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MARKET COMPETITION AND SHOCK PROPAGATION: IMPLICATIONS FOR MARGINS AND DISTRESS

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 adverse shocks lead both directly affected firms and their unaffected competitors to reduce profit margins by approximately 0.8 percentage points. These reductions stem from intensified market competition, driven by mechanisms including predatory pricing, inventory liquidation, and weakened tacit collusion. As unaffected competitors cut margins nearly one-for-one in response, their financial distress rises significantly, though not directly shocked. Spillover effects are concentrated in tradable industries and those with high entry barriers, large inventories, greater price flexibility, or tight financial constraints, revealing a novel channel for shock propagation across the economy.

Winston Wei Dou
University of Pennsylvania
The Wharton School
and NBER
wdou@wharton.upenn.edu

Shane A. Johnson
Texas A&M University
shaneajohnson@tamu.edu

Wei Wu
Texas A&M University
Department of Finance
wwu@mays.tamu.edu

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

1 Introduction

Strategic market competition is a powerful force shaping firms' cash flows and distress risk. Over recent decades, a small number of market leaders have come to dominate many industries. These firms sustain their market power through highly strategic behavior, often relying on tacit collusion or implicit coordination to preserve "competitive balance" and avoid destructive price wars. This strategic interaction has contributed to persistently high profit margins, whose fluctuations explain much of the variation in corporate earnings and carry important asset pricing implications.[1]

Beyond individual firms, strategic interactions through market competition interconnect firms across the economy, serving as channels for shock propagation. While much of the existing literature focuses on vertical propagation via input-output linkages (e.g., Jacobson and von Schedvin, 2015; Barrot and Sauvagnat, 2016) and horizontal propagation via firms' internal networks of establishments (e.g., Giroud and Mueller, 2019; Giroud et al., 2024), this paper uncovers a novel yet intuitive channel: horizontal propagation of shocks across competing firms within the same industry. Idiosyncratic adverse shocks to one firm can spill over to its competitors through intensified market competition within the same industry and, through multi-industry firms, propagate across industries. This mechanism constitutes a channel through which firm-specific shocks can aggregate, contributing to macroeconomic fluctuations and shaping the general equilibrium effects of industrial policy and regulation.

While strategic interactions among firms within an industry are recognized as a potentially important channel for shock propagation and aggregation, relatively little is known about how an "adverse shock," defined as a sudden decline in cash flows or destruction in collateral, affects not only the shocked firm's own profit margins and distress risk,[2] but also those of its industry competitors across a broad range of industries. Such a shock raises the firm's effective discount rate, reducing its valuation of future profits

[1]See, e.g., Bouchaud et al. (2019) and Dou, Ji and Wu (2021).

[2]"Distress risk" refers to the probability of covenant violation or default within the next year.

and making it behave as if it were less patient. Most existing studies focus on a few specific industries and rarely examine cross-firm spillovers. This paper addresses that gap by investigating how firm-level adverse shocks propagate through strategic market competition.

Our analysis provides comprehensive causal evidence that when a firm experiences an adverse shock, both the affected firm and its unaffected competitors within the same industry reduce their profit margins in the short run, typically over one to two years. This margin compression is driven by intensified strategic competition in product markets. In theory, it arises generically from strategic complementarity in how firms set their profit margins. When one firm lowers its profit margins, others in the same industry are incentivized to follow. However, the specific market competition mechanisms behind this profit margin compression, including predatory pricing, inventory liquidation, and weakened tacit collusion, may differ across settings. Earnings-based borrowing constraints then translate lower profit margins into heightened financial distress. As a result, even firms not directly affected by the initial shock may face elevated distress risk. Although this outcome may seem counterintuitive because one might expect firms to benefit when a competitor is distressed, it reflects fundamental aspects of competitive dynamics in strategic interactions, where a firm's short-term financial distress can increase when its competitors experience severe adverse shocks, despite the potential for longer-term gains in market power. This highlights the complex nature of strategic market competition among industry rivals, similar in spirit to the bankruptcy spillovers (Bernstein et al., 2019).

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 maintaining competitive balance in the industry to prevent a downward spiral in price competition that could destabilize the entire sector.[3]

To formally develop the hypothesis, we propose three economic mechanisms, grounded in strategic market competition, that link idiosyncratic adverse shocks to endogenous increases in competitive intensity: (i) predatory pricing, (ii) inventory fire sales, and (iii) weakened tacit collusion. These mechanisms are not mutually exclusive and may operate concurrently, reinforcing one another. Moreover, when earnings-based borrowing constraints are prevalent, intensified competition and the resulting compression of profit margins naturally increase the financial distress of competitors by raising their likelihood of covenant violations or default.

Establishing causal evidence of spillover effects among competing firms within the same industry, driven by strategic market competition, requires addressing several key identification challenges. The first is endogeneity. Unobserved confounders, such as anticipated market entry, may simultaneously influence both distress risk and competitive intensity. This problem is compounded by endogenous industry selection, as firms often sort into the same industries based on common underlying characteristics (e.g., Leary and Roberts, 2014). The second challenge arises from treatment externalities, or interference: spillover effects violate the stable unit treatment value assumption (SUTVA), a critical condition for identifying treatment effects (e.g., Cox, 1958; Rubin, 1980; Manski, 1993, 2013). The third challenge lies in distinguishing spillovers driven by market competition from those arising through alternative economic linkages. Even if an adverse shock to one firm leads to lower profit margins and higher distress risk for its competitors within the same industry, such patterns may instead reflect overlapping exposures, including input-output relationships, concurrent disaster-induced demand shocks, or shared creditors or blockholders, rather than direct effects of competitive interaction.

To overcome the first challenge, we leverage major local natural disasters in the United

[3] Additional examples of within-industry spillover effects are detailed in Online Appendix 1.

States over the past 25 years as a source of exogenous variation. Following Barrot and Sauvagnat (2016), who study shock propagation through production networks, we focus on disasters that caused substantial property losses. These events serve as valid instruments for exogenous idiosyncratic adverse shocks, as they trigger sharp declines in cash flows or destruction of collateral, leading to heightened distress risk for the affected firms, consistent with prior findings (e.g., Gan, 2007; Chaney, Sraer and Thesmar, 2012). To further mitigate endogeneity concerns, we employ two additional quasi-experiments to identify spillover effects among competitors within the same industry: the 2004 American Jobs Creation Act (AJCA), which introduced a repatriation tax holiday (e.g., Faulkender and Petersen, 2012), and the collapse of Lehman Brothers (e.g., Chodorow-Reich, 2014; Chodorow-Reich and Falato, 2021). These one-time aggregate shocks generated heterogeneous effects on firms, leading to cross-sectional variation in distress risk that is unrelated to changes in product market competition intensity. Consistent evidence from these quasi-experiments reinforces our main findings and enhances the robustness of our conclusions.

To tackle the second challenge, we implement a formal difference-in-differences (DID) approach that jointly estimates the direct treatment effect on shocked firms and the spillover effects on their untreated competitors, while accounting for potential cross-industry spillovers. This method builds on foundational work in the statistical and econometric literature, including Rubin (1978, 1990). To identify causal effects, we match treated firms (i.e., those affected by major local natural disasters) with their non-treated competitors within the same industry based on similar firm characteristics. We find that both treated firms and their matched, unaffected competitors experience significant declines in profit margins and increases in distress risk, indicating that adverse shocks propagate through market competition within the industry.

To address the third challenge, we examine alternative channels that may overlap with market competition relationships and potentially contribute to the observed spillover effects among firms within the same industry. These include input-output linkages, concurrent disaster-induced demand shocks, shared creditors, and common blockholders.

