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EVIDENCE ON THE IMPORTANCE OF MARKET COMPETITION IN DISTRESS PROPAGATION

Winston Wei Dou
Shane A. Johnson
Wei Wu

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ABSTRACT

Using local natural disasters as a quasi-experimental setting, we show that heightened distress risk in shocked firms drives both these firms and their unshocked competitors to cut profit margins by about 0.8 percentage points. These reductions stem from predatory pricing, inventory liquidation, and weakened tacit collusion in product markets. Distress propagates horizontally as unshocked competitors rationally respond almost 1-for-1 with profit-margin cuts, significantly increasing their distress risk. Spillovers are more pronounced in tradable industries or those with higher barriers to leadership, larger inventories, greater price flexibility, or tighter financial constraints, revealing a novel channel for distress propagation across the economy.

Winston Wei Dou
The Wharton School
University of Pennsylvania
2318 Steinberg-Dietrich Hall
3620 Locust Walk
Philadelphia, PA 19104
and NBER
wdou@wharton.upenn.edu

Shane A. Johnson
Texas A&M University
Wehner Building, 4113 TAMU
College Station, TX 77845
shaneajohnson@tamu.edu

Wei Wu
Department of Finance
Mays Business School
360 Wehner Building (4218)
Texas A&M University
College Station, TX 77843-4218
wwu@mays.tamu.edu

A data appendix is available at http://www.nber.org/data-appendix/w33463

1 Introduction

Strategic competition in product markets is a powerful force shaping firms' cash flows and distress risk. Over recent decades, a small number of market leaders have increasingly dominated product markets. These leaders sustain their persistent market power through highly strategic competition, often relying on tacit collusion to maintain "competitive balance" and avoid destructive price wars.[1] This strategic product market behavior has resulted in persistently high markups for firms, with their fluctuations explaining much of the variation in corporate earnings.

Beyond individual firms, strategic interactions in product markets interconnect firms across the economy, facilitating the propagation of shocks. While much of the existing literature focuses on vertical propagation via input-output linkages, this paper uncovers a new yet intuitive channel: the horizontal propagation of distress risk among product market competitors. Specifically, idiosyncratic shocks to a single firm can propagate horizontally to product market competitors and, through multi-industry firms, ripple across industries. This mechanism introduces a critical source of risk that can drive aggregate economic fluctuations and shape the broader equilibrium outcomes of industry policies and regulations, such as price controls.[2]

Despite the clear importance of distress risk spillovers through strategic product market competition,[3] little is known, in general, about how a firm's heightened distress risk systematically affects its profit margins in a broad range of industries. Prior studies have primarily focused on a few specific industries, with even less attention to spillover effects between firms. Indeed, no empirical research has thoroughly examined how a firm's distress risk affects its product market competitors' profit margins or distress risk levels. This paper fills this gap by investigating within-industry spillover effects of distress risk through the strategic product market competition channel.

Our analysis provides comprehensive causal evidence that when a firm experiences an adverse shock and heightened distress risk, both the directly shocked firm and its unshocked competitors within the same product market reduce their profit margins in the short run (approximately 1 to 2 years post-shock) as competition intensifies, facilitated by the strategic complementarity in profit margins. In turn, earnings-based borrowing constraints translate the reduced earnings from intensified competition into greater financial distress. As a result, unshocked competitors also face heightened distress risk, even without

[1] Recent studies document the use of strategic tactics, including but not limited to tacit collusion, across various industries (e.g., Harrington and Skrzypacz, 2011; Miller and Weinberg, 2017; Miravete, Seim and Thurk, 2018; Miller, Sheu and Weinberg, 2021; Doraszelski et al., 2023; Clark, Horstmann and Houde, 2024).

[2] Extensive research has studied the impact of price controls (e.g., Carranza, Clark and Houde, 2015).

[3] By "distress risk," we refer to the probability of covenant violation or debt default within the next year.

experiencing an initial shock themselves. Thus, a firm's distress risk can increase in the short run when its competitors suffer severe financial distress or abrupt failure, despite the potential for long-term market power gains. While counterintuitive, this outcome is a natural consequence of competitive dynamics.

An illustrative example underscores these competitive dynamics. Alan Mulally, then CEO of Ford, testified before Congress in November 2008, advocating for a bailout of Ford's primary competitors, GM and Chrysler. Mulally cautioned against the potentially devastating impact heightened price competition could have on the entire industry if GM and Chrysler failed, causing thousands of dealerships to engage in fire sales of their inventory (e.g., Goolsbee and Krueger, 2015). Such pressure, he argued, would compel Ford to cut its own profit margins to retain customer demand, ultimately increasing its financial distress risk. He further emphasized the importance of preserving competitive balance within the industry to prevent a destructive race to the bottom on pricing. Additional examples of within-industry spillover effects are detailed in Online Appendix 1.

To explain these empirical patterns, particularly the observed negative impact of a firm's distress risk on its own and its competitors' profit margins, we propose three mechanisms grounded in strategic product market competition: (i) predatory pricing, (ii) inventory fire sales, and (iii) weakened tacit collusion. These mechanisms are not mutually exclusive and may operate simultaneously, reinforcing one another to explain the observed patterns. Moreover, with the prevalence of earnings-based borrowing constraints, intensified competition and the resulting lower profit margins naturally increase competitors' distress risk, increasing their likelihood of violating financial covenants or defaulting on debt.

The first mechanism, predatory pricing, involves competitors aggressively lowering prices to drive a distressed firm out of the market, enabling them to later gain market power and increase profit margins. This strategy is pursued even at the cost of short-term losses, as firms temporarily accept reduced profit margins during the period of intensified competition.

The second mechanism, inventory fire sales, involves distressed firms aggressively cutting profit margins to stimulate short-term demand through rapid inventory liquidation, aiming to meet immediate liquidity needs (e.g., Koijen and Yogo, 2015; Kim, 2021). In response, competitors in the same product market often rationally lower their own profit margins to retain customers.

The third mechanism, weakened tacit collusion, involves a small group of market leaders, some of which are financially distressed, repeatedly interacting in the product market and implicitly coordinating on profit margins to maintain competitive balance and prevent destructive price wars. Tacit collusion is sustained through the threat of retaliation, where deviation triggers a shift to non-collusive competition with lower profit margins.[4] A theory of distressed competition in the form of tacit collusion has been recently proposed by Chen et al. (2022).[5] According to this theory, a firm's heightened distress risk makes it more impatient and less concerned with future cooperation, weakening the ability of both the firm and its competitors to sustain tacit collusion. As a result, competitors are pressured to lower their profit margins, even without experiencing an initial shock themselves.

Establishing causal evidence for within-industry spillover effects driven by strategic product market competition mechanisms requires addressing several key challenges. The first challenge is the endogeneity issue. Latent confounders, such as potential new entrants, can simultaneously affect distress risk and competition. Endogenous selection further complicates this issue, as firms often self-select into industries based on shared underlying factors (e.g., Leary and Roberts, 2014). The second challenge arises from treatment externality or interference. Spillover effects violate the stable unit treatment value assumption (SUTVA), which is critical for causal effect estimation (e.g., Cox, 1958; Rubin, 1980; Manski, 1993, 2013). The third challenge is disentangling the role of strategic product market competition from other potential economic linkages. Even if a firm's increased distress risk and reduced profit margins are causally linked to higher distress risk for its competitors, it remains unclear whether this relationship is driven by variations in product market competition intensity, as proposed, or by alternative factors such as production network connections, disaster-induced demand shocks, lender commonality, or blockholder commonality.

To overcome the first challenge, we leverage major local natural disasters in the United States over the past 25 years as a source of exogenous variation. Following Barrot and Sauvagnat (2016), who study the propagation of idiosyncratic shocks through production networks, we focus on a set of disasters that caused substantial property losses. We demonstrate that these local disasters serve as valid instruments for exogenous idiosyncratic distress shocks by documenting significant losses and heightened distress risk among affected firms. To further address endogeneity concerns, we employ two additional quasi-experiments to identify within-industry spillover effects: the American Jobs Creation Act (AJCA) of 2004, which introduced a repatriation tax holiday (e.g., Faulkender and Petersen, 2012), and the Lehman Brothers crisis (e.g., Chodorow-Reich, 2014; Chodorow-Reich and Falato, 2021). These two one-time aggregate shocks induce heterogeneous changes in distress risk across firms, unrelated to changes in product market competition intensity.

[4]This mechanism becomes particularly relevant, as a small number of market leaders come to dominate product market (e.g., Gutiérrez and Philippon, 2017; Autor et al., 2020; De Loecker, Eeckhout and Unger, 2020; Dou, Ji and Wu, 2021, Online Appendix B).

[5]Tacit collusion does not involve explicit agreements in the legal sense and can also be referred to as "tacit coordination" (e.g., Ivaldi et al., 2007; Green, Marshall and Marx, 2014, and references therein).

Consistent evidence from these additional quasi-experiments reinforces our hypotheses and strengthens the robustness of our findings.

To address the second challenge, we use a formal Difference-in-Differences (DID) approach to estimate the treatment effect on treated firms and its spillover effects on non-treated industry rivals while accounting for cross-industry spillovers. This method has been extensively studied in the statistical and econometric literature, with foundational contributions from Rubin (1978, 1990) and others.[6] To establish causal relationships, we match treated firms (i.e., those affected by major local natural disasters) with their non-treated product market rivals based on asset size, tangibility, and age. Our analysis shows that both treated firms and their non-treated product market rivals experience significant increases in distress risk, indicating spillover effects triggered by the treated firms.

To address the third challenge, we examine various alternative channels that could explain the observed within-industry spillover effects, such as disaster-induced demand shocks, production network spillovers, and common creditor or blockholder channels. Our analysis reveals that these alternative channels are unlikely to account for the observed effects, reinforcing the role of strategic product market competition in driving the spillover dynamics of profit margins and distress risk.

To further confirm that product market competition, rather than alternative channels, drives these within-industry spillover effects, we empirically examine how these effects vary across industries, as predicted by strategic product market competition mechanisms. Our findings reveal that these spillover effects are stronger in tradable industries or in those with higher barriers to market leadership, larger inventories, greater price flexibility, or tighter financial constraints. In contrast, industries with lower tradability, lower barriers to market leadership, smaller inventories, less price flexibility, or looser financial constraints exhibit negligible or insignificant spillover effects. These findings strongly align with the proposed strategic product market competition mechanisms, reinforcing their key role in distress risk propagation.

Specifically, we find that firms' disaster-induced losses persist for an average of two years after experiencing major local natural disasters, with a cumulative loss of approximately 2.6% of sales over this period. Since the average net profit margin of public US firms is about 2.4 percentage points, these losses significantly increase the likelihood of debt default, thereby elevating distress risk. This heightened risk is reflected in bond yield spreads for affected firms, which rise by approximately 20 basis points, and CDS spreads, which increase by about 24 basis points. These increases are not only statistically significant but

[6]Applications of causal inference with interference in economics and finance include Miguel and Kremer (2004), Leary and Roberts (2014), Athey, Eckles and Imbens (2018), Boehmer, Jones and Zhang (2020), Berg, Reisinger and Streitz (2021), Bustamante and Frésard (2021), and Grieser et al. (2022).

also economically sizable, relative to the sample averages of a 298 basis point bond yield spread and a 108 basis point CDS spread. Additionally, the one-year-ahead probability of failure for affected firms increases to approximately 3.56 percentage points, compared to the pre-disaster sample average of 2 percentage points per year.

In response to this heightened distress risk, directly affected firms reduce their profit margins by about 80 basis points over the following one to two years and lower their output prices by approximately 7.6% relative to pre-disaster levels. These estimated effects on profit margins and output prices are both statistically significant and economically sizable. Importantly, unaffected product market competitors respond almost one-for-one, with similar reductions in profit margins and prices. These spillover effects raise the one-year-ahead probability of failure for unaffected competitors by approximately 1.1 percentage points per year, compared to the pre-disaster sample average of 2 percentage points per year. Moreover, bond yield spreads for unaffected competitors increase by about 18 basis points, while their CDS spreads rise by approximately 34 basis points. These changes are both statistically and economically significant.

