \geq \max\left\{\frac{\partial\theta^{(i)}}{\partial x}, \frac{\partial\theta^{(j)}}{\partial x}\right\}$. Other inequalities can be shown in the same way. Specifically, we shall prove this inequality by exhausting all 8 cases.

In case 1, $\theta^{(i)} = \frac{x_i}{\eta-\gamma}$, $\theta^{(c)} = \frac{x_{c^i}+\gamma\theta^{(i)}}{\eta-\gamma}$, and $\theta^{(j)} = \frac{x_j}{\eta-\gamma}$, thus it holds that $\frac{\partial\theta^{(i)}}{\partial x} = \frac{\partial\theta^{(j)}}{\partial x} = \frac{\beta}{\eta-\gamma}$ and $\frac{\partial\theta^{(c)}}{\partial x} = \frac{\eta\beta}{(\eta-\gamma)^2}$. It is obviously true that $\frac{\partial\theta^{(c)}}{\partial x} \geq \max\left\{\frac{\partial\theta^{(i)}}{\partial x}, \frac{\partial\theta^{(j)}}{\partial x}\right\}$.

In case 2, $\theta^{(i)} = \frac{x_i}{\eta-\gamma}$, $\theta^{(c)} = \frac{x_{c^i}+\gamma\theta^{(i)}}{\eta-\gamma}$, and $\theta^{(j)} = \frac{x_{c^j}+\gamma\theta^{(c)}}{\eta-\gamma}$, thus it holds that $\frac{\partial\theta^{(i)}}{\partial x} = \frac{\beta}{\eta-\gamma}$, $\frac{\partial\theta^{(c)}}{\partial x} = \frac{\eta\beta}{(\eta-\gamma)^2}$, and $\frac{\partial\theta^{(j)}}{\partial x} = \frac{(\eta-\gamma)^2+\gamma\eta}{(\eta-\gamma)^3}\beta$. It is true that $\frac{\partial\theta^{(c)}}{\partial x} \geq \max\left\{\frac{\partial\theta^{(i)}}{\partial x}, \frac{\partial\theta^{(j)}}{\partial x}\right\}$.

In case 3, $\theta^{(i)} = \frac{x_i}{\eta - \gamma}$, $\theta^{(c)} = \frac{x_{c^j} + \gamma\theta^{(j)}}{\eta - \gamma}$, and $\theta^{(j)} = \frac{x_j}{\eta - \gamma}$, thus it holds that $\frac{\partial\theta^{(i)}}{\partial x} = \frac{\partial\theta^{(j)}}{\partial x} = \frac{\beta}{\eta - \gamma}$ and $\frac{\partial\theta^{(c)}}{\partial x} = \frac{\eta\beta}{(\eta - \gamma)^2}$. It is true that $\frac{\partial\theta^{(c)}}{\partial x} \geq \max\left\{\frac{\partial\theta^{(i)}}{\partial x}, \frac{\partial\theta^{(j)}}{\partial x}\right\}$.

In case 4, $\theta^{(i)} = \frac{x_i}{\eta - \gamma}$, $\theta^{(c)} = \frac{x_{c^j} + \gamma\theta^{(j)}}{\eta - \gamma}$, and $\theta^{(j)} = \frac{x_{c^j} + \gamma\theta^{(c)}}{\eta - \gamma}$, thus it holds that $\frac{\partial\theta^{(i)}}{\partial x} = \frac{\beta}{\eta - \gamma}$ and $\frac{\partial\theta^{(c)}}{\partial x} = \frac{\partial\theta^{(j)}}{\partial x} = \frac{\beta}{\eta - 2\gamma}$. It is true that $\frac{\partial\theta^{(c)}}{\partial x} \geq \max\left\{\frac{\partial\theta^{(i)}}{\partial x}, \frac{\partial\theta^{(j)}}{\partial x}\right\}$.

In case 5, $\theta^{(i)} = \frac{x_{c^i} + \gamma\theta^{(c)}}{\eta - \gamma}$, $\theta^{(c)} = \frac{x_{c^i} + \gamma\theta^{(i)}}{\eta - \gamma}$, and $\theta^{(j)} = \frac{x_j}{\eta - \gamma}$, thus it holds that $\frac{\partial\theta^{(i)}}{\partial x} = \frac{\partial\theta^{(c)}}{\partial x} = \frac{\beta}{\eta - 2\gamma}$ and $\frac{\partial\theta^{(j)}}{\partial x} = \frac{\beta}{\eta - \gamma}$. It is true that $\frac{\partial\theta^{(c)}}{\partial x} \geq \max\left\{\frac{\partial\theta^{(i)}}{\partial x}, \frac{\partial\theta^{(j)}}{\partial x}\right\}$.

In case 6, $\theta^{(i)} = \frac{x_{c^i} + \gamma\theta^{(c)}}{\eta - \gamma}$, $\theta^{(c)} = \frac{x_{c^i} + \gamma\theta^{(i)}}{\eta - \gamma}$, and $\theta^{(j)} = \frac{x_{c^j} + \gamma\theta^{(c)}}{\eta - \gamma}$, thus it holds that $\frac{\partial\theta^{(i)}}{\partial x} = \frac{\partial\theta^{(c)}}{\partial x} = \frac{\partial\theta^{(j)}}{\partial x} = \frac{\beta}{\eta - 2\gamma}$. It is true that $\frac{\partial\theta^{(c)}}{\partial x} \geq \max\left\{\frac{\partial\theta^{(i)}}{\partial x}, \frac{\partial\theta^{(j)}}{\partial x}\right\}$.

In case 7, $\theta^{(i)} = \frac{x_{c^i} + \gamma\theta^{(c)}}{\eta - \gamma}$, $\theta^{(c)} = \frac{x_{c^j} + \gamma\theta^{(j)}}{\eta - \gamma}$, and $\theta^{(j)} = \frac{x_j}{\eta - \gamma}$, thus it holds that $\frac{\partial\theta^{(i)}}{\partial x} = \frac{(\eta - \gamma)^2 + \gamma\eta}{(\eta - \gamma)^3}\beta$, $\frac{\partial\theta^{(j)}}{\partial x} = \frac{\beta}{\eta - \gamma}$, and $\frac{\partial\theta^{(c)}}{\partial x} = \frac{\eta\beta}{(\eta - \gamma)^2}$. It is true that $\frac{\partial\theta^{(c)}}{\partial x} \geq \max\left\{\frac{\partial\theta^{(i)}}{\partial x}, \frac{\partial\theta^{(j)}}{\partial x}\right\}$.

In case 8, $\theta^{(i)} = \frac{x_{c^i} + \gamma\theta^{(c)}}{\eta - \gamma}$, $\theta^{(c)} = \frac{x_{c^j} + \gamma\theta^{(j)}}{\eta - \gamma}$, and $\theta^{(j)} = \frac{x_j}{\eta - \gamma}$, thus it holds that $\frac{\partial\theta^{(i)}}{\partial x} = \frac{\partial\theta^{(j)}}{\partial x} = \frac{\partial\theta^{(c)}}{\partial x} = \frac{\beta}{\eta - 2\gamma}$. It is true that $\frac{\partial\theta^{(c)}}{\partial x} \geq \max\left\{\frac{\partial\theta^{(i)}}{\partial x}, \frac{\partial\theta^{(j)}}{\partial x}\right\}$.

Taken together, it is always true that $\frac{\partial\theta^{(c)}}{\partial x} \geq \max\left\{\frac{\partial\theta^{(i)}}{\partial x}, \frac{\partial\theta^{(j)}}{\partial x}\right\}$.

