# Who Bears the Cost of Natural Disasters?*

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**Abstract**

Using establishment-level data and scanner retail prices, we show that the number of firms decreases and retail prices increase in counties affected by natural disasters. Price increases are particularly pronounced for essential goods and low-priced products, as well as in counties with fewer bank branches per capita, where fewer firms enter following natural disasters. Our results suggest that the costs of climate-related disasters, which are increasingly frequent negative realizations of physical risk, are ultimately borne by consumers.

Keywords: natural disasters; consumer prices; industry structure; external finance; physical risk

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# 1 Introduction

A growing body of research in finance explores the extent to which asset prices incorporate climate risks (Giglio et al., 2021). However, measuring the effects of physical risks—defined as risks of direct impairment of productive assets resulting from climate change—on equity prices has proved elusive (Li et al., 2024; Sautner et al., 2023), even though climate-related disasters result in substantial costs (Barrot and Sauvagnat, 2016). This is surprising because institutional investors believe that climate risks have financial implications for their portfolio firms, but claim that while equity valuations may not fully reflect these risks, significant overvaluation is unlikely (Krueger et al., 2020). Investor inattention and firms' adaptation efforts have often been considered as the reasons why physical risks have elusive effects on firms' valuations. It is possible, however, that corporations can transfer the costs of negative realizations of physical risks to their customers, with limited impact on their profits.

To evaluate the merit of this hypothesis, this paper explores the effects of natural disasters, which are increasingly frequent negative realizations of physical risk, on the retail prices of affected counties. We show that natural disasters have heterogeneous effects across companies. While firms' exit rates increase in the aftermath of natural disasters, some companies may ultimately benefit from negative realizations of physical risk thanks to increased market shares and higher product prices. In this way, the costs of natural disasters could ultimately be borne by consumers, with small or negligible consequences for the revenues of the surviving firms, especially the large ones.

We exploit natural disasters, which are shocks that cause significant destruction and impose high costs on affected firms (Barrot and Sauvagnat, 2016; Ersahin et al., 2024). While not all natural disasters are climate-related, they provide a useful laboratory to study the redistributive effects of disruption on industrial structure. We study their consequences using establishment-level data on all listed and unlisted companies in the US, as well as granular barcode-level sales and price data from approximately 35,000 retail stores. These data enable us to evaluate how the industrial structure of local industries and local consumer prices change in the years following natural disasters.

We begin by examining the entry and exit dynamics of firms operating in disaster-affected areas. We observe that natural disasters are followed by higher exit rates and lower entry rates, even four years after the disaster. Arguably, as a result, employment becomes more concentrated in counties affected by natural disasters. We also evaluate the effects of natural disasters on wholesale and retail firms, which are arguably more relevant in setting local retail prices. Additionally, we consider the sales of specific products, distinguishing between small and large firms. We find that while sales at large firms increase, those at small firms contract, suggesting that large firms are more efficient in reorganizing their operations.

Higher concentration may be driven by differences in firms' efficiency in dealing with disaster-related damage, uncertainty about future disasters, and, more generally, unfavorable conditions leading to economic shrinkage. Even if higher concentration does not imply an increase in market power (Syverson, 2019), natural disasters may decrease household welfare and have distributional consequences. To evaluate whether this is the case, we examine the effects of these disasters on consumer prices using scanner data. Thanks to the granularity of our bar-code data, we can compare the prices of very similar tradable goods sold in areas affected by a natural disaster with their prices in unaffected areas. The existing literature suggests that firms make product supply decisions at the national level, without distinguishing among locations (Hyun and Kim, 2019). For this reason, the average price of a barcode-level product is typically considered to be the manufacturer's product price (see, e.g., Kim (2021)). We thus consider differences in product prices across locations to arise from changes in the competitive environment of the retail and wholesale sectors. By introducing interactions of product and time fixed effects, we effectively compare how markups for the same product vary between counties affected by natural disasters and those unaffected. This allows us to abstract from the effect of supply shocks on the production costs of the good sold.

We observe that prices gradually increase in affected areas over the four years following the natural disaster. We do not observe an increase in the county's sales or income, which suggests that positive demand shocks arising from post-disaster rebuilding do not raise local prices. Importantly, price increases in counties affected by natural disasters appear to be driven by essential products, which are typically necessary for survival, health, and the basic functioning of households. These products have a lower elasticity of demand, which makes it optimal for firms with market power to implement large price increases. We also observe that the cheapest varieties of a given product experience higher price increases. Such a phenomenon, dubbed "cheapflation," has been observed in inflationary environments (Cavallo and Kryvtsov, 2024), suggesting that low-income households may be disproportionately affected by natural disasters and climate-related disruptions. Additionally, we do not observe that price increases for essential products or cheaper product varieties are accompanied by changes in the relative demand for these products. Instead, it appears that retailers and wholesalers can pass on the increased operating costs in disaster areas to products with lower demand elasticity, thereby affecting low-income households in particular.

We show that the impact of natural disasters on industrial structure and subsequent price changes is partially mitigated by easier access to external finance, as measured by the density of bank branches per capita. Better access to external finance favors firm entry and results in relatively lower price increases, again suggesting that natural disasters are followed by a decrease in competition. We also investigate whether the observed effects are attenuated in counties highly exposed to climate risk. In these counties, firms may make stronger adaptation efforts and be less exposed to natural disasters. This, in turn, could preserve the industry structure and the competitive environment. However, we do not find that this is the case. If anything, the exit rate following natural disasters is higher in counties highly exposed to climate risk, arguably leading to local price increases that exceed those in other counties.

We contribute to a growing body of literature examining the impact of climate-related disasters on firms. Most of the literature focuses on the effects of high temperatures. Ponticelli et al. (2023) find that temperature shocks in a county increase energy costs and lower productivity only for small plants, suggesting that large plants adapt and acquire market share. Moreover, multi-establishment companies that do not incur financial constraints adapt to high temperatures by transferring employment to unaffected locations (Acharya et al., 2023). Further supporting successful corporate adaptation, Deschênes and Greenstone (2007) estimate a small positive effect of changes in temperature and precipitation on agricultural profits.

By focusing on natural disasters rather than chronic physical risks, we show that some firms can mitigate their costs by raising prices, especially for essential and low-priced products. In this respect, our contribution is to emphasize that consumer prices should be taken into account when assessing the costs of climate change. Our results align with evidence indicating that extreme weather events, like hurricanes, increase return dispersion for affected firms, with some firms unexpectedly outperforming control firms (Kruttli et al., 2025). We propose that shifts in market share may explain this surprising evidence.

We also contribute to the literature that explores the effects of natural disasters on the economy. The literature has shown that the negative effects of natural disasters propagate throughout the supply chain (Barrot and Sauvagnat, 2016), negatively affect growth (Baker et al., 2024), impact capital structure (Dessaint and Matray, 2017), and undermine supply chain stability (Ersahin et al., 2024). Hurricanes have also been shown to affect temporary earnings changes, whose signs vary across sectors (Belasen and Polachek, 2008). Surprisingly, we know little about how natural disasters affect the industrial structure and to what extent consumers ultimately bear the costs. This paper takes up this challenge. We show that higher firm exit rates follow natural disasters. Firm entry rates also decrease, leading to a consequent drop in the number of firms active in affected counties. These changes in industry dynamics result in higher concentration in the wholesale and retail sectors, leading to increased local retail prices.

Finally, our work is related to a strand of research that uses bar-code level data or specific products' prices (such as airline tickets). Stroebel and Vavra (2019) and Coibion et al. (2015) explore geographical variation in price setting in relation to business cycles and demonstrate that the local wholesale-retailer industrial organization matters. Another strand of this literature studies the effects of corporate E&S policies on product demand and supply. Specifically, Hillmann et al. (2025) shows that airlines increase ticket prices following ESG incidents and infer that consumers bear the higher costs associated with improved sustainability policies. Meier et al. (2023) focus on large producers with sustainability ratings and show that they have larger sales in liberal and high-income counties. Instead of considering sustainability policies, we study the consequences of natural disasters on local prices and sales.

# 2 Data

We rely on a variety of datasets that we describe below. Table A1 provides detailed variable definitions.

## 2.1 Natural Disasters

We study the effects of natural disasters, including blizzards, earthquakes, floods, and hurricanes. We obtain the affected counties' dates, estimated damages, and FIPS codes from SHELDUS (Spatial Hazard and Loss Database for the United States), a database maintained by the Center for Emergency Management and Homeland Security at Arizona State University. We focus on large events that cause total damage exceeding 10 million in 2022 US dollars (equivalent to \$ 616 per capita, using the median population, and 2.16% of the median county-level GDP, which is \$ 462.8 million). While existing literature on the propagation effects of natural disasters through listed companies considers only those with truly catastrophic damages above \$1 billion (Barrot and Sauvagnat, 2016) at the national level, our focus on the disruption of small firms' operations justifies considering a larger set of events.[1] Our approach is also supported by macroeconomic research, which shows that natural disasters with damages exceeding 1% of GDP per capita affect macroeconomic outcomes, including growth (Nguyen et al., 2025). Tables A2 and A3 show that results are not driven by counties with low GDP or population.

Due to data availability, our longest sample spans 2006 to 2020. During our sample period, natural disasters affected a broad range of U.S. states and counties. Natural disasters are generally very localized, and each disaster typically affects only one county. Yet, there are multiple disasters in a year. On average, 25 counties are affected each year. The number of affected counties per year ranges from 4 to 65, with a total of 426 unique counties out of 1280 affected during our sample period.

## 2.2 Establishment Level data

We obtain establishment-level data on all U.S. plants from the National Establishment Time-Series (NETS) Database. NETS gathers data from firms and other sources, including the Yellow Pages and credit scoring services. From these data, we obtain plant counties' (FIPS) codes, headquarters' linkages, industry classification, and the number of employees at each plant. While the data include measures of plant sales, these have been criticized, especially for the plants of unlisted companies, for being imputed. For this reason, all our analyses involving plant size rely on employment data, which have been used in numerous studies of employment growth and distribution in the US (Acharya et al., 2023; Denes et al., 2023).