Our analysis reveals that these alternative channels are unlikely to account for the observed patterns, reinforcing the conclusion that intensified market competition is the primary driver of the spillover effects from adverse shocks on the profit margins and distress risk of unaffected competitors.

To further confirm that market competition, rather than alternative channels, drives the observed spillover effects among competing firms within the same industry, we examine how these effects vary across industries with different competitive structures and characteristics. Consistent with the predictions of market competition mechanisms, we find that spillover effects are stronger in tradable industries and in those characterized by higher barriers to market leadership, larger inventories, greater price flexibility, or tighter financial constraints. This pattern of heterogeneity provides further support for the proposed hypothesis and the underlying mechanisms of market competition.

In more detail, 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 39 basis points. These increases are not only statistically significant but also economically sizable, relative to the sample averages of a 303 basis point bond yield 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 adverse shock, 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 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, which is both statistically and economically significant.

The Online Appendix presents additional analyses that help rule out alternative explanations, provide evidence of cross-industry spillover effects, and strengthen causal inference using quasi-experimental variation from major events, including the 2004 AJCA tax holiday and the 2008 Lehman Brothers collapse.

Related Literature. This study contributes to the literature on shock propagation in the economy. Prior research has primarily focused on shock propagation through input-output linkages and production networks connecting 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, 2023). However, most of these studies have not examined the implications for profit margins or financial distress. Some exceptions include Jacobson and von Schedvin (2015) and Adelino et al. (2022), who document the propagation of distress risk along vertical supply chains through trade credit. Related research has also explored the horizontal transmission of local economic shocks through firms' internal networks of establishments (e.g., Giroud and Mueller, 2019; Giroud et al., 2024). In contrast, our study focuses on the horizontal transmission of adverse shocks through strategic market competition, both within and across industries, highlighting effects on profit margins and financial distress.

Further supporting this paper's proposed hypothesis and the underlying market competition mechanisms, Dou and Wu (2023) show that an industry's equity returns can be predicted by the lagged returns of other industries linked through multi-industry firms. Their findings suggest that information about spillovers among competing firms within an industry propagates gradually across industries, particularly when investor attention is limited or information processing is constrained. These asset pricing results closely align with and reinforce the competitive spillover mechanisms identified in our study.

This study also contributes to the literature on how financial distress and constraints shape firms' strategic behavior in market competition. A large body of theoretical and empirical work, beginning with Titman (1984), Bolton and Scharfstein (1990), and Maksimovic and Titman (1991), shows that financially constrained or distressed firms tend to reduce profit margins, either to preserve liquidity or to retain market share under pressure. Subsequent studies, including Chevalier (1995), Phillips (1995), Kovenock and Phillips (1995, 1997), Chevalier and Scharfstein (1996), and Zingales (1998), provide further support for this mechanism. More recent empirical evidence confirms that financial constraints and elevated distress risk are associated with lower profit margins both across firms and over time (e.g., Maksimovic, 1988; Busse, 2002; Hortaçsu et al., 2011, 2013; Phillips and Sertsios, 2013; Koijen and Yogo, 2015; Kim, 2021; Chen et al., 2022).[4] These findings are broadly consistent with our empirical results. That said, prior studies have shown that in industries with highly inelastic demand and sticky customer base, financially constrained firms may set higher markups than less constrained firms in cross-sectional comparisons (e.g., Chevalier and Scharfstein, 1996; Gilchrist et al., 2017). However, Dou and Ji (2021) demonstrate in a general theoretical framework that this result holds only under extreme conditions, when demand elasticity is very 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 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 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

[4]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).

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.

2 Economic Mechanisms and Hypothesis Development

In this section, we illustrate how strategic market competition, combined with the prevalence of earnings-based borrowing constraints in the corporate sector,[5] gives rise to short-run spillover effects: When a firm experiences an adverse shock, which we define as a sudden decline in cash flows or destruction of collateral, its competitors within the same industry also reduce their profit margins. This reduction, in turn, increases their financial distress risk.

Specifically, an adverse shock intensifies competition through three key mechanisms of strategic interaction: (i) predatory pricing, (ii) inventory fire sales, and (iii) weakened tacit collusion. The resulting increase in competitive pressure compresses profit margins not only for the shocked firm but also for its competitors, thereby elevating their financial distress risk under earnings-based borrowing constraints. A central feature of this process is strategic complementarity in profit margin setting, whereby a reduction in one firm's margins creates incentives for others in the industry to do the same, regardless of the specific mechanism at work.

2.1 Mechanisms of Strategic Market Competition

We now describe the three spillover mechanisms among competing firms that arise from strategic market competition in an industry. These mechanisms are not mutually exclusive and often operate simultaneously, reinforcing one another. Accordingly, we do not seek to

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

isolate their individual contributions to the overall spillover effects. The main contribution of this paper is to demonstrate that adverse shocks to one firm can affect competitors' profit margins and financial distress through the channel of market competition, regardless of the specific mechanism at work.

Mechanism 1: Predatory Pricing.

One channel for spillover effects on profit margins and distress risk is predatory pricing by competitors. Predatory pricing involves aggressively cutting prices to force a distressed rival out of the market, with the aim of securing long-term market dominance. After the exit of the distressed firm, the predator raises prices to recoup initial losses. While this strategy can increase the predator's own short-term distress risk due to profit margin compression, it is pursued for long-run gains (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. The 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 in profit margin setting among competing firms with in the same industry, where price flexibility and profitability comovement among competitors tend to be greater. However, its effectiveness is limited in non-tradable industries, where competition is localized and customer bases are geographically fragmented. In such industries, limited market overlap among firms diminishes the impact of predatory pricing, exerting minimal pressure on adversely shocked competitors, even within the same industry.

The predatory pricing mechanism can be further reinforced by the other two mechanisms: inventory fire sales and tacit collusion. In industries with substantial inventory holdings, spillovers from predatory pricing become more pronounced, as competitors are able to sell greater quantities at steep discounts, especially in anticipation of fire sales by distressed rivals seeking liquidity. High inventory levels thus amplify the competitive pressure and profit margin compression triggered by predatory pricing. In parallel, in industries where competitive balance is typically maintained through tacit collusion, unshocked firms are better positioned to strategically undercut prices when a rival suffers an adverse shock. The breakdown of tacit coordination in the face of such shocks enables these firms to further compress profit margins, intensifying competitive pressure and amplifying the financial distress of the affected competitor.

Mechanism 2: Inventory Fire Sales.

The spillover effects on 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.[6] To restore liquidity quickly, these firms often sharply reduce profit margins to stimulate demand and draw customers from competitors. Competitors often respond by lowering their profit margins to defend or expand market share. This response is more pronounced in industries with stronger strategic complementarity in profit margin setting, where price flexibility and profitability comovement among firms tend to be greater. However, the effectiveness of this mechanism is limited in non-tradable industries such as supermarkets, retail stores, and restaurants, where competition is primarily local and customer bases are geographically fragmented. In such industries, limited market overlap among firms reduces the spillover effects of inventory fire sales on competitors, even within the same industry. 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.

Importantly, even before firms enter severe distress, adverse shocks can prompt precautionary inventory fire sales for at least two reasons. First, when firms suffer adverse

[6] 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).

shocks, they become increasingly concerned about customers' strategic waiting behavior. Anticipating that the firm's financial condition may further deteriorate, customers may delay their purchases in expectation of deeper future discounts (see Birge et al., 2017).[7] To preempt this behavior, firms often lower profit margins more aggressively after an adverse shock. Second, in industries with high barriers to achieving market leadership, shocked firms often anticipate aggressive predatory pricing from competitors seeking to trigger price wars and drive them out. To preempt such tactics, these firms may initiate early inventory fire sales to rapidly raise liquid assets such as cash.