B Measures for Distress Risk

We use two empirical measures to examine firms' distress risk.

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.

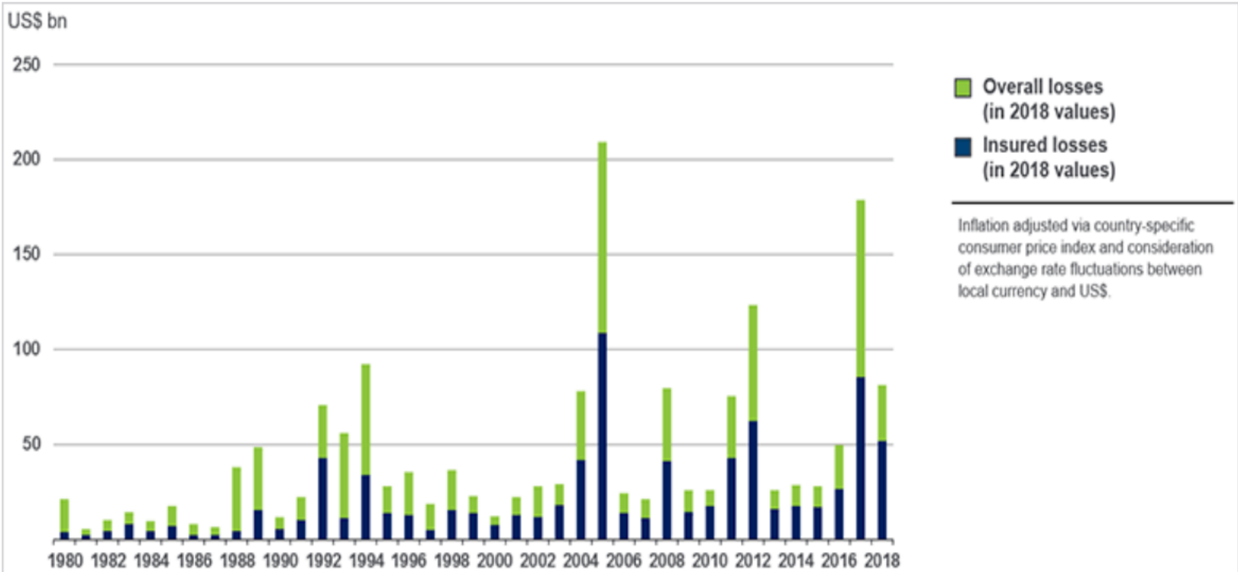
C Natural Disasters and Distress Risk

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).

C.2 Hurricanes Harvey and Irma: An Example

Hurricanes Harvey and Irma caused huge amount of damage to the U.S. 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). This finding is consistent with our theory which predicts intensified product market competition in response to firms' increased distress risk.



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

Note: This figure plots the overall and insured losses from U.S. natural disasters from 1980 to 2018. The figure is taken from the research report titled "Facts + Statistics: U.S. 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 U.S. natural disasters from 1980 to 2018.

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).

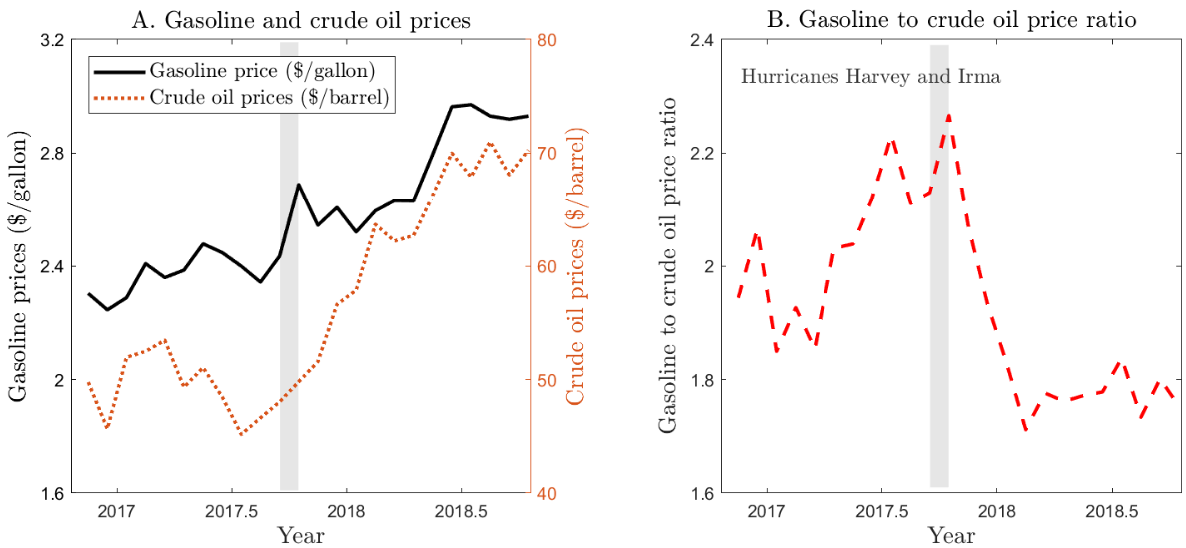
Degree Centrality. Degree centrality is the number of direct links a node has with other nodes in the network. The more links the node has, the more central this node is in the network. The mathematical definition for degree centrality is:

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

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:

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



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.

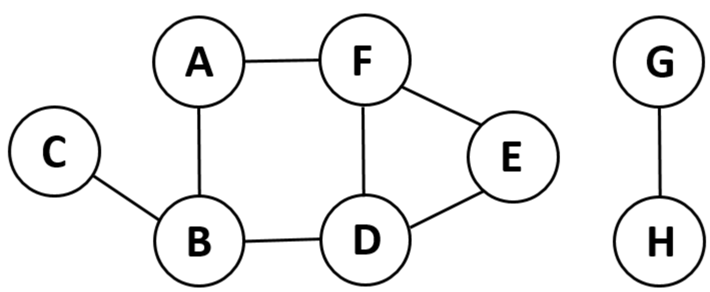


Figure A.3: An example network.

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.

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

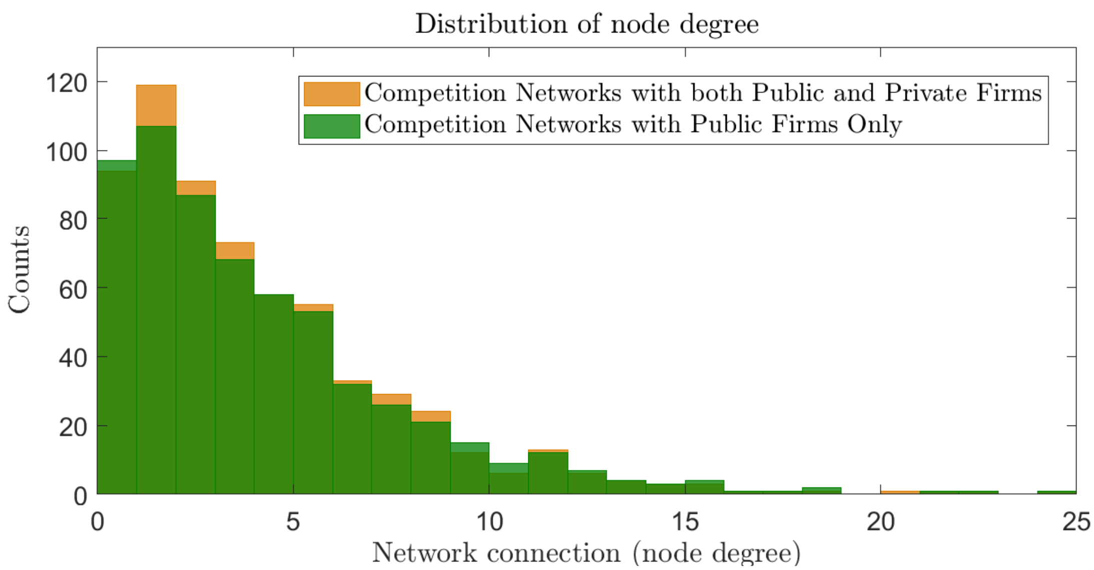


Figure A.4: Node degree of the competition networks with and without private firms at the four-digit SIC industry level in 1994.