Related Literature. A key innovation of this study is its integration of insights from the literature on strategic product market competition into the analysis of how financial risks driving capital market dynamics are propagated and aggregated across the economy. While these insights have been incorporated into corporate finance research, the idea that strategic competition drives financial risk propagation and aggregation in capital markets is both novel and timely. Our study focuses on strategic competition among firms, where competition intensity endogenously varies over time and across industries. The modern literature on industrial organization and competition highlights the market power of firms sustained by highly strategic competition tactics, including but not limited to tacit collusion and implicit coordination, across various industries (e.g., Harrington and Skrzypacz, 2011; Clark and Houde, 2013; Miller and Weinberg, 2017; Miravete, Seim and Thurk, 2018; Byrne and de Roos, 2019; Garrod, Harrington and Olczak, 2021; Miller, Sheu and Weinberg, 2021; Doraszelski et al., 2023; Clark, Horstmann and Houde, 2024). Understanding the dynamics of strategic competition among market leaders is more crucial than ever, as product markets have become increasingly concentrated over the past few decades.[7] Recent advances particularly emphasize how firms strategically respond to economic conditions and policies, generating endogenous variations in competition behavior and intensity. These variations play a critical role in shaping the transmission and pass-through of shocks (e.g., Miravete, Seim and Thurk, 2018, 2020; Clark, Horstmann and Houde, 2024; Clark, Duarte

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

and Houde, 2025). However, despite the importance of these advances, strategic product market competition remains understudied in the context of financial risk propagation, particularly in understanding how firms respond to distress risk shocks and how these responses, shaped by capital market frictions, drive the propagation of financial distress through changes in competition dynamics.

Moreover, this study contributes to the literature examining the impact of distress risk and financial constraints on firms' competitive behaviors in product markets. This line of research, 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, has demonstrated theoretically and empirically that a firm's distress risk and financial constraints tend to reduce its own profit margins in both the time-series and the cross-section (e.g., Maksimovic, 1988; Chevalier, 1995; Busse, 2002; Hortaçsu et al., 2011, 2013; Phillips and Sertsios, 2013; Koijen and Yogo, 2015; Kim, 2021; Chen et al., 2022).[8] These findings broadly align with our empirical results. However, in industries with low price elasticity of demand and a highly sticky customer base, financially constrained firms may charge higher markups than their less constrained counterparts in the cross-section (e.g., Chevalier and Scharfstein, 1996; Gilchrist et al., 2017). In a general theoretical framework, Dou and Ji (2021) demonstrate that higher markups under tightened financial constraints occur only when customer demand elasticity is extremely low and the customer base is highly sticky.

Specifically, our study contributes to this literature in four main ways. First, we examine a general environment of product market competition, rather than focusing on specific markets, such as local grocery stores, where customer bases are highly sticky and price elasticity of demand is very low. Second, we emphasize the time-series variation in profit margins, similar to Kim (2021) and Clark, Horstmann and Houde (2024), among others, in contrast to the cross-sectional comparative analysis of Gilchrist et al. (2017). Third, we address endogeneity concerns by leveraging major local natural disaster shocks and other distress shocks to identify the causal impact of distress risk on the strategic responses of affected firms and their rivals. Fourth, we investigate the effects of distress risk shocks not only on the profit margins and prices of the shocked firms but also on unshocked firms within the same industry and across industries connected through multi-industry firms.

Finally, this study also contributes to the existing literature on shock propagation in the

[8]In addition, recent studies have highlighted the influence of distress risk and financial constraints on other aspects of firms' competitive behaviors. These include product quality, market preemption, new product introduction, investment, talent retention, supplier relation, and innovation activities (e.g., Maksimovic and Titman, 1991; Campello, 2006; Matsa, 2011; Cookson, 2017; Phillips and Sertsios, 2017; Grieser and Liu, 2019; Dou et al., 2021).

economy. Previous studies have primarily focused on how shocks propagate through input-output linkages and production networks across firms, industries, and sectors (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). Additionally, recent literature has examined the transmission of local economic shocks within firms' internal networks of establishments (e.g., Giroud and Mueller, 2019; Giroud et al., 2021). In a similar vein to our research, recent studies emphasize on the significance of horizontal product market rivalries in the diffusion of technologies and industry growth (e.g., Bloom, Schankerman and Van Reenen, 2013; Ahern, Kong and Yan, 2021). In contrast to prior studies, our research examines the propagation of distress risk through strategic horizontal product market competition both within and across industries. Our results shed new light on the mechanisms through which distress risk propagates through the economy via strategic product competition. To further support the findings of this paper, Dou and Wu (2023) find that the equity returns of a specific industry can be predicted by the past returns of industries linked through multi-industry firms. This suggests delayed reactions to spillover effects from other industries, particularly when investors' attention is limited or their ability to process information is constrained. Their results in the asset pricing domain strongly align with the core economic mechanisms outlined in this paper.

The remainder of this paper is organized as follows: Section 2 describes the data sources and empirical measures. Section 3 presents evidence of distress spillover effects arising through product market strategic competition channels, using major local natural disasters as a key identification strategy. Section 4 explores the underlying economic mechanisms through various heterogeneity tests. Section 5 concludes. The online appendix contains examinations of alternative explanations, evidence for cross-industry spillover effects, and additional causal evidence from significant events such as the passage of the AJCA in 2004 and the Lehman crisis in 2008. Moreover, a note on additional materials can be found in Dou, Johnson and Wu (2023), which is available on the authors' personal websites.

2 Data and Measurement of the Variables

We assemble data from various sources. This section details the main data and empirical measures, with additional descriptions of supplementary data and measures provided in Online Appendix 2.

2.1 Data Description

We rely on local natural disaster occurrences to study the distress spillover in a causal framework. We gather data on property losses induced by natural disasters hitting the US territory from the Spatial Hazard Events and Loss Databases for the US (SHELDUS). This dataset, widely used in recent studies (e.g., Morse, 2011; Barrot and Sauvagnat, 2016; Dou, Kogan and Wu, 2022), encompasses natural hazards such as thunderstorms, hurricanes, floods, wildfires, and tornados, as well as perils like flash floods and heavy rainfall. 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 following Barrot and Sauvagnat (2016).[9] The merged location data span the period from 1994 to 2018.

Our study focuses on strategic competition among firms whose products are close substitutes. We therefore use four-digit SIC codes to define industries, following the literature (e.g., Bils and Chang, 2000; Hou and Robinson, 2006; Gomes, Kogan and Yogo, 2009; Frésard, 2010; Giroud and Mueller, 2010, 2011; Bustamante and Donangelo, 2017). Like Bustamante and Donangelo (2017), we use four-digit SIC codes in Compustat instead of historical SIC codes from CRSP to define industries, as prior research has generally found Compustat-based SIC codes to be 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 issue, we replace SIC codes ending in 0 or 9 with those of the firm's main segment from the Compustat segment data, consistent with the approach of Bustamante and Donangelo (2017). Firms whose adjusted SIC codes still end in 0 or 9 are excluded from the analysis.

We use the Compustat Historical Segment data to determine the sales and SIC industry codes for corporate segments of public firms. This dataset has been extensively used in the literature (e.g., Lamont, 1997; Rajan, Servaes and Zingales, 2000; Li, Qiu and Wang, 2019). The data contain segment-level variables for corporate segments such as sales, operating profit, capital expenditures, depreciation, and identifiable total assets. Each segment is assigned a primary four-digit SIC code based on the majority of its sales, and, if applicable,

[9] 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. This dataset has been widely utilized in the IO literature (e.g., Barrot and Sauvagnat, 2016; Clark, Horstmann and Houde, 2024).

a secondary SIC code. This reporting structure is aligned with the Statement of Financial Accounting Standards 14 (SFAS 14) since 1976, which mandates publicly traded firms to categorize their major business segments.

We use the NielsenIQ Retail Scanner Data to measure changes in product prices.[10] The NielsenIQ data are used widely in the literature (see, e.g., Aguiar and Hurst, 2007; Hottman, Redding and Weinstein, 2016). The NielsenIQ 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 NielsenIQ data cover more than 3.5 million unique products identified by Universal Product Codes (UPCs), representing 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). As detailed in Online Appendix 2, we match the NielsenIQ data to CRSP/Compustat using firm names. The merged sample includes product prices for 653 firms across 174 three-digit SIC industries from 2006 to 2016.

We conduct various heterogeneity tests to investigate the economic mechanisms driving distress spillovers, with a key test focusing on industry heterogeneity in price flexibility. To assess the price flexibility of four-digit SIC industries, we draw on the methodology established by Bils and Klenow (2004). They estimated the frequency of price changes for 350 consumption categories using monthly price data from the US Bureau of Labor Statistics (BLS). We align these consumption categories with four-digit SIC industries, resulting in 556 four-digit SIC industries covering all 350 consumption categories. Since a single four-digit SIC industry can correspond to multiple consumption categories, we calculate the industry's price flexibility as the weighted average frequency of price changes across its associated consumption categories. The weights reflect each consumption category's share of spending in the Consumer Expenditure Survey.

2.2 Measures for Distress Risk

We employ several empirical measures to assess distress risk. The first measure is the distress risk measure from Campbell, Hilscher and Szilagyi (2008). This measure evaluates the probability of a firm's bankruptcy or failure with a one-year forecasting horizon. The second measure is the distance to default measure with a one-year forecasting horizon constructed using the naive Merton default probability as in Bharath and Shumway (2008).

[10] Researcher(s)' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

This measure is inversely related to distress risk, with lower values indicating higher distress risk. Both measures are calculated annually and partly rely on market prices, enhancing their ability to capture potential spillover effects. Details on the construction of these measures are provided in Online Appendix 2.

Additionally, we use two alternative measures of distress risk: bond yield spread and CDS spread. The bond yield spread is calculated as the average yield spread across all bonds issued by a firm. Consistent with 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 with the Trade Reporting and Compliance Engine (TRACE) database from 2005 to 2018. We clean the Mergent FISD and TRACE data following Collin-Dufresn, Goldstein and Martin (2001) and Dick-Nielsen (2009). For each transaction, we calculate the bond yield spread by taking the difference between the bond yield and the Treasury yield with corresponding maturity. We obtain CDS spread from Markit. Following previous studies (e.g., Klingler and Lando, 2018; Collin-Dufresne, Junge and Trolle, 2020), we focus on CDS contracts with "XR" (no restructuring) as restructuring clause and examine the par-equivalent CDS spread. The bond yield spread and CDS spread are market-based measures of distress risk and, as such, arguably capture distress risk more directly than the measure of Campbell, Hilscher and Szilagyi (2008) or the distance-to-default measure. However, a key limitation of these two measures is their relatively limited cross-sectional coverage. The bond yield spread dataset spans the period from 1973 to 2018, covering 421 to 746 firms annually in the CRSP-Compustat merged sample, representing an average of approximately 11.2% of firms in the cross-section. Similarly, the CDS dataset spans 2001 to 2018, covering 90 firms in 2001 and 310 to 584 firms annually from 2002 to 2018, averaging around 7.5% of firms in the CRSP-Compustat cross-section.

2.3 Measures for Profit Margins

Consistent with recent literature (e.g., Antras, Fort and Tintelnot, 2017; Autor et al., 2020; De Loecker, Eeckhout and Unger, 2020), we calculate gross profit margins as the wedge between sales and variable production costs in our main empirical analyses. The cost of goods sold (COGS) as listed in the firm's financial statement serves as an empirical proxy for the variable production cost. The COGS item aggregates all expenses directly attributable to the production of the goods sold by the firm, including materials and intermediate inputs, ordinary labor cost, energy, and so forth. Specifically, gross profit margins are computed as the difference between sales and COGS, divided by sales. The sales and COGS data are sourced from Compustat. For robustness, we also measure net profit margins using the wedge between sales and total operating costs of the firm (see Online Appendix 2 for details). Our measures are derived from the so-called "accounting profits approach" for estimating profit margins (e.g., Baqaee and Farhi, 2019; Autor et al., 2020). Gross profit margins are used to focus on firms' production profits, while net profit margins capture their operating profits. As emphasized by Baqaee and Farhi (2019), the accounting profits approach has the advantage of requiring minimal manipulation of raw data and is robust to potential mis-specifications in user-cost estimation and production function estimation methods.

2.4 Construction of the Competition Network

We consider the competition network that connects industries through common market leaders operating across different industries (i.e., product markets). The concept and empirical construction of this competition network were originally proposed by Chen et al. (2020). We construct the competition network at the four-digit SIC industry level, excluding financial industries with SIC codes ranging from 6000 to 6999. To determine whether two industries are connected on the competition network, we examine whether they have at least one shared common market leader. We rely on Compustat historical segment data to gather information on the four-digit SIC codes for all the segments in which firms operate. We consider a firm 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 market leaders and is updated annually. We also use the sales and segment information on private firms obtained from the Capital IQ database to augment the competition network in the Online Appendix, and we find that our main results remain unchanged.

It is crucial to emphasize that the competition network is fundamentally distinct from the production network. Only a minimal fraction (about 1%) of connections are shared between the two, with the vast majority of connected industry pairs differing. This "orthogonality" between the vertical production network and the horizontal competition network is intuitive, as firms typically avoid relying on primary competitors within the same industry as their main suppliers, and industry peers often share common suppliers. We empirically show that the within-industry and cross-industry spillover effects of distress are not driven by production network externalities.

3 Distress Spillover via Strategic Market Competition

In this section, we leverage the occurrence of major local natural disasters as exogenous, idiosyncratic shocks to firms' distress risk to examine the distress spillover effects that emerge through strategic market competition channels.

Major Local Natural Disasters.

