Competition Network: Distress Spillovers and Predictable Industry Returns

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Abstract

We build a competition network of industries — two industries are connected if they share at least one multi-industry firm that competes as a major player in both. Exploiting quasi-experiments induced by the local-natural-disaster occurrences, Lehman failure, and American-Jobs-Creation-Act passage, we find that firms hit by adverse (positive) distress shocks decrease (increase) profit margins, and in response, their "untreated" industry peers, driven by intensified (eased) competition, also cut (raise) profit margins and become more (less) distressed. Further, distress shocks and the resulting changes in competition intensity can propagate to other industries through common major players. Such cross-industry spillovers, with investors' learning frictions, rationalize industry return predictability through the competition-network links.

Keywords: Cross-industry momentum, Economic and financial distress, Natural disasters, Spillover effect, Treatment externality. (**JEL**: G32, G33, L11, L14)

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1 Introduction

Strategic competition among market leaders in product markets plays a vital role in determining firms' cash flows and thus their distress levels, reflecting both economic and financial distress. The reason is threefold. First, product markets are often concentrated in the hands of a few market leaders, some of which are considered superstar firms.[1] Second, market leadership is rather persistent, which stimulates highly strategic competition. Third, markups and profitability, sustained by strategic competition in concentrated industries, are high, and their changes account for a substantial fraction of variation in corporate earnings, especially for the market leaders.[2]

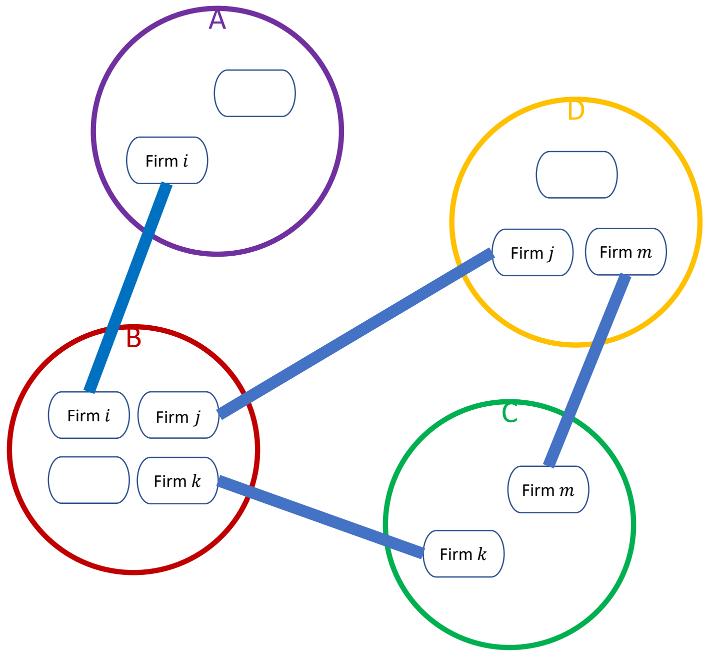
Motivated by these facts, there have been theoretical and empirical studies showing that strategic competition behavior, such as price-setting behavior, and distress risk strongly interact with each other.[3] However, until recently there has been relatively little evidence on the (direct) causal effect of distress shocks on the profit margin of a treated firm, and there has been even less evidence on its (indirect) spillover effects on the profit margins and distress levels of the unaffected industry peers, not to mention evidence on the exact mechanisms of product market competition through which distress shocks are propagated cross different industries. As a result, distress propagation through horizontal industry competition, as well as its implications on industry-level expected returns, has been overlooked by the literature. This paper provides the first elements to fill the gap in the literature by showing that strategic competition among industry peers serves as a salient channel through which distress shocks propagate and creates important implications for asset prices.

We first introduce a novel form of network that connects industries through common market leaders (i.e., conglomerates) in product markets. Each industry is a node on the competition network, and two industries as two nodes are linked if and only if they share common market leaders which are multi-industry firms (see Figure 1). We compare the competition network with the production network of industries at the same level, and find that they have distinctive network structures with little overlap. We show that there are indeed many multi-industry market leaders that connect the related industries on the competition network in the data, consistent with the findings of Hoberg and Phillips

[1]See, e.g., Gutiérrez and Philippon (2017), Autor et al. (2020), De Loecker, Eeckhout and Unger (2020), and Dou, Ji and Wu (2021*a*, Online Appendix B).

[2]See, e.g., Gutiérrez, Jones and Philippon (2019), Grullon, Larkin and Michaely (2019), and Corhay, Kung and Schmid (2020*b*) for evidence on high markups and high profit margins, and Dou, Ji and Wu (2021*a*) and Anderson, Rebelo and Wong (2021) for evidence on strongly pro-cyclical net profit margins.

[3]See, e.g., Maksimovic (1988), Chevalier (1995), Busse (2002), Hortaçsu et al. (2013), Phillips and Sertsios (2013), Koijen and Yogo (2015), Kim (2021), and Chen et al. (2022), with more discussions on existing references and the contributions of this paper in the literature review section.



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.

(2020). Importantly, the majority of the common market leaders are actually not the largest firms nor the least financially distressed firms.

We then exploit three quasi-experiments induced by the occurrences of the local natural disasters, the breakout of the Lehman Brothers bankruptcy, and the passage of the American Jobs Creation Act (AJCA) to estimate the direct, spillover, and total effects of a distress shock on profit margins and distress levels in the short run (i.e., the effect in approximately 1 or 2 years after the treatment). To fix the concept of "distress" in our analysis, we focus on the probability of failure in the short run (i.e., in approximately 1 or 2 years), similar to the concept of distress adopted by Campbell, Hilscher and Szilagyi (2008). Thus, conceptually, both economic and financial distress are considered. We find that firms hit by an adverse distress shock (i.e., the treated firms) decrease profit margins substantially, and in response, their unaffected industry peers, pressed by the intensified product market competition, also cut profit margins by an amount similar to the profit margin cut of the treated firms, and thus become more distressed. We further show that such spillover effect is more pronounced in industries with high entry barriers. On top of within-industry spillovers, distress shocks, together with intensified competition, can also propagate to other industries through common market leaders. Such cross-industry spillover effect is more pronounced when the common market leaders, as the links of the competition network, are more financially consolidated. These results cannot be explained by demand commonality, lender commonality, blockholder commonality, or production network externality.

Inspired by the spillover effects on the competition network, we take the next step to investigate the asset pricing implications of the competition network. Because of the cross-industry spillover effects on the competition network, we expect stock returns of the industries connected through the competition network to comove positively. Moreover, the positive correlation in the industry returns should be, on average, stronger for industries with higher centrality on the competition network because of the "knock-on effect", and for industries whose common market leaders are more financially consolidated. In the presence of investor attention constraints (e.g., Cohen and Frazzini, 2008), we expect that news about peer industries will not be immediately incorporated into the stock prices of the focal industries, thereby generating industry return predictability through competition network. The return predictability should be stronger for focal industries with lower levels of analyst coverage and institutional ownership when investors are more likely to have attention constraints. We find strong evidence supporting the above predictions in the data. Our paper illustrates the cross-industry momentum effects through competition network, which are distinct from previously documented stock-level momentum effects (Jegadeesh and Titman, 1993, 2001) and industry-level momentum effects (Moskowitz and Grinblatt, 1999).

There are at least two different economic mechanisms that can rationalize the observed negative average effect of distress on a firm's profit margin, as well as its negative average within- and cross-industry spillover effects. Admittedly, at an individual industry level, the effect of distress on a firm's profit margin and its spillover effects can vary largely from an industry to another depending on the market structure, even with the sign of these effects flipped in some extreme situations. But, our focus is the average direct and spillover effects over all industries, especially for the asset pricing analysis. We build the idea of competition network into a simple theoretical framework that allows us to derive closed-form model solutions and illustrate the core economic mechanism in a transparent manner in Online Appendix. Although the main contributions of this paper are the empirical findings, the model serves as a coherent conceptual framework to facilitate us to formally set forth the hypotheses, guide the empirical tests, and make sense of the data patterns that we find. Anecdote examples are provided in Online Appendix.

One economic mechanism is the distressed competition under the form of tacit collusion,[4] a theory proposed by Chen et al. (2022). We hypothesize that market leaders

[4]"Tacit collusion" need not involve any collusion with explicit agreements in the legal sense, and an

compete in repeated games and can tacitly collude on their profit margins. If one deviates from the implicit agreement on profit margins, the peers will retaliate by refusing to cooperate any more and compete non-collusively. To ensure that no deviation would occur on the equilibrium path, the benefit of reaping higher short-run profits by undercutting their rivals (i.e., deviating from the implicit agreement) is dominated by the cost of deviation by losing future cooperation value. Higher distress effectively makes firms more impatient and care less about future cooperation, thereby leading to lower collusion capacity and profit margins. In some extreme cases where entry barriers are very high, predatory behaviors and full-blown price wars can occur following an adverse distress shock — financially healthy ("deep-pocket") market leaders may undertake aggressive pricing, even a price war, against weaker rivals to push them out of the business at the cost of lower profits and higher distress in the short run (e.g., Chen et al., 2022). An adverse idiosyncratic distress shock to a market leader thus forces its rivals in the same industry to lower their profit margins because of decreased collusion capacity, making them more distressed in the short-run. Moreover, if some rivals are common market leaders that connect this industry to others, the initial adverse idiosyncratic distress shock can propagate to the connected industries, which leads to the observed patterns of industry returns.

The other economic mechanism is that distressed competitors tend to cut profit margins aggressively to boost the short-run demands in hopes of meeting their high liquidity needs. Particularly, distressed competitors usually find it optimal to sell products (especially, their inventories) in fire sales to boost short-run demand and survive the liquidity shortage (e.g., Kim, 2021). Moreover, distressed competitors can be forced to cut profit margins to prevent their (potential) customers from leaving. This is because consumers naturally become more concerned about the quality of the products when the sellers or producers become more distressed, with a higher likelihood of exiting the business and a higher likelihood of losing key talents in the near future (e.g., Maksimovic and Titman, 1991; Hortaçsu et al., 2013; Dou et al., 2021). In fact, both of the aforementioned specific forces can often be simultaneously in play in reality (e.g., Koijen and Yogo, 2015). Importantly, this economic mechanism does not rely upon the form of competition — collusion or non-collusion. We hypothesize that market leaders that face an adverse distress shock decrease their profit margins by selling products in fire sales (especially, liquidating inventory) to meet liquidity needs, or by cutting prices to retain customers who may expect that the quality of the distressed firms' products would decrease. If one cuts its profit margin aggressively, the peers will react by reducing their profit margins to

interchangeable term is "tacit coordination" (e.g., Ivaldi et al., 2007; Green, Marshall and Marx, 2014).

defend the customer base, making themselves more distressed in the short-run. Similar to the first mechanism above, the initial adverse idiosyncratic distress shock can propagate to the connected industries through the common market leaders, generating the observed patterns of industry returns.

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

The second challenge is to deal with treatment externality (i.e., interference) in the difference-in-differences (DID) setting. The existence of the spillover effect violates the stable unit treatment value assumption (SUTVA), which has served as the basis of causal effect estimation (e.g., Rubin, 1980; Manski, 1993, 2013). To tackle this challenge, we adopt the approach of quasi-natural experiments with partial interference to simultaneously identify the total treatment effect of the treated firms and the spillover effect to non-treated industry peer firms using the DID approach with the group-level spillover effects well controlled for. Similar empirical problem and methods have been studied in the statistical and econometric literature (e.g., Rubin, 1978, 1990; Sobel, 2006; Rosenbaum, 2007; Hudgens and Halloran, 2008; Liu and Hudgens, 2014; Basse and Feller, 2018).[5] We match treated firms (i.e., firms hit by the local natural disasters) with their non-treated industry peer firms in the same industry by asset size, tangibility, and age. We find that the treated firms experience significant increases in distress risk and significant decreases in distance to default, indicating that these firms see increased distress following major natural disasters. Following increases in distress, the treated firms compete more aggressively, as evidenced by significantly reduced gross profit margins. Importantly, consistent with the hypothesis implied by various economic mechanisms, the DID analysis indicates the

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

existence of a strong within-industry spillover effect. Specifically, we find that industry peers that are unaffected directly by natural disasters also exhibit a significant increase in their distress levels.

We explore the heterogeneity of the within-industry spillover effects and also test a list of alternative explanations using the natural disaster setting. We find that the spillover effects are stronger in industries with higher entry barriers. This finding is consistent with the theory work of Chen et al. (2022), who show that firms will compete more aggressively with their distressed peers in industries with higher entry barriers because the winners of a price war in these industries enjoy larger economic rents after pushing out their competitors who are unlikely to be replaced by new entrants. The spillover effects are also stronger in industries with worse economic conditions and higher levels of financial constraints, which is intuitive because firms in these industries are effectively less patient and thus have more incentives to compete after the arrival of negative shocks. We then show that the within-industry spillover effects are unlikely rationalized by a list of alternative explanations including demand commonality, production network externality, lender commonality, and institutional blockholder commonality.

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

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

Related Literature. Our paper contributes to the literature that studies the propagation of shocks in the economy. The extant literature has primarily focused on how shocks propagate across firms, industries, and sectors through input-output linkages, also referred to as production network linkages (e.g., Horvath, 1998, 2000; Cohen and Frazzini, 2008; Acemoglu et al., 2012; Di Giovanni, Levchenko and Mejean, 2014; Barrot and Sauvagnat, 2016; Costello, 2020; Dew-Becker, Tahbaz-Salehi and Vedolin, 2020; Dew-Becker, 2021). Recently, a growing body of research has suggested that the production network externality has important asset pricing implications (e.g., Cohen and Frazzini, 2008; Menzly and Ozbas, 2010; Ahern, 2013; Herskovic, 2018; Herskovic et al., 2020; Gofman, Segal and Wu, 2020; Grigoris, Hu and Segal, 2021; Ozdagli and Weber, 2021). This paper differs from the literature by examining distress propagation through the competition network that connects different product markets. Our analysis is similar to that of Chen et al. (2022) in this regard, but we differ from their paper by being the first to study the distress propagation through product market competition in a causal framework and to document the industry return predictability through the competition network.

Other forms of economic links that connect firms, industries, or sectors have been recently studied in the literature. Some of them are indirect economic links that result in correlated outcomes of different firms. For example, Barrot and Sauvagnat (2016) show that suppliers can exhibit correlated outcomes if they share common business customers on the production network; Coval and Stafford (2007) suggest that stocks can have correlated realized returns if they have common institutional blockholders, and it is possible for the ownership commonality to generate correlated corporate outcomes of firms as well; more generally, the correlated realized returns can be caused by 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); similarly, the correlated performance of investors can be caused by common (or interdependent) assets in these investors' portfolios (e.g., Bebchuk and Goldstein, 2011); in addition, Shue (2013) show that, within an HBS class, firm outcomes are significantly more similar among those whose executives are graduates from the same section than among those whose executives are graduates from different sections. We show that our results cannot be explained by the alternative forms of economic links.

Our paper further contributes to the literature studying the impact of distress risk on firms' competitive behaviors in the product market, pioneered by Titman (1984), Bolton and Scharfstein (1990), Maksimovic and Titman (1991), Chevalier (1995), Phillips (1995), Kovenock and Phillips (1995), Chevalier and Scharfstein (1996), Kovenock and

Phillips (1997), and Zingales (1998), among others. Many papers have theoretically and empirically shown that firms would behave more aggressively in the product market by reducing their own profit margins when they are more distressed both in the time series and in the cross section (e.g., Maksimovic, 1988; Chevalier, 1995; Busse, 2002; Hortaçsu et al., 2013; Phillips and Sertsios, 2013; Koijen and Yogo, 2015; Kim, 2021; Chen et al., 2022), which are consistent with our empirical findings. On the contrary, some customer market theories suggest that firms would behave less aggressively in the product market by increasing profit margins when they are more distressed (at least) in the cross section when the short-run price elasticity of demand is extremely low due to very sticky customer base (e.g., Chevalier and Scharfstein, 1996; Gilchrist et al., 2017; Dou and Ji, 2021), which can well be the dominating force for certain industries in the reality. Financial distress and constraint can also affect firms' competitive behaviors other than profit margins, such as product quality, market preemption, new product introduction, investment, and innovation activities (e.g., Campello, 2006; Matsa, 2011*a*,*b*; Cookson, 2017; Phillips and Sertsios, 2017; Grieser and Liu, 2019). We contribute to the literature in several ways. First, we exploit the natural disaster setting to study the causal impact of distress risk on firms' product market behaviors. By addressing endogeneity concerns, our paper differs from previous studies on the product market implications of firms' (voluntary) decisions on financial structure (e.g., Phillips, 1995; Chevalier, 1995; Kovenock and Phillips, 1997). Second, not only do we study the effect of distress shock on the profit margin of the treated firm, but we also investigate the within- and cross-industry spillover effects of distress shocks on profit margins. Until recently, these spillover effects have been understudied in the literature. Third, we systematically examine changes in the profit margins of distressed firms and their industry peers in a broad sample of industries, which differentiates our paper from previous studies that have focused primarily on product market behaviors in one specific industry (e.g., Zingales, 1998; Busse, 2002; Matsa, 2011*a*,*b*; Hadlock and Sonti, 2012; Hortaçsu et al., 2013; Phillips and Sertsios, 2013; Cookson, 2017, 2018). Fourth, we document a cross-industry distress spillover effect through the competition network, and we show that such a spillover effect is fundamentally different from the spillover of shocks through the production network links.

Our paper also advances the understanding of a core topic in asset pricing — industry equity returns (e.g., Fama and French, 1997). This constitutes a contribution to the asset pricing literature because industry returns are the main driver, rather than merely a sideshow or by-product of salient firm-level equity return patterns. There have been a growing body of studies that aim to improve our understanding of industry returns through the lens of product market characteristics and forces. For example, previous studies have examined the relationship between industry returns and demographic demand shifts (e.g., DellaVigna and Pollet, 2007), industry concentration (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*), durability of products (e.g., Gomes, Kogan and Yogo, 2009), expected inflation (e.g., Boudoukh, Richardson and Whitelaw, 1994), and persistence of market leadership and capacity of tacit coordination (e.g., Dou, Ji and Wu, 2021*a*,*b*; Chen et al., 2022). This paper contributes to the literature by showing that stock returns of the industries connected through the competition network comove positively, and there exists robust industry return predictability through competition network in the presence of investor attention constraints.