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.

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.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
5.74**	3.88	7.12***	8.29***	9.17***	3.43**
[2.20]	[1.53]	[2.88]	[3.32]	[3.61]	[2.34]

Panel B: alphas of the long-short portfolios sorted on competition centrality

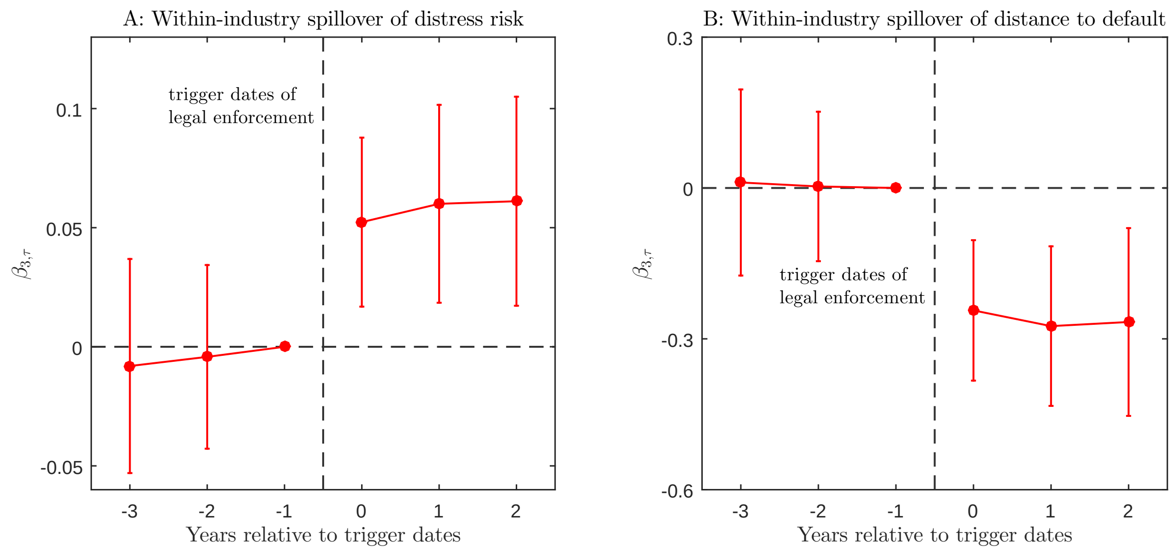
CAPM α (%)	Fama-French three-factor α (%)	Carhart four-factor α (%)	Fama-French five-factor α (%)	Hou-Xue-Zhang q-factor α (%)
2.96**	3.03*	3.66**	5.08***	5.72***
[1.98]	[1.90]	[2.13]	[3.15]	[3.25]

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 $t+1$. The sample period of the data is from July 1977 to June 2018. Because common leaders operate in more than one industries, we exclude them in computing industry returns. We exclude financial and utility industries and 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. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

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

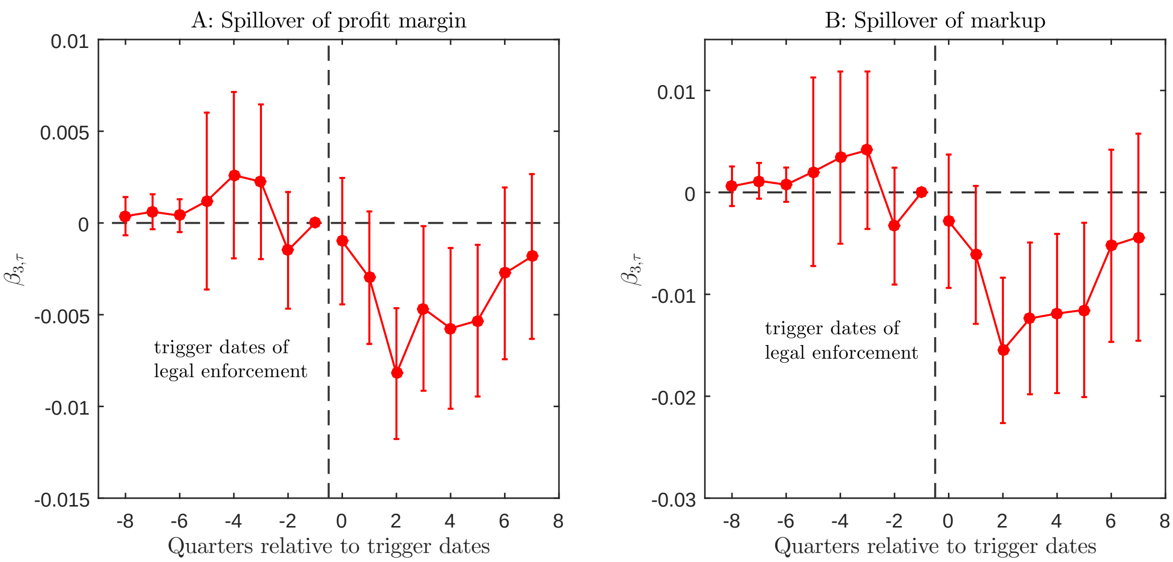
	(1)	(2)	(3)	(4)	(5)	(6)
			$Ret_{i,t}$ (%)			
$Competition\_Centrality_{i,t-1}$	0.151***	0.151***	0.093***	0.083***	0.088***	0.152***
	[2.961]	[2.907]	[2.838]	[2.590]	[2.798]	[3.404]
$Production\_Centrality_{i,t-1}$		0.079	−0.008	−0.026	−0.026	−0.112
		[1.555]	[−0.177]	[−0.578]	[−0.572]	[−1.440]
$Lnsize_{i,t-1}$			0.209**	0.286***	0.305***	0.486***
			[2.376]	[3.414]	[3.610]	[3.840]
$LnBEME_{i,t-1}$				0.150**	0.179***	0.352***
				[2.362]	[2.751]	[3.812]
$GP_{i,t-1}$					0.147**	0.266***
					[2.547]	[3.053]
$HHI_{i,t-1}$						−0.020
						[−0.319]
Constant	0.987***	0.973***	0.792***	0.783***	0.778***	0.537*
	[3.762]	[3.621]	[2.775]	[2.774]	[2.763]	[1.784]
Average obs/month	204	204	200	199	199	98
Average R-squared	0.005	0.010	0.031	0.044	0.057	0.102