We restrict the sample to county-industries with at least 5 plants over the entire sample period.[2] Our final sample spans the period from 2006 to 2020 and includes a total of 11,591,273 plants belonging to 11,186,230 firms, of which 1,738,778 plants (belonging to 1,633,128 firms) are affected by a natural disaster. Since most of our tests explore local retail prices following natural disasters, we also consider changes in the industrial structure

[1] Barrot and Sauvagnat (2016) natural disasters affect a multiplicity of counties at the same time. Hence, the cutoff we choose is not necessarily (much) smaller.

[2] This restriction does not affect the thrust of our analysis.

of the retail and wholesale industries, which are most likely to affect local prices. Our sample includes 2,086,383 plants from 1,937,496 firms in wholesale and retail, of which 307,265 (from 272,236 firms) are affected by a natural disaster.

Furthermore, since our objective is to focus on a county's competitive environment, we aggregate plants at the firm-county level and examine the number of firms active in a county, as well as their entry and exit rates. Thanks to the establishment-level data, we can identify the location of firms' activities and when a firm ceases to operate in a county. To smooth out volatility, we use the midpoint growth rate in the number of firms. Likewise, we define entry rates as the new firms created at time $t$, relative to the average number of firms in a county and industry at $t$ and $t-1$, and the exit rate as the number of firms that were in a county and industry at $t-1$ but are no longer at $t$, relative to the average number of firms in a county and industry at $t$ and $t-1$.

## 2.3 Retail Sales and Price Data

We use the Nielsen Retail Measurement Services (RMS) Scanner Database, provided by the Nielsen Data Center at the University of Chicago Booth School of Business. These data include comprehensive information on the quantity and price of product sales at the retail store level, collected weekly.

Since 2006, over 40,000 participating grocery, drug, mass merchandiser, and other stores (varying by year) from 90 retail chains have voluntarily contributed to the database with prices and sales data for a variety of products. Retailers also report product size together with the price. This information is essential to ensure the comparability of the price level both across different cross-sections and over time.

Nielsen scanner data are widely used in research (Kim, 2021; Fracassi et al., 2022; Meier et al., 2023; Baker et al., 2020) and cover over 50% of sales at drug and grocery stores in the U.S. Each product is uniquely identified by a Universal Product Code (UPC code), where the first 6-9 digits represent a unique identifier of the company (GCP code) that manufactures the product as assigned by GS1 US, the organization responsible for assigning barcodes. Nielsen covers over 2 million unique UPC codes, classified into three nested layers of aggregation: 11 departments, 118 product groups, and 1,284 product categories, also referred to as modules. Naturally, almost the totality of product modules in our dataset is affected by a natural disaster in a subset of counties during the sample period (specifically, 1275 product modules are affected).

We use Nielsen data in two ways. First, we examine sales for different retailers in a particular county over a year or a month. Second, we define monthly product prices by county.

Since the same product can be sold in packages of different sizes and multi-unit packages, we compute prices as follows:

$$y_{i,s,c,w} = \frac{\frac{price_{i,s,c,w}}{prmult_{i,s,c,w}}}{sizeamount_{i,s,c,w} \times multi_{i,s,c,w}},$$

where $price_{i,s,c,w}$ is the price of product $i$ sold at store $s$ in county $c$ during week $w$; $prmult_{i,s,c,w}$ is the price multiplier referring to the number of units; $sizeamount_{i,s,c,w}$ is the numeric quantity of the good in individual packaging, which refers to a specific unit of measurement also provided by the database; finally, $multi_{i,s,c,w}$ is the number of goods in a given pack.

Thus, if we consider two six-can packages of Coke, with cans of 500 ml sold at the price of \$24, our formula would yield the following price per ml:

$$\frac{24/2}{500 \times 6} = \$0.004/\text{ml}$$

Since the product hierarchy underwent significant changes in 2021, our sample ends in 2020.[3]

Our first measure of unit price is based on the simple average of sales for a UPC product

[3]The new hierarchy is no longer a one-to-one hierarchy of Product Modules, Product Groups, and Departments.

over a week. Since the amount of a product's sales occurring at different prices may differ, we also use an alternative measure of product price, which, like in Baker et al. (2020), weighs transaction prices by the number of units sold each week ($unit_{i,s,c,w}$) as follows:

$$y_{i,s,c,t} = \frac{\sum_{w=1}^{52} \frac{price_{i,s,c,w}}{prmulti_{i,s,c,w}} \times unit_{i,s,c,w}}{\sum_{w=1}^{52} unit_{i,s,c,w}}.$$

In the empirical analysis, we drop extreme values, as is common in the literature (see e.g., Baker et al. (2020)). Specifically, we drop prices that are below 1/3 or above 3 times the median price at the UPC-month level.[4]

Due to the large size of the data, further magnified by our focus on county-level prices, we consider the product price in most of our analysis to be the average price of the unique UPC codes within a module for a given month in a specific county to ensure processing feasibility. Therefore, we average a product's price at the product, county, and month levels.

# 3 Methodology

Our objective is to investigate the impact of natural disasters on industry structure and product prices within a county.

To capture the effects of natural disasters on industry dynamics, we estimate a specification at the county-industry-year level:

$$\mathrm{y}_{f,s,c,t} = \beta \times \text{Disaster}_{f,c,t} + \gamma_{f,c} + \delta_{s,t,c} + \epsilon_{f,s,c,t},$$

where $f$ refers to the county (FIPS code), $s$ to the SIC-2 digit code, $c$ to the specific natural disaster (cohort) and $t$ to the time. By accounting for cohort effects, we capture the staggered treatment arising from natural disasters. We thus avoid a bad comparison problem (Baker et al., 2022) by employing a stacked-cohort generalized difference-in-differences strat-

[4]The results are robust to using the raw prices (see Table A4) or alternative winsorization methods, such as dropping prices below 1/3 or above 3 times the median price at the product-module code month level.

egy as in Gormley and Matsa (2011). Specifically, we compare treated counties—defined as those affected by a natural disaster during our sample period—to counties that are never affected by a natural disaster, considering the four years preceding and the four years following each natural disaster. We then pool the data across cohorts (natural disasters) and include interactions of county and cohort fixed effects, as well as time, industry, and cohort fixed effects. Thus, our specification accounts for any industry-level shocks that may affect industry dynamics and country time-invariant characteristics. For robustness, we also implement dynamic estimates using the estimator proposed by Sun and Abraham (2021), which relies on never-treated and last-treated observations as a control. We cluster standard errors at the county level.

We also explore how local retail prices evolve following natural disasters. We observe the prices consumers pay, which are the sum of the producer's wholesale price and the retailer's markup. By studying local prices alongside changes in retail sector concentration, we interpret local price changes as arising from retailers' markups. We account for nationwide changes in product prices through the fixed effects. Specifically, since the same product is sold in both affected and unaffected counties, we capture differences in the price of a given product module by including interactions of module and cohort fixed effects, or even the interactions of module, time, and cohort fixed effects, which absorb any shocks to the price of a product. We also account for differences in price levels across counties by including county fixed effects, which are always interacted with the disaster cohort, and absorb time-series shocks by including year fixed effects (also interacted with the disaster cohort).

We thus estimate the following model at the module (p), county (c), and month (t) level using the stacked regression:

$$\mathrm{y}_{p,f,c,t} = \beta \times \text{Disaster}_{f,c,t} + \gamma_{f,c} + \delta_{t,c} + \xi_{p,f,c} + \epsilon_{p,f,c,t}.$$

Since we observe product prices monthly, we consider a 4-year (48-month) window around each natural disaster. We cluster standard errors at the county level.[5]

We estimate similar empirical models of sales for large and small retailers at the product module level to confirm the plant-level findings on industrial structure and the economic mechanism.

## 4 Changes in Industrial Structure

Table 2 examines the impact of natural disasters on industry dynamics, focusing on the percentage change in the number of firms within a county and all two-digit SIC industries, as well as the rates of entry and exit.

Panel A shows that natural disasters are associated with higher firm exit rates in affected counties. Specifically, in column 3, the exit rate increases by approximately 3 percentage points relative to the median county. The rate of entry of new firms in an industry also decreases in affected counties (column 2), and affected counties experience an overall drop in the number of firms (column 1). Since we control for county effects, these findings cannot be attributed to differences in industry dynamics across locations. Also, we account for industry-level shocks by absorbing their effects through interactions between industry and year fixed effects, which implies we cannot capture differences arising from affected counties' industry specialization. Instead, they show that the net creation of new firms decreases across all industries after a county experiences a natural disaster.

We also consider the possibility that counties prone to natural disasters experienced higher exit rates and lower entry rates before the natural disaster. To this end, Figure 1 shows the growth rate of new firms, the entry rates, and the exit rates in the years around the natural disaster. We do not observe any statistically significant differences in industry dynamics up to the year of the disaster. The exit rates remain elevated for all four years after the disasters, while entry rates recover to the levels of unaffected counties after two

[5]If more than one disaster occurs within a four-year interval, we include the four years preceding the first disaster and the four years following the last disaster in the sample. All our results are robust if we consider only the first disaster occurring during our sample period.

years. As a result, the net creation of new firms is significantly lower in affected counties during all four years following a natural disaster. Overall, this evidence indicates that the effects of natural disasters on industry dynamics are not driven by pre-existing trends and suggests that natural disasters can have permanent effects on a county's industrial structure.

Since our objective is to investigate the effects of natural disasters on local prices, in Panel B, we consider the subsample of firms in the retail and wholesale industries, as these, rather than nationwide product producers, are likely to set local prices. The effects are similar in this subsample. While fewer firms may also imply greater efficiency, especially if marginal, low-productivity firms exit (Syverson, 2019), these findings indicate that natural disasters are followed by an increase in concentration.

