Rebuilding After the Storm: Firm Turnover and Consumer Welfare After Hurricane Harvey *

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Abstract

How do adverse shocks affect firm exit, entry, and consumer welfare? The long-term impacts of a negative shock depend on the value of exiting firms relative to that of those that replace them. We study these issues in the context of Hurricane Harvey, which led to substantial retail turnover. To quantify the impact of turnover on consumers, we estimate a model of demand and find that the average exiting store contributes 36% less to consumer surplus than the average entrant and 51% less than the average surviving incumbent. However, because a subset of exiting firms creates substantial welfare gains and most entry takes place far from the neighborhoods with the highest exit rates, some consumers experience large welfare losses. We therefore consider the welfare effects of a business aid program that reduces the likelihood that damaged stores exit. We find that most businesses contribute less to consumer welfare than the cost of aid they require, which suggest little scope for aid policy. However, we also find that a program that target firms on observable characteristics would identify a large fraction of the few businesses that generate substantial net gains.

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1 Introduction

Negative economic shocks, such as recessions, natural disasters, or the COVID-19 pandemic, may impact the survival of firms and, by extension, the welfare of consumers who purchase from them. However, the consequences of such shocks depend heavily on the firm exit and entry process. Going back to Schumpeter (1934), economists have argued that these events may have a "cleansing" effect by clearing out lower-value firms and creating space for more valuable entrants. In this view, the welfare impact of a transitory shock may be small. On the other hand, if the shock induces higher-value firms to exit or new firms are slow to enter, it may have a "scarring" effect, causing larger and more persistent welfare effects and leaving scope for policy intervention.[1]

In this paper, we study the firm exit and entry process and its impact on consumer welfare in the context of one particular shock—Hurricane Harvey, which affected the Gulf Coast in 2017. Harvey created an ideal laboratory to study these issues: it caused over $125B in damage with substantial heterogeneity over space, resulting in wide variation in storm damage across firms. Further, Hurricane Harvey had the characteristics of a large temporary shock (i.e., it did not result in significant outmigration and had little impact on consumer spending in the medium to long run). Understanding the impact of natural disasters on firms and consumers more generally is important in its own right, as these events become more common and more costly due to climate change (Holland and Bruyère, 2014, Emanuel, 2017, Balaguru et al., 2018, Bhatia et al., 2019). Finally, natural disasters are of direct policy importance; the U.S. government spent an estimated $186 billion on disaster aid from 2011 to 2021 through FEMA alone (Congressional Budget Office, 2022).

To quantify how Hurricane Harvey impacted firm exit, entry, and consumer welfare, we proceed in three steps. First, we use high-frequency transaction data to quantify exit and subsequent entry among retail establishments and restaurants. Second, we use these data to estimate a model of consumer behavior that allows us to measure the consumer surplus created by each establishment and the net impact of exit and entry on welfare. Third, we

[1]Market frictions and externalities are one justification for policies that provide temporary subsidies to firms, including the pandemic-era Paycheck Protection Program, subsidized disaster loans provided by the Small Business Administration (SBA), and grant-based aid programs administered by the U.S. Department for Housing and Urban Development (HUD).

examine whether the benefits of a grant-based aid program would exceed its cost.

Our analysis combines granular measures of localized flooding with high-frequency credit and debit card data to examine the impact of the hurricane on local retail establishments and consumers. A unique strength of our data is that it allows us to measure the precise timing and duration of closures, which we infer from card transactions. We focus on three hard-hit metropolitan statistical areas (MSAs) in Texas: Houston, Corpus Christi, and Beaumont. We show that across these MSAs the exit rate in the month of the storm is eight times larger than the baseline level and is significantly higher in more flooded areas, suggesting that a large fraction of exits were caused by the storm. Overall, we find that about 1.2% of stores (390 stores) permanently exited in the month after the landing of Harvey and 2.8% of stores (863) closed temporarily for two months or more.[2] We find that exits were geographically concentrated, with 7% of the Census tracts accounting for nearly 40% of permanent closures despite containing just 4% of establishments. Exit rates were higher in the smaller MSAs of Beaumont and Corpus Christi than in Houston, as well as for establishments unaffiliated with large chains.

Although hundreds of establishments closed after the storm, these stores may be replaced by new entrants, partially offsetting consumer harm from closures. Further, store turnover may benefit consumers if higher-value entrants replace low-value options. We identify 1,109 entrants (3.6% of the pre-storm total) who opened between September 2017 and December 2018. We find that, on average, entrants had more transactions and higher sales than stores in the same industry that exited, suggesting that entrants contributed more to consumer welfare than exiters. However, at the neighborhood level, the number of entrants did not fully replace exits, and we find that hard-hit areas had a net decrease in the number of active stores.

We next illustrate how disaster-induced closures affected consumer welfare through two channels: increased travel distance and substitution to less preferred stores.[3] We do this using a sample of credit card holders who, before the storm, visited at least one of the 20

[2]The monthly baseline exit rate was 0.16% before the storm between January and July 2017. We compare these baseline exit rates with those calculated by the U.S. Census Bureau in Appendix C.2.

[3]A third channel through which natural disasters may impact consumers is through changes in retail prices. In Appendix D, we show that Hurricane Harvey did not cause medium- to long-term price changes.

largest stores that closed after the hurricane. After closure, the distance these consumers traveled to make a purchase increased by about 15%. This increase in distance traveled was entirely driven by transactions at the same chain as the closure, where distance traveled increased by about 50%, suggesting strong chain-specific preferences.

We next estimate a consumer demand model that accounts for travel distance and store preferences. In the model, consumers in each neighborhood choose between a differentiated set of available stores within a category. Our model accounts for observed and unobserved preference heterogeneity, allowing tastes to vary across and within each neighborhood. We estimate the model for 12 store categories using pre-storm purchase data in each of our three MSAs.[4]

We first use the demand model to quantify the consumer welfare contribution of each store. We find that the median exiting establishment would create about $121,000 of surplus over the 16-month post-storm period, relative to $190,000 for the median entrant and $245,000 for the median surviving incumbent.[5] This is broadly consistent with models of creative destruction, in which a negative shock purges the least valuable establishments. However, we also find evidence of significant dispersion among stores that exit; the 90th percentile exiting store creates more than $1M in surplus over the same period. This implies that while many establishments that closed would have created only marginal amounts of social surplus, some were significantly more valuable, and their closures led to sizeable consumer harm.

We then use the model to measure the aggregate consumer welfare effects of retail turnover after the hurricane from September 2017 to December 2018, accounting for the net impact of both entry and exit. Because our data include the location of consumers, we can measure the impacts flexibly across consumers who live in different neighborhoods. We find that welfare impacts are highly heterogeneous across Census tracts, with some neighborhoods experiencing no welfare loss and others losing over 9% of pre-storm consumption through December 2018. While consumer welfare benefits of new entry are significant, en-

[4]Our sample includes 11 3-digit retail NAICS categories beginning with 44 and 45, plus restaurants (NAICS 722), which together cover about 90% of brick-and-mortar payment card spending.

[5]In comparison, average store revenues over 16 months would be about $404,000 for the median post-storm exiting store, relative to $867,000 for the median entrant and $1.01M for the median surviving incumbent.

trants tend to locate sufficiently far from the most hard-hit areas. Therefore, consumers in these areas suffer a large welfare loss despite new entry.

On average, losses were greater in Corpus Christi and Beaumont, where exit rates were higher and fewer alternative store choices were available than in Houston. We also find larger impacts in low-income neighborhoods across the three MSAs conditional on flood exposure. The bottom 40% of tracts (by median household income) in each MSA suffered a welfare loss between 1.5 and 15 times larger than the highest quintile of tracts. This differential impact is partially driven by more limited access to retail options in low-income neighborhoods relative to higher-income ones, increasing the welfare impact of closures. Our findings highlight the potential for shocks to disproportionately impact smaller and lower-income places.

We then consider the impact of a grant-based business aid policy, as has been discussed in Congress after major disasters (Simon and De Avila, 2017). If the value consumers place on the stores that close is sufficiently high, a subsidy program to firms may justify its cost. Evaluating a business aid policy requires estimates of both the costs and benefits of such a program. To do this, we model the re-entry decision for stores that closed temporarily after the storm. The model exploits the relationship between establishment re-entry decisions and monetized storm damage, which we measure using novel data collected by the property tax authority for establishments in Houston to identify the impact of aid on firm survival.

We use the model to quantify how the aid program impacts each store's permanent exit probability. We compare the cost of aid to the program's expected benefit: the sum of the change in consumer welfare from keeping that outlet in the consumer choice set and the unemployment benefits that would be paid to its workers multiplied by the change in exit probability induced by the aid package. We find that, generally, few establishments generate sufficient benefit to justify the cost of aid (about 20% of establishments in our baseline scenario). However, there is a substantial subset of establishments for which the proposed subsidy program would generate positive net value.

To illustrate this, we consider two variants of the baseline aid program. In the first one, we assume policymakers can identify and target establishments that generate positive net value. Under perfect targeting, gains from the aid program are substantial—each dollar of aid generates $2.24 in benefits. In the second one, we consider a situation where the

policymaker can target establishments based only on their observable characteristics. While in the first variant, by construction, all subsidized firms contribute more to welfare than the cost of aid, we find that targeting on observables allows a policymaker to achieve about 70% of the net gain of the perfect targeting variant or a benefit of $1.73 per dollar spent.

Overall, our results illustrate that many of the stores that closed after the hurricane have only a modest impact on consumer surplus, suggesting a partial cleansing effect in aggregate and implying limited scope for policy intervention. However, because of the spatial heterogeneity in the effects of the storm, consumers living in the most affected areas suffer substantial and persistent welfare losses, providing evidence of localized scarring. These welfare impacts are particularly pronounced in lower-income neighborhoods and smaller MSAs, highlighting the potential for large shocks to widen welfare inequality. Despite evidence of some cleansing effects, we find that a subset of exiting stores creates consumer benefits large enough to justify a business aid program, and a targeted subsidy could create substantial welfare gains.

1.1 Related literature

We are related to a broad literature that studies the firm entry and exit process and its effects on allocative efficiency. A strand of that literature in industrial organization has focused on the evolution of productivity through firm turnover using detailed production data, including Olley and Pakes (1996), Collard-Wexler and De Loecker (2015), Foster et al. (2008), and Igami (2017), among others. Another set of papers has focused on the impact of recessions and other shocks on productivity through a more theoretical lens, sometimes calibrated using aggregated data. Within this set, some papers have emphasized the cleansing role of negative shocks in inducing the exit of low productivity firms (Caballero and Hammour, 1994), while others have highlighted potential scarring effects that hurt allocative efficiency (Barlevy, 2002, 2003). Our contribution to this literature is to analyze the impact of a specific shock that affects firms heterogeneously in an exogenous way. Our study differs from much of the prior work that focuses on productivity differences across exiting and entering firms; we instead use the contribution of each establishment to consumer surplus as our primary measure of store value, which we estimate from detailed microdata on consumer choices.

This paper is also related to a small but growing body of literature that examines the impact of natural disasters on firms and the design of aid policy. Basker and Miranda (2018) and Cole et al. (2019) find that the firms most likely to exit after natural disasters were smaller and had lower productivity.[6] Collier et al. (2024) exploit discontinuities in SBA lending criteria to study the impact of subsidized loans on firm survival. This work is the first to think directly about the welfare consequences of firm turnover after natural disasters. Our work complements Collier et al. (2024) in that we also estimate the effectiveness of aid for firms, but we adopt a different modeling approach by focusing on the relationship between establishment exit decisions and a monetized measure of storm damage.

Our paper also relates to a large literature measuring the welfare effects and distributional consequences of changing retail environments (Allcott et al., 2019a,b, Dubois et al., 2014, 2020, Handbury, 2021, Klopack, 2024). We adopt tools similar to those used in many of these papers to estimate consumer welfare but focus on a natural disaster setting using data on multiple industries.

Finally, our paper relates to the literature on the optimal allocation of scarce aid resources, including Brown et al. (2018), Alatas et al. (2012), Gordon et al. (2023), and Fu and Gregory (2019). Our paper highlights that the welfare impacts of aid depend on how effectively policymakers can target the most valuable businesses, and we find that a program that targets on establishment observables realizes about two thirds of the maximum gains under perfect targeting.

2 Background

Hurricane Harvey was a major storm that made landfall in Texas on August 25, 2017. It was the second most costly natural disaster and had the highest recorded rainfall in United States history, with most of the damage coming from flooding (NOAA, 2022, National Weather Service, 2017). Hurricane Harvey provides a useful setting to examine the effect of adverse shocks on firms. One reason for this is that the location of flooding was largely unanticipated:

[6]Other papers that measure firm exit rates after disasters include Jia et al. (2022), Gallagher et al. (2023), Collier et al. (2020), and Collier et al. (2022a).

the majority of flooded structures were outside of the pre-storm FEMA 100-year flood plain, and observables including geospatial and socio-demographic characteristics explain only 7% of the variation in flooding across Census blocks (Billings et al., 2022). Further, as we show in Appendix E, there was very little out-migration and little correlation between flood damage and post-storm consumption, implying limited change in demand, consistent with the findings of Farrell and Greig (2017). Given this, we interpret the hurricane primarily as a temporary shock to supply infrastructure, but not as a permanent shock to demand.

Natural disasters generally and hurricanes more specifically are important shocks to study—natural disasters have caused more than $100 billion of damage per year on average since 2010 (NOAA, 2022), with hurricanes accounting for a large and growing fraction (rising from 21% in the 1980s to 54% in the 2010s). Climate scientists predict that major rainfall events in particular, like Hurricane Harvey, will become increasingly common due to climate change (Emanuel, 2017, Beradelli, 2019).

What resources do firms have to respond to natural disasters like flooding? The primary form of business aid from the U.S. Federal government comes from the Small Business Administration (SBA) which provides subsidized, low-interest, and long-term loans to firms that experienced harm from natural disasters (U.S. Small Business Administration, 2017). However, SBA has historically approved only 40% of applications and many firms do not apply, with many citing reluctance to take on additional debt as a primary reason (Collier et al., 2022b). Additional aid is provided through the U.S. Department of Housing and Urban Development (HUD) Community Development Block Grant Disaster Recovery (CDBGDR) program but CDBGDR grants are often disbursed years after the natural disaster (Jaroscak, 2020, Gimont, 2022).[7] Finally, firms may have private flood insurance. However, evidence from Collier et al. (2022b) suggests this is a minority; they report only 15% of firms affected by Harvey used insurance to finance storm-related losses. Because of limited business aid programs following disasters, one focus of our paper is to examine the impact of a larger aid program.

[7]For Hurricane Harvey specifically, there was approximately $100 million allocated for business aid, and the first disbursement of funds did not occur until spring 2021 and was conditional on firm survival. Source: Conversations with grant administrators at Texas General Land Office. See also Texas General Land Office (2021).

3 Data sources and sample construction

3.1 Data sources

To examine the impact of Hurricane Harvey on businesses and consumer welfare, we compile information from multiple sources. In this section, we describe our primary datasets and provide additional information in Appendix A.

Flood data: Our data on flood exposure come from FEMA in the form of a raster file. This file gives an estimated flood depth at the 3 meter-by-3 meter pixel level. FEMA produces these estimates by combining high water measurements taken at various points with topographical elevation data. Figure Figure 1 maps flood depth and the location of retail establishments in central Houston. Both this figure and the larger multi-county flood exposure maps in Appendix B show significant geographical variation in flooding exposure. These levels of flooding are highly destructive, as FEMA considers even 1.5 feet of water within a structure as likely to cause major damage (FEMA, 2020). The high granularity of the flood data allows us to identify differences in flood exposure at a highly local level.

Credit and debit transaction data: Our primary data source on local stores and consumer purchases comes from a payment card company. Each observation in the underlying data is a transaction between a cardholder and a merchant. On the merchant side, the data contain the merchant name and numeric identifier, the location of the store, and a NAICS category. On the card side, each transaction is linked to a unique card identifier. The data contain no information on the specific goods or services purchased or the prices of those items. The sample is completely anonymized and does not contain the cardholder's name, address, or any other personally identifiable information. For approximately 70% of credit cards (but none of the debit cards), we also observe the home billing location of the card at the ZIP+4 level and the estimated income of the cardholder.[8] We are unable to link multiple accounts to the same individual and thus treat each credit account as a separate consumer. Our sample includes transactions in the Houston, Corpus Christi, and Beaumont

[8]These variables are provided to the payment card company by a major credit bureau.

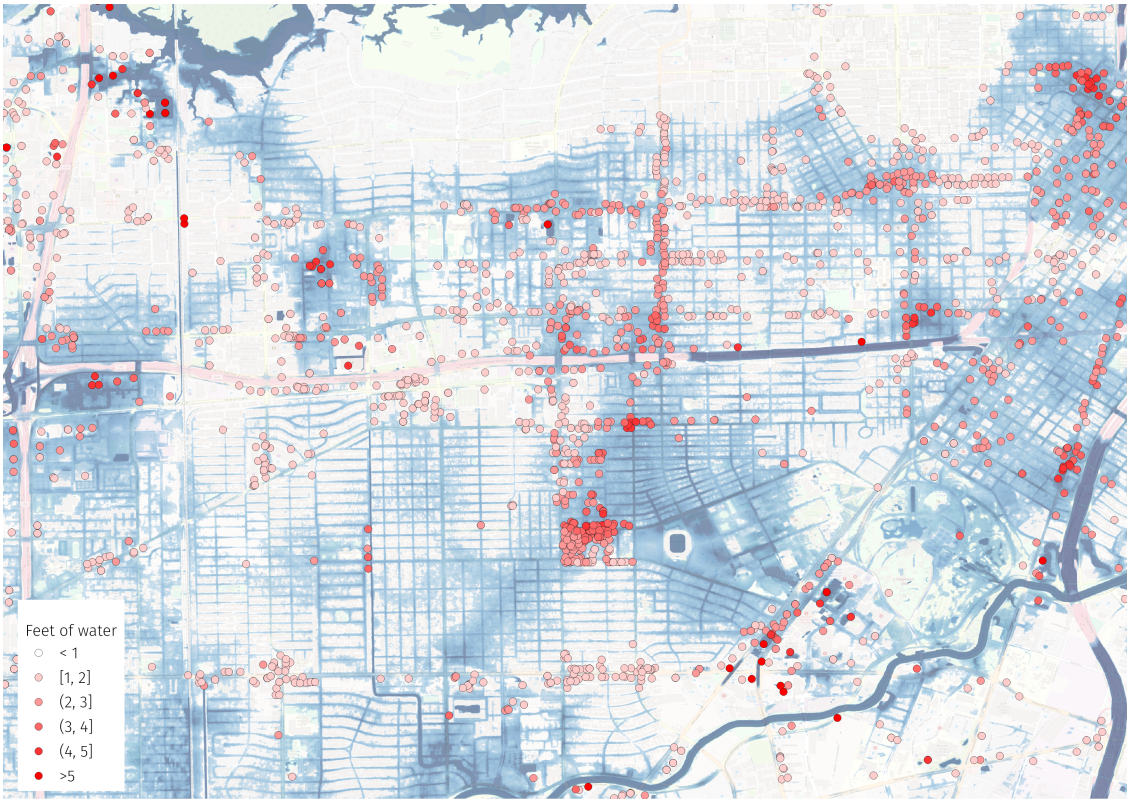


FIGURE 1: Businesses' exposure to flooding in central Houston.

Note: The figure reports, in blue, water levels as measured by FEMA at the 3 meter-by-3 meter pixel level. We top-code flood measures at 5 feet. In the figure, dots identify business locations in central Houston. The different shades of red report exposure to flooding measured as described in the text (calculating mean water levels within a 50-meter radius around each business).

MSAs between January 2017 and December 2018.

The payment card data are unique in several ways. First, they allow us to observe a significant share of economic activity, as transactions through this payment-card company account for about 20% of U.S. consumption (Dolfen et al., 2023) across multiple purchase categories. Second, because the data are available at the transaction level, we observe the precise geographic location and date at which these took place. This allows us to measure the precise timing of closure and re-entry decisions, which is not typically available in data from the Census or firm-level surveys used in other studies. Third, the data allow us to measure the distributional effects of store closures in a very granular way. We separately observe the areas where households live and shop, and thus can decompose welfare losses across residential neighborhoods with different demographic profiles.

Our payment card data correspond to a subset of all retail spending. We therefore scale

welfare numbers by 1/0.43 because retail spending by cards issued by our data provider accounts for about 43% of all retail consumption in the United States.[9]

Harris Central Appraisal District (HCAD) property assessment data: HCAD is the organization that assesses property values and collects taxes for jurisdictions (such as municipalities) within Harris County, which contains the city of Houston. We use this data in Section 6 where we estimate the efficacy of aid. HCAD performs assessments of real property at the parcel level (land and buildings), and personal property at the establishment level (e.g., inventory, equipment, vehicles, and other property owned by the retail establishment). HCAD also collects data on the square footage occupied by the business. Values of properties were assessed as of January 1st of each year, including in 2017 (pre-Harvey) and 2018 (post-Harvey). In addition, a subset of tax jurisdictions, which we refer to as "reappraisal districts", had real property value reassessments performed shortly after Hurricane Harvey based on surveys and inspections of damaged buildings.[10]

Other data sources: Our analysis utilizes various other data sources: first, we use Google and Yelp to verify our firm exit and entry measures, as discussed below in Section 3.2. Second, we incorporate demographic information from the 2017 American Community Survey (ACS) at the census tract and block group levels and Census Bureau estimates of annual population at the county level. Third, we use Data Axle for establishment-level employment numbers and Bureau of Labor Statistics for average wages at the county by NAICS level. Fourth, we use data on Small Business Administration (SBA) loan applicants and recipients. Fifth, we use a variety of jurisdictional databases on state, county, census tract, census block group, and superneighborhood boundaries, as well as spatial landcover data from the National Land Cover Database and flood zone designations from FEMA.

