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

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Abstract

Environmental catastrophes can have large impacts on households and businesses. We examine how adverse shocks impact firm dynamics and consumer welfare, using Hurricane Harvey as a case study. Using data on consumer purchases in 12 large store categories, we estimate consumer demand and show that exiting stores contribute 36% less to consumer surplus than entrants and 51% less than surviving incumbents. Despite this, some exiting businesses provide significant welfare gains, while entry often occurs far from the most affected neighborhoods, leading to substantial localized welfare losses in hard-hit neighborhoods. Counterfactual simulations reveal that uniform subsidies to all damaged businesses are inefficient, with fiscal costs exceeding consumer and employee benefits. However, targeted aid directed toward certain high-value firms yields substantial net welfare gains. Our results highlight the importance of policy design in disaster recovery and the role of firm selection in determining the incidence and effectiveness of government aid.

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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. Additionally, Hurricane Harvey exhibited the characteristics of a large but temporary shock (i.e., it did not result in significant outmigration and had little impact on consumer spending in the medium to long run), making it a valuable case study for understanding how natural disasters affect firms and consumers, a critical area of study as these events become more frequent and costly due to climate change (Holland and Bruyère, 2014, Emanuel, 2017, Balaguru et al., 2018, Bhatia et al., 2019). Finally, natural disasters are of significant policy relevance; for example, 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 estimate a model of entry to examine the impact of a grant-based air program on re-entry and crowd out and to determine whether its benefits would exceed its cost.

Our analysis combines granular measures of localized flooding with high-frequency credit and debit card data to examine the hurricane's impact on local retail establishments and

[1]Market frictions and externalities provide 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).

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, as well as for establishments unaffiliated with large chains.

Although hundreds of establishments closed after the storm, new entry may partially offset consumer harm from closures. Further, consumers may benefit 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. However, at the neighborhood level, entry did not fully replace exits, and 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 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 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 retail sector. Our model accounts for observed and unobserved preference heterogeneity, allowing tastes to vary across and within neighborhoods. We estimate the model for 12 store categories using pre-storm purchase data in each of our three MSAs.[4]

[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 Supplemental Appendix C.2.

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

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

We use the demand model to quantify each store's contribution to consumer welfare. 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 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 only contributed marginal amounts of social surplus, some were significantly more valuable, and their closures led to significant 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 the consumer welfare benefits of new entry are significant, entrants tend to locate sufficiently far from the hardest-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 that of the highest quintile of tracts. This differential impact is partially driven by more limited access to retail options in low-income neighborhoods than in 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 and if aid does not crowd out many new entrants, a subsidy program to stores 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 re-entry decisions and monetized storm damage, which we measure

[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.

using novel post-Harvey property tax appraisal data from Houston.

We use the model to quantify how the aid program impacts each store's permanent exit probability and crowd out of new entrants. We first find that aid has negligible crowd out of new entrants. We then 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, in general, few establishments generate sufficient benefits to justify the cost of aid (about 20% 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 about $3 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 80% of the net gain of the perfect targeting variant, equivalent to a benefit of $2.40 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. We also 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 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 similar tools to estimate consumer welfare but focus on a natural disaster setting with data on multiple industries.

Finally, our paper relates to the literature on the optimal allocation of scarce aid resources, including Brown et al. (2018), 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 stores, 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 highest recorded rainfall event in United States history and one of the most costly storms to hit the U.S., 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

[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).

was largely unanticipated: 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 Supplemental 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? 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 were harmed by 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 the limitations of existing business aid programs following disasters, one focus of our paper is to examine the impact of a more generous grant-based 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 Supplemental 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, allowing us to identify differences in flood exposure at a highly local level. FEMA produces these estimates by combining high water measurements taken at various points with topographical elevation data. 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 Supplemental 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 likely to cause major damage (FEMA, 2020).