This conjecture is confirmed in Table 3, where we examine the effects of natural disasters on concentration, considering the entire sample of industries within a county (Panel A) and the retail and wholesale industries (Panel B). The results show that the changes in industry dynamics we highlight lead to higher industry concentration. We measure industry concentration as the proportion of employees employed by the top 3 and top 5 companies, as sales are less reliably reported in NETS, especially for private firms (Acharya et al., 2023). Consistent with our earlier results, we find that industry concentration increases for both the top 3 and the top 5 firms. These results are robust to the inclusion of county, industry, and year fixed effects. Even though the effect is slightly smaller for the top 3 measure of concentration in the whole sample when we control for industry-year level shocks, it remains statistically significant, implying that the top 3 share increases by 0.2 percentage points (0.48% relative to the mean). The corresponding estimate for the top 5 concentration measure is no longer statistically significant at conventional levels in the whole sample.

To the contrary, the estimated effects are particularly large and statistically significant in the retail and wholesale sector subsample (Panel B). In this subsample, the top 3 share increases by 0.7 percentage points (1.5% relative to the mean) following a natural disaster. The top 5 share increases by 0.6 percentage points (1.3% relative to the mean).

We also consider the sales evolution for large and small retailers in a county, as observed from the Nielsen Scanner Database. Specifically, we measure a retailer's sales within a county by aggregating the dollar value of each product sold by the retailer in the county over a year. Since retailers reporting to the Nielsen Scanner Database tend to be large, we restrict the sample to the largest and smallest retailers to achieve meaningful variation in retailer size. Specifically, we define retailers with sales above the top 10% of the whole sample in 2006 as large. Retailers with sales below the bottom 10% in 2006 are classified as small. As in the previous tests, we consider a four-year window around the natural disaster. We control for the fact that large retailers may have different market shares across counties by including interactions of county fixed effects with the large retailer dummy (as always interacted with disaster cohort effects) across specifications. Furthermore, in column 1, we consider that the market share of large retailers may have been increasing due to a trend towards higher concentration, which we account for by including interactions between the large retailer dummy and the year fixed effects. In column 2, we absorb this variation by including more granular interactions of firm and time-fixed effects. As necessary for the implementation of a staggered estimator, these fixed effects are always interacted with the disaster cohort effects.

The estimates are consistent across specifications. Specifically, the positive and significant coefficient on *Treat* $\times$ *Post* $\times$ *Large* in Table 4 indicates that the sales of the largest retailers increase following natural disasters in the affected counties, while the sales of small retailers decrease, as implied by the negative coefficient on *Treat* $\times$ *Post*. This finding confirms that natural disasters lead to a higher concentration. In the following section, we examine the extent to which concentration is associated with higher sales prices.

# 5 Changes in Retail Prices

## 5.1 Main Results

Table 5 explores the effects of natural disasters on consumer prices. It shows that the average product price in a county increases after a natural disaster. We observe similar patterns for both price definitions we use, as well as when we absorb unobserved variation with increasingly finer fixed effects. Throughout the table, we control for differences in price levels between counties by including county fixed effects, interacted with disaster cohort effects. The estimated effect is only partially reduced when we absorb shocks to the price of a given product during a year with fixed effects (columns 2 and 5) and substantially invariant when we include interactions of module and month fixed effects (columns 3 and 6). Importantly, these specifications, which include interactions between module and time fixed effects, indicate that the price increase is not driven by a nationwide increase in product costs, but rather by the natural disaster. Thus, price increases are specific to the disaster counties. To the extent that the average national price of a product captures the producer price, our estimates indicate that the natural disaster is associated with an increase in local retailers' markups, which could cover higher operating costs or translate into higher profits.

In columns 1 to 3, we exploit our precise definition of unit price. The more conservative estimates in column 2 imply that the effect is not only statistically but also economically meaningful, as the estimated 5-cent increase in unit price corresponds to a 2% increase relative to the mean. In columns 4-6, we adopt the price definition of Baker et al. (2020) and estimate similar effects. Specifically, in column 6, we observe a price increase of 3.8 cents, corresponding to a 0.9% increase relative to the mean, following natural disasters. Importantly, Figure 2 shows that the effect emerges in the years following the natural disaster, again suggesting no pre-existing trends and permanently higher local prices in counties affected by natural disasters. Importantly, we do not observe an immediate jump in the year of the disaster but a gradual increase, suggesting that temporary shortages in the aftermath of the disaster are unlikely to drive our findings. The steady rise in prices in the years following the disaster rather indicates that gradual changes in industrial structure favor the pass-through of the shock to consumers.

One may also wonder whether retailers, facing higher demand following the natural disaster, increase prices. The evidence in Table 4 suggests that overall sales in disaster counties do not tend to increase but rather shift from small to large retailers, who presumably are more resilient to the disruption brought about by the disaster. This conclusion is confirmed in column 1 of Table 6, where we aggregate Nielsen sales at the county and year levels. Overall, we do not observe an increase in sales in disaster-affected counties. To address concerns that we observe only a subsample of retailers, the remainder of Table 6 presents additional county-level outcomes, which support the conclusion that demand is unlikely to increase in counties affected by natural disasters. The table shows that GDP per capita and income per capita in affected counties decrease following the natural disaster, while population and unemployment remain invariant on average. Overall, this evidence suggests the increase in local prices following natural disasters is not driven by a positive demand shock.[6]

One possible concern with the results we have presented so far is that we rely on the average product price within a module. A potential concern is that changes in purchase patterns may drive our results. This is unlikely because our results are robust when we use simple averages. Nevertheless to mitigate any concerns, we perform our tests using as unit of observations prices defined at the finer UPC product category. Since the number of observations increases dramatically in our product, month, and county level dataset, to overcome computational limitations, we consider only the first disaster within our sample. Table presents the results. The estimates obtained, controlling for changes in production costs by including interactions of UPC and year fixed effects (as always interacted with cohort fixed effects), show that our results are qualitatively invariant.

[6] Appendix Tables A2 and A3 show that these results are not driven by countries with low GDP per capita or low population, indicating that the effects we uncover are economically important.

## 5.2 Cross-sectional Differences between Products

We also consider whether there is heterogeneity in price increases across product types. If retailers' market power or operating costs increase following natural disasters, we should observe that they raise the prices of products with low demand elasticity by more than other products. Households' elasticities of demand should be lower for essential products, which are necessary for survival, health, and the basic functioning of households. We thus define essential products, following this criterion, to include rice, pasta, dry beans, baby food, cooking essentials, medications, cleaning products, and other household maintenance items. We consider all remaining products as non-essential. To test whether essential products experience more pronounced price increases in counties affected by natural disasters, we augment our basic specification by including the triple interaction term $Treat \times Post \times Essential$. The estimates in Table 9 support our conjecture that products with low demand elasticity experience more pronounced price increases in the affected counties following natural disasters. We do not observe more pronounced increases in sales of essential products, suggesting that natural disasters are unlikely to have driven demand shocks that led to local price increases for these products. In addition, we control nonparametrically for the average product price across the US. Since producer prices tend to be homogeneous across locations, we cannot capture changes in production costs. Persistent local price increases of some products are more likely to reflect local retailers' pass-through of the shock.

To further explore the importance of a product's demand elasticity, we consider that recent work has shown that inflation pressures tend to be more pronounced in the cheapest categories of a product, which, like essential products, are likely to have lower demand elasticity (Cavallo and Kryvtsov, 2024). We thus expect that, within each product module, the cheapest product varieties are those that experience the largest price increases in counties affected by natural disasters. To test this hypothesis, we sort UPC-level products within a module by their unit prices at the beginning of the sample period in 2006, and define the lowest quartile as "cheap" and the highest quartile as "expensive". We then consider the average price of cheap and expensive products within a module, so that, for each product, module, county, and month, we have two observations: one for cheap products and one for expensive products. We augment our basic specification by including the triple interaction term $Treat \times Post \times Cheap$.

In Table 10, the positive effect of natural disasters on product prices appears to be entirely driven by the cheaper version of a product. Also in this case, the price increase does not appear to be accompanied by a rise in sales of inexpensive products. The low-priced varieties of a product are likely to have lower demand elasticity, allowing retailers to transfer increased operating costs arising from natural disasters or to simply exercise greater market power. In either case, this suggests that lower-income households are likely to be more affected by price increases.

# 6 Cross-Sectional Differences between Counties

## 6.1 Access to External Finance

Access to external finance can be crucial to a firm's ability to respond to external shocks. For instance, the local availability of credit influenced whether and how farmers adapted to the prolonged drought of the 1950s in the US (Rajan and Ramcharan, 2025). More closely related to us, Ponticelli et al. (2023) finds that better access to external finance is associated with lower increases in concentration following extremely high temperatures. Similar effects are likely to be at play following natural disasters, which cause destruction and thereby increase firms' financial needs.

To capture differences in small and medium firms' access to external finance across counties, we obtain bank branch locations from the FDIC and exploit variation in the density of bank branches per capita at the beginning of our sample period.

Table 11 shows that the changes in industry dynamics we have highlighted so far are partially driven or accentuated by financial frictions. We divide counties into three groups based on their bank branch density, defined as the number of bank branches in an MSA divided by the MSA's population at the beginning of the sample period in 2006. Not only do we control for county fixed effects to capture differences in industry dynamics, but we also allow industry-level shocks to differ in counties in different terciles of bank credit. We find that entry rates and growth rates in the number of firms are even lower in low-credit-access counties, while exit rates increase regardless of bank credit availability following natural disasters. For wholesale and retail, counties with the lowest level of credit access experience an additional decrease of 1.2 percentage points in the growth rate of the number of firms and a 0.6 percentage-point decrease in the entry rate, relative to counties with the highest level of credit access. The effects are comparable when the sample is extended to all industries (Panel A). We observe an additional decrease in the firm number growth rate of 1.0 percentage points and a 0.6-percentage-point lower entry rate in counties with the lowest credit access compared to those with the highest credit access.

Changes in industry dynamics in counties with different access to external finance appear to matter for consumer prices. Table 12 examines how retail prices change following natural disasters in counties with varying access to external finance, as defined in Table 11. Since changes in industrial structure due to natural disasters are more pronounced in counties with fewer bank branches, we should observe higher increases in retail product prices in these areas, where large retailers can presumably increase their market shares to a larger extent. In column 1, we find that indeed price increases are more pronounced in counties with bank branches per capita in the bottom two terciles. Local prices do not appear to change following natural disasters only in counties with bank branches per capita in the top tercile.