Finally, our paper adds to the large literature on equity return predictability. One strand of this literature focuses on the return predictability at the market level (e.g., Shiller, 1984; Keim, 1985; Keim and Stambaugh, 1986; Campbell and Shiller, 1988; Fama and French, 1988; Stambaugh, 1999; Lettau and Ludvigson, 2001; Ang and Bekaert, 2007; Cochrane, 2008; Welch and Goyal, 2008). Another strand of this literature examines return predictability at the stock level, with the types of predictive signals including past own stock returns (e.g., Jegadeesh and Titman, 1993, 2001), past customer stock returns (e.g., Cohen and Frazzini, 2008), investor sentiment (e.g., Baker and Wurgler, 2006; Stambaugh, Yu and Yuan, 2012), investor attention (e.g., Da, Engelberg and Gao, 2011), corporate insider trading (e.g., Jaffe, 1974; Cohen, Malloy and Pomorski, 2012), and mutual fund flows (e.g., Lou, 2012). The return predictability at the industry level, unlike that at the market or stock level, is relatively understudied. Our paper contributes to this strand of literature by documenting the cross-industry momentum effects through competition network and it complements previous studies on the cross-industry momentum effects through production network (Menzly and Ozbas, 2006). The cross-industry momentum effects we document in this paper are distinct from previously documented stock-level momentum effects (Jegadeesh and Titman, 1993, 2001) and industry-level momentum effects (Moskowitz and Grinblatt, 1999). Similar to our paper, Schlag and Zeng (2019) also study the industry return predictability among industries that share horizontal links. We differ from their paper by building a competition network of industries linked through multi-industry firms that compete simultaneously in different industries as major players ("common market leader") and providing causal evidence on the real spillover effects of profit margins and distress levels based on quasi-experiments.

2 Economic Mechanisms and Hypothesis Development

Economic Mechanisms. The hypotheses we set forth and test are based on the idea that market leaders hit by an adverse distress shock, on average, decrease profit margins, and in response, their unaffected industry peers are also likely to cut profit margins pressed by competition, that is, there exist strategic complementarities in profit margins among market leaders in the same industry. We consider two economic mechanisms behind this idea: (i) competition with tacit collusion and (ii) competition with inventory and fragile customer base.

We first consider the mechanism of strategic competition with tacit collusion, which has been empirically shown to be prevalent across different industries.[6] Theoretically, pioneered by Fudenberg and Maskin (1986) and Rotemberg and Saloner (1986), among others, competition with tacit collusion has been studied under the repeated-game framework with the grim trigger strategies in which deviations from the tacit collusion scheme are punished in subsequent periods by reversing to the non-collusive Nash equilibrium of the stage game.

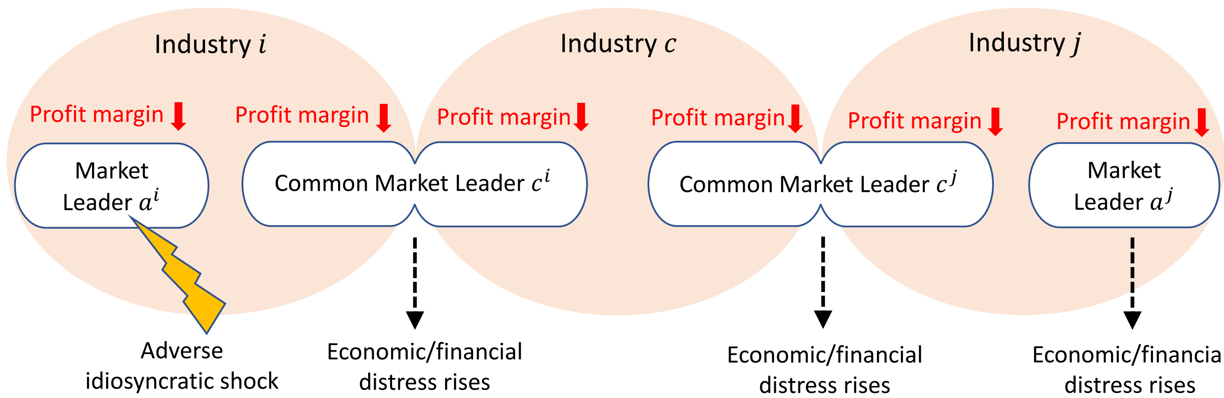
In particular, we hypothesize that market leaders compete in repeated games and can tacitly collude on their profit margins. If one deviates from the implicit agreement on profit margins, the peers will retaliate by refusing to cooperate any more and compete non-collusively in the future. To prevent the deviation from happening on the equilibrium path, the benefit of deviation by reaping higher short-run profits via undercutting their rivals must be dominated by the cost of deviation by losing future cooperation value. Higher distress effectively makes firms more impatient and care less about future cooperation, which leads to lower current collusion capacity and thus pushes down the profit margins. In some extreme cases where entry barriers are very high, predatory behaviors and full-blown price wars can occur as a result of an adverse distress shock. Specifically, financially healthy ("deep-pocket") market leaders that are unaffected by adverse distress shocks may undertake aggressive pricing, even a price war, against weaker rivals that are directly hit by adverse distress shocks to push them out of the business and enjoy the monopoly rents, even though such predatory pricing behaviors are costly to these financially healthy market leaders in the short run due to lower profits and higher distress. Therefore, when an adverse idiosyncratic distress shock hits a market leader, the rivals in the same industry are likely to lower their profit margins because of decreased collusion capacity and thus become more distressed in the short-run. Moreover, if some rivals are common market leaders that connect this industry to others, the initial adverse

[6] There have been extensive granular and direct empirical evidence on tacit collusion in various product markets (see, e.g., Chen et al., 2022, for a review of the existing evidence in the literature).

idiosyncratic distress shock can propagate to the connected industries. This point is made formally in the illustrative model of competition network with tacit collusion (in Online Appendix 2), which is a simplified variant of the full-fledged quantitative dynamic model of Chen et al. (2022).

We next consider an alternative economic mechanism that features product market competition in which distressed competitors tend to cut profit margins aggressively to meet their liquidity needs and to keep their customer base. Distressed competitors often sell products, especially inventories, in fire sales to survive the liquidity shortage (e.g., Kim, 2021). Distressed competitors can also be forced to cut profit margins to maintain the customer base, when customers become more concerned about the product quality due to a higher likelihood of the distressed firms exiting the business and losing key talents (e.g., Maksimovic and Titman, 1991; Hortaçsu et al., 2013; Dou et al., 2021). The above two economic forces can take place simultaneously in reality (e.g., Koijen and Yogo, 2015). Importantly, the alternative economic mechanism we consider here works regardless of the form of competition — collusion or non-collusion. Theoretically, competition with inventory and fragile customer base can be studied under the dynamic game framework with Markov perfect equilibria, in which exit can be an equilibrium outcome and the possibility of a major rival's exit induces predatory pricing, further increasing the probability of exit, in the equilibrium (e.g., Bolton and Scharfstein, 1990; Cabral and Riordan, 1994; Besanko, Doraszelski and Kryukov, 2014).

In particular, we hypothesize that market leaders hit by an adverse distress shock are likely to decrease their profit margins by selling products in a fire sale (especially by liquidating inventory) to meet the liquidity needs, or by cutting prices to guard their fragile customer bases (especially to retain customers who may expect that the quality of the distressed firms' products would decrease), or by both forces. For instance, when life insurance companies fall into distress, regulators require them to restore liquidity to keep operating in business and customers are concerned with the quality of the life insurance products. Koijen and Yogo (2015) show that life insurance companies sell products with negative markups to meet liquidity needs and retain the customer base. If one cuts its profit margin aggressively, the peers will react by reducing their profit margins to defend the customer bases, making themselves more distressed in the short run. Similarly, the initial adverse idiosyncratic distress shock can also propagate to the connected industries through the common market leaders. This point is made formally in the illustrative model of competition network with inventory and fragile customer base (in Online Appendix 2).



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

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

Hypothesis Development. It is not surprising that the distress conditions of competitors are interdependent within an industry. Our paper pushes one step further by investigating the economic mechanisms of product market competition and delineating the specific channels through which distress shocks propagate from one market leader to its major rivals in a given industry, and from one industry to others via the common market leaders as well. The hypotheses below can be visualized and demonstrated using Figure 2. We relegate the formal proofs to Online Appendix 3 and explain the intuition for each hypothesis below.

The within-industry spillover effects follow naturally from the negative impact of a distress shock on the profit margin of the treated firm, as well as the strategic complementarity of profit margins between the treated firm and its rivals in the same industry. Such within-industry spillover effects are, on average, stronger for industries with higher entry barriers, because predatory pricing incentives are stronger when entry barriers are higher.

Hypothesis 1. *When a market leader is hit by an adverse (favorable) distress shock, its major rivals in the same industry reduce (increase) their profit margins and thus become more (less) distressed in the short run. Such within-industry spillover effects are, on average, stronger for industries with higher entry barriers.*

Given the within-industry spillover effects, the cross-industry spillover effects on the competition network follow naturally if some rivals are common market leaders that connect this industry to others. Specifically, an adverse idiosyncratic distress shock that hits a market leader makes the common market leaders more depressed, and consequently, these common market leaders in turn reduce their profit margins in the connected industries, which further leads to lower profit margins and higher distress levels of major rivals in these connected industries. Such cross-industry spillover effects are, on average, stronger for common market leaders that are more financially consolidated (i.e., common market leaders that have more efficient internal capital markets), because a distress shock that affects one subsidiary in an industry has stronger impact on the distress level of another subsidiary in a different industry when the common market leader is more financially consolidated.

Hypothesis 2. *When market leaders are hit by an adverse (favorable) distress shock, the major rivals of their major rivals in the different yet connected industries on the competition network reduce (increase) their profit margins and thus become more (less) distressed in the short run. Such cross-industry spillover effects are, on average, stronger for common market leaders that are more financially consolidated.*

Because of the cross-industry spillover effects on the competition network, stock returns of the industries connected through the competition network comove positively. Such positive correlation in the industry returns is, on average, stronger for industries with higher centrality on the competition network because of the "knock-on effect", and for industries whose common market leaders are more financially consolidated. In the presence of investor attention constraints (e.g., Cohen and Frazzini, 2008), news about peer industries is not immediately incorporated into the stock prices of the focal industries, thereby generating industry return predictability through competition network. The return predictability is stronger for focal industries with lower levels of analyst coverage and institutional ownership when investors are more likely to have attention constraints.

Hypothesis 3. *Stock returns of the industries connected through the competition network comove positively. Such positive correlation in the industry returns is, on average, stronger for industries with higher centrality on the competition network, and for industries whose common market leaders are more financially consolidated. In the presence of investor attention constraints, news about peer industries is not immediately incorporated into the stock prices of the focal industries, thereby generating industry return predictability through competition network. The return predictability is stronger for focal industries with lower levels of analyst coverage and institional ownership.*

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 study focuses on strategic competition among a few oligopolistic firms whose products are close substitutes. We therefore use four-digit SIC codes to define industries, following the literature (e.g., Hou and Robinson, 2006; Gomes, Kogan and Yogo, 2009; Frésard, 2010; Giroud and Mueller, 2010, 2011; Bustamante and Donangelo, 2017).[7]

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

Measures for Distress Risk. We use several empirical measures for distress risk. The first measure is the distress risk measure constructed as in Campbell, Hilscher and Szilagyi (2008), which measures the probability of firm bankruptcy or failure. The second measure is the distance to default measure constructed using the naive Merton default probability as in Bharath and Shumway (2008). The distance to default measure negatively captures the distress risk; namely, lower distance to default measure means higher distress risk. In Online Appendix 4.1, we explain the construction method of the above two measures in detail. The above two empirical measures for distress risk are yearly and partly depend on market price, which enables them to better capture potential spillover effects.

We use bond yield spread and CDS spread as two additional measures for distress risk. Bond yield spread is the average yield spread of all bonds issued by a firm. As in Chen et al. (2018) and Chen et al. (2022), our bond yield spread data combine the Mergent Fixed Income Securities Database (FISD) from 1973 to 2004 and the TRACE database from 2005 to 2018. We clean the Mergent FISD and TRACE data following Collin-Dufresn, Goldstein and Martin (2001) and Dick-Nielsen (2009). For each transaction, we calculate the bond

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

yield spread by taking the difference between the bond yield and the Treasury yield with corresponding maturity. We obtain CDS spread from Markit. Following previous studies (e.g., Klingler and Lando, 2018; Collin-Dufresne, Junge and Trolle, 2020), we focus on CDS contracts with "XR" (no restructuring) as restructuring clause and we examine the par-equivalent CDS spread. The bond yield spread and CDS spread are market-based measures for distress risk, and thus arguably more directly capture distress risk than the measure of Campbell, Hilscher and Szilagyi (2008) and the distance to default measure. The disadvantage of these two measures is that their coverage is relatively small in the cross section. The bond yield spread dataset spans the period from 1973 to 2018 and covers a cross section of 421 to 746 firms in the CRSP-Compustat merged sample (i.e., on average around 11.2% of firms in the cross section of CRSP-Compustat). The CDS dataset spans the period from 2001 to 2018, and it covers 90 firms in the CRSP-Compustat merged sample in 2001 and a cross section of 310 to 584 firms from 2002 to 2018 (i.e., on average around 7.5% of firms in the cross section of CRSP-Compustat).

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

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

Our measures are based on the so-called "accounting profits approach" to estimate profit margins and markups (e.g., Baqaee and Farhi, 2019; Autor et al., 2020).[8] We consider gross profit margins and markups to focus on production profits of firms, while we consider net profit margins and operating markups to capture the operating profits of firms. As emphasized by Baqaee and Farhi (2019), the accounting profits approach has the virtue of requiring very little manipulation of the raw data and being robust to potential mis-specification in the user-cost estimation approach and the production function estimation approach.

Product Price Data. We use the Nielsen Retail Scanner Data to measure changes in product prices.[9] The Nielsen data are used widely in the macroeconomics literature (see, e.g., Aguiar and Hurst, 2007; Broda and Weinstein, 2010; Hottman, Redding and Weinstein, 2016; Argente, Lee and Moreira, 2018; Jaravel, 2018). The Nielsen data contains prices and quantities of every unique product that had any sales in the 42,928 stores of more than 90 retail chains in the US market from January 2006 to December 2016. In total, the Nielsen data cover more than 3.5 million unique products identified by Universal Product Codes (UPCs); they represent 53%, 55%, 32%, 2%, and 1% of all sales in grocery stores, drug stores, mass merchandisers, convenience stores, and liquor stores, respectively (see, e.g., Argente, Lee and Moreira, 2018). We match the Nielsen data to CRSP/Compustat based on firm names. The details of our matching procedures are explained in Online Appendix 4.4. Our merged sample covers the product prices of 653 firms from 174 three-digit SIC industries, and the sample period spans from 2006 to 2016.

Natural Disaster Data. We obtain information on the property losses caused by natural disasters hitting the US territory from the Spatial Hazard Events and Loss Databases for the United States (SHELDUS). The dataset has been widely used in the recent finance

[8] To differentiate the profit margin and markup measures based on the accounting profits approach from the conceptual "marginal" profit margin and markup, Baqaee and Farhi (2019) use the term "average" markup when referring to the accounting-based measures.

[9] The analyses are conducted by us based in part on data from The Nielsen Company (US), LLC and marketing databases provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at the University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are our own and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

literature (e.g., Morse, 2011; Barrot and Sauvagnat, 2016; Bernile, Bhagwat and Rau, 2017; Cortés and Strahan, 2017; Alok, Kumar and Wermers, 2020; Dou, Ji and Wu, 2021*b*; Dou, Kogan and Wu, 2021), and it covers natural hazards such as thunderstorms, hurricanes, floods, wildfires, and tornados, as well as perils such as flash floods and heavy rainfalls. For each event, the database provides information on the start date, end date, and the identifiers of all affected counties. We map public firms in Compustat-CRSP to SHELDUS based on the locations of their headquarters and establishments. We collect the locations of firms' headquarters from their 10-K filings downloaded from the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system. We collect the locations of firms' establishments from the Infogroup Historical Business Database.[10] The merged location data span the period from 1994 to 2018.

Production Network Data. We identify firm-level supplier-customer links based on Compustat customer segment data and Factset Revere data following Barrot and Sauvagnat (2016) and Gofman, Segal and Wu (2020). We identify industry-level supplier-customer links based on the BEA Input-Output Accounts data following previous studies (e.g., Fan and Lang, 2000; Menzly and Ozbas, 2010; Acemoglu and Azar, 2020). We explain the detailed method of identifying the industry-level supplier-customer links in Online Appendix 4.5. We further supplement the industry-level production network connections based on the firm-level supplier-customer links constructed from Compustat customer segment data and Factset Revere data.

Firms' Individual Consumer Data. We identify the geographic locations of firms' individual consumers using a detailed dataset from Baker, Baugh and Sammon (2020), which provides firms' sales to individual consumers at the city level from 2010 to 2015.[11] The individual consumer dataset is constructed based on a transaction-level database that covers debit and credit card spending across around two million American users to gain insights about the firms that they patronize, and it mainly covers firms in the consumer-facing industries (i.e., airlines, grocery stores, hotels, retailers, restaurants, utilities, and many online services).

Credit Lending Data. We use Thomson Reuters LPC DealScan syndicated loan data to capture lenders' exposure to natural disasters and to construct the firm-specific credit

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

[11]We thank Scott Baker for generously allowing us to access this dataset.

supply shocks during the Lehman crisis. The DealScan database contains comprehensive historical information on loan characteristics, such as borrower names, lender names, pricing, start dates, end dates, and loan purposes. The loan characteristics are compiled from filings of the US Securities and Exchange Commission (SEC) and other resources. The DealScan database covers between 50% and 75% of commercial loans in the US (e.g., Carey and Hrycray, 1999). We merge borrowers in DealScan to Compustat-CRSP based on the link table built by Chava and Roberts (2008). We merge lenders in DealScan to Compustat-CRSP based on the link table built by Schwert (2018).

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

Other Data. We obtain analyst coverage from I/B/E/S, and institutional owernship from Thomson/Refinitiv 13-F data. In Online Appendix 1.1, we use Continental Airlines as an anecdote example for the within-industry spillover, and we construct air ticket prices using Department of Transportation's Airline Origin and Destination Survey DB1B database.

4 Empirical Results

We describe our empirical findings in this section. Section 4.1 illustrates how we build the competition network through common market leaders. Sections 4.2 and 4.3 exploit the natural disaster setting to examine the within-industry spillover effects and the cross-industry spillover effects, respectively. Section 4.4 presents additional evidence from the AJCA tax holiday and the Lehman crisis. Section 4.5 show evidence of industry return predictability through competition network.

4.1 Competition Network

Construction of Competition Network. Motivated by our proposed economic mechanisms, we construct the competition network of industries linked by common market

Table 1: Connected four-digit SIC pairs of the competition and production networks.