[9]Our data provider accounts for 53% of card spending in the U.S. (McCann, 2022), and card spending makes up 82% of retail (Gravier, 2022).

[10]Reappraisals took place between September 22nd and October 16th of 2017. Source: Private communication with HCAD officials.

3.2 Variable construction

Flood exposure: We measure each firm's flooding exposure during Harvey by combining the store location and FEMA flooding data. To do this, we take the latitude-longitude coordinates for each business and compute the average flooding depth in feet in a 50-meter circle around its coordinates, as illustrated in Figure 1.

Consumer and store characteristics: The demand model that we propose in Section 5 includes the distance between a consumer and a store as an explanatory variable. We compute this distance between each store's coordinates and the consumer's home billing zip+4, which we observe for 70% of sample credit cards. We also use this location to define a consumer's home Census tract.

We use the payment card data to construct several brand-level characteristics that affect a store's demand. We count the nationwide locations with the same brand identifier to identify whether a store was part of a chain.[11] As a proxy for a store's unobserved product characteristic, we compute its customers' average "affluence", which we define as the average total monthly spending across all categories for cards that purchase at any of its U.S. outlets.

Measuring entry and exit: We first construct a panel of stores that were operating in our three MSAs, subject to a modest size threshold.[12] We infer the operational status of each firm over time using the payment card data. To do this, we aggregate transactions at the merchant-zip code level and count a store as open in a given week if it reported transactions. We identify stores that closed after Harvey as those that stopped processing transactions. Some of these stores later re-opened and resumed processing transactions, which we code as temporary closures, and measure the length of temporary closure by the number of weeks with few or no transactions.[13] We identify permanent closures as establishments that do not have more transactions before the end of our sample in December 2018. We follow a similar

[11] The data do not allow us to distinguish between franchised and company-owned outlets.

[12] We drop stores from the data that processed fewer than 100 transactions, were open for less than 3 months, or processed fewer than 5 transactions per week.

[13] Some stores continued to process a very small number of transactions even while closed (possibly due to misclassified online transactions). We count a store as open in a given week if, in that week, it recorded at least 10% of its average pre-Harvey transaction volume.

procedure to identify new entrants: when we see a new merchant-zip code combination in the data, we infer that it is a new entrant and record its opening date as the first week it begins processing transactions.

A key measurement challenge is that a merchant's identifier in the payment card data can change over time, which can generate spurious entries or exits. To deal with this, we verify the timing of each entry and exit using data from Yelp and Google. To verify exits, we start with the set of merchant-zip code combinations that disappear from the data prior to the end of the sample. We search for each firm on Yelp and Google. If we are able to find a match, we look for whether the firm is marked as "closed" at the time we searched it, as well as the date of its first and last reviews. We mark a potential exit as verified if it is either marked as permanently closed or if the date of its last recorded review is no later than 6 months after its last transaction. We drop any exiting firms that we are unable to verify.[14] We follow a similar process to verify entries. We are able to verify 43% of potential exits and 35% of entries. We keep all other stores that did not permanently exit or enter during the sample period, even if we are not able to match them to Yelp data. We describe this process in detail in Appendix A.

Sample construction: Throughout our analysis, we focus on stores in the 11 retail trade NAICS categories (beginning with codes 44 and 45), as well as restaurants (NAICS code 722). These 12 categories include 88% of offline transactions and 56% of the establishments in our data. The largest categories not included in this set are medical providers, laundry services, machine repair shops, and hotels. Our sample contains 31,087 establishments over the three MSAs during the three months before Hurricane Harvey (May to July 2017).

[14]For exits that we are unable to verify, we hand-checked each one using the text of its reviews and Google's Street View for evidence that it remained closed through the end of 2018.

4 Descriptive evidence

4.1 Impact of Hurricane Harvey on firms

We first analyze the impact of Harvey on the closure rates of incumbent stores. Table 1 presents summary statistics of the data by MSA. The top panel shows the share of stores that closed temporarily and permanently, revealing that Houston experienced a smaller share of long-term and permanent closures than Beaumont and Corpus Christi. The share of stores that permanently exit varies from 1.1% in Houston to about 2.7% in Corpus Christi (a total of 390 establishments across the three MSAs). By comparison, in typical months, the average monthly exit rate is 0.16%, which we show in Figure 2a.[15] Many more establishments closed temporarily for at least a month, ranging between 3.5% in Houston to 10.0% in Corpus Christi (a total of 1,274 establishments).

The bottom panel of Table 1 shows the distribution of establishments by flood exposure. Across all establishments, median flood exposure was 0.6 feet and the 90th percentile was 3.1 feet. We find that the share of firms with three or more feet of water was highest in Houston and lowest in Corpus Christi, despite higher exit rates in Corpus Christi. This likely reflects that nearly all of the damage in Houston was due to flooding, whereas Corpus Christi also experienced wind-related damage (Crow, 2018). This heterogeneity may also reflect underlying differences in the resiliency of firms in smaller cities relative to large metro areas with more resources.

Figure 2b shows the (normalized) number of stores active by week from May 2017 to December 2018, aggregated across MSAs. The dashed grey line counts incumbents only, and shows a large drop after the landfall of Harvey with a quick but incomplete recovery that plateaus at about 98% of the pre-storm value. The solid black line includes post-Harvey entries, which shows that the aggregate number of stores fully recovered to its pre-Harvey level by the end of 2017.

[15] Our baseline exit rates are smaller than estimates from government data, such as the Census Bureau's Business Dynamics Statistics who report monthly turnover rates of 0.68%. In Appendix C.2, we discuss possible reasons for this that are related to our data cleaning and sample selection criteria, including the fact that our sample does not include stores that do not accept credit cards, use a third-party payment processor, or have no online presence. These stores are likely to have a high exit rate relative to stores in our sample. We discuss the implications of our data and sample selection criteria for our analysis in sections 5 and 6.

TABLE 1: Share of stores by closure status and flooding level

Closure status	Houston	Beaumont	Corpus Christi
No closure	81.9%	53.4%	76.1%
Temporary closure			
1-3 weeks	13.5%	38.3%	11.2%
4-8 weeks	1.5%	3.2%	4.3%
8+ weeks	2.0%	3.8%	5.7%
Perm closure	1.1%	1.2%	2.7%
Flood levels	**Houston**	**Beaumont**	**Corpus Christi**
No flooding	21.2%	10.8%	23.9%
0-1 ft	38.0%	38.4%	36.7%
1-2 ft	18.6%	24.7%	19.9%
2-3 ft	11.0%	16.0%	11.3%
3-4 ft	5.0%	6.3%	3.2%
4+ ft	6.2%	3.9%	5.0%
Total # stores	27071	1776	2240

Notes: The top panel of the table shows the share of stores that closed temporarily and permanently in each of the three sample MSAs. The bottom panel shows the distribution of stores by their degree of flooding exposure, measured in feet. The table includes all stores that were active prior to Hurricane Harvey (open as of July 2017).

Figure 2c shows the (normalized) number of incumbent stores that were active each week by flood level. The figure shows that stores with minimal flooding exposure reopened almost immediately after the storm, while those that were heavily flooded faced a much slower recovery. By December 2017, areas with four or more feet of flooding had nearly 5% fewer stores than their pre-storm average. The recovery process continued through the spring of 2018 as more firms reopened before stabilizing at a lower level. Overall, the number of active firms in the most flooded locations was about 3% lower by the end of our sample period. Finally, Table C.1 in Appendix C explores the relationship between firm characteristics and exit. We find that relative to independent stores and small chains, stores belonging to large chains with more than 100 locations are significantly less likely to close (both permanently and temporarily) and more likely to reopen after long closures.

The patterns in firm exit shown above do not rule out that some of these closures would have occurred in the absence of Harvey. However, two pieces of evidence suggest that a majority are related to hurricane damage: First, Figure 2a shows there was a large spike

in exits at the time of Harvey relative to pre-storm months. Second, Figure 2c shows that establishments in highly flooded areas had significantly higher exit rates. The welfare analysis that follows does not directly depend on whether a given exit is caused by the hurricane. Rather, we take firm turnover in the post-Harvey period as given and measure the net impact for consumers.

Table 2 shows the rates of temporary and permanent closures for the 12 store categories in our data, which reveals significant heterogeneity. Among these categories, gasoline stations have the fewest closures, with 91.0% never closing and only 0.2% of establishments exiting permanently. In contrast, only 81.3% of restaurants and 64.9% of clothing stores never close. Conditional on closing for at least 4 weeks, 33% of restaurants never reopen, and 17% of clothing stores never reopen.

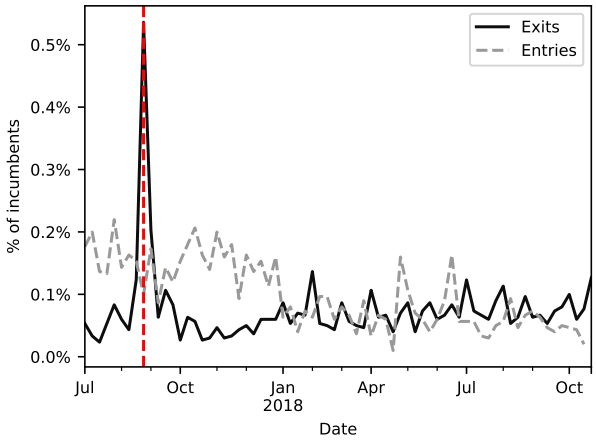
TABLE 2: Exit and closure rates by store category.

NAICS	No closure	1-4 weeks	4-8 weeks	8+ weeks	Exit
Restaurants	81.3%	13.0%	1.5%	2.2%	2.0%
Groceries	87.1%	7.8%	1.8%	2.6%	0.8%
Gasoline	91.0%	5.0%	1.3%	2.4%	0.2%
Gen. Merch.	87.2%	8.4%	1.2%	2.8%	0.5%
Pharmacy	78.7%	18.3%	1.0%	1.5%	0.6%
Clothing	64.9%	29.2%	2.2%	2.7%	1.0%
Building supply	79.6%	16.1%	2.9%	1.1%	0.2%
Misc. retail	70.3%	22.6%	2.7%	3.2%	1.2%
Sports, books, hobby	69.7%	22.7%	3.0%	3.1%	1.4%
Auto parts	84.3%	12.3%	1.5%	1.5%	0.4%
Furniture	70.7%	23.5%	2.2%	2.5%	1.1%
Electronics	79.4%	15.1%	1.5%	2.6%	1.5%
Total	79.9%	14.8%	1.8%	2.3%	1.3%

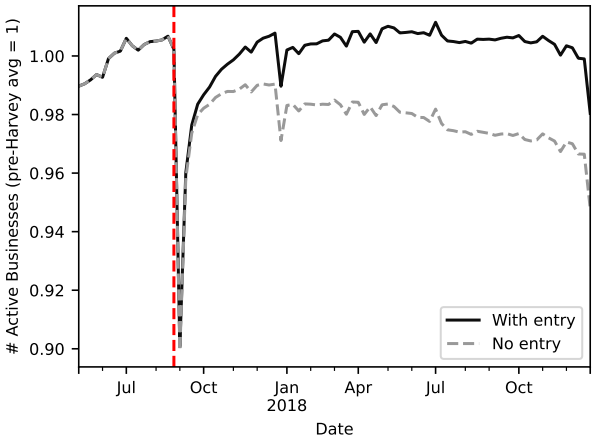
Notes: The table shows the share of stores in each NAICS category that closed temporarily, permanently, or not at all. Categories are ranked by transaction volume.

4.2 New entry

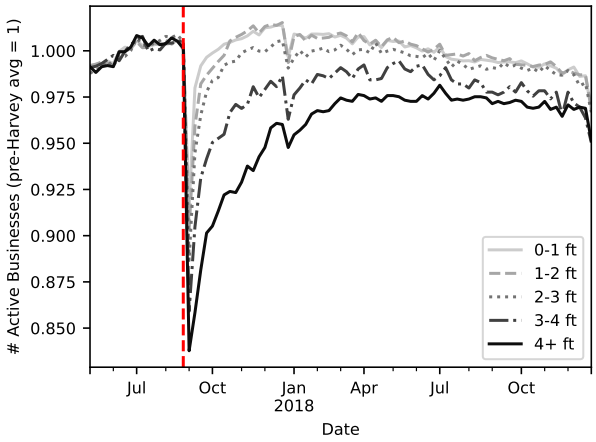
To what extent did entry replace exits? In the Houston MSA, we observe 307 permanent exits one month after Harvey and 1,201 new entrants in the 16 months after Harvey. Relative to the Houston MSA, replacement rates were lower in Beaumont and Corpus Christi: Beaumont



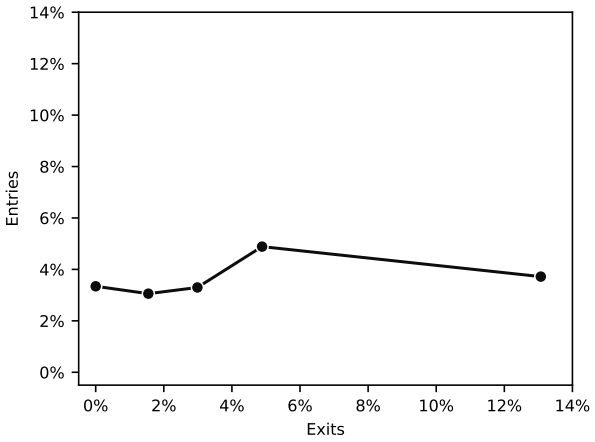
(A) Weekly exits and entries over time



(B) Number of active firms with and without entry



(C) Number of active firms by flooding level, incumbents only



(D) Entry and exit rates by exit rate quintile

FIGURE 2: Exit and entry comparisons

Note: Panel (A) shows the number of establishments across all three MSAs that enter and exit in each week as a share of the number of pre-Harvey incumbents. Panel (B) shows the number of active firms in each week, inclusive of establishments that opened after Harvey (solid black) and counting only incumbents open before Harvey (grey). Panel (C) shows the number of active establishments in each week by flooding exposure, counting only incumbents. Panel (D) shows a binscatter plot of exit and entry rates by Census tract. Tracts in all three MSAs are binned into quintiles by the share of stores that exited in the month after Harvey (September 2017). The corresponding y-value shows the number of post-Harvey entries (between October 2017 and December 2018) in the quintile as a share of the number of pre-Harvey firms.

had 22 permanent exits and 37 entrants, while Corpus Christi had 61 permanent exits and 66 entrants. Figure 2a shows that entry rates were between two and three times higher pre-Harvey. At the time of Harvey, entry rates are dwarfed by exit rates. However, post-Harvey, entry rates remain either slightly larger than or equal to exit rates throughout the rest of

our sample period.

Across the three MSAs, we find that the new entry did not happen disproportionately in the areas with the most exits or damage. Figure 2d plots a binscatter where the x-axis shows the fraction of incumbent stores that exit permanently in the month after the hurricane and the y-axis shows the number of cumulative entries between September 2017 and December 2018 as a fraction of incumbents. The figure shows that the number of entries was essentially constant in neighborhoods with low and high exit rates. The neighborhoods with the highest exit rates saw a net decrease in the number of establishments that operated in them, even when taking entry into account. This pattern holds when we examine entry and exit within each MSA separately.

To what extent did storm damage induce the closure of the smallest and least profitable stores? Table C.2 in Appendix C shows the results of descriptive regressions of the log of transactions and sales on establishment characteristics and dummies for closure. The table shows that relative to incumbent firms that did not close, firms that exited permanently had about 58% fewer transactions, with similar numbers for firms that closed temporarily and reopened. In contrast, new entrants had only about 35% fewer transactions relative to incumbents. We find similar results when examining sales.

The pattern reported in Figure 2d implies that there was a net decrease in the number of establishments in the hardest-hit areas. To what extent does this reflect businesses updating their beliefs about future flooding and moving to less flood-prone locations? While the sample of establishments in our card data only goes through December 2018, we explore longer-run recovery patterns using auxiliary data that records alcohol sales for bars and restaurants in each month, which we use as a proxy for whether an establishment is open (available from the Texas Comptroller of Public Accounts and previously used by Goldfarb and Xiao (2024)). Figure C.3 plots the number of open bars and restaurants by level of flood exposure during Harvey. The figure shows a steep dip in the most flooded locations after the storm, but a longer run recovery. The total number of establishments in damaged places recovers to its pre-Harvey level by late 2019 implying that, in the longer run, there is not an aggregate relocation to less flood-prone areas.

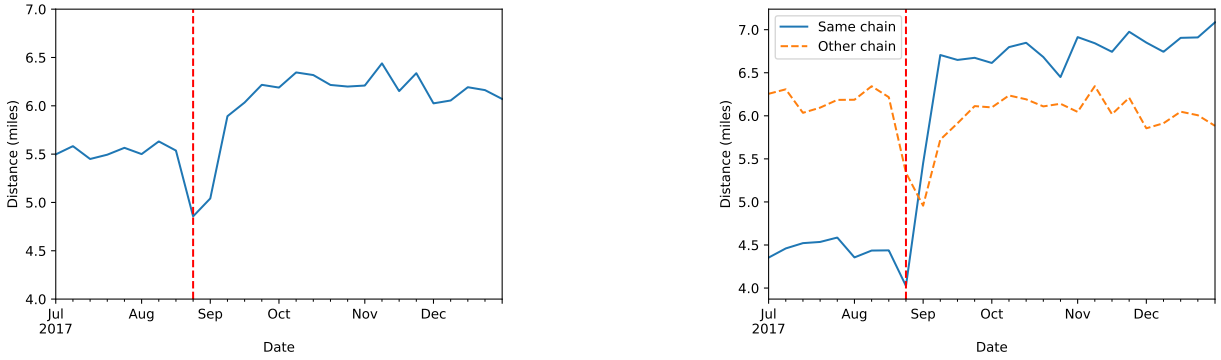
4.3 Impact on consumers

In this section, we illustrate key data patterns that drive the welfare estimates reported in the next section. We focus on two channels through which store exits can impact consumers: travel distance and substitution to a less preferred alternative. To quantify the impact of exits on travel distance, we take the 20 store closures with the most transactions (either permanent exits or closures of at least four months) and build a sample of consumers who shopped at each store in July 2017 before their closure. For each card, we compute the one-way travel distance by week between the card's home location and the store's location for all transactions to stores in the same NAICS code as the closure.

We show travel distance for this sample of consumers in Figure 3a. There is a temporary drop during the week of the storm, followed by a persistent increase of about 15% from 5.5 miles to 6.3 miles. This implies an average increase in travel costs of $2.72 per trip, which translates to $2 million of harm over the four months post-storm, or about $50 per card.[16] We repeat this exercise in Figure 3b where we decompose the travel distance by whether the trip was to a store of the same brand as the closed store. The figure shows that travel distance for same-chain trips increases by nearly 50%, while we observe no persistent change for trips to other chains. The fact that some consumers drive much further to visit the same chain suggests that accounting for brand preferences is a crucial part of the welfare effects of store closures, which is not reflected in travel distance alone.

The increase in travel distance shown in Figure 3 gives a lower bound for consumer welfare losses, as it does not account for losses due to substitution to less preferred stores. As a descriptive analog of the upper bound, we measure the fraction of total pre-Harvey retail spending that went to establishments that later closed (for at least eight weeks). In Figures C.1 and C.2 in Appendix C.3, we show this share across consumers by Census tract of residence for the three MSAs in our sample. The figures show that for some tracts, up to a third of pre-storm spending was displaced by closures. While the impacts are largest for consumers living in the most flooded areas, the figure also shows evidence of dispersed

[16] Following Dolfen et al. (2023), we convert miles between a consumer and a store into dollars using information on the median wage and the IRS mileage reimbursement rate to reflect time and direct costs of travel, leading to a total of $3.44 per mile between the consumer and the store.



(A) Travel distance

(B) Travel distance by chain

FIGURE 3: Average travel distance following store closures

Note: The figure shows average travel distance over time among consumers who shopped at stores that closed during Hurricane Harvey, where we limit analysis to the 20 largest stores that either closed permanently or temporarily, where the size of the store is measured by expenditures. The left panel shows the average distance computed over all purchases in the NAICS category of the closure. The right panel shows the average distance broken out by whether the purchase occurred at another outlet within the same chain as the closed retailer or an unaffiliated store.

impacts across each MSA, often driven by the closure of a large single store (such as a grocery or general merchandise store) that impacts consumers in many neighborhoods.

In addition to causing damage to businesses, the hurricane flooded many homes, which may have caused consumers to move away from their original neighborhood or to change their purchasing behavior. We investigate this in Appendix E. Using county-level Census data, Table E.1 shows that there was limited outmigration following the hurricane. Figure E.1 plots aggregate spending across quartiles of neighborhood-level flooding exposure and finds that consumer expenditures follow similar patterns regardless of flood levels. We also show similar analyses specific to restaurant, grocery, and gasoline spending, which show no evidence of compositional shifts in demand in the medium and long run.

4.4 Impact on retail prices

To be added (pending Nielsen review)

5 Consumer welfare impacts of entry and exit

5.1 A model of consumer preferences over stores

The evidence presented in the previous section showed that Hurricane Harvey's impact varied significantly across locations, with entry not replacing exits in the hardest-hit areas. Further, surviving incumbents and entrants have higher sales than exiting stores, suggesting they may also create more value for consumers. To quantify each store's contribution to consumer welfare and study the distributional effects associated with the spatial distribution of entry and exit, we propose and estimate a discrete choice model of consumer demand that allows us to identify each of these effects.