These results are robust, whether we control for time-series shocks using interactions between the low credit dummies and year fixed effects (columns 1 and 2) or month fixed effects (column 3).

## 6.2 Effects of Natural Disasters in Counties with Different Exposure to Climate Risk

As climate change increases the frequency of natural disasters, firms and counties could engage in adaptation efforts that limit disruptions and the effects on industry dynamics and consumer prices.

To evaluate whether this is the case, we define an indicator variable that equals 1 for counties that experienced multiple natural disasters during our sample period, indicating higher exposure to physical risk. We conjecture that if firms and counties take steps to mitigate the adverse effects of natural disasters, the effects we uncover should be attenuated in counties more exposed to natural hazards. This would indicate that the observed effects on concentration and price levels are transitory, alleviating policymakers' concerns.

To test whether the effects of natural disasters are attenuated in counties highly exposed to natural hazard risk, we augment our baseline specifications for industry dynamics and prices by including the triple interaction term $Treat \times Post \times Multiple$, where $Multiple$ captures high physical risk counties.

Table 13 considers the effects of natural disasters in counties with different exposure to physical risk. The effects of natural disasters on the decline in the number of firms are significantly more severe in counties with high physical risk exposure. In the retail and wholesale sectors, higher exit rates appear to be entirely driven by counties with high physical risk, suggesting that firms experiencing damage anticipate a high likelihood of recurrence and are more likely to exit. We observe no differential effect on the entry rate. Importantly, these estimates account for industry-level shocks across counties with high and low exposure to natural hazards, while controlling for county fixed effects.

These findings indicate that firms' adaptation responses are unlikely to impact the significance of our findings over time. Accordingly, in Table 14, we observe that the effects of climate disasters on product prices are more than double in counties with high exposure to natural hazards, that is, the counties that experience larger changes in industry dynamics.

These results highlight that the effects of natural disasters on industry structure and product prices are not merely transitory, emphasizing the importance of our findings.

# 7 Conclusion

Negative climate-related physical risk realizations have a minimal impact on the valuations of listed companies. We show that natural disasters and extreme weather events affect firm survival and industrial structure in a manner that can enhance the competitive advantage of large companies.

Using plant-level data and scanner product prices at the county level, we show that exit rates increase and new firm creation suffers when a natural disaster occurs. Consequently, surviving firms benefit from increased concentration, as they are able to raise product prices. It also appears that large retailers earn market shares. This channel benefits the profitability of large listed companies and suggests a mechanism for why physical risk has a small effect on the valuations of listed companies, which are naturally large. However, while stock returns do not suffer, society may experience large negative welfare effects as consumer surplus decreases, and low-income households are likely to suffer the most.

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# 8 Tables and Figures

### Table 1: Descriptive Statistics

| Variable | Obs | Mean | Std. Dev. | P1 | P50 | P99 |
|---|---|---|---|---|---|---|
| **All industries** | | | | | | |
| **County-2-digit SIC-year level** | | | | | | |
| Nr of firms | 3821939 | 57.206 | 204.005 | 3 | 20 | 626 |
| Growth rate (g) | 3809711 | .007 | .132 | -.375 | 0 | .429 |
| Entry rate | 3809711 | .082 | .095 | 0 | .059 | .462 |
| Exit rate | 3809711 | .076 | .08 | 0 | .06 | .357 |
| Top 3 share of employment | 3821939 | .537 | .268 | .065 | .521 | 1 |
| Top 5 share of employment | 3821939 | .649 | .268 | .1 | .668 | 1 |
| HHI | 3821939 | .204 | .201 | .006 | .137 | .953 |
| **County level (2006)** | | | | | | |
| Bank branch density | 1041 | .000083 | .000066 | 8.00e-06 | .000073 | .000265 |
| **Wholesale and retail** | | | | | | |
| **County-2-digit SIC-year level** | | | | | | |
| Nr of firms | 827405 | 46.87 | 95.253 | 3 | 22 | 410 |
| Growth rate (g) | 827384 | -.004 | .119 | -.353 | 0 | .345 |
| Entry rate | 827384 | .083 | .083 | 0 | .069 | .4 |
| Exit rate | 827384 | .085 | .08 | 0 | .071 | .364 |
| Top 3 share of employment | 827405 | .523 | .235 | .117 | .5 | 1 |
| Top 5 share of employment | 827405 | .641 | .234 | .175 | .641 | 1 |
| HHI | 827405 | .183 | .174 | .014 | .124 | .86 |
| **County level (2006)** | | | | | | |
| Bank branch density | 1033 | .000082 | .000065 | 8.00e-06 | .000068 | .000265 |
| **Nielsen data** | | | | | | |
| **Module code-county-year-month level** | | | | | | |
| Unit Price | 683549631 | 2.332 | 6.099 | .019 | .308 | 40.802 |
| Sale-weighted price | 685370559 | 4.161 | 4.548 | .608 | 2.768 | 30.403 |
| Top quartile unit price | 369846779 | 4.608 | 12.158 | .052 | .6 | 89.99 |
| Bottom quartile unit price | 404993333 | .53 | 1.316 | .007 | .136 | 9.49 |
| **Retailer parent-county-year level** | | | | | | |
| Sales (in thousand USD) | 173810 | 9040.439 | 20876.86 | 215.23 | 2262.271 | 101915 |
| Bottom 10% firms' sales (in thousand USD) | 4245 | 1072.361 | 1082.022 | 92.295 | 868.848 | 3102.009 |
| Top 10% firms' sales (in thousand USD) | 87811 | 10819.31 | 21410.61 | 276.141 | 3552.877 | 100640.6 |
| **County Characteristics at the year level** | | | | | | |
| Sales | 64729 | 24.3 | 56.3 | 0.29 | 7.6 | 271 |
| GDP per capita (thousand dollar) | 97537 | 37.343 | 23.369 | 11.061 | 30.878 | 145.045 |
| Income per capita | 97537 | 35305.65 | 10575.01 | 18975 | 33139 | 77620 |
| Population | 97537 | 28242.48 | 48747.85 | 673 | 16250 | 207571 |
| Unemployment rate (%) | 97522 | .067 | .029 | .023 | .061 | .153 |

This table reports descriptive statistics of all variables in the paper. Variable definitions can be found in Table A1.

**Table 2: Natural Disasters and Firm Dynamics**

Panel A: All Industries

| | g (1) | Entry rate (2) | Exit rate (3) |
|---|---|---|---|
| Treat x Post | -0.005*** | -0.003*** | 0.003*** |
| | (0.001) | (0.001) | (0.001) |
| Cohort x FIPS FE | Yes | Yes | Yes |
| Cohort x SIC2 x Year FE | Yes | Yes | Yes |
| Adj. R2 | 0.307 | 0.331 | 0.270 |
| No of obs | 3,809,600 | 3,809,600 | 3,809,600 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Wholesale and Retail

| | g (1) | Entry rate (2) | Exit rate (3) |
|---|---|---|---|
| Treat x Post | -0.004*** | -0.003*** | 0.001 |
| | (0.001) | (0.001) | (0.001) |
| Cohort x FIPS FE | Yes | Yes | Yes |
| Cohort x SIC2 x Year FE | Yes | Yes | Yes |
| Adj. R2 | 0.262 | 0.249 | 0.263 |
| No of obs | 827,384 | 827,384 | 827,384 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports estimates from stacked difference-in-differences regressions at the county-industry-year level. The dependent variables are the change in firm number at t, divided by the average of the number of firms in a county, SIC2 industry at t and t-1, the entry rate, defined as number of new firms at time t, divided by the average of the number of firms in a county, SIC2 industry at t and t-1, and the exit rate, defined as the number of firms that existed at t-1 but do not exist any longer at t, divided by the average of the number of firms in a county, SIC2 industry at t and t-1. *Treat* takes the value of 1 for counties that were ever affected by a natural disaster with damage value above 10 million USD, and 0 otherwise. *Post* takes the value of 1 for the disaster year and the four subsequent years, and 0 in the four years before. Panel A presents estimates for the whole sample of industries, while Panel B includes only observations relative to wholesale and retail. The data source is NETS. We include only county-industry observations with at least two companies before the shock. We also restrict each county-cohort to have more than two years both before and after the shock. Fixed effects are included as indicated in the table. Standard errors are clustered at the county-year level and included in parentheses.

**Table 3: Natural Disasters and Industry Concentration**

Panel A: All Industries

| | Top 3 % | | Top 5 % | | HHI | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Treat x Post | 0.005*** | 0.005*** | 0.002*** | 0.002*** | 0.009*** | 0.010*** |
| | (0.001) | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) |
| Cohort x SIC2 FE | Yes | No | Yes | No | Yes | No |
| Cohort x Year FE | Yes | No | Yes | No | Yes | No |
| Cohort x FIPS FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cohort x SIC2 x Year FE | No | Yes | No | Yes | No | Yes |
| Adj. R2 | 0.663 | 0.668 | 0.707 | 0.714 | 0.538 | 0.543 |
| No of obs | 3,821,939 | 3,821,826 | 3,821,939 | 3,821,826 | 3,821,939 | 3,821,826 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Wholesale and Retail

| | Top 3 % | | Top 5 % | | HHI | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Treat x Post | 0.008*** | 0.007*** | 0.007*** | 0.007*** | 0.005*** | 0.005*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Cohort x SIC2 FE | Yes | No | Yes | No | Yes | No |
| Cohort x Year FE | Yes | No | Yes | No | Yes | No |
| Cohort x FIPS FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cohort x SIC2 x Year FE | No | Yes | No | Yes | No | Yes |
| Adj. R2 | 0.641 | 0.645 | 0.697 | 0.702 | 0.539 | 0.541 |
| No of obs | 827,405 | 827,405 | 827,405 | 827,405 | 827,405 | 827,405 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports estimates from stacked difference-in-differences at the county-industry (2-digit SIC code)-year level. The dependent variable is the fraction of employment at the top 3 companies in an industry and county at time t in column 1 and 2, the fraction of employment at the top 5 companies in an industry and county at time t in column 3 and 4, and HHI in an industry and county at time t in column 5 and 6. *Treat* takes the value of 1 for counties that were ever affected by a natural disaster with damage value above 10 million USD, and 0 otherwise. *Post* takes the value of 1 for the disaster year and the four subsequent years, and 0 in the four years before. Panel A presents estimates for the whole sample of industries, while Panel B includes only observations relative to wholesale and retail. The data source is NETS. We include only county-industry observations with at least two companies before the shock. We also restrict each county-cohort to have more than two years both before and after the shock. Fixed effects are included as indicated in the table. Standard errors are clustered at the county-year level and included in parentheses.

