Natural disasters and the gradual decline of main street*

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March 20, 2025

Abstract

This paper examines how natural disasters reshape county-level economic landscapes by analyzing foot traffic to local businesses. Perhaps surprisingly, there is little change in total foot traffic after disasters at the monthly level. However, publicly traded companies are able to capture a larger share of foot traffic after disasters, especially in the retail sector where foot traffic closely tracks sales. This cannot be explained by business size alone, but it is related to firms' cost of capital and geographic footprint. The counties seeing the greatest shift from small businesses to large public businesses are those with smaller, predominantly minority populations. Dollar stores, which are known to target these areas, see a sharp increase in foot traffic share that endures post-disaster, a trend mirrored in their stock performance. Overall, these findings reveal how certain business models benefit from disruptions in disaster-stricken communities.

keywords: natural disasters, public and private businesses, foot traffic, small businesses, dollar stores
JEL codes: Q54, L10, L20, D20

*Views and opinions expressed are those of the authors and do not necessarily represent official positions or policies of the OFR or Treasury. We thank John Bizjak, Mark Carey, Ding Du, Corey Garriott, Ben Gillen, Paul Irvine, Swami Kalpathy, Steve Karolyi, Dasol Kim, Vassil Mihov, Mark Paddrik, Toan Phan, Stacey Schreft, Alex Zentefis, and seminar participants at OFR, OCC, and Federal Reserve Bank of Philadelphia for helpful comments. All errors are our own. First version: March 2024.

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1 Introduction

Risks posed by natural disasters are of growing concern and, by all metrics, the number and intensity of disaster events is rapidly increasing (Hsiang and Kopp, 2018).[1] Such natural hazards affect households, communities, and businesses, potentially damaging property and impeding business activity. Of these potential impacts, little is understood about the direct impact of natural disasters on businesses, especially the small private firms that are likely hardest hit. Furthermore, even less is known about the impact of smaller-scale but more frequent disasters, as the majority of the extant literature focuses on larger-scale generational events (De Mel et al., 2012; Kocornik-Mina et al., 2020).

This paper provides a comprehensive cross-sectional view of the effects that natural disasters have on businesses, with a focus on smaller scale natural disasters that are becoming increasingly common. A challenge to answering this question is access to reliable data that is granular enough both in geography and also in time. We combine location-specific, monthly data on foot traffic to businesses from Safegraph with comprehensive data on disasters in the USA from SHELDUS to provide quantitative evidence on the dynamics of economic activity following natural disasters.

Using foot traffic data to proxy for economic activity offers a few distinct advantages. First, it provides visibility into small local businesses, which may not be possible with traditional datasets. To date, much of the work assessing small business recovery post-disaster has relied on survey evidence (Hiti et al., 2022). By contrast, foot traffic data has the potential to offer quantitative, objective insights into post-disaster recovery.[2] In addition, foot

[1] This includes large events worldwide, billion-dollar events in the USA, and smaller events in the USA.

[2] While administrative data at the establishment level could be used, it is not available at a high enough frequency to properly measure changes surrounding natural disasters.

traffic data is less endogenous to choices made by the firm that could impact traditional data on fundamental performance, such as possible discretion in reporting exhibited by both public and private firms (Schipper, 1989; Ball and Shivakumar, 2005; Dechow et al., 2010).

We employ a staggered difference-in-differences approach to study foot traffic dynamics at the county-month level. We compare foot traffic of counties that were hit and those that were not hit by natural disasters, both before and after disaster dates. Following recent advances in the literature on differences-in-differences with variation in treatment timing, we estimate robust coefficients following the methods proposed in Callaway and Sant'Anna (2021), Sun and Abraham (2021), and De Chaisemartin and d'Haultfoeuille (2020). Our main analyses rely on foot traffic shares within a county, which inherently controls for geography-specific trends and time-of-year patterns in foot traffic.

Our analysis focuses on 2019, when Safegraph data coverage begins, to ensure that our results are not driven by outcomes related to the COVID-19 pandemic. COVID directly impacted foot traffic to many businesses, making inferences problematic especially because its impact was heterogeneous across business type and size (Bartik et al., 2020; Humphries et al., 2020) as well as across county characteristics (Bizjak et al., 2022).

We find that that the natural disaster events we study do not impact total foot traffic at the monthly horizon, both in aggregate and to retail locations specifically. Relative to control counties, total foot traffic levels remain similar in disaster-stricken counties. This is consistent with a JP Morgan Chase study on Hurricanes Harvey and Irma which found that businesses recovered within weeks, rather than months (Farrell and Wheat, 2018). These findings indicate that any economic activity that is displaced by natural disasters recovers quickly. However, it is possible that these aggregate trends mask some heterogeneity in the

types of firms that are better-positioned to recover more quickly.

Given that natural disasters damage property, disrupt supply chains (Park et al., 2013), impact local labor supply (Tran et al., 2023), and necessitate significant capital reinvestment (Botzen et al., 2019), we hypothesize that firms with greater resources along these dimensions should better be able to recover. Publicly traded and private firms offer a natural divide to study this, as public firms typically have a larger geographic footprint (Cornaggia et al., 2021), have better access to the labor market and can better shift labor across locations (Borisov et al., 2021), and have access to cheaper financing (Goyal et al., 2011). To investigate this, we examine the *share* of foot traffic going to private firms within a county ("private share"). We find that a county's private share decreases following a natural disaster and continues to decrease up to 6-months post-disaster. We interpret this result as implying that public firms recover more quickly after a disaster, such that they capture and retain market share at the expense of private firms.

We focus the remainder of our analysis on retail stores to best highlight the industry for which the link between foot traffic and revenue is strongest. We test and find that the negative effects on private share are particularly strong for the retail industry. In the next section of the paper, we examine a few mechanisms by which public retail stores may be able to recover more quickly and effectively than private stores: public retailers are generally larger, have lower cost of capital, and are more geographically diversified.

To test for the impact of size, we examine foot traffic for the top three retailers in a county. If size is the primary driver of our findings, then these largest retailers should see an increased share of foot traffic following natural disasters. However, we find that the post-disaster share of foot traffic going to the top three retailers in a county remains stable. We then split the

sample into the top three public retailers and the top three private retailers in a county. We find that even when focusing on these largest retailers in a county, foot traffic share going to the top three private retailers decreases. Taken together, these findings suggest that size is unlikely the sole advantage public firms have in recovering business following a natural disaster.

The primary difference between public and private firms is that public firms have access to public equity markets and access to cheaper debt financing compared to private firms. This means that private firms have a higher cost of capital and so less access to cheap financing for rebuilding and reconstituting their places of business with inventory and employees. We examine this potential mechanism *within* public companies where we can measure cost of capital. Splitting public firms by their cost of capital, we find that firms with a lower cost of capital see an increase in their foot traffic following natural disasters, while those with a high cost of capital do not see an increased market share. Because private firms generally have a higher cost of capital, this indicates that cheaper financing may in part drive public firms' better resiliency to natural disasters.

Another salient difference between public and private firms is that private firms typically have a smaller geographic footprint (Cornaggia et al., 2021).[3] Geographic diversity could produce useful redundancies in a supply chain and in finding replacement labor, advantaging public firms in their recovery from natural disasters. Any advantage in sourcing products and labor could lead to greater market share. Moreover, geographic diversification provides businesses with valuable financial diversification, allowing for internal capital flows to cross-

[3]This may be the case, at least in part, because private firms have a more concentrated ownership and have less separation between ownership and control, making a smaller geographic footprint more advantageous to owners.

subsidize impacted locations. We find that retailers with another location outside of the impacted area increase their share of foot traffic. Furthermore, the effects are particularly strong for those with a store in an adjacent county to the one hit by disaster, indicating that ease of substitution along the labor and supply chain dimensions can aid in disaster recovery. When we split public and private firms by those with and without an adjacent store, we find that it is mainly the public retailers with an adjacent store that benefit from disaster, at the expense of private retailers without an adjacent store.

Next, we explore demographic heterogeneity between counties as previous survey evidence suggests that counties that are less populous or have higher minority populations face the biggest difficulty in recovering from natural disasters. In particular, survey evidence shows that small businesses, especially those owned by minorities, face the biggest challenges in disaster recovery (Hiti et al., 2022). With our data, we find that private share decreases are greatest in the bottom tercile of counties by population. Among these less populous counties, it is the bottom tercile of those counties by minority share that see even greater decreases.

A subset of public firms may take advantage of their resilience and ability to recover more quickly from natural disasters. Dollar stores such as Dollar Tree and Dollar General espouse an aggressive expansion model, particularly targeting less populous areas where real estate is comparatively cheap. Their store models are particularly resilient to natural disasters, with a product line that is uniform across stores making supply chains easy to restore or divert when necessary. In addition, dollar stores are smaller, have lower operating costs, and standardized floor plans compared to traditional retail stores, allowing them to quickly

construct and open new locations.[4] However, dollar store expansion has come at the expense of small corner stores and local grocery stores, and have been blamed for limiting access to fresh food in some portions of the country (Caspi et al., 2016). We explore foot traffic share going to dollar stores following natural disasters to explore the potential for dollar store resilience and adaptability. We find that the percent of retail foot traffic going to dollar stores spikes immediately in the month of the disaster, and remains elevated in the months following.

The final part of the paper examines stock market reactions to public retailers following natural disasters. There are two main forces at play, which pull in opposite directions. Recovering from natural disasters is costly, which can cut into profits. On the other hand, if public retailers can gain and retain market share post-disaster, elevated future cash flows can more than offset direct costs. We build a monthly time series of aggregate property damage from natural disasters going back to 1960, and find that higher damage in the current month predicts higher retail stock returns in the next month. This effect is even stronger when examining returns to dollar stores specifically.

Related Literature. This paper studies business outcomes related to natural disasters in the cross-section, which is relatively under-explored. The majority of work in this area focuses on a single event and assesses impact and recovery using survey data. A number of papers focus on real estate and household outcomes and find nuanced patterns of destruction and recovery (Issler et al., 2021; Tran et al., 2023). Dahlhamer and Tierney (1998) survey businesses following the 1994 Northridge earthquake and find size to be an important

[4] CNN: Dollar stores are everywhere. That's a problem for poor Americans

determinant of a firm's ability to recover. Lee (2019) surveyed businesses after Hurricane Harvey and found property damage, loss of employees, and demographic effects to directly impact reopening probability. Collier et al. (2020) also survey businesses exposed to Hurricane Harvey and find that independent businesses struggled while larger firms did not show signs of distress. A number of papers also use data on light intensity at night as a proxy for economic activity to analyze post-disaster effects (Barton-Henry and Wenz, 2022; Kocornik-Mina et al., 2020; Qiang et al., 2020). This paper complements the existing literature by providing a quantitative highly granular view of the dynamics of economic activity across different types of businesses, and for a myriad of disaster events.

A related literature examines the causal impact of natural disasters on economic growth. On the one hand, a natural disaster could lead to increases in economic activity, stimulating innovation (Skidmore and Toya, 2002), or driving the replacement of an outdated capital stock (Crespo Cuaresma et al., 2008; Hallegatte and Dumas, 2009). On the other hand, growth could suffer for a short time, eventually returning to baseline, due to the time it takes for the migration of capital and people (Yang, 2008; Strobl, 2011), or there could be no recovery to baseline if the loss of capital is sufficiently large (Field et al., 2012). For example, countries experiencing extremely damaging cyclones appear to see permanent drops in economic growth (Hsiang and Jina, 2023; Bakkensen and Barrage, 2019). Using highly granular within-country dynamics, we complement these findings by showing that the typical disasters businesses face do not produce discernible reductions in economic activity on aggregate. Nonetheless, we find that public firms are better able to take advantage of the disruption produced by natural disasters, something that cannot be explained by *county*-level trends in economic activity.

Our findings also fit within a strand of literature on business preparation and outcomes as it relates to natural disaster risk. Jia et al. (2022) find a negative relationship between flood risk and firm entry, employment, and output. Addoum et al. (2020) and Addoum et al. (2023b) study the impact of extreme temperatures on business outcomes. They find no impact on sales, but find that extreme temperatures impact corporate profitability. Addoum et al. (2023a) find that wildfire smoke negatively impacts store visits and sales. Our paper complements these findings by studying a wide range of natural disasters and providing some visibility into non-public, small businesses for which data is often not available.

Finally, we add to the discussion surrounding the expansion of dollar stores across America. Dollar stores can crowd out local supermarkets and corner stores, limiting access to fresh food (Chenarides et al., 2021; Caspi et al., 2016). Dollar stores target lower cost areas, and their relative advantage comes from their efficient supply chain, access to cheap financing, and geographic diversification (Hitt, 2011). As it relates to our results, all of these are factors that also make dollar stores more resilient to disasters.

Organization. The remainder of the paper is organized as follows. Section 2 introduces the data. Section 3 discusses the empirical design. Section 4 presents the main results. Section 5 shows results for dollar stores. Section 6 shows evidence on stock market reactions. Section 7 concludes.

2 Data and Sample Construction

2.1 Natural Disaster Data

We use data on natural disasters from the Spatial Hazard Events and Losses Database for the United States (SHELDUS). SHELDUS contains monthly data on counties impacted by natural hazards such as thunderstorms, floods, wildfires, floods, and tornadoes going back to 1960. Importantly, the dataset also includes information on the aggregate and per capita dollar amounts of damage caused. SHELDUS sources its data from National Centers for Environmental Information (NCEI) Storm Data, and takes the lower estimate of damages when NCEI reports a range of damages. Therefore, property damages in SHELDUS can be thought of as a lower bound (see Wylie et al. (2024) for a longer discussion).

Table 2 Panel A shows the process by which we select disaster-stricken counties to use as our control and treated samples. Due to limitations in the foot traffic data we describe in **Section 2.2**, we restrict our focus to events occurring in 2019 for our primary analysis. However, we use events in 2018 to filter out previously impacted counties that are unsuitable to use as a treatment or control county. This leaves a total of 22,791 county-month events in the SHELDUS sample covering 2018 and 2019.

The dataset is quite comprehensive, so it also includes many small disaster events. We restrict our sample to disasters that caused at least $100,000 in property damage (in 2019 dollars) and at least $3.58 property damage per capita (in 2019 dollars), both of which represent the top 10% of most destructive events in the sample. This leaves 1,553 unique county-months that were impacted by a sufficiently damaging natural disaster. 814 out of 1,553 are from 2019, our primary sample period.

2.2 Foot Traffic Data

We use the Safegraph database to collect data on foot traffic. SafeGraph gathers GPS data from users' mobile phone applications and offers granular information on store traffic for both public and private businesses. This data provides us with a real-time indicator of economic activity that will be important in assessing the impacts of natural disasters, which can have both immediate and long-lasting effects.

Safegraph covers over 13 million points of interest (POIs), including public and private companies in industries such as retail, food service, hotel, and entertainment. We aggregate the foot traffic data to the county-month level, which is the main unit of analysis in this paper. For POIs that are associated with publicly traded corporations, Safegraph provides the stock symbol of the corporation. This link enables us to connect POIs with their respective corporate entities and decompose the total foot traffic into components attributable to public and private businesses.

Our sample begins in January 2019, and we restrict our analysis to 2019 in order to avoid the COVID-period effects that greatly impacted foot traffic dynamics. It is especially important for us to remove the COVID period because we are interested in studying differential impacts of natural disasters on private businesses. Prior research has shown that small businesses were impacted very differently, oftentimes harder, by COVID due to being more financially fragile and having a more difficult time accessing aid from the CARES act (Bartik et al., 2020; Humphries et al., 2020). In addition, even though our main analysis is at the county-level, counties differed in their restrictions such as mask mandates and quarantine periods (Bizjak et al., 2022). As a result, the effects of natural disasters on businesses during

the COVID period may be different than during non-pandemic times. The main analysis in this paper is cross-sectional in nature, comparing disaster-stricken counties with unaffected counties. Therefore, we are able to isolate changes in foot traffic dynamics to treated counties even with a relatively short time period.

2.3 Merged Sample

We merge natural disaster shocks from SHELDUS with our Safegraph sample. **Table 2 Panel B** shows the filters we employ to create our final sample of treated and control counties. For 2019, there are a total of 3,391 counties covered in Safegraph. First, we restrict the sample to counties that did not experience a qualifying disaster in 2018.[5] Because we explore foot traffic dynamics up to 6+ months post-disaster, this ensures that we are not picking up effects from a previous shock. Next, we cut out counties that were hit by multiple disasters in 2019 in order to isolate the effects of a single disaster. Finally, we restrict to counties in the Safegraph data for which we have observations for every month in 2019 and for which total foot traffic to retail institutions in January 2019 was at least 1,000.[6]

The final sample includes 2,397 counties, including 387 treated counties and 2,010 control counties. **Figure 1** shows the geographic distribution of treated and control counties throughout the United States. Treated counties are not concentrated in a particular geographic area, save for a cluster of counties in Southwest Michigan hit by wind and winter

[5] As described in Section 2.1, qualifying disasters amount to at least $100,000 in property damage (in 2019 dollars) and at least $3.58 property damage per capita (in 2019 dollars).

[6] In order to protect users' privacy, Safegraph obscures true visitor counts in a way that makes data more noisy for areas with low raw count (see Sakong and Zentefis (2023)). Our restriction of at least 1000 total visitor counts in a county-month cuts out a small number of counties for which this issue can be prevalent, as well as counties where Safegraph coverage may be poor.

weather storms in February 2019.[7] **Table 3 Panel A** shows the distribution of treated counties by month and disaster type. Although a sizable portion of treated counties are hit between February and May (corresponding to heavy flooding months and tornado season in the USA), there is substantial variation in treatment month and disaster type. It is useful for us that a small majority of treatments happen in the first half of the year because it helps us estimate the longer-run impacts of disasters on foot traffic.

Table 3 Panel B shows summary statistics on the amount of damage caused by natural disasters in the treated counties. The distribution is right skewed, with the average affected county having $12 million in property damages ($112 per capita), and the median affected county having $550,000 in property damages ($20 per capita).[8]

2.4 Supplementary Data

We supplement our primary datasets with data on county-level population and minority share as of 2019 from the U.S. Census Bureau. We use these variables in heterogeneity analysis to identify counties where the effects on foot traffic may be stronger.

Our stock market data comes from standard sources. We download monthly data on returns to Fama-French factors and industries from Ken French's website. Returns to individual dollar stores (Dollar Tree and Dollar General) are from CRSP.

[7] All results shown in this paper are robust to removing Michigan.

[8] **Appendix Table A1** splits the sample of SHELDUS disasters into those that were a FEMA-declared disaster and those that were not. FEMA-declared disasters tend to be slightly larger in terms of both total property damage and property damage per capita. Our main results are similar for the sample of FEMA-declared disasters and the remaining disasters in the SHELDUS data.