Formally, we assume that, within a given NAICS, the utility that consumer i, who lives in neighborhood n, enjoys from visiting store j at date t is given by:

$$u_{i_{(n)},j,t} = x_{i_{(n)},j,t} \cdot \theta_{i_{(n)}} - \theta^d_{i_{(n)}} d_{i_{(n)},j} + \xi_{j,n,t} + \varepsilon_{i_{(n)},j,t} \tag{1}$$

where we omit the NAICS subscript for simplicity. The utility of choosing the outside option is $u_{i_{(n)},0,t} = \varepsilon_{i_{(n)},0,t}$, where $\varepsilon_{i_{(n)},j,t}$ and $\varepsilon_{i_{(n)},0,t}$ are i.i.d. draws from a type-1 extreme value distribution. $d_{i_{(n)},j}$ denotes the distance between the consumer i's home (identified by the zip code +4) and store j. In the vector $x_{i_{(n)},j,t}$, we include distance interacted with the consumer's income, a measure of a store's consumers' "affluence," and a chain indicator interacted with income. Further, we include correlated random coefficients on the store's affluence and the distance between a card and the store. Specifically, we assume that the random coefficient on distance is lognormal, while the one on affluence is normal with mean zero:

$$\begin{pmatrix} \theta^a_{i_{(n)}} \\ \log \theta^d_{i_{(n)}} \end{pmatrix} \sim \mathcal{N}\left[\begin{pmatrix} 0 \\ \mu_d \end{pmatrix}, \begin{pmatrix} \sigma^2_{\theta^a} & \rho \\ \rho & \sigma^2_{\theta^d} \end{pmatrix} \right]$$

The inclusion of $x_{i_{(n)},j,t} \cdot \theta_{i_{(n)}}$ in the specification of the utility function allows the model to capture within-neighborhood taste heterogeneity across income groups – for example, high-

and low-income consumers who live in the same neighborhood may have different preferences over budget vs. gourmet grocery stores. This specification enables us to speak to the distributional effects of closures within neighborhoods across consumers of different income levels. Finally, the term $\xi_{j,n,t}$ captures the mean utility that store j provides to residents of neighborhood n, which allows the value of a store to vary flexibly across neighborhoods.

5.1.1 Estimation

We estimate our demand model by Simulated Maximum Likelihood, where we utilize the fact that we observe multiple purchases per card as in Revelt and Train (1998). We estimate demand separately for each NAICS in our data.[17] We compute standard errors using a block bootstrap procedure that samples consumers with replacement from each neighborhood. We report technical details of estimation in Appendix F.

For estimation, we define neighborhoods as Census tracts. For the Census tracts with the largest number of cards, we randomly sample a subset of the cards to appear in the estimation routine. For each neighborhood, we draw a 15-mile buffer to determine which stores are within the neighborhood choice set. Table F.1 reports summary statistics for this sample by MSA and NAICS category. We define the outside option as a purchase made within that same NAICS but outside the 15-mile buffer.

Our estimation sample goes from May to July 2017 – the three months prior to Hurricane Harvey. We use this sample to estimate NAICS-specific parameters θ and store-neighborhood values of $\xi_{j,n,t}$ for the stores open before Harvey. However, for counterfactuals, we also need measures of $\xi_{j,n,t}$ for new entrants. To capture these, we also estimate demand for the five post-storm quarters after Harvey—2017Q4 to 2018Q4—where we hold estimated demand parameters θ fixed from our May-July 2017 sample but estimate new values of $\xi_{j,n,t}$ for all of the stores operating post-Harvey. We then use a linear projection using our pre- and post-storm estimates of $\xi_{j,n,t}$ to predict what pre-storm values of $\xi_{j,n,t}$ would be for new entrants. Further details are in Appendix F.2.

[17] We exclude Electronics (NAICS 443) in Corpus Christi and Beaumont because our sample contains many neighborhoods that purchase from only one or two stores.

5.2 Estimates

Table 3 reports parameter estimates separately for each of the top six NAICS and the three MSAs (see Table F.5 for the full set of parameter estimates with standard errors). The mean of the estimated distribution of distance sensitivity $E[\theta^d_{i(n)}] = \exp(\mu^d + 0.5 \cdot \sigma^2_{\theta^d})$ is consistently large, in line with estimates reported in the existing literature that show that consumers are sensitive to travel distance (Klopack, 2024, among others). We also find that dislike for distance decreases slightly with consumer income.[18] Our average distance sensitivity across all NAICS in Houston is 0.532, which implies that moving a store one mile further away decreases the probability it is chosen by 41.3% (40.6%) for the lowest (highest) income consumer in our sample.[19]

The coefficients on the interaction of consumer income and a store's affluence are positive for all but three NAICS in Corpus Christi and Beaumont (where they are statistically indistinguishable from zero), implying that higher-income consumers strongly prefer stores that cater to affluent customers.[20] The highest income consumer in our sample in Houston is 66.2% more likely to go to a store with a 90th percentile affluence level than the lowest income consumer.[21] While not surprising, this flexibility in the model allows a given store closure to differentially impact consumers across income groups based on the characteristics of the store. Finally, we find that higher-income consumers dislike chains more than lower-income consumers.

Our specification includes random coefficients, allowing for unobserved heterogeneity in taste for distance and store affluence, as well as for correlation in taste for distance and affluence. The resulting variance of the distance parameter is large relative to the distance coefficient, implying significant variation in sensitivity to travel distance across consumers.[22]

[18] Consumer income is measured from the credit bureau data and is top-coded (by the data provider) at \$250,000 and divided by \$1,000,000, so this variable ranges between 0 and 0.25.

[19] The ratio of choice probabilities for two stores j and j' which are identical except that j' is one mile further away is $P_{ijt}/P_{ij't} \approx 1/\exp(E[\theta^d_{i(n)}])$. The mean of $E[\theta^d_{i(n)}]$ across all Houston NAICS for a consumer with zero income is -0.532, which implies that $P_{ijt}/P_{ij't} = 1/\exp(-0.532) = 0.587$. For a consumer with annual income of \$250k, this is $1/\exp(-0.532 + 0.044 \times 0.25) = 0.594$.

[20] Store affluence is top-coded at \$5,000 and divided by \$1,000, so this variable ranges between 0 and 5.

[21] The ratio of choice probabilities between a high- and low-income consumer for a store with the 90th percentile affluence level of \$2,976 using the average estimated coefficient in Houston is $P_{ijt}/P_{ij't} \approx \exp(0.683 \times 0.25 \times 2.976)/\exp(0) = 1.662$.

[22] The variance of $\theta^d_{i(n)}$ is $\text{Var}(\theta^d_{i(n)}) = [\exp(\sigma^2_{\theta^d}) - 1] \cdot \exp(2\mu^d + \sigma^2_{\theta^d})$, which in Houston ranges between

We also consistently find a positive covariance parameter ρ, implying that, because distance enters negatively in equation 1, consumers who are less sensitive to travel distance are also more likely to prefer low-affluence stores.

5.3 Quantifying the welfare effects of store closures

We use the demand estimates to quantify the impact of entry and exit on consumer surplus under the assumption that preferences remain stable after the hurricane, which is supported by the analysis presented in Appendix E.

We measure consumer welfare associated with a specific choice set using the logit inclusive value

$$IV_{i_{(n)}}(J_n) \equiv E \log \left(\sum_{j \in J_n} \exp \left(x_{i_{(n)},j,t} \cdot \theta_{i_{(n)}} - \theta^d_{i_{(n)}} d_{i_{(n)},j} + \xi_{j,n,t} \right) \right) + C$$

where $i_{(n)}$ denotes a consumer in neighborhood n, C is Euler's constant, and the expectation is taken over the distribution of $\theta_{i_{(n)}}$ and $\theta^d_{i_{(n)}}$(McFadden, 1978). The impact in dollars of a change in choice set from $J_{n,t}$ to $\tilde{J}_{n,t}$ is then:

$$\Delta CS_{i_{(n)}} = \$3.44 \cdot \frac{1}{E[\theta^d_{i_{(n)}}]} (IV_{i_{(n)}}(\tilde{J}_{n,t}) - IV_{i_{(n)}}(J_{n,t})) \tag{2}$$

where $E[\theta^d_{i_{(n)}}]$ is the (category-specific) mean sensitivity to distance and \$3.44 is the cost of traveling one mile (Dolfen et al., 2023).

We first present estimates of the contribution of each store to consumer welfare. Classical models of creative destruction predict that a negative shock will lead to a cleansing of the least profitable and least productive firms (Caballero and Hammour, 1994). We examine an analog of this hypothesis: do exiting stores generate less consumer welfare than surviving incumbents or new entrants? To measure this, we compute $\Delta CS_j = \sum_i \Delta CS_{i_{(n)}}$ for each establishment j using equation 2, where we define J as the choice set including j and $\tilde{J}$ as the choice set excluding j. We sum the change in surplus that consumers receive from the availability of j across all sample consumers and over time (September 2017 to December 2018).

0.054 (restaurants) and 0.706 (pharmacy).

TABLE 3: Parameter estimates from the demand model

Houston

Parameter	Restaurants	Groceries	Gasoline	Gen. Merch.	Pharmacy	Clothing	Avg. (all NAICS)
μ^d	-1.068	-0.653	-0.887	-0.686	-0.616	-1.248	-0.976
$\sigma^2_{\theta^d}$	0.292	0.540	0.760	0.585	0.758	0.525	0.634
$\sigma^2_{\theta^a}$	1.012	2.208	2.605	3.370	3.200	1.073	1.748
ρ	0.250	0.478	0.859	0.723	0.866	0.331	0.527
$\theta^{\text{inc x dist}}$	0.089	0.096	0.000	0.284	0.031	0.052	0.044
$\theta^{\text{inc x aff}}$	0.282	0.659	0.274	1.260	0.324	1.097	0.683
$\theta^{\text{inc x chain}}$	-0.532	-0.447	-0.255	-3.793	-0.248	-1.580	-0.848

Corpus Christi

Parameter	Restaurants	Groceries	Gasoline	Gen. Merch.	Pharmacy	Clothing	Avg. (all NAICS)
μ^d	-1.386	-0.661	-1.204	-0.926	-0.604	-2.203	-1.469
$\sigma^2_{\theta^d}$	0.429	0.540	1.111	0.566	0.808	0.892	0.758
$\sigma^2_{\theta^a}$	1.535	2.962	4.256	3.897	6.955	1.802	2.553
ρ	0.324	0.529	1.159	0.634	1.257	0.723	0.627
$\theta^{\text{inc x dist}}$	0.191	0.251	0.359	0.116	0.156	0.005	0.122
$\theta^{\text{inc x aff}}$	0.974	0.415	-0.948	2.431	0.790	1.365	0.674
$\theta^{\text{inc x chain}}$	-0.488	-0.878	-0.881	-4.640	-1.588	-2.218	-1.342

Beaumont

Parameter	Restaurants	Groceries	Gasoline	Gen. Merch.	Pharmacy	Clothing	Avg. (all NAICS)
μ^d	-1.478	-0.800	-1.189	-1.181	-0.944	-1.842	-1.370
$\sigma^2_{\theta^d}$	0.438	0.692	0.959	0.729	0.803	0.586	0.658
$\sigma^2_{\theta^a}$	2.183	4.331	3.720	3.318	7.302	1.735	2.719
ρ	0.467	0.656	0.962	0.684	1.231	0.416	0.609
$\theta^{\text{inc x dist}}$	0.094	0.201	0.014	0.366	0.192	0.047	0.102
$\theta^{\text{inc x aff}}$	1.681	0.123	1.419	3.741	0.663	2.497	1.285
$\theta^{\text{inc x chain}}$	-0.521	-0.663	-1.627	-7.668	-0.498	-2.908	-1.964

Notes: Demand model estimated separately for each NAICS by MSA. Table shows estimated parameters for the top 6 NAICS by transaction volume and average parameter estimates over all 12 NAICS. Distance is measured in miles and ranges between 0 and 15. Income is measured in annual dollars divided by 100,000 and is top-coded, so the range is between 0 and 0.25 (corresponding to \$0 and \$250,000). Affluence refers to the average customer spending of a store (computed at the chain level) and is measured in dollars divided by 1,000, so that the range of the variable is from 0 to 5. We report the full set of parameter estimates with bootstrapped standard errors in Table F.5.

Figure 4 plots the kernel density of ΔCS_j over these 16 months separately for permanent exits, surviving incumbents, and post-storm entrants. The figure shows that exiting stores, on average, generate less surplus than both entrants and surviving incumbents, consistent with evidence from Section 4.2 that exiting stores have fewer transactions and sales. The median exiting establishment produced about \$121,000 of consumer surplus evaluated at the post-storm choice set, compared to \$190,000 for entrants and \$245,000 for surviving incumbents. In comparison, average store revenues over a 16 month period would be about \$404,000 for the median post-storm exiting store, relative to \$867,000 for the median entrant and \$1.01M for the median surviving incumbent. These measures of store-level contribution to consumer surplus are very similar when we compute them using the pre-Harvey choice set (see Figure F.1).

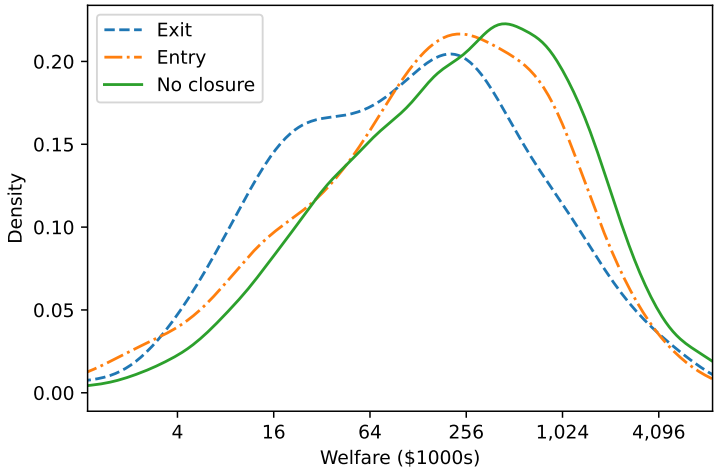


FIGURE 4: Store-level consumer welfare contribution.

Note: Density plots of the marginal welfare contribution of each store (the axis is on log scale), separated by whether the store permanently exits (blue), never closes (green), or is a new entrant (yellow). The figure shows the distributions conditional on the set of stores present post-Harvey. Consumer welfare benefits are calculated as the total consumer welfare aggregated over a 16-month period after the landing of Hurricane Harvey.

By itself, this pattern may suggest creative destruction, whereby lower-quality establishments exit and are replaced by new, more valuable entrants, which may even make consumers better off. However, Figure 4 also shows significant dispersion in store values among the exiting group; the 90th percentile exit creates more than \$1M in surplus. Thus, while many exits during Harvey are associated with relatively small welfare effects, there is a right tail

of establishments whose closure generates much larger losses. There is also an important spatial mismatch between the locations of entering and exiting stores as we show in Figure 2d; exits occur disproportionately in heavily flooded areas, while entry was fairly uniform. This pattern results in a reallocation of firms from more affected to less affected areas.

We next quantify the net impact of entry and exit on consumer welfare as well as how those impacts vary across neighborhoods and consumer demographics.[23] Our data is well-suited to measure distributional effects, as we can compute surplus at a very fine level of aggregation (down to the consumer) across a large sample. Again using equation 2, we compute the change in welfare for each consumer $i_{(n)}$ in each week t in the post-storm period, and then aggregate over time (between September 2017-December 2018). In each week, we define $\tilde{J}_{n,t}$ to be the set of stores that are open in post-storm week t (which includes entrants and incumbents that had re-opened by that point) and $J_{n,t}$ to be the set of stores open prior to Harvey. To isolate the welfare impact of new entry, we also present a version of the calculation in which we exclude entrants from $\tilde{J}_{n,t}$. We report the estimated welfare effects as a percentage of pre-storm expenditure.

In Table 4, we report statistics of the distribution of welfare losses aggregated at the Census tract level by NAICS and MSA. In the Houston MSA, our estimates of average welfare losses across all tracts range between 0.07 percent (auto parts) and 0.39 percent (gas stations and sporting goods) of pre-storm expenditure in each category. However, these estimates hide significant heterogeneity across neighborhoods within NAICS. For example, while the mean welfare loss in the groceries category was 0.29 percent, the maximum reached 11.72 percent. On average, across all NAICS in Houston, the estimated mean welfare loss is 0.28 percent. This represents a consumer welfare loss of approximately $200 million between September 2017 and December 2018.

Consumer welfare losses in Corpus Christi and Beaumont are somewhat larger (as a share of expenditures) but with significant variation across NAICS. For example, the mean

[23] As we note in Section 4, our data do not include some small establishments that do not meet our sample selection criteria. If these stores exit at higher rates, the welfare estimates we report in this section may underestimate the true effect. However, because these stores also have lower revenue, their contributions to surplus are likely to be small. Finally, this is less of a concern for the store-level analysis (Figure 4 and the counterfactuals in Section 6), which compares the costs and benefits of each individual store and is insensitive to our measurement of the exit rate.

welfare loss for restaurants was 1.43% in Corpus Christi and 1.52% in Beaumont (relative to 0.30% in Houston). Aggregated across NAICS, the worst-hit neighborhoods experienced particularly large welfare losses in Corpus Christi, where the maximum loss reached over 9% of all expenditures over a 16-month period. These larger overall effects are driven by the fact that Beaumont and Corpus Christi have higher exit rates, less entry, and fewer stores prior to Harvey, which increases the marginal effect of each closure because of fewer available substitutes.

Figure 5 graphs welfare losses by neighborhood, aggregated across NAICS categories. Importantly, we aggregate these welfare numbers using the post-Harvey spending shares across NAICS, which captures potential compositional changes in demand across retail categories. We find that damages in the Houston MSA are largest in the Kingwood area of northeast Harris County. In Corpus Christi, damages were especially high in the Port Aransas area on the northeast side of the MSA. In Beaumont, there is less geographic heterogeneity in welfare effects, although the city of Port Arthur in the south received less damage than most of the rest of the MSA.

Our findings show that the damage caused by Hurricane Harvey was significantly concentrated in small geographical areas. This is driven by the fact that store closures are spatially concentrated and correlated across NAICS, compounding the welfare impacts for consumers in these places. For example, the correlation between welfare losses from closures of grocery stores and closures of restaurants is 0.70, while this correlation reaches 0.63 for losses associated with closures of grocery stores and closures of general merchandise stores. This fact highlights the importance of analyzing multiple spending categories, as focusing on a single product category will underestimate overall welfare losses.