In sum, when a firm is hit by an adverse shock, it often responds by liquidating its products, especially inventories, at significantly reduced profit margins. Competitors, in turn, lower their own profit margins to defend or expand market share, particularly in industries where strategic complementarity in profit margins is strong. Beyond these defensive responses, competitors may also engage in predatory pricing, further compressing profit margins for both the shocked firm and its competitors. As a result, they face a heightened risk of covenant violations or debt defaults in the short run. Moreover, because predatory pricing can amplify inventory fire sales, these within-industry spillovers tend to be more pronounced in industries with higher barriers to achieving market leadership.

Mechanism 3: Weakened Tacit Collusion.

The third channel through which adverse shocks spill over to profit margins and distress risk of competitors is the weakening of tacit collusion in product markets. Empirical research has documented the prevalence of tacit collusion across many industries. Theoretical foundations for distressed competition in the presence of tacit collusion have been developed by Maksimovic (1988) and Chen et al. (2022).[8] Tacit collusion is sustainable

[7] Strategic customer waiting behavior 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).

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

only when the cost of deviation, which is the loss of the present value of future cooperative profits due to punishment, exceeds the short-term gain from undercutting rivals.

Under distressed competition, an adverse shock raises a firm's effective discount rate, reducing its valuation of future cooperative gains and weakening its incentive to sustain tacit collusion. As a result, both the shocked firm and its competitors face narrower current profit margins. The effect is particularly pronounced in industries with high barriers to market leadership, where market leaders have strong incentives to exploit weakened rivals through predatory pricing, leading to further profit margin compression and heightened short-run distress risk. As tacit collusion becomes harder to maintain, even competitors not directly affected by the shock come under pressure to lower their profit margins. Some may go further, intensifying pricing aggression as a strategic move to force distressed rivals out of the market and position themselves to capture future monopoly rents. These dynamics are amplified in industries with greater strategic complementarity in profit margin setting, where firms tend to exhibit higher price flexibility and stronger profitability comovement. In contrast, the mechanism is weaker in non-tradable industries, where competition is localized and customer bases are geographically fragmented, making tacit collusion difficult to sustain from the outset.

2.2 Hypothesis Development

We next formalize the implications of spillover mechanisms driven by product market competition for profit margins and financial distress into testable hypotheses.

Hypothesis 1. *An adverse shock, defined as a sudden drop in cash flows or the destruction of collateral, experienced by a firm within an industry triggers a ripple effect, causing its competitors to lower their profit margins and, in turn, face increased short-term financial distress.*

We test **Hypothesis 1** above in Section 4. **Hypothesis 2** below focuses on the heterogeneity of these spillover effects across different industry structures and characteristics. We test this heterogeneity in Section 5.

Hypothesis 2. *The spillover effect among competing firms within the same industry is more pronounced in tradable industries and in those characterized by higher barriers to market leadership, larger inventories, tighter financial constraints, and greater price flexibility. In contrast, the effect tends to be weaker and may become statistically insignificant in non-tradable industries or in those with lower barriers to market leadership, smaller inventories, looser financial constraints, or limited price flexibility.*

3 Data and Measurement of the Variables

We assemble data from various sources. This section describes the main datasets and empirical measures, with further details on supplementary data and variable construction provided in Online Appendix 2.

3.1 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

[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.

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, 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;

[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.

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.

3.2 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).

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 the bond yield spread as an alternative measure of distress risk. For each firm, we compute this spread as the average difference between the yields on its outstanding bonds and the yields on Treasury securities of comparable maturity. Following Chen et al. (2018) and Chen et al. (2022), we construct this measure using data from the Mergent Fixed Income Securities Database (FISD) for 1973-2004 and the Trade Reporting and Compliance Engine (TRACE) for 2005-2018. We clean the FISD and TRACE data following the methodologies in Collin-Dufresn, Goldstein and Martin (2001) and Dick-Nielsen (2009). As a market-based measure, the bond yield spread arguably captures distress risk more directly than the measure of Campbell, Hilscher and Szilagyi (2008), which relies primarily on accounting data, or the distance-to-default metric derived from structural models. We restrict the treatment effect analysis to firms with bond yield spreads below 500 basis points, as firms with higher spreads are typically classified as highly speculative or deeply distressed. These firms generally borrow in segmented credit markets that are separate from those accessed by typical corporate borrowers who are not highly speculative (e.g., Collin-Dufresne, Goldstein and Martin, 2001; Dou, Wang and Wang, 2023). A key limitation, however, is its relatively narrow cross-sectional coverage: between 1973 and 2018, the data include 421 to 746 firms annually, representing approximately 20% of the CRSP-Compustat U.S. nonfinancial, non-utility universe.

3.3 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.

3.4 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.

4 Market Competition as a Spillover Channel

In this section, we use major local natural disasters as exogenous, idiosyncratic adverse shocks to firms to examine how such shocks propagate through strategic product market competition, affecting competitors' profit margins and financial distress.

Major Local Natural Disasters.

When drawing causal inferences about spillover effects among competitors within the same industry, it is important to address potential endogeneity in the observed correlation between a firm's profit margin or distress risk and those of its competitors. The key challenge is to ensure that this correlation reflects the causal impact of an adverse shock experienced by one firm — rather than the influence of confounding factors — on its competitors' profit margins and financial distress. This is inherently difficult, as many confounding factors are latent, unobservable, and challenging to model or control for accurately. For example, firms often sort into the same industry based on shared but unobserved characteristics. To overcome this challenge, we rely on idiosyncratic, exogenous adverse shocks, defined as sudden declines in cash flows or destruction of collateral. These shocks provide plausibly exogenous variation that is not systematically related to underlying industry dynamics.

Specifically, we use major local natural disasters as an instrumental variable to capture exogenous and idiosyncratic declines in firm cash flows or collateral values. Prior research has documented the negative impact of such disasters on firms' financial conditions, including sharp reductions in cash flow and asset values.[11] Natural disasters disrupt revenue generation by forcing operational shutdowns, severing supply chains, and triggering contractual breaches. Simultaneously, they raise operating costs through emergency repairs, inventory replacement, relocation expenses, and increased labor and logistics costs. These shocks also reduce firms' collateral capacity by damaging pledgeable assets such as real estate, machinery, and equipment. 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 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.[12]

These events naturally raise distress risk by generating large financial losses and eroding collateral values through damage to physical capital and property, thereby tightening firms'

[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).

[12]Prolonged delays in insurance settlements and public disaster assistance further amplify the adverse impact of partial insurance coverage on affected firms (e.g., Aretz, Banerjee and Pryshchepa, 2019; Brown, Gustafson and Ivanov, 2021; Seetharam, 2018).

access to credit (e.g., Gan, 2007; Chaney, Sraer and Thesmar, 2012). In addition, adversely affected firms often face liquidity pressures from needing to retain customers by extending trade credit, which imposes further financial strain (e.g., Ersahin, Giannetti and Huang, 2024). Taken together, major local natural disasters lead to higher default risk, elevated borrowing costs, and more restrictive loan terms.

Firm Losses from Major Local Natural Disasters.

The key identification assumption underlying our use of major local natural disasters as exogenous, idiosyncratic adverse shocks is that these events cause significant and unanticipated financial losses or collateral destruction for the directly 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).[13]

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.[14]

[13]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.