3 Empirical Design

3.1 Variable Construction

All of the variables of interest are aggregated to the county-month level, which is the level of observation in the SHELDUS natural disasters data. Because the SafeGraph foot traffic data is highly granular, it further allows for different aggregations by business types or characteristics based on the questions we wish to answer. For example, we are particularly interested in the share of foot traffic that goes to specific sectors such as retail, and specific business classifications such as public vs. private firms. Furthermore, we can split foot traffic shares by business characteristics such as size, cost of capital, and geography.

Our variables of interest, all of which are measured at the county-month level, are described in **Table 1**. First, we construct variables of per capita foot traffic going to all points of interest and then specifically to retail businesses, the industry most dependent on foot traffic for cash flows. For our main analyses, we also identify the shares of foot traffic going to different business types. Private share measures the proportion of foot traffic that goes to businesses not owned by a public corporation. Importantly, the private share measure captures foot traffic share to small local businesses. To assess mechanisms, we use foot traffic share to stores based on size, cost of capital, and geography. In the final part of the paper, we dig deeper on the foot traffic share of a specific type of retailer, dollar stores, whose business models may provide them an advantage following natural disasters. The value of using share measures is that any tests we run inherently control for county-level patterns in total foot traffic, and the measure is also more easily comparable across counties.

Table 4 shows summary statistics for variables of interest. In **Panel A**, we explore

total foot traffic at the county-month level. The average county has around 350,000 visits to points of interest per month, with 280,000 of that going to private companies. Out of the numerous industries covered, retail makes up the largest percentage of visits at around 30%.

Table 4 Panel B shows summary statistics for total foot traffic scaled by county population. This is one of our main variables of interest, and allows for easier comparability between counties than total foot traffic. Safegraph data picks up around 2.25 total visits per person per month, with 0.87 going to retail businesses. This scaled measure is less skewed than total foot traffic. The standard deviation of per capita foot traffic across the whole sample is 1.35, while the within-county standard deviation is 0.33.

Table 4 Panel C shows summary statistics for variables of interest that we constructed related to proportions of foot traffic going to specific types of stores. For the average county, foot traffic to private businesses makes up 76% of total foot traffic. Within retail, the split between public and private is more balanced: around 60% of foot traffic goes to private businesses while 40% are accumulated to large public retailers such as Walmart and Target. **Figure 2** shows the geographic distribution of private share, which is lower in the Southeastern and Midwestern counties where big box retailers have proliferated. Retailers with multiple storefronts make up around 60% of the total retail foot traffic while dollar stores have a smaller but meaningful 7% share.

There is sizable variation across counties in these metrics, but the distribution of foot traffic *within county* is relatively sticky. For example, the standard deviation of retail private share within county is 2.0% (compared to 13.7% for the full panel) and the standard deviation of dollar store share within county is 0.7% (compared to 5.7% for the full panel). Our main analysis will study within-county changes in foot traffic patterns, so the within-county

standard deviations serve as the important frame of reference.

3.2 Differences Between Treated and Control

Table 5 shows differences between treated and control counties. Treated counties are slightly smaller in terms of population and along total foot traffic measures, but the differences are not statistically significant. There is very little difference between treated and control counties for our main variables of interest, *private share* and *dollar store share*. On average, 63% of foot traffic goes to private retailers in treated counties, compared to 62% of foot traffic in control counties. Differences in dollar store share are even smaller: 6.9% of retail foot traffic goes to dollar stores in treated counties compared to 6.8% in control counties. Given that the shocks we are studying are weather-related events that hit counties indiscriminately, it is not surprising that differences between treated and control counties are small.

3.3 Empirical Tests

We estimate the causal impact of natural disasters on foot traffic dynamics through a difference-in-differences strategy allowing for staggered treatment periods. The baseline specification we consider is a two-way fixed-effect (TWFE) model. First, we run a static version to recover the average treatment effect on the treated:

$$Y_{c,t} = \beta \times Dis_c \times Post_{c,t} + \alpha_c + \delta_t + \epsilon_{c,t} \tag{1}$$

where $Y_{c,t}$ is a variable of interest at the county-month level from **Section 3.1**, Dis_c is an indicator equal to 1 if the county was impacted by a disaster, and $Post_{c,t}$ is an indicator

equal to 1 if a month period is after the disaster for a particular county. α_c represent county fixed effects and δ_t represent time fixed effects. The coefficient of interest, β, is the static effect of being hit by a disaster on various foot traffic metrics of interest.

In order to examine pre-trends and time dynamics, we also run a specification that allows for identification of the treatment effect in each month relative to the disaster event:

$$Y_{c,t} = \beta_{\mathbf{i}} \times Dis_c \times \sum_{i=-4}^{8} (RelativeMonth_{c,i}) + \alpha_c + \delta_t + \epsilon_{c,t} \tag{2}$$

where $RelativeMonth_{c,i}$ is a set of indicator variables equal 1 if, for county c, the disaster event month was i months away. We use foot traffic in month -1, the month directly preceding the disaster, as the omitted month.

Recent advances in the staggered difference-in-differences literature have shown that the conventional TWFE approach may be biased if treatment effects are not homogeneous across groups or time. This is certainly a concern in our setting, where the treatment is based on unpredictable natural disaster events that are distributed unevenly across counties and months. Therefore, we re-estimate equations (1) and (2) using robust estimators introduced in Callaway and Sant'Anna (2021) [CS, henceforth], Sun and Abraham (2021) [SA, henceforth], and De Chaisemartin and d'Haultfoeuille (2020) [DD, henceforth].

4 Results

4.1 Total Foot Traffic

In order to assess the direct impact of natural disasters on foot traffic, we first run specifications (1) and (2) with per capita foot traffic as the variable of interest. **Table 6 Panel A** shows the impact of natural disasters on county-level per capita foot traffic using the baseline TWFE specification and the more robust specifications. In general, we do not find an impact on total foot traffic: the $Dis \times Post$ coefficient is insignificant for each of the specifications. **Figure 4 Panel A** shows the dynamics of foot traffic in treated versus control counties in the months preceding and directly following month 0, the month of the disaster. There is little pre-trend prior to the disaster, and there is also little action post-disaster.

Table 6 Panel B and **Figure 4 Panel B** restrict the sample to only retail businesses. Retail is of particular interest because the link between foot traffic and business cash flow is strongest for this industry. In terms of per capita foot traffic, The pattern we observe for retail is similar to the whole sample. There is little pre-trend prior to disaster, and disaster impacts on per capita foot traffic are small both in aggregate and when splitting into post-disaster months. To our knowledge, this is the first evidence documenting that total foot traffic is relatively unaffected on the monthly time horizon for a diverse set of counties and disaster types.

4.2 Private vs. Public Share of Foot Traffic

Natural disasters are disruptive, both to consumer behavior and to the operations of firms. Moreover, natural disasters may harm physical capital, requiring swift and substantial rein-

vestment by firms. With that in mind, we turn our attention to the heterogeneity in economic impacts across firms. Given the volatility and disruption caused by natural disasters, firms that are more resilient to and better equipped to recover from natural disasters may have an opportunity to garner market share.

In particular, we hypothesize that relative to private stores, stores owned by public companies should be more resilient to disasters as a result of their geographic diversification, more established supply chains, and better access to capital to facilitate recovery investment via cheaper financing. To test this, we build a measure of *private share*, which is the percent of foot traffic going to private businesses.

Table 7 Panel A shows how *private share* is impacted by natural disasters for all businesses. We find that, on average, private share in treated counties drops by around 0.2% in treated counties post-disaster. This represents around a 0.14 within-county standard deviation change in private share, an economically meaningful change in a measure that tends to be persistent within-county.

Figure 5 Panel A shows the dynamics of how private share evolves in the months around natural disasters. There is no noticeable pre-trend in the months leading up to the event month. Post-disaster, private share trends downward until around month 5 before stabilizing. At the trough, private share drops around 0.45%, equivalent to 0.31 within-county standard deviations.

Next, we examine retail businesses specifically and show results in **Table 7 Panel B**. For retail stores, private share in treated counties drops by around 0.5% on average post-disaster, representing a 0.25 within-county standard deviation change in private share. **Figure 5 Panel B** again shows that there is no discernible pre-trend in retail private share. The

effect is persistent up to 6+ months post-disaster and reaches a trough of around 0.75%.[9]

Taken together with the results in **Section 4.1**, which showed little change in the total foot traffic following disasters, our private share results point to large public companies gaining market share post-disaster. This happens even as the total size of the foot traffic pie remains constant. The effects are persistent in the 6+ months after disaster. We cautiously interpret this as evidence that natural disasters may lead to persistently elevated future cash flows for large public companies. In sum, public firms are likely advantaged by their greater resiliency to and quicker recovery from natural disaster risks.[10]

4.3 Potential Mechanisms

In this section, we explore the likely mechanisms driving the decline in foot traffic share to private firms following a natural disaster. We show that while larger stores are likely to better sustain under disaster conditions, even the largest private retailers in a county suffer foot traffic losses. We also find that, among public companies, it is those firms with below median weighted average cost of capital that are able to take advantage of disaster conditions, whereas those with higher than median weighted average cost of capital see no benefit. This finding on the intensive margin of public companies highlights the likely impact that higher cost of capital has for private firms in sustaining and recovering following natural disasters.

[9] In **Appendix Figure A1**, we study total foot traffic and private share to hardware stores, which are a subset of retail businesses. We find a small increase in foot traffic to hardware stores around month 0 and month 1 after disaster that dissipates in the months after, consistent with rebuilding efforts in the immediate aftermath. The private share of foot traffic to hardware stores does not systematically increase post-disaster. The lack of lasting effects for hardware stores suggests that our main results are not driven by this specific type of store.

[10] In **Appendix Figure A2**, we also examine the extensive margin of store closings and find little direct evidence of increased store closures following natural disasters. We define a store closure as an instance where foot traffic to a store dropped by at least 90% relative to the beginning of the period.

Finally, we explore whether impacted businesses have other locations, with a particular focus on those with locations in adjacent counties. We document that geographic diversification is an important driver of increased foot traffic share following natural disasters.

For the remainder of the paper, we focus on retail businesses, the sector that is most impacted by disasters and relies most on foot traffic for their cash flows. Throughout the analysis, we aggregate foot traffic to stores of different types in order to study potential mechanisms involved in public stores capturing and maintaining greater market share following natural disasters.

4.3.1 Size

Public and private firms have many differences but chief among them is size. Large firms have more resources (employees, capital, connections), are typically older and have more experience, and are necessarily more structured, all of which could aid in recovery from a natural disaster. On the other hand, larger firms have a greater disconnect between ownership and management, have more decentralized control, and occupy a greater footprint from which to suffer from disasters, all of which could impede recovery from a natural disaster. We test whether or not size is a determining factor in disaster resiliency and recovery.

We measure size using beginning of period foot traffic data. This self-contained measurement allows for internal consistency across tests and direct comparisons to the tests we performed earlier. Moreover, focusing on foot traffic produces a consistent comparison across public and private firms, while focusing on heterogeneity related to the measure of economic impact we are most interested in evaluating. Given the lack of quality data on

private firm qualities such as assets held and other balance sheet items, this also ensures that any measurement error biases against our findings.

We construct county-level measures of the pre-period share of retail foot traffic going to the top three stores in a county (*Top 3 Share*). We do this for all counties and also create analogous measures for the share of foot traffic going to the top three public stores (*Top 3 Public Share*) and the share of foot traffic going to the top three private stores (*Top 3 Private Share*). It is useful to note that the unconditional average *Top 3 Public Share* (19.34%) is very similar to the unconditional average *Top 3 Private Share* (17.85%). This means that the size and concentration of public and private retail stores is comparable within-county, and differences we observe between the effects of disasters on *Top 3 Public Share* and *Top 3 Private Share* may be attributed to the public-private divide.

We estimate specifications (1) and (2) with each of these seize measures as dependent variables. **Figure 6** displays point estimates and 95% confidence intervals demonstrating how *Top 3 Share*, *Top 3 Public Share*, and *Top 3 Private Share* evolve differently in treated and control counties surrounding disaster events. Importantly, there is little detectable pre-trend for any of the three variables. **Table 8 Panel A** shows that there is no significant difference between treated and control counties in the proportion of foot traffic going to the top three retailers following natural disasters. In other words, larger establishments are no better at recovering from disasters.

When we redefine our tests using the top public and top private stores in a county, a different pattern emerges. As shown in **Table 8 Panel B**, the share of foot traffic going to the top three public stores increases in the months following a natural disaster. In contrast, **Table 8 Panel C** demonstrates that the share of foot traffic going to the top three private

stores decreases. In total, these tests indicate that size is not the only differentiating factor between public and private firms that drives resiliency. Because large public stores and large private stores see a divergence in foot traffic share, other inherent qualities must play a role.

4.3.2 Cost of Capital

Natural disasters are disruptive in ways that incur substantial costs for firms. Whether it is repairing physical premises, spending to replace inventory, or hiring additional employees, a business will recover more quickly if it has access to cheaper sources of financing. One key difference between private firms and public firms is access to public equity markets. Access to public equity markets provides investors in that firm with diversification and the public firm with an additional option that private firms do not have. This means that, all else equal, a public retailer should have a lower cost of capital, so cheaper financing, than a private firm.

We examine the role of cost of capital on the intensive margin within public firms. We do this for two reasons. First, the cost of capital for private firms is, by the nature of private firms, difficult if not impossible to measure. However, we can draw some interesting conclusions by examining heterogeneity within public firms. If public companies with lower cost of capital are those that benefit following natural disasters, that would imply that private firms' higher cost of capital may impede disaster recovery efforts, leading to decreased market share post-disaster.

We construct firm-level measures of the weighted average cost of capital for all public retailers in our sample. We then separate public companies into those that have below-median (*Low WACC Public Share*) vs. above-median weighted average cost of capital (*High WACC Public Share*). We estimate specifications (1) and (2) with each of these as dependent

variables. **Figure 7** displays point estimates and 95% confidence intervals demonstrating how *Low WACC Public Share* and *Low WACC Public Share* change differently in treated and control counties surrounding disaster events. **Table 9 Panel A** shows that there is a significant difference between treated and control counties in the proportion of foot traffic going to those public retailers with below median WACC following natural disasters. **Table 9 Panel B** shows that there is no such effect for public retailers with above median WACC.

Because banks constrain the use of credit facilities by borrowers (Sufi, 2009), it is likely that firms with access to cheap capital will also be able to access capital more quickly via, for example, revolving lines of credit. Firms with access to public debt (Santos and Winton, 2008) and public equity (Saunders and Steffen, 2011; Schenone, 2010) markets face cheaper bank spreads on average. In this context, our findings suggest that a firm's cost of capital has strong effects on their ability to recover more quickly and efficiently following natural disasters. In other words, it is likely that private share decreases in part due to private firms having a higher cost of capital, and therefore less access to cheap financing to rebuild, buy inventory, and otherwise reconstitute the business.

4.3.3 Geographic Diversification

Natural disasters impact geographies heterogeneously. Thunderstorms, tornadoes, floods, wildfires, and even hurricanes are localized or regional phenomena, impacting one county and not another. Because public firms have more locations on average, they are more geographically diversified compared to private firms. This means public firms are more likely to have a location that is not impacted. This could aid in resilience through a few different channels via the unfettered operations at other locations, such as unimpeded cash

flows, inventory management, trained (and transferable) employees, and a diversified supply chain.

We investigate whether geographic diversification is driving the differences between public and private firms. We classify firms into those that have at least one location in a separate county. Importantly, this group of stores is comprised of both public and private retailers.[11] We run specifications (1) and (2) with share of foot traffic to geographically diversified stores as the dependent variable. **Table 10 Panel A** shows that this increases by about 0.35% on average post-disaster, equating to 0.16 within-county standard deviations. **Figure 8 Panel A** shows that the share is elevated starting around 1 month post-disaster, remains elevated throughout the post period, and peaks at about 0.53% six months after disaster.

Next, we dig deeper into the subset of stores with multiple outlets and test whether the presence of a store in an *adjacent* county helps in terms of recovery and capturing market share post-disaster. Having a neighboring store can be important above and beyond just having multiple outlets because labor and supplies can be more easily shifted to the disaster-stricken location. In each county, we split the sample of retail stores into those that have a store in an adjacent county, and those that do not. **Table 10 Panel B** and **Figure 8 Panel B** show the dynamics of foot traffic to retail stores with an outlet in an adjacent county following a disaster. The market share captured by these particular stores grows significantly post-disaster, at around 0.45%, representing an even larger rate than just stores with multiple outlets.

In the final part of this section, we double-split stores in our sample along the public-

[11] **Table 4 Panel C** shows that on average, a county sees 60.9% of retail foot traffic go to geographically diversified stores, compared to 38.1% going to public retail stores.

private dimension and the dimension of whether or not they have a store in an adjacent county Results for public stores are shown in **Panels C** and **D** of **Table 10** and **Figure 8**, and results for private stores are shown in **Panels E** and **F** of **Table 10** and **Figure 8**. We find that the majority of the main documented effect on private share decreasing following disasters is driven by an increase to public stores *with* an adjacent store, at the expense of private stores *without* an adjacent store. Public retailers with an adjacent store see an increase of around 0.53% in foot traffic share, while private retailers without an adjacent store see a drop of around 0.43%. Taken together, these results suggest that a combination of both the public-private divide and having another store in an adjacent county are important factors in business recovery following natural disasters.

4.4 Heterogeneous Effects

Recent literature in economics has shown that vulnerable populations, particularly those living in poorer, less populous, higher minority regions bear a disproportionate share of natural disaster risk (Avtar et al., 2021; Wylie et al., 2024). As it relates to businesses, the disproportionate impact of natural disaster risks is less studied, mostly due to data limitations. Thus far, the most convincing evidence has come from surveys such as the Federal Reserve's Small Business Credit Survey (SBCS). Using the SBCS, authors have found that minority-owned small businesses are the most vulnerable to disaster-related losses (Hiti et al., 2022). While the survey evidence is useful and important, we aim to fill a gap by being among the first to provide quantitative evidence that private and small businesses in vulnerable communities bear the brunt of the impact of natural disasters. One limitation

we face relative to survey evidence is that we do not have the exact identities of business owners, so we must rely on county-level demographics as a proxy.

We first split our sample of counties into terciles based on county population and study the effect of natural disasters on private share separately for the three groups. The results are shown in **Table 11**. **Panel A** shows that private share drops by over 0.95% for low population counties following a natural disaster event, almost twice as large as the observed effect across the whole sample. When splitting counties by minority share, as in **Panel B**, high minority share counties experience a slightly higher drop in private share compared to low minority share counties, but the difference is much smaller than for splits by population. However, the effects for high minority counties are not evenly distributed. **Panel C** analyzes the subsample of low population counties following a double split by population and minority share. Within counties in the lowest tercile of population, those that are also in the highest tercile of minority share experience an over 1.9% drop in private share following natural disasters. The 1.9% drop is almost four times as large as the full sample effect, and reflects close to a 1 within-county standard deviation drop in private share. This is evidence that small private businesses in areas that are typically thought of as more vulnerable struggle disproportionately post-disaster.