When drawing causal inferences about spillover effects among product market competitors, it is crucial to account for the potential endogeneity bias in the correlation between a firm's profit margin or distress risk level and those of its product market competitors. A key challenge in establishing causality is ensuring that this correlation is not driven by confounding factors, but rather reflects the causal impact of a firm's profit margin or distress risk on its competitors. This is inherently difficult, as many confounding factors are latent, unobservable, and challenging to model or control for accurately. For example, firms often endogenously select into specific industries or product markets. When two firms choose to operate in the same product market, it is likely because they are intrinsically influenced by shared latent factors. To address this, we leverage idiosyncratic exogenous distress shocks.

A key challenge in establishing causality is ensuring that any confounding factors generating this correlation affect only the treated firm directly, without simultaneously impacting its product market competitors. This is inherently difficult, as many confounding factors are latent, unobservable, and challenging to model or control for accurately. For example, firms endogenously select certain industries or product markets, likely because they are intrinsically influenced by common latent factors. To address this identification challenge, we leverage idiosyncratic exogenous distress shocks.

Specifically, we utilize major local natural disaster shocks as an instrumental variable to capture an exogenous, idiosyncratic increase in a firm's distress risk. Existing literature demonstrates the adverse impact of natural disasters on a firm's cash flow and financial health.[11] Even though catastrophe insurance is available, firms are typically only partially covered. For example, Henry et al. (2013) report that nearly half of all natural disaster losses between 1980 and 2018 were uninsured annually. Several factors contribute to this incomplete coverage. One major reason is that catastrophe insurance is often significantly overpriced and in limited supply, primarily due to capital market imperfections and the market power of insurers (e.g., Froot, 2001). As a result, even insured firms frequently face incomplete coverage because the cost of full insurance is prohibitively high. This

[11] See, e.g., Garmaise and Moskowitz (2009), Strobl (2011), Baker and Bloom (2013), Cavallo et al. (2013), Barrot and Sauvagnat (2016), Seetharam (2018), and Boustan et al. (2020).

aligns with the findings of Garmaise and Moskowitz (2009), who show that firms often partially hedge against natural disaster risks. With only partial insurance coverage, firms inevitably suffer significant losses when their headquarters or primary establishments are affected by major local natural disasters. These disasters substantially increase distress risk by causing significant financial losses and eroding collateral values, which, in turn, limit access to credit. Moreover, prolonged delays in insurance settlements and significant lags in public disaster assistance further exacerbate the distress risk for affected firms (e.g., Aretz, Banerjee and Pryshchepa, 2019; Brown, Gustafson and Ivanov, 2021; Seetharam, 2018). Taken together, major local natural disaster shocks are associated with heightened borrower default rates, increased borrowing costs, and less favorable loan terms. These shocks thus serve as a valid instrumental variable, capturing an exogenous, idiosyncratic increase in a firm's distress risk.

Losses of Firms Caused by Major Local Natural Disasters.

The identification assumption underlying the use of major local natural disasters as exogenous idiosyncratic shocks to a firm's distress risk is that these disasters lead to significant, unexpected losses for the affected firms. While this is intuitively supported by the discussion above, we also provide direct empirical evidence to justify this assumption. To quantify the losses incurred by firms due to a major local natural disaster, we utilize the "special items" (Compustat item SPI) reported on the income statement. These items capture significant, one-off expenses or income that firms anticipate as non-recurring in the future years (e.g., Johnson, Lopez and Sanchez, 2011).[12]

To estimate the impact of major local natural disasters on firm losses, we employ a difference-in-differences (DID) regression approach. Our first step involves defining "treated" firms affected by natural disasters. We then identify matched product market competitors that are unaffected by any natural disasters, serving as "control" firms, to construct counterfactual scenarios. Following the approach of Barrot and Sauvagnat (2016), our criteria for designating a firm as adversely affected by a local natural disaster in a given year is based on whether, during that year, a major local natural disaster results in substantial property damage in the county where the firm's headquarters or a major establishment is located. An establishment is considered "major" for the firm if it contributes to at least 75% of the firm's total sales.[13]

[12]We opt for "special items" over "extraordinary items" because, according to Compustat, any entry that might be classified as an extraordinary item is already encompassed within "special items." Importantly, "special items" include asset write-downs resulting from natural disasters.

[13]We perform robustness tests using alternative cutoffs, such as 25% and 50%, and find our results to be consistent across various thresholds.

Major local natural disasters are defined as those causing at least \$1 billion in estimated property damages and lasting fewer than 30 days. In accordance with existing literature (e.g., Aretz, Banerjee and Pryshchepa, 2019), we stipulate that the affected counties must experience a minimum of \$0.25 million in total estimated property damages. We show that our results are robust to alternative cutoff values of \$1 million, \$5 million, and \$10 million. In Online Appendix 3, we list the major local natural disasters included in our sample and show that the disasters are geographically widespread.

To construct a counterfactual, we pair each affected firm with up to five unaffected peer firms within the same four-digit SIC industry with similar asset size, tangibility, and age.[14] To study both treatment and spillover effects, we ensure that matched peer firms are not directly affected by major local natural disaster shocks. Specifically, we require that matched peer firms have no establishments, including headquarters, in any county that experiences any positive property damage caused by major local natural disasters during the year they serve as a match. Our results are robust to an additional check that requires matched peer firms to be located outside any states affected by major local natural disasters and at least 100 miles from any counties impacted by such disasters. Furthermore, to ensure our findings are not confounded by production network externalities, we require that matched peer firms are neither suppliers nor customers of the treated firms.

We then analyze the effects of major local natural disaster shocks on firm losses using the following DID approach:

$$Special\_items_{i,t}/Sales_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}. \quad (3.1)$$

The dependent variable $Special\_items_{i,t}/Sales_{i,t}$ represents special items scaled by firm sales, with negative values indicating firm losses. The independent variable $Treat_{i,t}$ is a binary indicator taking the value 1 if firm i is negatively impacted by a major local natural disaster in year t, and $Post_{i,t}$ is a binary indicator set to 1 for years following major local natural disasters. θ_i and δ_t denote firm and year fixed effects, respectively.

For the regression in (3.1), we use data spanning four years for each treated firm and its controls: two years before and two years after the associated major local natural disasters. Our primary focus is on the coefficient β_1, which measures firm losses following these disasters. Panel A of Table 1 shows that, on average, firms in counties affected by major local natural disasters incur losses equivalent to approximately 1.3% of their sales.

[14] 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. For firms identified as common market leaders, we match it to non-treated peer firms in all four-digit SIC industries in which this treated firm operates. When dealing with multi-industry firms that do not qualify as common market leaders, we match it to non-treated peer firms in its primary industry as per Compustat records.

Table 1: Losses and Core Expenses Following Major Natural Disasters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Disaster losses (normalized by $Sales_{i,t}$)		Panel B: Firms' core expenses (normalized by $Assets_{i,t-1}$)					
	$Special\_items_{i,t}$		$COGS_{i,t}$		$SG\&A_{i,t}$		$COGS_{i,t} + SG\&A_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$ (β_1)	−0.013**	−0.012**	−0.000	−0.003	−0.001	−0.001	−0.003	−0.007
	[−2.145]	[−2.131]	[−0.039]	[−0.606]	[−0.362]	[−0.692]	[−0.455]	[−1.221]
$Treat_{i,t}$ (β_2)	0.012**	0.005	0.055***	0.010**	−0.036***	0.003	0.023	0.014**
	[2.445]	[1.036]	[3.841]	[2.023]	[−5.713]	[1.616]	[1.228]	[2.108]
$Post_{i,t}$ (β_3)	0.007*	0.004	0.005	−0.004	0.000	0.000	0.004	−0.004
	[1.851]	[1.241]	[1.106]	[−1.363]	[0.233]	[0.233]	[0.700]	[−1.092]
Firm FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	135320	135290	132944	132792	114828	114660	114828	114660
R-squared	0.004	0.276	0.042	0.852	0.014	0.845	0.044	0.838

Panel C: Summary statistics of the firm-year panel

	Obs. #	Mean	Median	Stdev	p10th	p25th	p75th	p90th
$Special\_items_{i,t}$	94276	−0.054	0	0.335	−0.071	−0.015	0	0.002
$COGS_{i,t}$	91299	0.748	0.588	0.599	0.121	0.282	1.044	1.684
$SG\&A_{i,t}$	80279	0.324	0.255	0.253	0.056	0.123	0.461	0.727
$COGS_{i,t} + SG\&A_{i,t}$	80279	1.105	0.935	0.719	0.313	0.565	1.464	2.233

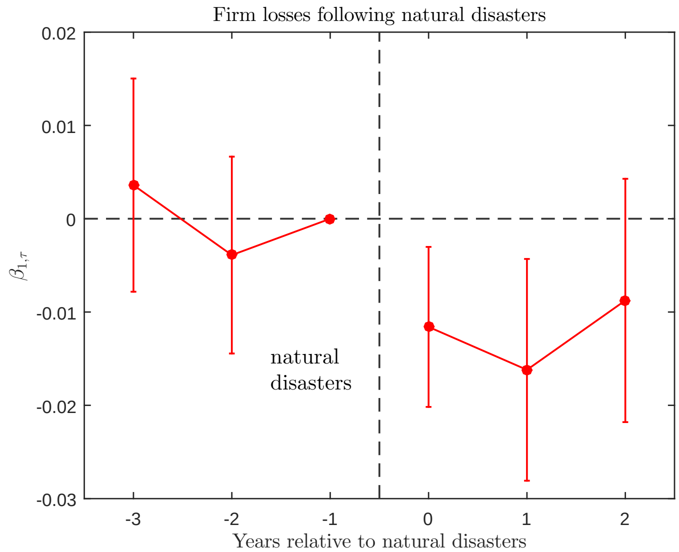
Notes. This table examines the amount of disaster losses (Panel A) and firms' core expenses (Panel B) following major natural disasters using a DID analysis. $Special\_items_{i,t}$ represents special items scaled by firm sales. Negative amount of special items represents firm losses. $COGS_{i,t}$ represents cost of goods sold normalized by lagged assets. $SG\&A_{i,t}$ represents SG&A expenses normalized by lagged assets. $COGS_{i,t} + SG\&A_{i,t}$ represents the sum of cost of goods sold and SG&A expenses normalized by lagged assets. $Treat_{i,t}$ 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. Panel C of this table shows the summary statistics for the firm-year panel from 1994 to 2018. 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.

We also conduct an event study analysis centered on major local natural disasters using a dynamic DID regression approach to examine the time-series dynamics of firm losses around these events. This dynamic analysis addresses the concern that the β_1 coefficient in regression (3.1) may pick up changes in gains or losses unrelated to natural disasters and serves as a pre-trend test for the parallel trend assumption. The analysis includes six yearly observations for each firm, covering three years before and three years after a major local natural disaster. The regression model is:

$$Special\_items_{i,t}/Sales_{i,t} = \sum_{\tau=-3}^{2} \beta_{1,\tau} \times Treat_{i,t} \times ND_{i,t-\tau} + \beta_2 \times Treat_{i,t} + \sum_{\tau=-3}^{2} \beta_{3,\tau} \times ND_{i,t-\tau} + \theta_i + \delta_t + \varepsilon_{i,t}, \tag{3.2}$$

where $\mathrm{ND}_{i,t-\tau}$ is an indicator variable equal to 1 if either firm i experiences major local natural disaster shocks in year $t - \tau$ as a treated firm, or the treated firm it is matched to (in the case firm i is a matched non-treated firm) experiences major local natural disaster

Figure 1: Firm Losses Caused by Major Natural Disasters.



Notes. This figure plots firm losses around major local natural disasters. 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 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.

shocks in year $t - \tau$. The term θ_i represents firm fixed effects, and the term δ_t represents year fixed effects. To avoid collinearity in categorical regressions, we impose constraints: $\beta_{1,-1} = \beta_{3,-1} = 0$, thereby designating the year immediately preceding the disaster as the reference period.

Figure 1 plots the estimated coefficients $\beta_{1,\tau}$ with $\tau = -3, -2, \ldots, 2$, and their 90% confidence intervals. We use 90% confidence intervals to make it more stringent to reject the two-sided null hypothesis of parallel trends, while maintaining the 5% one-sided critical value for detecting treatment effects. Figure 1 shows that reported firm losses increase only after major local natural disaster shocks, with no significant change in the reporting of special items prior to these events. The figure also indicates that firms incur significant losses, reflected in special items, with a cumulative average loss of approximately 2.6% over two years. Given that the average net profit margin of public US firms is about 2.4%, these losses substantially raise the likelihood of debt default, thereby increasing distress risk. Columns (1)-(4) in Panel A of Table 2 confirm that the total treatment effect is significantly different from zero, indicating that firms affected by major local natural disasters face substantially higher distress risk. This evidence supports our assertion that major local natural disaster shocks are a valid instrument for identifying exogenous idiosyncratic shocks to distress risk.