[14]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 competitors within the same four-digit SIC industry with similar asset size, tangibility, and age.[15] To study both treatment and spillover effects, we ensure that matched competitors are not directly affected by major local natural disaster shocks. Specifically, we require that matched competitors 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 the matched unaffected competitors are neither suppliers to 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:

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

The dependent variable $Special\_items_{i,t}/Sales_{i,t}$ represents special items scaled by firm

[15] 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 competitors 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 competitors 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.

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 (4.1), 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.

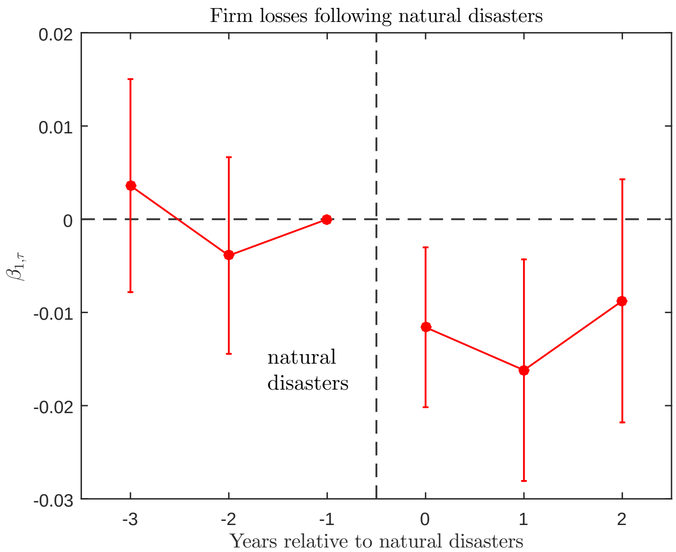
We also conduct an event study analysis centered on major local natural disasters using a dynamic DID regression approach to examine the time-series dynamics of firm losses around these events. This dynamic analysis addresses the concern that the β_1 coefficient in regression (4.1) may pick up changes 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:

$$\begin{aligned} Special\_items_{i,t}/Sales_{i,t} = &\sum_{\tau=-3}^{2} \beta_{1,\tau} \times Treat_{i,t} \times ND_{i,t-\tau} + \beta_2 \times Treat_{i,t} \\ &+ \sum_{\tau=-3}^{2} \beta_{3,\tau} \times ND_{i,t-\tau} + \theta_i + \delta_t + \varepsilon_{i,t}, \end{aligned} \tag{4.2}$$

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 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) through (6) in Panel A of Table 2 show that the total treatment effect of major local natural disasters on the distress risk of affected firms, captured by $\beta_1 + \beta_3$ in those regressions, is significantly different from zero. This indicates that firms hit by such

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.

disasters face substantially higher distress risk. Taken together, these results support our assertion that major local natural disaster shocks serve as a valid instrument for identifying exogenous, idiosyncratic "adverse shocks" that raise the distress risk of affected firms.

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.

Spillover Effects of Adverse Shocks on Competitors' Financial Distress.

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:

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

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 ($Dist\_to\_Default_{i,t}$), or the bond yield spread ($Yield\_Spread_{i,t}$) of firm i in year t. The independent variables $Treat_{i,t}$ and $Post_{i,t}$ are defined as in (4.1). 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

Table 2: Impact of Major Natural Disasters on Competitors' Financial Distress.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Difference-in-Differences (DID) regressions					
	$Risk\_of\_Failure_{i,t}$		$Dist\_to\_Default_{i,t}$		$Yield\_Spread_{i,t}$	
$Treat_{i,t} \times Post_{i,t}$ (β_1)	0.023**	0.023**	−0.087*	−0.088*	0.208*	0.208*
	[2.275]	[2.299]	[−1.717]	[−1.743]	[1.668]	[1.668]
$Treat_{i,t}$ (β_2)	−0.011	−0.011	0.096*	0.097*	−0.128	−0.128
	[−1.189]	[−1.196]	[1.940]	[1.953]	[−1.464]	[−1.458]
$Post_{i,t}$ (β_3)	0.055***	0.054***	−0.122***	−0.115***	0.176**	0.182**
	[8.223]	[8.120]	[−3.882]	[−3.695]	[2.024]	[2.093]
$\ln(1+n(\mathcal{C}_{i,t}))$		0.018**		−0.083**		−0.069
		[2.351]		[−2.295]		[−1.109]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	136181	136181	110581	110581	14818	14818
R-squared	0.597	0.598	0.667	0.667	0.702	0.702
Test p-value: $\beta_1 + \beta_3 = 0$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$	$<10^{-3}$

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	3.030	1.898	3.263	0.698	1.062	3.827	6.284
$\ln(1+n(\mathcal{C}_{i,t}))$	98562	0.747	0.693	0.739	0	0	1.386	1.792

Notes. This table examines the spillover effects of major local natural disasters on distress risk, focusing on both directly affected firms and their competitors within the same industry that are not directly shocked by the 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. 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 for failure risk, distance to default, and bond yield spread span the period 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.

common 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 $n(\mathcal{C}_{i,t})$.[16] 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-

[16]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.

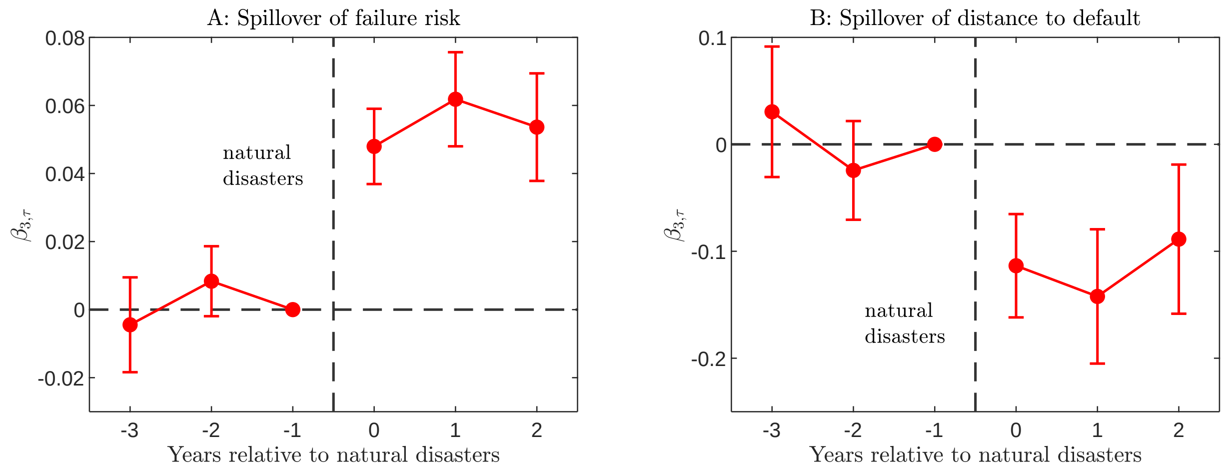
to-default measure (an inverse measure of default risk) of the treated firms decreases significantly. In columns (1) through (4), the respective p-values for testing the null hypothesis that the total treatment effect is zero, i.e., $\beta_1 + \beta_3 = 0$, are less than 0.001. Thus, treated firms experience increased distress risk following natural disasters, consistent with prior research. We also use the bond yield spread 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 39 basis points (p-values $<$ 0.001), which is economically significant relative to the average bond yield spread of 303 basis points in our sample.