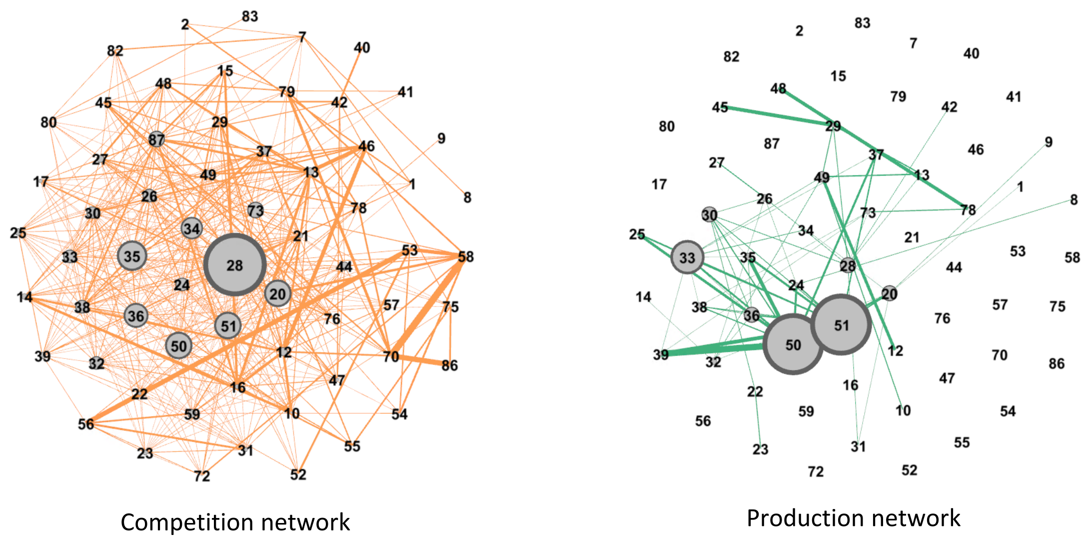
		Competition network		
		0	1	Total
Production network	0	531,791	1,129	532,920
	1	1,129	12	1,141
	Total	532,920	1,141	534,061

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

When constructing the competition network, we use Compustat historical segment data that provide information on the SIC codes for all the segments in which firms operate. Compustat historical segment data are widely used in the literature to identify the segments in which firms operate (e.g., Lamont, 1997; Rajan, Servaes and Zingales, 2000; Li, Qiu and Wang, 2019). The coverage of the data starts in 1976. We define a firm as a common market leader for a pair of four-digit SIC industries i and j if the firm is ranked among the top 10 based on the segment-level sales in both industries. The competition network at any point in time t is a collection of industries linked by common leaders. The network is updated dynamically every year according to our definition of common market leaders.

We construct the competition network at the four-digit SIC industry level. We drop financial industries (SIC codes from 6000 to 6999) in constructing the network. Two industries are connected on the competition network if they share at least one common market leader. To illustrate the difference between competition network and production network, we use the network structure in 1994 (i.e., the first year of our data in the natural disaster analysis) as an example. There are 1,141 pairs of connected industries out of 534,061 possible industry pairs in the competition network of 1994. We construct the production network based on the BEA Input-Output Accounts data following Fan and Lang (2000). Specifically, we compute the production network connectedness between two four-digit SIC industries based on the amount of output of one industry used to produce \$1 output of the other industry.[12] Two industries are connected on the production network if the connectedness measure is above a cutoff value, set at the level such that

[12]Suppose industry i uses \$$a$ of industry j's output to produce \$1 of its output, and industry j uses \$$b$ of industry i's output to produce \$1 of its output, the production network connectedness between industry i and j is $(a+b)/2$.



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

Figure 3: Competition network versus production network.

the total number of connections on the production network matches with that of the competition network in the 1994 snapshot. By doing this, we effectively normalize the total number of connections, enabling us to focus on the difference in the distribution of connections among industry pairs (i.e., the extent to which the competition network is overlapped with the production network).

Table 1 compares the connected four-digit SIC pairs of the competition network with those of the production network. These two networks share only 1.0% of connections, and the vast majority of the connected industry pairs are different between the two networks. Figure 3 further visualizes the structure of the two networks. We aggregate the industry connections to the two-digit SIC level in this plot to make the number of nodes manageable. The plot clearly shows that the competition network we construct and examine in this paper is distinct from the production network emphasized in the extant literature. Such a clear distinction between the two networks is evident in every year of our data sample. Consistently, in Sections 4.2 and 4.3, we show that the within-industry and cross-industry spillover effects of distress risk cannot be explained by production network externality. In Section 4.5, we show that the industry return predictability through competition network is distinct from the return predictability through production network.

Common Market Leaders. Common market leaders operate in more than one industries. Although they are larger than an average firm, common market leaders are not necessarily the largest firms in the economy. As shown in Table 2, there are around 496 common market leaders each year. Only 6.43% of the common market leaders are "superstar" firms (i.e., top 50 firms ranked by sales). The majority of the common market leaders are actually not the largest firms. For example, more than 87% of common market leaders are ranked outside of top 100 firms in terms of sales, while more than 55% of common market leaders are ranked outside of top 500 firms. Within the subset of the largest firms ranked by sales, about half or more are stand-alone firms that are not common market leaders. For example, in the top 100 firms, on average 59 of them are common market leaders and the rest are stand-alone firms. In the top 500 firms, on average 220 of them are common market leaders and the rest are stand-alone firms.

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

Panel C of Table 2 shows the distribution of the number of industries in which industry market leaders operate. We find that common market leaders mostly operate in two or three industries and this pattern is stable over time. The distribution pattern suggests that it is unlikely for common market leaders to fully eliminate their distress risk through diversification, which is consistent with what we see in Figure 4.

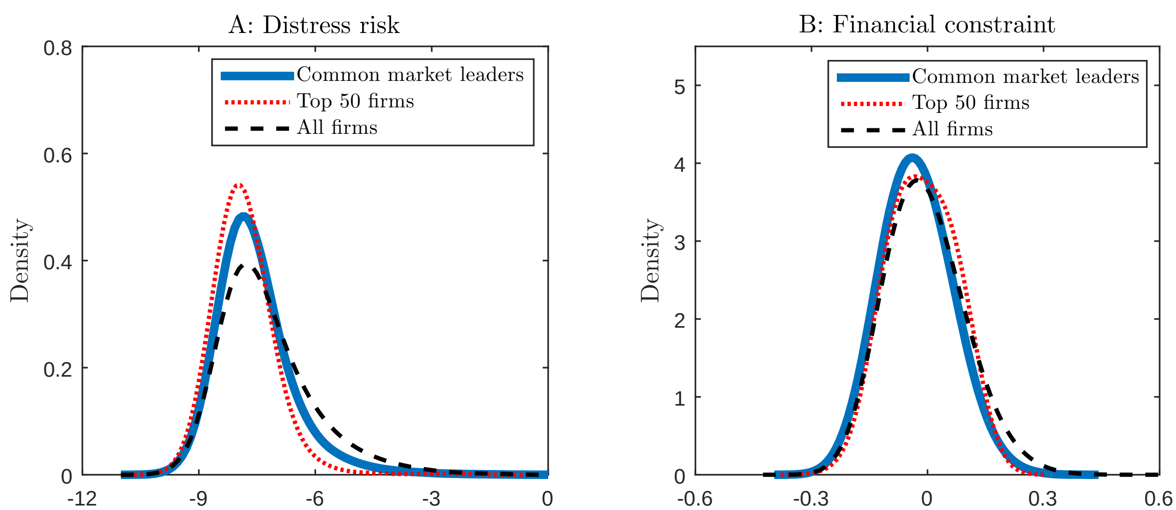
Table 2: Common market leaders.

	Panel A: number of common market leaders in the largest firms								
	Mean	Median	SD	Min	p10th	p25th	p75th	p90th	Max
Top 50 firms	30.7	31	3.8	20	26	28	34	35	37
Top 100 firms	58.5	59	7.0	34	51	54	63	68	71
Top 200 firms	108.7	106	14.5	73	95	99	119	133	140
Top 500 firms	219.6	211	35.9	150	186	190	232	284	295
All firms	495.8	448	107.6	317	399	415	560	687	726

	Panel B: # of common market leaders in the largest firms normalized by the total # of common market leaders (%)								
	Mean	Median	SD	Min	p10th	p25th	p75th	p90th	Max
Top 50 firms	6.43	6.53	1.36	3.31	4.31	5.54	7.42	8.15	8.52
Top 100 firms	12.11	12.43	1.82	8.26	9.80	10.45	13.36	14.36	14.84
Top 200 firms	22.31	22.56	2.19	17.63	19.22	20.43	23.81	25.06	25.97
Top 500 firms	44.78	45.20	3.04	39.14	40.30	42.02	47.15	48.61	49.55

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

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



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

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

4.2 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 in Section 4.2 and the cross-industry spillover effects in Section 4.3.[13]

The negative impact of natural disasters on economic activities has been widely studied in the literature (e.g., Garmaise and Moskowitz, 2009; Strobl, 2011; Baker and Bloom, 2013; Cavallo et al., 2013; Hsiang and Jina, 2014; Barrot and Sauvagnat, 2016; Dessaint and Matray, 2017; Seetharam, 2018; Aretz, Banerjee and Pryshchepa, 2019; Boustan et al., 2020; Brown, Gustafson and Ivanov, 2021). Insurance coverage and public disaster assistance can only partially offset firms' losses from natural disasters (see Online Appendix 5 for detailed discussion). As a result, natural disaster shocks negatively affect firms' cash flow (e.g., Brown, Gustafson and Ivanov, 2021) and increase firms' distress risk exogenously (e.g., Aretz, Banerjee and Pryshchepa, 2019). In this section, we first use DID analysis to identify the spillover effects of natural disasters within industries. We then show that the spillover effects are stronger for industries with higher levels of entry barrier and financial constraint. Finally, we show that the within-industry spillover effects cannot be rationalized by a list of alternative explanations including demand commonality, production network externality, lender commonality, and institutional blockholder commonality.

4.2.1 DID Analysis

Treated and Matched Peer Firms. We follow Barrot and Sauvagnat (2016) in defining a firm as being negatively affected by a natural disaster in a given year if the county in which the firm's headquarter or one of its major establishments is located experiences property losses due to a major natural disaster during that year.[14] We follow Aretz, Banerjee and Pryshchepa (2019) to require the counties of headquarters or the major establishments of the affected firms to experience at least \$0.25 million total estimated property damages. Although the cutoff value may appear low, the counties in which the treated firms are located experience on average (weighted by the number of the firms in the counties) \$1.9 billion in property losses in the disaster years. Moreover, the amount of

[13] Besides the natural disaster shocks, in Online Appendix 7, we also exploit the setting where firms suffer from distress due to firm-specific enforcement actions against financial frauds and use the DID econometric specification with partial interference to examine the spillover impact of firms' idiosyncratic adverse distress shocks on their industry peers.

[14] We follow Barrot and Sauvagnat (2016) to define major natural disasters as those that cause at least \$1 billion in total estimated property damages and that last fewer than 30 days. We define a major establishment 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).

property losses represents the lower bound of the negative economic impact caused by major natural disasters, because it only includes direct property damage and does not include other economic losses (e.g., reduction in revenue and growth) of the firms. The results of our paper are robust to other cutoffs values to define the affected firms such as \$1 million, \$5 million, and \$10 million. We list the major natural disasters included in our sample in Table OA.4 of the Online Appendix, and we plot the frequency of major natural disasters for each county in the US mainland from 1994 to 2018 in Figure OA.7 of the Online Appendix. As shown in Panel A of Table 4, major natural disasters affect around 10% of firms in the Compustat firm-year panel.

We match each treated firm with up to 5 non-treated peer firms in the same four-digit SIC industry with similar asset size, tangibility, and age.[15] Because we are interested in studying the spillover effect, it is important for us to make sure that the matched peer firms are not directly affected by major natural disaster shocks. In particular, we require the matched peer firms to have no establishment (including headquarters) in any county that experiences any positive amount of property damage during a major natural disaster. We use the cutoff value of \$0 million instead of \$0.25 million to define matched peer firms to ensure that they are not directly affected by natural disasters. To make sure that the spillover effects we document are distinct from production network externality, we require that the matched peer firms are not suppliers or customers of the treated firms. In two of the robustness tests, we further require that the matched peer firms are outside of any states affected by major natural disasters and are at least 100 miles from any counties affected by major natural disasters, respectively. Our findings remain robust in these two robustness tests.

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

$$Special\_items_{i,t}/Sales_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}. \quad (4.1)$$

Dependent variable $Special\_items_{i,t}/Sales_{i,t}$ is the special items scaled by firm sales. Negative amount of special items represents firm losses. Independent variable $Treat_{i,t}$ is an indicator variable that equals 1 if firm i is negatively affected by a major natural

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

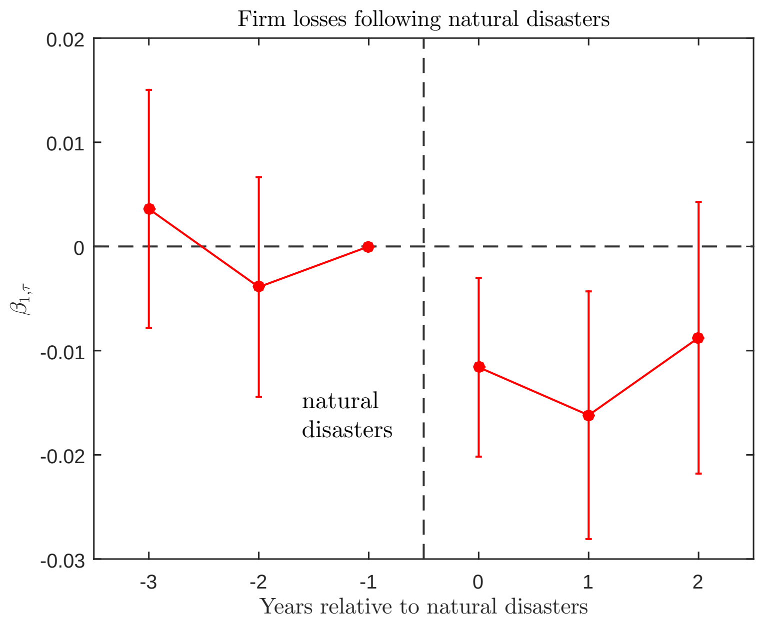
Table 3: Firm losses following major natural disasters.

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

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

disaster in year t. $Post_{i,t}$ is an indicator variable that equals 1 for observations after major natural disasters. The term θ_i represents firm fixed effects, and the term δ_t represents year fixed effects. For each treated firm or matched non-treated peer firm, we include four yearly observations (i.e., 2 years before and 2 years after major natural disasters) in the analysis. The coefficient β_1 is the coefficient of interest and it captures the amount of firm losses following major natural disasters. As shown in Table 3, a firm on average reports losses that amount to more than 1.2% of its sales when the county in which it is located is hit by a major natural disaster.

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



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

Figure 5: Firm losses following major natural disasters.

regression specification as follows:

$$Special\_items_{i,t}/Sales_{i,t} = \sum_{\tau=-3}^{2} \beta_{1,\tau} \times Treat_{i,t} \times ND_{i,t-\tau} + \beta_2 \times Treat_{i,t} + \sum_{\tau=-3}^{2} \beta_{3,\tau} \times ND_{i,t-\tau} + \theta_i + \delta_t + \varepsilon_{i,t}. \quad (4.2)$$

$Treat_{i,t}$ is an indicator variable that equals 1 if firm i is a treated firm. $ND_{i,t-\tau}$ is an indicator variable that equals 1 if firm i (when firm i is a treated firm) or the treated firm to which firm i is matched (when firm i is a matched non-treated firm) experiences natural disaster shocks in year $t-\tau$. The term θ_i represents firm fixed effects, and the term δ_t represents year fixed effects. When running the regression, we impose $\beta_{1,-1} = \beta_{3,-1} = 0$ to avoid collinearity in categorical regressions, and by doing this, we set the years immediately preceding the disaster years as the benchmark. In Figure 5, we plot estimated coefficients $\beta_{1,\tau}$ with $\tau = -3, -2, \cdots, 2$, as well as their 90% confidence intervals with standard errors clustered at the firm level. We find that the increase in the reported firm losses takes place only after the occurrence of natural disaster shocks. There is no significant change in the reporting of special items prior to natural disaster shocks. This pattern further confirms that the estimates in Table 3 reflect natural disaster losses of the affected firms.

Regression Specifications to Identify Within-Industry Spillover Effects. To clearly identify and dissect out within-industry spillover effects, it is important to recognize that cross-industry spillover effects also exist simultaneously in the background. For example, to test whether a firm affected by natural disasters can generate a within-industry spillover effect to a non-treated peer firm 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 through the competition network. This is because although natural disasters are idiosyncratic shocks, the concurrent natural disasters can simultaneously affect firms in industries A and B and thus can lead to biased estimates of within-industry spillover effects. To control for the strength of cross-industry spillover effects, we construct variable $Ln(1 + n(\mathcal{C}_{i,t}))$, which is the natural log of 1 plus the number of industries connected to firm i's industry through the competition network and shocked by natural disasters in year t. As a robustness, we also use an alternative measure, $ln(1 + \mathcal{D}_{i,t})$, to capture the cross-industry spillover effects, which is the natural log of 1 plus the average amount of property damage (in millions of dollars) caused by major natural disasters in year t across industries that are connected to firm i's industry through competition networks, denoted by $\mathcal{D}_{i,t}$.

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

$$Y_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1 + n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}, \quad (4.3)$$

$$Y_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1 + \mathcal{D}_{i,t}) + \theta_i + \delta_t + \varepsilon_{i,t}. \quad (4.4)$$

Dependent variable $Y_{i,t}$ represents the distress risk ($Distress_{i,t}$) and the distance-to-default measure ($DD_{i,t}$) of firm i in year t. Independent variable $Treat_{i,t}$ is an indicator variable that equals 1 if firm i is negatively affected by a major natural disaster in year t. $Post_{i,t}$ is an indicator variable that equals 1 for observations after major natural disasters.

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

DID Analysis Findings. We tabulate the results of the DID regressions for firm distress in columns (1) to (6) of panel B in Table 4. We find that the distress risk of the treated firms increases substantially, while the distance-to-default measure of the treated firms decreases substantially following the natural disaster shocks. The p-value for the null hypothesis that the total treatment effect is 0 (i.e., $\beta_1 + \beta_3 = 0$) is lower than 0.001. These findings suggest that the treated firms become more distressed following major natural disasters. Our results are consistent with those of Aretz, Banerjee and Pryshchepa (2019), who show that hurricane strikes substantially increase firms' distress risk.

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

Table 4: Identifying within-industry spillover effects using DID analysis.