### Table 4: Natural Disasters and Sales at Small and Large Retailers

| | log(sales) (1) | log(sales) (2) |
|---|---|---|
| Treat x Post | -0.067** | -0.076** |
| | (0.034) | (0.034) |
| Treat x Post x Large | 0.094** | 0.087** |
| | (0.037) | (0.036) |
| Cohort x Firm FE | Yes | No |
| Cohort x Large x Year FE | Yes | No |
| Cohort x Large x FIPS FE | Yes | Yes |
| Cohort x Firm x Year FE | No | Yes |
| Adj. R2 | 0.860 | 0.868 |
| No of obs | 91,945 | 91,941 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports estimates from stacked difference-in-differences at the retailer ($r$)-county ($f$)-year ($t$) level following the specification below:

$$\mathrm{y}_{r,f,t,c} = \beta_0 \times \mathrm{Treat}_f \times \mathrm{Post}_t + \beta_1 \times \mathrm{Treat}_f \times \mathrm{Post}_t \times \mathrm{Large}_r + \mathtt{FE} + \epsilon_{r,f,t,c}$$

The dependent variable is the natural logarithm of 1 + sales of a retailer in a given county and year. $c$ refers to the natural disaster cohort and is used to implement the stacked regressor. *Treat* takes the value of 1 for counties that were ever affected by a natural disaster with damage value above 10 million USD, and 0 otherwise. We include a window of four years around each natural disaster. *Post* takes the value of 1 for the disaster year and subsequent years, and 0 for all other years. *Large* equals 1 (0) for retailers whose sales rank in the top (bottom) 10% in 2006. The sample covers data from Nielsen from 2006 to 2020. Fixed effects are included as indicated in the table. Standard errors are clustered at the county-year level and included in parentheses.

**Table 5: The Effects of Natural Disasters on Retail Prices**

| | Unit Price | | | Sale-weighted price | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Treat x Post | 0.033*** | 0.033*** | 0.033*** | 0.037*** | 0.036*** | 0.036*** |
| | (0.006) | (0.006) | (0.006) | (0.007) | (0.007) | (0.007) |
| Cohort x FIPS FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cohort x Module code FE | Yes | No | No | Yes | No | No |
| Cohort x Year FE | Yes | No | No | Yes | No | No |
| Cohort x Module code x Year FE | No | Yes | No | No | Yes | No |
| Cohort x Module code x Year-month FE | No | No | Yes | No | No | Yes |
| Adj. R2 | 0.842 | 0.854 | 0.860 | 0.844 | 0.855 | 0.860 |
| No of obs | 683,549,601 | 683,549,475 | 683,542,780 | 683,543,828 | 683,543,702 | 683,536,993 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports estimates from stacked difference-in-differences at the product module-county-year-month level following the specification below:

$$\mathrm{y}_{f,p,c,t} = \beta \times \mathrm{Treat}_f \times \mathrm{Post}_t + \mathtt{FE} + \epsilon_{f,p,c,t},$$

where $p$ is the product module code, $f$ the county, $t$ the month, and $c$ the disaster cohort. The dependent variables are unit price (columns 1-3) and the sale-weighted price (columns 4-6). *Treat* takes the value of 1 for counties that were ever affected by a natural disaster with damage value above 10 million USD, and 0 otherwise. *Post* takes the value of 1 for the disaster year and the four subsequent years, and 0 in the four years before. The sample covers all retail prices from Nielsen from 2006 to 2020. Standard errors are clustered at the county-year level and included in parentheses.

**Table 6: Natural Disasters and Economic Outcomes**

| | log(sales) (1) | log(population) (2) | GDP per capita (3) | Income per capita (4) | Unemployment rate (%) (5) |
|---|---|---|---|---|---|
| Treat x Post | 0.008 | 0.004 | -1.312*** | -658.636*** | 0.000 |
| | (0.026) | (0.003) | (0.406) | (185.648) | (0.001) |
| Cohort x FIPS FE | Yes | Yes | Yes | Yes | Yes |
| Cohort x Year FE | Yes | Yes | Yes | Yes | Yes |
| Adj. R2 | 0.969 | 0.999 | 0.911 | 0.921 | 0.848 |
| No of obs | 64,638 | 97,537 | 97,537 | 97,537 | 97,521 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the estimates from stacked difference-in-differences at the county-cohort-year level. The dependent variables are the natural logarithm of 1 + sales, the natural logarithm of population, the GDP per capita (in thousands of USD), the income per capita (in thousands of USD), and the unemployment rate in a given county and year. *Treat* takes the value of 1 for counties that were ever shocked by a natural disaster with damage value above 10 million USD, and 0 otherwise. *Post* takes the value of 1 for the years when and after the disaster happened, and 0 before. We include a window of four years around each natural disaster. Standard errors are clustered at the county level and included in parentheses.

**Table 7: UPC level results**

| | Unit price<br>(1) | Sale-weighted price<br>(2) |
|---|---|---|
| Treat x Post | $0.016^{**}$ | $0.006^{**}$ |
| | (0.006) | (0.003) |
| Cohort x FIPS FE | Yes | Yes |
| Cohort x UPC x Year FE | Yes | Yes |
| Adj. R2 | 0.977 | 0.976 |
| No of obs | 3,481,210,865 | 3,482,076,220 |

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

This table reports estimates from stacked difference-in-differences at the product module-county-year-month level following the specification below:

$$\mathrm{y}_{f,u,c,t} = \beta \times \mathrm{Treat}_f \times \mathrm{Post}_t + \mathtt{FE} + \epsilon_{f,u,c,t},$$

where $u$ is universal product code (UPC), $f$ the county, $t$ the month, and $c$ the disaster cohort. The dependent variables are unit price (column 1) and the sale-weighted price (column 2). *Treat* takes the value of 1 for counties that were ever affected by a natural disaster with damage value above 10 million USD, and 0 otherwise. *Post* takes the value of 1 for the disaster year and the four subsequent years, and 0 in the four years before. The sample covers all retail prices from Nielsen from 2006 to 2020. Standard errors are clustered at the county-year level and included in parentheses.

**Table 8: UPC level results**

| | Unit price (1) | Sale-weighted price (2) |
|---|---|---|
| Treat x Post | 0.042*** | 0.010*** |
| | (0.009) | (0.003) |
| Cohort x FIPS FE | Yes | Yes |
| Cohort x UPC x Year FE | Yes | Yes |
| Adj. R2 | 0.977 | 0.976 |
| No of obs | 3,299,889,965 | 3,300,733,350 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports estimates from stacked difference-in-differences at the product module-county-year-month level following the specification below:

$$y_{f,u,c,t} = \beta \times \text{Treat}_f \times \text{Post}_t + \texttt{FE} + \epsilon_{f,u,c,t},$$

where $u$ is universal product code (UPC), $f$ the county, $t$ the month, and $c$ the disaster cohort. The dependent variables are unit price (column 1) and the sale-weighted price (column 2). *Treat* takes the value of 1 for counties that were ever affected by a natural disaster with damage value above 10 million USD, and 0 otherwise. *Post* takes the value of 1 for the disaster year and the four subsequent years, and 0 in the four years before. The sample covers all retail prices from Nielsen from 2006 to 2020. We restrict the sample to FIPS that are present in 2006. Standard errors are clustered at the county-year level and included in parentheses.

**Table 9: Essential Products and Natural Disasters**

| | Unit price | | | Sale-weighted price | | | log(sales) | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Treat x Post | 0.012*** | 0.013*** | 0.013*** | 0.023*** | 0.019*** | 0.019*** | 0.084*** | 0.087*** | 0.087*** |
| | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) | (0.005) | (0.018) | (0.018) | (0.018) |
| Treat x Post x Essential | 0.041*** | 0.037*** | 0.038*** | 0.031*** | 0.034*** | 0.034*** | -0.012 | -0.013 | -0.013 |
| | (0.006) | (0.006) | (0.006) | (0.007) | (0.007) | (0.007) | (0.009) | (0.009) | (0.009) |
| Cohort x FIPS FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Cohort x Module code FE | Yes | No | No | Yes | No | No | Yes | No | No |
| Cohort x Year FE | Yes | No | No | Yes | No | No | Yes | No | No |
| Cohort x Module code x Year FE | No | Yes | No | No | Yes | No | No | Yes | No |
| Cohort x Module code x Year-month FE | No | No | Yes | No | No | Yes | No | No | Yes |
| Cluster level | FIPS | FIPS | FIPS | FIPS | FIPS | FIPS | FIPS | FIPS | FIPS |
| Adj. R2 | 0.843 | 0.856 | 0.861 | 0.847 | 0.858 | 0.863 | 0.783 | 0.790 | 0.806 |
| No of obs | 681,244,574 | 681,244,448 | 681,238,044 | 681,244,515 | 681,244,389 | 681,237,985 | 681,799,453 | 681,799,348 | 681,793,038 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports estimates from stacked difference-in-differences at the product module-county-year-month level following the specification below:

$$\mathrm{y}_{f,p,c,t} = \beta_1 \times \mathrm{Treat}_f \times \mathrm{Post}_t + \beta_2 \times \mathrm{Essential}_p \times \mathrm{Treat}_f \times \mathrm{Post}_t + \mathtt{FE} + \epsilon_{f,p,c,t},$$



where $p$ is the product module code, $f$ the county, $t$ the month, and $c$ the disaster cohort. The indicator variable *Essential* takes the value of 1 for product groups that are considered essential. Essential products are product module codes belonging to product groups classified as essential for daily life and disaster recovery. The dependent variable is the unit price in column 1-3, the sale-weighted price in column 4-6, and log(sales) in column 7-9. *Treat* takes the value of 1 for counties that were ever affected by a natural disaster with damage value above 10 million USD, and 0 otherwise. *Post* takes the value of 1 for the disaster year and the four subsequent years, and 0 in the four years before. The sample covers all retail prices from Nielsen from 2006 to 2020. Standard errors are clustered at the county-year level and included in parentheses.