5 Dollar Stores

"I would tell you we do very good in good times and we do fabulous in [. . .] in bad times."

–Todd Vasos, CEO, Dollar General, May 28, 2020

Dollar stores are a unique subset of public retailers that may be best positioned to take

advantage of natural disasters as a result of their business model. Dollar stores target rural, low-population, and low real estate cost areas where private, small retailers have historically operated. They leverage their robust supply chain to provide goods and shelf-stable groceries to people at lower costs. However, recent research argues that the success of this model contributes to the proliferation of a phenomenon referred to as "food deserts," wherein communities face limited access to affordable healthful foods. The focus on cheap, shelf-stable groceries has potentially crowded out small retailers that typically supply fresher groceries but at higher costs (Chenarides et al., 2021).

Importantly, in the context of our paper, dollar stores' optimized supply chain over a diverse geography and access to cheap capital via public markets can help them recover much more quickly post-disaster. In addition, natural disasters may depress the value of real estate in an area (Addoum et al., 2021; Clayton et al., 2021), making it easier for dollar stores to expand. **Figure 3** shows the geography of dollar store share, which is higher in the Southeast, Mid-Atlantic, and Midwest at the expense of private businesses (as seen in **Figure 2**). Interestingly, these high dollar store share regions are also among the highest natural disaster risk areas as documented by Wylie et al. (2024).

Table 4 Panel C shows that foot traffic to dollar stores makes up a significant portion of retail foot traffic within counties. On average, 7.14% of retail foot traffic goes to dollar stores, equally weighted. This is a strikingly large percentage for just three chain retailers, and makes evident the proliferation of dollar stores in the USA. The standard deviation of dollar store share across the entire panel is 5.68% (compared to 0.73% within-county), meaning that there is sizable variation across counties in this measure. Congruent with their business model, dollar store share is generally higher in low population, rural areas compared

to higher population metro areas.

Table 12 shows how dollar store foot traffic share is impacted by natural disasters. We find an average increase of around 0.25% post-disaster, equivalent to 0.34 within-county standard deviations and 4.2% of the median dollar store share. **Figure 9** shows that the effect peaks two months post-disaster at 0.35%, but stays elevated up to 6+ months out. These results suggest that natural disasters present an opportunity for dollar stores to gain market share. Moreover, these stores appear to be able to retain their newly acquired customer-base in the following months.

Notably, the effect on dollar store foot traffic share is positive and significant across most specifications starting in the event month. This may be due to people going to dollar stores to find supplies in anticipation of natural disasters. Alternatively, in contrast to other businesses, dollar stores often choose to remain open in the days and hours directly prior to, during, and following disasters. While this can boost their sales in times of disaster,[12] it comes at the cost of worker safety and is consistent with some OSHA complaints that have been filed against Dollar Tree, Family Dollar, and Dollar General.[13] There are also reports of dollar stores raising prices on essential supplies prior to hurricanes, which has the potential of increasing revenue per unit of foot traffic.[14]

[12] Reuters: Dollar General's comp sales, profit beat on hurricane-fueled demand

[13] OSHA: Department of Labor announces corporate-wide settlement agreement with Dollar Tree, Family Dollar to address hazards at thousands of US stores

[14] ABC News: Price gouging concerns hit Tampa ahead of Hurricane Dorian; Miami Herald: Reasonable profit or price gouging? State attorney investigating complaints

5.1 Heterogeneous Effects for Dollar Stores

Part of the informal business model of dollar stores is to target communities in less populous, rural areas for expansion (Lopez et al., 2023). Our results suggest that natural disasters may help expedite the process by which dollar stores gain market share once they have opened stores. Combining these insights, we test whether dollar stores are disproportionately effective in capturing market share post-disaster in the low population counties they typically target.

Table 13 Panel A splits counties into terciles by population, testing for differential impacts between these three groups. We find that dollar store share rises the most in bottom tercile counties by population in the post-disaster period. For low population counties, the size of the effect is around 0.4%, about 1.8 times larger than the full sample average. This is evidence that natural disasters can expedite dollar store expansion, especially in the low population areas they typically target.

Table 13 Panel B shows tercile splits by minority share and does not reveal sizable differences in tested effects across counties. Finally, we examine a double split between population and minority share. **Panel C** shows results for the low population subsample. Although the coefficient is dependent on the exact specification and lacks statistical significance in some cases, the size of the coefficient is notably higher for low population, high minority counties. This is suggestive evidence that the effects of dollar store expansion may disproportionately impact minority groups, at least in low population counties.

6 Stock Market Reactions

The implications of natural disasters for investors are theoretically ambiguous. On the one hand, natural disasters disrupt operations and cause direct property damage that is costly for retailers to repair. On the other hand, our foot traffic results suggest that public firms may be able to capture foot traffic share from private businesses post natural disaster. If foot traffic reflects market share, garnering greater foot traffic should translate to elevated cash flows in the future. It is therefore an empirical question whether public firms' market reactions to natural disasters are positive or negative.

We leverage the longer time period of the SHELDUS data to test stock market reactions following natural disasters. We aggregate property damage (in 2019 dollars) each month and examine returns to specific firms and industries in the month following. For each firm or portfolio of firms, we calculate the monthly 4-factor (Fama and French 3-Factor plus Momentum) adjusted return.

The first group of firms we examine are dollar stores, which experience a spike in foot traffic during the month of the disaster that remains elevated at least six months in the future. There are two publicly traded dollar store stocks in the United States, Dollar Tree and Dollar General. In **Table 14 Panel A**, we regress monthly 4-factor adjusted returns on the natural logarithm of the past month's total property damages, $log(DMG_{t-1})$. In Columns (1)-(3) , we show that a 1 standard deviation increase in past month $log(DMG_{t-1})$ is associated with a 1.28% increase in Dollar Tree's 4-factor adjusted return in the current month and a 0.71% increase in Dollar General's 4-factor adjusted return in the current month. The average effect on dollar stores is a statistically significant and economically

meaningful 1.21% increase in the 4-factor adjusted return.

The remainder of **Table 14 Panel A** shows the relationship between lagged disaster-caused property damages and retail-related industries as defined by Fama and French. In Column (4), we report that the 4-factor adjusted return of "Retail" from Fama and French's 49 industry portfolio is positively related to lagged damage. A 1-standard deviation increase in past month $log(DMG_{t-1})$ is related to a 0.20% increase in the Retail portfolio return. In Column (5), we report the return of the more broadly-defined "Shops" portfolio from Fama and French's 10 industry classification, which includes wholesale and some services in addition to pure retail. The effect is slightly smaller, at 0.16%, and is not statistically significant. **Table 14 Panel B** shows the performance of the other Fama-French 10 industries post disaster. Relative to the other industries, Shops performs by far the best following months with significant damages due to natural disasters.

7 Conclusion

Natural disasters and their impacts on firms have come under greater scrutiny in recent times. In this paper, we study the heterogeneous impacts of natural disasters on businesses using data on foot traffic to local businesses. The foot traffic measure we use is highly granular and is free from reporting biases. This facilitates comparisons across time and business types, private and public, that may not be possible using administrative or survey data.

We find little evidence that natural disasters have an impact on total economic activity, as proxied by foot traffic, at the county-month level. However, natural disasters are known

to alter consumer behavior and disrupt business activities and supply chains. This provides scope for some businesses to gain market share from others that may be less resilient to such disruptions. We find that public businesses gain foot traffic share following disasters, at the expense of small, private businesses. This effect is particularly large for the retail industry, where the link between foot traffic and sales is likely strongest.

We examine channels underlying this phenomenon and find that while establishment size is not particularly important to resilience, cost of capital and geographic diversification of public companies likely is. We find greater impacts for less populous rural counties, and especially those with a larger minority population. We further examine dollar stores specifically, as they are a subset of public companies whose business models convey an advantage in the wake of natural disasters in low population areas. We find that dollar stores are particularly effective at garnering market share post-disaster. Moreover, dollar store stocks and retail stocks perform well in the month following a high natural disaster period.

Our work contributes to the literature on the differences between public and private businesses. Moreover, our findings can be used to add nuance to the understanding of the impacts of natural disasters. While the natural disasters we study do not appear to have overall impacts on local economies, they do advantage some firms over others. These findings could be valuable to researchers understanding the impacts of natural disaster risks, practitioners interested in the businesses that can take advantage of the volatility inherent to these and related disasters, and to policymakers considering the impacts of disaster relief.

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8 Figures

Figure 1: **Map of Treated and Control Counties**

This figure shows a map of treated and control counties in the USA. See **Section 2.3** and **Table 2** for a detailed description of how counties were sorted into treated, control, and NA groups.
Sources: SHELDUS, Authors' analysis

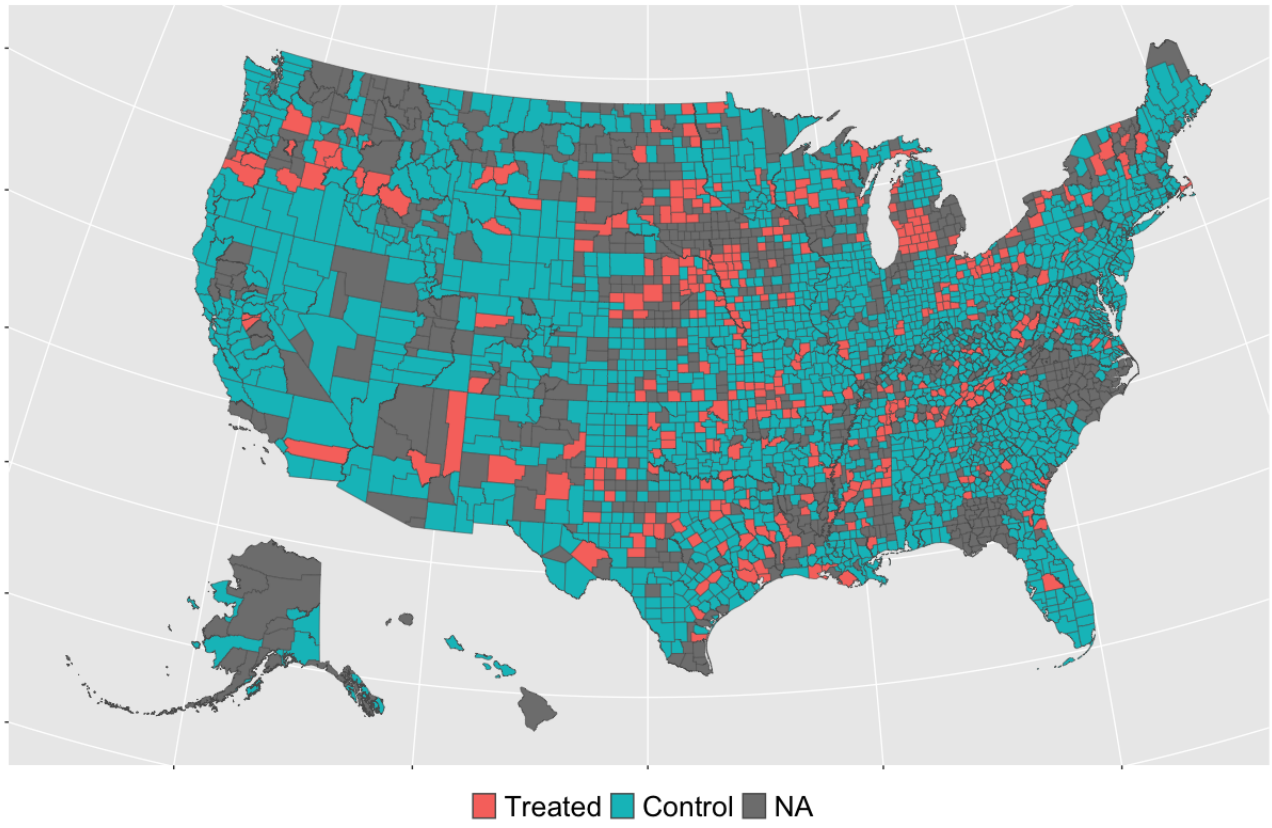


Figure 2: **Geography of Private Share**

This figure shows the geography of private share. See **Table 1** and **Section** 3.1 for a detailed description of the private share variable. The top figure shows private share to all businesses in Safegraph. The bottom figure restricts to retail businesses.
Sources: SafeGraph, Authors' analysis

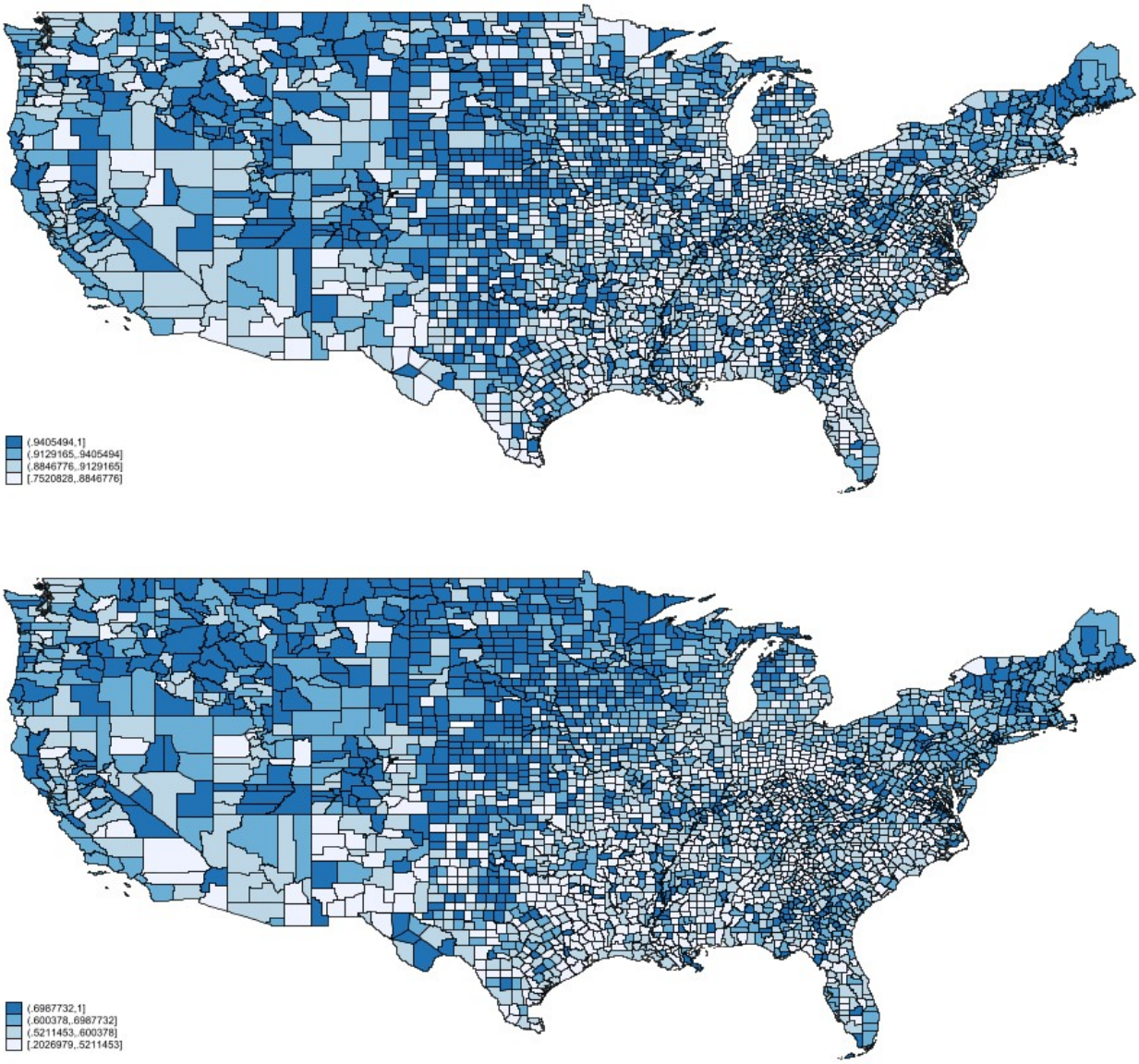


Figure 3: **Geography of Dollar Store Share**

This figure shows the geography of dollar store share of retail foot traffic . See **Table 1** and **Section** 3.1 for a detailed description of the dollar store share variable.
Sources: SafeGraph, Authors' analysis