Panel A: Summary statistics of the firm-year panel

	Obs. #	Mean	Median	SD	p10th	p25th	p75th	p90th
$ND_{i,t}$	88297	0.100	0	0.301	0	0	0	1
$Distress_{i,t}$	92185	−7.228	−7.489	1.005	−8.317	−7.986	−6.701	−5.618
$DD_{i,t}$	80858	5.321	4.506	4.254	0.292	2.070	7.833	11.884
$PM_{i,t}$	96269	0.346	0.338	0.264	0.092	0.206	0.519	0.703
$Markup_{i,t}$	96140	0.515	0.412	0.451	0.097	0.230	0.731	1.208
$Ln(1+n(\mathcal{C}_{i,t}))$	98562	0.747	0.693	0.739	0	0	1.386	1.792
$Ln(1+\mathcal{D}_{i,t})$	92684	3.190	2.814	2.959	0	0.017	5.399	7.464

Panel B: Identifying within-industry spillover effects using the DID analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		$Distress_{i,t}$			$DD_{i,t}$			$PM_{i,t}$			$Markup_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.019	0.019	0.027**	−0.087*	−0.088*	−0.103*	−0.001	−0.001	0.000	−0.001	−0.001	0.000
	[1.538]	[1.556]	[2.130]	[−1.717]	[−1.743]	[−1.933]	[−0.196]	[−0.218]	[0.098]	[−0.267]	[−0.291]	[0.011]
$Treat_{i,t}$	−0.014	−0.014	−0.017	0.096*	0.097*	0.092*	−0.001	−0.001	−0.001	−0.001	−0.001	−0.000
	[−1.250]	[−1.257]	[−1.436]	[1.940]	[1.953]	[1.775]	[−0.189]	[−0.181]	[−0.162]	[−0.151]	[−0.143]	[−0.023]
$Post_{i,t}$	0.053***	0.052***	0.046***	−0.122***	−0.115***	−0.098***	−0.007**	−0.007**	−0.007**	−0.010***	−0.010**	−0.011***
	[6.498]	[6.411]	[5.597]	[−3.882]	[−3.695]	[−3.063]	[−2.283]	[−2.149]	[−2.370]	[−2.649]	[−2.496]	[−2.673]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.018*			−0.083**			−0.006**			−0.009**	
		[1.952]			[−2.295]			[−2.227]			[−2.449]	
$Ln(1+\mathcal{D}_{i,t})$			0.005**			−0.025**			−0.002*			−0.002*
			[1.960]			[−2.325]			[−1.821]			[−1.909]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130099	130099	119053	110581	110581	101308	135037	135037	124047	134924	134924	123949
R-squared	0.565	0.565	0.579	0.667	0.667	0.676	0.745	0.746	0.748	0.773	0.773	0.777
Test p-value:												
$\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.004	0.006	0.012	$<10^{-3}$	0.001	0.003

Note: This table examines within-industry spillover effects following major natural disasters. Panel A of this table shows the summary statistics for the firm-year panel from 1994 to 2018. $Distress_{i,t}$ is the distress risk constructed as in the work of Campbell, Hilscher and Szilagyi (2008). $DD_{i,t}$ is the distance to default constructed following the naive approach illustrated in Bharath and Shumway (2008). $PM_{i,t}$ is the gross profit margin defined as the difference between sales and cost of goods sold divided by sales. $Markup_{i,t}$ is the markup, defined as the natural log of the ratio between sales and cost of goods sold. $ND_{i,t}$ is an indicator variable that equals 1 if firm i is negatively affected by major natural disasters in year t. $Ln(1+n(\mathcal{C}_{i,t}))$ captures the strength of cross-industry spillover effects, and it is the natural log of 1 plus the number of industries connected to firm i's industry through the competition network and shocked by natural disasters in year t. $Ln(1+\mathcal{D}_{i,t})$ is an alternative measure to control for cross-industry spillover effects, and it is the natural log of 1 plus the average amount of property damage (in millions of dollars) caused by major natural disasters in year t across industries that are connected to firm i's industry through competition networks. Panel B of this table reports the results from the DID analysis. For each treated firm (i.e., the firm whose headquarter or any of its major establishments is located in a county that is negatively affected by major natural disasters), we match it with up to five non-treated peer firms in the same four-digit SIC industry. We perform the matching based on the values of three matching variables (i.e., firm asset size, tangibility, and age) prior to natural disaster shocks using the shortest distance method. We require that the matched peer firms are not suppliers or customers of the treated firms. We identify the supplier-customer links using Compustat customer segment data and Factset Revere data. For each major natural disaster, we include in the analysis four yearly observations (i.e., 2 years before and 2 years after the major natural disaster) for the treated firms and their matched non-treated peers. The regression specification in columns (1), (4), (7), and (10) 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 regression specification in columns (2), (5), (8), and (11) 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 regression specification in columns (3), (6), (9), and (12) is: $Y_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1+\mathcal{D}_{i,t}) + \theta_i + \delta_t + \varepsilon_{i,t}$. $Treat_{i,t}$ is an indicator variable that equals 1 if firm i is a treated firm. $Post_{i,t}$ is an indicator variable that equals 1 for observations after major natural disasters. The term θ_i represents firm fixed effects, and the term δ_t represents year fixed effects. In the last row of the table, we present the p-value for the null hypothesis that the total treatment effect for the treated firms is zero (i.e., $\beta_1 + \beta_3 = 0$). The sample of this table spans from 1994 to 2018. Standard errors are clustered at the firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

In addition, again based the Nielsen data, we study the spillover effects in the changes of product prices around the Lehman crisis in Section 4.4.2, in which we focus on variations in the cross section following the literature (e.g., Chodorow-Reich, 2014; Kim, 2021).

To quantify the changes in treated firms' gross profit margins, we again use the regression specifications (4.3) and (4.4), with dependent variable $Y_{i,t}$ representing the gross profit margin and markup of firm i in year t. As shown in columns (7) to (12) of panel B in Table 4, we find that the treated firms significantly reduce their gross profit margins and markups, suggesting that these firms decide to reduce profitability and compete more aggressively in the product market after increased distress risk. This finding is consistent with **Hypothesis 1**.

Next, we test the hypothesis on the within-industry spillover effects. Specifically, our hypothesis predicts that industry peers will compete more aggressively with the distressed firms, which in turn will make the peers themselves more distressed. We find strong supporting evidence for this prediction. Coefficient β_3 in columns (7) to (12) of panel B in Table 4 is negative and statistically significant, suggesting that the industry peers that are unaffected directly by natural disasters also reduce their profit margins significantly. The intensified product market competition makes the non-treated industry peers also suffer from a significant increase in distress risk. Coefficient β_3 in columns (1) to (3) of panel B in Table 4 is positive and statistically significant, while coefficient β_3 in columns (4) to (6) of panel B in Table 4 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 affected by natural disaster shocks.

Panel B of Table 4 also reports the coefficients for cross-industry spillover effects (i.e., β_4). These coefficients are statistically significant and the sign of these coefficients is consistent with our hypothesis on cross-industry spillover effects. When more industries linked to the focal industry through competition networks are shocked by natural disasters, the firms in the focal industry experience a larger increase in distress and compete more aggressively in the product market. In Section 4.3, we study cross-industry spillover effects in greater detail and highlight the role of common leaders as the key players that transmit shocks across industries through the competition network.

It is worth discussing the relative magnitude between the direct effects captured by coefficient β_1 and the within-industry spillover effects captured by coefficient β_3. For the levels of distress, the direct effects are marginally statistically significant. For distress measure of Campbell, Hilscher and Szilagyi (2008), the magnitude of the direct effects is about one half of that of the within-industry spillover effects (see columns 1 to 3 of Table 4). For the distance to default measure, the magnitude of the direct effects is about same as that of the within-industry spillover effects (see columns 4 to 6). These results suggest that the firms directly hit by natural disasters are on average more distressed than their industry peers. On the other hand, the relative magnitude between coefficients β_1 and β_3 for profit margins exhibits a completely different pattern. The direct effects are virtually zero for profit margin and markups (see columns 7 to 12), suggesting that industry peers fully match the profitability cut of the affected firms. This result makes sense because price competition in the product market is often neck and neck, forcing firms to match prices of their peers.[16]

Besides using the distress measure of Campbell, Hilscher and Szilagyi (2008) and the distance to default measure, we also examine the spillover effect of distress risk using the bond yield spread and the CDS spread. Table 5 presents the findings. The within-industry spillover effect captured by the coefficient β_3 is positive and statistically significant for both the bond yield spread and the CDS spread. Following the natural disaster shocks to the focal firms, the bond yield spread and the CDS spread of the unaffected industry peer firms increase by 18 and 34 basis points, respectively, which are large economically compared to the means and medians of the spreads. We should note that the coverage of the spread data is relatively small in the cross section, which is around 10% of the CRSP-Compustat merged sample. In addition, the CDS spread sample is only available after 2001. The limitation in sample coverage likely accounts for the insignificant coefficients for cross-industry spillover effects (i.e., β_4) in Table 5.

Besides using the profit margin and markup measures, we also examine the spillover effect of product market competition using firm-level product prices computed based on the Nielsen data. Specifically, we first aggregate product prices across all products (i.e., unique UPCs) of firm i in product category c in year t using three methods: geometric average (see Kim, 2021), equal-weighted average, and sales-weighted average. We then compute firm-level product prices by aggregating the product prices across all product categories within firm i based on sales. Table 6 presents the findings. The within-industry spillover effect captured by the coefficient β_3 is negative and statistically significant for firm-level product prices aggregated using different methods. Following the natural disaster shocks to the focal firms, the product prices of the unaffected industry peer firms

[16] The relative magnitude between the direct effects and the within-industry spillover effects obviously depends on the empirical settings of idiosyncratic shocks. In Section 7 of the online appendix, we explore the setting where firms suffer from distress due to firm-specific enforcement actions against financial frauds. For the levels of distress, we show that the magnitude of the direct effects are much stronger than that of the within-industry spillover effects, although both effects are statistically and economically significant (see columns 1 to 4 of Table OA.22 of the online appendix). This is because firms prosecuted by the SEC and DOJ are intuitively more distressed than their industry peers. For profit margins, we again find that the direct effects are virtually zero while the spillover effects are statistically and economically significantly (see columns 5 to 8 of Table OA.22), which is consistent with the idea that firms need to match prices with their industry peers once they engage in price competition.

Table 5: Within-industry spillover effects in bond yield spreads and CDS spreads.

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

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

Note: This table examines within-industry spillover effects in bond yield spread and CDS spread following major natural disasters. Panel A of this table shows the summary statistics for the firm-year panel from 1994 to 2018. $Bond\_yield\_spread_{i,t}$ is the bond yield spread, which is the average bond yield spread of all bonds issued by a firm. For each transaction, we calculate the bond yield spread by taking the difference between the bond yield and the Treasury yield with corresponding maturity. $CDS\_spread_{i,t}$ is the par-equivalent spread of CDS with 1-year maturity. Both the bond yield spread and CDS spread in year t are the spread in the last quarter so the spreads capture credit risk at the year end. Panel B of this table reports the results from the DID analysis. The regression specification is: $Y_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1+n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}$. Definition for the independent variables are given in Table 4. The sample of bond yield spread spans from 1994 to 2018, while the sample of CDS spread spans from 2001 to 2018. Standard errors are clustered at the firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

reduce by around 7%, a magnitude that is large economically.[17] Similar to the coverage of the spread data, the coverage of Nielsen data is relatively small in the cross section, focusing on health and beauty aids, groceries, alcohol, and general merchandise. In addition, the Nielsen data are only available after 2006. The limitation in sample coverage likely accounts for the insignificant coefficients for cross-industry spillover effects (i.e., β_4) in Table 6.

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

[17] Using the Nielsen data, Kim (2021) finds that firms facing a negative credit supply shock during Lehman Brothers crisis decrease their output prices approximately 15% more than their unaffected counterparts. The magnitude of the spillover effects associated with the major natural disasters is roughly one half of that associated with the credit supply shock during the Lehman crisis.

Table 6: Within-industry spillover effects in product prices.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln(Price\_Geo)_{i,t}$		$\ln(Price\_EW)_{i,t}$		$\ln(Price\_VW)_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.022	0.020	0.016	0.013	0.012	0.009
	[0.540]	[0.486]	[0.374]	[0.316]	[0.291]	[0.226]
$Treat_{i,t}$	−0.029	−0.029	0.010	0.010	−0.005	−0.005
	[−0.583]	[−0.576]	[0.190]	[0.195]	[−0.096]	[−0.089]
$Post_{i,t}$	−0.074**	−0.076**	−0.075**	−0.077**	−0.073**	−0.076**
	[−2.321]	[−2.384]	[−2.202]	[−2.265]	[−2.260]	[−2.335]
$Ln(1+n(\mathcal{C}_{i,t}))$		0.034		0.039		0.042
		[0.866]		[0.843]		[0.977]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4414	4414	4414	4414	4414	4414
R-squared	0.524	0.525	0.546	0.547	0.529	0.530
Test p-value: $\beta_1 + \beta_3 = 0$	0.092	0.076	0.081	0.058	0.056	0.038

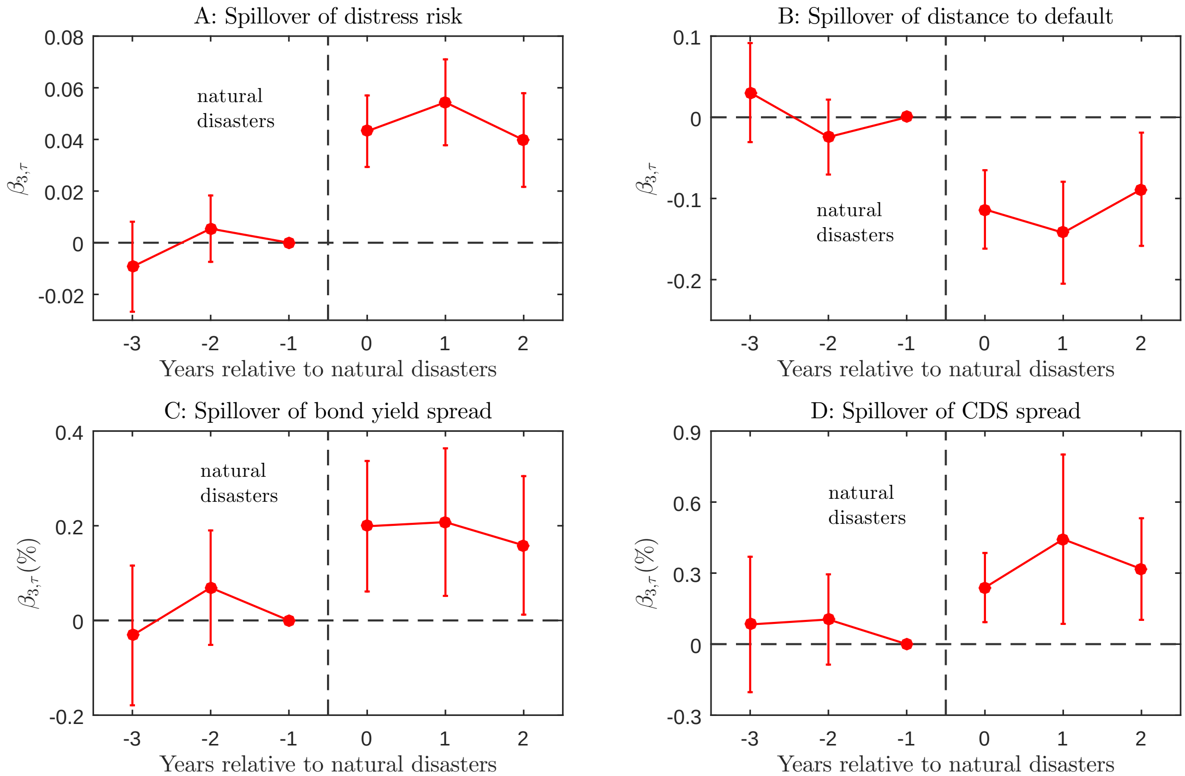
Note: This table examines within-industry spillover effects in product prices following major natural disasters. The regression specification is: $\ln(Price)_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln[1+n(\mathcal{C}_{i,t})] + \theta_{ind} + \delta_t + \varepsilon_{i,t}$. The dependent variables are the natural log of the firm-level product prices computed based on the Nielsen data. Specifically, we first aggregate product prices across all products (i.e., unique UPCs) of firm i in product category c in year t using three methods: geometric average ($Price\_Geo_{i,c,t}$, see Kim, 2021), equal-weighted average ($Price\_EW_{i,c,t}$), and sales-weighted average ($Price\_VW_{i,c,t}$). We then compute firm-level product prices $Price_{i,t}$ by aggregating the product prices across all product categories within firm i based on sales. Definition for the independent variables are given in Table 4. We control for industry fixed effects rather than firm fixed effects because of limited sample coverage. The sample spans from 2006 to 2016. 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.

better illustrate the dynamics of the spillover effects. Specifically, we consider the yearly regression specification as follows:

$$Y_{i,t} = \sum_{\tau=-3}^{2} \beta_{1,\tau} \times Treat_{i,t} \times ND_{i,t-\tau} + \beta_2 \times Treat_{i,t} + \sum_{\tau=-3}^{2} \beta_{3,\tau} \times ND_{i,t-\tau}$$
$$+ \beta_4 \times Ln(1+n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}. \tag{4.5}$$

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

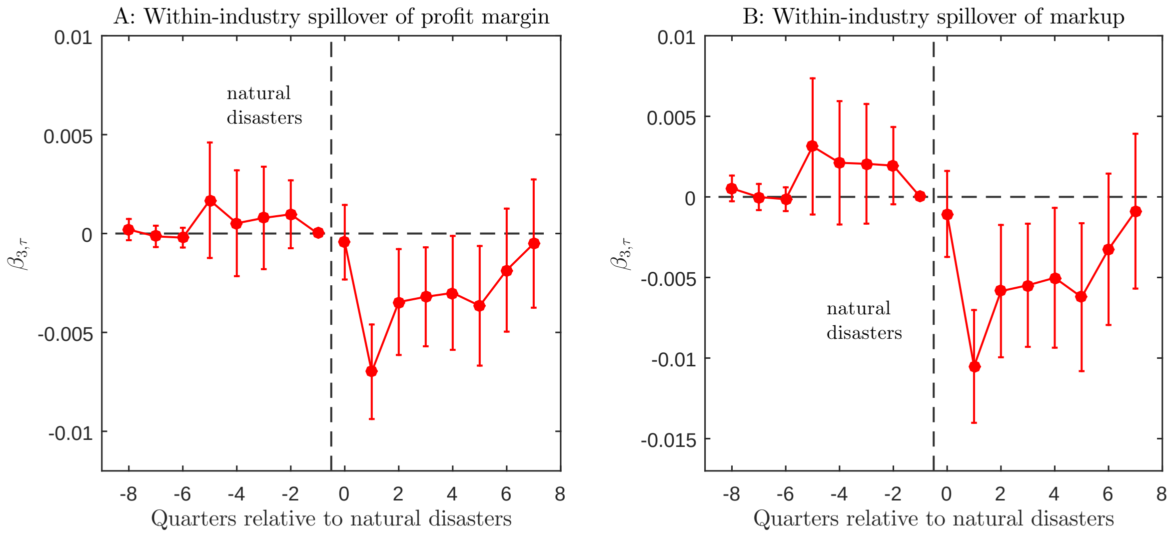
We find that the spillover effect emerges only after the occurrence of natural disaster shocks. There is no significant change in the distress risk or distance to default prior to



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

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

natural disaster shocks, which provides evidence supporting the parallel trend assumption for the DID analysis. We also examine the dynamics of the spillover effects for profit margin. Because data for the measures of profit margin and markup can be computed from Compustat at a quarterly frequency, we follow Barrot and Sauvagnat (2016) in showing the quarterly dynamic effects. As shown in Figure 7, a reduction in profit margin and markup takes place within two quarters after the occurrence of natural disasters. There is no significant change in profit margin or markup prior to natural disaster shocks,



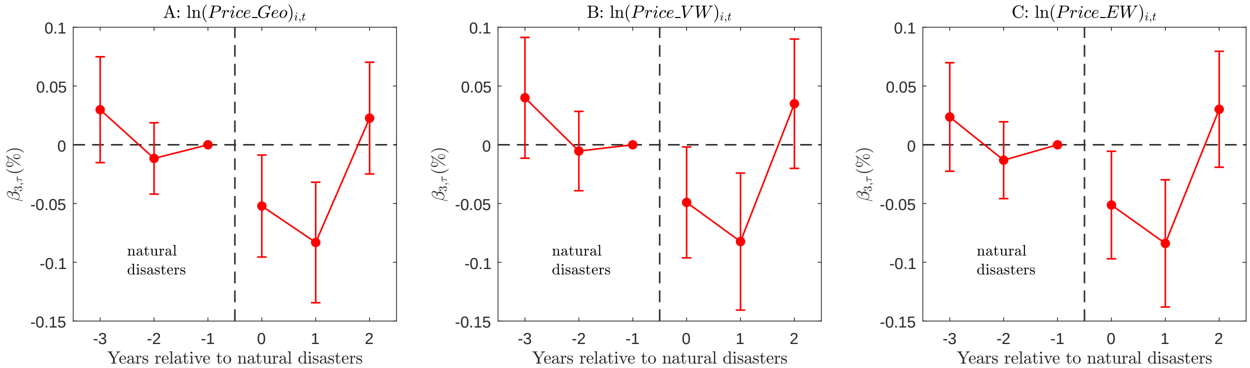
Note: This figure plots the within-industry spillover effects of profit margin around major natural disasters. For each treated firm (i.e., the firm whose headquarter or any of its major establishments is located in a county that is negatively affected by major natural disasters), we match it with up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

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

which again provides evidence supporting the parallel trend assumption for the DID analysis. The spillover effects in profitability last for around 2 years, a time window that is roughly consistent with other natural disaster impacts documented in the literature.[18] Similarly, we plot the spillover effects of product prices in Figure 8 based on the Nielsen data. Consistent with Figure 7, we find that after major natural disasters hit the focal firms, the product prices of their industry peers drop significantly in the two-year window after the disaster shocks.