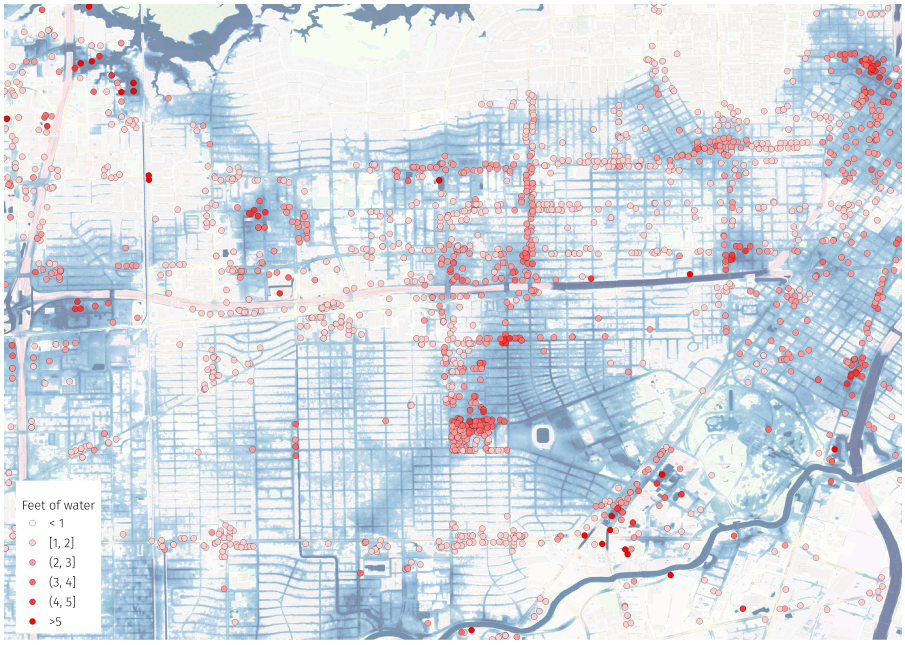


FIGURE 1: Businesses' exposure to flooding in central Houston.

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).

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 include the merchant name and numeric identifier, the store location, 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] In measuring entry and exit, we use transactions across all credit and debit cards, while in demand estimation we use only the set of matched credit cards. 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 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

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

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

(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 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 the Kilts Center NielsenIQ Household Panel to examine price responses following Hurricane Harvey. Fourth, we use Data Axle for establishment-level employment numbers and the Bureau of Labor Statistics for average wages at the county level by NAICS. Fifth, we use data on Small Business Administration (SBA) loan applicants and recipients. Sixth, 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. Last, we use monthly alcohol sales by establishment from the Texas Comptroller of Public Accounts as a proxy for restaurant presence.

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

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

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 expenditure for all U.S.-based cards that purchase at any of its U.S. outlets.

Measuring entry and exit: We first construct a panel of operating stores in our three MSAs, subject to a modest size threshold.[12] We infer the operational status of each store 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 reopened 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 stores that do not have more transactions before the end of our sample in December 2018. We follow a similar procedure to identify new entrants: when we see a new merchant-zip code combination in the data, we infer 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 Supplemental 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

[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.

[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.

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).

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 from 3.5% in Houston to 10.0% in Corpus Christi.

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 Harvey's landfall, followed by 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 Supplemental 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

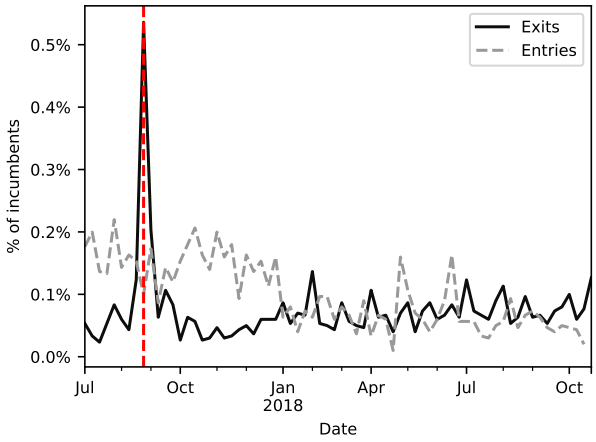
Closure status	Houston	Beaumont	Corpus Christi
No closure	81.9%	53.4%	76.1%
Temporary closure			
1-3 weeks	13.5%	38.3%	11.2%
4-8 weeks	1.5%	3.2%	4.3%
8+ weeks	2.0%	3.8%	5.7%
Perm closure	1.1%	1.2%	2.7%
Flood levels	**Houston**	**Beaumont**	**Corpus Christi**
No flooding	21.2%	10.8%	23.9%
0-1 ft	38.0%	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).