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 size ($Lnsize_{i,t-1}$), 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 size is the market equity 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). 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 U.S. Census which covers manufacturing industries. All the independent variables are standardized to have means of 0 and standard deviations of 1. The sample period of the data is from 1977 to 2018. Because common leaders operate in more than one industries, we exclude them in computing industry returns and characteristics. We exclude financial and utility industries and industries that contain fewer than three firms from the analysis. . *, **, 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. $StockRet_{i,t-3:t-1}$ is the average stock returns of firm i from year $t-3$ to 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 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 line represents 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. $StockRet_{i,t-12:t-1}$ is the average stock returns of firm i from quarter $t - 12$ to quarter 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 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 line represents 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)
					$Competition\_Centrality_{i,t}$					
$Production\_Centrality_{i,t}$	0.042	0.042	0.049	0.035	0.045	0.032	0.045	0.033	0.005	−0.002
	[1.284]	[1.290]	[1.488]	[1.064]	[1.347]	[0.967]	[1.373]	[1.004]	[0.079]	[−0.040]
$Lnsize_{i,t}$			−0.018	0.038	−0.001	0.050	−0.004	0.046	0.136	0.152
			[−0.563]	[0.885]	[−0.030]	[1.127]	[−0.116]	[0.984]	[1.487]	[1.488]
$LnBEME_{i,t}$					0.054**	0.041	0.050*	0.033	0.052	0.022
					[1.996]	[1.470]	[1.901]	[1.210]	[0.870]	[0.354]
$GP_{i,t}$							−0.011	−0.023	−0.156*	−0.171*
							[−0.317]	[−0.659]	[−1.719]	[−1.876]
$HHI_{i,t}$									0.103	0.112
									[1.067]	[1.159]
Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	8996	8996	8849	8849	8827	8827	8802	8802	3253	3253
R-squared	0.002	0.018	0.002	0.020	0.005	0.021	0.005	0.022	0.034	0.065

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. $Lnsize_{i,t}$ is the natural log of industry size, which is the market equity of an industry. $LnBEME_{i,t}$ 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 U.S. 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. The sample period of the data is from 1977 to 2018. Because common leaders operate in more than one industries, we exclude them in computing industry returns and characteristics. We exclude financial and utility industries and industries that contain fewer than three firms from the analysis. *, **, 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					
6.10*	6.52*	6.35*	6.94**	9.54***	3.43**
[1.93]	[1.93]	[1.76]	[2.28]	[2.89]	[2.19]
Panel B: double sort on industry size					
6.17*	6.61*	6.16*	7.07**	9.66***	3.49**
[1.94]	[1.96]	[1.80]	[2.20]	[2.97]	[2.23]
Panel C: double sort on industry book-to-market ratio					
5.13	6.40*	7.26**	7.41**	9.38***	4.25***
[1.60]	[1.90]	[2.04]	[2.39]	[2.87]	[2.64]
Panel D: double sort on industry gross profitability					
5.57*	6.53*	6.67*	7.65**	8.95***	3.38**
[1.67]	[1.95]	[1.96]	[2.43]	[2.75]	[2.13]
Panel E: double sort on industry concentration ratio					
4.16	7.28**	7.31**	8.25**	9.16***	5.01***
[1.30]	[2.13]	[2.18]	[2.47]	[2.89]	[3.21]

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 $t+1$. The sample period of the data is from July 1977 to June 2018. Because common leaders operate in more than one industries, we exclude them in computing industry returns and characteristics. We exclude financial and utility industries and 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 market equity 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 U.S. Census which covers manufacturing industries. Newey-West standard errors are estimated with one lag. We annualize average excess returns by multiplying them by 12. 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 α (%)	Fama-French three-factor α (%)	Carhart four-factor α (%)	Fama-French five-factor α (%)	Hou-Xue-Zhang q-factor α (%)
		Panel A: double sort on production network centrality		
3.13^{*}	2.90^{*}	3.75^{**}	3.92^{**}	5.09^{**}
[1.96]	[1.80]	[2.07]	[2.39]	[2.59]
		Panel B: double sort on industry size		
3.33^{***}	3.28^{**}	3.82^{**}	5.16^{***}	5.90^{***}
[2.09]	[1.99]	[2.10]	[3.12]	[3.01]
		Panel C: double sort on industry book-to-market ratio		
3.95^{**}	4.17^{**}	4.42^{**}	5.53^{***}	6.25^{***}
[2.43]	[2.47]	[2.40]	[3.17]	[3.08]
		Panel D: double sort on industry profitability		
3.38^{**}	3.41^{**}	3.18^{*}	4.04^{**}	4.13^{*}
[2.10]	[2.03]	[1.65]	[2.23]	[1.86]
		Panel E: double sort on industry concentration ratio		
4.98^{***}	5.13^{***}	5.42^{***}	6.43^{***}	7.19^{***}
[3.17]	[3.15]	[2.98]	[3.79]	[3.63]

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 $t+1$. The sample period of the data is from July 1977 to June 2018. Because common leaders operate in more than one industries, we exclude them in computing industry returns and characteristics. We exclude financial and utility industries and 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 market equity 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 U.S. Census which covers manufacturing industries. Newey-West standard errors are estimated with one lag. We annualize alphas by multiplying them by 12. 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 five non-treated peer firms							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.019	0.019	−0.082	−0.083*	−0.001	−0.001	−0.002	−0.002
	[1.516]	[1.532]	[−1.626]	[−1.649]	[−0.364]	[−0.389]	[−0.370]	[0.389]
$Treat_{i,t}$	−0.015	−0.015	0.092*	0.092*	−0.000	−0.000	0.001	0.002
	[−1.293]	[−1.301]	[1.872]	[1.877]	[−0.145]	[−0.134]	[0.288]	[0.296]
$Post_{i,t}$	0.054***	0.053***	−0.129***	−0.121***	−0.005**	−0.005**	−0.011**	−0.010**
	[6.453]	[6.367]	[−4.158]	[−3.933]	[−2.254]	[−2.072]	[−2.483]	[−2.359]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.018**		−0.089**		−0.006***		−0.009**
		[1.976]		[−2.417]		[−2.773]		[−2.146]
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	0.563	0.563	0.666	0.666	0.759	0.759	0.766	0.766
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.003	0.005	0.001	0.002

	Panel B: Matching one treated firm with up to three non-treated peer firms							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.019	0.019	−0.074	−0.075	−0.000	−0.000	−0.000	−0.000
	[1.437]	[1.448]	[−1.424]	[−1.440]	[−0.072]	[−0.085]	[−0.039]	[−0.047]
$Treat_{i,t}$	−0.017	−0.018	0.088*	0.088*	0.001	0.001	0.003	0.003
	[−1.428]	[−1.433]	[1.659]	[1.663]	[0.354]	[0.359]	[0.634]	[0.637]
$Post_{i,t}$	0.058***	0.056***	−0.142***	−0.134***	−0.005**	−0.005**	−0.012***	−0.012***
	[6.170]	[6.082]	[−4.147]	[−3.979]	[−2.577]	[−2.464]	[−2.892]	[−2.841]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.017*		−0.072*		−0.004*		−0.004
		[1.870]		[−1.944]		[−1.832]		[−1.168]
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	0.567	0.567	0.672	0.672	0.765	0.765	0.772	0.772
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.004	0.007	0.001	0.001

Note: This table examines the spillover effects of the major natural disasters with alternative matching ratios between treated firms and non-treated peer firms. In panel A, we match each treated firm with up to five 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 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 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: $Y_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1 + n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}$. 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. $Ln(1 + n(\mathcal{C}_{i,t}))$ 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. In the last row of each 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.9: Matching industry peers with text-based network industry classifications

	Panel A: DID regressions			
	(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	-0.003	-0.007
	[1.011]	[-0.592]	[-1.099]	[-1.263]
$Treat_{i,t}$	-0.010	0.030	0.005^{**}	0.012^{**}
	[-0.930]	[0.622]	[2.014]	[2.347]
$Post_{i,t}$	0.044^{***}	-0.154^{***}	-0.004^{**}	-0.009^{**}
	[5.550]	[-5.119]	[-2.113]	[-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	0.766	0.765
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	0.001	$<10^{-3}$