Robustness Checks. We perform a battery of robustness checks. In Table OA.5 of the Online Appendix, we show that our findings are robust to alternative matching ratios

[18]For example, Barrot and Sauvagnat (2016) show that natural disaster shocks dampen sales growth for the customers of treated firms for about 2 years. In Section 4.2.3, we show that the within-industry spillover effect we document here cannot be explained by the production network externality, a channel that is the main focus of Barrot and Sauvagnat (2016).



Note: This figure plots the within-industry spillover effects of product prices around major natural disasters. For each treated firm (i.e., the firm whose headquarter or any of its major establishments is located in a county that is negatively affected by major natural disasters), we match it with up to ten non-treated peer firms in the same four-digit SIC industry. We require that the matched peer firms are not suppliers or customers of the treated firms. For each major natural disaster shock, we include six yearly observations (i.e., 3 years before and 3 years after a major natural disaster) for the treated firms and their matched non-treated peers in the analysis. To estimate the dynamics of the spillover effect, we consider the yearly regression specification as follows: $\ln(Price)_{i,t} = \sum_{\tau=-3}^{2} \beta_{1,\tau} \times Treat_{i,t} \times ND_{i,t-\tau} + \beta_2 \times Treat_{i,t} + \sum_{\tau=-3}^{2} \beta_{3,\tau} \times ND_{i,t-\tau} + \beta_4 Ln(1 + n(\mathcal{C}_{i,t})) + \theta_{ind} + \delta_t + \varepsilon_{i,t}$. The dependent variables are firm-level product prices computed based on the Nielsen data, which are explained in Table 6. Definition for the independent variables are given in Figure 6. We control for industry fixed effects rather than firm fixed effects because of limited sample coverage. The sample spans from 2006 to 2016. We plot estimated coefficients $\beta_{3,\tau}$ with $\tau = -3, -2, \cdots, 2$, as well as their 90% confidence intervals with standard errors clustered at the firm level. The vertical dashed lines represent the occurrence of major natural disasters.

Figure 8: Within-industry spillover effects of product prices.

between the treated firms and non-treated peer firms (i.e., one to ten and one to three). In Table OA.6 of the Online Appendix, we show that our findings are robust to alternative industry classifications. Specifically, we choose peer firms based on the text-based network industry classifications (TNIC) developed by Hoberg and Phillips (2010, 2016), and we show that the within-industry spillover effects remain robust. In Table OA.7 of the Online Appendix, we show that the within-industry spillover effects remain robust when we use net profit margin to measure profitability.

One potential concern for our DID method is that the matched peer firms may be geographically close to areas affected by natural disasters, and thus these firms may be directly affected by natural disasters even when the countries they locate in report zero property loss. To alleviate this concern, we conduct two robustness tests. First, in panel A of Table OA.8 of the Online Appendix, we require that the matched peer firms to be outside of any states affected by major natural disasters. Second, in panel B of Table OA.8, we require that the matched peer firms to be geographically far from the natural disaster areas in the DID analysis. Specifically, we require the matched peer firms to have headquarters and major establishments located more than 100 miles from any zip code negatively affected by major natural disasters in a given year. In both robustness tests, our findings of the within-industry spillover effects remain robust.

Because we have focused on the major natural disasters in the US, it is helpful to

Table 7: Heterogeneity across industries with different levels of entry barriers.

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

Note: This table examines the within-industry spillover effects following major natural disasters across industries with different levels of entry barriers. The regression specification is: $Y_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 Ln(1+n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}$. Definition for the dependent and independent variables are given in Table 4. We present results from DID analysis in industries with high entry barriers (top tertile) and low entry barriers (middle and bottom tertiles). The entry barrier of a four-digit SIC industry is measured by the sales-weighted average of fixed assets across firms in this industry. We sort industries into tertiles based on the industry-level entry barriers 1 year prior to natural disaster shocks. The number of firm-year observations in the subsample of low entry barriers is not exactly twice that in the subsample of high entry barriers because the number of treated firms is not uniformly distributed across industries. The sample spans from 1994 to 2018. Standard errors are clustered at the firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

check whether our findings of the spillover effects are indeed driven by industries whose profits mainly come from the domestic market. This is because firms primarily compete in the foreign markets should be less likely affected by shocks in the US. In Table OA.9 of the Online Appendix, we exclude from the DID analysis the industries with the highest fraction of foreign profits (i.e., top quintile), and we show that the spillover effects remain robust. In fact, the economic magnitudes of the spillover effects become larger compared to those in Table 4. These findings further validate our identification strategy.

4.2.2 Heterogeneity in Spillover Effects within An Industry

We expect the within-industry spillover effects to be stronger in industries with higher entry barriers. As shown by Chen et al. (2022), firms will compete more aggressively with their distressed peers in these industries because the winners of a price war in these industries enjoy larger economic rents after pushing out their competitors who are unlikely to be replaced by new entrants. To test this prediction, we measure the entry barrier of a four-digit SIC industry using the sales-weighted average fixed assets, following previous studies (e.g., Li, 2010). We then sort industries into tertiles based on the industry-level entry barriers 1 year prior to natural disaster shocks and then examine the within-industry spillover effects in the industries with high entry barriers (top tertile) and low entry barriers (middle and bottom tertiles) using DID analysis. Table 7 tabulates the results. Consistent with our prediction, we find that the within-industry spillover effects captured by coefficient β_3 mostly concentrate in industries with high entry barriers, while they are almost absent in industries with low entry barriers. Examining the patterns of total treatment effects (captured by the sum of β_1 and β_3) offers additional insights on the heterogeneity of spillover effects. The total treatment effects are significant for all industries when we examine the distress levels of treated firms (see the last row of columns 1 to 4 in Table 7). This is because natural disasters make the treated firms more distressed in all industries. However, the total treatment effects for profit margin are only significant in industries with high entry barriers (see the last row of columns 5 to 8 in Table 7), suggesting that the distressed treated firms engage in price competition only in industries with high entry barriers. As illustrated by our proposed economic mechanisms, it is the intensified product market competition that increases the distress levels of the industry peers. Consistent with our hypothesis, we observe strong within-industry spillover effects of distress only in industries with high entry barriers.

We also expect the within-industry spillover effects to be stronger in industries whose market leaders are more likely to tacitly collude with each other. To test this prediction, we proxy the prevalence of tacit collusion by the levels profitability comovement, which is the average pairwise correlation of the net profitability for top four firms ranked by sales in this industry. The pairwise correlation between two firms is calculated as the correlation coefficient of their net profitability in the previous ten years. We then sort industries into two groups based on the industry-level profitability comovement 1 year prior to natural disaster shocks and then examine the within-industry spillover effects in the industries with high profitability comovement (above median) and low profitability comovement (below median) using DID analysis. Table OA.10 of the Online Appendix tabulates the results. Consistent with our prediction, we find that the within-industry spillover effects captured by coefficient β_3 mostly concentrate in industries with high profitability comovement, while they are much weaker in industries with low profitability comovement.

Finally, we expect the within-industry spillover effects to be stronger in industries with worse economic and financial conditions prior to natural disasters. This is because firms in these industries are effectively less patient and thus have more incentive to compete after the arrival of negative shocks. To test this prediction, we measure the economic condition of a four-digit SIC industry using the change of the return on assets (ROA) in the industry from the previous year. We then sort industries into two groups based on the industry-level economic conditions 1 year prior to the natural disaster shocks and then examine the within-industry spillover effects in the industries with good economic conditions (top half) and bad economic conditions (bottom half) using DID analysis. Panel A of Table OA.11 of the Online Appendix tabulates the results. Consistent with our prediction, we find that the within-industry spillover effects captured by coefficient β_3 mostly concentrate in industries with bad economic conditions, while they are almost absent in industries with good economic conditions. The total treatment effects are significant in all industries when we examine the distress levels of treated firms (see the last row of columns 1 to 4 in panel A), but they are only significant in industries with bad economic conditions when we examine the profit margins of the treated firms (see the last row of columns 5 to 8 in panel A). These findings are consistent with the prediction of our hypothesis, and they suggest that distressed treated firms engage in price competition only in industries with bad economic conditions, which leads to distress propagation to their industry peers.

We measure the financial constraint of a four-digit SIC industry using the sales-weighted average of the delay investment score (Hoberg and Maksimovic, 2015). This measure is constructed based on textual analysis of firms' 10-K filings and thus captures the degree of financial constraints directly. We sort industries into tertiles based on the industry-level financial constraints 1 year prior to natural disaster shocks and then examine the within-industry spillover effects in the industries with high financial constraints (top tertile) and low financial constraints (middle and bottom tertiles) using DID analysis. Panel B of Table OA.11 of the Online Appendix tabulates the results. Again, consistent with our prediction, we find that the within-industry spillover effects mostly concentrate in industries with high financial constraints. The total treatment effects are significant in all industries when we examine the distress levels of treated firms (see the last row of columns 1 to 4 in panel B) but they are only significant in industries with high financial constraints when we examine the profit margins of the treated firms (see the last row of columns 5 to 8 in panel B). These findings suggest that distressed treated firms engage in price competition only in industries with high levels of financial constraints.

4.2.3 Testing Alternative Explanations

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

Demand Commonality. The first alternative explanation that we test is demand commonality. This alternative explanation argues that natural disasters lead to negative demand shocks directly hurting both the treated firms and their industry peers, and thus the within-industry spillover effects can be potentially explained by demand commonality. We present a set of evidence suggesting that this is unlikely to be the case.[19]

First, in Table OA.8 of the Online Appendix, we have already excluded matched peer firms that are geographically close to the natural disaster areas, and we show that the within-industry spillover effects remain robust. By doing this, we exclude a set of peer firms that are more susceptible to the negative demand shocks caused by natural disasters.

Although a matched peer firm is geographically far from the natural disaster areas, its customers may mainly come from these areas, and thus, this peer firm may still be directly affected by the demand shocks. For example, Barrot and Sauvagnat (2016) show that suppliers can exhibit correlated outcomes if they share common business customers. To rule out this possibility, we further require the matched peer firms to have no customers negatively affected by natural disasters. We consider both business customers and individual consumers in our analysis. We identify firms' business customers and their geographic locations using Compustat customer segment data and Factset Revere data. We identify firms' individual consumers and their geographic locations using a detailed dataset from Baker, Baugh and Sammon (2020), which provides firms' sales to individual consumers at the city level.[20] In Table OA.12, we require that the matched peer firms to (i) be outside of the states affected by the natural disasters (panel A) or be far away from natural disaster areas (panel B), (ii) have no business customers affected by natural disasters, and (iii) have no individual customers from areas affected by natural disasters. The within-industry spillover effects are still robust, suggesting that demand commonality is unlikely to be the main driver for the within-industry spillover effects.

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

[19]Note that we do not aim to rule out the possibility that negative demand shocks make firms directly affected by natural disasters more distressed. In fact, demand shock is one of the channels through which natural disasters can lead to economic and financial distress of treated firms. The alternative explanation we aim to rule out here is that the demand shocks caused by natural disasters also make the treated firm and its non-treated industry peers become more distressed simultaneously.

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

First, we note that in the baseline DID test shown in Table 4, we have already required the matched peer firms not to be either suppliers or customers of the treated firms. The fact that we find strong within-industry spillover effects in Table 4 suggests that these effects are unlikely caused by suppliers or customers of the treated firms. Second, to strengthen our results, in Table OA.13 of the Online Appendix, we further require that the matched peer firms do not share any common customers or any common suppliers with treated firms. By doing so, we rule out the alternative explanation that the within-industry spillover effects are caused by common customers or suppliers of both treated firms and their industry peers.[21] Moreover, we also remove the matched peer firms that are related to the treated firms vertically in the DID analysis. By doing so, we drop firms that are potential customers or suppliers of the treated firms from the pool of matched firms. We define two firms as connected vertically if their vertical relatedness scores are ranked in the top 10% among the scores of all firm pairs (see, Frésard, Hoberg and Phillips, 2020). As shown in Table OA.13, the within-industry spillover effects remain robust.

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

To test this possibility, we require the matched peer firms to share no common lenders with the treated firms in the DID analysis. We also control for firms' exposure to natural disasters through lenders ($Lender\_Exposure_{i,t-1}$). We identify the borrower-lender relationship using the LPC DealScan database and construct $Lender\_Exposure_{i,t-1}$ in two steps. First, we find out each lender l's exposure to natural disasters in year t, which is the outstanding loans issued by lender l from $t-5$ to $t-1$ to firms that experience natural disasters in year t normalized by the total amount of outstanding loans issued by lender l from $t-5$ to $t-1$.[22] Second, for each firm i, we compute $Lender\_Exposure_{i,t-1}$ by averaging the lender-level exposure across all lenders of the firm. The average is weighted based on the amount of outstanding loans borrowed from different lenders. As shown in Table OA.14 of the Online Appendix, our findings remain robust after controlling

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

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

for $Lender\_Exposure_{i,t-1}$ and removing the matched peer firms that share any common lender with the treated firms, suggesting that lender commonality unlikely explains the within-industry spillover effects.[23]

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

To test this possibility, we require the matched peer firms to share no common institutional blockholders with the treated firms in the DID analysis based on 13F institutional holdings data. Following previous studies (e.g., Hadlock and Schwartz-Ziv, 2019), we define blockholders of a firm as the owners that hold 5% of the firm's market cap or above. As shown in Table OA.15 of the Online Appendix, the within-industry spillover effects remain robust, suggesting that institutional blockholder commonality unlikely explains our findings.

Controlling for All Alternative Channels Simultaneously. In Table OA.16 of the Online Appendix, we examine the within-industry spillover effects by controlling for multiple alternative channels simultaneously. For each treated firm, we match it with up to five non-treated peer firms in the same four-digit SIC industry. We construct a set of indicator variables to label the matched peer firms that share common demand with the treated firms ($Common\_Demand_{i,t}$), that are connected to the treated firms through the production networks ($Production\_Network_{i,t}$), that share common lenders with the treated firms ($Common\_Lender_{i,t}$), and that share common institutional blockholders with the treated firms ($Common\_Lender_{i,t}$). We then add these dummies and their interactions with the $Post_{i,t}$ term to regression specification (4.3). We find that within-industry spillover effects captured by the coefficient for $Post_{i,t}$ remain robust after controlling for all four alternative channels simultaneously.

[23]Because DealScan data are mainly collected from commitment letters and credit agreements drawn from SEC filings, the database mainly covers medium to large-size loans (e.g., Carey, Post and Sharpe, 1998). We limit our analysis in Table OA.14 of the Online Appendix to the firms covered by the DealScan data because we cannot accurately measure lender exposure for the firms outside of the DealScan universe.

4.3 Cross-Industry Spillover Effects with Natural Disaster Shocks

In Section 4.2.1 above, we provide some evidence for cross-industry spillover effects. In particular, panel B of Table 4 shows that the coefficient for the cross-industry spillover term (i.e., β_4 in equation 4.3) is statistically significant, with the signs consistent with the predictions of our hypothesis. In this section, we further study cross-industry spillover effects by highlighting the role of the common market leaders in transmitting shocks across industries.

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

$$Y_t^{(c_{i,j})} = \sum_{m=1}^{3} \beta_m ND\_mild_{j,t}^{(m)} + \sum_{s=1}^{3} \beta_s ND\_severe_{j,t}^{(s)} + \varepsilon_t^{(c_{i,j})}. \tag{4.6}$$

Dependent variable $Y_t^{(c_{i,j})}$ is the distress risk and profit margin of common market leader $c_{i,j}$, which is a market leader in both industry i and industry j. The independent variables, $ND\_mild_{j,t}^{(m)}$, are indicator variables that equal 1 if the m^{th} $(m = 1, 2, 3)$ largest firm (ranked by sales) in industry j in year t experiences mild damage during natural disaster shocks. Similarly, $ND\_severe_{j,t}^{(s)}$, are indicator variables that equal 1 if the s^{th} $(s = 1, 2, 3)$ largest firm (ranked by sales) in industry j in year t experiences severe damage during natural disaster shocks.[24] We include both the $ND\_mild_{j,t}^{(m)}$ and $ND\_severe_{j,t}^{(s)}$ dummies to reflect the fact that the impact of natural disasters depends on the magnitude of damage caused.