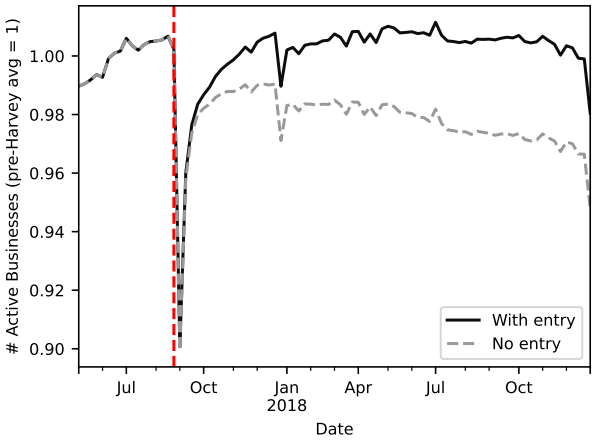
Figure 2c shows that stores with minimal flooding reopened almost immediately, while heavily flooded areas recovered much more slowly. By December 2017, areas with four or more feet of flooding had nearly 5% fewer stores than their pre-storm average. By the end of our sample, they remained about 3% below pre-storm levels. In Table C.1 of Supplemental Appendix C, we show 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 the possibility 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 Harvey. We take firm turnover in the post-Harvey period as given and measure the net impact for consumers.

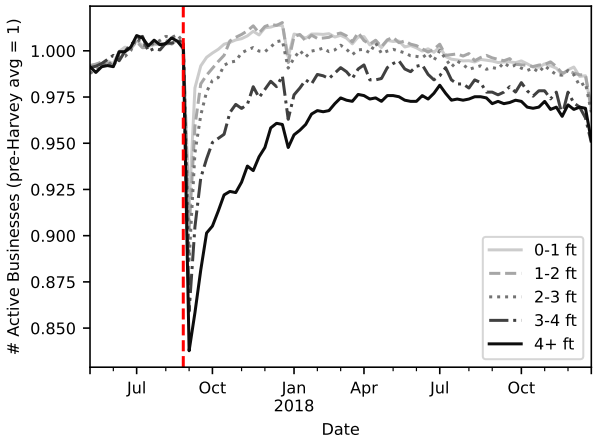
Table 2 shows the rates of temporary and permanent closures for the 12 store categories in our data, which reveal significant heterogeneity. Among these categories, gasoline stations



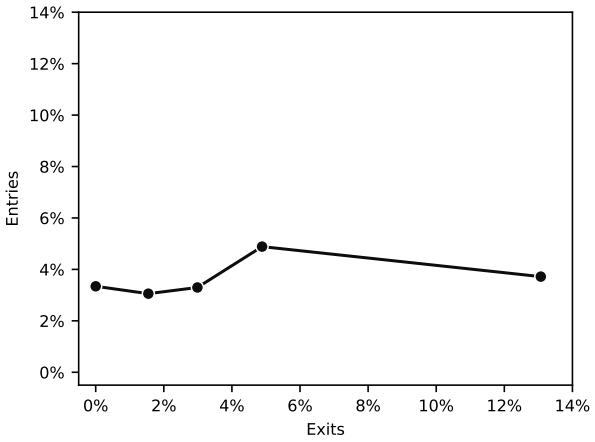
(A) Weekly exits and entries over time



(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 each week, including establishments that opened after Harvey (solid black) and only incumbents that opened 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.

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	1-3 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. Replacement rates were relatively lower in Beaumont and Corpus Christi, with 22 permanent exits and 37 entrants in Beaumont and 61 permanent exits and 66 entrants in Corpus Christi. Figure 2a shows that entry rates were between two and three times higher pre-Harvey relative to post-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.

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 the number of incumbents. The figure shows that the number of entries was essentially constant across neighborhoods with low and high exit rates. The neighborhoods with the highest exit rates saw a net decrease in the number of operating establishments, even when accounting for entry. 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 Supplemental Appendix C shows the results of descriptive regressions of the log of transactions and sales on establishment characteristics and closure dummies. 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? To examine whether businesses relocated to less flood-prone areas, we use auxiliary data on monthly alcohol sales as a proxy for establishment activity.[16] Figure C.3 shows a steep post-Harvey dip in the most flooded areas, but the total number of establishments recovers to pre-Harvey levels by late 2019, suggesting no aggregate relocation to less flood-prone areas.