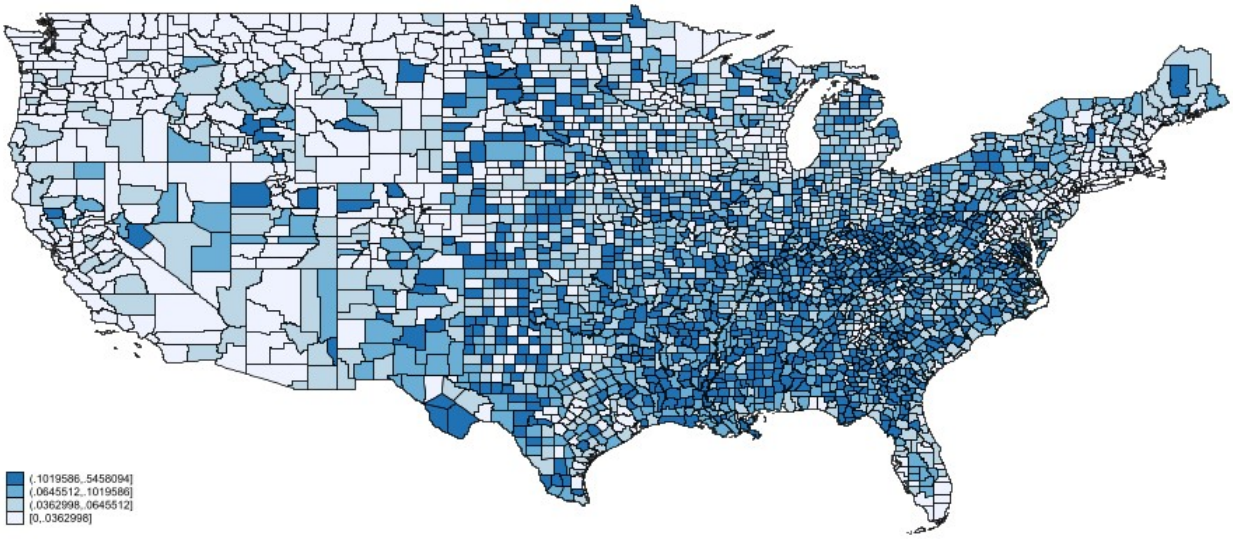
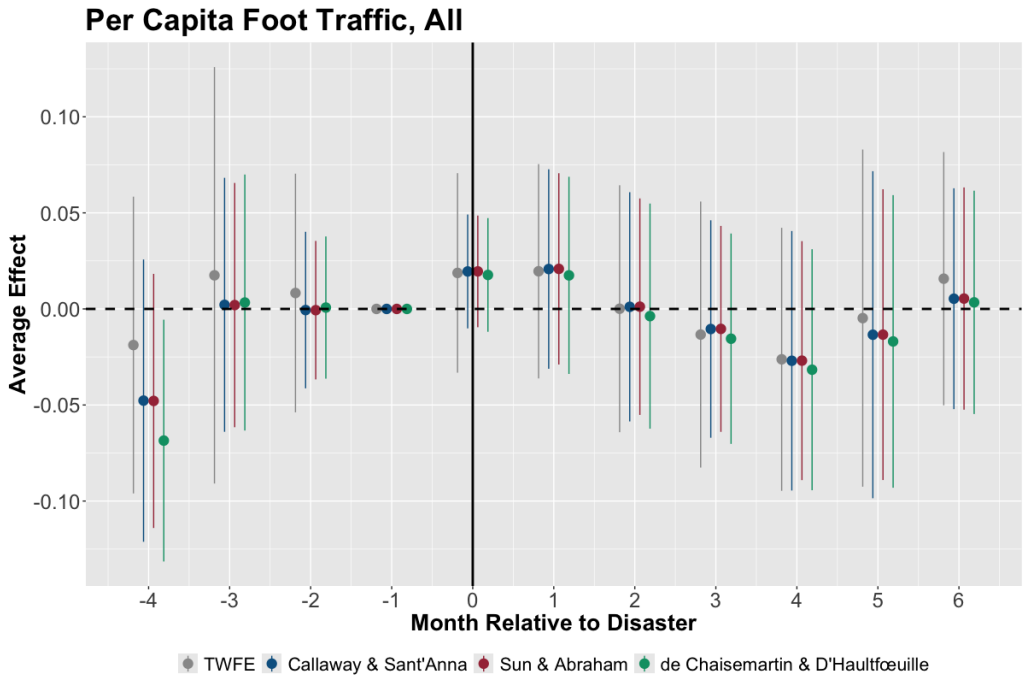


Figure 4: **Dynamics of Foot Traffic (Population Scaled) Around Natural Disasters**

This figure shows the dynamics of per capita foot traffic at the county level in the four months prior and the six months following a natural disaster event. The control group is a set of counties that were not hit by natural disasters. The figures plot coefficients and 95% confidence intervals from a dynamic staggered difference-in-differences specification. See **Section 3.3** for details. The top figure shows results for the full sample of business covered by Safegraph. The bottom figure restricts to retail establishments.
Sources: SafeGraph, SHELDUS, U.S. Census Bureau, Authors' analysis



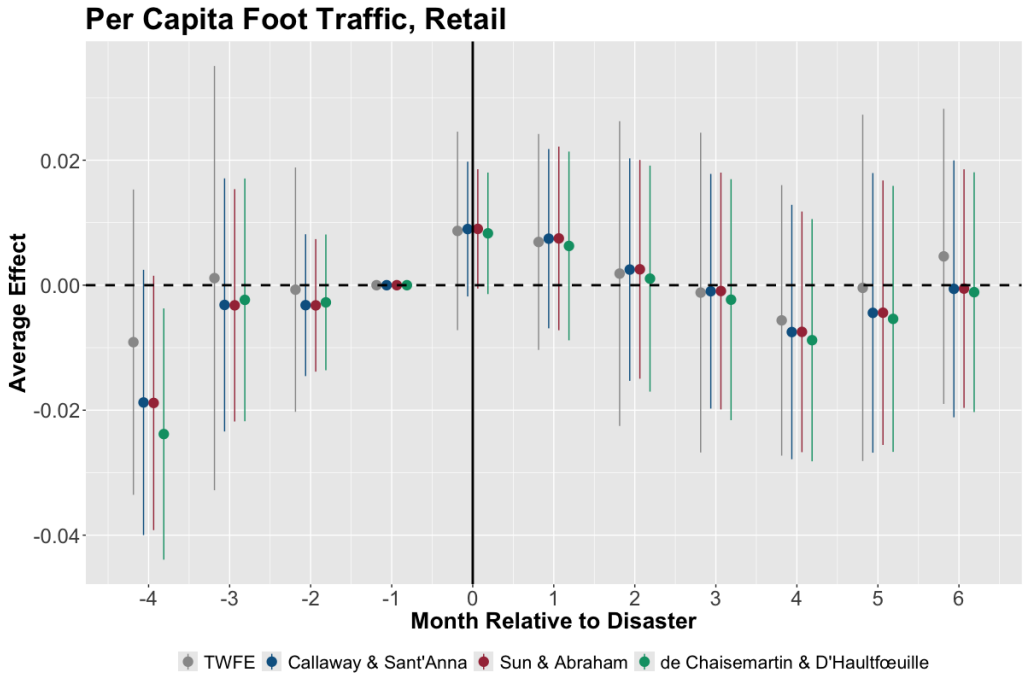


Figure 5: **Dynamics of Private Share Around Natural Disasters**

This figure shows the dynamics of private share in the four months prior and the six months following a natural disaster event. Private share is defined as the proportion of foot traffic in a county going to private businesses. The control group is a set of counties that were not hit by natural disasters. The figures plot coefficients and 95% confidence intervals from a dynamic staggered difference-in-differences specification. See **Section 3.3** for details. The top figure shows results for the full sample of business covered by Safegraph. The bottom figure restricts to retail establishments.
Sources: SafeGraph, SHELDUS, Authors' analysis

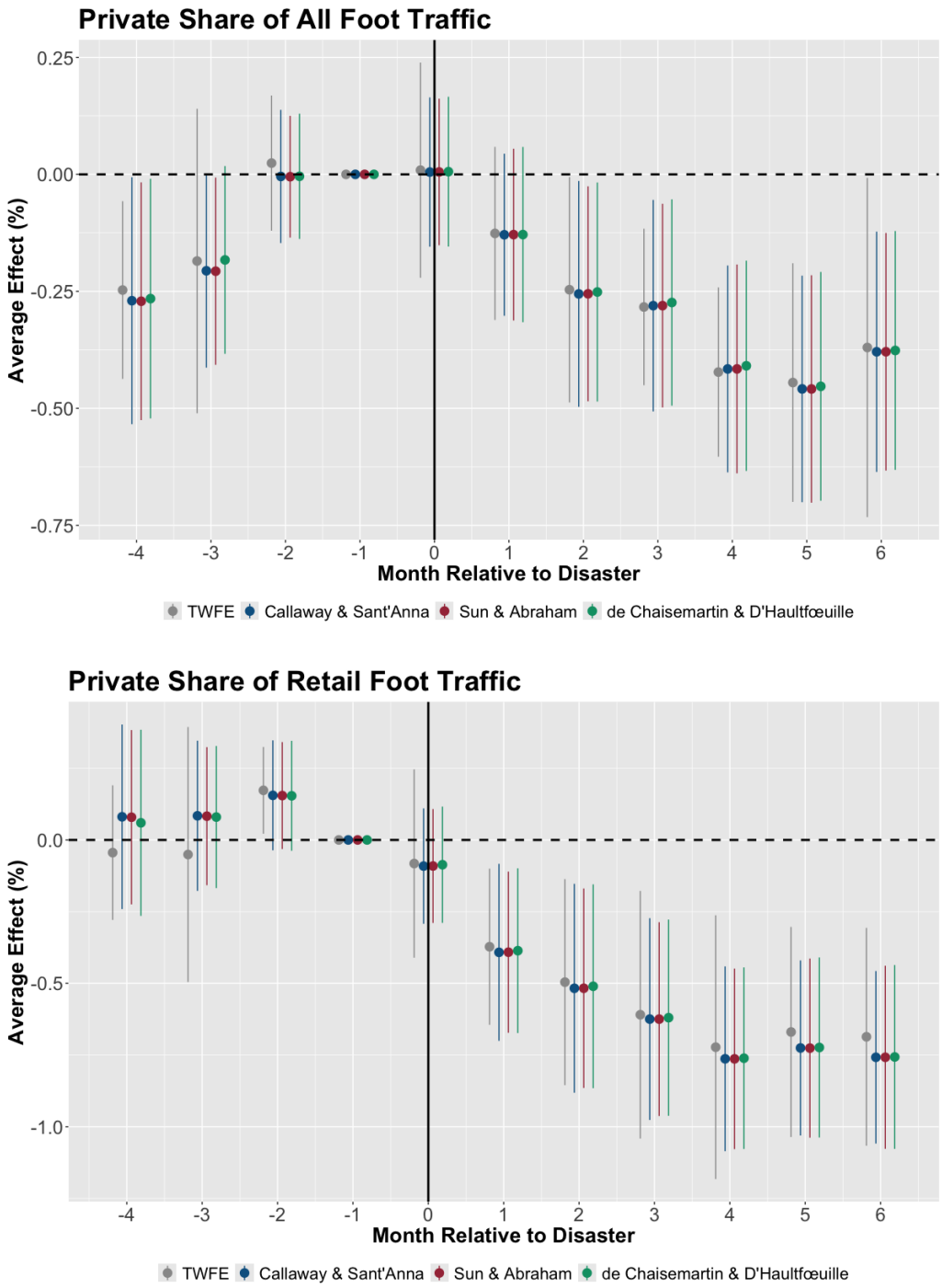


Figure 6: **Dynamics of Foot Traffic to Largest Retailers Around Natural Disasters**

This figure shows the dynamics of retail foot traffic going to the top 3 stores in a county by beginning-of-period foot traffic share in the four months prior and the six months following a natural disaster event. The control group is a set of counties that were not hit by natural disasters. The figures plot coefficients and 95% confidence intervals from a dynamic staggered difference-in-differences specification. See **Section 3.3** for details. The top figure shows results for the top 3 stores. The middle figure shows results for the top 3 public stores. The bottom figure shows results for the top 3 retail stores. *Sources: SafeGraph, SHELDUS, Authors' analysis*

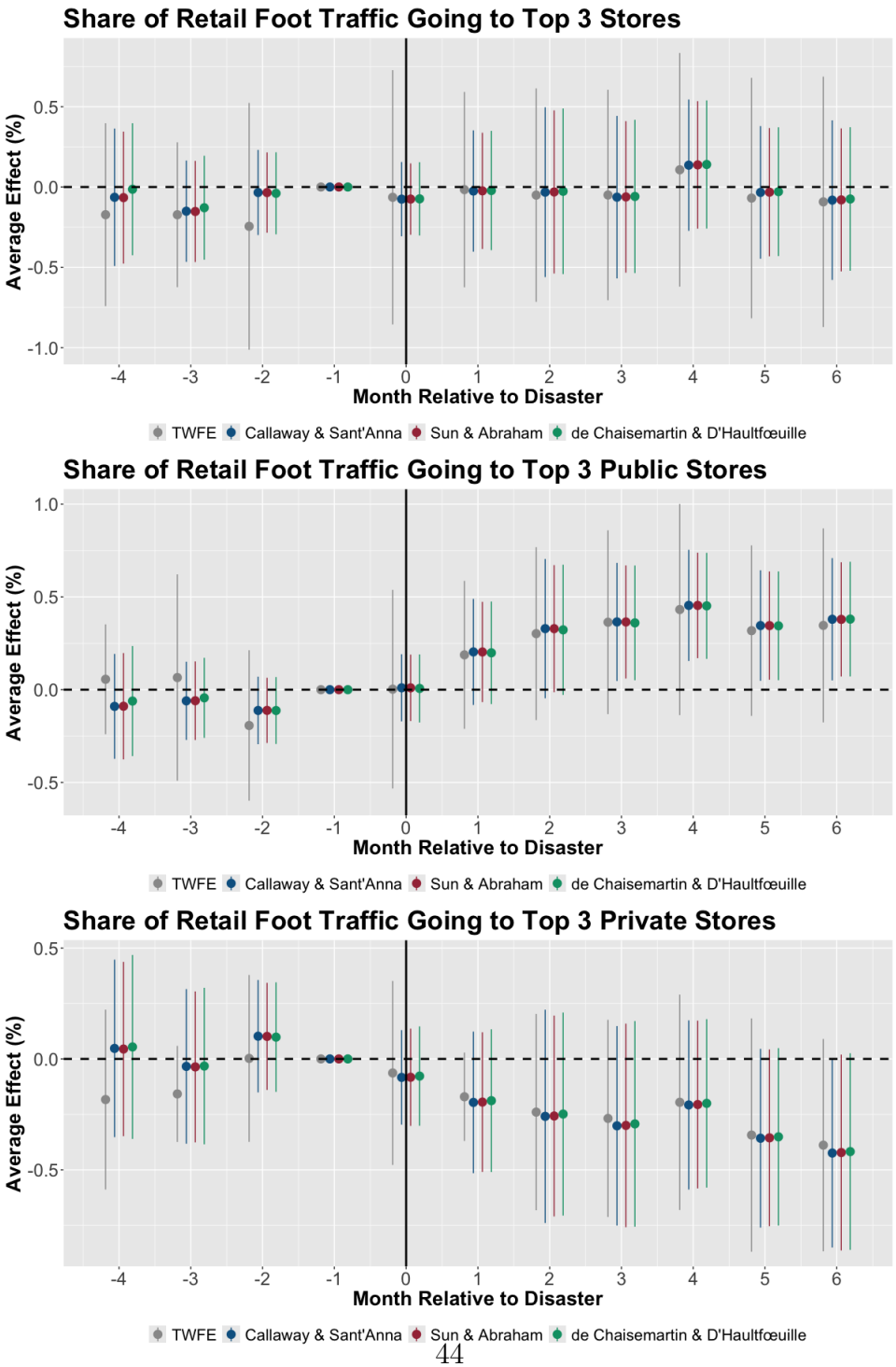


Figure 7: **Foot Traffic to Public Stores Split by WACC Around Natural Disasters**

This figure shows the dynamics of foot traffic to public retail stores split by weighted average cost of capital (WACC) in the four months prior and the six months following a natural disaster event. The control group is a set of counties that were not hit by natural disasters. Low WACC retailers have a WACC below the median retail store. High WACC retailers have a WACC above the median retail store. The figures plot coefficients and 95% confidence intervals from a dynamic staggered difference-in-differences specification. *Sources: SafeGraph, SHELDUS, Authors' analysis*