	Panel B: Firm-peer pairwise panel regressions							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$ND\_Peer_{i,p,t}$	0.010^{**}	0.013^{***}	-0.091^{***}	-0.122^{***}	-0.012^{**}	-0.016^{**}	-0.013^{***}	-0.016^{***}
	[2.479]	[2.719]	[-6.235]	[-6.765]	[-2.143]	[-2.348]	[-3.571]	[-3.609]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No	Yes	No	Yes	No
Peer firm FE	Yes	No	Yes	No	Yes	No	Yes	No
Firm-peer pair FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	4400092	3612527	3509874	2807009	4537208	3751022	4528759	3743574
R-squared	0.585	0.626	0.647	0.712	0.740	0.786	0.764	0.815

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). Panel A presents the results from the DID analysis. 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., $\beta_1 + \beta_3 = 0$). Panel B presents the results from the firm-peer pairwise panel regressions. The data set of this table is a panel that contains pairwise observations between the focal firms and their TNIC industry peers in each year. The regression specification is: $Y_{i,t} = \beta_1 ND\_Peer_{i,p,t} + \Gamma' Controls_{i,t-1} + \theta_{i,p} + \delta_t + \varepsilon_{i,p,t}$. $ND\_Peer_{i,p,t}$ is an indicator variable that equals one if the peer firm p's headquarter or one of its major establishments is negatively affected by a major natural disaster in year t. Control variables are the lagged focal firm characteristics including the natural log of lagged asset size, the natural log of the lagged fixed-asset-to-total-asset ratio, and the natural log of firm age. The term $\theta_{i,p}$ represents firm-peer pair fixed effects, and the term δ_t represents year fixed effects. The sample of this table spans from 1994 to 2018. Standard errors are clustered at the firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

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

	Panel A: DID regressions							
	(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**	0.037***	−0.087*	−0.108**	−0.002	−0.002	−0.006	−0.004
	[2.173]	[2.782]	[−1.723]	[−2.064]	[−0.753]	[−0.612]	[−0.977]	[−0.692]
$Treat_{i,t}$	−0.015	−0.019*	0.086*	0.089*	−0.002	−0.001	−0.001	−0.001
	[−1.318]	[−1.671]	[1.836]	[1.809]	[−0.596]	[−0.467]	[−0.192]	[−0.173]
$Post_{i,t}$	0.048***	0.041***	−0.129***	−0.105***	−0.006**	−0.006**	−0.012***	−0.012**
	[5.856]	[5.006]	[−4.331]	[−3.507]	[−2.504]	[−2.311]	[−2.626]	[−2.551]
$Ln(1+\overline{Damage(\mathcal{C}_{i,t})})$		0.006*		−0.020*		−0.002***		−0.004**
		[1.927]		[−1.797]		[−2.795]		[−2.300]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	194736	178066	161877	148070	202605	186008	202431	185855
R-squared	0.554	0.569	0.656	0.665	0.753	0.756	0.760	0.763
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.001	$<10^{-3}$	$<10^{-3}$

	Panel B: Firm-peer pairwise panel regressions							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$ND\_Peer_{i,p,t}$	0.017***	0.010**	−0.054***	−0.033**	−0.014**	−0.012**	−0.016***	−0.014***
	[3.792]	[2.408]	[−3.261]	[−1.980]	[−2.564]	[−2.282]	[−4.643]	[−4.049]
$Ln(1+\overline{Damage(\mathcal{C}_{i,t})})$		0.024***		−0.077***		−0.011***		−0.014***
		[5.949]		[−5.565]		[−2.595]		[−5.030]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-peer pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2834990	2714096	2110815	2029339	2998774	2883602	2990258	2875917
R-squared	0.626	0.628	0.726	0.728	0.793	0.790	0.821	0.821

Note: This table uses an alternative measure to control for cross-industry spillovers. Specifically, we use $Ln(1+\overline{Damage(\mathcal{C}_{i,t})})$ to capture the strength of cross-industry spillover, and it 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. Panel A presents the results from the DID analysis. 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. 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: $Y_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1+\overline{Damage(\mathcal{C}_{i,t})}) + \theta_i + \delta_t + \varepsilon_{i,t}$. 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. $Ln(1+\overline{Damage(\mathcal{C}_{i,t})})$ captures the strength of cross-industry spillover via the competition network. 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., $\beta_1 + \beta_3 = 0$). Panel B presents the results from the firm-peer pairwise panel regressions. The data set of this table is a panel that contains pairwise observations between the focal firms and their TNIC industry peers in each year. The regression specification is: $Y_{i,t} = \beta_1 ND\_Peer_{i,p,t} + \beta_2 Ln(1+\overline{Damage(\mathcal{C}_{i,t})}) + \Gamma' Controls_{i,t-1} + \theta_{i,p} + \delta_t + \varepsilon_{i,p,t}$. $ND\_Peer_{i,p,t}$ is an indicator variable that equals one if the peer firm p's headquarter or one of its major establishments is negatively affected by a major natural disaster in year t. Control variables are the lagged focal firm characteristics including the natural log of lagged asset size, the natural log of the lagged fixed-asset-to-total-asset ratio, and the natural log of firm age. The term $\theta_{i,p}$ represents firm-peer pair fixed effects, and the term δ_t represents year fixed effects. The sample of this table spans from 1994 to 2018. Standard errors are clustered at the firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.11: Heterogeneity across financial leverage

	Panel A: Heterogeneity across financial leverage of the non-affected focal firms							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
Focal firm leverage	High	Low	High	Low	High	Low	High	Low
$ND\_Peer_{i,p,t}$	0.030***	0.004	−0.072***	0.021	−0.030***	−0.009	−0.031***	−0.007
	[3.156]	[0.730]	[−3.132]	[0.285]	[−3.196]	[−0.908]	[−4.075]	[−1.462]
$Ln(1+n(\mathcal{C}_{i,t}))$	0.151***	0.017	−0.283***	−0.288	−0.049***	0.029	−0.070***	0.014
	[6.101]	[0.543]	[−5.223]	[−0.915]	[−2.581]	[0.763]	[−4.807]	[0.678]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-peer pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	821575	924717	891175	115108	903438	935722	902889	931367
R-squared	0.660	0.652	0.757	0.657	0.783	0.835	0.783	0.866

	Panel B: Heterogeneity across financial leverage of the affected peer firms							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
Peer firm leverage	High	Low	High	Low	High	Low	High	Low
$ND\_Peer_{i,p,t}$	0.030***	0.002	−0.049**	−0.019	−0.014***	−0.001	−0.018***	−0.003
	[4.028]	[0.595]	[−2.060]	[−1.127]	[−2.837]	[−0.291]	[−3.048]	[−1.096]
$Ln(1+n(\mathcal{C}_{i,t}))$	0.098***	0.051***	−0.196***	−0.177***	−0.043***	−0.010	−0.067***	−0.016
	[7.173]	[2.763]	[−5.215]	[−2.812]	[−6.452]	[−1.040]	[−7.830]	[−1.410]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-peer pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	765008	794178	632551	535940	813283	840828	811301	838066
R-squared	0.659	0.658	0.760	0.746	0.802	0.849	0.813	0.856