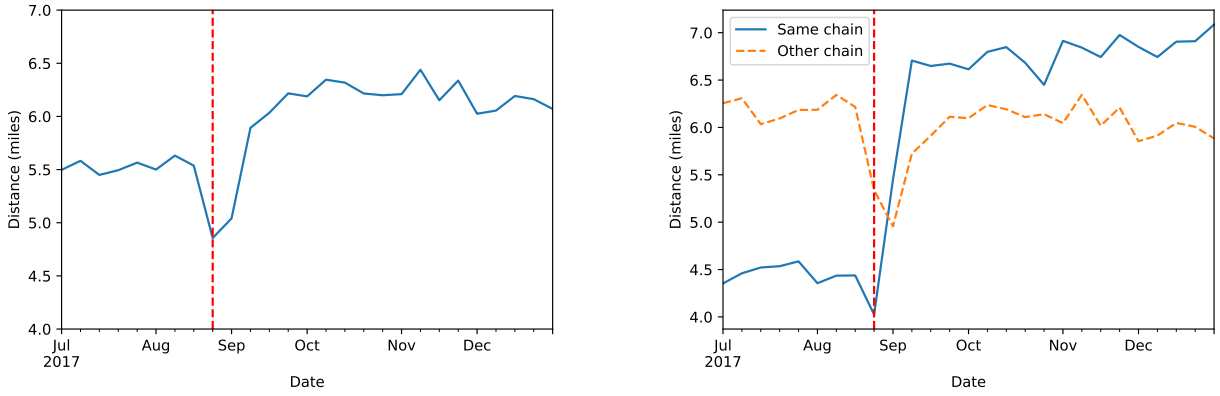
4.3 Impact on consumers

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.[17] 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

[16] Available from the Texas Comptroller of Public Accounts and previously used by Goldfarb and Xiao, 2024.

[17] 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 (by expenditures) that either closed permanently or temporarily. The sample of consumers used to create this figure includes only credit cards with a valid billing zip code. 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 down by whether the purchase was made at another outlet within the same chain as the closed retailer or at an unaffiliated store.

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 Supplemental 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 dispersed 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 damaging businesses, the hurricane flooded many homes, which may have led consumers to move away from their original neighborhoods or change their purchasing behavior. We investigate this in Supplemental 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

Storm-induced closures may also impact the competitiveness of local retail markets, leading to changes in pricing behavior. In Supplemental Appendix D, we use the NielsenIQ Homescan Consumer Panel to examine the impact of Harvey on retail prices in impacted areas relative to other areas in Texas. We find no meaningful medium- or long-term price effects other than a short-lived spike in the week of Harvey's landfall, driven by discount stores.

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, and that surviving incumbents and entrants have higher sales than exiting stores, suggesting they create more value for consumers. To quantify each store's contribution to consumer welfare and to study the distributional effects of the spatial distribution of entry and exit, we propose and estimate a discrete-choice model of consumer demand that allows us to identify 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, assuming 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.[18] We compute standard errors using a block bootstrap procedure that samples consumers with replacement from each neighborhood. We report technical details of estimation in Supplemental 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 matched credit cards with a valid billing zip code to include 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 spans 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 based on 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 Supplemental Appendix F.2.

5.2 Estimates

Table 3 reports parameter estimates for Houston across all NAICS (estimates are similar for Corpus Christi and Beaumont, which we report in Tables F.3-F.4). 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

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

are sensitive to travel distance (Klopack, 2024, among others). We also find that distance sensitivity decreases slightly with consumer income.[19] 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.[20]

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 prefer stores that cater to affluent customers.[21] 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.[22] While not surprising, this flexibility 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 correlated random coefficients, allowing for unobserved heterogeneity in taste for distance and store 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.[23] 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, assuming that preferences remain stable after the hurricane, which is supported by the analysis presented in Supplemental Appendix E. We measure consumer welfare associated

[19]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.