We next turn to examining the distributional effects of Harvey across income groups. Natural disasters may affect income groups differentially for various reasons, including differences in the severity of flooding, the composition of spending across NAICS categories, the resiliency of nearby businesses, and access to alternative stores. We compute welfare losses at the consumer-NAICS level and regress them, by MSA, on a set of controls, including NAICS fixed effects and dummies for quintiles of tract-level median income, tract-level flooding exposure, and card-level income. We show the (normalized) regression coefficients

TABLE 4: Distribution of welfare effects by neighborhood and NAICS

Houston

NAICS	Avg.	P10	P50	P90	Min
Restaurants	-0.30%	-1.10%	-0.42%	0.39%	-4.31%
Groceries	-0.29%	-0.72%	-0.19%	-0.00%	-11.72%
Gasoline	-0.39%	-0.76%	-0.34%	-0.08%	-4.79%
Gen. Merch.	-0.20%	-0.57%	-0.11%	-0.02%	-2.63%
Pharmacy	-0.31%	-0.50%	-0.18%	-0.02%	-18.52%
Clothing	-0.13%	-0.49%	-0.19%	0.06%	-1.96%
Misc retail	-0.24%	-0.82%	-0.24%	0.06%	-2.56%
Sporting Goods	-0.39%	-0.84%	-0.35%	-0.07%	-2.00%
Hardware	-0.23%	-0.47%	-0.25%	-0.04%	-1.93%
Auto parts	-0.07%	-0.15%	-0.07%	-0.03%	-0.66%
Furniture	-0.19%	-0.30%	-0.04%	-0.01%	-7.26%
Electronics	-0.04%	-0.06%	-0.01%	0.00%	-0.92%
Total	-0.29%	-0.84%	-0.36%	0.15%	-3.25%

Corpus Christi

NAICS	Avg.	P10	P50	P90	Min
Restaurants	-1.43%	-2.01%	-0.34%	0.03%	-15.89%
Groceries	-0.13%	-0.30%	-0.08%	-0.00%	-1.17%
Gasoline	-2.31%	-4.26%	-1.02%	-0.35%	-28.36%
Gen. Merch.	-0.27%	-0.60%	-0.08%	-0.04%	-2.81%
Hardware	-0.31%	-0.75%	-0.06%	0.06%	-12.59%
Pharmacy	-0.63%	-0.61%	-0.12%	-0.03%	-33.74%
Clothing	-0.98%	-1.34%	-0.62%	-0.05%	-11.30%
Sporting Goods	-0.86%	-1.53%	-0.82%	-0.03%	-5.02%
Misc retail	-1.56%	-4.04%	-0.94%	-0.40%	-8.75%
Auto parts	-0.17%	-0.34%	-0.10%	-0.04%	-1.85%
Furniture	-0.53%	-1.03%	-0.28%	-0.05%	-3.29%
Total	-1.21%	-3.70%	-0.41%	-0.16%	-11.90%

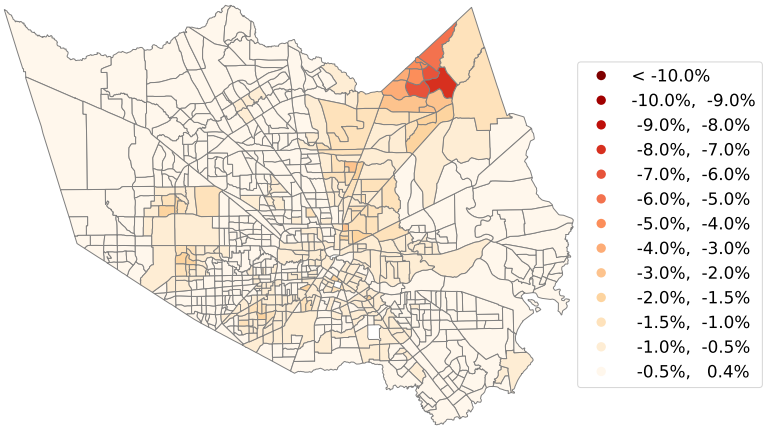
Beaumont

NAICS	Avg.	P10	P50	P90	Min
Restaurants	-1.52%	-2.23%	-1.46%	-0.72%	-3.71%
Gasoline	-0.43%	-0.86%	-0.38%	-0.12%	-2.99%
Groceries	-0.60%	-1.43%	-0.26%	-0.07%	-6.04%
Gen. Merch.	-0.33%	-0.67%	-0.34%	-0.17%	-2.19%
Pharmacy	-0.38%	-0.87%	-0.32%	-0.11%	-1.26%
Hardware	-0.13%	-0.58%	-0.16%	0.40%	-2.02%
Clothing	-1.21%	-1.94%	-1.16%	-0.40%	-2.99%
Sporting Goods	-1.62%	-3.01%	-0.47%	-0.14%	-6.72%
Misc retail	-0.83%	-1.45%	-0.51%	-0.21%	-9.35%
Auto parts	-0.19%	-0.34%	-0.13%	-0.02%	-2.18%
Furniture	-0.27%	-0.63%	-0.22%	-0.02%	-1.68%
Total	-1.04%	-1.48%	-1.05%	-0.56%	-2.68%

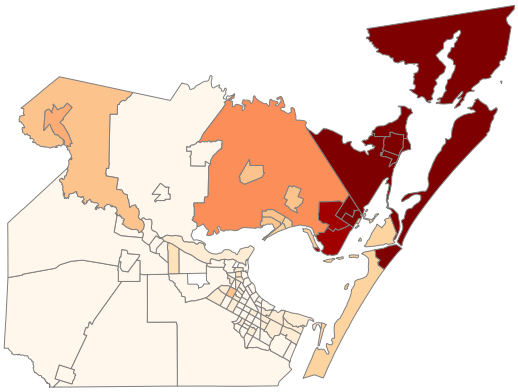
Note: The table shows the distribution of welfare effects across Census tracts by store category. We compute consumer welfare losses (as a share of spending) between September 2017 and December 2018 for each consumer and in each NAICS category. We then aggregate by the residential Census tract of consumers and report statistics of this distribution by NAICS and MSA. The "Total" row reports statistics of the aggregate welfare loss across NAICS categories, where we weight each category by its share of spending.

FIGURE 5: Distribution of aggregate welfare effects by neighborhood

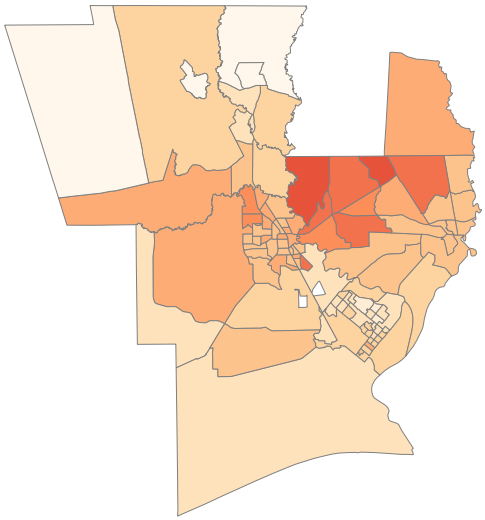
(A) Houston



(B) Corpus Christi

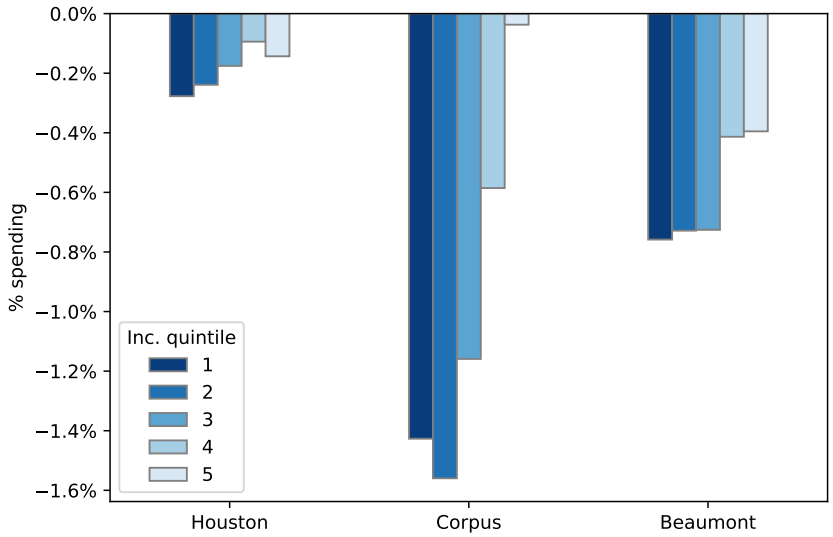


(C) Beaumont



The figure shows the aggregated welfare losses across NAICS categories, as a share of total spending, by Census tract. Welfare losses are computed between September 2017 and December 2018.

FIGURE 6: Welfare effects by tract-level income



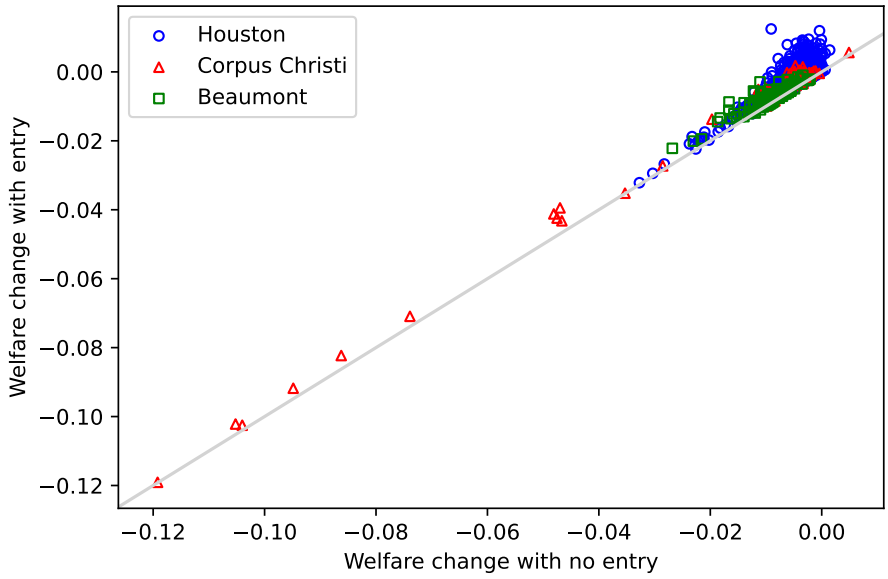
Note: The figure shows welfare losses as a share of total spending through December 2018 by quintiles of tract-level median household income for the three MSAs in our sample. To produce the figure, we compute welfare changes (net of entry) at the card-NAICS level and regress them, by MSA, on NAICS fixed effects, tract-level median income dummies, card-level income dummies, and flooding controls. The plot shows the tract-level median income coefficients from these regressions, normalized so that the mean of the bars in each MSA shows the aggregate welfare loss in the MSA. We show the complete regression output in Table F.2.

on tract-level income in Figure 6 (Table F.2 contains the complete regression output). The figure shows that lower-income neighborhoods suffered larger impacts in all three MSAs conditional on flood exposure. We also find similar results without conditioning on flood exposure (Figure F.2), although the gradient with respect to income is flatter in Houston than in Figure 6. Our results suggest consumers in lower-income neighborhoods have access to fewer nearby retail options than in higher-income places, and so each closure has a larger welfare impact. This pattern illustrates that even when flooding exposure is relatively uniform across groups, the impacts can be disproportionate for lower-income consumers.

5.3.1 The impact of entry on welfare

To what extent did entry ameliorate the welfare loss caused by exit? To examine this, we also compute the welfare counterfactual where $\tilde{J}_{n,t}$ only includes incumbent stores (including temporary closures that re-open) but excludes new entrants. In Figure 7, we graph the neighborhood-by-neighborhood change in welfare effects in our baseline case with entry (vertical axis) and in the version where we exclude entry (horizontal axis). By construction,

FIGURE 7: Welfare effects by neighborhood both with and without new entry



Note: The plot shows the effect of entry on consumer welfare losses (measured as a share of spending) at the Census tract level. The vertical axis graphs the change in welfare for each tract when $J_{n,t}$ includes new entrants. The horizontal axis graphs the change in welfare when $J_{n,t}$ does not include new entrants. Welfare losses are calculated between September 2017 and December 2018 and are aggregated across store categories.

including entrants in the choice set makes consumers weakly better off relative to when entrants are excluded, so all points in Figure 7 lie on or above the 45-degree (in grey). However, the plot highlights the limited impact of new stores for the most affected places; in the neighborhoods with the largest welfare losses, the points lie close to the diagonal. Instead, it is the relatively less affected neighborhoods in which entry has the largest impacts. This finding is driven by the spatial mismatch between the locations of exits and entries, quantifying the impact of the pattern in Figure 2d on consumer welfare.

Finally, we examine the extent to which welfare losses are explained by changes in travel distance vs. substitution to less preferred stores. Using the estimated parameters of the model, we predict the probability that each card i will visit each store within the choice sets $J_{n,t}$ and $\tilde{J}_{n,t}$ and then use the store-card distance to compute expected travel distance. Multiplying this by \$3.44 gives us the predicted change in welfare from a change in driving distance. We find that increased travel distance explains approximately 40% of the decrease in welfare, implying that estimates of welfare based on travel distance alone, as we reported in Section 4.3, understate welfare effects by about half.

6 Efficacy of aid and aid targeting

In the previous section, we showed that Harvey-induced store closures were geographically concentrated and not fully replaced by new entrants, leading to significant consumer harm. We next consider the welfare impacts of a business aid program. If private closure decisions differ from those of a social planner—for example, because of consumer surplus externalities or credit market frictions—business aid may be desirable. Whether providing such aid is justified depends on the consumer welfare benefits of the store, the dollar cost of aid, and how much aid reduces the probability of closure.

To evaluate the desirability and targeting of business aid, we first build a model of store re-entry, in which stores that close temporarily after Harvey decide to reopen or permanently exit. We focus on establishments located in Harris County, the largest county within the Houston MSA, where we leverage novel data from county tax appraisals performed shortly after Harvey's landing to build a measure of store-level damage. The model exploits the relationship between monetized storm damage and store re-entry decisions to predict the effect of a given dollar amount of aid on re-entry rates. We then calculate the implied benefit of aid as the product of the change in probability of re-entry and the sum of the store-specific contribution to consumer surplus and the unemployment benefits that would be paid to its workers.

6.1 A model of store re-entry

We model the re-entry decisions of stores that close for at least a week after Harvey. Each store decides whether to re-enter or exit permanently, weighing its expected stream of future profits against the re-entry cost associated with repairing its storm damage. A store j faces the following profit function if it re-opens:

$$\pi_j = \mathbb{E} \sum_{t=0}^{\infty} \delta_j^t R_{jt} \cdot m_j - F_j(d_j) \tag{3}$$

In equation (3), $\mathbb{E} \sum_{t=0}^{\infty} \delta_j^t R_{jt} m_j$ denotes the expected present value of the flow of future revenues R_{jt} times a margin m_j. $F_j(d_j)$ denotes the one-time fixed cost of re-entry, which

depends on the establishment's storm damage d_j. The other option is to exit permanently, which gives a normalized payoff of zero.

To estimate the model, we make the following parametric assumptions. First, we assume that $\mathbb{E}\, R_{jt} = R_j$, where R_j is the average monthly revenues for May-July 2017, the three months before Hurricane Harvey. We assume that the log of store j's margin can written as $\log(m_j) = \alpha_c^0 + \alpha^1 x_j + \psi_j^m$, where α_c^0 is a NAICS-specific component, x_j is a vector of store characteristics, and ψ_j^m is an unobservable component. We assume the discount factor δ_j is common across stores in the same NAICS category, which captures industry-specific survival rates. Second, we assume that the fixed costs of re-entry $F_j(d_j)$ depend on a measure of storm damage d_j, the establishment's square footage, an industry-specific component, the vector of store characteristics, and an unobservable term. Given these assumptions, we write $\log F_j = \gamma_n^0 + \gamma^1 \log(sqft_j) + \gamma^2 d_j + \gamma^3 x_j + \psi_j^d$.

We can write the probability that establishment j permanently exits as:

$$\begin{aligned}
\mathbb{P}(j \text{ exits}) &= \mathbb{P}\left(\mathbb{E} \sum_{t=0}^{\infty} \delta_j^t R_{jt} \cdot m_j - F_j(d_j) < 0 \right) \\
&= \mathbb{P}\left(\log(m_j) + \log\left(\frac{1}{1-\delta_n}\right) + \log(R_j) < \log\left(F_j(d_j)\right) \right) \\
&= \mathbb{P}(\beta_n^0 + \beta^1 \log(R_j) + \beta^2 \log(sqft_j) + \beta^3 d_j + \beta^4 x_j + \psi_j < 0) \qquad (4)
\end{aligned}$$

Imposing the assumption that ψ_j^m and ψ_j^d are normally distributed, we estimate equation (4) as a probit regression. We include in our vector of establishment characteristics x_j chain size fixed effects and an indicator for the FEMA 100-year flood plain (which may proxy for whether a store has flood insurance).

Measuring damage Estimating equation (4) requires a measure of storm damage for each establishment d_j. We obtain this by combining flood exposure data with novel property tax appraisal data from HCAD, the central tax authority for Harris County.

To calculate d_j, we exploit reappraisals that HCAD conducted in the fall of 2017, shortly after Hurricane Harvey, for a subset of tax districts. Real properties within these reappraisal districts were physically inspected by tax assessors and given a new (typically lower) assessed

value based on the extent of the damage, applied through a higher depreciation rate, reducing their tax burden.[24] We compute d_j as the percentage change in the establishment's building value between January 1st, 2017 and its post-Harvey reappraisal. The value of d_j is generally negative.[25]

$$d_j = \frac{V_{b(j),post} - V_{b(j),pre}}{V_{b(j),pre}} \tag{5}$$

Because d_j is observed only for properties located within reappraisal districts, we use a Random Forest regressor to predict $\hat{d}_j$ for all properties in Harris County. As features in the model, we include the level of flood exposure (feet of water) and building characteristics, including the quality and type of the building, among others. We provide further details in Appendix G.

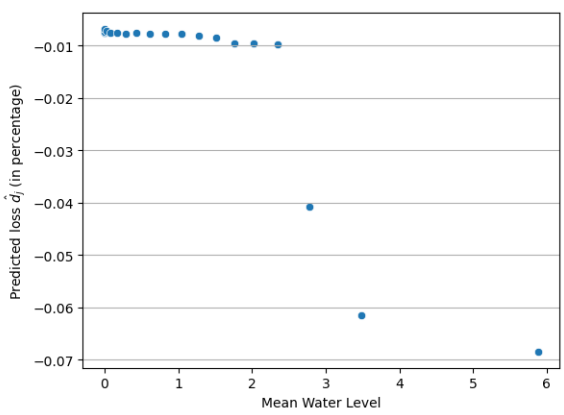
Figure 8a reports the predicted $\hat{d}_j$ from this exercise against flood exposure in a binscatter plot. For each bin, we report the mean water level on the horizontal axis and the mean predicted percentage change in value for fall 2017 on the vertical axis. Figure 8a shows that flood amounts less than 2.5 feet tended to cause drops in value of 1% or less, but damage significantly increases with deeper flooding. This is consistent with commercial building practices where many buildings have foundation heights 0.25 to 0.5 feet above nearby ground and electrical outlets are typically placed 1-1.5 feet above floor level (FEMA, 2020, National Structure Inventory, 2024). In what follows, we use the establishment-specific predicted percentage change in building value $\hat{d}_j$ as our measure of d_j in estimating equation 4.

Estimation We estimate equation 4 via Maximum Likelihood and report the estimated parameters in Table 5. Column 1 reports coefficients for all restaurants and retail stores together, while columns 2 and 3 report coefficients when we estimate the model for only restaurants (about 40% of temporary exits) and only retail stores, respectively. For all three columns, the signs of the estimated parameters are the expected ones: the coefficient on damage d_j is negative, implying that stores with more storm damage (more negative values of $\hat{d}_j$) are more likely to exit. The coefficient on log revenues is also negative, which is consistent

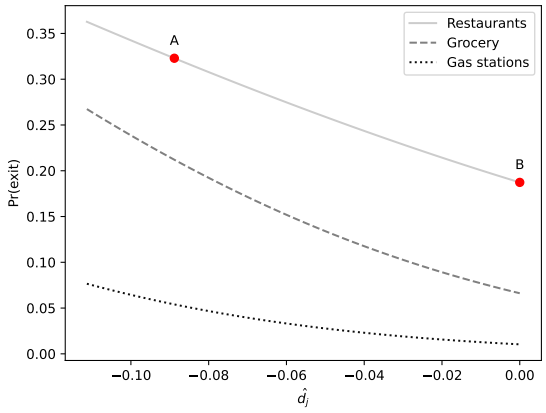
[24] 12% of commercial properties appraised by HCAD were located in reappraisal districts. In Appendix G.3, we find that flood exposure for properties in reappraisal and non-reappraisal districts was largely similar.

[25] Real property valuations are at the property level, and a given property may include multiple retail establishments. We assume that every establishment within the same real property gets the same percentage damage d_j.

with higher-revenue establishments being less likely to exit. Finally, the coefficient on square footage is positive, which implies that larger stores are more likely to exit, conditional on revenues and damage.



(A) Predicting $\hat{d}_j$



(B) Predicting permanent exit

FIGURE 8: Predicting damage d_j and predicting permanent exit.

Note: Panel A reports damage $\hat{d}_j$ as a function of flooding, as predicted by the Random Forest algorithm. Panel B shows predicted exit probabilities as a function of damage, as predicted by our estimation of equation 4 in columns (2) and (3) of Table 5. Point A and point B show predicted exit probabilities for a restaurant with $\hat{d}_j = -0.09$ and $\hat{d}_j = 0.0$, respectively.

In Figure 8b, we plot the implied relationship between $\hat{d}_j$ and the probability of exit using the predicted values computed from columns 2 and 3 of Table 5 for three NAICS categories: restaurants, grocery stores, and gas stations. Conditional on temporarily closing, an establishment with no damage is between 7 percentage points (gasoline stations) and 20 percentage points (grocery stores) less likely to exit than a store within the same category with the maximum observed damage in our sample. Mirroring the evidence presented in Table 2, there is significant heterogeneity across store categories: restaurants are more likely to exit than grocery stores, which are more likely to exit than gas stations. In addition, a given percentage reduction in damage has a larger effect on the probability of exit for restaurants than for grocery stores, which, in turn, is larger than the effect on the probability of exit for gas stations.

Our model of establishment re-entry does not consider potential interdependence between re-entry decisions. Interdependence could result from strategic interactions between stores (as in classic models of oligopolistic entry; Bresnahan and Reiss, 1991), geographical

agglomeration (e.g., stores located in a strip center), or correlated re-entry decisions within a chain. Our modeling approach abstracts away from these considerations because the typical establishment in Harris County faces hundreds of nearby competitors, and thus their re-entry decision is unlikely to be affected by the actions of a small number of competitors that temporarily close. In addition, modeling the interdependent actions of a large number of establishments is likely to be intractable.

TABLE 5: Parameter estimates from re-entry model

	Dependent variable: 1(Exit)		
	(1)	(2)	(3)
Sample	All stores	Restaurants	No restaurants
$\hat{d}_j$	-6.293	-4.822	-7.941
	(1.245)	(1.698)	(1.838)
Log(weekly rev.)	-0.129	-0.147	-0.098
	(0.030)	(0.038)	(0.047)
Log(sqft)	0.100	0.091	0.065
	(0.051)	(0.080)	(0.066)
2-100 locations	0.105	0.189	-0.030
	(0.088)	(0.113)	(0.145)
101-1000 locations	-0.232	-0.386	-0.127
	(0.145)	(0.229)	(0.192)
1001+ locations	-0.108	-0.432	0.211
	(0.140)	(0.215)	(0.194)
1(Flood plain)	-0.029	-0.045	-0.016
	(0.103)	(0.138)	(0.156)
Observations	3030	1199	1831
Pseudo R^2	0.082	0.054	0.058

The table shows results from estimation of equation (4), with standard errors in parentheses. Column (1) includes all damaged Harris County establishments that close at least temporarily after Harvey. Column (2) includes only restaurants, while column (3) includes all non-restaurant stores. Columns (1) and (3) include NAICS fixed effects. Flood plain is an identifier equal to one if an establishment is located in a FEMA flood plain. See Appendix A for details.