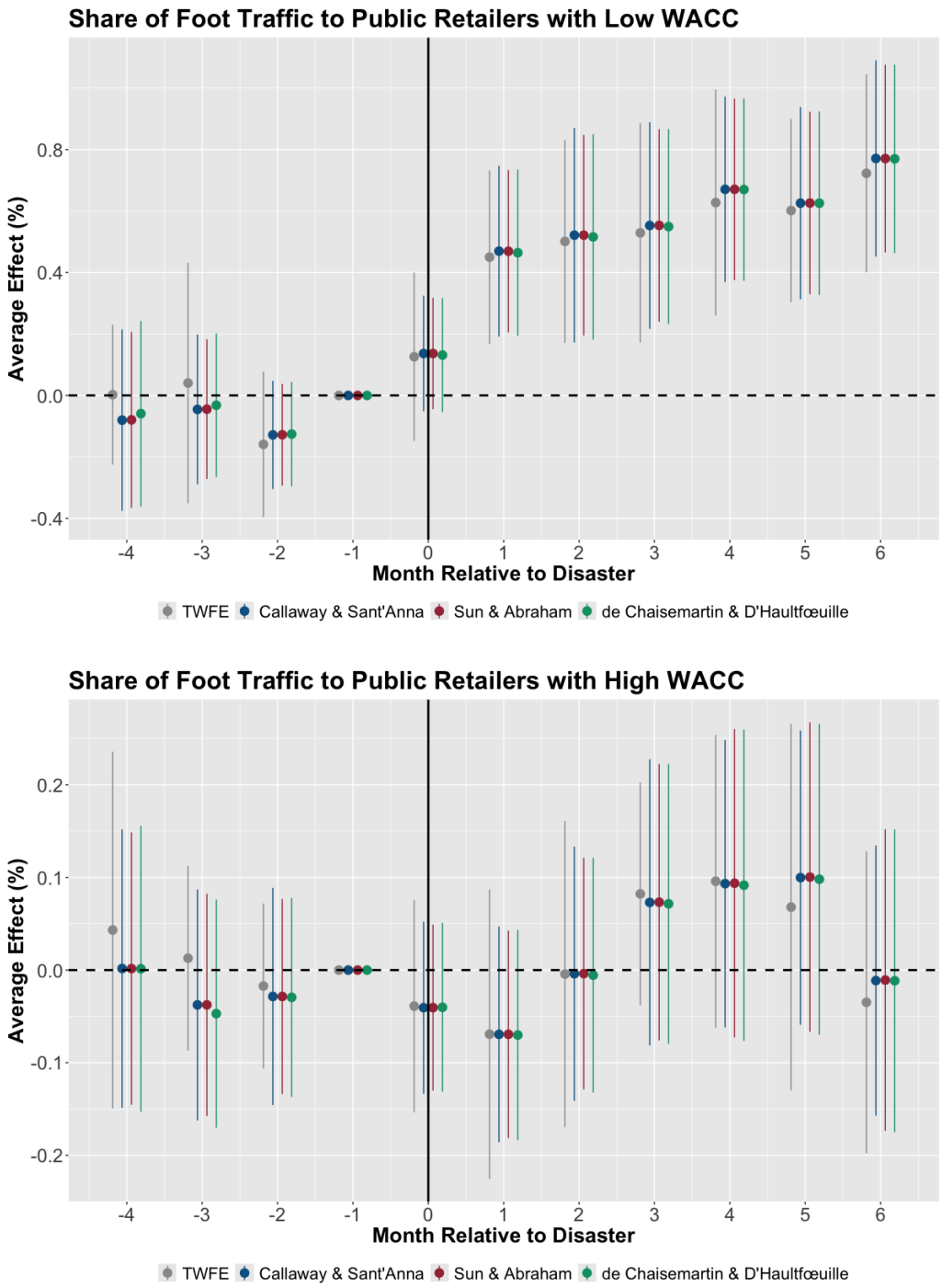
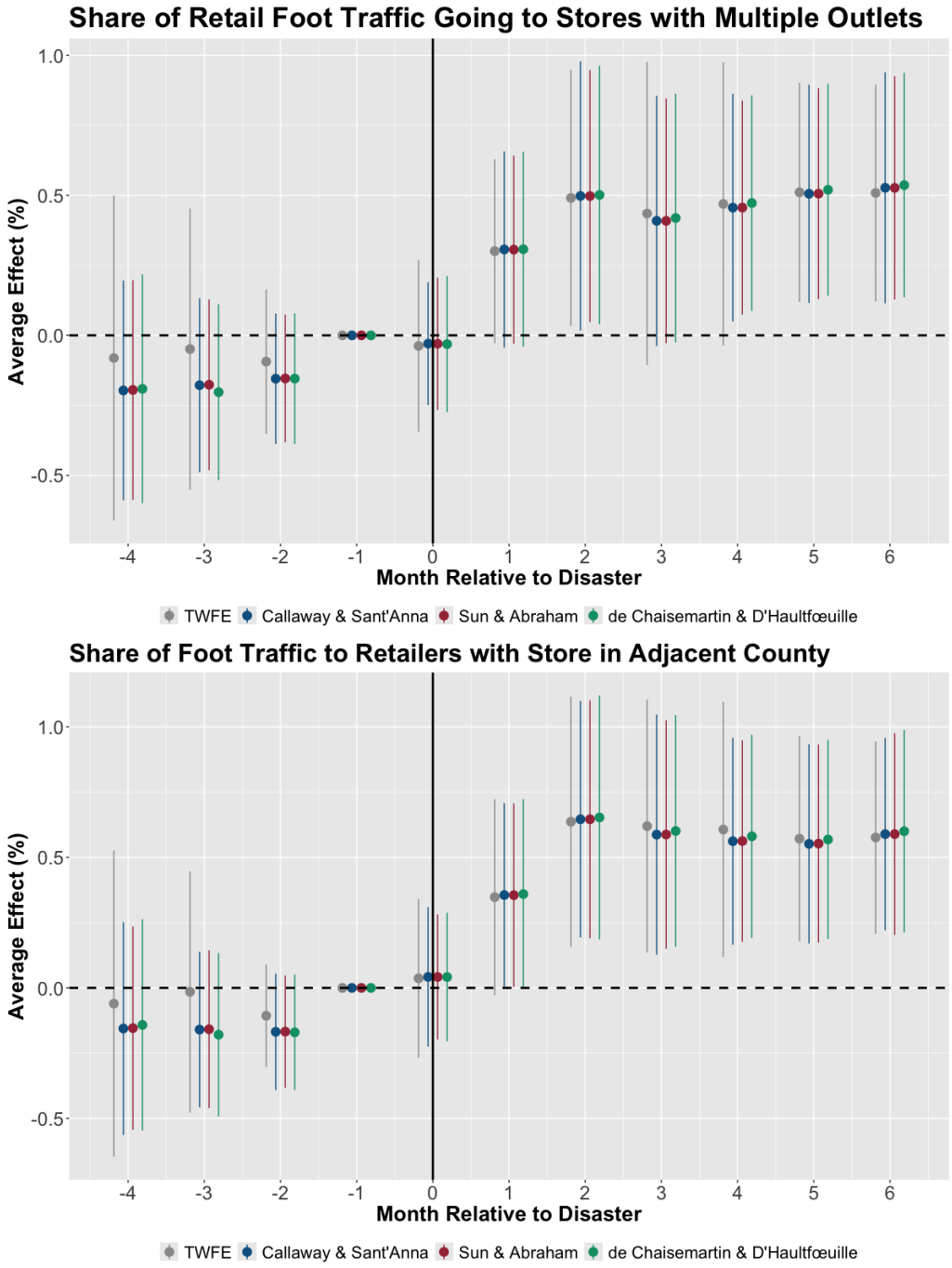
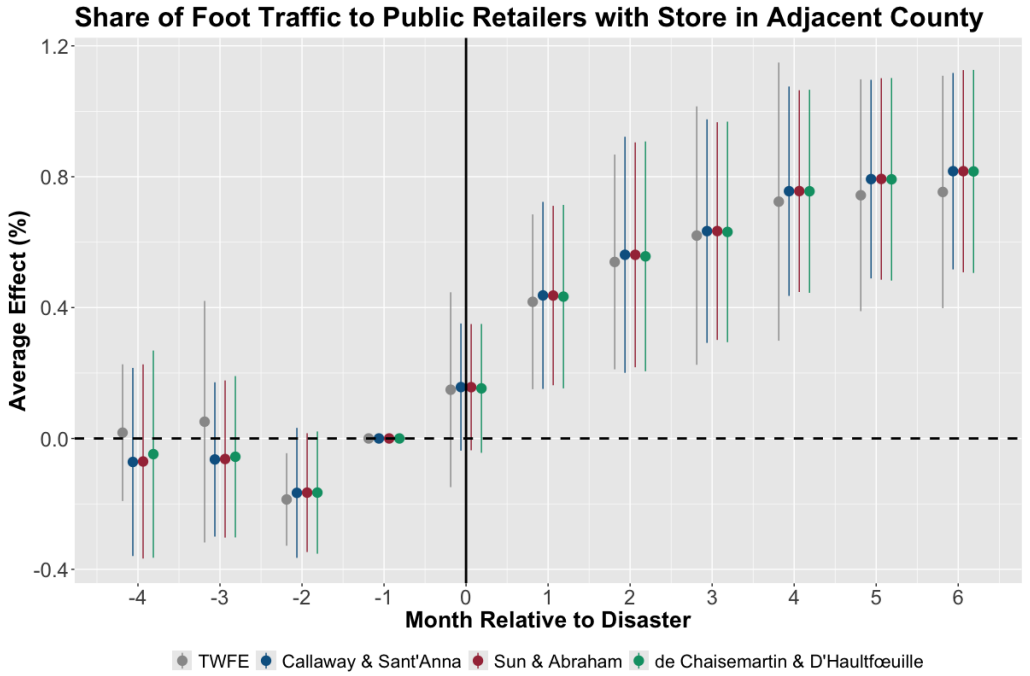
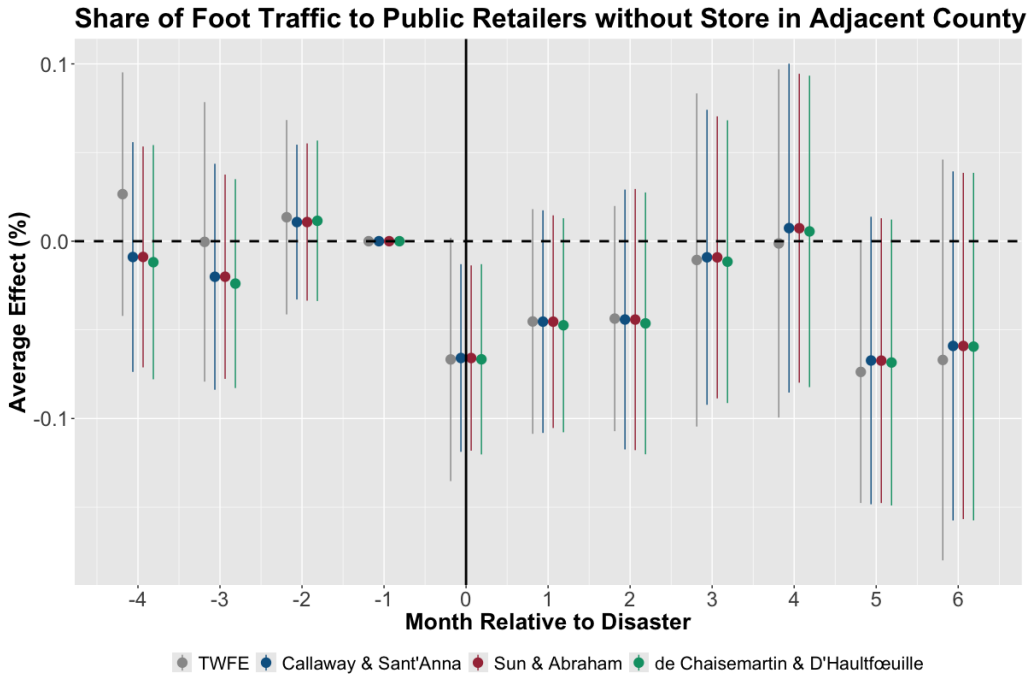


Figure 8: **Dynamics of Foot Traffic to Stores with Outlets in Adjacent Counties Around Natural Disasters**

This figure shows the dynamics of retail foot traffic going to stores with multiple outlets in the four months prior and the six months following a natural disaster event. The control group is a set of counties that were not hit by natural disasters. The figures plot coefficients and 95% confidence intervals from a dynamic staggered difference-in-differences specification. See **Section 3.3** for details.
Sources: SafeGraph, SHELDUS, Authors' analysis




Share of Foot Traffic to Public Retailers with Store in Adjacent County
Average Effect (%)
1.2
0.8
0.4
0.0
-0.4
-4
-3
-2
-1
0
1
2
3
4
5
6
Month Relative to Disaster
TWFE
Callaway & Sant'Anna
Sun & Abraham
de Chaisemartin & D'Haultfœuille


Share of Foot Traffic to Public Retailers without Store in Adjacent County
Average Effect (%)
0.1
0.0
-0.1
-4
-3
-2
-1
0
1
2
3
4
5
6
Month Relative to Disaster
TWFE
Callaway & Sant'Anna
Sun & Abraham
de Chaisemartin & D'Haultfœuille


Share of Foot Traffic to Private Retailers with Store in Adjacent County
Average Effect (%)
0.50
0.25
0.00
-0.25
-0.50
-4
-3
-2
-1
0
1
2
3
4
5
6
Month Relative to Disaster
TWFE
Callaway & Sant'Anna
Sun & Abraham
de Chaisemartin & D'Haultfœuille

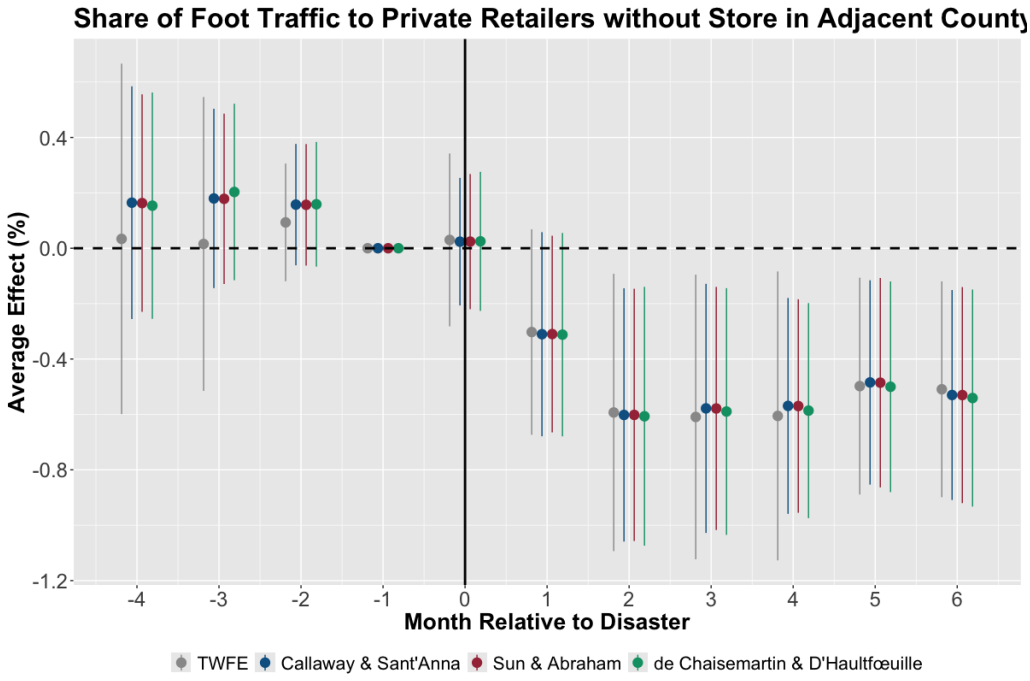
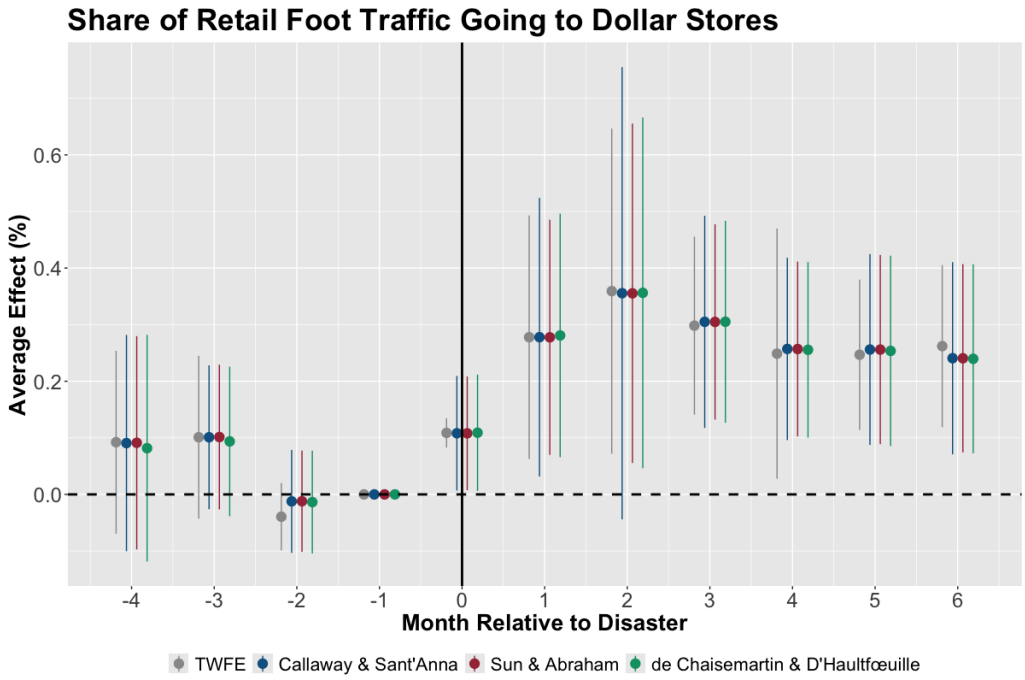

Share of Foot Traffic to Private Retailers without Store in Adjacent County
Average Effect (%)
0.4
0.0
-0.4
-0.8
-1.2
-4
-3
-2
-1
0
1
2
3
4
5
6
Month Relative to Disaster
TWFE
Callaway & Sant'Anna
Sun & Abraham
de Chaisemartin & D'Haultfœuille

Figure 9: **Dynamics of Foot Traffic to Dollar Stores Around Natural Disasters**

This figure shows the dynamics of retail foot traffic going to dollar stores in the four months prior and the six months following a natural disaster event. The control group is a set of counties that were not hit by natural disasters. The figures plot coefficients and 95% confidence intervals from a dynamic staggered difference-in-differences specification. See **Section 3.3** for details.
Sources: SafeGraph, SHELDUS, Authors' analysis



9 Tables

Table 1: **Variable definitions**

Variable name	**Description**
Dis (aster)	A dummy variable that equals one if a disaster occurred that had damages greater than $100,000 and damages per capita greater than $3.58, and zero otherwise.
Post	A dummy variable that equals one in the month a disaster takes place for the treated county and zero otherwise.
Foot Traffic to All Points of Interest	The sum of foot traffic to all points of interest, scaled by the county's population.
Foot Traffic to Retail Businesses	The sum of foot traffic to retail stores, scaled by the county's population.
Private Share, All	The share of foot traffic going to private businesses (as opposed to public businesses).
Private Share, Retail	The share of retail foot traffic going to private businesses (as opposed to public businesses).
Top 3 Share	The share of retail foot traffic going to stores that were in the top three in retail foot traffic in the county as of January 2019.
Top 3 Private Share	The share of retail foot traffic going to stores that were in the top three in private retail foot traffic in the county as of January 2019.
Top 3 Public Share	The share of retail foot traffic going to stores that were in the top three in public retail foot traffic in the county as of January 2019.
Share, with Multiple Outlets	The share of retail foot traffic going to stores that had a separate branch in other counties as of January 2019.
Share, to Dollar Stores	The share of retail foot traffic going to dollar stores.
Population	County population as of 2019
Minority Share	County minority share as of 2019

Table 2: **Sample Construction**

This table details how the treated and control counties used in the main analysis were constructed. Panel A starts with the full list of disasters from SHELDUS in 2018 and 2019, and subsets to those above the size threshold. Panel B shows the county-level sample from Safegraph in 2019, and the split between treated and control counties after merging with SHELDUS. *Sources: SafeGraph, SHELDUS, U.S. Census Bureau, Authors' analysis*

Panel A: County Level Disasters from SHELDUS

Sample	Observations (county-month)
Full 2018-2019 Sample	22,791
Property Damage (2019-Adjusted) $\geq \$100,000$*	2,593
Property Damage Per Capita (2019-Adjusted) $\geq \$3.58$*	1,741
Non-Duplicate County-Month	1,553
2018 Disaster	739
2019 Disaster	814

*Top 10%

Panel B: Counties in Safegraph Data

Sample	Observations (county)
Full 2019 Sample	3,391
Non-2018 Disaster	2,798
Non-Multiple Disaster	2,715
Balanced Panel	2,537
January 2019 Retail Foot Traffic ≥ 1000	2,397
Control	2,010
Treated	387

Table 3: **Treated Counties**

This table shows summary statistics for the treated counties. Panel A shows the number of counties treated in each month in 2019, and the number of disasters of each type. Panel B shows summary statistics on property damage for the treated counties.
Sources: SHELDUS, U.S. Census Bureau, Authors' analysis

Panel A: Counts by Month and Type

Treated Month	Count	Disaster Type	Count
January	1	Flooding	184
February	63	Tornado	106
March	68	Wind	43
April	55	Winter Weather	19
May	71	Lightning	12
June	36	Hail	10
July	26	Severe Storm / Thunderstorm	5
August	13	Hurricane / Tropical Storm	3
September	20	Wildfire	2
October	24	Landslide	2
November	6	Avalanche	1
December	4		

Panel B: Treated Sample Summary Statistics (N=387)

	Mean	Median	SD
Property Damage ($)	12,038,331	515,000	106,317,380
Per Capita Property Damage ($)	112.52	19.65	495.59

Table 4: **Summary Statistics**

This table presents summary statistics for our main variables of interest at the county-month level. Panel A shows summary statistics for the total foot traffic at the county-month level. Panel B shows summary statistics for total foot traffic scaled by county population. Panel C shows summary statistics for the percent of foot traffic to various groups of businesses that we are interested in. See **Table 1** for a full list of variable definitions.
Sources: SafeGraph, SHELDUS, U.S. Census Bureau, Authors' analysis

Panel A: Total Foot Traffic, County-Month Level

	N	Mean	Median	SD (full)	SD (within)
All	28,764	356,206	54,135	1,158,923	40,134
All, Public	28,764	75,085	14,350	219,333	8,294
All, Private	28,764	281,121	39,196	948,265	33,167
Retail	28,764	107,288	22,577	306,391	11,168
Retail, Public	28,764	44,645	9,574	125,773	5,475
Retail, Private	28,764	62,643	12,957	185,394	6,275