The coefficient β_3, associated with the *Post* indicator, plays a central role in our analysis, as its significance directly tests the component of **Hypothesis 1** pertaining to distress risk. As shown in Table 2, the spillover effects are both statistically and economically significant across all measures of distress risk, indicating that even industry competitors not directly affected by major local natural disasters experience a substantial increase in distress risk. Given the matched control design in our quasi-natural experiment, the significance of β_3 provides strong evidence that adverse shocks to one firm increase the distress risk of its competitors within the same industry. The coefficients in columns (1) and (2) indicate that the spillover effect increases the annual probability of failure for unaffected competitors within the same industry by approximately 1.1 percentage points. The total treatment effect increases the annual probability of failure for firms that experience major local natural disasters from 2 percentage points to approximately 3.56 percentage points, on average.[17] Columns (5) and (6) indicate that the spillover effect increases the bond yield spread for unaffected competitors within the same industry by approximately 18 basis points. This increase is economically significant when compared to the average bond yield spread of 303 basis points in our sample.

Similar to the dynamic DID specification presented in equation (4.2), which is centered

[17] In our sample, the average annual probability of failure just before the occurrence of major local natural disasters is around 2 percentage points.

Figure 2: Spillovers on Competitors' Risk of Failure and Distance to Default.

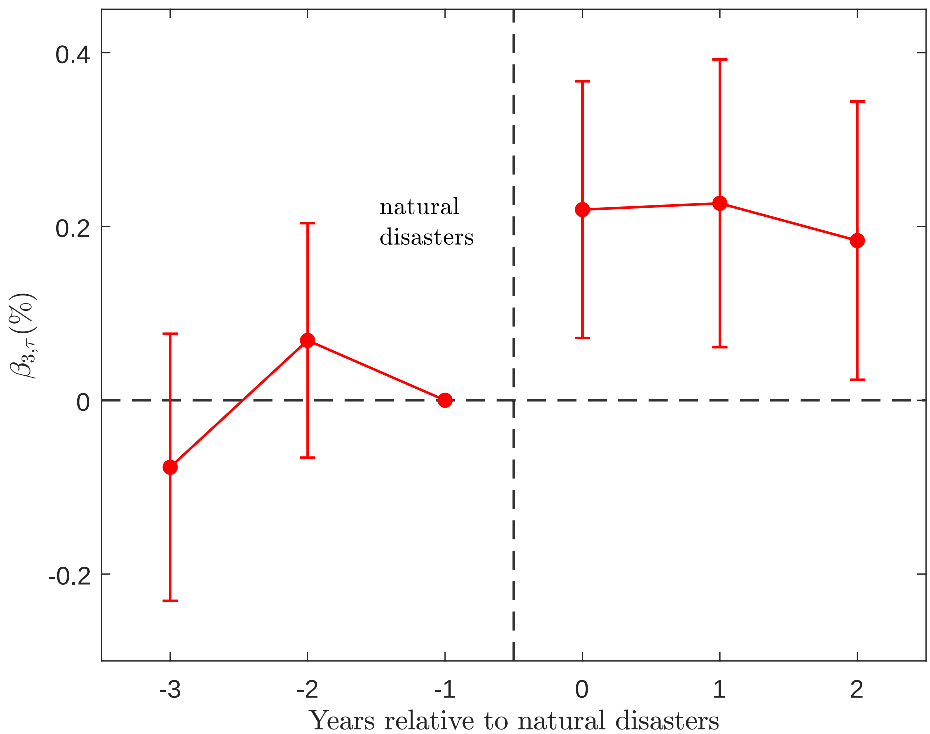


Notes. This figure plots the evolution of competitors' failure risk and distance to default around the occurrence of major natural disasters, providing evidence of the spillover effects triggered by these adverse shocks. For each treated firm, we match it with up to five non-treated competitors in the same four-digit SIC industry according to the matching procedure described in Section 4. 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.

on major local natural disasters, we conduct an event study to examine the spillover effects of adverse shocks affecting one firm on the distress risk of its competitors within the same industry. The dynamic DID framework helps address concerns that the estimated β_3 coefficient may be driven by underlying industry-wide trends in distress risk. To capture the time-series dynamics of the shock's impact more clearly and comprehensively, we construct a balanced panel comprising six annual observations per firm, spanning three years before and three years after the disaster event. Figures 2 and 3 display the time-series of the estimated coefficients $\beta_{3,\tau}$ for $\tau = -3, -2, \ldots, 2$, along with their 90% confidence intervals. Across all three 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 ($\beta_1 + \beta_3$) and the spillover effect to competitors (β_3), we now turn to the additional treatment effect on directly shocked firms, captured by β_1. For the failure risk measure ($Risk\_of\_Failure_{i,t}$), the additional treatment effect is

Figure 3: Spillovers on Competitors' Bond Yield Spreads.



Notes. This figure plots the evolution of competitors' bond yield spreads around the occurrence of major natural disasters, providing evidence of the spillover effects triggered by these adverse shocks. For each treated firm, we match it with up to five non-treated competitors in the same four-digit SIC industry according to the matching procedure described in Section 4. 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.

approximately half the size of the spillover effect to unaffected competitors, as reported in columns (1) and (2) of Table 2. For the distance-to-default measure ($Dist\_to\_Default_{i,t}$), the additional treatment effect is roughly equal in magnitude to the spillover effect to unaffected competitors in columns (3) and (4). Likewise, for the bond yield spread ($Yield\_Spread_{i,t}$), the additional treatment effect is similar in size to the spillover effect to unaffected competitors reported in columns (5) and (6). These findings show that firms directly affected by major local natural disasters experience a greater increase in distress risk than their unaffected competitors, whose distress rises through within-industry spillovers driven by market competition.

Spillover Effects of Adverse Shocks on Competitors' Profit Margins.

We next examine product prices and profit margins to test the component of **Hypothesis 1** concerning spillover effects on profit margins. This analysis provides further insight into the mechanism by which an adverse shock raises competitors' distress risk — namely, intensified market competition triggered by the adverse shock. Specifically, when a firm experiences an adverse shock, competitive pressures increase within the industry, prompting competitors to compress their own profit margins. As a result, these competitors face a heightened risk of financial distress. If this mechanism holds, an adverse shock should lead to a decline in the shocked firm's profit margin, accompanied by a concurrent margin compression among its industry competitors.

Our primary analysis centers on profit margins rather than output prices, although we also present consistent evidence on output prices using the Nielsen subsample. This focus is motivated by several key considerations. 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 output prices. However, such price increases do not necessarily indicate a reduction in competition intensity. Fourth, obtaining accurate and detailed data on output prices across diverse industries is challenging. Even if such data were available, many underlying economic factors, such as implicit discounts (e.g., trade credits), coupons, 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 output prices for treated firms and their industry competitors, using NielsenIQ data. This dataset focuses on specific consumer categories, including food, nonfood grocery items, health and beauty products, and select general merchandise, rather than covering the full range of industries in our main analysis. As a result, the output price evidence is limited in scope but nonetheless provides complementary support for our findings on profit margins.

To examine the spillover effect on the profit margins of competitors not directly affected by major natural disasters, we estimate a DID regression using the specification in Equation (4.3). The dependent variable, $Y_{i,t}$, represents the profit margin or output price of firm i in year t. As shown in Panel A of Table 3, columns (1) and (2), treated firms experience a significant decline in 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 negative effects of distress risk on profit margins.[18]

More importantly, columns (1) and (2) of Table 3 show that, following major local natural disasters, not only do the directly affected firms experience significant reductions in profit margins, but their competitors within the same industry also exhibit significant margin declines, as indicated by the significantly negative coefficient β_3 on the *Post* term. These results suggest that unshocked competitors also face intensified market competition, leading to substantial compression in profit margins. For firms subject to earnings-based covenants, this decline in margins likely translates into heightened financial distress, reinforcing the spillover effects on distress risk documented earlier in Table 2.