Managers might strategically misclassify core expenses as special items to inflate reported core earnings (e.g., McVay, 2006; Fan et al., 2010). To further validate our interpretation of the significant adverse impacts of major local natural disasters on firms, Panel A of Table 1 examines whether directly affected firms significantly reduce reported core expenses, particularly Cost of Goods Sold (COGS) and Selling, General, and Administrative expenses (SG&A), compared to unaffected product market competitors. Our findings show that affected firms do not significantly reduce reported core expenses, which is inconsistent with opportunistic classification shifting, where core expenses are reclassified as special items following disasters.

Spillovers of Distress Risk Among Competitors.

We now investigate whether major local natural disasters increase the distress risk for directly affected firms, and whether such distress risk propagates to their product market competitors. To do so, we employ the following DID regression specifications:

$$Y_{i,t} = \beta_1 Treat_{i,t} \times Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \beta_4 \ln(1 + n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}. \quad (3.3)$$

Here, the dependent variable $Y_{i,t}$ represents the level of distress risk, measured by the probability of failure ($Risk\_of\_Failure_{i,t}$), the distance-to-default measure ($Dist\_to\_Default_{i,t}$), the bond yield spread ($Yield\_Spread_{i,t}$), or the credit default swap (CDS) spread ($CDS\_Spread_{i,t}$) of firm i in year t. The independent variables $Treat_{i,t}$ and $Post_{i,t}$ are defined as in (3.1). Firm fixed effects (θ_i) and year fixed effects (δ_t) are included to account for unobserved heterogeneity across firms and time. We include four yearly observations for each treated firm or matched non-treated product market competitors, spanning two years before and two years after the major local natural disasters.

Importantly, in the presence of potential spillover effects between the treated firms and their matched non-treated product market competitors, the sum of the coefficients β_1 and β_3 captures the total treatment effect for the treated firms, while the coefficient β_3 of the *Post* term alone captures the spillover effects to the competitors within the same industry. This DID approach is consistent with established methodologies in the literature (e.g., Boehmer, Jones and Zhang, 2020). The staggered occurrence of major local natural disasters across different years enables a clear separation of within-industry spillover effects, captured by β_3, from aggregate time-series variation, which is controlled for by the year fixed effects δ_t.

To accurately capture the within-industry spillover effect, β_3, and the additional treatment effect, β_1, it is crucial for us to recognize the concurrent presence of cross-industry spillover effects. For instance, when identifying the spillover effect from a disaster-affected (treated) firm to an unaffected competitor within the same industry, it is critical to account for cross-industry spillover effects arising from other industries connected through common

Table 2: Spillover of Distress Risk Among Product Market Competitors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Difference-in-Differences (DID) regressions							
	$Risk\_of\_Failure_{i,t}$		$Dist\_to\_Default_{i,t}$		$Yield\_Spread_{i,t}$		$CDS\_Spread_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$ (β_1)	0.023**	0.023**	−0.087*	−0.088*	0.022	0.021	−0.103	−0.104
	[2.275]	[2.299]	[−1.717]	[−1.743]	[0.198]	[0.193]	[−0.638]	[−0.641]
$Treat_{i,t}$ (β_2)	−0.011	−0.011	0.096*	0.097*	0.030	0.031	0.083	0.084
	[−1.189]	[−1.196]	[1.940]	[1.953]	[0.353]	[0.365]	[0.607]	[0.610]
$Post_{i,t}$ (β_3)	0.055***	0.054***	−0.122***	−0.115***	0.176**	0.180**	0.340**	0.347**
	[8.223]	[8.120]	[−3.882]	[−3.695]	[2.115]	[2.174]	[2.090]	[2.052]
$\ln(1 + n(\mathcal{C}_{i,t}))$		0.018**		−0.083**		−0.052		−0.107
		[2.351]		[−2.295]		[−0.869]		[−0.734]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	136181	136181	110581	110581	15731	15731	7467	7467
R-squared	0.597	0.598	0.667	0.667	0.721	0.721	0.628	0.628
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.016	0.015	0.094	0.094

Panel B: Summary statistics of the variables presented in the panel above

	Obs. #	Mean	Median	Stdev	p10th	p25th	p75th	p90th
$Risk\_of\_Failure_{i,t}$	96654	−7.504	−7.709	0.875	−8.513	−8.201	−6.933	−6.090
$Dist\_to\_Default_{i,t}$	80858	5.321	4.506	4.254	0.292	2.070	7.833	11.884
$Yield\_Spread_{i,t}$(%)	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
$\ln(1 + n(\mathcal{C}_{i,t}))$	98562	0.747	0.693	0.739	0	0	1.386	1.792

Notes. This table examines within-industry spillover effects following major local natural disasters. $Risk\_of\_Failure_{i,t}$ is the failure risk constructed as in the work of Campbell, Hilscher and Szilagyi (2008). $Dist\_to\_Default_{i,t}$ is the distance to default constructed following the naive approach illustrated in Bharath and Shumway (2008). $Yield\_Spread_{i,t}$ is the average bond yield spread of all bonds issued by a firm, calculated 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 bond yield spread and CDS spread in year t are the spread in the last quarter, capturing credit risk at year-end. Panel A of this table reports the results from the DID analysis. 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., $\beta_1 + \beta_3 = 0$). Panel B of this table shows the summary statistics for the firm-year panel. The samples of failure risk, distance to default, and bond yield span 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.

market leaders. To control for this cross-industry spillover effect, we introduce the variable $\ln(1 + n(\mathcal{C}_{i,t}))$, defined as the natural logarithm of 1 plus the number of industries connected to firm i's industry via common market leaders and affected by major local natural disasters in year t, denoted by $n(\mathcal{C}_{i,t})$.[15] The coefficient β_4 captures the cross-industry spillover effects through common market leaders.

Table 2 reports the results of the DID regressions for firms' distress risk. Columns (1) and (2) show that the distress risk of the treated firms increases significantly following major local natural disaster shocks, and columns (3) and (4) show that the distance-to-default measure (an inverse measure of default risk) of the treated firms decreases significantly.

[15] As a robustness check (see Online Appendix 3), we also utilize an alternative measure, denoted by $\ln(1 + \mathcal{D}_{i,t})$, to capture the strength of cross-industry spillover effects. This variable is expressed as the natural logarithm of 1 plus the average amount of property damage (in millions of dollars) caused by major local natural disasters in year t across industries that are connected to firm i's industry through common market leaders.

In columns (1) through (4), the respective p-values for testing the null hypothesis that the total treatment effect is zero, i.e., $\beta_1 + \beta_3 = 0$, are less than 0.001. Thus, treated firms experience increased distress risk following natural disasters, consistent with prior research. We also use the bond yield spread and the CDS spread to examine the effect of major local natural disaster shocks on firms' distress risk. Columns (5) and (6) show that the total treatment effect on the bond yield spread is approximately 20 basis points (p-values $<$ 0.05). Correspondingly, columns (7) and (8) reveal that the total treatment effect on the CDS spread is about 24 basis points, statistically significance at the 10% level.

The coefficient β_3, associated with the *Post* term, is central to our analysis. As shown in Table 2, it is both statistically and economically significant across all measures of distress risk. This result indicates that even product market competitors not directly affected by major local natural disasters experience a substantial increase in distress risk. Given the design of the matched controls in our quasi-natural experiment, the significance of the β_3 coefficient provides strong evidence of an economically meaningful spillover effect of distress risk from directly impacted firms to their product market competitors. The coefficients in columns (1) and (2) imply that the spillover effect increases the probability of failure for unaffected product market competitors by approximately 1.1 percentage point per annum. The total treatment effect increases the probability of failure for firms that experience major local natural disasters from 2 percentage points to approximately 3.56 percentage points per annum, on average. In our sample, the average probability of failure just before the occurrence of major local natural disasters is around two percentage points per annum. Columns (5) and (6) indicate that the spillover effect increases the bond yield spread for unaffected product market competitors by approximately 18 basis points, and columns (7) and (8) indicate that the spillover effect increases the CDS spread for unaffected product market competitors by approximately 34 basis points. These increases are economically significant when compared to the average bond yield spread ($Yield\_Spread_{i,t}$) of 298 basis points and the average CDS spread ($CDS\_Spread_{i,t}$) of 108 basis points in our sample.

Similar to the dynamic DID regression presented in (3.2) centered on major local natural disasters, we employ an event study analysis to examine the spillover of distress risk among product market competitors to address the concern that the β_3 coefficient might pick up industry trends in the level of distress risk. In our dynamic DID analysis, we incorporate six yearly observations for each firm, spanning three years prior to and three years subsequent to a major local natural disaster, to more clearly and comprehensively depict the time-series evolution of impacts. Figure 2 displays the time-series of the estimated coefficients $\beta_{3,\tau}$ for $\tau = -3, -2, \ldots, 2$, along with their 90% confidence intervals. Across all four empirical measures, the elevation in distress risk occurs exclusively after the major local natural disaster shocks, with no significant changes observed in the pre-shock period.

Having examined the total treatment effect captured by $\beta_1 + \beta_3$ and the spillover effect captured by β_3, we now focus on the additional treatment effects captured solely by the coefficient β_1. The magnitude of the additional treatment effect on the risk of failure ($Risk\_of\_Failure_{i,t}$) is roughly half that of the within-industry spillover effects, captured by β_3, in columns (1) and (2) of Table 2. Similarly, for the distance-to-default measure ($Dist\_to\_Default_{i,t}$), the magnitude of the additional treatment effects is approximately the same as that of the within-industry spillover effect, as reported by columns (3) and (4). These findings show that the distress risk for firms directly affected by major local natural disasters increases more substantially than for their product market competitors who are not directly affected.[16]

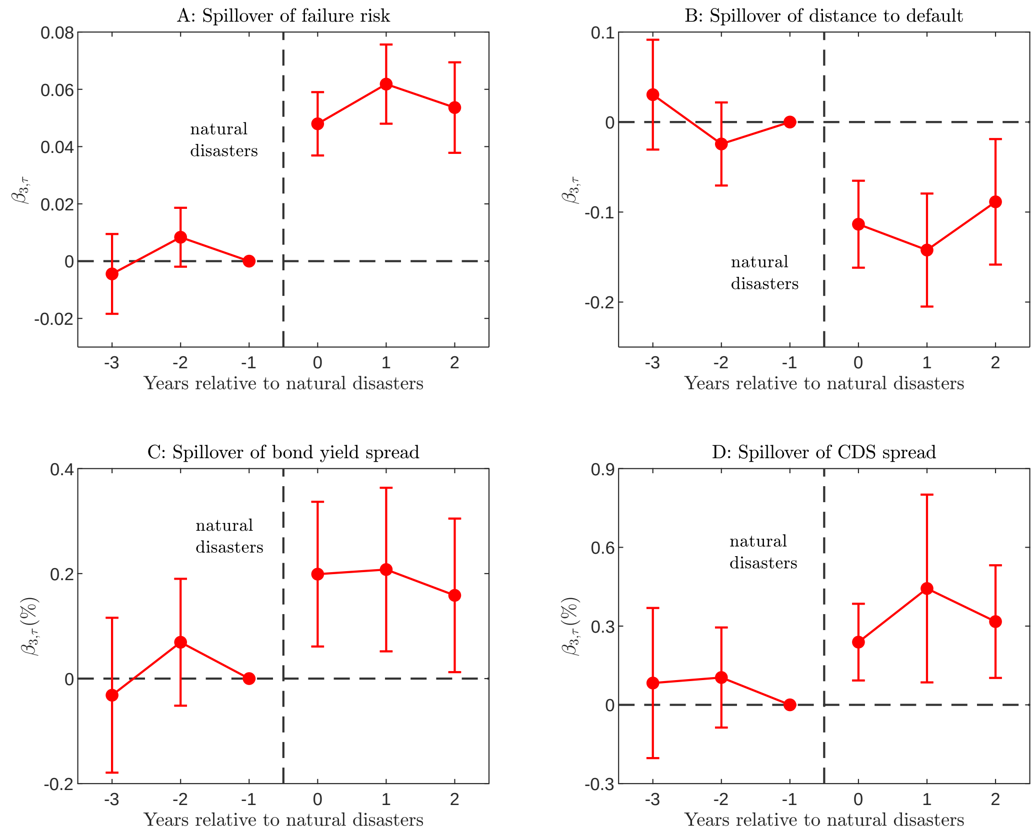
Spillover Effects: How a Firm's Distress Risk Impacts Competitors' Profit Margins

We next examine product market competition behaviors, focusing on product prices and profit margins, to test the hypothesis that distress risk propagates from a firm to its competitors primarily through intensified market competition in the short run. Specifically, a negative shock to a leading firm's distress risk intensifies competition within its product market, driving competitors to lower product prices and compress profit margins. Consequently, these competitors may face a heightened risk of distress. If this mechanism holds, an adverse distress risk shock would lead to a decline in the affected firm's profit margin, accompanied by a concurrent reduction in the profit margins of its product market competitors.