Panel B: Per Capita Foot Traffic, County-Month Level

	N	Mean	Median	SD (full)	SD (within)
All	28,764	2.25	2.04	1.35	0.33
All, Public	28,764	0.55	0.48	0.38	0.08
All, Private	28,764	1.71	1.52	1.07	0.26
Retail	28,764	0.87	0.80	0.46	0.12
Retail, Public	28,764	0.35	0.31	0.24	0.05
Retail, Private	28,764	0.52	0.47	0.29	0.08

Panel C: % Foot Traffic, County-Month Level

	N	Mean	Median	SD (full)	SD (within)
Private Share (All)	28,764	76.01%	75.88%	9.22%	1.47%
Private Share (Retail)	28,764	61.07%	59.66%	13.72%	2.00%
Dollar Stores	28,764	7.14%	5.95%	5.68%	0.73%
Multiple Locations	28,764	60.90%	63.57%	14.75%	2.25%
Top 3	28,764	27.35%	25.72%	15.90%	1.97%
Top 3 Public	28,764	19.34%	17.99%	11.25%	1.51%
Top 3 Private	28,764	17.85%	13.77%	14.39%	1.77%

Table 5: **Differences Between Treated and Control**

This table examines differences between treated and control counties at the beginning of the sample. For each variable of interest, we show the full sample mean, the treated sample mean, the control sample mean, the difference between the treated and control sample mean, a T-test of the difference between the means, and a Wilcoxon test of the difference between the means. Groups that are significantly different from each other at the 5% level are highlighted in red. See **Table 1** for a full list of variable definitions.
Sources: SafeGraph, SHELDUS, U.S. Census Bureau, Authors' analysis

Panel A: Total Foot Traffic, January

	Full Sample	Treated	Control	Difference	T-test	Wilcoxon
All	307,938	256,327	317,875	-61,548	0.33	0.50
All, Public	62,981	57,963	63,948	-5,985	0.64	0.32
All, Private	244,957	198,364	253,928	-55,564	0.27	0.59
Retail	93,258	83,290	95,178	-11,887	0.52	0.53
Retail, Public	37,240	35,232	37,627	-2,395	0.76	0.26
Retail, Private	56,018	48,059	57,550	-9,492	0.37	0.75

Panel B: Per Capita Foot Traffic, January

	Full Sample	Treated	Control	Difference	T-test	Wilcoxon
All	1.84	1.80	1.84	-0.04	0.44	0.70
All, Public	0.43	0.43	0.43	0.00	0.81	0.77
All, Private	1.41	1.37	1.42	0.05	0.27	0.58
Retail	0.70	0.72	0.70	0.02	0.34	0.21
Retail, Public	0.28	0.28	0.28	0.00	0.96	0.89
Retail, Private	0.43	0.44	0.42	0.02	0.13	0.03

Panel C: % Foot Traffic, January

	Full Sample	Treated	Control	Difference	T-test	Wilcoxon
Private Share (All)	76.82%	77.14%	76.75%	0.39%	0.42	0.71
Private Share (Retail)	62.19%	63.26%	61.98%	1.28%	0.09	0.10
Dollar Stores	6.81%	6.94%	6.79%	0.15%	0.60	0.09
Multiple Locations	59.77%	57.74%	60.16%	-2.42%	0.00	0.00
Top 3	27.23%	26.36%	27.40%	-1.04%	0.16	0.89
Top 3 Public	18.83%	18.59%	18.88%	-0.29%	0.60	0.79
Top 3 Private	18.17%	17.48%	18.30%	-0.83%	0.23	0.48

Panel D: Demographics, County Level

	Full Sample	Treated	Control	Difference	T-test	Wilcoxon
Population	113,222	95,242	116,684	-21,442	0.24	0.08
Minority Share	0.10	0.09	0.11	-0.02	0.04	0.00

Table 6: **Foot Traffic to Businesses Following Natural Disasters**

This table shows the effects of natural disasters on per capita foot traffic in the impacted county. *Dis* is an indicator variable equal to 1 for treated counties that were impacted by a natural disaster. *Post* is an indicator equal to 1 in months after the disaster for treated counties. $Post_i$ are indicators equal to 1 in month i after disaster. In Panel A, the dependent variable is the foot traffic to all points of interest in the county as covered by Safegraph, scaled by the county's population as of December 2019. In Panel B, we subset points of interest to be only retail establishments. We present coefficients from a Two-Way Fixed Effects [TWFE] model, as well as robust estimators introduced in Callaway and Sant'Anna (2021) [CS], Sun and Abraham (2021) [SA], and De Chaisemartin and d'Haultfoeuille (2020) [DD]. Standard errors are clustered by county.
Sources: SafeGraph, SHELDUS, U.S. Census Bureau, Authors' analysis

Panel A: Foot Traffic to All Points of Interest (N=28,764)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Dis * Post$	0.018		0.017		0.017		0.011	
	(0.740)		(0.619)		(0.690)		(0.451)	
$Dis * Post0$		0.019		0.020		0.020		0.018
		(0.722)		(1.317)		(1.345)		(1.196)
$Dis * Post1$		0.020		0.021		0.021		0.017
		(0.703)		(0.800)		(0.838)		(0.681)
$Dis * Post2$		0.000		0.001		0.001		-0.004
		(0.003)		(0.037)		(0.042)		(-0.128)
$Dis * Post3$		-0.013		-0.010		-0.010		-0.015
		(-0.385)		(-0.370)		(-0.388)		(-0.566)
$Dis * Post4$		-0.026		-0.027		-0.027		-0.032
		(-0.766)		(-0.799)		(-0.866)		(-1.009)
$Dis * Post5$		-0.005		-0.013		-0.013		-0.017
		(-0.109)		(-0.315)		(-0.354)		(-0.444)
$Dis * Post6$		0.016		0.005		0.005		0.003
		(0.478)		(0.185)		(0.186)		(0.118)
Model	**TWFE**	**TWFE**	**CS**	**CS**	**SA**	**SA**	**DD**	**DD**

Panel B: Foot Traffic to Retail Businesses (N=28,764)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Dis * Post$	0.009		0.006		0.006		0.004	
	(1.071)		(0.745)		(0.765)		(0.521)	
$Dis * Post0$		0.009*		0.009*		0.009*		0.008
		(1.094)		(1.666)		(1.886)		(1.708)
$Dis * Post1$		0.007		0.007		0.007		0.006
		(0.801)		(1.038)		(1.019)		(0.832)
$Dis * Post2$		0.002		0.002		0.003		0.001
		(0.152)		(0.281)		(0.290)		(0.116)
$Dis * Post3$		-0.001		-0.001		-0.001		-0.002
		(-0.093)		(-0.103)		(-0.098)		(-0.241)
$Dis * Post4$		-0.006		-0.007		-0.007		-0.009
		(-0.520)		(-0.737)		(-0.776)		(-0.908)
$Dis * Post5$		-0.000		-0.004		-0.004		-0.005
		(-0.031)		(-0.396)		(-0.416)		(-0.507)
$Dis * Post6$		0.005		-0.001		-0.001		-0.001
		(0.391)		(-0.057)		(-0.057)		(-0.117)
Model	**TWFE**	**TWFE**	**CS**	**CS**	**SA**	**SA**	**DD**	**DD**

*p<0.1; **p<0.05; ***p<0.01

Table 7: **Private Share Following Natural Disaster**

This table shows the effects of natural disasters on private share in the impacted county. Private share is defined as the proportion of foot traffic going to private businesses in the county. *Dis* is an indicator variable equal to 1 for treated counties that were impacted by a natural disaster. *Post* is an indicator equal to 1 in months after the disaster for treated counties. $Post_i$ are indicators equal to 1 in month i after disaster. In Panel A, the dependent variable is the private share to all points of interest in the county as covered by Safegraph. In Panel B, we subset points of interest to be only retail establishments. We present coefficients from a Two-Way Fixed Effects [TWFE] model, as well as robust estimators introduced in Callaway and Sant'Anna (2021) [CS], Sun and Abraham (2021) [SA], and De Chaisemartin and d'Haultfoeuille (2020) [DD]. Standard errors are clustered by county.
Sources: SafeGraph, SHELDUS, Authors' analysis

Panel A: Private Share of Foot Traffic for All (N = 28,764)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Dis * Post$	-0.164**		-0.238***		-0.238***		-0.229***	
	(-2.090)		(-2.993)		(-3.027)		(-2.881)	
$Dis * Post0$		0.009		0.005		0.005		0.006
		(0.078)		(0.062)		(0.066)		(0.072)
$Dis * Post1$		-0.126		-0.129		-0.129		-0.129
		(-1.365)		(-1.490)		(-1.403)		(-1.375)
$Dis * Post2$		-0.247**		-0.255**		-0.255**		-0.251**
		(-2.048)		(-2.117)		(-2.223)		(-2.149)
$Dis * Post3$		-0.283***		-0.281**		-0.281**		-0.274**
		(-3.390)		(-2.483)		(-2.578)		(-2.484)
$Dis * Post4$		-0.422***		-0.416***		-0.416***		-0.409***
		(-4.672)		(-3.763)		(-3.727)		(-3.642)
$Dis * Post5$		-0.445***		-0.458***		-0.459***		-0.453***
		(-3.490)		(-3.789)		(-3.775)		(-3.706)
$Dis * Post6$		-0.370**		-0.379***		-0.379***		-0.376***
		(-2.041)		(-2.953)		(-2.986)		(-2.949)
Model	**TWFE**	**TWFE**	**CS**	**CS**	**SA**	**SA**	**DD**	**DD**

Panel B: Private Share of Foot Traffic in Retail (N = 28,764)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Dis * Post$	-0.483***		-0.506***		-0.506***		-0.502***	
	(-3.603)		(-3.925)		(-4.216)		(-4.163)	
$Dis * Post0$		-0.082		-0.091		-0.091		-0.086
		(-0.501)		(-0.906)		(-0.915)		(-0.853)
$Dis * Post1$		-0.372***		-0.392**		-0.391***		-0.386***
		(-2.736)		(-2.541)		(-2.786)		(-2.689)
$Dis * Post2$		-0.496***		-0.517***		-0.517***		-0.510***
		(-2.761)		(-2.840)		(-2.974)		(-2.873)
$Dis * Post3$		-0.610***		-0.625***		-0.625***		-0.620***
		(-2.824)		(-3.551)		(-3.698)		(-3.623)
$Dis * Post4$		-0.723***		-0.763***		-0.763***		-0.761***
		(-3.143)		(-4.738)		(-4.851)		(-4.809)
$Dis * Post5$		-0.670***		-0.725***		-0.726***		-0.724***
		(-3.656)		(-4.753)		(-4.648)		(-4.610)
$Dis * Post6$		-0.686***		-0.758***		-0.758***		-0.757***
		(-3.615)		(-5.040)		(-4.749)		(-4.722)
Model	**TWFE**	**TWFE**	**CS**	**CS**	**SA**	**SA**	**DD**	**DD**

*p<0.1; **p<0.05; ***p<0.01

Table 8: **Share of Foot Traffic to Top Retailers Following Natural Disaster**

This table shows the effects of natural disasters on Top Share in the impacted county. Top Share is defined as the share of foot traffic going to the top 3 stores by beginning of period foot traffic in a county. *Dis* is an indicator variable equal to 1 for treated counties that were impacted by a natural disaster. *Post* is an indicator equal to 1 in months after the disaster for treated counties. $Post_i$ are indicators equal to 1 in month i after disaster. In Panel A, the dependent variable is the Top Share among all retail stores. In Panel B, the independent variable is the share of foot traffic going to the top 3 public retail stores. In Panel C, the independent variable is the share of foot traffic going to the top 3 private retail stores. We present coefficients from a Two-Way Fixed Effects [TWFE] model, as well as robust estimators introduced in Callaway and Sant'Anna (2021) [CS], Sun and Abraham (2021) [SA], and De Chaisemartin and d'Haultfoeuille (2020) [DD]. Standard errors are clustered by county.
Sources: SafeGraph, SHELDUS, Authors' analysis

Panel A: Top 3 Share of Retail Foot Traffic (N = 28,764)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Dis * Post$	0.079		-0.036		-0.034		-0.023	
	(0.627)		(-0.209)		(-0.211)		(-0.142)	
$Dis * Post0$		-0.064		-0.076		-0.075		-0.074
		(-0.162)		(-0.654)		(-0.677)		(-0.646)
$Dis * Post1$		-0.016		-0.025		-0.024		-0.022
		(-0.054)		(-0.133)		(-0.132)		(-0.118)
$Dis * Post2$		-0.050		-0.032		-0.031		-0.027
		(-0.152)		(-0.122)		(-0.121)		(-0.104)
$Dis * Post3$		-0.050		-0.063		-0.062		-0.059
		(-0.152)		(-0.250)		(-0.262)		(-0.246)
$Dis * Post4$		0.107		0.136		0.138		0.140
		(0.295)		(0.666)		(0.694)		(0.704)
$Dis * Post5$		-0.069		-0.034		-0.032		-0.029
		(-0.184)		(-0.163)		(-0.161)		(-0.145)
$Dis * Post6$		-0.092		-0.082		-0.080		-0.075
		(-0.237)		(-0.329)		(-0.361)		(-0.334)
Model	**TWFE**	**TWFE**	**CS**	**CS**	**SA**	**SA**	**DD**	**DD**

Panel B: Top 3 Public Share of Retail Foot Traffic (N = 28,764)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Dis * Post$	0.287**		0.320***		0.319***		0.322***	
	(2.125)		(2.827)		(2.839)		(2.859)	
$Dis * Post0$		0.003		0.010		0.010		0.007
		(0.010)		(0.112)		(0.111)		(0.073)
$Dis * Post1$		0.188		0.204		0.203		0.199
		(0.942)		(1.424)		(1.505)		(1.438)
$Dis * Post2$		0.302		0.329*		0.329*		0.323*
		(1.297)		(1.753)		(1.921)		(1.838)
$Dis * Post3$		0.364		0.365**		0.365**		0.360**
		(1.468)		(2.295)		(2.395)		(2.329)
$Dis * Post4$		0.432		0.454***		0.454***		0.452***
		(1.518)		(3.033)		(3.195)		(3.163)
$Dis * Post5$		0.318		0.346**		0.345**		0.344**
		(1.385)		(2.321)		(2.368)		(2.348)
$Dis * Post6$		0.347		0.380**		0.379**		0.380**
		(1.326)		(2.304)		(2.463)		(2.462)
Model	**TWFE**	**TWFE**	**CS**	**CS**	**SA**	**SA**	**DD**	**DD**

Panel C: Top 3 Private Share of Retail Foot Traffic (N = 28,764)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Dis * Post$	-0.164		-0.254		-0.252		-0.252	
	(-1.243)		(-1.599)		(-1.606)		(-1.598)	
$Dis * Post0$		-0.063		-0.083		-0.083		-0.077
		(-0.305)		(-0.781)		(-0.754)		(-0.691)
$Dis * Post1$		-0.171*		-0.196		-0.195		-0.188
		(-1.713)		(-1.228)		(-1.237)		(-1.169)
$Dis * Post2$		-0.240		-0.259		-0.257		-0.249
		(-1.084)		(-1.077)		(-1.137)		(-1.086)
$Dis * Post3$		-0.268		-0.301		-0.300		-0.293
		(-1.207)		(-1.341)		(-1.307)		(-1.264)
$Dis * Post4$		-0.196		-0.208		-0.206		-0.200
		(-0.805)		(-1.089)		(-1.088)		(-1.055)
$Dis * Post5$		-0.343		-0.357*		-0.356*		-0.351*
		(-1.305)		(-1.774)		(-1.785)		(-1.756)
$Dis * Post6$		-0.389		-0.424**		-0.422*		-0.418*
		(-1.624)		(-1.993)		(-1.912)		(-1.885)
Model	**TWFE**	**TWFE**	**CS**	**CS**	**SA**	**SA**	**DD**	**DD**

*p<0.1; **p<0.05; ***p<0.01

Table 9: **Share of Foot Traffic to Public Retailers Split by WACC**

This table shows the effects of natural disasters on the share of foot traffic going to public companies split by weighted average cost of capital (WACC). Public retailers are split into those with lower than median weighted average cost of capital (LWACC) and higher than average weighted average cost of capital (HWACC). *Dis* is an indicator variable equal to 1 for treated counties that were impacted by a natural disaster. *Post* is an indicator equal to 1 in months after the disaster for treated counties. $Post_i$ are indicators equal to 1 in month i after disaster. In Panel A, the dependent variable is the share of foot traffic to public retailers with low WACC. In Panel B, the dependent variable is the share of foot traffic to public retailers with high WACC. We present coefficients from a Two-Way Fixed Effects [TWFE] model, as well as robust estimators introduced in Callaway and Sant'Anna (2021) [CS], Sun and Abraham (2021) [SA], and De Chaisemartin and d'Haultfoeuille (2020) [DD]. Standard errors are clustered by county. *Sources: SafeGraph, SHELDUS, Authors' analysis*

Panel A: FT Share to Low WACC Public Retailers (N = 28,764)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Dis * Post$	0.492***		0.501***		0.501***		0.501***	
	(4.184)		(4.323)		(4.361)		(4.342)	
$Dis * Post0$		0.126		0.136		0.136		0.131
		(0.919)		(1.449)		(1.505)		(1.416)
$Dis * Post1$		0.450***		0.470***		0.469***		0.464***
		(3.192)		(3.380)		(3.550)		(3.433)
$Dis * Post2$		0.501***		0.522***		0.522***		0.516***
		(3.034)		(2.988)		(3.195)		(3.087)
$Dis * Post3$		0.529***		0.553***		0.553***		0.550***
		(2.962)		(3.290)		(3.532)		(3.461)
$Dis * Post4$		0.628***		0.671***		0.671***		0.670***
		(3.414)		(4.447)		(4.544)		(4.512)
$Dis * Post5$		0.602***		0.626***		0.626***		0.626***
		(4.032)		(4.001)		(4.216)		(4.191)
$Dis * Post6$		0.723***		0.771***		0.771***		0.770***
		(4.483)		(4.831)		(5.052)		(5.024)
Model	**TWFE**	**TWFE**	**CS**	**CS**	**SA**	**SA**	**DD**	**DD**