We next assess the validity of the zero-industry-trend assumption. Specifically, we verify that the negative coefficient β_3 on the *Post* term in Table 3 reflects the causal effect of major local natural disasters on the profit margins of unaffected competitors, rather than an underlying industry-wide trend. To do so, we estimate a dynamic DID regression, similar to the one presented in (4.2), to examine the time-series evolution of profit margins for unaffected competitors within the same industry around the disaster shock. 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 4, we plot the estimated coefficients $\beta_{3,\tau}$ with $\tau = -8, -7, \ldots, 7$,

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

Table 3: Impact of Major Natural Disasters on Competitors' Margins and 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

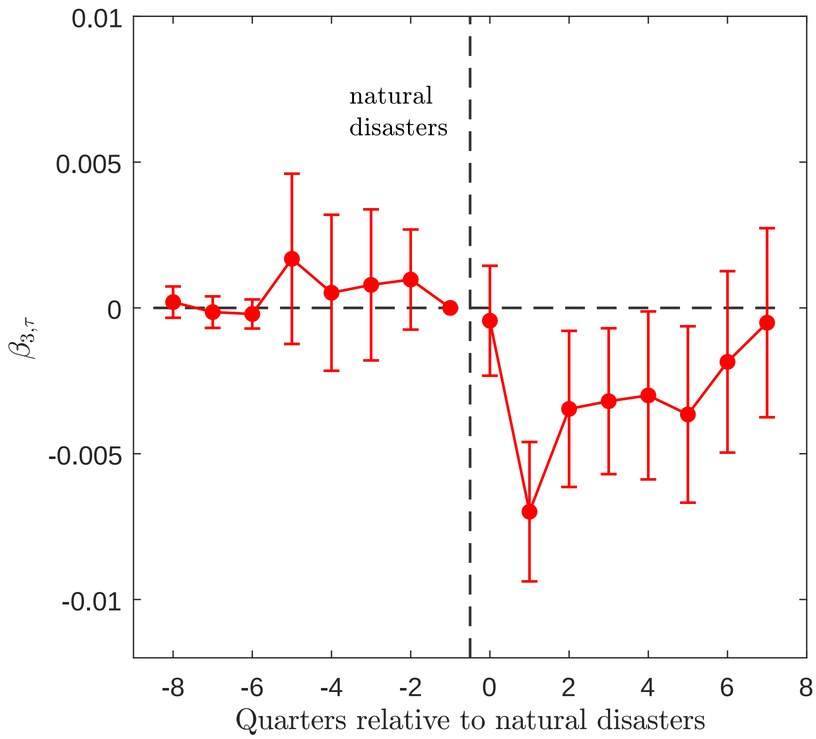
	Obs. #	Mean	Median	Stdev	p10th	p25th	p75th	p90th
$Profit\_Margin_{i,t}$	96269	0.346	0.338	0.264	0.092	0.206	0.519	0.703
$\ln(Price\_Geo_{i,t})$	4049	1.640	1.591	0.841	0.525	1.081	2.204	2.863
$\ln(Price\_EW_{i,t})$	4049	1.855	1.792	0.935	0.637	1.191	2.505	3.183
$\ln(Price\_VW_{i,t})$	4049	1.789	1.727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

Notes. This table examines the impact of major local natural disasters, which serve as instruments for exogenous and idiosyncratic adverse shocks, on the profit margins of directly affected firms and their competitors within the same industry who were not directly shocked. Panel A of this table reports the results from the DID analysis. In columns (1) and (2), the dependent variable is the 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.

as well as their 90% confidence intervals. 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 analyze the spillover effects on market competition by examining firm-level output prices using data from NielsenIQ. To construct firm-level output 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, the equal-weighted average, and the sales-weighted average. Next, we compute firm-level output prices by aggregating the category-level prices across all product categories for each firm i, using sales as weights.

Figure 4: Spillovers on Competitors' Profit Margins.



Notes. This figure plots the evolution of competitors' profit margins around the occurrence of major natural disasters, providing evidence of the spillover effects triggered by these adverse shocks. 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 4. 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.

While previous research has emphasized the importance of accounting for shifts in product quality and variety when evaluating output price dynamics (e.g., Nakamura and Steinsson, 2012; Hottman, Redding and Weinstein, 2016), idiosyncratic adverse shocks unrelated to market competition are unlikely to materially affect the quality-variety component of output prices. In our setting, major local natural disasters originate outside the realm of market competition, making it unlikely that treated firms or their industry competitors would optimally respond by immediately adjusting product quality or variety in setting their output prices.

Panel A of Table 3, columns (3) through (8), presents our findings on firm-level output prices aggregated using various methods. The coefficient β_3 shows a negative and statistically significant spillover effect on the output prices of 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 additional treatment effects on output prices, as captured by β_1, are statistically insignificant, as shown in columns (3) through (8). This pattern aligns with expectations: intensified market competition leads competitors to lower their output prices by nearly the same magnitude in response.[19]

Robustness of Spillover Effects Induced by Market Competition.

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 competitors within the same industry, including one-to-ten and one-to-three ratios. The results also hold when defining industry competitors using the text-based network industry classifications (TNIC) developed by Hoberg and Phillips (2010, 2016). Furthermore, the observed spillover effects on competitors' profit margins remain robust when using net profit margin as an alternative measure of profitability.

To address concerns that matched competitors within the same industry may be geographically proximate to areas affected by natural disasters, we conduct two robustness tests, detailed in Online Appendix 3. First, we restrict the matched competitors in the DID estimation to those whose headquarters and major establishments are located outside states directly impacted by major local natural disasters. Second, we further tighten this restriction by requiring that matched competitors' headquarters and major establishments be located more than 100 miles from any zip code adversely affected by a major local natural disaster in the corresponding year. Our results remain robust under both tests.

[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 output prices across retailers within each manufacturer firm, following the approach commonly used in the literature (Hottman, Redding and Weinstein, 2016). 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.

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).

Ruling Out Alternative Spillover Channels.

The observed spillover effects of adverse shocks on competitors' profit margins, output prices, and distress risk within the same industry may not be driven solely by market competition mechanisms (as discussed in Section 2.1); they could also arise from other economic linkages that overlap with competitive relationships within the same industry. These include: (i) negative demand shocks from concurrent disasters, (ii) production network connections, (iii) shared creditors, and (iv) common blockholders. In this section, we evaluate channels (i) and (ii), while detailed analyses of additional alternative channels are provided in Online Appendix 3.4.

We first examine channel (i), negative demand shocks from concurrent disasters, as a potential alternative explanation. This channel posits that concurrent natural disasters may directly trigger demand shocks that also affect matched, unaffected competitors within the same industry, thereby lowering their profit margins and increasing distress risk. However, we provide two sets of direct evidence indicating that this channel is unlikely to be the primary driver of the observed spillover effects among industry competitors.

The first piece of evidence addresses the possibility that untreated competitors experience demand shocks induced by concurrent disasters. Panel A of Table 6 in Section 5 shows that spillover effects are concentrated in tradable industries with geographically dispersed, often international, customer bases. Given this broad dispersion, local natural disasters affecting treated firms are unlikely to meaningfully disrupt overall demand. This makes the demand-shock channel from concurrent disasters an implausible explanation

Table 4: Ruling out the channel of disaster-induced common demand shocks.