Our main analysis focuses on profit margins rather than product prices, although we also uncover consistent findings on product prices, for several key reasons. First, we aim to examine the real impact of market competition on firms' cash flows and distress risk, where profit margins, rather than nominal prices, are the critical factor. Second, competition and price wars primarily target eroding competitors' profit margins, rather than merely reducing their output prices. Third, natural disasters may raise production costs, leading to higher product prices. However, such price increases do not necessarily indicate a reduction in competition intensity. Fourth, obtaining accurate and detailed data on output prices and marginal costs across diverse industries is challenging. Even if such data were available, many underlying economic factors, such as implicit discounts (e.g., trade credits), coupons,

[16]The data coverage for corporate bond yields and CDS spreads is limited, representing only about 10% of the CRSP-Compustat merged sample, with CDS spread data available only from 2001 onward. This limited coverage likely explains the statistical insignificance of the additional treatment effect, captured by β_1, in columns (5) through (8) of Table 2. Such sample limitations make it more challenging to detect these effects compared to the *Post* terms.

Figure 2: Spillover of Distress Risk: Distress Risk of Unaffected Competitors.



Notes. This figure plots the within-industry spillover effects of distress risk around major natural disasters. For each treated firm, we match it with up to five non-treated peers in the same four-digit SIC industry according to the matching procedure described in Section 3. For each major natural disaster shock, we include six yearly observations (i.e., 3 years before and 3 years after a major local 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: $Y_{i,t} = \sum_{\tau=-3}^{2} \beta_{1,\tau} \times Treat_{i,t} \times ND_{i,t-\tau} + \beta_2 \times Treat_{i,t} + \sum_{\tau=-3}^{2} \beta_{3,\tau} \times ND_{i,t-\tau} + \beta_4 \times \ln(1 + n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}$. 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 local natural disasters.

rebates, and gifts, often remain unobservable to economists. Finally, while price levels are not directly comparable across industries, profit margins provide a consistent measure.

That said, we also analyze changes in product prices for treated firms and their industry peers. This product price analysis uses NielsenIQ data, which covers categories such as food, nonfood grocery items, health and beauty aids, and select general merchandise, rather than a broader range of industries.

To examine the impact of increased distress risk on market competition, particularly its effect on the profit margins of directly affected firms and their product market competitors, we conduct a regression analysis using the DID specification in Equation (3.3). The dependent variable, $Y_{i,t}$, represents the gross profit margin of firm i in year t. The DID

Table 3: Impact of Major Natural Disasters on Profit Margins and Output Prices.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Difference-in-Differences (DID) regressions							
	$Profit\_Margin_{i,t}$		$\ln(Price\_Geo)_{i,t}$		$\ln(Price\_EW)_{i,t}$		$\ln(Price\_VW)_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$ (β_1)	−0.001	−0.001	0.022	0.020	0.016	0.013	0.012	0.009
	[−0.196]	[−0.218]	[0.540]	[0.486]	[0.374]	[0.316]	[0.291]	[0.226]
$Treat_{i,t}$ (β_2)	−0.001	−0.001	−0.029	−0.029	0.010	0.010	−0.005	−0.005
	[−0.189]	[−0.181]	[−0.583]	[−0.576]	[0.190]	[0.195]	[−0.096]	[−0.089]
$Post_{i,t}$ (β_3)	−0.007**	−0.007**	−0.074**	−0.076**	−0.075**	−0.077**	−0.073**	−0.076**
	[−2.283]	[−2.149]	[−2.321]	[−2.384]	[−2.202]	[−2.265]	[−2.260]	[−2.335]
$Ln(1 + n(\mathcal{C}_{i,t}))$		−0.006**		0.034		0.039		0.042
		[−2.227]		[0.866]		[0.843]		[0.977]
Industry FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	135037	135037	4414	4414	4414	4414	4414	4414
R-squared	0.745	0.746	0.524	0.525	0.546	0.547	0.529	0.530
Test p-value: $\beta_1 + \beta_3 = 0$	0.004	0.006	0.092	0.076	0.081	0.058	0.056	0.038

Panel B: Summary statistics of the variables presented in the panel above

	Obs. #	Mean	Median	Stdev	p10th	p25th	p75th	p90th
$Profit\_Margin_{i,t}$	96269	0.346	0.338	0.264	0.092	0.206	0.519	0.703
$\ln(Price\_Geo_{i,t})$	4049	1.640	1.591	0.841	0.525	1.081	2.204	2.863
$\ln(Price\_EW_{i,t})$	4049	1.855	1.792	0.935	0.637	1.191	2.505	3.183
$\ln(Price\_VW_{i,t})$	4049	1.789	1.727	0.863	0.687	1.179	2.380	3.037

Notes. This table examines the effect of major local natural disasters (used as instruments for exogenous variations in distress risk) on the profit margin of the directly impacted firm and its product market competitors that were not directly affected by the disasters. Panel A of this table reports the results from the DID analysis. In columns (1) and (2), the dependent variable is the gross profit margin, $Profit\_Margin_{i,t}$, defined as the difference between sales and cost of goods sold divided by sales. In columns (3) through (8), the dependent variable is the natural log of the firm-level product prices computed based on the NielsenIQ 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 different 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. In the last row of the table, we present the p-value for the null hypothesis that the total treatment effect for the treated firms is zero (i.e., $\beta_1 + \beta_3 = 0$). The sample of this table spans from 1994 to 2018. Standard errors are clustered at the firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Panel B of this table shows the summary statistics for the firm-year panel from 1994 to 2018.

framework used to examine the endogenous response of product prices and profit margins is similar to the approach of Clark, Horstmann and Houde (2024). As shown in Panel A of Table 3, columns (1) and (2), treated firms experience significant reductions in gross profit margins, with the negative sum of $\beta_1 + \beta_3$ statistically significant at the 1% level. These findings are consistent with prior research documenting the adverse effects of distress risk on profit margins.[17]

More importantly, columns (1) and (2) of Table 3 show that, following major local natural disasters, not only do the affected (or treated) firms experience significant reductions in their gross profit margins, but their product market competitors also experience significant reductions, evident from the significantly negative β_3 associated with the *Post* term. These

[17]See, e.g., Maksimovic (1988), Chevalier (1995), Busse (2002), Hortaçsu et al. (2013), Phillips and Sertsios (2013), Koijen and Yogo (2015), and Kim (2021).

findings suggest that competitors not directly impacted by the disasters also face substantial profit margin declines due to intensified product market competition. Moreover, this heightened competition likely amplifies distress risk for competitors not directly affected by the disasters, especially those bound by earnings-based covenants, such as net profit covenants. This results in distress risk spillovers among product market competitors, as further supported by the findings in Table 2.

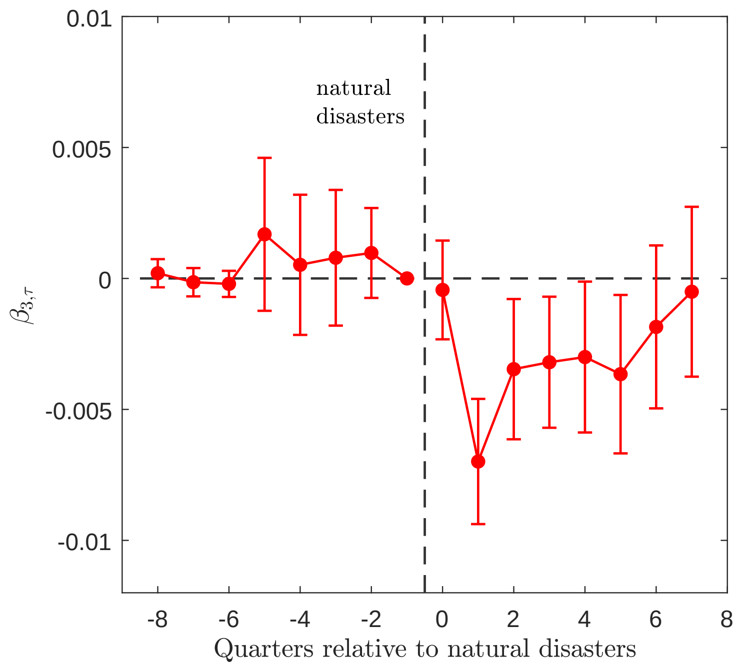
We next validate the zero-industry trend assumption. Specifically, we need to ensure that the negative coefficient, β_3, associated with the *Post* term, accurately represents the causal impact of major local natural disasters on the profit margins of product market competitors not directly affected by these events, rather than simply reflecting an industry-level trend in profit margins. We implement a dynamic DID regression, similar to the one presented in (3.2), to investigate the time-series dynamics of profit margins for unaffected product market competitors around the time of major local natural disasters. The analysis includes sixteen quarterly observations for each firm, spanning eight quarters before and eight quarters after a major local natural disaster, to capture the time-series evolution comprehensively. In Figure 3, we plot the estimated coefficients $\beta_{3,\tau}$ with $\tau = -8, -7, \ldots, 7$, as well as their 90% confidence intervals with standard errors clustered at the firm level. Our findings show that significant profit margin reductions occur only after the onset of major local natural disasters, indicating that the spillovers in the profit margin cannot be attributed to pre-shock industry trends.

As noted above, we also examine the impact of distress risk shocks on product market competition by analyzing firm-level product prices derived from NielsenIQ data.[18] To construct firm-level product prices, we first aggregate product prices across all unique UPCs of firm i within product category c and year t using three methods: the geometric average (as in Kim, 2021), the equal-weighted average, and the sales-weighted average. Next, we compute firm-level product prices by aggregating the category-level prices across all product categories for each firm i, using sales as weights.

While previous research has emphasized the importance of considering shifts in quality and variety when evaluating output price dynamics (e.g., Nakamura and Steinsson, 2012; Hottman, Redding and Weinstein, 2016), some recent studies (e.g., Kim, 2021) suggest that a distress risk shock originating from a source unrelated to product market rivalries has a minimal influence on the quality-variety margin of the output price index. In our study, major local natural disaster shocks originate from outside the realm of product market rivalries, so we view it as unlikely that treated firms and their product market competitors would immediately alter their product quality or variety as an optimal strategy for adjusting

[18]NielsenIQ data covers health and beauty aids, groceries, alcohol, and general merchandise. It is available only after 2006.

Figure 3: How Natural Disasters Affect Profit Margins of Unaffected Competitors



Notes. This figure plots the within-industry spillover effects of profit margin around major natural disasters. For each treated firm, we match it with up to 10 non-treated peers in the same four-digit SIC industry according to the matching procedure described in Section 3. Because the quarterly data are noisier than the yearly data, we use a larger matching ratio between the matched peers and treated firms. For each firm, we include sixteen quarterly observations (i.e., 8 quarters before and 8 quarters after a major local natural disaster) in the analysis. To estimate the dynamics of the spillover effect, we consider the quarterly regression specification: $Y_{i,t} = \sum_{\tau=-8}^{7} \beta_{1,\tau} \times Treat_{i,t} \times ND_{i,t-\tau} + \beta_2 \times Treat_{i,t} + \sum_{\tau=-8}^{7} \beta_{3,\tau} \times ND_{i,t-\tau} + \beta_4 \times \ln(1 + n(\mathcal{C}_{i,t})) + \theta_i + \delta_t + \varepsilon_{i,t}$. 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.

their output prices in response to major local natural disasters.

Panel A of Table 3, columns (3) through (8), presents our findings on firm-level product prices aggregated using various methods. The coefficient β_3 shows a negative and statistically significant impact of increased distress risk (resulting from major local natural disasters) on the output prices of product market competitors not directly affected by the disasters, with prices decreasing by approximately 7.6%, an economically significant decline. Consistent with our findings on profit margins, the direct treatment effects on output prices, captured by β_1, are statistically insignificant, as shown in columns (3) through (8). This aligns intuitively with expectations: intensified product market competition compels competitors to lower their output prices in response.[19]

[19] A potential limitation of NielsenIQ data is that it primarily reflects prices and sales, which may better capture the decisions of retailers or wholesalers purchasing products from manufacturers to sell to consumers, rather than those of manufacturers directly impacted by major local natural disasters and the resulting distress risk shock. To mitigate this issue, we aggregate variables across retailers within each manufacturer firm, following the approach commonly used in the literature (Hottman, Redding and Weinstein, 2016; Kim, 2021).

Robustness of the Observed Patterns.

We perform a comprehensive set of robustness checks, detailed in Online Appendix 3. Our results remain robust to alternative matching ratios between treated firms and non-treated product market competitors, including one-to-ten, one-to-five, and one-to-three ratios. We also find consistent results when using text-based network industry classifications (TNIC) developed by Hoberg and Phillips (2010, 2016) to define product market competitors. Furthermore, the impact of a firm's distress risk on its competitors' profit margins remains robust when using net profit margin as an alternative profitability metric.