Panel B: FT Share to High WACC Public Retailers (N = 28,764)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Dis * Post$	-0.006		0.006		0.007		0.003	
	(-0.112)		(0.131)		(0.132)		(0.063)	
$Dis * Post0$		-0.039		-0.041		-0.041		-0.040
		(-0.680)		(-0.874)		(-0.905)		(-0.883)
$Dis * Post1$		-0.069		-0.069		-0.069		-0.070
		(-0.886)		(-1.192)		(-1.238)		(-1.236)
$Dis * Post2$		-0.004		-0.004		-0.004		-0.005
		(-0.052)		(-0.058)		(-0.061)		(-0.087)
$Dis * Post3$		0.082		0.073		0.073		0.072
		(1.368)		(0.945)		(0.983)		(0.947)
$Dis * Post4$		0.096		0.093		0.094		0.092
		(1.213)		(1.203)		(1.126)		(1.090)
$Dis * Post5$		0.068		0.100		0.100		0.098
		(0.687)		(1.257)		(1.202)		(1.169)
$Dis * Post6$		-0.035		-0.011		-0.011		-0.012
		(-0.426)		(-0.156)		(-0.132)		(-0.141)
Model	**TWFE**	**TWFE**	**CS**	**CS**	**SA**	**SA**	**DD**	**DD**

*p<0.1; **p<0.05; ***p<0.01

Table 10: **Foot Traffic Share to Geographically Diversified Stores**

This table shows the effects of natural disasters to retailers based on geographic diversification. *Dis* is an indicator variable equal to 1 for treated counties that were impacted by a natural disaster. *Post* is an indicator equal to 1 in months after the disaster for treated counties. $Post_i$ are indicators equal to 1 in month i after disaster. In Panel A, the dependent variable is the share of foot traffic to stores with multiple outlets. In Panel B, the dependent variable is the share of foot traffic to retailers with an outlet in a adjacent county. Panels (C)-(F) show splits based on if a store is public or private, and if there is another branch of the same store in an adjacent county. We present coefficients from a Two-Way Fixed Effects [TWFE] model, as well as robust estimators introduced in Callaway and Sant'Anna (2021) [CS], Sun and Abraham (2021) [SA], and De Chaisemartin and d'Haultfoeuille (2020) [DD], Standard errors are clustered by county. *Sources: SafeGraph, SHELDUS, Authors' analysis*

Panel A: Share of Retail FT to Stores With Multiple Outlets (N = 28,764)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Dis * Post$	0.346***		0.359**		0.359**		0.363**	
	(2.686)		(2.476)		(2.454)		(2.370)	
$Dis * Post0$		-0.038		-0.030		-0.030		-0.031
		(-0.245)		(-0.271)		(-0.254)		(-0.258)
$Dis * Post1$		0.301*		0.307*		0.306*		0.308*
		(1.830)		(1.753)		(1.823)		(1.769)
$Dis * Post2$		0.491**		0.498**		0.497**		0.501**
		(2.147)		(2.072)		(2.212)		(2.172)
$Dis * Post3$		0.435		0.409*		0.409*		0.419*
		(1.608)		(1.830)		(1.871)		(1.889)
$Dis * Post4$		0.469*		0.456**		0.456**		0.473**
		(1.858)		(2.244)		(2.387)		(2.454)
$Dis * Post5$		0.511***		0.506***		0.506***		0.520***
		(2.613)		(2.596)		(2.689)		(2.746)
$Dis * Post6$		0.509***		0.527**		0.527***		0.536***
		(2.632)		(2.556)		(2.643)		(2.679)
Model	**TWFE**	**TWFE**	**CS**	**CS**	**SA**	**SA**	**DD**	**DD**

Panel B: Share of Retail FT to Stores with Adjacent Store (N = 28,764)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Dis * Post$	0.429***		0.465***		0.465***		0.455***	
	(3.346)		(3.217)		(3.172)		(3.037)	
$Dis * Post0$		0.037		0.042		0.042		0.042
		(0.242)		(0.338)		(0.350)		(0.339)
$Dis * Post1$		0.348*		0.356**		0.355**		0.359**
		(1.853)		(1.972)		(2.022)		(1.977)
$Dis * Post2$		0.637***		0.646***		0.646***		0.653***
		(2.659)		(2.805)		(2.836)		(2.795)
$Dis * Post3$		0.620***		0.587***		0.588***		0.601***
		(2.556)		(2.660)		(2.686)		(2.707)
$Dis * Post4$		0.607**		0.562***		0.562***		0.581***
		(2.484)		(2.848)		(2.916)		(2.987)
$Dis * Post5$		0.571***		0.552***		0.553***		0.569***
		(2.903)		(2.986)		(2.913)		(2.979)
$Dis * Post6$		0.576***		0.589***		0.589***		0.600***
		(3.127)		(3.157)		(3.052)		(3.093)
Model	**TWFE**	**TWFE**	**CS**	**CS**	**SA**	**SA**	**DD**	**DD**

*p<0.1; **p<0.05; ***p<0.01

Panel C: Share of Retail FT to Public Stores with Adjacent Store (N = 28,764)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Dis * Post$	0.523***		0.537***		0.537***		0.532***	
	(4.417)		(4.305)		(4.536)		(4.472)	
$Dis * Post0$		0.149		0.157*		0.157		0.153
		(1.000)		(1.660)		(1.625)		(1.554)
$Dis * Post1$		0.418***		0.437***		0.437***		0.434***
		(3.127)		(3.178)		(3.186)		(3.093)
$Dis * Post2$		0.539***		0.561***		0.561***		0.557***
		(3.287)		(3.156)		(3.267)		(3.170)
$Dis * Post3$		0.620***		0.634***		0.634***		0.631***
		(3.141)		(4.015)		(3.811)		(3.746)
$Dis * Post4$		0.724***		0.756***		0.756***		0.756***
		(3.406)		(4.789)		(4.904)		(4.869)
$Dis * Post5$		0.743***		0.793***		0.793***		0.792***
		(4.196)		(5.197)		(5.151)		(5.117)
$Dis * Post6$		0.753***		0.817***		0.817***		0.816***
		(4.241)		(4.911)		(5.287)		(5.260)
Model	**TWFE**	**TWFE**	**CS**	**CS**	**SA**	**SA**	**DD**	**DD**

Panel D: Share of Retail FT to Public Stores without Adjacent Store (N = 28,764)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Dis * Post$	-0.040		-0.031		-0.031		-0.030	
	(-1.027)		(-1.068)		(-1.069)		(-1.025)	
$Dis * Post0$		-0.067*		-0.066**		-0.066**		-0.067**
		(-1.944)		(-2.476)		(-2.522)		(-2.483)
$Dis * Post1$		-0.045		-0.045		-0.045		-0.047
		(-1.429)		(-1.461)		(-1.514)		(-1.571)
$Dis * Post2$		-0.044		-0.044		-0.044		-0.046
		(-1.375)		(-1.178)		(-1.200)		(-1.255)
$Dis * Post3$		-0.011		-0.009		-0.009		-0.012
		(-0.225)		(-0.224)		(-0.229)		(-0.290)
$Dis * Post4$		-0.001		0.007		0.007		0.006
		(-0.026)		(0.169)		(0.168)		(0.126)
$Dis * Post5$		-0.074**		-0.067		-0.067*		-0.068*
		(-1.995)		(-1.590)		(-1.677)		(-1.697)
$Dis * Post6$		-0.067		-0.059		-0.059		-0.059
		(-1.185)		(-1.122)		(-1.210)		(-1.213)
Model	**TWFE**	**TWFE**	**CS**	**CS**	**SA**	**SA**	**DD**	**DD**

*p<0.1; **p<0.05; ***p<0.01

Panel E: Share of Retail FT to Private Stores with Adjacent Store (N = 28,764)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Dis * Post$	-0.094		-0.072		-0.072		-0.077	
	(-0.959)		(-0.713)		(-0.719)		(-0.760)	
$Dis * Post0$		-0.112		-0.115		-0.115		-0.111
		(-0.967)		(-1.601)		(-1.601)		(-1.504)
$Dis * Post1$		-0.070		-0.081		-0.082		-0.074
		(-0.623)		(-0.810)		(-0.781)		(-0.685)
$Dis * Post2$		0.097		0.085		0.085		0.096
		(0.547)		(0.566)		(0.621)		(0.689)
$Dis * Post3$		-0.000		-0.047		-0.046		-0.030
		(-0.002)		(-0.331)		(-0.358)		(-0.231)
$Dis * Post4$		-0.117		-0.194		-0.194		-0.175
		(-0.726)		(-1.387)		(-1.415)		(-1.269)
$Dis * Post5$		-0.172		-0.241*		-0.240*		-0.224
		(-1.147)		(-1.696)		(-1.762)		(-1.629)
$Dis * Post6$		-0.177		-0.228		-0.228		-0.216
		(-1.127)		(-1.512)		(-1.594)		(-1.505)
Model	**TWFE**	**TWFE**	**CS**	**CS**	**SA**	**SA**	**DD**	**DD**

Panel F: Share of Retail FT to Private Stores without Adjacent Store (N = 28,764)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Dis * Post$	-0.389***		-0.434***		-0.434***		-0.425***	
	(-2.984)		(-2.892)		(-2.959)		(-2.836)	
$Dis * Post0$		0.030		0.024		0.024		0.025
		(0.192)		(0.191)		(0.197)		(0.198)
$Dis * Post1$		-0.303		-0.310*		-0.310*		-0.312*
		(-1.632)		(-1.648)		(-1.746)		(-1.700)
$Dis * Post2$		-0.593**		-0.602**		-0.602***		-0.607***
		(-2.369)		(-2.481)		(-2.642)		(-2.597)
$Dis * Post3$		-0.609**		-0.578***		-0.578***		-0.590***
		(-2.371)		(-2.782)		(-2.637)		(-2.648)
$Dis * Post4$		-0.605**		-0.569***		-0.570***		-0.586***
		(-2.322)		(-2.930)		(-2.958)		(-3.020)
$Dis * Post5$		-0.498**		-0.485***		-0.485**		-0.500***
		(-2.543)		(-2.618)		(-2.568)		(-2.630)
$Dis * Post6$		-0.509***		-0.530**		-0.530***		-0.541***
		(-2.615)		(-2.450)		(-2.719)		(-2.761)
Model	**TWFE**	**TWFE**	**CS**	**CS**	**SA**	**SA**	**DD**	**DD**

*p<0.1; **p<0.05; ***p<0.01

Table 11: **Heterogeneity of Private Share Result by Population and Minority Share**

This table shows the effects of natural disasters on private share in the impacted county, split by county population and county minority share. Panel A splits counties into terciles based on population. Panel B splits counties into terciles based on minority share. Panel C examines heterogeneity across minority share within low population counties. We present coefficients from a Two-Way Fixed Effects [TWFE] model, as well as a robust estimator introduced in Callaway and Sant'Anna (2021) [CS]. Standard errors are clustered by county.
Sources: SafeGraph, SHELDUS, U.S. Census Bureau, Authors' analysis

Dependent Variable: Retail Private Share						
Panel A: Split by County Population						
Population	**Low**	**Med**	**High**	**Low**	**Med**	**High**
	(1)	(2)	(3)	(4)	(5)	(6)
Post ∗ *Disaster*	-0.959***	-0.330	-0.119	-0.981***	-0.410**	-0.040
	(-4.227)	(-1.594)	(-0.859)	(-3.958)	(-2.474)	(-0.212)
Model	**TWFE**	**TWFE**	**TWFE**	**CS**	**CS**	**CS**
Obs	9,588	9,588	9,588	9,588	9,588	9,588
Med. Pop.	8,923	28,530	135,692	8,923	28,530	135,692
Panel B: Split by Minority Share						
Minority Share	**Low**	**Med**	**High**	**Low**	**Med**	**High**
	(1)	(2)	(3)	(4)	(5)	(6)
Post ∗ *Disaster*	-0.347	-0.547***	-0.516***	-0.445*	-0.532**	-0.474**
	(-1.433)	(-3.328)	(-3.416)	(-1.925)	(-2.511)	(-2.301)
Model	**TWFE**	**TWFE**	**TWFE**	**CS**	**CS**	**CS**
Obs	9,288	9,276	9,288	9,288	9,276	9,288
Med. Black Share	0.013	0.039	0.195	0.013	0.039	0.195
Panel C: Low Population, Split by Minority Share						
Minority Share	**Low**	**Med**	**High**	**Low**	**Med**	**High**
	(1)	(2)	(3)	(4)	(5)	(6)
Post ∗ *Disaster*	-0.443	-1.541***	-1.958***	-0.537	-1.601***	-1.932***
	(-1.310)	(-4.014)	(-4.464)	(-1.555)	(-3.202)	(-3.086)
Model	**TWFE**	**TWFE**	**TWFE**	**CS**	**CS**	**CS**
Obs	4,992	2,520	1,968	4,992	2,520	1,968
Med. Black Share	0.013	0.034	0.301	0.013	0.034	0.301
						*p<0.1; **p<0.05; ***p<0.01

Table 12: **Dollar Store Share of Retail Foot Traffic**

This table shows the effects of natural disasters on the proportion of retail foot traffic to dollar stores in impacted counties. *Dis* is an indicator variable equal to 1 for treated counties that were impacted by a natural disaster. *Post* is an indicator equal to 1 in months after the disaster for treated counties. $Post_i$ are indicators equal to 1 in month i after disaster. We present coefficients from a Two-Way Fixed Effects [TWFE] model, as well as robust estimators introduced in Callaway and Sant'Anna (2021) [CS], Sun and Abraham (2021) [SA], and De Chaisemartin and d'Haultfoeuille (2020) [DD]. Standard errors are clustered by county.
Sources: SafeGraph, SHELDUS, Authors' analysis

Share of Retail Foot Traffic to Dollar Stores (N = 28,764)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Dis * Post$	0.229***		0.263***		0.262***		0.267***	
	(3.376)		(3.433)		(3.747)		(3.706)	
$Dis * Post0$		0.109***		0.108**		0.108**		0.109**
		(8.425)		(2.133)		(2.150)		(2.125)
$Dis * Post1$		0.278**		0.278**		0.278***		0.281**
		(2.584)		(2.257)		(2.672)		(2.611)
$Dis * Post2$		0.359**		0.356*		0.355**		0.356**
		(2.501)		(1.780)		(2.370)		(2.299)
$Dis * Post3$		0.298***		0.305***		0.305***		0.305***
		(3.792)		(3.255)		(3.532)		(3.420)
$Dis * Post4$		0.249**		0.257***		0.257***		0.256***
		(2.250)		(3.193)		(3.328)		(3.293)
$Dis * Post5$		0.247***		0.256***		0.256***		0.254***
		(3.718)		(3.036)		(3.061)		(3.016)
$Dis * Post6$		0.262***		0.241***		0.24***1		0.240***
		(3.660)		(2.836)		(2.893)		(2.871)
Model	**TWFE**	**TWFE**	**CS**	**CS**	**SA**	**SA**	**DD**	**DD**

*p<0.1; **p<0.05; ***p<0.01

Table 13: **Heterogeneity of Dollar Store Result by Population and Minority Share**

This table shows the effects of natural disasters on dollar store foot traffic share in the impacted county, split by county population and county minority share. Panel A splits counties into terciles based on population. Panel B splits counties into terciles based on minority share. Panel C examines heterogeneity across minority share within low population counties. We present coefficients from a Two-Way Fixed Effects [TWFE] model, as well as a robust estimator introduced in Callaway and Sant'Anna (2021) [CS]. Standard errors are clustered by county. *Sources: SafeGraph, SHELDUS, U.S. Census Bureau, Authors' analysis*

Dependent Variable: Share of Retail Foot Traffic to Dollar Stores						
Panel A: Split by County Population						
Population	**Low**	**Med**	**High**	**Low**	**Med**	**High**
	(1)	(2)	(3)	(4)	(5)	(6)
Post ∗ *Disaster*	0.373**	0.202***	0.093**	0.426**	0.188***	0.114**
	(2.058)	(2.628)	(2.520)	(2.245)	(2.868)	(2.469)
Model	**TWFE**	**TWFE**	**TWFE**	**CS**	**CS**	**CS**
Obs	9,588	9,588	9,588	9,588	9,588	9,588
Med. Pop.	8,923	28,530	135,692	8,923	28,530	135,692
Panel B: Split by Minority Share						
Minority Share	**Low**	**Med**	**High**	**Low**	**Med**	**High**
	(1)	(2)	(3)	(4)	(5)	(6)
Post ∗ *Disaster*	0.193**	0.271*	0.189*	0.227**	0.218	0.332**
	(2.540)	(1.751)	(1.877)	(2.118)	(1.462)	(2.054)
Model	**TWFE**	**TWFE**	**TWFE**	**CS**	**CS**	**CS**
Obs	9,288	9,276	9,288	9,288	9,276	9,288
Med. Black Share	0.013	0.039	0.195	0.013	0.039	0.195
Panel C: Low Population, Split by Minority Share						
Minority Share	**Low**	**Med**	**High**	**Low**	**Med**	**High**
	(1)	(2)	(3)	(4)	(5)	(6)
Post ∗ *Disaster*	0.238*	0.667	0.634	0.289*	0.515	1.411*
	(1.852)	(1.249)	(1.492)	(1.665)	(0.825)	(1.854)
Model	**TWFE**	**TWFE**	**TWFE**	**CS**	**CS**	**CS**
Obs	4,992	2,520	1,968	4,992	2,520	1,968
Med. Black Share	0.013	0.034	0.301	0.013	0.034	0.301
						*p<0.1; **p<0.05; ***p<0.01

Table 14: **Natural Disaster Damages and Stock Market Returns**

This table documents the relationship between total damages from natural disasters in the previous month and stock market returns to relevant firms and industries. The dependent variable is the excess return on a stock or portfolio of stocks adjusted for the Fama and French 3-factor model plus momentum. The independent variable is the logged total property damage (2019-adjusted) from disasters in the previous month. Panel A shows dollar store stocks and portfolios of retail stocks. DT is Dollar Tree's stock return, DG is Dollar General's stock return, Avg Dol is the equal-weighted dollar store return, Retail is a portfolio of stocks from Fama and French's 49 industry classification, and Shops is a portfolio of stocks from Fama and French's 10 industry classification. Panel B shows results for the other nine industries in the Fama and French 10 industry classification. Newey-West adjusted standard errors are in parentheses.
Sources: SafeGraph, SHELDUS, CRSP, Ken French's Data Library, Authors' analysis