6.2 Cost-benefit analysis of aid

We now consider the effect of a grant-based aid program through the lens of our re-entry model. We use the model to calculate the effect of aid on re-entry probabilities and then compare the expected benefits of aid to its cost.

Effect of aid on re-entry probability: To predict the effect of aid on exit probability, we assume that a dollar of aid has the same impact as a dollar reduction in storm damage. Aid provided to a damaged establishment moves the establishment along its (industry-specific) damage-exit curve, as shown in Figure 8b, reducing its probability of exit. The change in the probability of exit caused by the grant program corresponds to the vertical difference between the point on the curve when the business faces damage $\hat{d}_j$ (for example, point A on the restaurants' curve) and the point when damage is reduced because of the grant (point B).

The re-entry model maps the relationship between an establishment's exit probability and damage $\hat{d}_j$ measured as a percentage of an establishment's real estate assets. To evaluate the effect of an aid package measured in dollars requires transforming $\hat{d}_j$ from a percentage to a dollar amount. We do this by assuming that j's losses come from both damage to equipment and inventory $K_{j,pre}$ and to building value $V_{b(j)}$, where the establishment's real estate loss is proportional to the square feet it occupies, as shown in equation (6) below. To measure $K_{j,pre}$, we use data from HCAD tax records on the assessed value of the business' personal property prior to the storm, which includes equipment, vehicles, inventory, and other property owned by the establishment. We compute the dollar-denominated loss D_j as:[26]

$$D_j = \hat{d}_j \times \left[\kappa K_{j,pre} + V_{b(j),pre} \times \frac{sqft_j}{sqft_{b(j)}} \right] \tag{6}$$

We do not have damage estimates for business capital and inventory $K_{j,pre}$ in the property tax data, and so we proceed by assuming that damage to K_j is proportional to the decline in the value of its building, with the parameter κ governing the rate of decay. We explore two scenarios for κ. In our first scenario, we set $\kappa = 1$, which assumes that the share of damaged capital is the same as for real property. This may not hold if machinery is destroyed more quickly by water than the physical building or if the establishment can remove valuable equipment before the storm. In our second scenario, we set $\kappa = 8.98$, which is calibrated

[26] To illustrate this calculation, suppose an establishment with \$20,000 of equipment occupies 1,000 square feet of a 10,000 square foot shopping center with an assessed value of \$1M in January 2017 that is reassessed at \$900k after Harvey. Therefore, $d_j = -0.1$ and establishment j's dollar-denominated damage is $D_j = (d_j) \times [\$20{,}000 + \$1{,}000{,}000 \times 1{,}000/10{,}000] = \$12{,}000$.

such that a store that receives the maximum predicted real estate damage experiences a 100% personal property loss.

We show summary statistics of the different components of D_j in Table H.1. For establishments with more than 4 feet of flooding exposure, the average estimated damage is approximately \$50k in our baseline case (58% of which is real estate damage), which is comparable to SBA loan amounts given after Hurricane Harvey, where the median loan amount was \$68,500 and the mean loan amount was \$116,471.

We compute the effect of a hypothetical aid program that gives a grant of size D_j to a damaged store, effectively reducing its exit probability by moving it along the damage curve in Figure 8b from the observed $\hat{d}_j$ to $\hat{d}_j = 0$. In doing so, we abstract away from several practical issues related to the disbursement of aid that we cannot account for given the nature of our data. First, we do not model contracting and agency frictions when the establishment and building owners differ. In practice, SBA disaster loans are often given to both building owners and establishments. We assume that aid is divided between the two parties proportional to the damage suffered. Second, our assumption that a dollar of aid has the same effect on the probability of exit as a dollar decrease in damage does not directly account for liquidity constraints and credit market failures. Third, our analysis does not consider moral hazard issues, such as establishments exerting less effort in protecting themselves from storm damage in hopes of being eligible for more aid. Despite these simplifications, the change in re-entry probabilities implied by our model is in line with quasi-experimental estimates of the impact of SBA loans from Collier et al. (2024).[27]

Consumer and employment benefits: To compute the benefits to consumers from store re-entry, we use each store's per-month consumer surplus contribution and explore two scenarios related to the duration of those benefits. In our first scenario, we sum consumer surplus from the date of Hurricane Harvey through the end of our sample period (December 2018) and assume a discount factor of one (shown in Figure 4). This is likely to be a lower bound, as establishments may persist beyond our sample period. However, accounting for

[27]For establishments with more than 4 feet of flooding, we estimate that aid decreases average exit probability by 6.2pp (on a basis of 9.7%). Collier et al. (2024) find that receiving an SBA loan reduces an applicant firm's exit probability in the year in which a disaster occurs by approximately 8-9pp (on a basis of 21% over the first three years after a disaster).

future benefits requires imposing additional assumptions about establishment survival and entry. To assess the sensitivity of our results to this assumption, we consider a second scenario in which we sum an infinite discounted stream of consumer surplus benefits using a monthly discount rate of approximately 2%.[28]

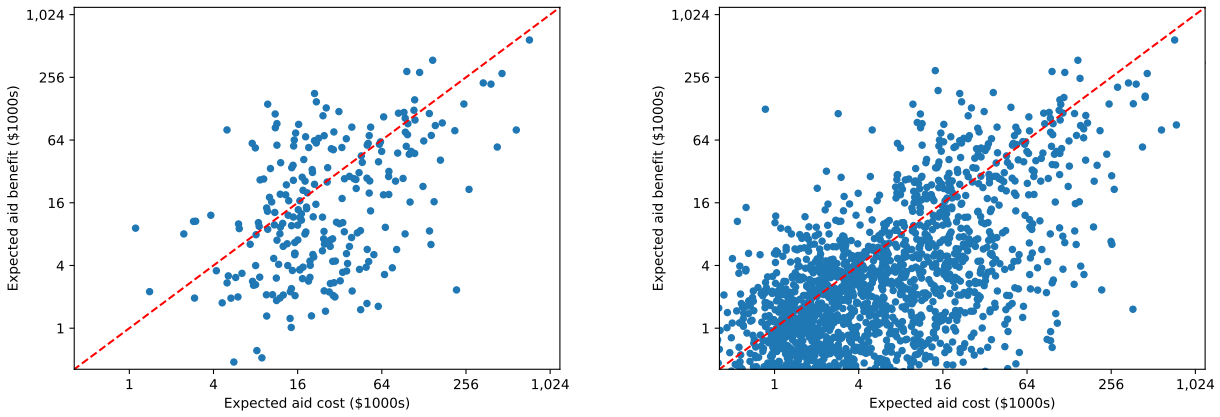
A store that re-enters also prevents the job loss associated with closure. To approximate these employment benefits, we compute the predicted unemployment insurance benefits employees would receive. To do this, we take the number of employees per establishment from Data Axle. We compute wages using Bureau of Labor Statistics data on NAICS by county wages assuming full-time employment and value a saved job at the maximum unemployment insurance benefits that the state of Texas would pay out. The average resulting benefit is \$5,994 per employee.[29] Further details on this calculation are in Appendix H.1.

Results: The counterfactual considers the impact of giving each establishment a one-time grant equal to the monetary amount of its estimated damage D_j. We conduct a cost-benefit analysis that compares the cost of aid D_j with its benefits, which we measure as the change in exit probability multiplied by the sum of the consumer surplus and employment benefits created by the store. We perform the analysis for four scenarios to illustrate the sensitivity of the efficacy of aid to our modeling choices. In the baseline scenario, consumer benefit from store re-entry extends only until the end of 2018, and $\kappa = 1$. Variation 1 modifies the baseline variation by using $\kappa = 8.98$. In variations 2 and 3, we assume infinitely discounted consumer benefits and use $\kappa = 1$ and $\kappa = 8.98$, respectively. In all scenarios, we use a marginal cost of public funds equal to 1.3 (Poterba, 1996).

Figure 9 shows the distribution of the costs and benefits of aid in our baseline scenario. Consider first the case of establishments exposed to four or more feet of water (Panel A), where damage is typically larger. The figure reports the cost of aid on the horizontal axis and the expected benefit of aid on the vertical axis. The 45-degree line plots the break-even point

[28]We calibrate this discount rate to 2.1%, which reflects the probability of establishment survival as well as the 3% annual discount rate (translated to a monthly rate of 0.25%) used by the Congressional Budget Office. We use estimates of establishment survival rates based on Luo and Stark (2014), who report the average lifespan of a restaurant (measured from BLS data) to be approximately 4.5 years, which implies a monthly hazard rate of 1.85%.

[29]We take this as a likely underestimate; a HUD-funded job creation program after Harvey gave subsidies of up to \$50,000 per employee (Texas General Land Office, 2021).



(A) $\geq$ 4 feet flooding (B) All

FIGURE 9: Benefits and cost of business aid

Note: Both panels show benefits from aid (vertical axis) vs. costs (horizontal axis) for damaged Harris County establishments that close at least temporarily after Harvey (both axes on log scale). Panel (A) is limited to those establishments with 4 or more feet of flooding; panel (B) includes all establishments.

where benefits equal costs. The figure shows that there are relatively few businesses for which an aid program would be justified based on their contribution to consumer welfare (31% of establishments). The average establishment in the plot generates $759,646 in consumer surplus and has 16.9 employees; it would receive an aid payment of $52,028, which would reduce its exit probability by 6.3 pp (on a base of 11.0%). At these average values, the net expected value of aid is -$15,609.[30] When considering the entire sample of damaged stores, only 21% of stores lie above the break-even line (panel B).

Across all the establishments, the costs of an unrestricted grant-based program generally exceed the benefits. We report results for this version of the subsidy program in the top panel of Table 6, where the first column shows results from our baseline scenario. Under these assumptions, the total cost associated with such a program is about $38M, which generates only about $20M of benefits, resulting in a net loss of $19M. Assuming a faster rate of capital decay (columns 2 and 4) increases the cost of aid, while computing surplus benefits over a long time frame (columns 3 and 4) increases the benefits of aid. In all four scenarios, a minority of establishments generate positive net value.

[30]The expected benefits of aid are equal to $\Delta\mathbb{P}(j \text{ exits}) \times (\Delta CS_j + W_j \times UI_j) = .063 \times (759{,}646 + 16.9 \times 5{,}994) = 54{,}239$ (where W_j denotes employees). The costs of aid are equal to $D_j \times MCPF = 52{,}028 \times 1.3 = 67{,}637$ (where $MCPF$ denotes the marginal cost of public funds).

TABLE 6: Cost-benefit analysis for establishment subsidies with targeting

	(1) **Baseline**	(2) **Variation 1**	(3) **Variation 2**	(4) **Variation 3**
Assumptions				
Rate of capital destruction	$\kappa = 1$	$\kappa = 8.98$	$\kappa = 1$	$\kappa = 8.98$
CS benefits duration	End of 2018	End of 2018	Inf. discounted	Inf. discounted
Aid to all damaged firms				
Cost	38,287,844	162,301,644	38,287,844	162,301,644
Benefit	19,775,644	19,775,644	55,977,711	55,977,711
CS benefit	16,649,109	16,649,109	52,854,314	52,854,314
# jobs	520	520	520	520
Net Value	-18,512,200	-142,526,000	17,689,867	-106,323,933
% firms positive value	21.4%	5.4%	41.5%	19.9%
# subsidized firms	2,540	2,540	2,540	2,540
Aid only to firms with positive net value				
Cost	4,815,635	2,661,491	13,978,605	11,457,064
Benefit	10,653,506	4,853,874	47,781,819	29,438,624
CS benefit	9,435,513	4,306,655	45,916,526	28,429,937
# jobs	226	102	332	192
Net Value	5,837,871	2,192,384	33,803,213	17,981,560
% firms positive value	100.0%	100.0%	100.0%	100.0%
# subsidized firms	543	136	1,054	505
Aid only to firms with predicted positive net value				
Cost	6,117,877	918,135	13,876,158	14,944,069
Benefit	10,007,664	1,646,692	41,374,435	26,785,025
CS benefit	9,074,055	1,557,212	39,592,670	25,876,015
# jobs	184	18	330	179
Net Value	3,889,786	728,556	27,498,277	11,840,956
% firms positive value	68.8%	62.9%	80.6%	69.7%
# subsidized firms	509	35	1,056	439

The table shows the results of a cost-benefit analysis from a subsidy program that considers payments to damaged Harris County stores that closed at least temporarily after Harvey. In the top panel, we report the results when all stores receive aid. In the middle panel, we assume aid is given only to stores where the expected benefits exceed the costs. In the bottom panel, we predict the probability that a store has a positive net value from its observable characteristics and subsidize the stores with the highest predicted values. We report results for each version of the subsidy program in four scenarios (across the columns). Columns (1) and (2) sum the consumer surplus impacts of the store only through December 2018, while in (3) and (4), we compute the infinite discounted sum of consumer surplus using a monthly discount factor of 0.979. Columns (1) and (3) assume that establishment capital is destroyed at the same rate as the physical building ($\kappa = 1$ in equation 6), while (2) and (4) assume capital is destroyed more quickly ($\kappa = 8.98$). For each scenario, we separate expected program benefits for consumers and employees, where we value jobs at the maximum unemployment insurance benefit (an average of $5994 per job).

Next, we consider two variants of the subsidy program that target aid more carefully to establishments with positive net value. In principle, knowing consumer preferences and each store's contribution to consumer welfare, a policymaker could provide aid only to stores where the expected benefits of aid exceed the costs. We show the results of this program under "perfect targeting" in the middle panel of Table 6. In our baseline scenario, this provides aid to 543 establishments, which would cost about \$5M and generate and nearly \$11M in expected benefits (\$2.21 per dollar of aid), resulting in a net gain of nearly \$6M. The net value is positive by construction in each of the four scenarios we consider, ranging from \$2.2M (136 establishments) to \$34M (1,285 establishments).

Of course, providing aid only to establishments with a positive net value may be infeasible; policymakers may lack the data or time to precisely measure the consumer surplus generated by each establishment. We next consider a program that targets aid to stores based on characteristics more easily observable to grant administrators. We run a logit regression of an indicator variable for whether an establishment has positive (expected) net value on establishment observables, including sales, store size, NAICS category, chain affiliation, flood exposure, and the number of nearby competitors within various radii. We report the results in Table H.2, which shows that, all else equal, establishments with more sales (which reflect greater consumer surplus) and smaller store sizes (which require less subsidy) are most likely to have net positive value from the subsidy program. We then compute the predicted probability that an establishment has a positive net value, $\hat{p}_j$, and choose a subsidy cutoff $\bar{p}$ to maximize the total net value of the program.

We show the results of this exercise in the bottom panel of Table 6. In our baseline scenario, this program provides subsidies to 509 establishments (20% of the total), of which 69% have positive net value. These subsidies generate a total net value of about \$3.9M (\$1.64 in benefits for each dollar spent) and achieve 67% of the net gain of the perfect targeting variant. The total net value is positive across all four scenarios we consider, although the number of establishments that receive subsidies varies with assumptions about the costs and benefits of aid.

A key finding across all the cases we consider is that although few establishments generate sufficient benefits to justify the cost of aid, the right tail of exiting stores creates substantial

welfare gains. Though the exact number of stores to subsidize depends on the modeling assumptions (as shown in Table 6), our findings show that a blanket aid program would be inefficient. However, a program that targets establishments based on observable characteristics can identify a substantial fraction of the establishments that would receive aid under perfect targeting.

7 Conclusion

How do adverse shocks to firms affect firm entry, exit, and consumer welfare? A large literature has explored the role of such disruptions on productivity and whether they lead to cleansing—where the least productive firms are replaced by superior entrants—or scarring. In this paper, we examine these issues within the context of Hurricane Harvey, which led to significant establishment turnover. We show that exiting stores, on average, are less valuable to consumers than entrants or surviving incumbents. However, there is also significant dispersion within the exits, including a right tail of exiting stores that contribute substantially to consumer welfare. Further, while entry fully replaces exits at the aggregate level, there is a net decrease in the number of stores in the hardest-hit neighborhoods, which leads to substantial welfare losses for consumers.

Our findings align with aspects of the Schumpeterian view of creative destruction, particularly in how lower-value incumbents tend to be replaced by more productive entrants. Taken at face value, our findings may suggest that policy aimed at preventing firm exit in the aftermath of an adverse shock, as has often been proposed in the U.S. and abroad, is not necessary. However, our results also highlight two important caveats to this interpretation: first, because of the spatial mismatch between entries and exits, firm turnover can have large impacts on consumers and important distributional consequences. We find the largest welfare losses in smaller MSAs and lower-income neighborhoods, suggesting that policymakers may wish to pay particular attention to these areas when designing aid policy. Second, while the average exiting store is marginal for consumer welfare, the most valuable exits are significantly more important, and a targeted subsidy could create substantial welfare gains.

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A Data sources and data processing

We use data from the following sources:

1. **Card data.** Our main dataset to identify business exit and re-entry comes from a payment card company that represents about 20% of U.S. consumption. The data include information on credit and debit card expenditures. We identify whether a business location is open by whether we observe transactions at that location in a specific week. Some closed locations continue to process a small number of transactions (possibly misclassified online activity); we thus count a business as open if it processes at least 10% of its pre-storm weekly average transaction volume. We also use these data to construct information on consumer expenditures. The data includes both debit and credit cards. For about half of the credit cards (and none of the debit cards), the home location of the card is identified at the zipcode+4 level. In estimation, we use only credit cards that have a non-missing home location. We use all transactions to infer whether a store is closed.

2. **Validating store exit and re-entry through Yelp and Google.** Beginning with a list of businesses from the card data, we take the following steps:

   (a) Using the Yelp API, we search for each business in the card data within Yelp. We use the Jaro-Winkler similarity score to measure the distance between two strings, the business name in the card data, and that in Yelp.

   (b) The Yelp API only returns businesses currently operating at the time of search using the API. To find the Yelp pages of closed businesses, we use a Google Custom Search Engine to find old Yelp records. Specifically, for businesses in the card data that cannot be matched to Yelp data in the previous step, we search for them using a custom Google search with the search terms consisting of establishment name, establishment address, and the word "Yelp". This returns search results from Yelp.

   (c) For establishments not found in the previous two steps, we search for them in the Google Places API. This returns a cleaned business name and a cleaned business address. Then, we use the Google Custom Search Engine with the cleaned business name and cleaned business address to identify Yelp pages for the establishment.

   (d) Using the set of Yelp pages from the previous three steps, we collect the dates of the first and last Yelp reviews for each establishment. We marked a store as a verified exit if (i) it was marked "permanently closed" at the time we searched it in Google Maps or Yelp, or (ii) the date of its final Yelp review occurred prior to the date of its last reported transaction plus six months. We marked a store as a verified entry if the date of its earliest review was no earlier than 6 months prior to its first transaction.

   (e) Finally, we hired RAs to hand-search unmatched businesses. They first searched for the business on Google, then looked up the address in Google Maps Street View to see if they could identify the business in old Street View photos. If the

business was either (i) reported closed on Yelp or Google or (ii) they saw the business before the date of its last transaction in a street view photo and the business was gone (or was visibly closed) in a photo after its last transaction date, they marked it as a verified closure. Every business was randomly assigned to two RAs who checked its status independently.

3. **FEMA flood depth data.** Raster data of FEMA estimates of flood depth (in feet) at the 3 meter by 3 meter level.

4. **FEMA flood zone data.** We use shapefiles from the FEMA Flood Map Service Center at `https://msc.fema.gov/portal/advanceSearch#searchresultsanchor` that identify the FEMA 100-year flood zones. After fixing polygon geometries (using QGIS), we combined the polygons of the counties in our sample. Finally, we performed a spatial join (i.e., point-in-polygon) to identify businesses located within an area that FEMA has categorized as a flood zone. We use the flood zone indicator in our estimation of equation 4 in Table 5.

5. **Harris County Appraisal District (HCAD) data.** We downloaded the year 2017 and 2018 records from `https://hcad.org/pdata/pdata-property-downloads.html` and acquired the 2017 post-Harvey reappraisal data through direct communication with HCAD. These data include personal property data at the establishment level and real property data at the parcel level. Personal property data includes the square footage of the establishment and the property's assessed value such as inventory, capital equipment, vehicles, etc. Real property data includes the square footage of the building or buildings on the property and the assessed value of land and buildings. For real property records, we also gather GIS shapefiles for the polygon boundaries of real property records (`https://hcad.org/pdata/pdata-gis-downloads.html`).

   We use the following matching methods to link establishment data from the card data with HCAD data:

   (a) To link establishment data from card data with personal property records from HCAD, we use machine and manual matching using information on establishment name and address.

   (b) To link establishment data from card data with real property records from HCAD, we first geocode establishment addresses yielding latitude and longitude. To find candidate matches within real property records, we limit real property records to those listed as retail. We then use a spatial join to link establishment data with the corresponding real property polygons to identify which corresponding real property each card-level establishment is in. Because many real property records have multiple establishments (e.g., malls or shopping centers), there are typically multiple establishments linked to a single real property record.

6. **American Community Survey.** We use the 5-year 2012-2016 ACS estimates of demographic characteristics at the Census block group level.

7. **Auxiliary jurisdictional shapefile data.** Our analysis uses polygon shapefile data from the US Census Bureau on county, census tract, and census block group boundaries. In our analysis in Appendix E, we also use data on the locations of Houston "superneighborhoods", which include multiple Census tracts, taken from `https://wginc.com/what-is-a-super-neighborhood-in-houston/`.

8. **Annual county population estimates from the US Census**. We use annual county-level population estimates from the US Census to examine population changes over time. We focus on 2015, 2016, 2017, 2018, and 2019 population estimates. The US Census Bureau creates these annual population estimates using data from the 2010 Census and later data on births, deaths, and migration. Estimates are to be interpreted as population as of July 1 of each year. We use this analysis in Appendix E.