Note: This table examines the heterogeneity of the within-industry spillover effects in the natural disaster setting. Panel A examines the heterogeneity across non-affected focal firms with different levels of financial leverage. Panel B examines the heterogeneity across affected peer firms with different levels of financial leverage. The data set of this table is a panel that contains pairwise observations between the focal firms and their four-digit SIC industry peers in each year. We exclude from our analysis the focal firms that experience natural disaster shocks themselves. The regression specification is: $Y_{i,t} = \beta_1 ND\_Peer_{i,p,t} + \beta_2 Ln(1+n(\mathcal{C}_{i,t})) + \Gamma' Controls_{i,t-1} + \theta_{i,p} + \delta_t + \varepsilon_{i,p,t}$. In panel A, we show the results of the regressions in subgroups with high (top tertile) and low (bottom tertile) levels of financial leverage of the non-affected focal firms. In panel B, we show the results of the regressions in subgroups with high (top tertile) and low (bottom tertile) levels of financial leverage of the affected peer firms. Financial leverage of a firm is measured by the debt-to-total-asset ratio. The dependent variables are the distress risk ($Distress_{i,t}$), distance to default ($DD_{i,t}$), gross profit margin ($PM_{i,t}$), and markup ($Markup_{i,t}$). $ND\_Peer_{i,p,t}$ is an indicator variable that equals one if the peer firm p's headquarter or one of its major establishments is negatively affected by a major natural disaster in year t. $Ln(1+n(\mathcal{C}_{i,t}))$ captures the strength of cross-industry spillover via the competition network. Control variables are the lagged focal firm characteristics including the natural log of lagged asset size, the natural log of the lagged fixed-asset-to-total-asset ratio, and the natural log of firm age. The term $\theta_{i,p}$ represents firm-peer pair fixed effects, and the term δ_t represents year fixed effects. 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 against the demand commonality channel

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Focal firms far from the disaster area (i.e., $\geq$ 100 miles)								
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$ND\_Peer_{i,p,t}$	0.019***	0.015**	−0.071***	−0.054**	−0.011***	−0.010**	−0.018***	−0.016***
	[2.758]	[2.269]	[−2.968]	[−2.309]	[−2.641]	[−2.539]	[−3.598]	[−3.345]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.062***		−0.196***		−0.010		−0.027**
		[3.394]		[−3.259]		[−1.009]		[−2.305]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-peer pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1897274	1897274	1440375	1440375	2023336	2023336	2017516	2017516
R-squared	0.644	0.645	0.742	0.742	0.805	0.805	0.817	0.817
Panel B: Focal firms far from the disaster area + without affected customers								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$ND\_Peer_{i,p,t}$	0.017**	0.013**	−0.063***	−0.047*	−0.013***	−0.012***	−0.020***	−0.019***
	[2.516]	[2.027]	[−2.579]	[−1.936]	[−3.067]	[−2.985]	[−4.033]	[−3.785]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.060***		−0.200***		−0.009		−0.028***
		[3.264]		[−3.303]		[−0.952]		[−2.433]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-peer pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1833603	1833603	1391703	1391703	1955832	1955832	1950028	1950028
R-squared	0.648	0.648	0.743	0.743	0.806	0.806	0.818	0.818
Panel C: Focal firms far from the disaster area + without affected customers + non-consumer facing industries								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$ND\_Peer_{i,p,t}$	0.030***	0.026***	−0.100***	−0.079**	−0.024***	−0.023***	−0.035***	−0.032***
	[2.913]	[2.676]	[−2.817]	[−2.283]	[−3.424]	[−3.357]	[−4.175]	[−3.934]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.038*		−0.188***		−0.010		−0.032**
		[1.858]		[−2.739]		[−0.845]		[−2.169]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-peer pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1074749	1074749	857469	857469	1114534	1114534	1110067	1110067
R-squared	0.640	0.640	0.732	0.733	0.791	0.791	0.786	0.786

Note: This table tests against the demand commonality channel. The data set of this table is a panel that contains pairwise observations between the focal firms and their four-digit SIC industry peers in each year. We exclude from our analysis the focal firms that experience natural disaster shocks themselves. In panel A, we remove focal firms that locate within 100 miles from any zip code negatively affected by the major natural disasters in a given year. In panel B, based on the sample in panel A, we further remove focal 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. In panel C, based on the sample in panel B, we further remove focal firms in the consumer-facing industries (i.e., airlines, grocery stores, hotels, retailers, restaurants, utilities, and many online services).The regression specification is: $Y_{i,t} = \beta_1 ND\_Peer_{i,p,t} + \beta_2 Ln(1+n(\mathcal{C}_{i,t})) + \Gamma' Controls_{i,t-1} + \theta_{i,p} + \delta_t + \varepsilon_{i,p,t}$. The dependent variables are the distress risk ($Distress_{i,t}$), distance to default ($DD_{i,t}$), gross profit margin ($PM_{i,t}$), and markup ($Markup_{i,t}$). $ND\_Peer_{i,p,t}$ is an indicator variable that equals one if the peer firm p's headquarter or one of its major establishments is negatively affected by a major natural disaster in year t. $Ln(1+n(\mathcal{C}_{i,t}))$ captures the strength of cross-industry spillover via the competition network. Control variables are the lagged focal firm characteristics including the natural log of lagged asset size, the natural log of the lagged fixed-asset-to-total-asset ratio, and the natural log of firm age. The term $\theta_{i,p}$ represents firm-peer pair fixed effects, and the term δ_t represents year fixed effects. 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: Removing firm-peer pairs linked through supply chains

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Removing peer firms that are suppliers or customers of the focal firms								
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$ND\_Peer_{i,p,t}$	0.017***	0.012***	−0.055***	−0.040**	−0.014**	−0.012**	−0.017***	−0.014***
	[3.808]	[2.922]	[−3.301]	[−2.449]	[−2.543]	[−2.173]	[−4.640]	[−4.138]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.076***		−0.192***		−0.032**		−0.039***
		[5.041]		[−3.813]		[−1.982]		[−4.045]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-peer pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2826313	2826313	2103284	2103284	2989874	2989874	2981367	2981367
R-squared	0.626	0.627	0.725	0.726	0.793	0.793	0.821	0.821
Panel B: Further removing firm-pairs with top 10% vertical relatedness scores								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$ND\_Peer_{i,p,t}$	0.017***	0.013***	−0.043**	−0.030*	−0.013**	−0.011*	−0.016***	−0.014***
	[3.778]	[2.976]	[−2.481]	[−1.723]	[−2.186]	[−1.876]	[−4.346]	[−3.897]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.078***		−0.190***		−0.032*		−0.040***
		[4.712]		[−3.412]		[−1.658]		[−3.668]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-peer pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2589296	2589296	1899712	1899712	2738863	2738863	2730469	2730469
R-squared	0.627	0.628	0.726	0.726	0.790	0.790	0.822	0.822