Our regression specification (4.6) essentially estimates the impact of idiosyncratic natural disaster shocks to the top three market leaders in industry j on the distress risk and profit margin of the common market leader (i.e., $c_{i,j}$) in year t. We compute fitted

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

value $\widehat{IdShock}_{j,t}^{(c_{i,j})}$ as follows:

$$\widehat{IdShock}_{j,t}^{(c_{i,j})} = \widehat{Y}_t^{(c_{i,j})} = \sum_{m=1}^{3} \hat{\beta}_m ND\_mild_{j,t}^{(m)} + \sum_{s=1}^{3} \hat{\beta}_s ND\_severe_{j,t}^{(s)}. \tag{4.7}$$

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

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

$$\widehat{IdShock}_{-i,t} = \frac{1}{n(\mathcal{I}_{i,t})} \sum_{j \in \mathcal{I}_{i,t}} \widehat{IdShock}_{j,t}^{(c_{j,i})}, \tag{4.8}$$

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

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

$$Y_{i,t}^{(-c)} = \beta_1 \widehat{IdShock}_{-i,t} + \varepsilon_{i,t}, \tag{4.9}$$

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

Cross-Industry Spillover Effects. We present the estimation results for the cross-industry spillover analysis in Table 8 and the corresponding summary statistics in Table OA.17 of the Online Appendix. Panel A of Table 8 presents the results from the first-step regressions. We find that the common leaders' distress risk (profit margin) is positively (negatively) associated with the natural disaster shocks to the top market leaders in the same industries. This pattern is more pronounced for severe natural disaster shocks. Panel B presents the second-step estimates on the cross-industry spillover effect. The coefficient of $\widehat{IdShock}_{-i,t}$ is positive and statistically significant, indicating that the distress risk and

Table 8: Distress spillover effects across industries

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

	Panel B: Cross-industry spillover (second step)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress_{i,t}^{(-c)}$		$DD_{i,t}^{(-c)}$		$PM_{i,t}^{(-c)}$		$Markup_{i,t}^{(-c)}$	
$\widehat{IdShock}_{-i,t}$	0.798**	0.805**	0.519**	0.525**	0.547**	0.544**	0.540**	0.534**
	[1.995]	[2.000]	[2.537]	[2.562]	[2.392]	[2.394]	[2.243]	[2.239]
$\widehat{IdShock}_{-i,t} \times Frac\_Peers\_as\_Customers_{-i,i,t}$		0.089		0.050		0.818**		1.268***
		[1.053]		[0.135]		[2.305]		[2.618]
$\widehat{IdShock}_{-i,t} \times Frac\_Peers\_as\_Suppliers_{-i,i,t}$		−0.119		−0.477		−0.880**		−1.078**
		[−1.488]		[−1.505]		[−2.485]		[−2.300]
Observations	5152	5148	5020	5016	5264	5260	5264	5260
R-squared	0.001	0.002	0.001	0.003	0.001	0.010	0.001	0.010

Note: This table reports the results of the two-step estimation of the cross-industry distress spillover effects. In panel A, we estimate the first-step specification: $Y_t^{(c_{i,j})} = \sum_{m=1}^{3} \beta_m ND\_mild_{j,t}^{(m)} + \sum_{s=1}^{3} \beta_s ND\_severe_{j,t}^{(s)} + \varepsilon_t^{(c_{i,j})}$ and denote the fitted value by $\widehat{IdShock}_{i,t}^{(c_{i,j})}$. The dependent variables $Distress_t^{(c_{i,j})}$, $DD_t^{(c_{i,j})}$, $PM_t^{(c_{i,j})}$, and $Markup_t^{(c_{i,j})}$ are the distress risk, distance to default, profit margin, and markup of common market leader $c_{i,j}$, respectively. The independent variables, $ND\_mild_{j,t}^{(m)}$, are indicator variables that equal 1 if the m^{th} $(m = 1, 2, 3)$ largest firm (ranked by sales) in industry j in year t experiences mild damage during natural disaster shocks. Similarly, $ND\_severe_{j,t}^{(s)}$, are indicator variables that equal 1 if the s^{th} $(s = 1, 2, 3)$ largest firm (ranked by sales) in industry j in year t experiences severe damage during natural disaster shocks. In panel B, we use the fitted value of the first step to construct independent variable $\widehat{IdShock}_{-i,t}$ as the simple average of $\widehat{IdShock}_{j,t}^{(c_{j,i})}$ over all industries connected to industry i through competition networks. The regression specification is: $Y_{i,t}^{(-c)} = \beta_1 \widehat{IdShock}_{-i,t} + \beta_2 \widehat{IdShock}_{-i,t} \times Frac\_Peers\_as\_Customers_{-i,i,t} + \beta_3 \widehat{IdShock}_{-i,t} \times Frac\_Peers\_as\_Suppliers_{-i,i,t} + \varepsilon_{i,t}$. The industry-level dependent variables $Y_{i,t}^{(-c)}$ are sales weighted across all firms excluding the common market leaders in year t. Variables $Frac\_Peers\_as\_Customers_{-i,i,t}$ and $Frac\_Peers\_as\_Suppliers_{-i,i,t}$ are the fraction of peer industries connected to the focal industry i through the competition network that are also the customer industries and supplier industries of the focal industry. 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.

profit margin of industry i are positively associated with other industries' idiosyncratic shocks that propagate to industry i through common market leaders. In summary, our results suggest that adverse idiosyncratic shocks in one industry can be transmitted to another industry through the common leaders that operate in both industries. These findings are consistent with the predictions of our hypothesis.

We further show that the cross-industry spillover results cannot be explained away by production network externality. Specifically, we control for the interaction between the predicted idiosyncratic shocks and the production network connectedness, measured by the fraction of peer industries connected to the focal industry i through the competition network that are also the customer industries and supplier industries of the focal industry i. As shown by panel B of Table 8, the coefficient for the predicted idiosyncratic shocks remains positive and statistically significant when the peer industries are neither the customers nor the suppliers of the focal industries, suggesting that the cross-industry spillover effect cannot be explained away by production network externality.[25]

One potential concern about the cross-industry spillover analysis is that we define industries at the SIC-4 level and thus it is possible that the cross-industry spillover effects may reflect the within-industry spillover effects in industries defined more broadly. To alleviate this concern, we conduct the cross-industry spillover analysis by examining how the predicted shocks from industries that do not share the same three-digit SIC code with the focal industry propagate to this focal industry. As shown in Table OA.18 of the Online Appendix, the coefficient of $\widehat{IdShock}_{-i,t}$ remains positive and statistically significant when we focus on industry spillover effects outside of the three-digit SIC industries.

In addition, we show that the cross-industry spillover effects remain robust after excluding industries whose common market leaders are mainly superstar firms (i.e., top 50 firms ranked by sales). Specifically, we exclude an industry from our analysis if half or more than half of the links between this industry and other industries in the competition network are connected through superstar firms. As shown in Table OA.19 of the Online Appendix, the coefficient of $\widehat{IdShock}_{-i,t}$ remains positive and statistically significant after dropping these industries, suggesting that the cross-industry spillover effects are not simply driven by superstar firms.

Heterogeneity in Spillover Effects across Industries. In the proposed economic mechanisms behind **Hypothesis 2**, cross-industry spillover effects rely critically on proper functioning of the internal capital market of common leaders. When the internal capital market breaks down, the distress of one segment of a given common leader will not lead

[25] As shown by Columns (5) to (8) of Table 8, the coefficient for the interaction term between $\widehat{IdShock}_{-i,t}$ and $Frac\_Peers\_as\_Suppliers_{-i,i,t}$ (i.e., β_3) is negative and statistically significant, which suggests that the cross-industry contagion spillover effect becomes weaker when the connected industries are also suppliers of the focal industry i. This result is not surprising because, in this situation, the connected industries' outputs are the inputs of the focal industry i. When the connected industries suffer from natural disasters, the resulting drop in their output prices pushes up the profit margin of the focal industry i. Although the coefficients of the interaction terms in Table 8 speak to the impact of the natural disaster shocks along the production network, our analysis differs from Barrot and Sauvagnat (2016) — our paper studies the spillover of the profit margin, whereas their paper focuses on the spillover of the sales growth rate.

to changes of product market behaviors in other segments of the common leader, because different segments do not share the balance sheet as a whole. Therefore, we expect cross-industry spillover effects to be stronger in industries with higher efficiency of the internal capital markets of common leaders. To test this prediction, we measure the efficiency of internal capital market of a four-digit SIC industry using the absolute value added by allocation in Rajan, Servaes and Zingales (2000) averaged across all common leaders in this industry. We sort industries into tertiles based on the industry-level efficiency 1 year prior to natural disaster shocks and then examine cross-industry spillover effects in the industries with high efficiency (top and middle tertile) and low efficiency (bottom tertile) of internal capital market. Table 9 tabulates the results. Consistent with the prediction of our hypothesis, we find that cross-industry spillover effects captured by the coefficient of $\widehat{IdShock}_{-i,t}$ mostly concentrate in industries with high efficiency of internal capital market of common leaders, while they are almost absent in industries with low efficiency of internal capital market of common leaders. These findings are robust both with and without controlling for production network connectedness.

4.4 Evidence from Two Additional Quasi-Natural Experiments

We provide collaborative evidence from two additional quasi-natural experiment settings in this section. In Section 4.4.1, we exploit the setting of the AJCA tax holiday to investigate the impact of a reduction in financial distress (i.e., positive distress shock) on industry peers. In Section 4.4.2, we exploit the setting of the Lehman crisis and examine the impact of an increase in financial distress (i.e., negative distress shock) on industry peers. Different from natural disasters, both the AJCA tax holiday and the Lehman crisis are one-time economy-wide shocks. Therefore, we use the econometric specification of heterogeneous average spillover effects across different industries to identify the spillover effects.

4.4.1 Evidence from the AJCA Tax Holiday

In this section, we study the impact of reduced financial distress on firms' product market behaviors and the distress levels of their peer firms. Specifically, we examine the impact of the AJCA, in which firms are allowed to repatriate foreign profits to the US at a 5.25% tax rate, rather than the existing 35% corporate tax rate. The passage of the AJCA reduces the distress levels of treated firms (i.e., those with a significant amount of pretax income from abroad), especially for those that were financially constrained prior to the AJCA (see Faulkender and Petersen, 2012), because the reduction of the repatriation tax rate not

Table 9: Heterogeneous cross-industry spillover effects across efficiency of the internal capital markets of common leaders.

	Panel A: Without controlling for production network connectedness							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress^{(-c)}_{i,t}$		$DD^{(-c)}_{i,t}$		$PM^{(-c)}_{i,t}$		$Markup^{(-c)}_{i,t}$	
Internal capital market efficiency	High	Low	High	Low	High	Low	High	Low
$\widehat{IdShock}_{-i,t}$	0.898**	0.498	0.680***	0.073	0.772***	0.195	0.733**	0.215
	[2.339]	[0.701]	[2.630]	[0.208]	[2.831]	[0.545]	[2.536]	[0.587]
Observations	3335	1609	3266	1554	3406	1640	3406	1640
R-squared	0.001	0.001	0.002	0.001	0.003	0.001	0.002	0.001

	Panel B: Controlling for production network connectedness							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Distress^{(-c)}_{i,t}$		$DD^{(-c)}_{i,t}$		$PM^{(-c)}_{i,t}$		$Markup^{(-c)}_{i,t}$	
Internal capital market efficiency	High	Low	High	Low	High	Low	High	Low
$\widehat{IdShock}_{-i,t}$	0.903**	0.536	0.681***	0.069	0.763***	0.199	0.717**	0.223
	[2.038]	[0.746]	[2.623]	[0.198]	[2.796]	[0.559]	[2.493]	[0.618]
$\widehat{IdShock}_{-i,t} \times Frac\_Peers\_as\_Customers_{-i,i,t}$	0.057	0.117	0.320	−0.565	0.921**	0.553	1.380***	0.998
	[0.591]	[0.924]	[0.831]	[−1.029]	[2.380]	[0.946]	[2.634]	[1.178]
$\widehat{IdShock}_{-i,t} \times Frac\_Peers\_as\_Suppliers_{-i,i,t}$	−0.066	−0.218*	−0.568	−0.443	−0.798**	−0.933	−0.894*	−1.311
	[−0.734]	[−1.661]	[−1.613]	[−0.981]	[−2.179]	[−1.515]	[−1.854]	[−1.521]
Observations	3331	1609	3262	1554	3402	1640	3402	1640
R-squared	0.001	0.005	0.004	0.005	0.011	0.008	0.011	0.010

Note: This table reports the heterogeneous cross-industry spillover effects across efficiency of the internal capital markets of common leaders. The regression specification of panel A is: $Y^{(-c)}_{i,t} = \beta_1 \widehat{IdShock}_{-i,t} + \varepsilon_{i,t}$. The regression specification of panel B is: $Y^{(-c)}_{i,t} = \beta_1 \widehat{IdShock}_{-i,t} + \beta_2 Frac\_Peers\_as\_Customers_{-i,i,t} + \beta_3 Frac\_Peers\_as\_Suppliers_{-i,i,t} + \varepsilon_{i,t}$. Definitions of the dependent and independent variables are given in Table 8. We present results in industries with high efficiency of internal capital market of common leaders (top tertile and middle tertile) and low efficiency of internal capital market of common leaders (bottom tertile). The efficiency of internal capital market is measured by the absolute value added by allocation in Rajan, Servaes and Zingales (2000). We sort industries into tertiles based on the average efficiency across all common leaders in the industry 1 year prior to natural disaster shocks. The sample spans the period from 1994 to 2018. Standard errors are clustered at the industry level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

only reduces firms' tax burden but also improves firms' internal capital market and better aligns the investment policy (e.g., Harford, Wang and Zhang, 2017). Consistent with the prediction of our hypothesis, we find that (i) firms that were financially constrained prior to the AJCA compete less aggressively in the product market after the passage of the AJCA, and (ii) the distress levels of the non-treated industry peers that were financially constrained prior to the AJCA reduce significantly after the passage of the AJCA.

Different from natural disasters, the AJCA tax holiday is a one-time shock. Therefore, we cannot use the DID specification (4.3) to identify the spillover effect because we will not be able to separate the spillover effects caused by the AJCA from unrelated aggregate time-series changes. To overcome this empirical challenge, we use the method highlighted by Berg, Reisinger and Streitz (2021) to identify spillover effects by exploiting the variation in the fraction of treated firms across industries. Specifically, we run the

Table 10: Spillover effects in the AJCA tax holiday setting.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta Distress_i$		ΔDD_i		ΔPM_i		$\Delta Markup_i$	
$AJCA_i$	0.029	0.027	−0.167	−0.150	−0.015*	−0.014*	−0.026*	−0.025
	[0.319]	[0.299]	[−0.348]	[−0.312]	[−1.733]	[−1.652]	[−1.653]	[−1.556]
$\overline{AJCA}_i$	−0.378**	−0.334*	2.059**	1.886**	0.042**	0.032*	0.079**	0.056*
	[−2.191]	[−1.884]	[2.217]	[1.968]	[2.442]	[1.781]	[2.526]	[1.706]
$High\_Cross\_Ind\_Shocks_i$		−0.060		0.246		0.013**		0.029***
		[−0.986]		[0.842]		[2.248]		[2.752]
Observations	590	590	436	436	624	624	622	622
R-squared	0.009	0.011	0.018	0.020	0.010	0.018	0.010	0.023

Note: This table examines the spillover effects in the AJCA tax holiday setting. We focus our analysis on the financially constrained firms (i.e., those with financial constraint ranked in the top quartile) prior to the passage of the AJCA. Financially constraint is measured as the average delay investment score of Hoberg and Maksimovic (2015) in the 5-year window prior to the the passage of the AJCA (i.e., 1999 to 2003). The regression specification is: $\Delta Y_i = \beta_1 AJCA_i + \beta_2 \overline{AJCA}_i + \beta_3 High\_Cross\_Ind\_Shocks_i + \varepsilon_i$. The dependent variables are the change of distress risk ($\Delta Distress_i$), change of distance to default (ΔDD_i), change of gross profit margin (ΔPM_i), and change of markup ($\Delta Markup_i$) from the pre-AJCA period to the post-AJCA period. The distress risk, distance to default, profit margin, and markup in the pre-AJCA period are the average values from 2001 to 2003, while those in the post-AJCA period are the values of 2005. We follow Grieser and Liu (2019) to define $AJCA_i$ is an indicator variable that equals 1 if firm i has more than 33% pretax income from abroad during the period from 2001 to 2003. $\overline{AJCA}_i$ is the industry treatment intensity which is the fraction of firms in firm i's industry with an $AJCA_i$ indicator that equals 1. $High\_Cross\_Ind\_Shocks_i$ captures the strength of cross-industry spillover effects through the competition network, and it is an indicator variable that equals one if the average industry treatment intensity for the industries connected to firm i's industry through competition networks is higher than 20%. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

following cross-sectional regression:

$$\Delta Y_i = \beta_1 AJCA_i + \beta_2 \overline{AJCA}_i + \beta_3 High\_Cross\_Ind\_Shocks_i + \varepsilon_i, \tag{4.10}$$

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

Table 10 tabulates the results from the regressions. Coefficient β_2 represents the within-industry spillover effects. It is positive and statistically significant for profit margin (see columns 5 and 6), and markup (see columns 7 and 8), suggesting that firms that are financially distressed prior to the AJCA compete less aggressively in the product market when a larger fraction of firms in the industry are shocked by the passage of the AJCA. Coefficient β_2 is negative and statistically significant for distress (see columns 1 and 2), and it is positive and statistically significant for distance to default (see columns 3 and 4), suggesting that firms that are financially distressed prior to the AJCA become less distressed when a larger fraction of firms in the industry are shocked by the passage of the AJCA. These results are consistent with the predictions of our hypothesis and demonstrate the existence of the within-industry spillover effects. In Table OA.20 of the Online Appendix, we further examine the within-industry spillover effects by allowing the treated firms and non-treated firms to have heterogenous spillover effects (see Berg, Reisinger and Streitz, 2021). We find that the spillover effects mainly exist from treated firms to non-treated firms, rather than from treated firms to other treated firms. We examine distress risk using bond yield spread and CDS spread as two additional measures. As shown in Table OA.21 of the Online Appendix, we find that the within-industry spillover effects are robust in both bond yield spread and CDS spread.

Table 10 also speaks to the cross-industry spillover effects. Coefficient β_3 is positive for profit margin (see columns 5 and 6), and markup (see columns 7 and 8), suggesting that when more industries connected to the focal industry through the competition network are shocked by the passage of the AJCA, the firms in the focal industries compete less aggressively in the product market. Coefficient β_3 is negative for distress (see columns 1 and 2), and it is positive for distance to default (see columns 3 and 4), suggesting that when more industries connected to the focal industry through the competition network are shocked by the passage of the AJCA, the distress levels of the firms in the focal industries decrease more. These results are consistent with the predictions of our hypothesis and demonstrate the existence of the cross-industry spillover effects.