**Table 10: Cheapflation and Natural Disasters**

| | Unit price | | | log(sales) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Treat x Post | -0.004 | -0.003 | -0.003 | 0.015** | 0.013** | 0.013** |
| | (0.004) | (0.004) | (0.004) | (0.006) | (0.006) | (0.006) |
| Treat x Post x Cheap | 0.013*** | 0.015*** | 0.015*** | 0.003 | 0.000 | 0.000 |
| | (0.004) | (0.004) | (0.004) | (0.003) | (0.003) | (0.003) |
| Cheap x Cohort x Year FE | Yes | Yes | No | Yes | Yes | No |
| Cheap x Cohort x Year-month FE | No | No | Yes | No | No | Yes |
| Cheap x Cohort x FIPS FE | Yes | No | No | Yes | No | No |
| Cheap x Cohort x Module code FE | Yes | No | No | Yes | No | No |
| Cheap x Cohort x FIPS x Module code FE | No | Yes | Yes | No | Yes | Yes |
| Adj. R2 | 0.936 | 0.955 | 0.955 | 0.659 | 0.832 | 0.833 |
| No of obs | 774,839,997 | 774,634,102 | 774,634,102 | 776,153,742 | 775,948,899 | 775,948,899 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$



This table reports estimates from stacked difference-in-differences at the product module-type-county-year-month level following the specification below:

$$\mathrm{y}_{f,p,x,c,t} = \beta_1 \times \mathrm{Treat}_f \times \mathrm{Post}_t + \beta_2 \times \mathrm{Cheap}_{p,x} \times \mathrm{Treat}_f \times \mathrm{Post}_t + \mathtt{FE} + \epsilon_{f,p,x,c,t},$$

where $p$ is the product module code, $x$ the UPC product type within the module code, which can be cheap or not, $f$ the county, $t$ the month, and $c$ the disaster cohort. Cheap products are those in the bottom quartile of their module based on their yearly average price. Therefore, we consider only modules with at least four products. The indicator variable *Cheap* takes the value of 1 for products within a module that are considered cheap, and takes the value of 0 for products with the highest quartile of price in 2006. The dependent variable is the unit price in column 1-3 and log(sales) in column 4-6. *Treat* takes the value of 1 for counties that were ever affected by a natural disaster with damage value above 10 million USD, and 0 otherwise. *Post* takes the value of 1 for the disaster year and the four subsequent years, and 0 in the four years before. The sample covers all retail prices from Nielsen from 2006 to 2020. Standard errors are clustered at the county-year level and included in parentheses.

**Table 11: Access to Finance and The Effects of Natural Disasters on Industry Dynamics**

Panel A: All Industries

| | g<br>(1) | Entry rate<br>(2) | Exit rate<br>(3) |
|---|---|---|---|
| Treat x Post | -0.005*** | -0.001* | 0.004*** |
| | (0.001) | (0.001) | (0.001) |
| Treat x Post x Low credit 2 | -0.001 | -0.002 | -0.000 |
| | (0.003) | (0.002) | (0.001) |
| Treat x Post x Low credit 3 | -0.008** | -0.005** | -0.000 |
| | (0.003) | (0.002) | (0.001) |
| Cohort x FIPS FE | Yes | Yes | Yes |
| Cohort x Low credit x SIC2 x Year FE | Yes | Yes | Yes |
| Adj. R2 | 0.313 | 0.336 | 0.274 |
| No of obs | 3,781,167 | 3,781,167 | 3,781,167 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Wholesale and Retail

| | g<br>(1) | Entry rate<br>(2) | Exit rate<br>(3) |
|---|---|---|---|
| Treat x Post | -0.005*** | -0.002* | 0.004*** |
| | (0.002) | (0.001) | (0.001) |
| Treat x Post x Low credit 2 | 0.001 | -0.001 | -0.004* |
| | (0.003) | (0.002) | (0.002) |
| Treat x Post x Low credit 3 | -0.011*** | -0.006** | -0.002 |
| | (0.004) | (0.003) | (0.002) |
| Cohort x FIPS FE | Yes | Yes | Yes |
| Cohort x Low credit x SIC2 x Year FE | Yes | Yes | Yes |
| Adj. R2 | 0.263 | 0.253 | 0.267 |
| No of obs | 820,629 | 820,629 | 820,629 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports estimates from stacked triple-difference-in-differences regressions at the county-industry-year level following the specification below:

$$\mathrm{y}_{f,i,c,t} = \beta_0 \times \mathrm{Treat}_f \times \mathrm{Post}_t + \beta_1 \times \mathrm{Treat}_f \times \mathrm{Post}_t \times \mathrm{Access\ to\ finance}_f + \mathtt{FE} + \epsilon_{f,i,c,t},$$

where $f$ refers to the county, $i$ to the 2-digit SIC code industry, $t$ to the year and $c$ to the natural disaster cohort. The dependent variables are the growth rate of the number of new firms, the entry rate, and the exit rate, defined as in Table 2. *Treat* takes the value of 1 for counties that were ever affected by a natural disaster with damage value above 10 million USD, and 0 otherwise. *Post* takes the value of 1 for the disaster year and the four subsequent years, and 0 in the four years before. We rank counties into 3 groups based on the number of bank branches per capita at the MSA level in 2006, and then interact the dummy variable *Access to finance*$_f$ with *Treat*Post*. The 1st tercile includes counties with the highest number of bank branches per capita, while the 3rd tercile includes counties with the lowest number of bank branches per capita. The sample covers all public and private firms in NETS. We restrict the unit of observation to have at least two companies throughout the analysis period. We also restrict each county-cohort to have more than two years both before and after the shock. Panel A presents estimates for the whole sample of industries, while Panel B includes only observations relative to wholesale and retail. Fixed effects are included as indicated in the table. Standard errors are clustered at the county-year level and included in parentheses.

**Table 12: Access to Finance and the Effects of Natural Disasters on Retail Prices**

| | Unit price | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Treat x Post | 0.000 | 0.002 | 0.002 |
| | (0.001) | (0.001) | (0.001) |
| Treat x Post x Low credit 2 | 0.005** | 0.005** | 0.005** |
| | (0.002) | (0.002) | (0.002) |
| Treat x Post x Low credit 3 | 0.004*** | 0.004** | 0.004** |
| | (0.002) | (0.002) | (0.002) |
| Cohort x Low credit x Year FE | Yes | Yes | No |
| Cohort x Low credit x Year-month FE | No | No | Yes |
| Cohort x FIPS FE | Yes | No | No |
| Cohort x Low credit x Module code FE | Yes | No | No |
| Cohort x FIPS x Module code FE | No | Yes | Yes |
| Adj. R2 | 0.915 | 0.939 | 0.939 |
| No of obs | 404,993,133 | 404,892,752 | 404,892,752 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports estimates from stacked triple-difference-in-differences at the product module-county-year-month level following the specification below:

$$y_{f,p,c,t} = \beta_0 \times \text{Treat}_f \times \text{Post}_t + \beta_1 \times \text{Treat}_f \times \text{Post}_t \times \text{Access to finance}_f + \texttt{FE} + \epsilon_{f,p,c,t},$$

where $p$ is the product module code, $f$ the county, $t$ the month, and $c$ the disaster cohort. The dependent variable is the unit price. *Treat* takes the value of 1 for counties that were ever affected by a natural disaster with damage value above 10 million USD, and 0 otherwise. *Post* takes the value of 1 for the disaster year and the four subsequent years, and 0 in the four years before. We rank observations based on the number of bank branches per capita at the MSA level in 2006 into 3 groups and interact the dummy variable Access to finance$_f$ with *Treat*Post*. The 1st tercile includes observations with the highest number of bank branches per capita, while the 3rd tercile includes observations with the lowest number of bank branches per capita. The sample covers all retail prices from Nielsen from 2006 to 2020. Standard errors are clustered at the county-year level and included in parentheses.

**Table 13: Multiple Disasters and the Effects of Natural Disasters on Firm Entry and Exit**

Panel A: All Industries

| | g<br>(1) | Entry rate<br>(2) | Exit rate<br>(3) |
|---|---|---|---|
| Treat x Post | -0.003** | -0.002*** | 0.002*** |
| | (0.001) | (0.001) | (0.001) |
| Treat x Post x Multiple | -0.006*** | -0.001 | 0.003*** |
| | (0.002) | (0.001) | (0.001) |
| Cohort x FIPS FE | YES | YES | YES |
| Cohort x Year x SIC x Multiple FE | YES | YES | YES |
| Adj. R2 | 0.307 | 0.330 | 0.269 |
| No of obs | 7,466,336 | 7,466,336 | 7,466,336 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Wholesale and Retail

| | g<br>(1) | Entry rate<br>(2) | Exit rate<br>(3) |
|---|---|---|---|
| Treat x Post | -0.001 | -0.003*** | 0.000 |
| | (0.002) | (0.001) | (0.001) |
| Treat x Post x Multiple | -0.008*** | -0.002 | 0.004** |
| | (0.003) | (0.002) | (0.002) |
| Cohort x FIPS FE | YES | YES | YES |
| Cohort x Year x SIC x Multiple FE | YES | YES | YES |
| Adj. R2 | 0.260 | 0.248 | 0.262 |
| No of obs | 1,625,682 | 1,625,682 | 1,625,682 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports estimates from stacked triple-difference-in-differences at the county-year level following the specification below:

$$\mathrm{y}_{f,i,c,t} = \beta_0 \times \mathrm{Treat}_f \times \mathrm{Post}_t + \beta_1 \times \mathrm{Treat}_f \times \mathrm{Post}_t \times \mathrm{Multiple}_f + \mathtt{FE} + \epsilon_{f,i,c,t},$$

where $f$ refers to the county, $i$ to the 2-digit SIC code industry, $t$ to the year, and $c$ to the natural disaster cohort. The dependent variables are the growth rate of the number of new firms, the entry rate, and the exit rate, defined as in Table 2. *Treat* takes the value of 1 for counties that were ever affected by a natural disaster with damage above 10 million USD, and 0 otherwise. *Post* takes the value of 1 for the disaster year and the four subsequent years, and 0 in the four years before. The dummy variable $\mathrm{Multiple}_f$ takes the value of 1 if the county was shocked more than once during our sample period. The sample in Panel A includes all industries. The sample in Panel B includes wholesale and retail sectors. Standard errors are clustered at the county-year level and reported in parentheses.