9. **National Land Cover Database (NLDC).** NLCD data includes information on landcover, such as whether any given location is a developed area (including high, medium, and low levels of development), as well as whether it is forest, wetland, or other non-developed area. We use NLCD data to calculate regional flood exposure for developed areas in Appendix E.

10. **SBA loan data.** From the Small Business Administration's (SBA) Disaster Loan program, we have information on all loans provided to businesses in the aftermath of Hurricane Harvey. For approved business loans, these data identify the business (including name, address, zip code, city, and county), loan amounts, and the date when the loan was approved. The data also contain information about denied loan applications; for these, we see the zip code of the applicant and the amount of the loan requested but do not have identifiable information about the business (e.g., name or address).

    The SBA data contains information from 1,679 businesses that received SBA loans. Recipients come from a wide variety of categories, including retail, restaurants, medical and dental providers, financial and tax service providers, daycare providers, contractors, hotels, apartment complexes, transit providers, and non-profits. We manually match these to the business dataset from our card provider. The matching process results in 152 matches.

11. **Data Axle.** Data Axle is a proprietary data provider that provides estimates of number of employees by establishment. We pull data from 2015-2019 Data Axle records for zip codes in Harris County. We use machine and manual matching to match these records to establishments in the card data for Harris County. To infer establishment employee count for 2017, we use 2017 Data Axle records. In cases where an establishment had missing employment data in Data Axle for 2017 but had non-missing data for 2015, 2016, 2018, or 2019, we used data from these other years. In cases where we could not match an establishment in the card data with Data Axle, we use the median employee count for the 3-digit NAICS code in the city where the establishment is located.

12. **Bureau of Labor Statistics.** We use Bureau of Labor Statistics (BLS) data on weekly wages in Harris County in 2017 by 3-digit NAICS code.

13. **Mixed Beverage Gross Receipts Tax data.** This data comes from the Texas Comptroller of Public Accounts. It contains a monthly panel of all establishments that sell, prepare or serve spirits, beer, ale, and wine. Data include information on establishment name, address, and receipts from alcohol sales. We use this information to examine longer run business presence by Harvey flood depth in Appendix C.4.

Coordinate reference systems We convert all GIS data to the NAD83 Texas Centric Albers Equal Area (EPSG:3083) projection.

B Additional flood maps

B.1 Flood maps for Harris County and Beaumont and Corpus Christi MSAs

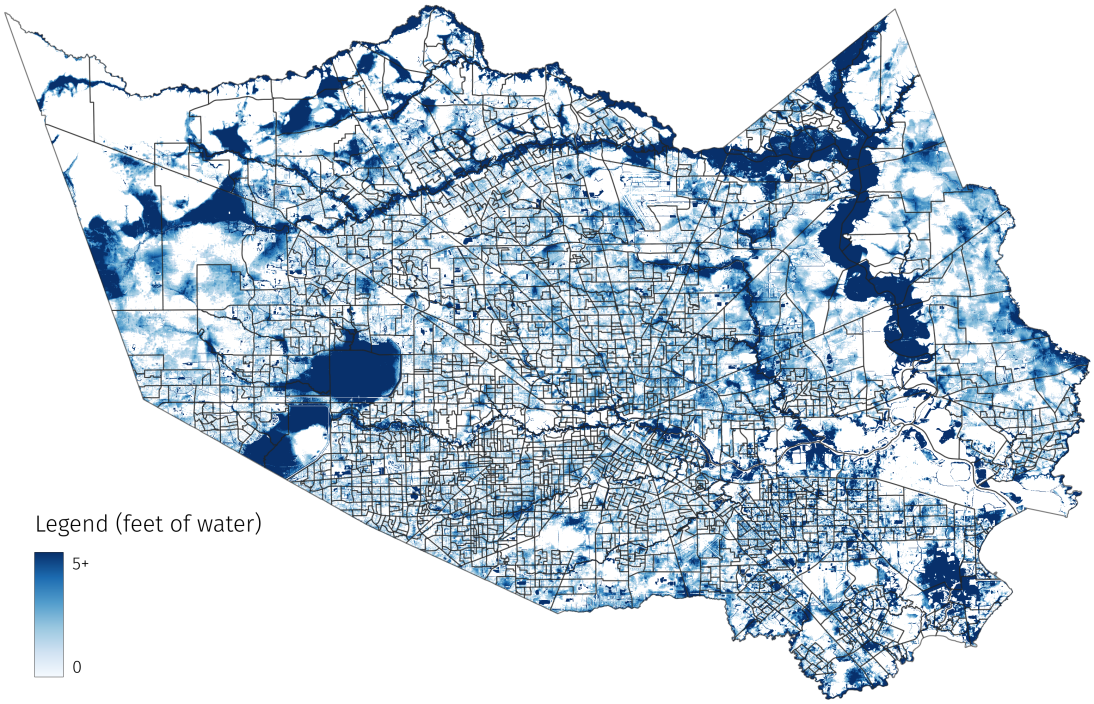
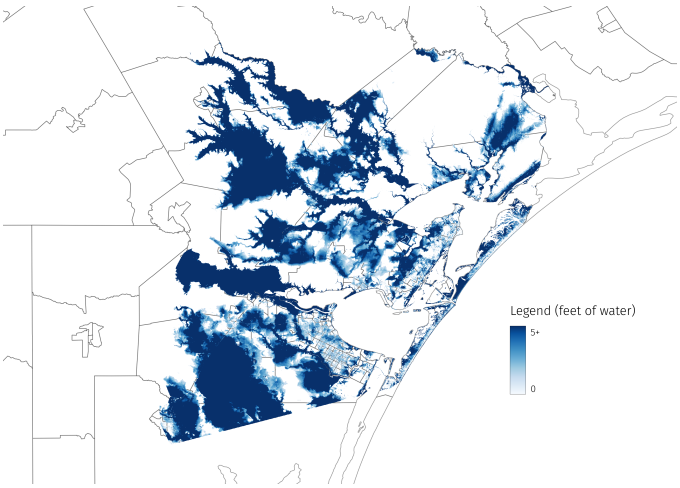
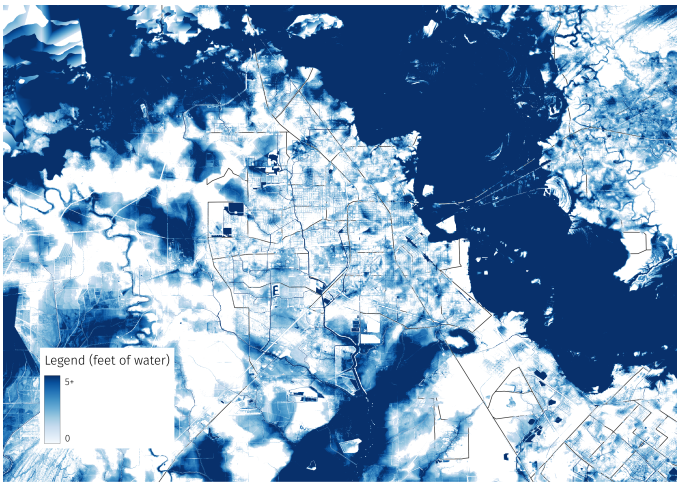


FIGURE B.1: Flooding level caused by Hurricane Harvey in Harris County.



(A) Corpus Christi



(B) Beaumont

FIGURE B.2: Flooding level caused by Hurricane Harvey in Beaumont, Corpus Christi, and surrounding areas.

C Descriptive evidence

C.1 Business characteristics, exit rates, entry and exit

In this Appendix, we examine how establishment characteristics relate to various outcomes, such as exit rates, transactions, and sales. First, Table C.1 reports the estimates of linear probability regressions of various measures of exit on NAICS fixed effects, a polynomial of flood levels interacted with MSA fixed effects, and indicators for various firm sizes. Firm size is measured as the number of locations nationwide. The estimates show that stores that belong to large chains are less likely to close (both temporarily and permanently). Further, column (3) shows that conditional on closing for at least 4 weeks, stores that belong to large chains are more likely to reopen after a long temporary closure.

Table C.1: Exit rates by business characteristics

	(1)	(2)	(3)
Dep. Var.	1(Perm. exit)	1(Temp. Closure)	1(Exit | Temp. closure)
1(Corpus)	0.007	0.017	0.103
	(0.005)	(0.017)	(0.064)
1(Houston)	0.003	-0.002	0.052
	(0.002)	(0.015)	(0.041)
Locations - 1001+	-0.010	-0.049	-0.051
	(0.004)	(0.006)	(0.033)
Locations - 101-1000	-0.010	-0.022	-0.072
	(0.002)	(0.008)	(0.013)
Locations - 2-100	-0.004	0.005	-0.042
	(0.001)	(0.005)	(0.008)
1(Beaumont) x Flood	0.006	0.013	0.058
	(0.003)	(0.011)	(0.034)
1(Corpus) x Flood	0.016	0.040	0.027
	(0.005)	(0.006)	(0.044)
1(Houston) x Flood	0.003	0.011	0.017
	(0.001)	(0.003)	(0.008)
1(Beaumont) x Flood sq	0.000	0.001	-0.006
	(0.001)	(0.002)	(0.004)
1(Corpus) x Flood sq	-0.001	-0.004	-0.001
	(0.001)	(0.001)	(0.007)
1(Houston) x Flood sq	-0.000	-0.001	-0.001
	(0.000)	(0.000)	(0.001)
NAICS FEs	x	x	x
R2	0.009	0.018	0.032
Observations	30454	30454	2645

Notes: The table shows regression results from a linear probability model. The dependent variable is defined as an indicator of whether a store permanently exited after Hurricane Harvey (column (1)), an indicator of whether a store returned to business before the end of 2018 after being closed for 4 or more weeks (column (2)), and an indicator for whether a store permanently exited conditional on being closed for 4 or more weeks (column (3)). Each regression contains NAICS fixed effects, city fixed effects, chain size fixed effects (defined as the number of nationwide locations), and a polynomial of flooding level within a 50m radius around the store (and clipped from above at 10 feet) interacted with MSA fixed effects.

In Table C.2 we compare the observable characteristics of entrants against those of incumbents, including both stores that remained open through our sample period, and stores that closed. The table reports estimates of regressions of log(transactions) and log(sales) on indicators for whether the store is a new entrant post-Harvey, exits temporarily at the time of Harvey but re-enters, or exits permanently at the time of Harvey, with the excluded group being incumbent stores that do not close after Harvey. The dependent variable in column (1) is the log number of transactions. We find that relative to incumbent stores that did not close, stores that exited permanently had about 58% fewer transactions, with similar numbers for stores that closed temporarily and reopened. In contrast, new entrants had about 35% fewer transactions relative to incumbents. We find similar results when examining sales in column (2).

TABLE C.2: Characteristics of exiting and entering stores

Dep. Var.	(1) Log(trans)	(2) Log(sales)
1(entry)	-0.347	-0.345
	(0.037)	(0.039)
1(exit)	-0.578	-0.619
	(0.069)	(0.071)
1(temp. closure 1-3 weeks)	-0.479	-0.443
	(0.111)	(0.055)
1(temp. closure 4-8 weeks)	-0.803	-0.817
	(0.065)	(0.068)
1(temp. closure 8+ weeks)	-0.580	-0.589
	(0.112)	(0.132)
1(1001+ locations)	1.668	1.122
	(0.148)	(0.253)
1(101-1000 locations)	1.391	1.167
	(0.153)	(0.244)
1(2-100 locations)	0.363	0.333
	(0.046)	(0.055)
NAICS FEs	x	x
R2	0.459	0.199
Observations	33156	33156

Notes: Both specifications include NAICS and MSA fixed effects.

C.2 Comparing baseline exit rates with Census estimates

We find a baseline exit rate equal to 0.16% prior to the storm. This estimate is smaller than the estimates from the Census Bureau's Business Dynamics Statistics (BDS), where the estimated annual exit rate corresponds to a monthly exit rate of 0.68%. Within Texas in particular, monthly exit rates from March 2016 to March 2017 were 0.66% for NAICS codes beginning with 44 and 45, and 0.74% for NAICS codes beginning with 72. The discrepancy is likely due to several factors:

1. In the case of long temporary exit and re-entry (for example, an establishment that closed in September 2017 and reopened in May 2018), we classify this as a temporary exit whereas BDS would likely classify this as a permanent exit and a new entry.

2. Because we aggregate data to the brand-zip code level, we will miss exits in which a chain operates multiple locations in a single zip code and closes only one outlet.

3. Our card data excludes stores that do not process card transactions.

4. Our data cleaning procedure drops stores with an unverified exit (e.g., because they have no internet presence), stores with inconsistent names over time, sparse credit card transactions, or missing/incorrect location information. These are likely to be disproportionately small stores that have higher entry/exit rates in the first place.

5. Our card data cleaning procedure also excludes stores that use third-party payment processors. Our card data does not record accurate name, location, nor NAICS information for such stores.

Therefore, the establishments excluded from our analysis are likely to be small, have a relatively small contribution to consumer welfare, and have a high exit rate relative to other stores. This last point is confirmed by Crane et al. (2022), who find that the estimated high exit rate is primarily driven by small firms.

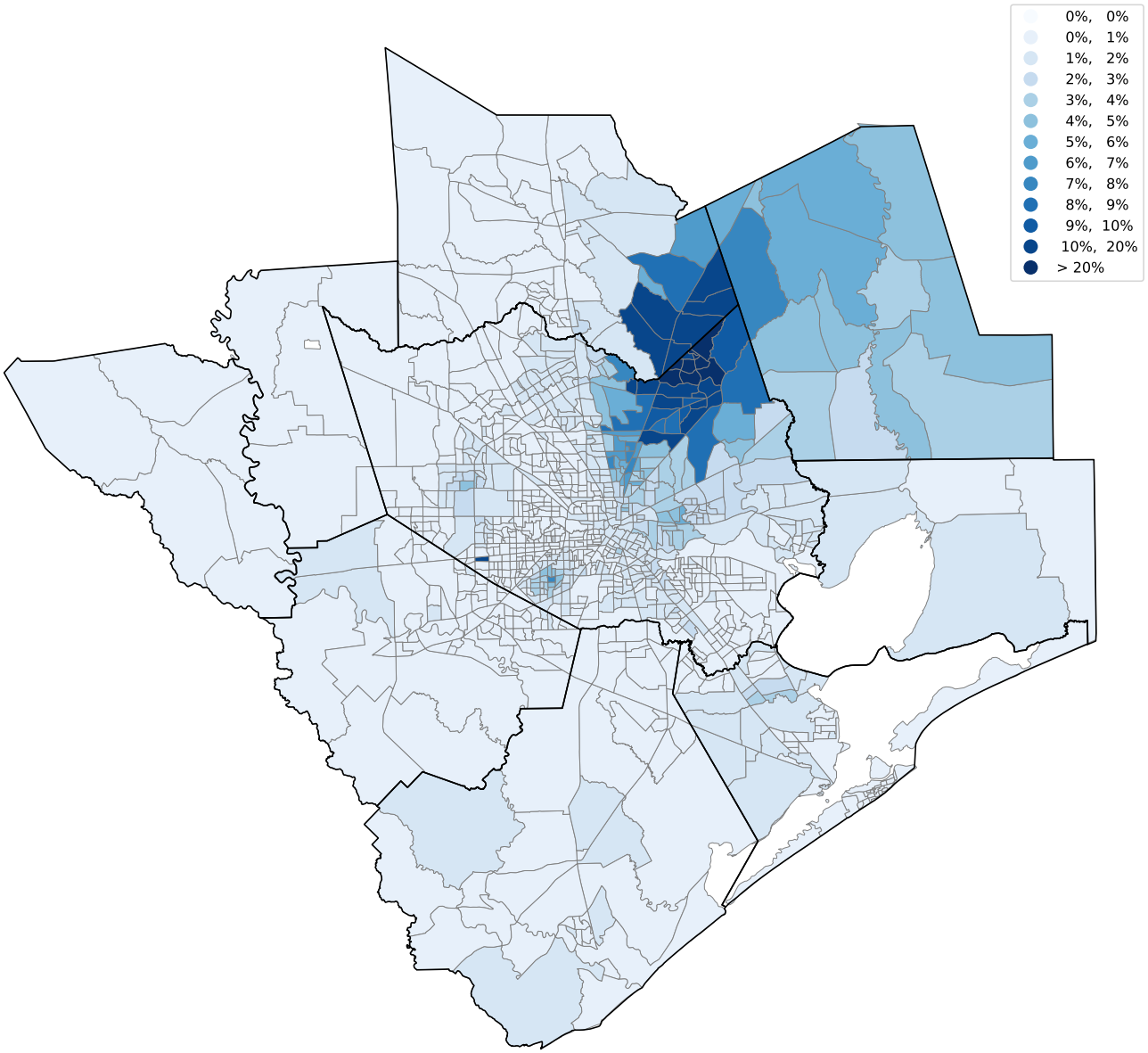
C.3 Share of pre-Harvey spending at closed stores

In this Appendix, we report the pre-Harvey share of spending at stores that closed for eight or more weeks in the Houston, Corpus Christi, and Beaumont MSAs. To construct these figures, we consider all payment cards in a Census tract and sum all spending performed by these cards between January and August 2017 by whether the establishment was later closed.

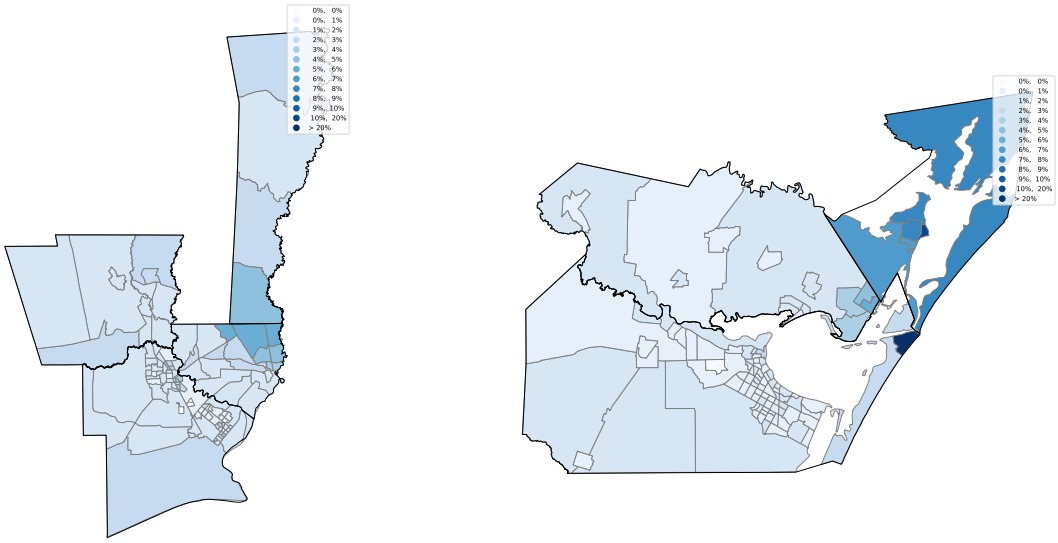
C.4 Evidence of longer run recovery

To what extent did the number of businesses recover in the long run in heavily damaged places? Figure 2d shows that areas with the highest exit rates saw a net decrease in the number of stores. If flooding during Harvey changed the beliefs of firm owners about the probability of future damage, this pattern may reflect adaptation, where stores move to less risky locations.

FIGURE C.1: Share of pre-Harvey spending at stores that closed for eight or more weeks in Houston



Note: This figure corresponds to the Houston MSA. The black lines show county borders while the grey lines show Census tracts. The shaded color indicates the share of transactions during January to July of 2017 that took place at establishments that later closed for 8 weeks or more after Hurricane Harvey.



(A) Beaumont (B) Corpus Christi

FIGURE C.2: Share of pre-Harvey spending at stores that closed for eight or more weeks in Beaumont and Corpus Christi

Note: These figures correspond to the Beaumont and Corpus Christi MSAs. The black lines show county borders while the grey lines show Census tracts. The shaded color indicates the share of transactions during January to July of 2017 that took place at establishments that later closed for 8 weeks or more after Hurricane Harvey.

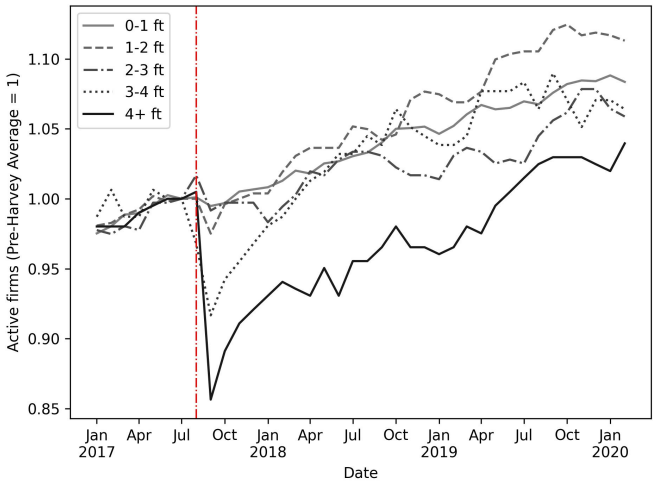


FIGURE C.3: Normalized count of establishments in MBGRT by Harvey flood level and month.

Note: The figure reports the normalized count of number of establishments that with positive alcohol sales by month and by the Harvey flood exposure at the establishment's address.