[20]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 $1/\exp(-0.532 + 0.044 \times 0.25) = 0.594$.

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

[22]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 $P_{ijt}/P_{ij't} \approx \exp(0.683 \times 0.25 \times 2.976)/\exp(0) = 1.662$.

[23]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 0.054 (restaurants) and 0.706 (pharmacy).

TABLE 3: Parameter estimates from the demand model - Houston

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

Notes: Demand model estimated separately for each NAICS by MSA. The table shows estimated parameters for Houston over all NAICS, ranked by transaction volume, with bootstrapped standard errors in parentheses. 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 total monthly spending of a store's customers (computed at the chain level), is top-coded at 5,000, and is divided by 1,000, so the variable ranges from 0 to 5. We report the parameter estimates for Corpus Christi and Beaumont in Tables F.3-F.4.

with a specific choice set using the logit inclusive value

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

where $i_{(n)}$ denotes a consumer in neighborhood n, $J_{n,t}$ is the choice set for neighborhood n in week t, 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:

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

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

We present estimates of each store's contribution 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 $\Delta CS_j = \sum_i \sum_t \Delta CS_{i_{(n)},t}$ 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 consumers receive from the availability of j across all sample consumers and over time (September 2017 to December 2018).

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, the median of store revenues over a 16-month period is \$404K for post-storm exiting stores but is \$867K for entrants and \$1.01M for surviving incumbents. 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).

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 entries were 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, and how those impacts vary across neighborhoods and consumer demographics.[24] Our data is well-suited to

[24]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

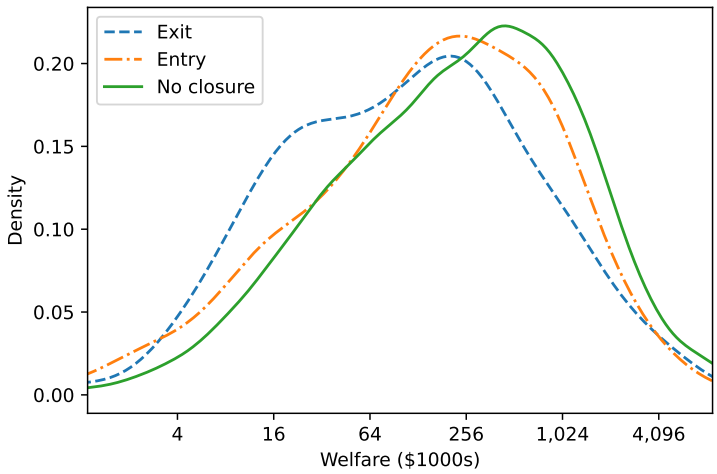


FIGURE 4: Store-level consumer welfare contribution.

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.

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 (September 2017 to 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 0.29 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

to our measurement of the exit rate.

share of expenditures) but with significant variation across NAICS. For example, the mean 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 11% over a 16-month period. These larger effects reflect higher exit rates, fewer entries, and a smaller pre-Harvey store base in these MSAs, which increases the marginal welfare impact of each closure.

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 damage in the Houston MSA is highest 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 somewhat less damage.

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 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, with separate regressions for each MSA. We show the (normalized) regression coefficients 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 flood-