To address concerns that matched product market competitors might be geographically close to areas affected by natural disasters, we perform two robustness tests, detailed in Online Appendix 3. First, we restrict matched competitors in the DID estimation to those located outside states directly impacted by major local natural disasters. Second, we ensure that matched competitors have headquarters and major establishments situated more than 100 miles from any zip code negatively affected by major local natural disasters during the year they serve as matches. Our findings remain robust in both tests.

We address potential concerns about DID regressions with staggered treatment timing. While recent econometric advances suggest that standard DID regression estimates with staggered treatments may sometimes yield biased results, this is not universally the case. To ensure robustness, we adopt the stacked regression estimator approach with "clean" controls, as recommended by Baker, Larcker and Wang (2022). Our results remain robust under this method (see Online Appendix 3).

Excluding Alternative Spillover Channels.

The observed within-industry spillover patterns in profit margins, product prices, and distress risk may arise from channels beyond the strategic product market competition mechanisms (i.e., those discussed in Section 4.1). Alternative spillover channels include (i) disaster-induced demand shocks, (ii) production network spillover effects, (iii) common creditors, and (iv) common blockholders, among others. In this section, we focus on channels (i) and (ii), with further detailed analyses provided in Online Appendix 3.4.

We first examine channel (i), disaster-induced demand shocks, as a potential alternative explanation. This channel proposes that natural disasters directly generate negative demand shocks, simultaneously affecting both treated firms and their matched unaffected industry peers, leading to reduced profit margins and increased distress risk. However, we present two sets of direct evidence showing that this explanation is unlikely to be the primary

Since each manufacturer in the dataset engages with an average of approximately 190 retailers, retailer-specific behaviors are effectively averaged out at the manufacturer level.

Table 4: Testing the disaster-induced demand shock channel.

Panel A: Matched non-treated firms outside of the affected states + without affected business and retailed customers						
	(1)	(2)	(3)	(4)	(5)	(6)
	$Risk\_of\_Failure_{i,t}$		$Dist\_to\_Default_{i,t}$		$Profit\_Margin_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.019*	0.019*	−0.036	−0.037	−0.003	−0.003
	[1.754]	[1.770]	[−0.665]	[−0.677]	[−0.491]	[−0.506]
$Treat_{i,t}$	−0.009	−0.009	0.066	0.066	0.002	0.002
	[−0.879]	[−0.889]	[1.250]	[1.258]	[0.365]	[0.376]
$Post_{i,t}$	0.057***	0.056***	−0.151***	−0.147***	−0.008*	−0.007*
	[7.635]	[7.537]	[−4.325]	[−4.227]	[−1.911]	[−1.821]
$\ln(1 + n(\mathcal{C}_{i,t}))$		0.016*		−0.047		
		[1.901]		[−1.210]		[−1.833]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124123	124123	99874	99874	123011	123011
R-squared	0.602	0.602	0.670	0.670	0.746	0.746
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.006	0.009

Panel B: Matched non-treated firms far from the disaster area (i.e., $\geq$ 100 miles) + without affected business and retailed customers						
	(1)	(2)	(3)	(4)	(5)	(6)
	$Risk\_of\_Failure_{i,t}$		$Dist\_to\_Default_{i,t}$		$Profit\_Margin_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.016	0.016	−0.064	−0.065	0.001	0.001
	[1.167]	[1.192]	[−0.895]	[−0.911]	[0.217]	[0.202]
$Treat_{i,t}$	−0.019	−0.019	0.119*	0.120*	0.001	0.001
	[−1.356]	[−1.389]	[1.664]	[1.685]	[0.163]	[0.187]
$Post_{i,t}$	0.071***	0.069***	−0.164***	−0.158***	−0.012**	−0.012**
	[6.019]	[5.889]	[−3.006]	[−2.907]	[−2.166]	[−2.126]
$\ln(1 + n(\mathcal{C}_{i,t}))$		0.029**		−0.075		−0.008*
		[2.407]		[−1.565]		[−1.662]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	98049	98049	78781	78781	97199	97199
R-squared	0.636	0.636	0.692	0.692	0.778	0.778
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.005	0.007

Note: This table tests the disaster-induced demand shock channel. In panel A, we perform DID analysis by requiring the headquarters and the major establishments of the matched peer firms to be outside of the states affected by major natural disasters in the focal year for which they serve the match. In panel B, we perform DID analysis by requiring the headquarters and the major establishments of the matched peer firms to be more than 100 miles away from any zip code negatively affected by major natural disaster in the focal year for which they serve the match. In both panels, we further require the matched peer firms to have no customers negatively affected by natural disaster. We identify firms' business customers using Compustat customer segment data and Factset Revere data. We identify firms' retail customers based on the household-level financial transaction data constructed by Baker, Baugh and Sammon (2020). The merged 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.

driver of the observed within-industry spillover effects.

The first piece of evidence addresses the possibility that both treated and untreated firms are experience common demand shocks induced by disasters. Panel A of Table 6 in Section 4.2 shows that spillover effects are concentrated in tradable industries with geographically dispersed, often international, customer bases. Given this dispersion, local natural disasters affecting the headquarters or major establishments of treated firms are unlikely to significantly disrupt common demand, making the disaster-induced demand shock channel an unlikely explanation for the observed within-industry spillover effects.

The second piece of evidence addresses the possibility that matched unaffected industry peers may also experience negative demand shocks if their customers are primarily located in areas affected by natural disasters. To account for this, we impose additional requirements on the matched industry peers, ensuring they have no customers, whether business clients or individual consumers, in the affected areas. We identify firms' business customers and their geographic locations using Compustat customer segment data and Factset Revere data, and individual consumers and their locations using detailed data from Baker, Baugh and Sammon (2020).[20] As shown in Table 4, the within-industry spillover effects remain robust even after imposing these requirements, further indicating that the disaster-induced demand shock channel does not explain the observed spillover effects.

We next examine channel (ii), the production network externality channel, as a potential explanation for the observed within-industry spillover effects. This channel suggests that these effects arise from spillovers along supply chains. However, we provide direct evidence showing that this explanation is unlikely to be the driver of the observed effects.

First, we consider direct supplier-customer relationships. In the baseline DID test, we already show that existing supplier-customer relationships are unlikely to account for the strong within-industry spillover effects. We extend the analysis by excluding not only existing supplier-customer relationships but also potential ones. We identify potential supplier-customer relationships using vertical relatedness scores, as described in Frésard, Hoberg and Phillips (2020), and define two firms as likely to have a bilateral supplier-customer relationship if their vertical relatedness score ranks in the top 10% among all firm pairs. In Table 5, we show that the within-industry spillover effects remain robust even after applying these additional restrictions on control firms.

Second, we consider indirect supplier-customer relations. To further strengthen our results, we impose an additional restriction in Table 5 that matched peer firms have no common customers or suppliers with the treated firms. This restriction eliminates the possibility that the observed within-industry spillover effects are driven by common customers or suppliers shared between treated firms and their product market competitors, such as through mechanisms like hub-and-spoke collusion (e.g., Garrod, Harrington and Olczak, 2021; Clark, Horstmann and Houde, 2024).

[20] This dataset includes over two million users from 2010 to 2015. We assume firms with sales to consumers in a city in 2010 (2015) also have sales in the same city before 2010 (after 2015).

Table 5: Testing the production network externality channel.

	(1)	(2)	(3)	(4)	(5)	(6)
	$Risk\_of\_Failure_{i,t}$		$Dist\_to\_Default_{i,t}$		$Profit\_Margin_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$	0.030***	0.030***	−0.111**	−0.112**	−0.002	−0.002
	[2.649]	[2.661]	[−1.987]	[−2.004]	[−0.259]	[−0.269]
$Treat_{i,t}$	−0.022**	−0.022**	0.146***	0.146***	0.002	0.002
	[−2.006]	[−2.010]	[2.590]	[2.600]	[0.304]	[0.308]
$Post_{i,t}$	0.053***	0.051***	−0.123***	−0.116***	−0.010**	−0.009*
	[6.741]	[6.667]	[−3.327]	[−3.187]	[−2.019]	[−1.942]
$\ln(1+n(\mathcal{C}_{i,t}))$		0.018**		−0.085**		−0.008
		[1.980]		[−1.967]		[−1.598]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	112647	112647	88542	88542	111387	111387
R-squared	0.595	0.595	0.668	0.669	0.740	0.740
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.009	0.013

Note: This table tests the production network externality channel. As in Table 2 of the main text, we ensure that the matched peer firms are neither suppliers nor customers of the treated firms. We also require that the matched peer firms do not share any common customers or any common suppliers with the treated firms. Different from Table 2 of the main text, we further remove matched peer firms related to the treated firms vertically in the DID analysis. We define two firms as vertically connected if their vertical relatedness scores are within top 10% of all firm pairs (see, Frésard, Hoberg and Phillips, 2020). The regression specification and the definition of the dependent and independent variables are explained in Table 2 of the main text. The merged 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.

4 Economic Mechanisms

In this section, we illustrate how strategic product market competition, combined with the prevalence of earnings-based borrowing constraints in the corporate sector, explains the observed short-run spillover effects, where a firm's heightened distress risk increases the distress risk of its product market competitors.

Through strategic product market competition mechanisms — including predatory pricing, inventory fire sales, and weakened tacit collusion — a firm's heightened distress risk intensifies competition, reducing profit margins for both the firm and its competitors. The strategic complementarity between a firm's profit margins and those of its competitors plays a crucial role in this process, regardless of the specific mechanism at play.

In turn, earnings-based borrowing constraints transmit these competitive pressures to financial distress. Specifically, lower profit margins from intensified competition reduce firms' earnings and cash flows, thereby increasing their likelihood of financial covenant violations or default. Covenant violations can trigger technical default, granting creditors legal rights to demand immediate repayment or renegotiate loan terms. This often results in higher interest rates, restricted credit access, constraints on capital expenditures, management replacement, or workforce reductions, all of which impose substantial costs on borrowers.[21] Importantly, for U.S. nonfinancial firms, approximately 80% of debt by value is closely tied to firms' cash flows, primarily through earnings-based debt covenants, which are especially prevalent among large firms.[22] Empirical evidence further highlights the frequency of covenant violations, emphasizing the critical role of earnings-based covenants in converting cash flow declines into distress risk.

4.1 Strategic Product Market Competition Mechanisms

In this section, we describe three economic mechanisms rooted in strategic market competition that explain how heightened distress risk in shocked firms leads both these firms and their unshocked competitors to reduce profit margins. These mechanisms are (i) predatory pricing, (ii) inventory fire sales, and (iii) weakened tacit collusion. They are not mutually exclusive and often co-occur, reinforcing each other's effects. Consequently, we do not attempt to disentangle their individual contributions to the spillover effects of distress risk through product market competition. Instead, we examine heterogeneous treatment effects across industries with different market structures. Evidence from these heterogeneity tests, presented in Section 4.2, suggests that all three mechanisms contribute to the observed effects.

Mechanism 1: Predatory Pricing.

The spillover effects on profit margins and distress risk can result from predatory pricing by competitors. Predatory pricing occurs when competitors aggressively lower prices to drive a distressed firm out of the market. After its exit, the competitors gain monopoly power and raise prices to recoup losses. This strategy aims to achieve long-term market dominance, even at the cost of higher short-term distress risk due to reduced profit margins (e.g., Bolton and Scharfstein, 1990; Cabral and Riordan, 1994; Besanko, Doraszelski and Kryukov, 2014; Chen et al., 2022). Extensive evidence confirms the prevalence of predatory pricing (e.g., Chevalier, 1995; Clark, Duarte and Houde, 2025), particularly against distressed firms. Specifically, this strategy is more effective in industries with higher barriers to market leadership, where it is harder for new competitors to grow into major players and challenge the predatory firm's position (e.g., Chen et al., 2022). It is also more effective in industries with stronger strategic complementarity between firms' profit margins.

The predatory pricing mechanism can be further amplified by the other two mechanisms. In industries with substantial inventory levels, the distress risk spillover effect through

[21]See, e.g., Beneish and Press (1993), Chava and Roberts (2008), Nini, Smith and Sufi (2009), Nini, Smith and Sufi (2012), and Falato and Liang (2016).

[22]See, e.g., Chava and Roberts (2008), Roberts and Sufi (2009), Sufi (2009), and Lian and Ma (2020).

predatory pricing becomes more pronounced. High inventory levels allow competitors to adopt more aggressive predatory pricing strategies, selling larger quantities of their products or services at substantially reduced prices, especially in anticipation of distressed firms conducting inventory fire sales to survive. Moreover, in industries where competitive balance is sustained through stronger tacit collusion, firms unaffected by distress shocks are better positioned to strategically lower prices and narrow profit margins as part of their predatory approach. This increases competitive pressure, further exacerbating the distress faced by their shock-affected competitors.