**Table 14: Multiple Shocks and the Effects of Natural Disasters on Product Prices**

| | Unit Price | | | Sale-weighted price | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Treat x Post | 0.022*** | 0.022*** | 0.022*** | 0.022** | 0.021** | 0.021** |
| | (0.007) | (0.007) | (0.007) | (0.009) | (0.008) | (0.008) |
| Treat x Post x Multiple | 0.036*** | 0.036*** | 0.036*** | 0.050*** | 0.050*** | 0.049*** |
| | (0.011) | (0.011) | (0.011) | (0.013) | (0.013) | (0.013) |
| Cohort x FIPS FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cohort x Multiple x Module code FE | Yes | No | No | Yes | No | No |
| Cohort x Multiple x Year FE | Yes | No | No | Yes | No | No |
| Cohort x Multiple x Module code x Year FE | No | Yes | No | No | Yes | No |
| Cohort x Multiple x Module code x Year-month FE | No | No | Yes | No | No | Yes |
| Adj. R2 | 0.842 | 0.854 | 0.860 | 0.844 | 0.855 | 0.860 |
| No of obs | 1,344,369,205 | 1,344,368,955 | 1,344,355,425 | 1,344,357,920 | 1,344,357,670 | 1,344,344,116 |

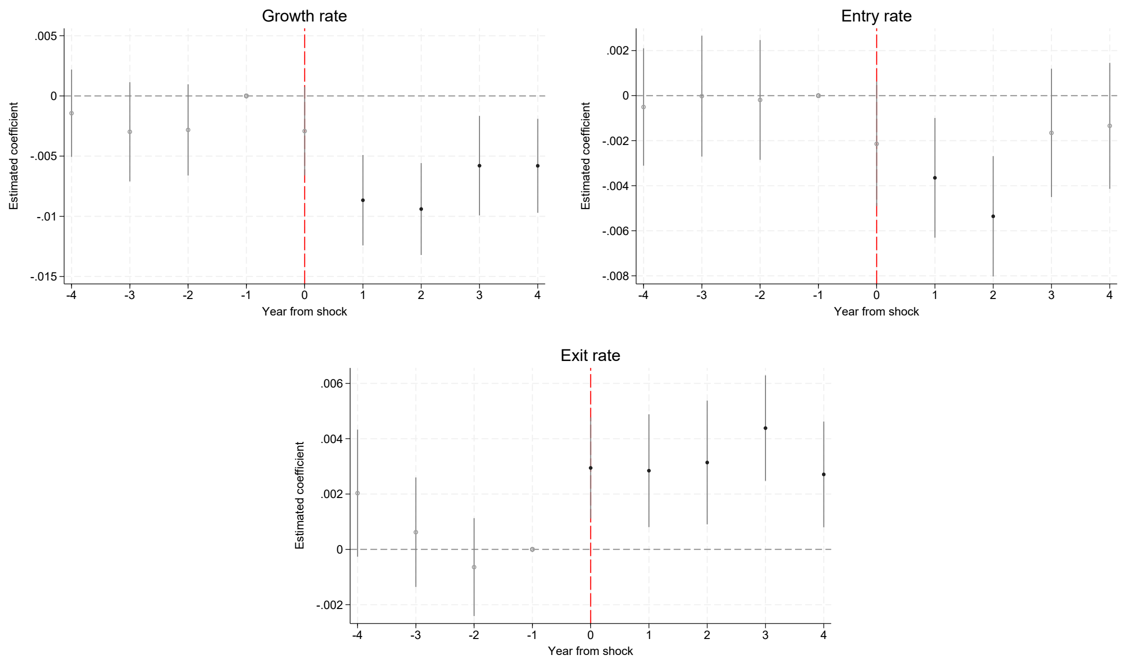
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports estimates from stacked triple-difference-in-differences at the product module-county-year-month level following the specification below:

$$\mathrm{y}_{f,p,c,t} = \beta_0 \times \text{Treat}_f \times \text{Post}_t + \beta_1 \times \text{Treat}_f \times \text{Post}_t \times \text{Multiple}_f + \texttt{FE} + \epsilon_{f,p,c,t},$$

where $p$ refers to the product module code, $f$ to the county, $t$ to the month, and $c$ to the disaster cohort. The dependent variable is the unit price in column 1-2, we price in column 3-4, and log(sales) in column 5-6. *Treat* takes the value of 1 for counties that were ever affected by a natural disaster with damage value above 10 million USD, and 0 otherwise. *Post* takes the value of 1 for the disaster year and the four subsequent years, and 0 in the four years before. The dummy variable $\text{Multiple}_f$ takes the value of 1 if the county was shocked more than once during our sample period. The sample covers all retail prices from Nielsen from 2006 to 2020. Standard errors are clustered at the county-year level and included in parentheses.

**Figure 1: Dynamic Effects of Natural Disasters on Industry Structure**

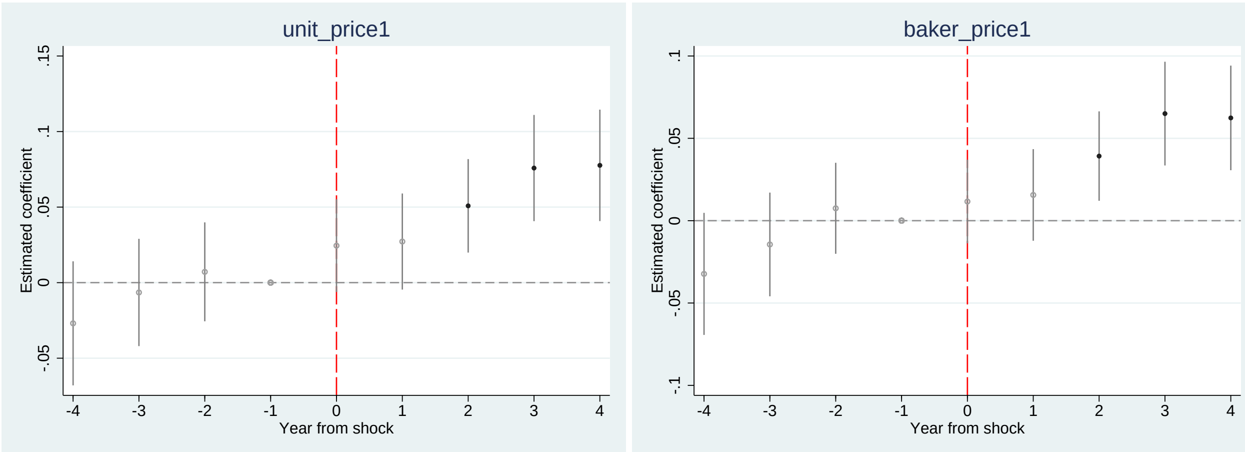



This figure shows the estimates of the $\beta_t$ coefficients (in dots) and their 95% confidence intervals (grey vertical line) from the following model:

$$\mathrm{y}_{f,i,t,c} = \mathrm{Treat}_f \times \sum_{t=-4}^{t=4} \beta_t \times D_t + \texttt{FE} + \epsilon_{f,i,t,c},$$

where f refers to the county, i to the industry, t to the calendar year, and c to the natural disaster cohort. *Treat* takes the value of one if a county has experienced a natural disaster with total damage value exceeding 10 million USD and zero otherwise. Cohort-by-industry (2-digit SIC)by-calendar-year fixed effects and cohort-by-county fixed effects are also included. Standard errors are clustered at the county-year level. Point estimates are $\beta_t$ for all years $t$ in the sample, where $t$ = -1—the year before the shock—is the omitted period. Black circles indicate significant results at the 5% level, while hollow circles indicate statistically insignificant results from zero. The sample covers all public and private firms. We consider only counties and industries that have at least two companies throughout the analysis period. We also restrict each county-cohort to have more than two years both before and after the shock.

**Figure 2: Dynamic Effects of Natural Disasters on Local Retail Prices**




This figure shows estimates of the $\beta_t$ coefficients (in dots) and their 95% confidence intervals (grey vertical line) from the following model:

$$\mathrm{y}_{f,p,c,t} = \mathrm{Treat}_f \times \sum_{t=-4}^{t=4} \beta_t \times D_t + \mathtt{FE} + \epsilon_{f,p,c,t},$$

where f refers to the county, i to the industry, t to the calendar month, and c to the natural disaster cohort. The dependent variable is the unit price in the left panel and sale-weighted price in the right panel. *Treat* takes the value of one if a county has experienced a natural disaster with total damage value exceeding 10 million USD and zero otherwise. The unit of observation is at product-module-code ($p$) by county ($f$) by year-month ($t$) level. Cohort by county fixed effects, product-module-code fixed effects, and cohort by year fixed effects are included. Standard errors are clustered at the county-year level. Point estimates are $\beta_t$ for all years $t$ in the sample, where $t$ = -1—the year before the shock—is the omitted period. Black circles indicate significant results at the 5% level, while hollow circles indicate statistically insignificant results from zero.