Our card data only allows us to measure entry through the end of 2018. To study longer-run business recovery, we examine data from the Mixed Beverage Gross Receipts Tax (MBGRT) data from the Texas Comptroller of Public Accounts. The data reports establishment-level alcohol receipts in each month, where having positive alcohol revenue is a proxy for whether the establishment is open, as well as the establishment address. We geocode each address and compute the flood exposure that address would have experienced from Hurricane Harvey. Then, to get a sense of overall recovery, we plot in Figure C.3 the normalized count of establishments by flood depth, where the count is normalized to 1 by flood depth before Harvey.

Figure C.3 shows that before Harvey, the count of establishments with positive alcohol sales followed a similar trend across places that would later experience different levels of flooding. Following Harvey, there is a larger drop in the number of establishments in areas with more severe flooding, particularly locations where flooding exceeded four feet. By the end of the period (early 2020, just before the COVID-19 pandemic), the locations that experienced four or more feet of flooding in 2017 had recovered to the same establishment count as before Harvey, and had nearly caught up to the set of locations where there was no flooding. This pattern suggests that hurricane-related damage had only a temporary effect, and that flooding did not lead to stores relocating to less storm-prone areas in the long run.

D Examining price responses to Hurricane Harvey

In this Appendix, we examine the extent to which retail prices changed during and after Hurricane Harvey.

To be added (pending Nielsen review)

E Demand response evidence

In this Appendix section, we examine evidence on overall population changes and overall spending changes pre- and post-Harvey. Throughout the counterfactuals, we assume that demand is stable in the medium run after the landfall of Hurricane Harvey. In support of this assumption, we show that Harvey did not result in significant outmigration from affected areas, nor did it appear to have material effects on the level or composition of spending across areas with differential flooding exposure.

To examine overall population change after Harvey, Table E.1 uses the US Census Bureau's estimates of annual county population. Table E.1 tabulates the estimated percent population change from July 1, 2016 to July 1, 2017 and the estimated percent population change from July 1, 2017 to July 1, 2018, computed separately for each county within Houston, Beaumont, and Corpus Christi MSAs. The table shows that population growth was stable in most counties (relative to the prior year) across the three MSAs. A notable exception is Aransas County, which had a population decrease of 0.6% from 2016 to 2017 but a 7.0% decrease in population from 2017 to 2018.

Table E.1: County population percentage changes for 2016-2017 and 2017-2018. Computed from Census County Population estimates

MSA	County	Change 2016-2017	Change 2017-2018
Houston	Austin	0.09%	0.68%
Houston	Brazoria	2.33%	2.14%
Houston	Chambers	3.86%	2.44%
Houston	Fort Bend	3.18%	3.01%
Houston	Galveston	1.70%	0.85%
Houston	Harris	1.37%	0.98%
Houston	Liberty	2.39%	3.19%
Houston	Montgomery	2.65%	3.50%
Houston	Waller	2.38%	3.55%
Corpus Christi	Aransas	-0.58%	-6.96%
Corpus Christi	Nueces	-0.04%	0.29%
Corpus Christi	San Patricio	-0.65%	-0.48%
Beaumont	Hardin	1.45%	0.12%
Beaumont	Jefferson	0.64%	-0.51%
Beaumont	Orange	0.10%	-1.73%

We also examine overall changes in spending over time. We examine overall card expenditure in our 12 NAICS as well as card expenditure for three of the largest spending categories: Groceries, gasoline, and restaurants. We aggregate card spending by store location within month by region, where region is defined as superneighborhoods for stores located within central Houston and counties for peripheral Houston as well as Corpus Christi and Beaumont. Flood exposure at the region level is computed as the average flood depth within the region when limited to locations that are listed as being "developed" (as opposed to forest, pasture, wetlands, etc.). We then separate regions into quartiles based on their flooding

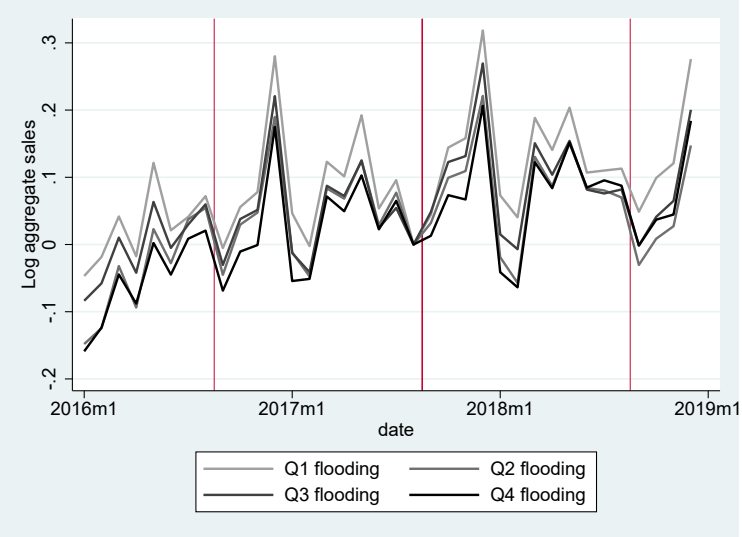


FIGURE E.1: Aggregate monthly spending by month x region

Note: Region is defined as Houston neigborhood for stores located within Houston superneighborhoods and defined as the county for stores located outside of Houston superneighborhoods. Vertical lines added between August and September of each year.

exposure and compute the log of aggregate spending by quartile, which we plot below. The level for each quartile is normalized to zero in the month before the landfall of Harvey.

If Harvey affected overall demand, we would expect to see different aggregate trends or compositional effects across places that differ in their flooding exposure. Figure E.1 graphs aggregate spending by average flood level, with the red line corresponding to the end of August in each year. The figure shows that spending in neighborhoods across all four quartiles followed similar seasonal trends before and after Harvey (a spike in the fall, followed by a drop in January and February). We don't see evidence that aggregate demand was persistently lower in more flooded places after the hurricane.

Figures E.2, E.3, and E.4 graph similar results for grocery, gasoline, and restaurant spending.[31] The figures again show largely parallel trends across areas with high and low flooding exposure. Consistent with the pattern in aggregate spending, these figures suggest that Harvey had limited long-term demand effects.

[31]The sample is limited to regions that have at least 5 stores operating in each month to comply with the terms of the data use agreement.

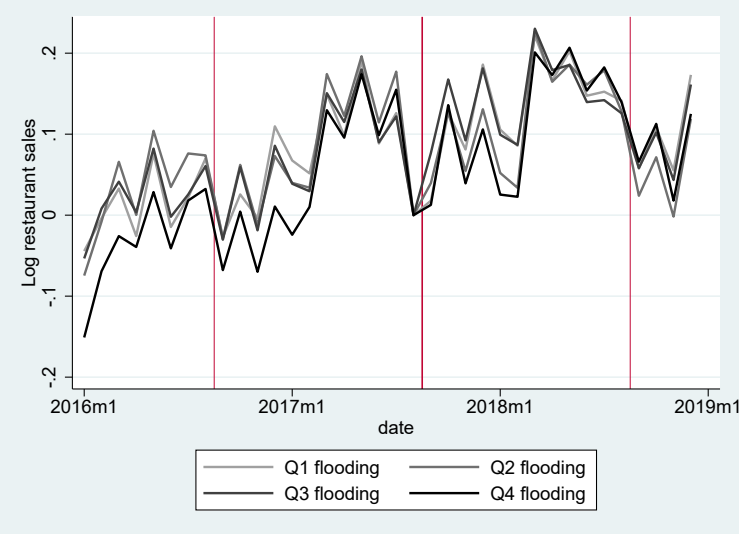


FIGURE E.2: Aggregate restaurant monthly spending by month x region

Note: Region is defined as Houston neigborhood for stores located within Houston superneighborhoods and defined as the county for stores located outside of Houston superneighborhoods. Vertical lines added at between August and September of each year.

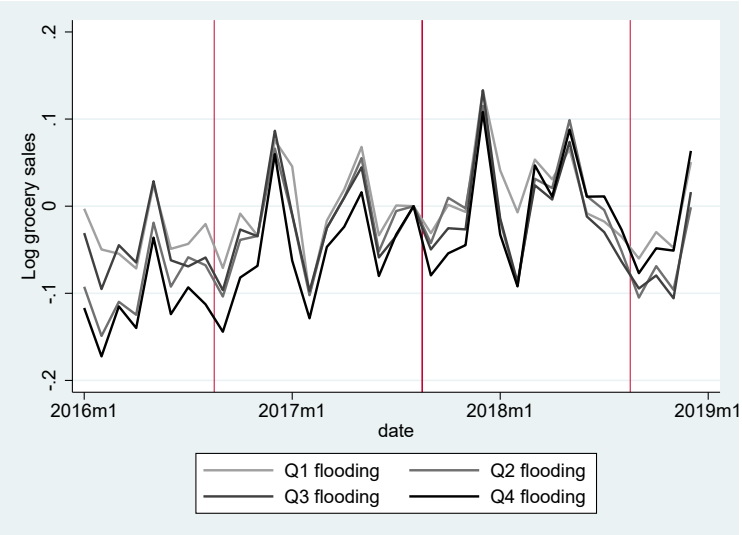


FIGURE E.3: Aggregate grocery monthly spending by month x region

Note: Region is defined as Houston neigborhood for stores located within Houston superneighborhoods and defined as the county for stores located outside of Houston superneighborhoods. Vertical lines added at between August and September of each year.

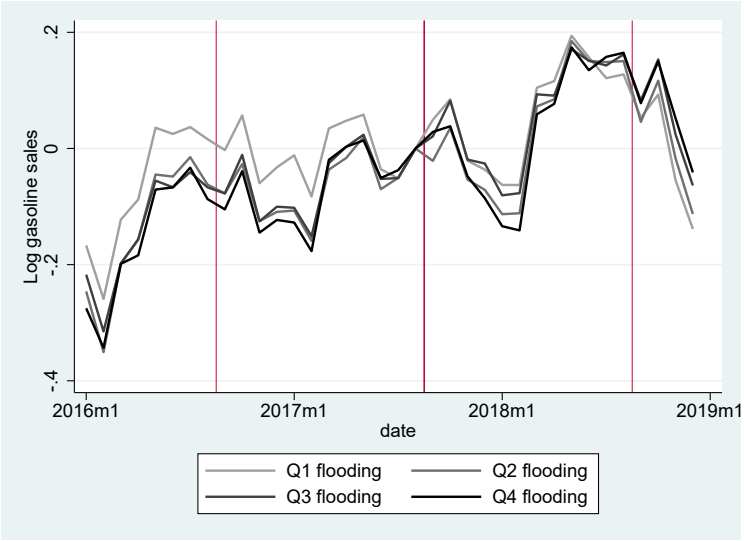


FIGURE E.4: Aggregate gasoline monthly spending by month x region

Note: Region is defined as Houston neigborhood for stores located within Houston superneighborhoods and defined as the county for stores located outside of Houston superneighborhoods. Vertical lines added at between August and September of each year.

F Further details on demand estimation and counterfactuals

F.1 Further details on demand estimation

Our estimation procedure defines a neighborhood as a Census tract. We assign cards to Census tracts using their home billing zipcode. In large tracts and in large NAICS categories that contain many consumers and transactions, we randomly sample a subset of cards. Specifically, in neighborhood-NAICS combinations that contain more than 10,000 transactions and more than 500 consumers, we randomly select 500 cards (without replacement). We experimented with alternative thresholds and found it made little difference in the results of estimation.

As described in Section 5, in estimation we exploit that we observe sequences of purchases for each card in our data. For this reason, we follow Revelt and Train (1998) and specify the probability that consumer i will visit store j in a given trip as[32]

$$P_{ij}(v_i) = P(y_i = j|v_i) = \frac{\exp(V_{ij})}{\sum_{j'} \exp(V_{ij'})},$$

where v_i denotes the random components of the utility function.

Because we observe a sequence of choices for each card, we follow Klopack (2024) and write the conditional probability of observing a sequence of choices by consumer i

$$P_{im}(v_i) = \Pi_t P_{im_t}(v_i),$$

where $\mathbf{m}_i = m_{1i}, \ldots, m_{Ti}$ denotes the observed sequence of choices by i.

In this context, we can specify the unconditional probability of the sequence $\mathbf{m}_i$:

$$L_{i\mathbf{m}} = \int P_{i\mathbf{m}}(v_i) f(v_i) dv_i.$$

In estimation, we concentrate out the linear terms of the utility function and use the SQUARE-M algorithm (Varadhan and Roland, 2008) to solve for the neighborhood-store fixed effects $\xi_{j,n,t}$. We implement our estimation routine using Jax (Bradbury et al., 2018) and GPU-specific tools that allow us to speed up estimation. Finally, we approximate the integral that defines the unconditional probability of the sequence using 50 scrambled Halton draws.

We compute standard errors using a block bootstrap procedure with 100 replications. We start with the estimation data and randomly sample consumers (and their associated transactions) with replacement by Census tract, so that each bootstrapped sample has the same number of consumers in each tract as in the original sample. We then run the estimation routine on each bootstrapped sample. Table F.5 reports the standard deviation of the bootstrapped estimates in parentheses.

[32]Recall that we estimate demand separately for each NAICS in our data. Therefore, the choice set faced by consumer i in a given trip is NAICS-specific.

F.2 Estimating $\xi_{j,n,t}$ for new entrants

Our main estimation sample is May through July 2017 for which we estimate the parameters θ and the store-neighborhood fixed effects $\xi_{j,n,t}$. This estimation sample does not allow us to estimate $\xi_{j,n,t}$ for entrants that enter post-Harvey. Therefore, we use the following steps to estimate $\xi_{j,n,t}$ for post-Harvey entrants:

After estimating demand using May through July 2017, we create five samples of post-Harvey demand: 2017Q4, 2018Q1, 2018Q2, 2018Q3, and 2018Q4. Then, for each of these post-storm quarters, we create new neighborhood choice sets consisting of those stores that are within the 15-mile buffer of the neighborhood and had opened by the start of the quarter. We then re-estimate demand using each of these post-storm quarterly samples of data, except that we hold the estimated θ fixed and only re-estimate the values of $\xi_{j,n,t}$. This results in a maximum of 6 different values of $\xi_{j,n,t}$ values for each store-neighborhood, one from the pre-storm estimation period and five from each of the post-storm estimation quarters.

We then impute what the pre-storm values of $\xi_{j,n,t}$ would be for new entrants by taking all estimated values of $\xi_{j,n,t}$ and projecting them on store fixed effects and time fixed effects:

$$\xi_{j,n,t} = \alpha_n + \alpha_j + \alpha_t + \varepsilon_{j,n,t}$$

We compute the predicted mean utility for each entrant store j in neighborhood n had it been available in the pre-storm choice set as $\hat{\xi}_{j,n,0} = \alpha_n + \alpha_j + \alpha_{t0}$.

F.3 Store-level consumer welfare contribution

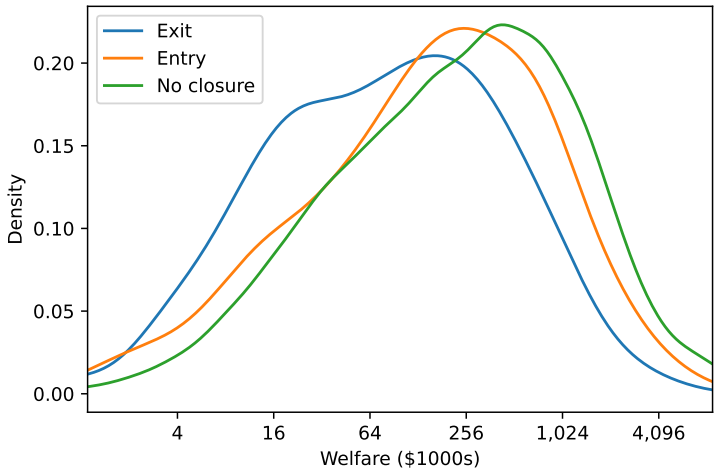


FIGURE F.1: Store-level consumer welfare contribution (pre-Harvey J).

Note: Density plots of the marginal welfare contribution of each store (the axis is on log scale), separated by whether the store permanently exits (blue), never closes (green), or is a new entrant (yellow). The figure shows the distributions conditional on the set of stores present pre-Harvey. Consumer welfare benefits are calculated as the total consumer welfare aggregated over a 16-month period after the landing of Hurricane Harvey.

Figure F.1 shows the welfare contribution of stores where J is set as the set of stores open

pre-Harvey. Contrast to Figure F.1 where J is set as the set of stores open post-Harvey.

TABLE F.1: Summary statistics for estimation sample

Houston

NAICS	Census Tracts	Consumers	Stores	Transactions	Dollars
Restaurants	1063	559,708	10,674	5,488,564	136,445,840
Groceries	1063	585,150	2,806	4,600,108	183,496,930
Gasoline	1063	682,305	1,786	3,231,010	77,968,340
Gen. Merch.	1063	717,230	838	3,320,748	211,554,560
Pharmacy	1063	566,137	1,134	1,701,916	64,425,910
Clothing	1063	573,807	2,394	1,685,467	158,324,690
Building materials	1063	406,638	702	1,312,176	101,747,500
Misc. retail	1063	409,768	2,269	916,763	57,161,600
Sports, Hobby, Music, Books	1063	427,444	802	959,539	69,001,240
Auto parts	1063	273,667	1,688	447,391	98,653,560
Furniture	1063	187,061	507	334,365	67,444,760
Electronics	1063	166,355	242	243,017	58,228,228
Total	1063	1,650,428	25,842	24,241,064	1,284,453,158

Corpus Christi

NAICS	Census Tracts	Consumers	Stores	Transactions	Dollars
Restaurants	99	45,039	847	375,800	9,092,030
Groceries	99	42,248	184	297,093	13,733,698
Gasoline	99	26,947	101	105,494	2,666,274
Gen. Merch.	99	37,189	86	154,349	9,058,695
Pharmacy	99	19,314	72	56,387	2,299,431
Clothing	99	18,705	153	43,485	3,562,549
Building materials	99	17,519	60	57,170	5,294,635
Misc. retail	99	13,595	158	26,630	1,706,072
Sports, Hobby, Music, Books	99	18,283	76	39,080	2,989,128
Auto parts	99	11,722	134	20,396	3,641,788
Furniture	99	4,141	47	5,743	1,845,792
Electronics	99	4,871	12	6,475	1,725,348
Total	99	72,297	1,930	1,188,102	57,615,442

Beaumont

NAICS	Census Tracts	Consumers	Stores	Transactions	Dollars
Restaurants	105	30,415	595	241,308	5,417,704
Groceries	105	28,195	228	181,550	7,677,398
Gasoline	105	25,406	163	128,025	3,166,913
Gen. Merch.	105	26,207	74	104,833	6,341,472
Pharmacy	105	16,084	80	47,094	1,910,148
Clothing	105	12,867	144	29,294	2,417,776
Building materials	105	12,112	62	36,994	3,375,709
Misc. retail	105	9,531	152	19,230	1,170,714
Sports, Hobby, Music, Books	105	11,885	48	24,884	1,918,498
Auto parts	105	8,262	131	13,890	2,725,232
Furniture	105	3,461	37	4,960	1,456,805
Electronics	105	3,735	14	4,972	1,160,863
Total	105	52,825	1,728	837,034	38,739,232

Notes: The table shows summary statistics of the estimation sample by MSA and NAICS category, which includes transactions between May and July 2017. NAICS categories are ranked by total transaction volume.

TABLE F.2: Welfare changes by income group

	Dependent variable: Welfare change (share of spending)		
	(1)	(2)	(3)
MSA	Houston	Corpus Christi	Beaumont
Tract med. inc. quartile 2	0.00038	-0.00133	0.00030
	(0.00002)	(0.00023)	(0.00015)
Tract med. inc. quartile 3	0.00102	0.00268	0.00033
	(0.00002)	(0.00024)	(0.00017)
Tract med. inc. quartile 4	0.00183	0.00841	0.00345
	(0.00002)	(0.00026)	(0.00028)
Tract med. inc. quartile 5	0.00134	0.01390	0.00363
	(0.00002)	(0.00042)	(0.00143)
Card inc. quartile 2	0.00030	-0.00079	0.00079
	(0.00002)	(0.00024)	(0.00016)
Card inc. quartile 3	0.00040	0.00323	0.00109
	(0.00002)	(0.00024)	(0.00017)
Card inc. quartile 4	0.00064	-0.00006	0.00146
	(0.00002)	(0.00026)	(0.00017)
Card inc. quartile 5	0.00026	-0.00196	0.00137
	(0.00002)	(0.00030)	(0.00021)
Tract flood quartile 2	-0.00025	-0.00677	-0.00280
	(0.00002)	(0.00025)	(0.00021)
Tract flood quartile 3	-0.00001	-0.00984	-0.00346
	(0.00002)	(0.00027)	(0.00021)
Tract flood quartile 4	0.00007	-0.01977	-0.00031
	(0.00002)	(0.00029)	(0.00021)
Tract flood quartile 5	-0.00031	-0.00230	-0.00192
	(0.00002)	(0.00023)	(0.00017)
Observations	5552845	251345	178812
R^2	0.02481	0.08950	0.16662

Notes: The table shows estimates from a regression of welfare changes by card and NAICS group on dummies for Census tract median income, card income, average tract flooding exposure, and NAICS fixed effects (not shown). Welfare changes are computed from September 2017-December 2018 inclusive of new entry.