Mechanism 2: Inventory Fire Sales.

The spillover effects of profit margins and distress risk can also be attributed to the rapid inventory liquidation behaviors of the affected firms. Distressed firms often engage in fire sales of their inventories to boost short-term sales, meet immediate liquidity needs, and mitigate distress risk to survive.[23] To restore liquidity quickly, these firms often sharply reduce profit margins to stimulate demand and draw customers from competitors. Specifically, in situations where firms are competing neck and neck, absent any tacit collusion, fire sales of inventories become a vital survival strategy to cope with liquidity shortages and financial constraints, as suggested by the findings of Koijen and Yogo (2015) and Kim (2021), among others. Crucially, competitors lower their profit margins to defend or expand market share, with this response being more pronounced in industries where strategic complementarity between firms' profit margins is stronger. This mechanism is consistent with the theory of asset fire sales by Shleifer and Vishny (1992), who also emphasize the interplay between financial constraints and product market rivalries.

Furthermore, even before firms fall into severe distress, an increase in distress risk may incentivize them to conduct inventory fire sales for at least two reasons. First, when firms face an increased level of distress risk, they are concerned about customers' strategic waiting behavior. Customers, perceiving that a firm's financial situation might worsen in the future, may decide to postpone their purchases in expectation of deeper discounts (see Birge et al., 2017).[24] This situation forces distressed firms to lower their profit margins more aggressively to preempt such strategic waiting behavior. Second, in industries characterized by significant barriers to achieving market leadership, firms facing increased levels of distress risk often anticipate aggressive predatory pricing strategies from competitors, aimed at triggering price wars to drive them out. To preempt such predatory tactics,

[23]High distress risk often drives firms to adopt precautionary strategies, such as building cash reserves and seeking rapid earnings improvements (e.g., Acharya, Davydenko and Strebulaev, 2012).

[24]The strategic waiting behavior of customers is well-documented in the literature (e.g., Silverstein and Butman, 2006; Chevalier and Goolsbee, 2009; Hendel and Nevo, 2013; Li, Granados and Netessine, 2014).

distressed firms may strategically opt for early inventory fire sales, enabling them to quickly accumulate much-needed liquid assets, such as cash.

In sum, when a firm is hit by an adverse idiosyncratic distress shock, it often responds by liquidating its products, especially inventories, at significantly reduced profit margins. In turn, product market competitors respond by lowering their profit margins in an effort to maintain or increase their market shares, particularly when strategic complementarity between firms' profit margins is stronger. Beyond these defensive strategies, competitors may also engage in predatory pricing, further compressing their margins. As a result, both the distressed firm and its competitors face an increased risk of covenant violations or debt defaults in the short run. Furthermore, since predatory pricing strategies can amplify the inventory fire sale mechanism, the within-industry spillover effect of distress risk becomes more pronounced in industries with higher barriers to attaining market leadership.

Mechanism 3: Weakened Tacit Collusion.

Finally, the within-industry spillover effects of profit margins and distress risk can be attributed to weakened tacit collusion within the product market. Empirical evidence has shown tacit collusion is prevalent across many industries.[25] The theoretical foundations of distressed competition within the context of tacit collusion have been studied by Maksimovic (1988) and Chen et al. (2022).[26] For tacit collusion to be sustained, the cost of deviation — specifically, the loss of the present value of future cooperation due to subsequent punishment — must outweigh the benefit of deviation, which comes from undercutting rivals to secure higher short-term profits.

A higher level of distress risk can increase firms' impatience and reduce their desire for future cooperation, leading to lower current collusion capacity and narrower profit margins. In industries with high barriers to market leadership, the negative impact of a firm's distress risk on both the firm's and its product market competitors' profit margins is particularly pronounced. Market leaders in such industries have strong incentives to engage in predatory pricing, potentially triggering price wars against financially weakened competitors. While competitors not directly affected by distress shocks are already pressured to reduce profit margins due to diminished tacit collusion capacity in the product market, they may further adopt aggressive pricing strategies to drive out weakened rivals and position themselves to capture future monopoly rents.

[25] In addition to the studies highlighted in the related literature section, substantial granular evidence documents explicit and tacit collusion across various product markets (e.g., Chen et al., 2022, for a review).

[26] Oligopolistic competition through tacit collusion, especially within the framework of repeated games using grim trigger strategies, was pioneered by Fudenberg and Maskin (1986) and Rotemberg and Saloner (1986), among others. In this framework, deviations from tacit collusion are punished in subsequent periods by reverting to the non-collusive Nash equilibrium of the stage game.

4.2 Heterogeneous Spillover Effects

We investigate the heterogeneity of spillover effects among product market competitors across industries, as implied by the strategic product market competition mechanisms, to provide direct empirical support for these underlying economic forces. This section explores the heterogeneous spillover effects through five distinct perspectives.

First, we emphasize that the three spillover mechanisms among product market competitors — (i) predatory pricing, (ii) inventory fire sales, and (iii) weakened tacit collusion — are more pronounced in tradable industries like manufacturing, mining, and oil, where competition occurs on a national scale. In contrast, these mechanisms are less significant in non-tradable industries such as supermarkets, retail stores, and restaurants, which rely heavily on local consumer demand. This difference arises because tacit collusion is harder to sustain in non-tradable industries, where competition is localized and focused on retail consumers. Additionally, the customer base in non-tradable sectors is more geographically dispersed and exhibits less overlap than in tradable industries. As a result, the spillover effects on profit margins and distress risk through product market competition are generally weaker in non-tradable industries.

Second, all three spillover mechanisms are expected to be more pronounced in industries with higher barriers to achieving market leadership. This is particularly true for the predatory pricing mechanism, which tends to be more effective in such contexts, potentially amplifying the effects of the other two mechanisms, as discussed in Section 4.1. Consequently, if the spillover effects of distress risk operate primarily through strategic market competition mechanisms, we would anticipate these effects to be more significant in industries with higher barriers to market leadership.

Third, in industries with significant inventory holdings, the competitive balance among firms, often sustained through tacit collusion on profit margins, becomes particularly fragile (e.g., Staiger and Wolak, 1992). Additionally, inventory fire sales are critical for firms seeking quick sales to meet immediate liquidity needs and reduce distress risk (e.g., Kim, 2021). At the same time, predatory pricing strategies become more prevalent among competitors aiming to exploit the vulnerabilities of firms affected by distress shocks, as large inventories provide abundant "ammunition" for aggressive pricing tactics.

Fourth, based on the three mechanisms described in Section 4.1, the impact of heightened competition intensity on the increase in firms' financial distress risk is expected to be significantly stronger in industries where firms are already under financial pressure.

Fifth, product markets differ significantly in price flexibility, as highlighted by Bils and Klenow (2004). Higher price flexibility often reflects stronger strategic complementarity in competitors' profit margins for an industry. As discussed in Section 4.1, the three proposed spillover mechanisms among product market competitors heavily rely on this complementarity. Consequently, industries with greater price flexibility are likely to exhibit more pronounced spillover effects of distress risk among competitors.

Taken together, when a leading firm in an industry experiences an adverse distress risk shock, it triggers a ripple effect, prompting major product market competitors to reduce their profit margins, thereby increasing their short-term distress risk. This within-industry spillover effect is expected to be more pronounced in tradable industries or those with higher barriers to market leadership, higher inventory levels, tighter financial constraints, or more flexible prices. On the contrary, in non-tradable industries or those characterized by lower barriers, lower inventory levels, less binding financial constraints, or less flexible prices, the spillover effect may be insignificant. Below, we empirically investigate these heterogeneous spillover effects of distress risk through product market competition.

Industry Tradability.

We classify industries as tradable or non-tradable following methods used in prior studies, including Mian and Sufi (2014), Bernstein et al. (2019), and Giroud and Mueller (2019). An industry is categorized as tradable if its imports plus exports exceed \$10,000 per worker or amount to \$500 million in total. Tradable industries typically include manufacturing sectors, whereas non-tradable industries are represented by retailers and restaurants. To test our hypothesis regarding heterogeneous spillover effects, we conduct a DID analysis based on this classification. The results, presented in Panel A of Table 6, reveal that within-industry spillover effects are primarily observed in tradable industries. This is evident when comparing Columns (1), (3), and (5) with Columns (2), (4), and (6) in Panel A. These results are in line with our hypothesis, grounded in the proposed product market competition mechanisms.

Specifically, Columns (2) and (4) in Panel A of Table 6 show that the total treatment effect on distress risk, captured by $\beta_1 + \beta_3$, is statistically and economically significant in non-tradable industries. However, the within-industry spillover effect of distress risk, captured by β_3 alone, is statistically insignificant. In fact, the economic magnitude of the total treatment effect on distress risk, $\beta_1 + \beta_3$, in non-tradable industries is comparable to that observed in tradable industries, as shown in Columns (1) and (3). The absence of spillover effects in non-tradable industries highlights their limited sensitivity to distress shocks. In Column (6), the total treatment effect on the treated firm's product market competition behavior, $\beta_1 + \beta_3$, has a p-value of 0.136, while the spillover effect on competitors, β_3, shows a t-statistic of 0.134 for profit margins.

Table 6: Heterogeneous Spillover Effects: Industry Tradability and Barriers

	(1)	(2)	(3)	(4)	(5)	(6)
	$Risk\_of\_Failure_{i,t}$		$Dist\_to\_Default_{i,t}$		$Profit\_Margin_{i,t}$	
	Panel A: Industry tradability					
Industry tradability	Yes	No	Yes	No	Yes	No
$Treat_{i,t} \times Post_{i,t}$ (β_1)	0.013	0.050*	−0.054	−0.256*	0.003	−0.004
	[1.000]	[1.839]	[−0.751]	[−1.770]	[0.381]	[−1.508]
$Treat_{i,t}$ (β_2)	−0.011	−0.031	0.016	0.330**	−0.004	0.004
	[−0.935]	[−1.035]	[0.238]	[1.970]	[−0.669]	[1.167]
$Post_{i,t}$ (β_3)	0.059***	0.022	−0.135***	−0.020	−0.017***	0.000
	[6.858]	[1.557]	[−2.957]	[−0.217]	[−3.185]	[0.134]
$\ln(1+n(\mathcal{C}_{i,t}))$	0.016	0.020	−0.053	−0.067	−0.010**	−0.003
	[1.601]	[1.000]	[−1.016]	[−0.600]	[−2.035]	[−1.451]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74890	12866	57671	10994	73294	12951
R-squared	0.597	0.613	0.661	0.678	0.745	0.862
Test p-value: $\beta_1 + \beta_3 = 0$	$< 10^{-3}$	0.001	$< 10^{-3}$	0.015	0.001	0.136
	Panel B: Levels of barriers to market leadership					
Level of barriers	High	Low	High	Low	High	Low
$Treat_{i,t} \times Post_{i,t}$ (β_1)	0.024**	0.025	−0.086	−0.100	0.001	−0.006
	[2.056]	[1.323]	[−1.476]	[−1.094]	[0.251]	[−1.620]
$Treat_{i,t}$ (β_2)	−0.014	−0.011	0.077	0.144*	−0.000	−0.004
	[−1.272]	[−0.587]	[1.304]	[1.650]	[−0.110]	[−1.136]
$Post_{i,t}$ (β_3)	0.065***	0.018	−0.134***	−0.083	−0.010**	0.004
	[8.424]	[1.470]	[−3.583]	[−1.466]	[−2.569]	[1.433]
$\ln(1+n(\mathcal{C}_{i,t}))$	0.031***	−0.006	−0.132***	0.000	−0.013***	0.005*
	[3.543]	[−0.420]	[−3.105]	[0.000]	[−3.716]	[1.908]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	103455	32691	82893	27617	102217	32803
R-squared	0.613	0.612	0.676	0.702	0.749	0.803
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	0.003	$<10^{-3}$	0.014	0.012	0.525

Notes. Panel A of the table focuses on examining the within-industry spillover effects that occur in the aftermath of major natural disasters, differentiating between tradable and non-tradable industries. Panel B of the table explores the heterogeneity of within-industry spillover effects across industries with varying levels of barriers to market leadership. The barrier to attaining market leadership within a four-digit SIC industry is measured by the sales-weighted average of fixed assets across firms in that industry. 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.

Industry Barriers to Market Leadership.

We expect stronger within-industry spillover effects in industries with higher barriers to market leadership. Leveraging the sales-weighted average fixed assets as a widely accepted proxy for these barriers (e.g., Li, 2010), we classify four-digit SIC industries into tertiles based on their barrier levels one year prior to major natural disasters. Through separate DID analyses for high-barrier industries (top tertile) and low-barrier industries (middle and bottom tertiles), we test and compare the magnitude of these spillover effects.