4.4.2 Evidence from the Lehman Crisis

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

Chodorow-Reich (2014) uses cross-sectional regressions to show that firms experiencing more negative credit supply shocks receive a higher interest rate when they borrow during the Lehman crisis. Kim (2021) exploits the same quasi-experiment and studies the changes of firms' product prices around the Lehman crisis based on the Neilsen data. He finds that firms experiencing more negative credit supply shocks in the cross section decrease their output prices more after the Lehman crisis, a finding that is consistent with our hypothesis. To further examine the existence of spillover effects in the reductions of product price, we go one step beyond by implementing the method highlighted by Berg, Reisinger and Streitz (2021) in the following cross-sectional regression:

$$\Delta \ln(Price)_i = \beta_1 Lehman_i + \beta_2 \overline{Lehman}_i + \beta_3 High\_Cross\_Ind\_Shocks_i + \varepsilon_i, \tag{4.11}$$

where $\Delta \ln(Price)_i$ represents the changes of product prices of firm i after the Lehman crisis. We use three different approaches to compute the price changes based on the Nielsen data. Specifically, we first aggregate product prices across all products (i.e., unique UPCs) of firm i in product category c in year t (2007 or 2009) using three methods: geometric average ($Price\_Geo_{i,c,t}$, see Kim, 2021), equal-weighted average ($Price\_EW_{i,c,t}$), and sales-weighted average ($Price\_VW_{i,c,t}$). We then compute the price growth rate for each firm-product-category from 2007 to 2009 as the difference of the log prices: $\Delta \ln(Price)_{i,c} = \ln(Price_{i,c,2009}) - \ln(Price_{i,c,2007})$. Finally, we compute $\Delta \ln(Price)_i$ by aggregating the price growth rates across all product categories within firm i based on sales. $Lehman_i$ is an indicator variable that equals 1 if firm i experiences a below-median credit supply shock (i.e., the firm's credit supply reduces more than the median firm) during the Lehman crisis. We measure firm-specific credit supply shocks following Chodorow-Reich (2014) and Kim (2021), with the detailed construction methods explained in Online Appendix 4.3. A lower level of credit supply shock implies that the lender health of the firm deteriorated more during the Lehman crisis. $\overline{Lehman}_{i,t}$ is the industry treatment intensity which is the fraction of firms in firm i's industry with an $Lehman_i$ indicator that equals 1. $High\_Cross\_Ind\_Shocks_{i,t}$ captures the strength of cross-industry spillover effects through the competition network, and it is an indicator variable that equals one if the average industry treatment intensity for the industries connected to firm i's industry through competition networks is higher than 20% in year t.[26]

Table 11 tabulates the results. The outcome variables in columns (1)–(6) are the changes of firm product prices. Coefficient β_2 represents the within-industry spillover effects. It is negative and statistically significant, suggesting that firms compete more

[26] We find that the coefficient β_3 is insignificant in Table 11, which is likely due to two reasons: 1) Unlike the natural disaster setting, the Lehman setting is mainly a cross-sectional test, which limits its power in quantifying the cross-industry spillover effects; 2) Although Nielsen data provide detailed product prices at the UPC level, the data cover relatively a limited number of firms. The coverage limitation in the cross section of firms applies to the bond yield spread data and the CDS spread data as well.

Table 11: Spillover effects in the Lehman crisis setting.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\Delta \ln(Price\_Geo)_i$		$\Delta \ln(Price\_EW)_i$		$\Delta \ln(Price\_VW)_i$		$\Delta Bond\_spread_i(\%)$		$\Delta CDS\_spread_i(\%)$	
$Lehman_i$	0.039	0.039	0.059	0.059	0.062	0.061	−0.106	−0.099	−0.040	−0.039
	[0.780]	[0.770]	[1.238]	[1.233]	[1.358]	[1.329]	[−0.866]	[−0.801]	[−0.533]	[−0.522]
$\overline{Lehman}_i$	−0.200**	−0.205**	−0.217**	−0.209**	−0.191**	−0.206**	0.526**	0.603**	0.368**	0.401**
	[−2.249]	[−2.206]	[−2.520]	[−2.371]	[−2.268]	[−2.372]	[1.982]	[2.122]	[2.076]	[2.074]
$High\_Cross\_Ind\_Shocks_i$		0.008		−0.012		0.028		−0.148		−0.041
		[0.191]		[−0.333]		[0.749]		[−0.967]		[−0.478]
Observations	384	384	384	384	384	384	419	419	453	453
R-squared	0.013	0.013	0.015	0.015	0.013	0.014	0.011	0.013	0.011	0.011

Note: This table examines the spillover effects in the Lehman crisis setting. The regression specification is: $\Delta Y_i = \beta_1 Lehman_i + \beta_2 \overline{Lehman}_i + \beta_3 High\_Cross\_Ind\_Shocks_i + \varepsilon_i$. The dependent variables in columns (1)–(6) are changes of firm product prices from 2007 to 2009. We use three different approaches to compute the price changes based on the Nielsen data. Specifically, we first aggregate product prices across all products (i.e., unique UPCs) of firm i in product category c in year t (2007 or 2009) using three methods: geometric average ($Price\_Geo_{i,c,t}$, see Kim, 2021), equal-weighted average ($Price\_EW_{i,c,t}$), and sales-weighted average ($Price\_VW_{i,c,t}$). We then compute the price growth rate for each firm-product-category from 2007 to 2009 as the difference of the log prices: $\Delta \ln(Price)_{i,c} = \ln(Price_{i,c,2009}) - \ln(Price_{i,c,2007})$. Finally, we compute $\Delta \ln(Price)_i$ by aggregating the price growth rates across all product categories within firm i based on sales. The dependent variables in columns (7) and (8) are changes of the bond yield spread from 2007 to 2009, while the dependent variables in columns (9) and (10) are changes of the CDS spread from 2007 to 2009. $Lehman_i$ is an indicator variable that equals 1 if firm i experiences a below-median credit supply shock during the Lehman crisis. The method we use to construct the measure of firm-specific credit supply shock is the same as that of Chodorow-Reich (2014), and it is explained in Online Appendix 4.3. A lower level of credit supply shock implies that the lender health of the firm deteriorated more during the Lehman crisis. $\overline{Lehman}_{i,t}$ is the industry treatment intensity which is the fraction of firms in firm i's industry with an $Lehman_i$ indicator that equals 1. $High\_Cross\_Ind\_Shocks_{i,t}$ captures the strength of cross-industry spillover effects through the competition network, and it is an indicator variable that equals one if the average industry treatment intensity for the industries connected to firm i's industry through competition networks is higher than 20% in year t. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

aggressively in the product market by reducing product prices when a larger fraction of firms in the industry experience adverse credit-supply shocks during the Lehman crisis. This finding is robust to the three methods we use to aggregate product prices.

Next, we examine the spillover effects in distress. Specifically, we replace the outcome variables in specification (4.11) with the bond yield spread and CDS spread.[27] We find that coefficient β_2 is positive and statistically significant for both spreads (see columns 7–10), suggesting that firms become more distressed when a larger fraction of firms in the industry experience adverse credit-supply shocks during the Lehman crisis. These findings are consistent with the predictions of our hypothesis and they demonstrate the existence of the within-industry spillover effects.

4.5 Industry Return Predictability Through Competition Network

In this section, we use both portfolio sorting analyses and Fama-MacBeth regressions to test **Hypothesis 3**. Specifically, we present evidence of industry return predictability

[27] We focus on the bond yield spread and CDS spread instead of the accounting-based distress measure because the spread measures are market-based and thus more suitable for the Lehman setting which is essentially an event study.

Table 12: Excess industry returns sorted on lagged returns of peer industries.

Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5 − Q1
Panel A: Annualized returns with one-month holding period					
7.12**	7.19**	9.26***	11.77***	11.27***	4.15***
[2.18]	[2.26]	[2.99]	[3.79]	[3.51]	[3.29]
Panel B: Annualized returns with three-month holding period					
7.76**	8.30***	9.21***	9.74***	11.35***	3.59***
[2.33]	[2.65]	[2.97]	[3.14]	[3.48]	[4.65]
Panel C: Annualized returns with six-month holding period					
8.37**	8.47***	9.33***	9.77***	10.58***	2.21***
[2.57]	[2.72]	[3.04]	[3.22]	[3.34]	[4.02]

Note: This table shows the annualized excess industry returns for calendar-time portfolios formed based on lagged returns of peer industries. At the beginning of each calendar month, we sort industries into quintiles based on the average 1-month lagged returns of peer industries connected through the competition network. The returns of each industry quintile portfolio are the equal-weighted returns across industries in this industry quintile portfolio. The holding periods are one month, three months, and six months in Panels A, B, and C, respectively. Because common leaders and conglomerates operate in more than one industry, we exclude them in computing industry returns. Industry returns are value-weighted from stock returns of the stand-alone firms in the industries based on firms' 1-month lagged market capitalization. We exclude from the analysis financial and utility industries. Newey-West standard errors are estimated with one lag, three lags, and six lags in Panels A, B, and C, respectively. The sample period of the data is from Jan 1977 to June 2018. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

through competition network. We show that focal industries have higher contemporaneous and future returns when their peer industries connected through the competition network have higher stock returns.

Portfolio Sorting Analysis. We first use portfolio sorting analysis to show evidence of return predictability through competition network. At the beginning of each calendar month t, we sort industries into quintiles based on the average returns of peer industries connected through the competition network in month $t-1$. We apply several filters in the construction of industry-level returns that are defined as the value-weighted average of firm-level returns in a given industry. First, we exclude common leaders from the sample in computing industry-level returns because they operate in more than one industry. Similar to Bustamante and Donangelo (2017), we further exclude firms that operate in more than three segments according to the Compustat segment data. By focusing on industry returns constructed from non-conglomerate firms in each industry, we address the concern of the double counting issue of market leaders' stock returns in different industries and the concern that the return predictability across different industries is driven by return momentum of the common market leaders. Finally, we exclude financial and utility industries.

Table 12 shows the average excess returns of the industry portfolios sorted on the lagged returns of peer industries. Following previous asset pricing studies that examine the returns of industry portfolios (e.g., Hou and Robinson, 2006; Bustamante and Donangelo, 2017), we compute the returns of an industry quintile portfolio as the equal-weighted returns across industries in this industry quintile portfolio.[28] We find that industries with higher lagged peer industry returns are associated with higher excess returns. The magnitudes of return spread are economically large. With one-month holding period, the spread in average excess returns between the industries with the highest peer industry returns (Q5) and the industries with the lowest peer industry returns (Q1) is 4.15%. These spreads are comparable to the equity premium and value premium. We find that the return spreads remain statistically significant when we increase the holding period to three months and six months, suggesting that the return predictability lasts for a few months. In Table 13, we also show that industries with higher lagged peer industry returns are associated with higher alphas (i.e., risk-adjusted excess returns) after adjusting for the market return, Fama-French three factors (Fama and French, 1993), Carhart momentum factor (Carhart, 1997), Pástor-Stambaugh liquidity factor (Pástor and Stambaugh, 2003), Stambaugh-Yuan mispricing factor (Stambaugh and Yuan, 2017), Hou-Xue-Zhang q factors (Hou, Xue and Zhang, 2015), and Fama-French five factors (Fama and French, 2015). These findings suggest that the industry return predictability through competition network is unlikely explained by heterogeneous exposures to systematic risks.

Event-Time Cumulative Returns. Figure 9 illustrates how returns of peer industries predict the returns of focal industries at different time horizons. The solid red line plots the cumulative returns from month $t-12$ to month $t+k$ (average across all calendar month t) on the long-short portfolio formed on the returns of peer industries in month t. It shows that, in the sorting period month t, stock prices of the focal industries move in the same direction contemporaneously as their peer industries connected through the competition network. Moreover, stock prices of the focal industries continue drifting in the same direction to the initial price response. The predictable positive returns of the long-short portfolio persist for about a year before fading away.

To construct the benchmark for the cumulative returns for the long-short portfolios, we simulate 1000 pseudo panels of competition networks by randomly reshuffling the nodes (i.e., SIC-4 industries) of the competition network. For each simulation, we reshuffle the nodes once and apply the reshuffled node definition to all cross sections in the panel of the competition network which allows us to preserve the persistence of the network structure. The dashed black line plots the average cumulative returns on the long-short portfolios formed on the returns of peer industries in the simulated competition networks, while the gray area plots the 99% confidence interval (i.e., [0.5%, 99.5%]) of the cumulative

[28]Our findings are robust to value-weighted returns of industry portfolios. The results are tabulated in Table OA.23 of the Online Appendix.

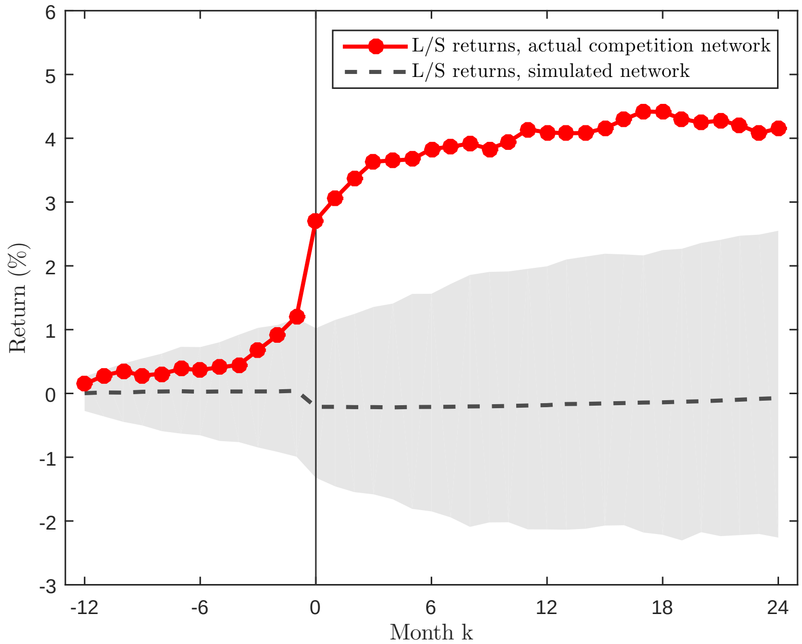
Table 13: Risk-adjusted excess industry returns sorted on lagged returns of peer industries.

CAPM model	Fama-French three-factor model	Carhart four-factor model	Pástor-Stambaugh liquidity-factor model	Stambaugh-Yuan mispricing-factor model	Hou-Xue-Zhang q-factor model	Fama-French five-factor model
Panel A: Annualized alphas with one-month holding period						
4.49***	4.28***	4.02***	4.26***	4.15***	4.57***	5.43***
[3.48]	[3.25]	[2.95]	[3.10]	[2.81]	[3.33]	[3.73]
Panel B: Annualized alphas with three-month holding period						
3.94***	4.00***	3.05***	3.97***	2.26**	3.52***	3.33***
[4.87]	[4.72]	[3.67]	[4.52]	[2.45]	[3.76]	[3.34]
Panel C: Annualized alphas with six-month holding period						
2.46***	2.49***	1.60***	2.43***	1.51***	2.38***	2.21***
[4.61]	[4.43]	[2.91]	[4.42]	[2.60]	[3.63]	[3.31]

This table shows the annualized alphas of the long-short industry quintile portfolio formed based on lagged returns of peer industries. The factor models include the capital asset pricing model (CAPM), Fama-French three-factor model (Fama and French, 1993), Carhart four-factor model (Carhart, 1997), Pástor-Stambaugh liquidity-factor model (Pástor and Stambaugh, 2003), Stambaugh-Yuan mispricing-factor model (Stambaugh and Yuan, 2017), Hou-Xue-Zhang q-factor model (Hou, Xue and Zhang, 2015), and Fama-French five-factor model (Fama and French, 2015). At the beginning of each calendar month, we sort industries into quintiles based on the average 1-month lagged returns of peer industries connected through the competition network. The returns of each industry quintile portfolio are the equal-weighted returns across industries in this industry quintile portfolio. The holding periods are one month, three months, and six months in Panels A, B, and C, respectively. Because common leaders and conglomerates operate in more than one industry, we exclude them in computing industry returns. Industry returns are value-weighted from stock returns of the stand-alone firms in the industries based on firms' 1-month lagged market capitalization. We exclude from the analysis financial and utility industries. Newey-West standard errors are estimated with one lag, three lags, and six lags in Panels A, B, and C, respectively. The sample period of the data is from Jan 1977 to June 2018. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

returns for the long-short portfolios formed on the returns of peer industries in the simulated competition networks. As shown in Figure 9, it is obvious that the predictable positive returns of the long-short portfolio cannot be explained by random network structure. If anything, the returns of the focal industries in the simulated networks are negatively correlated with the returns of the peer industries in the portfolio formation period (i.e., when $k = 0$) because focal industries are randomly drawn from the industries excluding the peer industries and thus they on average have lower returns when the peer industries have higher returns. The obvious difference between the returns of the long-short portfolio constructed based on the actual competition network and the simulated networks indicates that the industry return predictability through competition network reflects fundamental economic connections among industries linked by competition network.

Fama-MacBeth Regressions. We perform Fama-MacBeth tests in Table 14. The dependent variables are industry returns in month t ($Ret_{i,t}$), industry returns in month $t+1$ ($Ret_{i,t+1}$), industry returns from month $t+1$ to month $t+3$ ($Ret_{i,t+1\rightarrow t+3}$), and industry returns from month $t+1$ to month $t+6$ ($Ret_{i,t+1\rightarrow t+6}$). The main independent variable is the average returns of peer industries connected through the competition network in



Note: This figure plots the event-time cumulative returns of the long-short portfolios sorted based on the average returns of peer industries connected through the competition network. The solid red line plots the cumulative returns from month $t-12$ to month $t+k$ (average across all calendar month t) on the long-short portfolio formed on the returns of peer industries in month t. The long-short portfolio is a zero cost portfolio that holds the industries with highest returns of peer industries (top quintile) and sells the industries with lowest returns of peer industries (bottom quintile). The returns of each industry quintile portfolio are the equal-weighted returns across industries in this industry quintile portfolio. In Figure OA.10 of the Online Appendix, we reproduce this figure by computing the returns of each industry quintile portfolio as the value-weighted returns across industries in this industry quintile portfolio based on industries' 1-month lagged market capitalization. The pattern of that figure is similar to what we show here. To construct the benchmark for the cumulative returns for the long-short portfolios, we simulate 1000 pseudo panels of competition networks by randomly reshuffling the nodes (i.e., SIC-4 industries) of the competition network. For each simulation, we reshuffle the nodes once and apply the reshuffled node definition to all cross sections in the panel of the competition network which allows us to preserve the persistence of the network structure. The dashed black line plots the average cumulative returns on the long-short portfolios formed on the returns of peer industries in the simulated competition networks, while the gray area plots the 99% confidence interval (i.e., [0.5%, 99.5%]) of the cumulative returns for the long-short portfolios formed on the returns of peer industries in the simulated competition networks.