TABLE F.3: Parameter estimates - Houston

Parameter	Auto parts	Furniture	Electronics	Hardware	Groceries	Pharmacy	Gasoline	Clothing	Sporting Goods	Gen. Merch.	Misc retail	Restaurants
μ^d	-1.226	-1.207	-1.017	-0.840	-0.653	-0.616	-0.887	-1.248	-1.242	-0.686	-1.028	-1.068
	(0.016)	(0.021)	(0.022)	(0.008)	(0.006)	(0.007)	(0.007)	(0.011)	(0.011)	(0.006)	(0.011)	(0.007)
$\sigma^2_{\theta^d}$	0.761	0.772	0.743	0.467	0.540	0.758	0.760	0.525	0.562	0.585	0.840	0.292
	(0.031)	(0.033)	(0.041)	(0.009)	(0.007)	(0.011)	(0.014)	(0.012)	(0.015)	(0.007)	(0.020)	(0.004)
$\sigma^2_{\theta^a}$	0.712	1.120	2.471	0.863	2.208	3.200	2.605	1.073	0.818	3.370	1.519	1.012
	(0.014)	(0.022)	(0.077)	(0.011)	(0.017)	(0.039)	(0.021)	(0.010)	(0.010)	(0.025)	(0.014)	(0.006)
ρ	0.348	0.492	0.809	0.325	0.478	0.866	0.859	0.331	0.405	0.723	0.443	0.250
	(0.016)	(0.023)	(0.049)	(0.008)	(0.008)	(0.012)	(0.012)	(0.008)	(0.010)	(0.009)	(0.013)	(0.004)
$\theta^{\text{inc x dist}}$	-0.031	-0.034	0.052	0.037	0.096	0.031	0.000	0.052	0.002	0.284	-0.055	0.089
	(0.012)	(0.015)	(0.020)	(0.011)	(0.013)	(0.011)	(0.011)	(0.008)	(0.009)	(0.009)	(0.012)	(0.009)
$\theta^{\text{inc x aff}}$	0.588	1.087	0.622	0.303	0.659	0.324	0.274	1.097	0.650	1.260	1.051	0.282
	(0.045)	(0.063)	(0.126)	(0.049)	(0.074)	(0.078)	(0.089)	(0.035)	(0.040)	(0.081)	(0.054)	(0.056)
$\theta^{\text{inc x chain}}$	-0.375	-0.903	-0.450	-0.463	-0.447	-0.248	-0.255	-1.580	-0.872	-3.793	-0.262	-0.532
	(0.076)	(0.141)	(0.208)	(0.084)	(0.073)	(0.102)	(0.138)	(0.061)	(0.071)	(0.165)	(0.061)	(0.040)

Notes: Demand model estimated separately for each NAICS by MSA. Table shows estimated parameters for all 12 NAICS. Distance is measured in miles and ranges between 0 and 15. Income is measured in annual dollars divided by 100,000 and is top-coded, so that the range is between 0 and 0.25 (corresponding to $0 and $250,000). Affluence refers to the average customer spending of a store (computed at the chain level) and is measured in dollars divided by 1,000, so that the range of the variable is from 0 to 5. Bootstrapped standard errors are shown in parentheses.

TABLE F.4: Parameter estimates - Corpus Christi

Parameter	Auto parts	Furniture	Electronics	Hardware	Groceries	Pharmacy	Gasoline	Clothing	Sporting Goods	Gen. Merch.	Misc retail	Restaurants
μ^d	-1.434	-2.675	-	-1.465	-0.661	-0.604	-1.204	-2.203	-1.963	-0.926	-1.641	-1.386
	(0.095)	(2.872)	(-)	(0.066)	(0.025)	(0.055)	(0.038)	(0.132)	(0.116)	(0.045)	(0.111)	(0.027)
$\sigma^2_{\theta^d}$	0.623	0.647	-	0.612	0.540	0.808	1.111	0.892	0.758	0.566	1.348	0.429
	(0.095)	(5.728)	(-)	(0.078)	(0.021)	(0.074)	(0.069)	(0.174)	(0.125)	(0.038)	(0.169)	(0.021)
$\sigma^2_{\theta^a}$	1.074	0.820	-	0.684	2.962	6.955	4.256	1.802	1.593	3.897	2.506	1.535
	(0.086)	(0.217)	(-)	(0.039)	(0.094)	(0.654)	(0.179)	(0.099)	(0.101)	(0.137)	(0.165)	(0.034)
ρ	0.376	0.236	-	0.240	0.529	1.257	1.159	0.723	0.575	0.634	0.847	0.324
	(0.088)	(0.699)	(-)	(0.044)	(0.034)	(0.131)	(0.074)	(0.109)	(0.099)	(0.050)	(0.140)	(0.018)
$\theta^{\text{inc x dist}}$	-0.034	0.186	-	-0.055	0.251	0.156	0.359	0.005	0.132	0.116	0.030	0.191
	(0.067)	(0.154)	(-)	(0.061)	(0.058)	(0.082)	(0.058)	(0.062)	(0.053)	(0.063)	(0.068)	(0.038)
$\theta^{\text{inc x aff}}$	0.495	-0.020	-	0.719	0.415	0.790	-0.948	1.365	0.840	2.431	0.357	0.974
	(0.307)	(0.602)	(-)	(0.206)	(0.365)	(0.659)	(0.534)	(0.328)	(0.337)	(0.420)	(0.362)	(0.253)
$\theta^{\text{inc x chain}}$	-1.109	-1.307	-	-0.389	-0.878	-1.588	-0.881	-2.218	-1.165	-4.640	-0.099	-0.488
	(0.483)	(0.918)	(-)	(0.478)	(0.236)	(0.740)	(0.720)	(0.487)	(0.407)	(0.731)	(0.501)	(0.182)

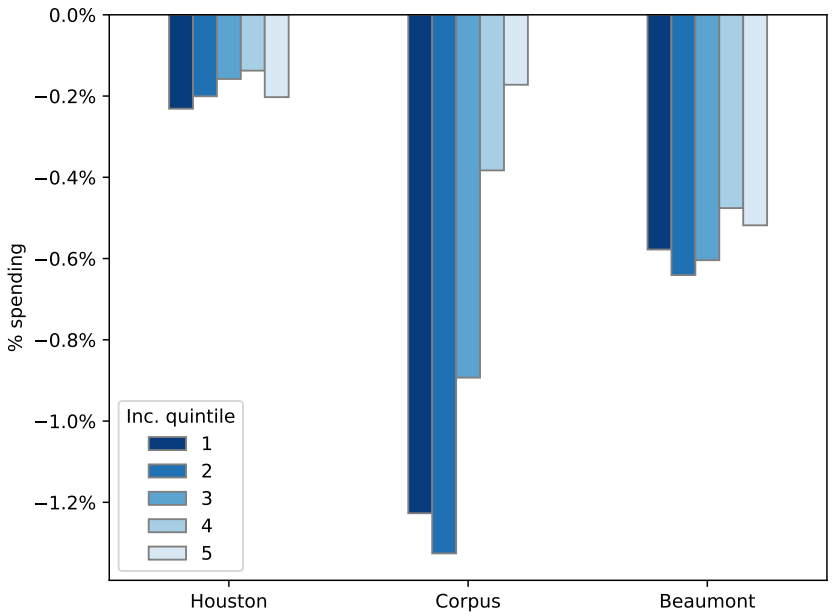
Notes: Demand model estimated separately for each NAICS by MSA. Table shows estimated parameters for all 12 NAICS. Distance is measured in miles and ranges between 0 and 15. Income is measured in annual dollars divided by 100,000 and is top-coded, so that the range is between 0 and 0.25 (corresponding to $0 and $250,000). Affluence refers to the average customer spending of a store (computed at the chain level) and is measured in dollars divided by 1,000, so that the range of the variable is from 0 to 5. Bootstrapped standard errors are shown in parentheses.

TABLE F.5: Parameter estimates - Beaumont

Parameter	Auto parts	Furniture	Electronics	Hardware	Groceries	Pharmacy	Gasoline	Clothing	Sporting Goods	Gen. Merch.	Misc retail	Restaurants
μ^d	-1.446	-1.664	-	-1.527	-0.800	-0.944	-1.189	-1.842	-1.629	-1.181	-1.373	-1.478
	(0.071)	(0.344)	(-)	(0.069)	(0.031)	(0.060)	(0.030)	(0.147)	(0.113)	(0.034)	(0.114)	(0.030)
$\sigma^2_{\theta^d}$	0.650	0.346	-	0.556	0.692	0.803	0.959	0.586	0.584	0.729	0.891	0.438
	(0.074)	(0.255)	(-)	(0.074)	(0.038)	(0.076)	(0.053)	(0.117)	(0.098)	(0.043)	(0.154)	(0.024)
$\sigma^2_{\theta^a}$	0.765	1.586	-	0.787	4.331	7.302	3.720	1.735	1.652	3.318	2.530	2.183
	(0.101)	(0.647)	(-)	(0.052)	(0.135)	(0.542)	(0.154)	(0.104)	(0.154)	(0.115)	(0.232)	(0.064)
ρ	0.319	0.459	-	0.327	0.656	1.231	0.962	0.416	0.639	0.684	0.540	0.467
	(0.070)	(0.259)	(-)	(0.050)	(0.061)	(0.137)	(0.052)	(0.108)	(0.101)	(0.052)	(0.108)	(0.025)
$\theta^{\text{inc x dist}}$	0.131	-0.238	-	0.142	0.201	0.192	0.014	0.047	0.090	0.366	0.082	0.094
	(0.071)	(0.213)	(-)	(0.062)	(0.082)	(0.109)	(0.047)	(0.072)	(0.069)	(0.048)	(0.089)	(0.042)
$\theta^{\text{inc x aff}}$	0.281	-0.111	-	0.422	0.123	0.663	1.419	2.497	0.637	3.741	2.786	1.681
	(0.290)	(0.837)	(-)	(0.296)	(0.575)	(0.939)	(0.563)	(0.383)	(0.566)	(0.468)	(0.470)	(0.397)
$\theta^{\text{inc x chain}}$	-1.183	-1.197	-	-0.830	-0.663	-0.498	-1.627	-2.908	-1.864	-7.668	-2.642	-0.521
	(0.445)	(1.093)	(-)	(0.772)	(0.401)	(0.714)	(0.772)	(0.466)	(1.097)	(0.863)	(0.474)	(0.191)

Notes: Demand model estimated separately for each NAICS by MSA. Table shows estimated parameters for all 12 NAICS. Distance is measured in miles and ranges between 0 and 15. Income is measured in annual dollars divided by 100,000 and is top-coded, so that the range is between 0 and 0.25 (corresponding to $0 and $250,000). Affluence refers to the average customer spending of a store (computed at the chain level) and is measured in dollars divided by 1,000, so that the range of the variable is from 0 to 5. Bootstrapped standard errors are shown in parentheses.

FIGURE F.2: Welfare effects by tract-level income - no flooding controls



Note: The figure shows unconditional welfare losses as a share of total spending through December 2018 by quintiles of tract-level median household income for the three MSAs in our sample. To produce the figure, we compute welfare changes (net of entry) at the card-NAICS level and aggregate them by MSA and income quintile.

G Measuring building damage with HCAD data

G.1 Matching HCAD real and property data with the payment card data

We use the HCAD data to measure the damage caused by Hurricane Harvey on properties in Harris County. To do this, we combine three sources of data. Our main dataset consist of the payment card data that represents the core dataset of the paper. This dataset identifies businesses with names and addresses and provides a unique identifier for each establishment. We combine these data with the HCAD personal and property data.

The HCAD Personal Property data is collected at the establishment level and contain the assessed value of inventory, machinery, and resources owned by each establishment, as well as establishment characteristics, such as square footage. The HCAD Real Property data include the assessed value of real estate and buildings at the parcel level (which may contain multiple establishments in the case of a shopping center or mall), as well as building characteristics (including total square footage, number of stories, and building materials, among others).

The matching process consists of several steps. First, we loop over all businesses in the payment card data and attempt to match to the personal property tax records. For each observation, we extract the zip code of the corresponding establishment and all businesses in the personal property data that are located within the same zip code. We then use string matching (with various metrics), as well as geographical distance, to produce a ranking of potential matches from the personal property data for the specific record of the payment card data. The ranking is based on address score, name score, and distance. The output of this first step is a ranked list of potential matches for each record in the payment card data. We keep the closest match for each establishment.

Second, we match the real property data with the payment card data. As before, we proceed in steps. We restrict the matching process to commercial buildings, which are identified as such in the data. We then match the card data to the real property data based on addresses. For records that we cannot match based on addresses, we match them to the record with the shortest geographical distance.

G.2 Predicting damage through a Random Forest Regressor

This section describes our approach to predicting damage caused by Hurricane Harvey. The objective of this exercise is to generate a measure of damage $\hat{d}_j$ that we use as an input when estimating equation 4.

In the Fall of 2017, soon after Hurricane Harvey landed, ten districts in Harris County performed a reappraisal exercise. This reappraisal was extraordinary, as properties are normally appraised on January 1st of each year. During this process, the appraisers calculated the building values of all properties in these districts (which we call reappraisal districts). Because the reappraisal process took place soon after the landing of Harvey, we can interpret the implied change in value as the damage caused by the storm.

In this exercise, we use the percentage change in building value as the target variable. Specifically, our objective is to train a machine learning algorithm to predict the percentage

change in building value between January 1st, 2017, and the moment the reappraisal took place in the Fall of 2017. Because the reappraisal considers properties in the reappraisal districts only, we train our model with data from these districts.

We train the model using data from HCAD. Specifically, in our model, we include variables that measure flood exposure, as well as variables that reflect building characteristics. Among these, we include the age of the building, building type, replacement cost, various measures of the area covered by the building (e.g., actual, improved, heated), the type and quality of the structure, as well as the economic class associated with the building.

To train the Random Forest regressor, we proceed as follows. First, we created a large grid of hyperparameters and performed a randomized grid search to tune these parameters. Second, to assess the generalizability of the model to new data, we performed 10-fold cross-validation within the randomized grid search. We then select the set of hyperparameters that had the best overall performance. None of the resulting parameters where on the boundary of the parameter grid.

Once we had chosen the set of hyperparameters with the best overall performance, we predicted the percentage change in building value at the moment of reappraisal for all properties in Harris County, including those in reappraisal districts and those in other districts that did not perform reappraisals. We labeled this prediction $\hat{d}_j$, and we treat it as data when estimating equation 4.

G.3 Balance between reappraisal and non-reappraisal districts

While reappraisal districts were not randomly determined, we find that the distribution of flood exposure for retail real property records is similar between reappraisal and non-reappraisal districts, as shown in Figure G.1.

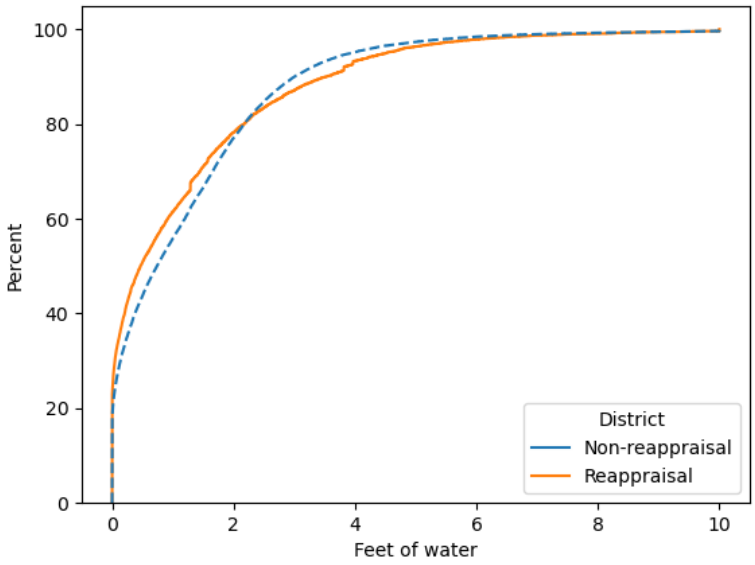


FIGURE G.1: CDF of flood exposure for reappraisal and non-reappraisal districts

Note: Flood exposure is calculated as average flood depth for commercial retail real property records in HCAD real property GIS shapefile data.

H Cost-benefit analysis of aid: Further details

H.1 Employment benefits

To compute the estimated impacts of business re-entry on employment benefits, we first match establishments in the card data from Harris County to establishment records from Data Axle to compute employee count by establishment, as discussed in Appendix A. We infer weekly employee wages using Bureau of Labor Statistics wage data for Harris County at the 3-digit NAICS level.

We use Texas Unemployment Insurance (UI) rules to compute the employment benefits of re-entry (Texas Workforce Commission, 2024). We assume that the employee-specific benefits of establishment re-entry are equal to the maximum UI benefits that would be paid to the employee, assuming weekly wages are equal to those from BLS data and full employment for the previous year. Denoting ww as the weekly wages for an individual, the weekly benefit amount wb and maximum UI benefits mb are calculated as:

$$wb = \max\{67, \min\{494, ww \cdot 13/25\}\} \tag{7}$$

$$mb = \min\{26 \cdot wb,\ 0.27 \cdot 13 \cdot ww\} \tag{8}$$

We assume that an establishment's total employment benefit of re-entry is equal to the maximal UI benefits mb for an individual evaluated at the NAICS-specific wage for the establishment multiplied by the number of employees in the establishment.

TABLE H.1: Damage estimates

Establishments with $\geq$ 4 feet of flooding

	Real estate damage	Capital damage - baseline	Total aid cost - baseline	Capital damage - larger κ	Total aid cost - larger κ
count	252	252	252	252	252
mean	30,006	22,022	67,637	197,827	296,184
50%	12,090	4,230	22,175	37,998	67,443
75%	24,652	13,594	52,000	122,111	184,555
90%	58,374	29,201	110,449	262,311	439,743
95%	90,071	81,476	191,163	731,906	1,002,602

All establishments

	Real estate damage	Capital damage - baseline	Total aid cost - baseline	Capital damage - larger κ	Total aid cost - larger κ
count	2,540	2,540	2,540	2,540	2,540
mean	6,891	4,705	15,074	42,262	63,898
50%	1,348	651	2,890	5,851	9,985
75%	4,219	2,106	8,745	18,919	31,120
90%	12,548	6,551	26,935	58,845	94,658
95%	24,570	14,999	55,383	134,738	207,314

Notes: The table shows summary statistics of the damage estimates for damaged Harris County stores that close at least temporarily after Harvey. The top panel shows estimates for stores with at least 4 feet of water exposure, while the bottom panel shows statistics across all stores with non-zero damage. Real estate damage is computed as the (predicted) decline in building value recorded by HCAD at reappraisal multiplied by the proportion of total building square footage occupied by the establishment: $\hat{d}_j \times V_{b(j),pre} \times \frac{sqft_j}{sqft_{b(j)}}$. Capital damage is computed as the 2017 HCAD personal property assessment multiplied by the percentage decline in building value times a factor κ: $\hat{d}_j \times \kappa K_{j,pre}$. We assume that $\kappa = 1$ in the baseline scenario (so that capital is damaged at the same rate as real estate). We set $\kappa = 8.98$ in an alternative scenario (in columns 4-5), which is calibrated so that capital is fully destroyed for stores that experienced the maximum observed real estate damage. The total cost of aid is computed as the sum of real estate and capital damage multiplied by the marginal cost of public funds, which we set to 1.3, following Poterba (1996). We provide additional details in Section 6.1.

TABLE H.2: Parameter estimates from targeting regression

Scenario	(1) Baseline	(2) Variant 1	(3) Variant 2	(4) Variant 3
Log(weekly rev.)	0.733	0.720	0.647	0.789
	(0.057)	(0.087)	(0.049)	(0.060)
Log(sqft)	-1.172	-1.314	-0.691	-1.075
	(0.106)	(0.156)	(0.078)	(0.107)
2-100 locations	0.387	0.798	0.042	0.412
	(0.152)	(0.216)	(0.143)	(0.157)
101-1000 locations	-0.153	-1.651	0.407	-0.748
	(0.206)	(0.536)	(0.199)	(0.217)
1001+ locations	-0.027	-1.616	1.668	-1.112
	(0.202)	(0.445)	(0.218)	(0.217)
Flood exposure (ft)	0.239	0.136	0.352	0.300
	(0.076)	(0.114)	(0.073)	(0.079)
Flood exposure sq. (ft)	-0.021	0.002	-0.029	-0.028
	(0.010)	(0.013)	(0.010)	(0.010)
log(comp. w/in 1 mile)	-0.171	-0.154	0.031	-0.125
	(0.124)	(0.179)	(0.115)	(0.126)
log(# comp. w/in 2 miles)	0.061	-0.370	-0.224	-0.126
	(0.185)	(0.264)	(0.167)	(0.188)
log(# comp. w/in 5 miles)	-0.045	0.600	-0.193	-0.056
	(0.240)	(0.379)	(0.202)	(0.244)
log(# comp. w/in 10 miles)	0.150	-0.169	0.279	0.294
	(0.215)	(0.350)	(0.183)	(0.218)
Rate of capital destruction	$\kappa = 1$	$\kappa = 8.98$	$\kappa = 1$	$\kappa = 8.98$
CS benefits duration	End of 2018	End of 2018	Inf. discounted	Inf. discounted
Observations	2540	2540	2540	2540
Pseudo R^2	0.395	0.333	0.450	0.410

The table shows results from a regression of an indicator for whether an establishment has a positive net value of aid on a set of observables, where the sample is the damaged Harris County establishments that closed at least temporarily after Harvey. Each column corresponds to a different set of assumptions about the costs and benefits of aid. Columns (1) and (2) sum consumer surplus benefits through the end of 2018, while (3) and (4) sum the infinite discounted sum of surplus using a discount factor of 0.979. Columns (1) and (3) assume that firm capital is destroyed at the same rate as real estate value, while (2) and (4) assume it is damaged more quickly (see Section 6.1 for additional details). All four columns include NAICS fixed effects.