The results in Panel B of Table 6 strongly support the predictions of our proposed spillover mechanisms among product market competitors. Within-industry spillover effects, captured by β_3 alone, are predominantly observed in industries with high barriers to market leadership, while they are nearly absent in industries with low barriers to market leadership. This distinction is clearly demonstrated through the comparison of Columns (1), (3), and (5) with Columns (2), (4), and (6) in Panel B.

Specifically, in Columns (2) and (4) of Panel B of Table 6, the within-industry spillover effect of distress risk, captured by β_3 alone, is not significantly different from zero in industries with low barriers to market leadership. However, the total treatment effect, captured by $\beta_1 + \beta_3$, is both statistically and economically significant for distress risk, with p-values of 0.003 and 0.014, respectively. The absence of significant spillover effects in low-barrier industries, compared to those with high barriers to market leadership, reveals the limited impact of distress shocks on product market competition in such contexts. This is further illustrated in Column (6), where the total treatment effect on the profit margins of treated firms in industries with low barriers, captured by $\beta_1 + \beta_3$, is statistically insignificant, with a p-value of 0.525. Unsurprisingly, the spillover effect on the profit margins of untreated competitors, captured by β_3 alone, is also insignificant.

Levels of Inventory.

We expect stronger within-industry spillover effects in industries with higher inventory levels. To test this, we classify industries into tertiles based on their inventory amounts one year prior to major local natural disaster shocks. Through separate DID analyses for high-inventory industries (top and middle tertiles) and low-inventory industries (bottom tertile), we test and compare the magnitude of these spillover effects. The results, presented in Panel A of Table 7, support our proposed mechanisms. Spillover effects, captured by β_3 alone, are significant in high-inventory industries but absent in low-inventory industries. Additionally, the total treatment effects on profit margins, captured by $\beta_1 + \beta_3$, are significant only in high-inventory industries. These findings on the total treatment effects on profit margins are consistent with Kim (2021), who found that firms affected by the Lehman Brothers collapse temporarily reduced product prices, particularly in industries with high inventory levels. Our results, however, go further by highlighting not only the total treatment effects but also the spillover effects on competitors within the same industry.

Tightness of Financial Constraints.

We predict that industries with tighter financial constraints prior to major local natural disasters will experience stronger within-industry spillover effects. To test this prediction, we measure the tightness of financial constraints of each four-digit SIC industry using the sales-weighted average of the delay investment score developed by Hoberg and Maksimovic

Table 7: Heterogeneous Spillover Effects: Inventory and Financial Constraints

	(1)	(2)	(3)	(4)	(5)	(6)
	$Risk\_of\_Failure_{i,t}$		$Dist\_to\_Default_{i,t}$		$Profit\_Margin_{i,t}$	
	Panel A: Levels of inventory					
Inventory	High	Low	High	Low	High	Low
$Treat_{i,t} \times Post_{i,t}$ (β_1)	0.025**	0.021	−0.060	−0.202**	0.000	−0.005
	[2.232]	[1.140]	[−1.057]	[−2.097]	[0.028]	[−1.057]
$Treat_{i,t}$ (β_2)	−0.013	−0.032*	0.024	0.435***	−0.001	0.001
	[−1.211]	[−1.751]	[0.420]	[4.185]	[−0.214]	[0.173]
$Post_{i,t}$ (β_3)	0.062***	0.018	−0.154***	0.003	−0.009**	0.004
	[8.157]	[1.497]	[−4.264]	[0.042]	[−2.431]	[1.447]
$\ln(1 + n(\mathcal{C}_{i,t}))$	0.025***	−0.011	−0.080*	−0.011	−0.013***	0.005*
	[2.868]	[−0.831]	[−1.915]	[−0.156]	[−3.844]	[1.649]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	106422	29727	85542	24955	105111	29908
R-squared	0.614	0.616	0.680	0.707	0.750	0.804
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	0.008	$<10^{-3}$	0.011	0.006	0.896
	Panel B: Levels of financial constraints					
Financial constraints	High	Low	High	Low	High	Low
$Treat_{i,t} \times Post_{i,t}$ (β_1)	0.008	0.037**	0.046	−0.096	0.000	0.000
	[0.390]	[2.567]	[0.458]	[−1.281]	[0.039]	[0.092]
$Treat_{i,t}$ (β_2)	−0.020	−0.030**	0.084	0.152*	0.005	0.008*
	[−0.953]	[−2.152]	[0.809]	[1.929]	[0.706]	[1.658]
$Post_{i,t}$ (β_3)	0.114***	0.015	−0.302***	−0.063	−0.029***	0.004
	[6.916]	[1.628]	[−4.034]	[−1.352]	[−2.934]	[1.208]
$\ln(1 + n(\mathcal{C}_{i,t}))$	0.029**	0.005	−0.120**	−0.087*	−0.019***	−0.006*
	[2.034]	[0.474]	[−2.026]	[−1.674]	[−3.045]	[−1.916]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32758	62186	27545	48609	32923	61851
R-squared	0.657	0.640	0.735	0.707	0.730	0.805
Test p-value: $\beta_1 + \beta_3 = 0$	$< 10^{-3}$	$< 10^{-3}$	0.002	0.009	$< 10^{-3}$	0.277

Notes. This table examines the heterogeneous spillover effects among product market competitors following major natural disasters, across industries with varying levels of inventory and financial constraints. The regression specification is as in equation (3.3). The financial constraint of a four-digit SIC industry is measured by the sales-weighted average of the delay investment score in the industry (Hoberg and Maksimovic, 2015). The sample spans from 1994 to 2018 in Panel A, while the sample spans from 1998 to 2016 in Panel B due to shorter sample period of the delay investment score. Standard errors are clustered at the firm level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

(2015). Industries are then sorted into tertiles based on this measure one year before the major local natural disaster shocks. Using separate DID analyses, we test and compare the within-industry spillover effects in industries with tight financial constraints (top tertile) and loose financial constraints (middle and bottom tertiles). Panel B of Table 7 presents the results. Columns (2) and (4) show that the within-industry spillover effect of distress risk, captured by β_3 alone, is statistically insignificant in industries with loose financial constraints. However, the total treatment effect on distress risk for industries with loose financial constraints, captured by $\beta_1 + \beta_3$, is both statistically and economically significant, with p-values of less than 0.001 and 0.009. The absence of spillover effects in

Table 8: Heterogeneous Spillover Effects: Price Flexibility and Profitability Comovement

	(1)	(2)	(3)	(4)	(5)	(6)
	$Risk\_of\_Failure_{i,t}$		$Dist\_to\_Default_{i,t}$		$Profit\_Margin_{i,t}$	
	Panel A: Levels of price flexibility					
Price flexibility	High	Low	High	Low	High	Low
$Treat_{i,t} \times Post_{i,t}$ (β_1)	0.019	0.045***	−0.044	−0.147*	0.001	−0.002
	[1.135]	[2.767]	[−0.518]	[−1.822]	[0.160]	[−0.302]
$Treat_{i,t}$ (β_2)	−0.011	−0.037**	0.091	0.248***	−0.003	0.003
	[−0.721]	[−2.327]	[1.188]	[2.777]	[−0.582]	[0.436]
$Post_{i,t}$ (β_3)	0.083***	0.014	−0.172***	−0.053	−0.017***	0.003
	[6.830]	[1.523]	[−3.002]	[−1.127]	[−2.624]	[0.854]
$\ln(1+n(\mathcal{C}_{i,t}))$	0.060***	−0.025*	−0.134**	−0.051	−0.021***	−0.004
	[4.781]	[−1.913]	[−2.235]	[−0.743]	[−4.038]	[−0.688]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46854	52755	37608	41641	47261	51113
R-squared	0.591	0.613	0.677	0.665	0.629	0.782
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	0.001	0.003	0.002	0.811
	Panel B: Levels of profitability comovement					
Profitability comovement	High	Low	High	Low	High	Low
$Treat_{i,t} \times Post_{i,t}$ (β_1)	0.017	0.032**	−0.085	−0.087	−0.006	0.004
	[1.158]	[2.225]	[−1.249]	[−1.190]	[−0.877]	[0.755]
$Treat_{i,t}$ (β_2)	−0.009	−0.017	0.065	0.171**	−0.004	0.002
	[−0.612]	[−1.144]	[0.880]	[2.089]	[−0.726]	[0.399]
$Post_{i,t}$ (β_3)	0.066***	0.043***	−0.181***	−0.034	−0.011**	−0.003
	[6.366]	[4.460]	[−3.694]	[−0.744]	[−2.116]	[−0.965]
$\ln(1+n(\mathcal{C}_{i,t}))$	0.032***	0.004	−0.067	−0.067	−0.016***	0.002
	[2.915]	[0.415]	[−1.353]	[−1.383]	[−3.738]	[0.481]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63129	63382	52734	49305	63231	62122
R-squared	0.626	0.633	0.704	0.696	0.706	0.803
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	0.043	$<10^{-3}$	0.867

Notes. This table examines the heterogeneous spillover effects among product market competitors following major natural disasters, across industries with varying levels of price flexibility and profitability comovement. The regression specification is as in equation (3.3). We measure the price flexibility based on the frequency of price changes for consumption categories (Bils and Klenow, 2004). We calculate profitability comovement as the average pairwise correlation of net profitability for the top four sales-ranked firms in each four-digit SIC industry. 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.

these industries, as opposed to those with tight financial constraints, suggests a limited impact of distress shocks on product market competition behaviors, particularly in terms of profit margins. This is further supported by the results in Column (6), which reveals that the total treatment effect on profit margins of the treated firm, captured by $\beta_1 + \beta_3$, is statistically insignificant. For industries with loose financial constraints, the spillover effect on the profit margins of untreated product market competitors, captured by β_3 alone, is also statistically insignificant.

Price Flexibility.

Based on the proposed mechanisms, we expect the spillover effects of distress risk through product market competition to primarily occur in industries with high price flexibility, rather than in those with low price flexibility. To test this, we measure the price flexibility of four-digit SIC industries using the frequency of price changes for 350 consumption categories calculated by Bils and Klenow (2004). Specifically, we calculate each industry's price flexibility as the sales-weighted average frequency of price changes across its associated consumption categories, using weights derived from the Consumer Expenditure Survey. Industries are then grouped into high-price flexibility (above the median) and low-price flexibility (below the median) categories based on data one year prior to major local natural disaster shocks. Using separate DID analysis, we examine within-industry spillover effects in these two groups. As shown in Panel A of Table 8, Columns (1), (3), and (5) for high-price flexibility industries stand in stark contrast to Columns (2), (4), and (6) for low-price flexibility industries. The results show that within-industry spillover effects are significantly more pronounced in industries with high price flexibility. However, it is important to note that the total treatment effect on distress risk, captured by $\beta_1 + \beta_3$, remains statistically significant across both groups of industries.

Price flexibility reflects the strength of strategic complementarity among product market competitors' profit margins. Consistent with the findings in Panel A of Table 8, we expect within-industry spillover effects to be predominantly observed in industries with high profitability comovement. To test this, we calculate profitability comovement as the average pairwise correlation of net profitability among the top four sales-ranked firms within each four-digit SIC industry over the preceding ten years. Industries are then divided into two groups based on profitability comovement levels one year before major local natural disaster shocks: high comovement (above the median) and low comovement (below the median). Using separate DID analyses, we estimate and compare the within-industry spillover effects for both groups. The results, presented in Panel B of Table 8, closely align with those in Panel A, highlighting the critical role of strategic complementarity in driving the spillover effects suggested by our proposed product market competition mechanisms.

5 Conclusion

We provide empirical evidence on the spillover effects of profit margins and distress risk within and across industries, highlighting within-industry spillover as the key driver of cross-industry effects. Our analysis identifies three complementary mechanisms underlying these spillovers in product market competition: (i) predatory pricing, (ii) rapid inventory liquidation, and (iii) weakened tacit collusion, which undermines "competitive balance."

To examine product-market spillover effects and their underlying mechanisms, we analyze the causal impact of firm-specific distress risk shocks on product market behaviors and their propagation to product market competitors. Using local natural disasters as exogenous shocks to identify idiosyncratic distress risk variations, we find that distress risk intensifies competition, prompting distressed firms and their competitors to lower profit margins and disrupt the competitive balance often sustained through tacit collusion. These spillovers heighten short-term distress risk for competitors, particularly in tradable industries or those characterized by high barriers to market leadership, large inventories, tight financial constraints, or high price flexibility. Our findings are robust and cannot be attributed to alternative channels, such as disaster-induced demand shocks, production network spillovers, common creditors, or common blockholders. We further validate our findings by examining the effects of major events like the AJCA in 2004 and the Lehman Brothers crisis in 2008. Through two-stage regressions and placebo tests, we demonstrate the propagation of distress risk across industries through the profit margin spillover due to intensified competition, supporting our proposed mechanisms.

These findings carry significant implications for firm-level credit risk and the financial stability of industries and the broader economy. They highlight the critical role of product-market-competition-driven spillovers in shaping market dynamics and contributing to systematic risk.

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