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%

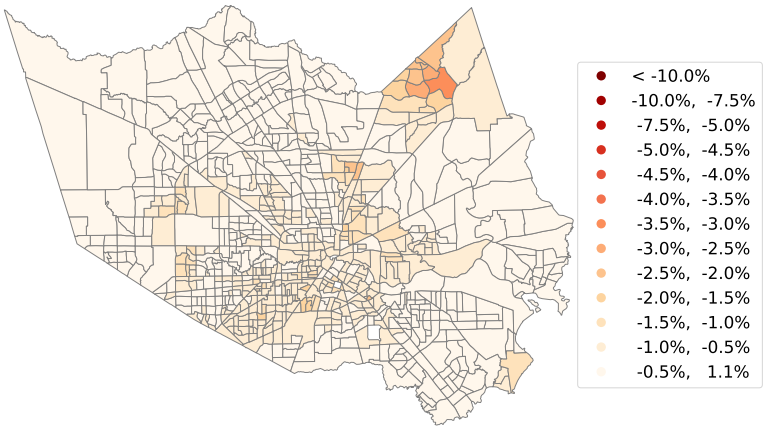
Beaumont

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%

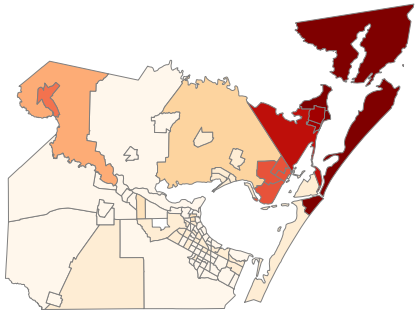
Note: The table shows the distribution of welfare effects across Census tracts by store category. We compute consumer welfare losses (as a share of spending) for each consumer and each NAICS category between September 2017 and December 2018. We then aggregate by the residential Census tract of consumers 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

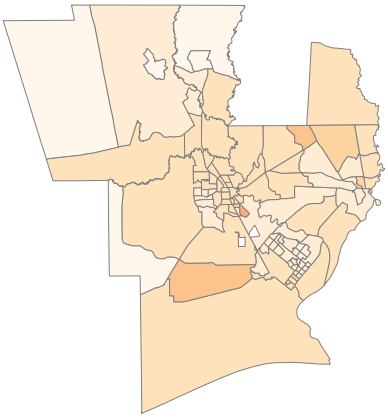
(A) Houston



(B) Corpus Christi

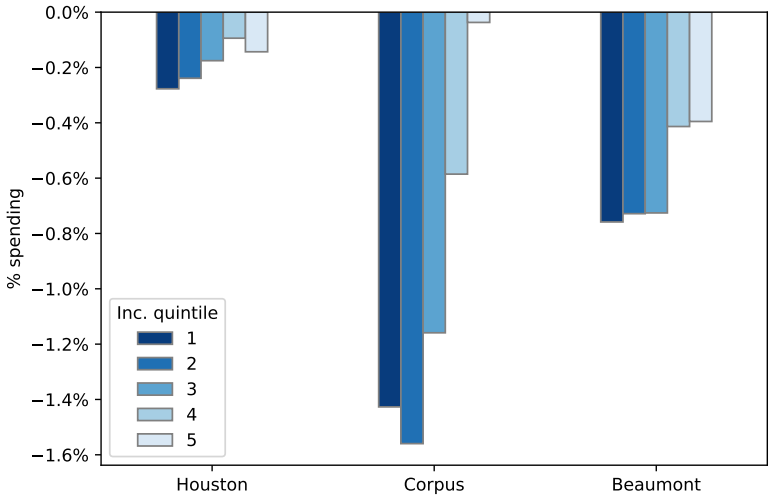


(C) Beaumont



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.

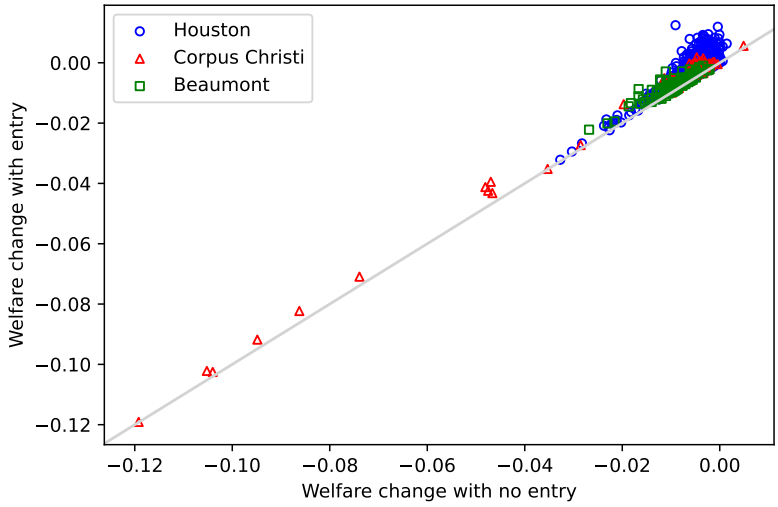
ing exposure is relatively uniform across groups, the impacts can be disproportionate for lower-income consumers.