Note: This table performs the pairwise analysis by removing firm-peer pairs linked through the supply chains. The data set of this table is a panel that contains pairwise observations between the focal firms and their four-digit SIC industry peers in each year. In panel A, we remove the observations in which the focal firm i is a supplier or a customer of the peer firm p. We identify the supplier-customer links using the Compustat customer segment data and the Factset Revere data. In panel B, we further remove the firm-pairs with top 10% of vertical relatedness scores (see, Frésard, Hoberg and Phillips, 2020). We exclude from our analysis the focal firms that experience natural disaster shocks themselves. The regression specification is: $Y_{i,t} = \beta_1 ND\_Peer_{i,p,t} + \beta_2 Ln(1+n(\mathcal{C}_{i,t})) + \Gamma' Controls_{i,t-1} + \theta_{i,p} + \delta_t + \varepsilon_{i,p,t}$. The dependent variables are the distress risk ($Distress_{i,t}$), distance to default ($DD_{i,t}$), gross profit margin ($PM_{i,t}$), and markup ($Markup_{i,t}$). $ND\_Peer_{i,p,t}$ is an indicator variable that equals one if the peer firm p's headquarter or one of its major establishments is negatively affected by a major natural disaster in year t. $Ln(1+n(\mathcal{C}_{i,t}))$ captures the strength of cross-industry spillover via the competition network. Control variables are the lagged focal firm characteristics including the natural log of lagged asset size, the natural log of the lagged fixed-asset-to-total-asset ratio, and the natural log of firm age. The term $\theta_{i,p}$ represents firm-peer pair fixed effects, and the term δ_t represents year fixed effects. 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: Response of profit margin to natural disaster shocks of suppliers and customers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$PM_{i,t}$		$Markup_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$ND\_Supplier_{i,s,t}$	-0.001	-0.001	-0.003	-0.003				
	$[-0.719]$	$[-1.134]$	$[-1.449]$	$[-1.488]$				
$ND\_Customer_{i,c,t}$					-0.001	-0.002	-0.003	-0.005
					$[-0.657]$	$[-1.181]$	$[-0.659]$	$[-0.774]$
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No	Yes	No	Yes	No
Supplier FE	Yes	No	Yes	No	/	/	/	/
Customer FE	/	/	/	/	Yes	No	Yes	No
Supplier-customer pair FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	79225	62299	79224	62298	69710	53392	69690	53376
R-squared	0.923	0.950	0.929	0.956	0.890	0.912	0.853	0.881

Note: This table examines the response of the focal firms' profit margin to natural disaster shocks of their suppliers and customers. The data set in columns (1) – (4) (columns 5 – 8) of this table is a panel that contains pairwise observations between the focal firms and their suppliers (customers) in each year. We identify the supplier-customer links using the Compustat customer segment data and the Factset Revere data. We exclude from our analysis the focal firms that experience natural disaster shocks themselves. The regression specification in columns (1) – (4) is: $Y_{i,t} = \beta_1 ND\_Supplier_{i,s,t} + \Gamma' Controls_{i,t-1} + \theta_{i,s} + \delta_t + \varepsilon_{i,s,t}$, and the regression specification in columns (5) – (8) is: $Y_{i,t} = \beta_1 ND\_Customer_{i,c,t} + \Gamma' Controls_{i,t-1} + \theta_{i,c} + \delta_t + \varepsilon_{i,c,t}$. The dependent variables are the gross profit margin ($PM_{i,t}$) and markup ($Markup_{i,t}$). $ND\_Supplier_{i,s,t}$ is an indicator variable that equals one if the supplier s of the focal firm i's headquarter or one of its major establishments is negatively affected by a major natural disaster in year t. $ND\_Customer_{i,c,t}$ is an indicator variable that equals one if the customer c of the focal firm i's headquarter or one of its major establishments is negatively affected by a major natural disaster in year t. Control variables are the lagged focal firm characteristics including the natural log of lagged asset size, the natural log of the lagged fixed-asset-to-total-asset ratio, and the natural log of firm age. The term $\theta_{i,s}$ and $\theta_{i,c}$ represent customer-supplier pair fixed effects, and the term δ_t represents year fixed effects. 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: Response of profit margin to natural disaster shocks of upstream and downstream firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$PM_{i,t}$		$Markup_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$ND\_Upstream_{i,u,t}$	0.000	0.000	0.000	0.000				
	[0.745]	[0.929]	[0.307]	[0.261]				
$ND\_Downstream_{i,d,t}$					0.000	0.000	−0.000	−0.000
					[0.068]	[0.221]	[−0.778]	[−0.600]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No	Yes	No	Yes	No
Upstream firm FE	Yes	No	Yes	No	/	/	/	/
Downstream firm FE	/	/	/	/	Yes	No	Yes	No
Upstream-downstream firm pair FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	40694793	35774837	40686572	35766799	40460271	35596054	40454064	35590404
R-squared	0.840	0.873	0.797	0.832	0.835	0.867	0.787	0.821

Note: This table examines the response of the focal firms' profit margin to natural disaster shocks of their upstream and downstream firms. The data set in columns (1) – (4) (columns 5 – 8) of this table is a panel that contains pairwise observations between the focal firms and their upstream (downstream) firms in each year. We identify the upstream-downstream relationship based on the top 10% of vertical relatedness scores in Frésard, Hoberg and Phillips (2020). We exclude from our analysis the focal firms that experience natural disaster shocks themselves. The regression specification in columns (1) – (4) is: $Y_{i,t} = \beta_1 ND\_Upstream_{i,u,t} + \Gamma' Controls_{i,t-1} + \theta_{i,u} + \delta_t + \varepsilon_{i,u,t}$, and the regression specification in columns (5) – (8) is: $Y_{i,t} = \beta_1 ND\_Downstream_{i,d,t} + \Gamma' Controls_{i,t-1} + \theta_{i,d} + \delta_t + \varepsilon_{i,d,t}$. The dependent variables are the gross profit margin ($PM_{i,t}$) and markup ($Markup_{i,t}$). $ND\_Upstream_{i,u,t}$ is an indicator variable that equals one if the headquarter county of the upstream firm u of the focal firm i's headquarter or one of its major establishments is negatively affected by a major natural disaster in year t. $ND\_Downstream_{i,d,t}$ is an indicator variable that equals one if the headquarter county of the downstream firm d of the focal firm i's headquarter or one of its major establishments is negatively affected by a major natural disaster in year t.. Control variables are the lagged focal firm characteristics including the natural log of lagged asset size, the natural log of the lagged fixed-asset-to-total-asset ratio, and the natural log of firm age. The term $\theta_{i,u}$ and $\theta_{i,d}$ represent customer-supplier pair fixed effects, and the term δ_t represents year fixed effects. 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.16: Removing firm-peer pairs linked through common customers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$ND\_Peer_{i,p,t}$	0.017***	0.012***	−0.055***	−0.040**	−0.014**	−0.012**	−0.017***	−0.014***
	[3.790]	[2.926]	[−3.295]	[−2.448]	[−2.560]	[−2.192]	[−4.727]	[−4.236]
$Ln(1 + n(\mathcal{C}_{i,t}))$		0.075***		−0.192***		−0.032**		−0.039***
		[4.939]		[−3.825]		[−1.961]		[−4.044]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-peer pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2767153	2767153	2057932	2057932	2928104	2928104	2919606	2919606
R-squared	0.627	0.628	0.726	0.726	0.794	0.794	0.823	0.823

Note: This table performs the pairwise analysis by removing firm-peer pairs linked through common customers. The data set of this table is a panel that contains pairwise observations between the focal firms and their four-digit SIC industry peers in each year. We remove the observations in which the focal firm i and the peer firm p share at least one common customer. We identify the supplier-customer links using the Compustat customer segment data and the Factset Revere data. We exclude from our analysis the focal firms that experience natural disaster shocks themselves. The regression specification is: $Y_{i,t} = \beta_1 ND\_Peer_{i,p,t} + \beta_2 Ln(1 + n(\mathcal{C}_{i,t})) + \Gamma' Controls_{i,t-1} + \theta_{i,p} + \delta_t + \varepsilon_{i,p,t}$. The dependent variables are the distress risk ($Distress_{i,t}$), distance to default ($DD_{i,t}$), gross profit margin ($PM_{i,t}$), and markup ($Markup_{i,t}$). $ND\_Peer_{i,p,t}$ is an indicator variable that equals one if the peer firm p's headquarter or one of its major establishments is negatively affected by a major natural disaster in year t. $Ln(1 + n(\mathcal{C}_{i,t}))$ captures the strength of cross-industry spillover via the competition network. Control variables are the lagged focal firm characteristics including the natural log of lagged asset size, the natural log of the lagged fixed-asset-to-total-asset ratio, and the natural log of firm age. The term $\theta_{i,p}$ represents firm-peer pair fixed effects, and the term δ_t represents year fixed effects. 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.17: Firms' profit margin and the distress risk of their customers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$PM_{i,t}$		$Markup_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$Distress\_Customers_{i,t}$	0.001	0.001	0.006**	0.004				
	[1.404]	[0.722]	[2.373]	[1.581]				
$DD\_Customers_{i,t}$					−0.001	−0.001	−0.005***	−0.002
					[−1.428]	[−1.110]	[−2.610]	[−1.468]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	20661	19663	20654	19657	20661	19663	20654	19657
R-squared	0.022	0.785	0.022	0.752	0.022	0.785	0.023	0.752