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., ≥ 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 shows that the observed spillover effects among industry competitors are unlikely to be driven by the possibility that matched, unaffected firms experience negative demand shocks due to having customers primarily located in areas affected by concurrent natural disasters. In Panel A, we conduct a DID analysis restricting matched competitors to those whose headquarters and major establishments are located outside the states affected by major natural disasters in the focal year in which they serve as controls. In Panel B, we conduct a DID analysis restricting matched competitors to those whose headquarters and major establishments are located more than 100 miles from any zip code affected by a major natural disaster in the focal year in which they serve as controls. In both panels, we further require that matched competitors have no customers adversely affected by natural disasters. We identify business customers using Compustat customer segment data and FactSet Revere data, and identify 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.

for the observed within-industry spillover effects.

The second piece of evidence further addresses the possibility that untreated competitors are exposed to demand shocks from concurrent disasters by imposing additional restrictions: matched competitors within the same industry must have no business clients or individual consumers in areas affected by other natural disasters. 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 spillover effects on competitors' financial distress and profit margins within the same industry remain robust even after imposing these restrictions, reinforcing the conclusion that negative demand shocks induced by concurrent disasters are unlikely to account for the observed spillover effects.

We next examine channel (ii), production network connections, as a potential alternative explanation for the observed spillover effects on competitors' profit margins and financial distress within the same industry. This channel posits that the effects may result from supply chain spillovers rather than market competition. However, as we show below, direct evidence suggests that this mechanism is unlikely to be the primary driver of the observed spillovers.

First, we consider direct supplier-customer relationships. In the baseline DID specification, we have already excluded from the control sample any firms that have existing supplier or customer links with the treated firms. We further extend this analysis by excluding not only existing but also potential supplier-customer relationships. To identify such potential ties, we use vertical relatedness scores as in Frésard, Hoberg and Phillips (2020), and classify a firm pair as likely to have a bilateral supplier-customer relationship if their vertical relatedness score ranks in the top 10% of all firm pairs. As shown in Table 5, the spillover effects on competitors' profit margins and financial distress within the same industry remain robust even after imposing these additional restrictions on control firms.

Second, we consider indirect supplier-customer relationships. To further strengthen our results, Table 5 imposes an additional restriction requiring that matched competitors share no common customers or suppliers with the treated firms. This restriction rules out

[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 channel of production network connections.

	(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 shows that the observed spillover effects among industry competitors are unlikely to be driven by production network linkages. As in Table 2, we ensure that matched competitors within the same industry are neither direct suppliers nor customers of the treated firms. We further exclude competitors that share any common suppliers or customers with treated firms. Additionally, we remove matched competitors with potential supplier-customer relationships, identified using vertical relatedness scores. We define two firms as having a potential supplier-customer relationship if their vertical relatedness score ranks in the top 10% of all firm pairs. The regression specification and the definition of the dependent and independent variables are explained in Table 2. 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.

the possibility that the observed spillover effects among industry competitors are driven by shared supply-chain linkages, such as through common trading partners, rather than direct market competition.

5 Heterogeneity of Spillover Effects Across Industries

We examine the heterogeneity of spillover effects across industries, as predicted by market competition mechanisms, to provide direct empirical support for these underlying economic forces and to test the validity of **Hypothesis 2**. Specifically, this section investigates heterogeneous spillover patterns along five distinct dimensions.

First, we emphasize that the three spillover mechanisms among competitors within the same industry — (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. By contrast, these mechanisms are less significant in non-tradable industries such as supermarkets, retail stores, and restaurants, which rely heavily on local consumer demand. In these sectors, competition is localized, tacit collusion is more difficult to sustain, and customer bases are geographically fragmented, with limited overlap among firms in the same industry. As a result, the spillover effects on profit margins and distress risk through 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 2.1. Therefore, if the spillover effects on competitors' profit margins and distress risk are primarily driven by market competition, we would expect these effects to be stronger in industries with higher barriers to leadership.

Third, in industries with substantial inventory holdings, competitive balance that is often supported by tacit collusion on profit margins becomes especially fragile. Firms under financial distress frequently resort to inventory fire sales to generate immediate cash flow and relieve liquidity pressures. At the same time, competitors with large inventories are better equipped to implement predatory pricing strategies, using inventory fire sales and aggressive discounts to exploit the vulnerabilities of firms affected by adverse shocks. Large inventories provide abundant "ammunition" for aggressive pricing tactics.

Fourth, as suggested by the three mechanisms in Section 2.1, the effect of intensified competition on the distress risk of competing firms is expected to be significantly stronger in industries where firms are already more financially constrained.

Fifth, industries vary considerably in price flexibility, as documented by Bils and Klenow (2004). Greater price flexibility often reflects stronger strategic complementarity in profit margins among competitors. As discussed in Section 2.1, the strength of the three proposed spillover mechanisms depends critically on this complementarity. Therefore, industries with higher price flexibility are expected to exhibit more pronounced spillover effects of adverse shocks on the profit margins and financial distress of competitors within the same industry.

Taken together, the spillover effects of major natural disaster shocks on competitors' profit margins and financial distress are expected to be more pronounced in tradable industries and in those with higher barriers to market leadership, larger inventory holdings, tighter financial constraints, or greater price flexibility. By contrast, in non-tradable industries or those with lower barriers to market leadership, smaller inventories, looser financial constraints, or less flexible prices, the spillover effects are expected to be much weaker or even statistically insignificant. Below, we empirically examine these heterogeneous spillover effects through market competition within the same industry.

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 **Hypothesis 2** regarding heterogeneous spillover effects across industries with different levels of tradability, we conduct separate DID analyses for tradable and non-tradable industries based on the classification described above. The results, shown in Panel A of Table 6, indicate that spillover effects on competitors' profit margins and financial distress are concentrated in tradable industries. This pattern is evident when comparing Columns (1), (3), and (5) with Columns (2), (4), and (6). These findings support **Hypothesis 2** and are consistent with the mechanisms of market competition. The spillover effects are statistically and economically significant in tradable industries but negligible in non-tradable industries, consistent with **Hypothesis 2** and the underlying 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

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 examines spillover effects on competitors' profit margins and financial distress within the same industry following major natural disasters, separately for tradable and non-tradable industries. Panel B of the table examines how the spillover effects of major natural disasters on competitors' profit margins and financial distress vary across industries with different levels of barriers to market leadership. Panel B of the table examines the heterogeneity of spillover effects on competitors' profit margins and financial distress within the same industry following major natural disasters, 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.

non-tradable industries. However, the spillover effect on competitors, captured by β_3 alone, is statistically insignificant. Importantly, the magnitude of the total treatment effect in non-tradable industries is comparable to that in tradable industries, as shown in Columns (1) and (3). The absence of significant spillover effects in non-tradable industries provides strong support for **Hypothesis 2** and the underlying market competition mechanisms. In Column (6), which focuses on non-tradable industries, the total treatment effect on profit margins, captured by $\beta_1 + \beta_3$, is not statistically significant. Accordingly, the spillover effect on competitors' profit margins within the same industry, captured by β_3, is also insignificant. This result again aligns with **Hypothesis 2** and supports the proposed mechanisms.

Industry Barriers to Market Leadership.

We expect spillover effects on competitors' profit margins and financial distress to be stronger in industries with higher barriers to market leadership. To proxy for these barriers, we follow Li (2010) and use the sales-weighted average of fixed assets, measured one year prior to each major natural disaster. Based on this proxy, we classify four-digit SIC industries into tertiles. To test **Hypothesis 2** on the heterogeneity of spillover effects across industries with varying barriers to market leadership, we conduct separate DID analyses for high-barrier industries (top tertile) and low-barrier industries (middle and bottom tertiles).