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 in which $\tilde{J}_{n,t}$ includes only incumbent stores (including temporary closures that reopen) and 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, 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

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.

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 diverge 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 fiscal cost of aid, and the extent to which aid reduces permanent exit.

To evaluate the desirability and targeting of business aid, we develop a model of the post-Harvey entry decisions of both temporarily closed establishments and potential new entrants, which we refer to as the entry model. The model features three types of firms:

surviving incumbents, temporarily closed establishments that decide whether to re-enter or exit permanently, and potential new entrants. We focus on establishments in Harris County, the largest county in the Houston MSA, where we leverage novel post-Harvey property tax appraisal data to construct a store-level measure of physical damage. The model exploits the relationship between monetized storm damage and store re-entry decisions to estimate how a given dollar amount of aid affects the probability that a temporarily closed store reopens and the likelihood of new-firm entry. This framework allows aid targeted to temporarily exiting firms to potentially crowd out subsequent new entry. A key feature of the model that pins down the impact of aid on crowd-out is the distribution of new entrant profits: only when the distribution is relatively narrow can a large fraction of new entrants be crowded out by aid to temporarily closed establishments. With these estimates in hand, we quantify the welfare benefits of aid as the product of changes in both re-entry and new-entry probabilities and the sum of store-level consumer surplus contributions – and also account for the unemployment benefits that would be paid to it workers at exiting firms. In practice, our estimates imply that the crowd-out channel from aid is quantitatively small, so the welfare effects of aid are driven primarily by increased re-entry among damaged establishments.

6.1 A model of store entry

We model the entry process following the hurricane as a two-stage game with incomplete information. We describe the key features of the model in this section, and refer the reader to Appendix G for implementation details.

6.1.1 Model description

Let J^{RE} denote the set of temporarily closed stores that may re-enter with $N^{RE} \subset J^{NE}$ the subset that choose to re-enter. Similarly, let J^{NE} denote the set of potential new entrants with $N^{NE} \subset J^{NE}$ the subset that choose to enter. Let N^I denote the set of incumbent stores that never close. Finally, for any store l, let δ_l and ε_l denote their mean utility and profit shock, respectively.

Timing and information. The entry process unfolds as a two-stage game with incomplete information. In the first stage, stores that temporarily closed for at least one week after Hurricane Harvey (i.e., potential re-entrants) decide whether to reopen or to exit permanently. At this stage, each store in J^{RE} observes the set of surviving incumbents N^I and their mean utilities, and they also observe the realizations of potential re-entrant mean utilities $\{\delta_m : m \in J^{RE}\}$. Each re-entrant observes its own idiosyncratic profit shock ε_j,

while the profit shocks of other stores in J^{RE} are private information. All firms know the distribution of profit shocks.

In the second stage, potential new entrants observe the re-entry decisions of temporarily closed stores and the mean utilities of all incumbents (N^I) and re-entrants (N^{RE}). Each potential entrant k observes its own mean utility δ_k and its own profit shock ε_k. While it does not observe the realizations of δ and ε for other potential entrants, it knows their distribution and forms expectations over their entry decisions. After entry and re-entry decisions are made, incumbents, re-entrants, and new entrants compete in the product market.

In each stage, stores form beliefs over their expected profits and thus their expected market share, which depends on the entry decisions of other competing stores. Because the number of firms in our setting is large, estimating a full equilibrium model of entry and re-entry with the rich demand system estimated in Section 5 is computationally infeasible. We therefore make two simplifying assumptions to estimate the entry game, both of which preserve symmetric beliefs across firms and yield a tractable fixed-point problem for equilibrium beliefs. First, we adopt a more stylized demand environment in which consumer utility from store j is summarized by a single mean-utility term δ_j and an i.i.d. idiosyncratic taste shock, so that $u_{ij} = \delta_j + \nu_{ij}$. The objects $\{\delta_j\}$ are disciplined by the earlier demand estimates: we use the flexible random-coefficients model to compute each store's implied aggregate market share, and then back out the values of δ_j that rationalize these shares in the stylized logit setting. Second, we adopt an oblivious equilibrium framework, in which firms do not internalize the effect of their own entry decisions on aggregate competition (Weintraub et al., 2008). Under this assumption, stores have symmetric beliefs regarding the resulting degree of competition. We describe each stage of the game.