Note: This table examines the relation between firms' profit margin and the distress risk of their customers. The data set of this table is a firm-year panel in which we exclude from our analysis the focal firms that experience natural disaster shocks. The regression specification in columns (1) – (4) is: $Y_{i,t} = \beta_1 Distress\_Customers_{i,t} + \Gamma' Controls_{i,t-1} + \theta_i + \delta_t + \varepsilon_{i,t}$, and the regression specification in columns (5) – (8) is: $Y_{i,t} = \beta_1 DD\_Customers_{i,t} + \Gamma' Controls_{i,t-1} + \theta_i + \delta_t + \varepsilon_{i,t}$. The dependent variables are the gross profit margin ($PM_{i,t}$) and markup ($Markup_{i,t}$). The independent variable $Distress\_Customers_{i,t}$ in columns (1) – (4) is the aggregate distress risk of all customers of firm i weighted based on the sales from firm i to the customer firms. The independent variable $DD\_Customers_{i,t}$ in columns (3) – (4) is the aggregate distance to default of all customers of firm i weighted based on the sales from firm i to the customer firms. We identify the supplier-customer links using the Compustat customer segment data and the Factset Revere data. Control variables are the lagged focal firm characteristics including the natural log of lagged asset size, the natural log of the lagged fixed-asset-to-total-asset ratio, and the natural log of firm age. The term θ_i represents firm fixed effects, and the term δ_t represents year fixed effects. 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.18: Testing against the credit lending channel

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}$		$DD_{i,t}$		$PM_{i,t}$		$Markup_{i,t}$	
$ND\_Peer_{i,p,t}$	0.051***	0.035***	−0.114***	−0.085**	−0.018**	−0.014**	−0.025**	−0.019**
	[3.841]	[3.109]	[−2.967]	[−2.370]	[−2.383]	[−2.077]	[−2.498]	[−2.115]
$Lender\_Exposure_{i,t-1}$	0.198	0.162	0.472	0.535	−0.021	−0.012	−0.068	−0.054
	[1.262]	[1.060]	[1.005]	[1.145]	[−0.493]	[−0.293]	[−1.227]	[−0.977]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.130***		−0.227***		−0.033***		−0.054***
		[4.745]		[−2.746]		[−3.755]		[−4.097]
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-peer pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	495725	495725	461662	461662	517713	517713	517575	517575
R-squared	0.665	0.666	0.787	0.788	0.762	0.762	0.848	0.849

Note: This table tests against the credit lending channel by including focal firms' exposure to natural disasters through lenders ($Lender\_Exposure_{i,t-1}$) as a control variable. We construct $Lender\_Exposure_{i,t-1}$ based on the LPC DealScan database. We first find out the exposure to natural disasters for each lender l in each year t. Specifically, we compute the dollar amount of loans that are issued by leader l from $t-5$ to $t-1$ and remain outstanding in year t to firms that experience natural disasters in year t. We then normalize this amount by the amount of loan outstanding. We focus on loans issued in the proceeding five-year window following the literature (e.g., Bharath et al., 2007). Next, for each firm i, we compute its exposure to natural disasters through lenders by aggregating the lender-level exposure across all lenders. The aggregation is value weighted based on the outstanding loan amount borrowed from different lenders. The data set of this table is a panel that contains pairwise observations between the focal firms and their four-digit SIC industry peers in each year. We exclude from our analysis the focal firms that experience natural disaster shocks themselves. The regression specification is: $Y_{i,t} = \beta_1 ND\_Peer_{i,p,t} + \beta_2 Lender\_Exposure_{i,t-1} + \beta_3 Ln(1+n(\mathcal{C}_{i,t})) + \Gamma' Other\_Controls_{i,t-1} + \theta_{i,p} + \delta_t + \varepsilon_{i,p,t}$. The dependent variables are the distress risk ($Distress_{i,t}$), distance to default ($DD_{i,t}$), gross profit margin ($PM_{i,t}$), and markup ($Markup_{i,t}$). $ND\_Peer_{i,p,t}$ is an indicator variable that equals one if the peer firm p's headquarter or one of its major establishments is negatively affected by a major natural disaster in year t. $Ln(1+n(\mathcal{C}_{i,t}))$ captures the strength of cross-industry spillover via the competition network. Other control variables are the lagged focal firm characteristics including the natural log of lagged asset size, the natural log of the lagged fixed-asset-to-total-asset ratio, and the natural log of firm age. The term $\theta_{i,p}$ represents firm-peer pair fixed effects, and the term δ_t represents year fixed effects. 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.19: Summary statistics for the cross-industry contagion analysis.

	Obs. #	Mean	Median	SD	p10th	p25th	p75th	p90th
$Distress_t^{(c_{i,j})}$	7058	-7.567	-7.727	0.702	-8.325	-8.091	-7.203	-6.437
$DD_t^{(c_{i,j})}$	6882	6.405	5.666	4.630	0.629	2.748	9.560	14.109
$PM_t^{(c_{i,j})}$	7166	0.314	0.300	0.140	0.131	0.200	0.412	0.538
$Markup_t^{(c_{i,j})}$	7166	0.415	0.356	0.269	0.141	0.223	0.530	0.773
$ND_{i,t}^{(1)}$	8415	0.104	0	0.306	0	0	0	1
$ND_{i,t}^{(2)}$	8415	0.109	0	0.312	0	0	0	1
$ND_{i,t}^{(3)}$	8415	0.114	0	0.318	0	0	0	1
$Distress_{i,t}^{(-c)}$	5346	-5.869	-6.732	2.332	-7.985	-7.564	-4.925	-1.770
$DD_{i,t}^{(-c)}$	5346	4.628	3.884	3.915	0.014	1.756	6.647	9.932
$PM_{i,t}^{(-c)}$	5346	0.264	0.263	0.146	0.068	0.155	0.364	0.469
$Markup_{i,t}^{(-c)}$	5346	0.361	0.320	0.256	0.078	0.180	0.483	0.674
$\widehat{IdShock}_{-i,t}(Distress)$	5346	-7.566	-7.582	0.026	-7.582	-7.582	-7.551	-7.515
$\widehat{IdShock}_{-i,t}(DD)$	5346	6.404	6.469	0.117	6.204	6.364	6.468	6.458
$\widehat{IdShock}_{-i,t}(PM)$	5346	0.314	0.3189	0.009	0.296	0.308	0.319	0.319
$\widehat{IdShock}_{-i,t}(Markup)$	5346	0.415	0.425	0.018	0.379	0.407	0.425	0.425
$Forward\_connectedness_{-i,i,t}$	5346	0.002	0	0.009	0	0	0	0
$Backward\_connectedness_{-i,i,t}$	5346	0.001	0	0.006	0	0	0	0

Note: This table reports the summary statistics for variables in Table 9.

Table A.20: 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 using a heterogenous spillover model. 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 (columns 1–4) and the HP index (columns 5–8). 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. 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.