# A Appendix

## A1 Variable definitions

**Table A1:** Variable Definitions

| Variable | Description |
|---|---|
| Treat | Indicator variable that equals one for counties that were ever shocked by a natural disaster with damage value above 10 million USD, and zero otherwise |
| Post | Indicator variable that equals one for the years when and after the disaster happened, and zero before |
| Top 3 share of employment | The monthly fraction of employment of the top 3 companies at the 2-digit SIC level for each county |
| Top 5 share of employment | The monthly fraction of employment of the top 5 companies within each county at the 2-digit SIC level for each county. |
| g | The change in the number of firms divided by lagged plus current number of firms at the county-SIC2-year level |
| Entry rate | The number of new firms divided by the average of the lagged plus the current number of firms at the county-SIC2-year level |
| Exit rate | The number of firms that existed at t-1 but are no longer present at t, divided by the average of the lagged plus the current number of firms at the county-SIC2-year level |
| Unit price0 | The mean price obtained adjusting the sale price for packaging units at the product-module-code-county-year-month level |
| Unit price | The mean price at the product module code-county-year-month level, after adjusting for packaging units and dropping UPCs with price above 3 times the median price or below 1/3 of the median price |
| Sale-weighted price0 | Mean price obtained as (total sales in dollars/total units sold) at the product module code-county-year-month level, following Baker et al. (2024) |
| sale-weighted price | Mean price at the product module code-county-year-month level following Baker et al. (2024), after dropping UPCs with price above 3 times the median price or below 1/3 of the median price |
| Cheap | Indicator variable that equals one if a product's price ranked in the bottom quartile in 2006 within its product module code, and zero if it is in the top quartile |
| Essential | Indicator variable that equals one if a product is essential for daily life and disaster recovery |
| Sales | Sales at retailer-county-year level |
| Large retailer | Indicator variable that equals one for retailer whose total sales ranked above the top 10% in Nielsen in 2006 |
| Small retailer | Indicator variable that equals one for retailer whose total sales ranked below the bottom 10% in Nielsen in 2006 |
| Multiple | Indicator variable that equals one for counties that experienced more than one shock in the sample period |

**Table A2: GDP per Capita, Population, and Effects of Natural Disasters—Industry Dynamics**

Panel A: All Industries

| | By GDP per capita | | | By Population | | |
|---|---|---|---|---|---|---|
| | g (1) | Entry rate (2) | Exit rate (3) | g (4) | Entry rate (5) | Exit rate (6) |
| Treat x Post | -0.007*** | -0.004*** | 0.003*** | -0.007*** | -0.004*** | 0.004*** |
| | (0.001) | (0.001) | (0.001) | (0.002) | (0.001) | (0.001) |
| Treat x Post x GroupDummy | 0.002 | 0.003** | 0.002 | 0.001 | 0.001 | -0.001 |
| | (0.002) | (0.002) | (0.001) | (0.002) | (0.002) | (0.001) |
| Cohort x FIPS FE | Yes | Yes | Yes | Yes | Yes | Yes |
| GroupDummy x Cohort x SIC2 x Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj. R2 | 0.311 | 0.334 | 0.273 | 0.312 | 0.336 | 0.274 |
| No of obs | 3,643,226 | 3,643,226 | 3,643,226 | 3,643,169 | 3,643,169 | 3,643,169 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Wholesale and Retail

| | By GDP per capita | | | By Population | | |
|---|---|---|---|---|---|---|
| | g (1) | Entry rate (2) | Exit rate (3) | g (4) | Entry rate (5) | Exit rate (6) |
| Treat x Post | -0.008*** | -0.004*** | 0.003*** | -0.009*** | -0.005*** | 0.004*** |
| | (0.002) | (0.001) | (0.001) | (0.002) | (0.002) | (0.001) |
| Treat x Post x GroupDummy | 0.005* | 0.003 | -0.002 | 0.003 | 0.002 | -0.002 |
| | (0.003) | (0.002) | (0.002) | (0.003) | (0.002) | (0.002) |
| Cohort x FIPS FE | Yes | Yes | Yes | Yes | Yes | Yes |
| GroupDummy x Cohort x SIC2 x Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj. R2 | 0.264 | 0.252 | 0.267 | 0.265 | 0.255 | 0.267 |
| No of obs | 790,279 | 790,279 | 790,279 | 790,279 | 790,279 | 790,279 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports estimates from stacked triple-difference-in-differences regressions at the county-industry-year level following the specification below:

$$\mathrm{y}_{f,i,c,t} = \beta_0 \times \mathrm{Treat}_f \times \mathrm{Post}_t + \beta_1 \times \mathrm{Treat}_f \times \mathrm{Post}_t \times \mathrm{GroupDummy}_f + \mathtt{FE} + \epsilon_{f,i,c,t},$$

where $f$ refers to the county, $i$ to the 2-digit SIC code industry, $t$ to the year and $c$ to the natural disaster cohort. The dependent variables are the growth rate of the number of new firms, the entry rate, and the exit rate, defined as in Table 2. *Treat* takes the value of 1 for counties that were ever affected by a natural disaster with damage value above 10 million USD, and 0 otherwise. *Post* takes the value of 1 for the disaster year and the four subsequent years, and 0 in the four years before. GroupDummy is High GDP per capita in the first three columns and High population in the last three columns. We rank counties based on GDP per capita (column 1-3) and population (column 4-6) in 2006 into two groups and interact the dummy variable GroupDummy with *Treat*Post*. The sample covers all public and private firms in NETS from 2006 to 2020. We restrict the unit of observation to have at least two companies throughout the analysis period. We also restrict each county-cohort to have more than two years both before and after the shock. Panel A presents estimates for the whole sample of industries, while Panel B includes only observations relative to wholesale and retail. Fixed effects are included as indicated in the table. Standard errors are clustered at the county-year level and included in parentheses.

## Table A3: County Heterogeneity and Natural Disasters—Retail Prices

| | By GDP per capita | | | By Population | | |
|---|---|---|---|---|---|---|
| | Unit price | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Treat x Post | 0.023** | 0.027*** | 0.026*** | 0.016 | 0.020* | 0.020* |
| | (0.010) | (0.010) | (0.010) | (0.011) | (0.011) | (0.011) |
| Treat x Post x GroupDummy | 0.016 | 0.009 | 0.010 | 0.011 | 0.007 | 0.006 |
| | (0.012) | (0.012) | (0.012) | (0.013) | (0.013) | (0.013) |
| GroupDummy x Cohort x FIPS FE | Yes | Yes | Yes | Yes | Yes | Yes |
| GroupDummy x Cohort x Module code FE | Yes | No | No | Yes | No | No |
| GroupDummy x Cohort x Year FE | Yes | No | No | Yes | No | No |
| GroupDummy x Cohort x Module code x Year FE | No | Yes | No | No | Yes | No |
| GroupDummy x Cohort x Module code x Year-month FE | No | No | Yes | No | No | Yes |
| Adj. R2 | 0.786 | 0.797 | 0.803 | 0.793 | 0.808 | 0.817 |
| No of obs | 625,242,410 | 625,242,044 | 625,225,867 | 625,237,172 | 625,236,806 | 625,220,586 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports estimates from stacked triple-difference-in-differences at the product module-county-year-month level following the specification below:

$$\mathrm{y}_{f,p,c,t} = \beta_0 \times \mathrm{Treat}_f \times \mathrm{Post}_t + \beta_1 \times \mathrm{Treat}_f \times \mathrm{Post}_t \times \mathrm{GroupDummy}_f + \mathtt{FE} + \epsilon_{f,p,c,t},$$

where $p$ is the product module code, $f$ the county, $t$ the month, and $c$ the disaster cohort. The dependent variable is the unit price. *Treat* takes the value of 1 for counties that were ever affected by a natural disaster with damage value above 10 million USD, and 0 otherwise. *Post* takes the value of 1 for the disaster year and the four subsequent years, and 0 in the four years before. GroupDummy is High GDP per capita in the first three columns and High population in the last three columns. We rank observations based on GDP per capita into two groups and interact the dummy variable High GDP per capita with $Treat \times Post$ in columns 1 to 3. We rank observations based on population into two groups and interact the dummy variable High Population with $Treat * Post$ in columns 4 to 6. The sample covers all retail prices from Nielsen from 2006 to 2020. Standard errors are clustered at the county-year level and included in parentheses.

**Table A4: Robustness – Raw Prices**

| | Unit Price | | | Sale-weighted price | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Treat x Post | 0.033*** | 0.033*** | 0.033*** | 0.038*** | 0.037*** | 0.037*** |
| | (0.006) | (0.006) | (0.006) | (0.007) | (0.007) | (0.007) |
| Cohort x FIPS FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cohort x Module code FE | Yes | No | No | Yes | No | No |
| Cohort x Year FE | Yes | No | No | Yes | No | No |
| Cohort x Module code x Year FE | No | Yes | No | No | Yes | No |
| Cohort x Module code x Year-month FE | No | No | Yes | No | No | Yes |
| Adj. R2 | 0.840 | 0.852 | 0.858 | 0.841 | 0.852 | 0.857 |
| No of obs | 684,120,968 | 684,120,863 | 684,114,262 | 684,115,216 | 684,115,111 | 684,108,500 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports estimates from stacked difference-in-differences at the product module-county-year-month level following the specification below:

$$y_{f,p,c,t} = \beta \times \text{Treat}_f \times \text{Post}_t + \texttt{FE} + \epsilon_{f,p,c,t}$$

The dependent variables are module-county-month level unit prices (columns 1-2) and Baker et al. (2024) prices (columns 3-4), without winsorization. *Treat* takes the value of 1 for counties that were ever shocked by a natural disaster with damage value above 10 million USD, and 0 otherwise. *Post* takes the value of 1 for the years when and four years after the disaster happened, and 0 in four years before. The unit of observation is at product-module-code ($p$) by county ($f$) by year-month ($t$) level. The sample covers all retail prices from Nielsen during 2006 and 2020. Standard errors are clustered at the county-year level and included in parentheses.