Figure 9: Event-time cumulative returns of the long-short portfolios.

month t ($PeerRet_{i,t}$). As Panel A of Table 14 shows, the slope coefficient for $PeerRet_{i,t}$ is positive and statistically significant for both the contemporaneous returns of the focal industries and the subsequent drifts. The slope coefficient remains virtually the same both statistically and economically after we control for the average returns of peer industries from month $t-11$ to month $t-1$ ($PeerRet_{i,t-11\to t-1}$), and the historical returns of the focal industries ($Ret_{i,t}$ and $Ret_{i,t-11\to t-1}$), suggesting that the industry return predictability through competition network cannot be explained by the industry momentum effect (e.g., Moskowitz and Grinblatt, 1999).

Previous studies have shown that customer returns can predict supplier returns (e.g., Cohen and Frazzini, 2008), which raises the possibility that the return predictability through competition network may stem from the return predictability through production

Table 14: Fama-MacBeth regressions.

	Panel A: Baseline regressions							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Ret_{i,t}$		$Ret_{i,t+1}$		$Ret_{i,t+1\rightarrow t+3}$		$Ret_{i,t+1\rightarrow t+6}$	
$PeerRet_{i,t}$	0.065***	0.063***	0.017***	0.019***	0.039***	0.038***	0.048***	0.046***
	[10.471]	[10.126]	[3.248]	[3.561]	[4.579]	[4.599]	[3.988]	[4.201]
$PeerRet_{i,t-11\rightarrow t-1} \times \frac{1}{11}$		0.063***		0.054***		0.125***		0.206**
		[3.849]		[3.240]		[3.058]		[2.560]
$Ret_{i,t}$				−0.024***		−0.009		0.017
				[−3.809]		[−0.787]		[1.067]
$Ret_{i,t-11\rightarrow t-1} \times \frac{1}{11}$		0.060**		0.107***		0.276***		0.404***
		[2.565]		[4.734]		[5.193]		[3.936]
Constant	0.012***	0.010***	0.011***	0.009***	0.034***	0.028***	0.068***	0.058***
	[5.021]	[4.361]	[4.402]	[3.833]	[4.911]	[4.209]	[5.414]	[4.735]
Average obs./month	311	291	312	291	309	289	305	286
Average R-squared	0.009	0.033	0.004	0.044	0.004	0.043	0.005	0.042

	Panel B: Controlling for the returns of customer industries							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Ret_{i,t}$		$Ret_{i,t+1}$		$Ret_{i,t+1\rightarrow t+3}$		$Ret_{i,t+1\rightarrow t+6}$	
$PeerRet_{i,t}$	0.054***	0.051***	0.019***	0.020***	0.038***	0.036***	0.045***	0.044***
	[7.647]	[7.045]	[3.103]	[3.405]	[4.250]	[3.950]	[3.406]	[3.714]
$PeerRet_{i,t-11\rightarrow t-1} \times \frac{1}{11}$		0.057***		0.049***		0.100**		0.160*
		[3.084]		[2.634]		[2.182]		[1.832]
$Ret_{i,t}$				−0.025***		−0.004		0.009
				[−3.489]		[−0.376]		[0.578]
$Ret_{i,t-11\rightarrow t-1} \times \frac{1}{11}$		0.040*		0.099***		0.256***		0.357***
		[1.682]		[4.280]		[4.471]		[3.271]
$CustomerRet_{i,t}$	0.092***	0.095***	0.027***	0.027***	0.070***	0.058***	0.103***	0.096***
	[10.044]	[10.395]	[2.926]	[3.064]	[4.044]	[3.667]	[3.744]	[3.817]
$CustomerRet_{i,t-11\rightarrow t-1} \times \frac{1}{11}$	0.098***	0.075***	0.101***	0.087***	0.225***	0.167**	0.364***	0.234*
	[3.850]	[3.091]	[3.503]	[3.107]	[3.196]	[2.521]	[2.675]	[1.749]
Constant	0.010***	0.009***	0.010***	0.009***	0.031***	0.027***	0.063***	0.056***
	[4.720]	[4.292]	[4.119]	[3.729]	[4.592]	[4.204]	[5.020]	[4.501]
Average obs./month	244	229	245	229	243	228	240	225
Average R-squared	0.025	0.052	0.017	0.064	0.018	0.064	0.020	0.064

Note: This table reports the slope coefficients and test statistics from Fama-MacBeth regressions. The dependent variables are industry returns in month t ($Ret_{i,t}$), industry returns in month $t+1$ ($Ret_{i,t+1}$), industry returns from month $t+1$ to month $t+3$ ($Ret_{i,t+1\rightarrow t+3}$), and industry returns from month $t+1$ to month $t+6$ ($Ret_{i,t+1\rightarrow t+6}$). The main independent variable is the average returns of peer industries connected through the competition network in month t ($PeerRet_{i,t}$). In Panel A, we control for the average returns of peer industries from month $t-11$ to month $t-1$ ($PeerRet_{i,t-11\rightarrow t-1}$), and the historical returns of the focal industries ($Ret_{i,t}$ and $Ret_{i,t-11\rightarrow t-1}$). In Panel B, we add the returns of the industries that are customers of the focal industries ($CustomerRet_{i,t}$ and $CustomerRet_{i,t-11\rightarrow t-1}$) to the list of control variables. Because common leaders and conglomerates operate in more than one industry, we exclude them in computing industry returns. Industry returns are value-weighted from stock returns of the stand-alone firms in the industries based on firms' 1-month lagged market capitalization. We exclude from the analysis financial and utility industries. Newey-West standard errors are estimated with one lag from Columns (1) to (4), three lags from Columns (5) to (6), and six lags from Columns (7) to (8), respectively. The sample period of the data is from Jan 1977 to June 2018. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

network. To test this possibility, we further add the returns of the industries that are customers of the focal industries ($CustomerRet_{i,t}$ and $CustomerRet_{i,t-11\rightarrow t-1}$) to the list of control variables. To increase the data coverage of the production network at the industry level, we put together the industry-level supply chain links from three datasets:

Compustat customer segment data, Factset Revere data, and the BEA Input-Output Accounts data. As shown in Panel B of Table 14, the slope coefficient of $PeerRet_{i,t}$ remains robustly positive after controlling for the returns of the customer industries, suggesting that the industry return predictability through competition network is largely orthogonal to industry return predictability through production network. Panel B also allows us to compare the economic magnitudes between the two types of return predictability. We find that the magnitudes of the slope coefficient of $CustomerRet_{i,t}$ in Panel B of Table 14 are similar to those documented by the previous studies (e.g., Menzly and Ozbas, 2010), while magnitudes of the slope coefficient of $PeerRet_{i,t}$ range from 44% to 74% of those of the slope coefficient of $CustomerRet_{i,t}$. These results suggest that the return predictability through competition network is economically sizable compared with the return predictability through the production network, which arguably represents a more direct form of economic connections among industries.

Heterogeneity of the Return Predictability. We perform several heterogeneity tests to better understand the economic mechanism of the industry return predictability through competition network. First, we examine the heterogeneity of the industry return predictability across the levels of analyst coverage and institutional ownership. Cohen and Frazzini (2008) show that stock returns of customers predict stock returns of suppliers because news about economically related firms is not immediately incorporated into stock prices in the presence of investor attention constraints. Consistently, Menzly and Ozbas (2010) show that the magnitude of return predictability along the production network decreases with the levels of analyst coverage and institutional ownership. In Panel A of Table 15, we adopt the same empirical approach as Menzly and Ozbas (2010). Specifically, we sort focal industries into tertiles based on their analyst coverage and institutional ownership. We then interact the tertile indicators with $PeerRet_{i,t}$ and use the interaction terms as the independent variables in the Fama-MacBeth regressions. We find that, the contemporaneous returns of focal industries with high levels (i.e., top tertile) of analyst coverage and institutional ownership react much more strongly to the returns of their peer industries compared to industries with lower levels of analyst coverage and institutional ownership (see Columns 1 and 2 in Panel A of Table 15). On the other hand, the subsequent return drift of the focal industries with high levels (i.e., top tertile) of analyst coverage and institutional ownership is much weaker than that of the industries with lower levels of analyst coverage and institutional ownership (see Columns 3 to 8). These findings suggest that information related to the peer industries is incorporated into stock prices of the focal industries more quickly with higher levels of analyst coverage and

Table 15: Heterogeneity of the industry return predictability.

	Panel A: Heterogeneity across analyst coverage and institutional ownership							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Ret_{i,t}$		$Ret_{i,t+1}$		$Ret_{i,t+1\to t+3}$		$Ret_{i,t+1\to t+6}$	
Tertiles sorted on:	analyst	IO	analyst	IO	analyst	IO	analyst	IO
$PeerRet_{i,t} \times 1^{st}\ Tertile_{i,t}(Low)$	0.024**	0.039***	0.041***	0.042***	0.083***	0.077***	0.085***	0.052*
	[2.206]	[3.329]	[3.763]	[3.534]	[4.751]	[3.866]	[3.283]	[1.712]
$PeerRet_{i,t} \times 2^{nd}\ Tertile_{i,t}$	0.085***	0.071***	0.009	0.019***	0.025*	0.037***	0.022	0.064***
	[10.213]	[9.317]	[1.122]	[2.729]	[1.852]	[3.134]	[1.178]	[3.934]
$PeerRet_{i,t} \times 3^{rd}\ Tertile_{i,t}(High)$	0.102***	0.097***	−0.006	−0.007	0.010	0.002	0.032	0.014
	[12.921]	[12.166]	[−0.868]	[−0.946]	[0.727]	[0.159]	[1.377]	[0.685]
Constant	0.012***	0.011***	0.011***	0.011***	0.034***	0.032***	0.068***	0.064***
	[5.016]	[4.471]	[4.435]	[4.122]	[4.900]	[4.412]	[5.390]	[4.781]
Average obs./month	311	311	312	312	309	309	305	305
Average R-squared	0.020	0.020	0.015	0.014	0.015	0.014	0.015	0.015

	Panel B: Heterogeneity across competition network centrality and internal capital market efficiency							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Ret_{i,t}$		$Ret_{i,t+1}$		$Ret_{i,t+1\to t+3}$		$Ret_{i,t+1\to t+6}$	
Tertiles sorted on:	centrality	ICME	centrality	ICME	centrality	ICME	centrality	ICME
$PeerRet_{i,t} \times 1^{st}\ Tertile_{i,t}(Low)$	0.046***	0.058***	0.018**	0.012	0.024*	0.021*	0.038**	0.034*
	[5.703]	[6.875]	[2.379]	[1.480]	[1.872]	[1.661]	[2.210]	[1.767]
$PeerRet_{i,t} \times 2^{nd}\ Tertile_{i,t}$	0.071***	0.051***	0.022***	0.014	0.042***	0.041***	0.044**	0.050***
	[8.269]	[5.543]	[2.791]	[1.524]	[3.497]	[2.744]	[2.450]	[2.760]
$PeerRet_{i,t} \times 3^{rd}\ Tertile_{i,t}(High)$	0.098***	0.072***	0.023**	0.029***	0.070***	0.053***	0.103***	0.063***
	[9.471]	[7.514]	[2.150]	[3.348]	[4.023]	[3.477]	[3.904]	[2.653]
Constant	0.012***	0.012***	0.011***	0.011***	0.034***	0.034***	0.068***	0.068***
	[4.944]	[5.023]	[4.387]	[4.414]	[4.888]	[4.900]	[5.404]	[5.426]
Average obs./month	311	299	312	301	309	298	305	294
Average R-squared	0.018	0.018	0.012	0.012	0.012	0.012	0.013	0.013

Note: This table examines the heterogeneity of the industry return predictability using Fama-MacBeth regressions. Panel A studies the heterogeneity across analyst coverage and institutional ownership, while Panel B studies the heterogeneity across competition network centrality and internal capital market efficiency. The dependent variables are industry returns in month t ($Ret_{i,t}$), industry returns in month $t+1$ ($Ret_{i,t+1}$), industry returns from month $t+1$ to month $t+3$ ($Ret_{i,t+1\to t+3}$), and industry returns from month $t+1$ to month $t+6$ ($Ret_{i,t+1\to t+6}$). We sort industries into tertiles based on the analyst coverage, institutional ownership (IO), competition network centrality, and the internal capital market efficiency (ICME) of the common market leaders. The main independent variables are the interaction between the indicators for industry tertile with the average returns of peer industries connected through the competition network in month t ($PeerRet_{i,t}$). Analyst coverage for an industry is the value-weighted (based on lagged market cap) average number of analyst coverage across all firms in this industry that are not common market leaders. Analyst coverage at the firm level is measured as the number of analyst forecasts for annual EPS at one-year horizon. We obtain the analyst coverage data from I/B/E/S. Institutional ownership for an industry is the value-weighted (based on lagged market cap) average level of institutional ownership across all firms in this industry that are not common market leaders. Institutional ownership at the firm level is measured as the percentage of stock shares owned by 13-F institutions. We obtain the institutional ownership from the Thomson/Refinitiv 13-F data. We compute the competition network centrality as the principal component of the four network centrality measures: closeness, degree, betweenness, and eigenvector. We measure the efficiency of internal capital market of a four-digit SIC industry using the absolute value added by allocation in Rajan, Servaes and Zingales (2000) averaged across all common leaders in this industry. Newey-West standard errors are estimated with one lag from Columns (1) to (4), three lags from Columns (5) to (6), and six lags from Columns (7) to (8), respectively. The sample period of the data is from Jan 1977 to June 2018. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

institutional ownership. Similar to the return predictability in the production network, the industry return predictability through competition network likely also relies on the presence of investor attention constraints.

We then examine the heterogeneity of the industry return predictability across the age of network links. We hypothesize that it takes investors longer time to learn the economic connections between focal industries and their peers if the network links are formed recently. Consistent with our prediction, Table OA.24 in the Online Appendix shows that it takes six months for the stock prices of the focal industries to react to the news about their peer industries when the network links are formed within two years, while the price reaction of the focal industries is much faster for network links formed earlier.

Next, we explore the heterogeneity across the centrality of industries in the competition network. Because of the "knock-on effect", we expect that industries with higher centrality on the competition network (i.e., industries that are more connected to others through common market leaders) will react more strongly to shocks of their peer industries and thus the industry return predictability should be stronger in these industries. We consider four centrality measures for all industries connected on the competition network — closeness, degree, betweenness, and eigenvector — following the literature (e.g., Sabidussi, 1966; Bonacich, 1972; Freeman, 1977; El-Khatib, Fogel and Jandik, 2015). The four centrality measures of competition network are highly correlated (see Table OA.2 of the Online Appendix). Given the fact that they comove significantly and positively with each other over time and each of them only captures some, but by no means all, aspects of the centrality of nodes on the competition network, we use the first principal component of the four centrality measures as the centrality measure in our test.[29] Consistent with our hypothesis, Panel B of Table 15 shows that stock returns of the focal industries with higher centrality on the competition network indeed react more positively to the returns of their peers. This pattern is true for both the contemporaneous returns (see Column 1 of Panel B) and the subsequent drift (e.g., see Column 7 of Panel B).

Finally, we explore the heterogeneity across the internal capital market of the common market leaders. Cross-industry spillover effects rely critically on proper functioning of the internal capital market of common leaders. When the internal capital market breaks down, the shocks to one segment of a given common leader will not lead to changes of product market behaviors in other segments of the common leader, because different segments do not share the balance sheet as a whole. Therefore, we expect the industry return predictability to be stronger in industries whose common leaders have higher efficiency of the internal capital markets. To test this prediction, we measure the efficiency of internal capital market of a four-digit SIC industry using the absolute value added by allocation in Rajan, Servaes and Zingales (2000) averaged across all common leaders in

[29] In Online Appendix 4.2, we provide mathematical formulas and a simple example to demonstrate the calculations of the four centrality measures. As shown in Table OA.3 of the Online Appendix, competition network centrality seems to be largely unrelated to other industry characteristics including production network centrality, industry size, industry-level book-to-market ratio, industry-level gross profitability, and Herfindahl-Hirschman index (HHI).

this industry. Consistent with the prediction of our hypothesis, Panel B of Table 15 shows that industry return predictability is stronger in industries with high efficiency of internal capital market of common leaders.

Robustness to the Definition of Competition Networks. We construct the competition network based on Compustat historical segment data. Here, we consider three robustness tests for alternative definitions of competition networks. In the first robustness test, we redefine the competition networks by incorporating private firms. This alternative definition alleviates the concern that we may miss some important industry links in the competition network connected by private common market leaders. We gather sales information and the industry classification of private firms from the Capital IQ data. In Online Appendix 8.3, we show that the resulting competition network is very similar to the one constructed based on public firms only. We also show that the industry return predictability through competition network remains robust after taking private firms into consideration (see Tables OA.26, OA.27, and OA.28 of the Online Appendix).

In the second robustness test, we redefine the competition networks by requiring that the focal industries and peer industries do not share the same three-digit SIC (SIC-3) codes. This alternative definition alleviates the concern that the industry return predictability may in fact reflect the within-industry spillover effects under broader industry definition. In Tables OA.29, OA.30, and OA.31 of the Online Appendix, we show that the industry return predictability through competition network remains robust when we only consider competition network links that connect two different SIC-3 industries.

In the third robustness test, we redefine the competition networks by excluding network links connected by the largest firms in the economy. This alternative definition alleviates the concern that the industry return predictability may be entirely driven by largest firms which ex ante may be less vulnerable to distress shocks. In Table OA.32 of the Online Appendix, we compute the returns of the peer industries by excluding network links connected by common market leaders that are also largest firms in the economy. We show that the industry return predictability through competition network remains robust after we exclude network links connected by common market leaders that are the top 50, 100, and 200 firms ranked by sales in the economy. These findings suggest that the return predictability through competition network is not entirely driven by a few largest firms in the economy.

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 evidence of industry return predictability through competition network. We find that focal industries have higher contemporaneous and future returns when their peer industries connected through the competition network have higher stock returns. To test the core mechanism, we examine the causal effects of firms' distress risk on their product market behaviors and the propagation of these firm-specific distress shocks through the competition network. We identify idiosyncratic distress risk by exploiting the occurrence of local natural disasters. We find that firms hit by disasters exhibit increased distress and then compete more aggressively in product markets by cutting their profit margins. In response, their industry peers also engage in more aggressive competition and exhibit their own increased distress, especially in industries with high entry barriers. Importantly, distress risk can propagate to other industries through common market leaders operating in multiple industries. These results cannot be explained by demand commonality or other network externality. We also find consistent results by examining the impact of the passage of AJCA in 2004 and the Lehman crisis in 2008, which lead to a reduction and an increase in the distress levels of the treated firms, respectively.

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