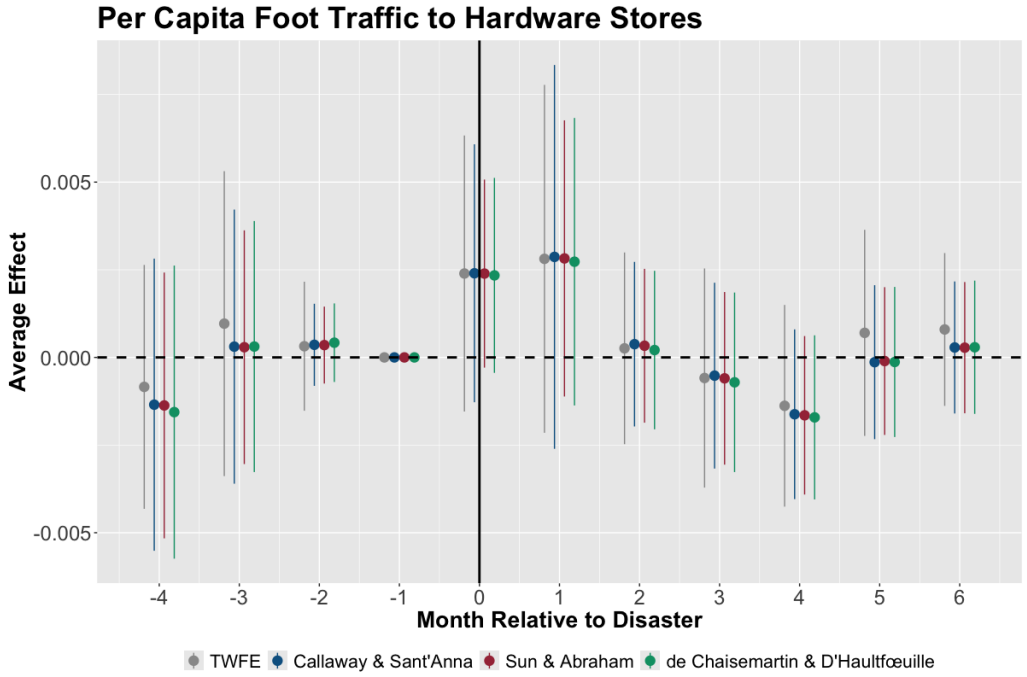
Dependent Variable: 4-Factor Adjusted Return					
Panel A: Retail Stocks					
	DT	**DG**	**Avg Dol**	**Retail**	**Shops**
	(1)	(2)	(3)	(4)	(5)
$log(DMG_{t-1})$	1.283**	0.713	1.210**	0.2048*	0.1581
	(2.393)	(1.489)	(2.491)	(1.752)	(1.602)
Years	1995-2021	2009-2021	1995-2021	1960-2021	1960-2021
Month FE	✓	✓	✓	✓	✓
Observations	322	146	322	743	743
R^2	0.062	0.077	0.063	0.052	0.047
Within R^2	0.015	0.011	0.014	0.004	0.004
Panel B: Other FF10 Industries					
	NoDur	**Durbl**	**Manuf**	**Enrgy**	**HiTec**
	(1)	(2)	(3)	(4)	(5)
$log(DMG_{t-1})$	-0.070	-0.112	0.084	-0.086	0.012
	(-0.813)	(-0.774)	(1.501)	(-0.542)	(0.122)
Years	1960-2021	1960-2021	1960-2021	1960-2021	1960-2021
Month FE	✓	✓	✓	✓	✓
Observations	743	743	743	743	743
R^2	0.029	0.016	0.041	0.018	0.030
Within R^2	0.001	0.001	0.002	0.000	0.000
	Telcm	**Hlth**	**Utils**	**Other**	
	(6)	(7)	(8)	(9)	
$log(DMG_{t-1})$	-0.147	-0.029	-0.097	0.028	
	(-1.347)	(-0.262)	(-0.859)	(0.457)	
Years	1960-2021	1960-2021	1960-2021	1960-2021	
Month FE	✓	✓	✓	✓	
Observations	743	743	743	743	
R^2	0.022	0.006	0.021	0.019	
Within R^2	0.002	0.000	0.001	0.000	

*p<0.1; **p<0.05; ***p<0.01

10 Appendix

Figure A1: **Foot Traffic to Hardware Stores**

This figure shows the dynamics of foot traffic to hardware stores at the county level in the four months prior and the six months following a natural disaster event. The control group is a set of counties that were not hit by natural disasters. The figures plot coefficients and 95% confidence intervals from a dynamic staggered difference-in-differences specification. The dependent variable in the top figure is per capita foot traffic to hardware stores. The dependent variable in the bottom figure is the private share of foot traffic to hardware stores.
Sources: SafeGraph, SHELDUS, U.S. Census Bureau, Authors' analysis



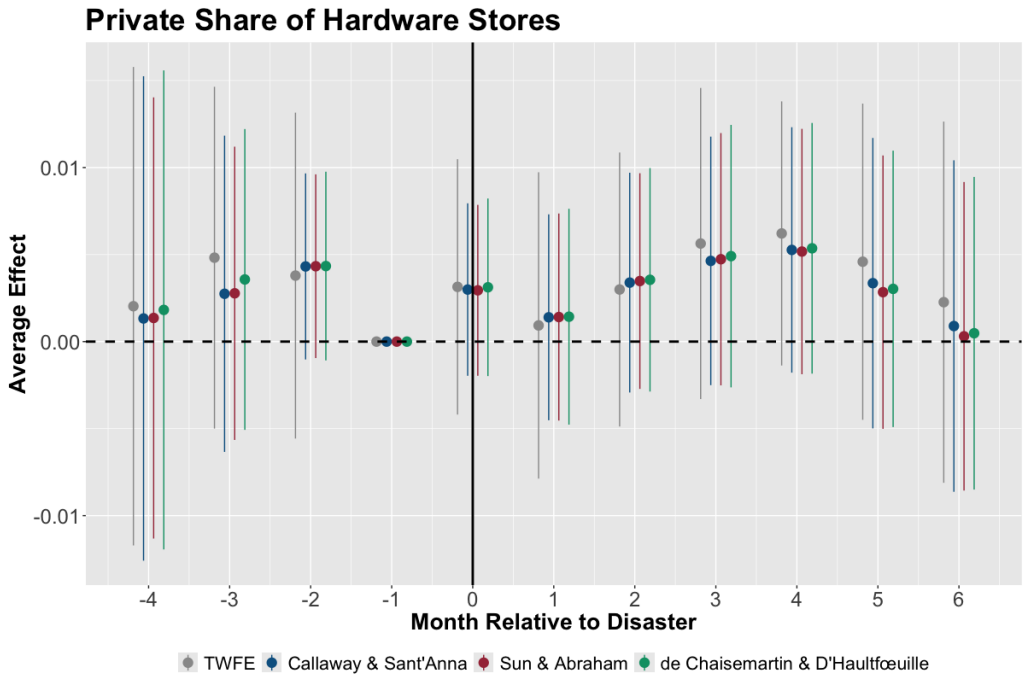


Figure A2: **Retail Store Closures Around Natural Disasters**

This figure shows the dynamics of retail store closures at the county level in the four months prior and the six months following a natural disaster event. The control group is a set of counties that were not hit by natural disasters. The figures plot coefficients and 95% confidence intervals from a dynamic staggered difference-in-differences specification. The top figure shows results for private retail stores. The bottom figure shows results for public retail stores.
Sources: SafeGraph, SHELDUS, Authors' analysis





Table A1: **FEMA Declared Disasters vs. Other Disasters**

This table shows main results split by FEMA declared disasters and other disasters in the SHELDUS data. Panel A shows summary statistics for each group. Panel B shows results from individual regressions (1) where the dependent variable is (a) per capita foot traffic to all stores, (b) per capita foot traffic to retail stores, (c) private share for all stores, (d) private share for retail stores, or (e) share of foot traffic to dollar stores. Regressions are estimated separately for FEMA declared disasters and other disasters in the SHELDUS data. Coefficients are estimated using the Callaway and Sant'Anna (2021) model. Standard errors are clustered by county.
Sources: SafeGraph, SHELDUS, U.S. Census Bureau, Authors' analysis

Panel A: Summary Statistics

	FEMA Declared	**Non-FEMA Declared**
Number of Disasters	141	246
Mean Property Damage ($)	14,385,974	10,692,730
Median Property Damage ($)	800,000	500,000
Mean Per Capita Property Damage ($)	215.66	53.40
Median Per Capita Property Damage ($)	34.36	16.54

Panel B: Coefficient on $Dis * Post$

	FEMA Declared	**Non-FEMA Declared**
Per Capita Foot Traffic, All	0.070	-0.020
	(1.107)	(-0.768)
Per Capita Foot Traffic, Retail	0.026*	-0.008
	(1.567)	(-0.905)
Private Share, All	-0.226*	-0.247**
	(-1.769)	(-2.484)
Private Share, Retail	-0.475**	-0.528***
	(-2.494)	(-3.295)
Dollar Store Share	0.246**	0.274***
	(2.523)	(2.656)

Table A2: **Results by US Census Region**

This table shows main results split by Census Region in the US: Northeast, Midwest, South, and West. Panel A shows summary statistics for each group. Panel B shows results from individual regressions (1) where the dependent variable is (a) per capita foot traffic to all stores, (b) per capita foot traffic to retail stores, (c) private share for all stores, (d) private share for retail stores, or (e) share of foot traffic to dollar stores. Regressions are estimated separately by region. Coefficients are estimated using the Callaway and Sant'Anna (2021) model. Standard errors are clustered by county.
Sources: SafeGraph, SHELDUS, U.S. Census Bureau, Authors' analysis

Panel A: Summary Statistics

	Northeast	**Midwest**	**South**	**West**
Number of Counties	177	755	1,090	308
Number of Disasters	21	181	157	28
Mean Property Damage ($)	1,967,500	9,108,723	17,915,422	5,575,584
Median Property Damage ($)	850,000	500,000	500,000	902,000
Mean Per Capita Property Damage ($)	32.99	161.01	75.37	67.02
Median Per Capita Property Damage ($)	13.62	22.85	16.42	33.03

Panel B: Coefficient on $Dis * Post$

	Northeast	**Midwest**	**South**	**West**
Per Capita Foot Traffic, All	-0.109**	-0.009	-0.005	0.207**
	(-2.144)	(-0.454)	(-0.083)	(2.560)
Per Capita Foot Traffic, Retail	-0.026**	-0.010	0.000	0.073*
	(-2.183)	(-1.282)	(0.000)	(1.831)
Private Share, All	-0.044	0.000	-0.413***	-0.320
	(-0.122)	(0.002)	(3.319)	(0.791)
Private Share, Retail	-0.176	-0.458**	-0.518***	-0.001
	(-0.484)	(-2.570)	(-2.578)	(-0.001)
Dollar Store Share	0.098	0.201*	0.272**	0.183
	(0.894)	(1.945)	(2.044)	(1.583)

Table A3: **Results by Disaster Type**

This table shows main results split by disaster type: Flooding, Tornado, Wind, and Other. Panel A shows summary statistics for each group. Panel B shows results from individual regressions (1) where the dependent variable is (a) per capita foot traffic to all stores, (b) per capita foot traffic to retail stores, (c) private share for all stores, (d) private share for retail stores, or (e) share of foot traffic to dollar stores. The set of untreated counties are used as controls in each regression. Coefficients are estimated using the Callaway and Sant'Anna (2021) model. Standard errors are clustered by county.
Sources: SafeGraph, SHELDUS, U.S. Census Bureau, Authors' analysis

Panel A: Summary Statistics

	Flooding	**Tornado**	**Wind**	**Other**
Number of Disasters	184	106	43	54
Mean Property Damage ($)	8,740,776	27,258,509	1,345,037	1,912,826
Median Property Damage ($)	550,000	500,000	500,000	660,000
Mean Per Capita Property Damage ($)	159.88	91.66	40.06	49.78
Median Per Capita Property Damage ($)	23.99	18.21	17.79	15.45

Panel B: Coefficient on $Dis * Post$

	Flooding	**Tornado**	**Wind**	**Other**
Per Capita Foot Traffic, All	0.090*	-0.067**	-0.097	0.011
	(1.713)	(-2.237)	(-0.797)	(0.218)
Per Capita Foot Traffic, Retail	0.028**	-0.018	-0.017	0.009
	(2.119)	(-1.397)	(-0.655)	(0.449)
Private Share, All	-0.214*	-0.325**	-0.482**	0.043
	(-1.907)	(-2.186)	(-2.346)	(0.178)
Private Share, Retail	-0.615***	-0.301	-0.718*	-0.330
	(-3.904)	(-1.495)	(-1.905)	(-0.833)
Dollar Store Share	0.186**	0.361**	0.250	0.362
	(2.436)	(2.298)	(1.378)	(0.957)

Table A4: **Foot Traffic Dynamics to Hardware Stores Around Natural Disasters**

This table shows the effects of natural disasters foot traffic to hardware stores. *Dis* is an indicator variable equal to 1 for treated counties that were impacted by a natural disaster. *Post* is an indicator equal to 1 in months after the disaster for treated counties. $Post_i$ are indicators equal to 1 in month i after disaster. In Panel A, the dependent variable is the per capita foot traffic to hardware stores. In Panel B, the dependent variable is the private share of foot traffic to hardware stores. We present coefficients from a Two-Way Fixed Effects [TWFE] model, as well as robust estimators introduced in Callaway and Sant'Anna (2021) [CS], Sun and Abraham (2021) [SA], and De Chaisemartin and d'Haultfoeuille (2020) [DD]. Standard errors are clustered by county. *Sources: SafeGraph, SHELDUS, U.S. Census Bureau, Authors' analysis*

Panel A: Per Capita FT to Hardware Stores (N = 28,764)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Dis * Post$	0.001		0.001		0.001		0.001	
	(1.642)		(0.985)		(0.937)		(0.819)	
$Dis * Post0$		0.002		0.002		0.002*		0.002*
		(1.216)		(1.267)		(1.783)		(1.683)
$Dis * Post1$		0.003		0.003		0.003		0.003
		(1.134)		(1.047)		(1.434)		(1.332)
$Dis * Post2$		0.000		0.000		0.000		0.000
		(0.190)		(0.321)		(0.304)		(0.186)
$Dis * Post3$		-0.001		-0.001		-0.001		-0.001
		(-0.376)		(-0.401)		(-0.485)		(-0.555)
$Dis * Post4$		-0.001		-0.002		-0.002		-0.002
		(-0.960)		(-1.375)		(-1.461)		(-1.462)
$Dis * Post5$		0.001		-0.000		-0.000		-0.000
		(0.477)		(-0.120)		(-0.098)		(-0.121)
$Dis * Post6$		0.001		0.000		0.000		0.000
		(0.732)		(0.290)		(0.297)		(0.305)
Model	**TWFE**	**TWFE**	**CS**	**CS**	**SA**	**SA**	**DD**	**DD**

Panel B: Private Share of FT to Hardware Stores (N = 28,764)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Dis * Post$	0.001		0.004		0.004		0.004	
	(0.339)		(1.331)		(1.322)		(1.338)	
$Dis * Post0$		0.003		0.003		0.003		0.003
		(0.857)		(1.245)		(1.200)		(1.224)
$Dis * Post1$		0.001		0.001		0.001		0.001
		(0.211)		(0.471)		(0.474)		(0.461)
$Dis * Post2$		0.003		0.003		0.003		0.004
		(0.761)		(1.011)		(1.123)		(1.106)
$Dis * Post3$		0.006		0.005		0.005		0.005
		(1.261)		(1.301)		(1.306)		(1.302)
$Dis * Post4$		0.006		0.005		0.005		0.005
		(1.638)		(1.447)		(1.468)		(1.489)
$Dis * Post5$		0.005		0.003		0.003		0.003
		(1.011)		(0.810)		(0.723)		(0.763)
$Dis * Post6$		0.002		0.001		0.000		0.000
		(0.437)		(0.205)		(0.069)		(0.107)
Model	**TWFE**	**TWFE**	**CS**	**CS**	**SA**	**SA**	**DD**	**DD**

*p<0.1; **p<0.05; ***p<0.01

Table A5: **Retail Store Closures Around Natural Disasters**

This table shows the effects of natural disasters on retail store closures. . *Dis* is an indicator variable equal to 1 for treated counties that were impacted by a natural disaster. *Post* is an indicator equal to 1 in months after the disaster for treated counties. $Post_i$ are indicators equal to 1 in month i after disaster. In Panel A, the dependent variable is number of private store closures. In Panel B, the dependent variable is the number of public store closures. We present coefficients from a Two-Way Fixed Effects [TWFE] model, as well as robust estimators introduced in Callaway and Sant'Anna (2021) [CS], Sun and Abraham (2021) [SA], and De Chaisemartin and d'Haultfoeuille (2020) [DD]. Standard errors are clustered by county. *Sources: SafeGraph, SHELDUS, Authors' analysis*

Panel A: Private Store Closures (N = 28,884)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Dis * Post$	-0.002		-0.015		-0.015		-0.024	
	(-0.035)		(-0.258)		(-0.269)		(-0.439)	
$Dis * Post0$		0.029		0.020		0.020		0.019
		(0.339)		(0.441)		(0.446)		(0.405)
$Dis * Post1$		0.045		0.046		0.047		0.042
		(0.622)		(0.763)		(0.798)		(0.709)
$Dis * Post2$		0.060		0.054		0.054		0.048
		(0.570)		(0.699)		(0.719)		(0.648)
$Dis * Post3$		-0.019		-0.028		-0.028		-0.035
		(-0.254)		(-0.528)		(-0.540)		(-0.674)
$Dis * Post4$		-0.056		-0.030		-0.030		-0.039
		(-0.843)		(-0.447)		(-0.458)		(-0.586)
$Dis * Post5$		-0.121		-0.096		-0.096		-0.104
		(-1.535)		(-1.431)		(-1.411)		(-1.513)
$Dis * Post6$		-0.091		-0.049		-0.049		-0.054
		(-1.032)		(-0.513)		(-0.543)		(-0.588)
Model	**TWFE**	**TWFE**	**CS**	**CS**	**SA**	**SA**	**DD**	**DD**

Panel B: Public Store Closures (N=28,884)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Dis * Post$	0.001		-0.005		-0.005		-0.005	
	(0.088)		(-0.472)		(1.000)		(-0.634)	
$Dis * Post0$		-0.001		-0.000		-0.000		-0.000
		(-0.079)		(-0.033)		(-0.032)		(-0.035)
$Dis * Post1$		0.001		0.001		0.001		0.001
		(0.089)		(0.084)		(0.082)		(0.054)
$Dis * Post2$		0.003		0.002		0.002		0.001
		(0.159)		(0.122)		(0.126)		(0.102)
$Dis * Post3$		0.003		0.001		0.000		0.000
		(0.177)		(0.032)		(0.022)		(0.004)
$Dis * Post4$		-0.003		-0.000		-0.000		-0.001
		(-0.212)		(-0.007)		(-0.024)		(-0.057)
$Dis * Post5$		-0.009		-0.007		-0.007		-0.008
		(-0.784)		(-0.533)		(-0.557)		(-0.581)
$Dis * Post6$		-0.012		-0.014		-0.014		-0.014
		(-0.981)		(-0.937)		(-0.987)		(-0.988)
Model	**TWFE**	**TWFE**	**CS**	**CS**	**SA**	**SA**	**DD**	**DD**

*p<0.1; **p<0.05; ***p<0.01