The results in Panel B of Table 6 provide strong support for **Hypothesis 2** and are consistent with the predictions of the market competition mechanisms among competitors within the same industry. Specifically, the spillover effects, captured by β_3, are concentrated in industries with high barriers to market leadership and are nearly absent in industries with low barriers. This contrast is clearly illustrated by comparing 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 spillover effects of adverse shocks on competitors' profit margins and financial distress within the same industry, captured by β_3, are not statistically different from zero in industries with low barriers to market leadership. In contrast, the total treatment effects, captured by $\beta_1 + \beta_3$, are 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, highlights the limited impact of adverse shocks on market competition in these industries. This pattern is further illustrated in

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 heterogeneous spillover effects on competitors' profit margins and financial distress within the same industry following major natural disasters, across industries with different levels of inventory holdings (Panel A) and financial constraints (Panel B). The regression specification is as in equation (4.3). 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.

Column (6), where the total treatment effect on the profit margins of treated firms, captured by the sum of coefficients β_1 and β_3, is statistically insignificant, with a p-value of 0.525. Consistent with this, the spillover effect on the profit margins of untreated competitors, captured by β_3 alone, is also insignificant.

Levels of Inventory.

We expect stronger spillover effects on competitors' profit margins and financial distress in industries with higher inventory holdings. To test this prediction, we classify four-digit SIC industries into tertiles based on average inventory levels measured one year before each major local natural disaster. We then conduct separate DID analyses for high-inventory industries (top and middle tertiles) and low-inventory industries (bottom tertile) to compare the magnitude of the resulting spillover effects.

The results, reported in Panel A of Table 7, provide support for **Hypothesis 2** and the underlying market competition mechanisms. Spillover effects, captured by β_3, are statistically significant in high-inventory industries but not in low-inventory industries. Similarly, total treatment effects on profit margins, captured by $\beta_1 + \beta_3$, are significant only in high-inventory industries. These findings are consistent with prior research, but our results go further by highlighting not only the direct treatment effects but also spillovers to unaffected competitors within the same industry.

Tightness of Financial Constraints.

Hypothesis 2 predicts that the spillover effects of disaster shocks from affected firms to unaffected competitors will be more pronounced in industries facing tighter financial constraints prior to major local natural disasters. To test this prediction, we measure financial constraint tightness for each four-digit SIC industry using the sales-weighted average of the delay investment score developed by Hoberg and Maksimovic (2015). Industries are then sorted into tertiles based on this measure, calculated one year prior to each disaster. We conduct separate DID analyses to test and compare the spillover effects on competitors' profit margins and financial distress in industries with tight financial constraints (top tertile) versus those with looser constraints (middle and bottom tertiles).

Panel B of Table 7 presents the results. Columns (2) and (4) show that the spillover effects of adverse shocks on competitors' profit margins and financial distress, captured by β_3, are 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

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

	(1) $Risk\_of\_Failure_{i,t}$	(2)	(3) $Dist\_to\_Default_{i,t}$	(4)	(5) $Profit\_Margin_{i,t}$	(6)
	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 (4.3). 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.

than 0.001 and 0.009. The absence of statistically significant spillover effects in industries with loose financial constraints, particularly when compared with the strong effects in tightly constrained industries, indicates that market competition plays a limited role in transmitting adverse shocks in these settings. This pattern provides strong support for **Hypothesis 2**. Column (6) further reinforces this conclusion: the total treatment effect on the profit margins of treated firms, captured by $\beta_1 + \beta_3$, is statistically insignificant, and the spillover effect on untreated competitors, captured by β_3 alone, is likewise insignificant in industries with loose financial constraints.

Price Flexibility.

According to the proposed mechanisms and their implications for heterogeneous spillover effects, as summarized in **Hypothesis 2**, the spillover effects of adverse shocks through market competition should be strongly pronounced in industries with high price flexibility and minimal or absent in those with low 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 measure each industry's price flexibility as the sales-weighted average frequency of price changes across its associated consumption categories, using expenditure weights from the Consumer Expenditure Survey. Industries are then classified as having high or low price flexibility based on whether they fall above or below the median of this measure in the year prior to each major local natural disaster. We then conduct separate DID analyses to examine spillover effects on competitors' profit margins and financial distress within the same industry across these two groups.

As shown in Panel A of Table 8, Columns (1), (3), and (5) for high-price flexibility industries contrast sharply with Columns (2), (4), and (6) for low-price flexibility industries. The results indicate that spillover effects on competitors' profit margins and financial distress are statistically significant only in industries with high price flexibility, while they are insignificant in low-flexibility industries. Intuitively, the total treatment effect on financial distress, reported in Columns (1) through (4) and captured by $\beta_1 + \beta_3$, remains statistically significant in both groups, highlighting that the direct negative impact of adverse shocks on affected firms remain robustly strong regardless of industry-level price flexibility. However, the total treatment effect on profit margins is statistically significant only in industries with high price flexibility, as shown in Columns (5) and (6).

Price flexibility reflects the degree of strategic complementarity in profit margins among competitors within the same industry. Consistent with the findings in Panel A of Table

8, we expect spillover effects on competitors' profit margins and financial distress to be concentrated in industries exhibiting high comovement in profitability. 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. Based on this measure, industries are classified into high-comovement and low-comovement groups depending on whether they fall above or below the median in the year prior to each major local natural disaster. Using separate DID analyses, we estimate and compare the spillover effects on competitors' profit margins and financial distress across the two groups. The results, presented in Panel B of Table 8, closely mirror those in Panel A, reinforcing the important role of strategic complementarity in driving spillover effects among competitors through market competition within the same industry.

6 Conclusion

We provide empirical evidence on the spillover effects of adverse shocks on competitors' profit margins and distress risk within the same industry. Our analysis supports three complementary mechanisms that drive these effects: (i) predatory pricing, (ii) rapid inventory liquidation, and (iii) weakened tacit collusion that destabilizes "competitive balance."

To investigate spillover effects among competitors within the same industry and the mechanisms driving them, we estimate the causal impact of idiosyncratic adverse shocks on competitors' profit margins and financial distress. We use major local natural disasters as a source of exogenous, idiosyncratic shocks, defined as sudden idiosyncratic declines in cash flows or destruction of collateral values. These shocks intensify market competition, prompting both affected firms and their industry competitors to lower profit margins and disrupting the competitive balance. The resulting margin compression raises short-term distress risk for unaffected competitors, especially in tradable industries and those with 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 that may partially overlap with competitive relationships within the same industry, such as concurrent disaster-induced demand shocks, production network linkages, common creditors, or shared blockholders. We further validate our results using two quasi-experimental settings: the 2004 AJCA tax holiday and the 2008 Lehman Brothers collapse. Empirical analyses based on these events provide additional robust support for the proposed hypotheses and the underlying market competition mechanisms. In the Online Appendix, we also present evidence of cross-industry spillover effects transmitted through multi-industry firms, stemming from initial spillovers among competing firms within the same industry. Specifically, we conduct two-stage regressions and placebo tests to show that intensified market competition following adverse shocks serves as the primary channel through which distress risk propagates across industries via multi-industry firms.

These findings have important implications for firm-level credit risk and the broader financial stability of industries and the overall economy. They highlight the critical role of spillovers among competitors within the same industry, driven by intensified market competition, and the resulting cross-industry transmission of margins and distress through multi-industry firms in shaping competitive dynamics and amplifying systemic risk.

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