Second stage: new entrants. Potential new entrant k observes the set of re-entrants N^{RE}, their mean utilities, and its own value of $(\delta_k, \varepsilon_k)$. Its expected profits are given by:

$$\mathbb{E}[\pi_k] = M \cdot \exp(\delta_k) \cdot B^{NE} \cdot \zeta_k^{NE} - C_k^{NE} \cdot \exp(\varepsilon_k) \tag{3}$$

where M denotes total market revenue, $\exp(\delta_k) \cdot B^{NE}$ denotes store k's share of revenue, ζ_k^{NE} is its margin, C_k^{NE} is its fixed cost of entry, and ε_k is a profit shock. The subset $N^{NE} \subset J^{NE}$ is those stores for which question 3 is positive. Beliefs about the degree of competition B^{NE} are determined by the beliefs about the distribution of δ_k and ε_k among all potential new entrants. In particular, the expected degree of competition B^{NE} is defined in equation 4 as the expectation of the market share denominator for new entrants, where ι_e is an indicator that the potential new entrant has positive profits from entry in equation 3. The key computational simplification from the oblivious equilibrium is that in computing

the denominator in equation 4, store e is oblivious of its impact on the denominator and instead takes an expectation over all potential new entrants' entry decisions, including its own. Computationally, we solve for B^{NE} as a nested fixed point where conditional on the distribution of new entrant parameters δ_k and ε_k, the value of B^{NE} rationalizes observed entry.

$$B^{NE} = \mathbb{E}\left[1/\Big(\sum_{e \in J^{NE}} \iota_e \cdot \exp(\delta_e) + \sum_{m \in N^{RE}} \exp(\delta_m) + \sum_{l \in N^I} \exp(\delta_l)\Big)\right]. \tag{4}$$

First stage: re-entry. Each potential re-entrant $j \in J^{RE}$ knows its own $(\delta_j, \varepsilon_j)$ and the realized mean utilities of all other potential re-entrants δ_{-j}, for all $-j \in J^{RE}$. Store j's expected profits are given by:

$$\mathbb{E}[\pi_j] = M \cdot \exp(\delta_j) \cdot B^{RE} \cdot \zeta_j^{RE} - F_j(X_j) \cdot \exp(\varepsilon_j) \tag{5}$$

The term $F_j(X_j) = C_j^{RE} \cdot \exp(\beta) X_j$ is the fixed cost of re-entry which depends on a vector of covariates including physical damage to the building (which we discuss below), the size of the store, and chain size indicators. The subset $N^{RE} \subset J^{RE}$ is those stores for which equation 5 is positive. Beliefs about the degree of competition B^{RE} are determined by beliefs about the distribution of profit shocks ε_j among potential re-entrants as well as beliefs about the distributions of mean utility δ_k and profit shocks ε_k among potential new entrants in the second stage. In particular, the expected degree of competition B^{RE} is defined in equation 6 as the expectation of the market share denominator, where ι_k is an indicator that the potential new entrant has positive profits from entry (in equation 3) and ι_m is an indicator that the potential re-entrant has positive profits from entry (in equation 5). As with computing B^{NE} above, we make the oblivious equilibrium assumption that store j is oblivious of its impact on the denominator in equation 6, and instead takes an expectation over all potential entry decisions, including its own. We use a nested fixed point approach to solve for B^{RE} as the value that rationalizes observed re-entry rates.

$$B^{RE} = \mathbb{E}\left[1/\Big(\sum_{k \in J^{NE}} \iota_k \cdot \exp(\delta_k) + \sum_{m \in J^{RE}} \iota_m \exp(\delta_m) + \sum_{l \in N^I} \exp(\delta_l)\Big)\right] \tag{6}$$

6.1.2 Parameterization, Estimation, and Results

Measuring damage. The re-entry decision of stores that temporarily close and, therefore, the new entry of potential entrants depend on the extent of the damage caused by Hurricane Harvey. For this reason, the cost and benefit of an aid program are also determined by the

extent of this damage. Therefore, to estimate our entry and re-entry game, we construct a measure of storm damage for each establishment d_j.

We construct our measure of damage by combining flood-exposure data with novel property-tax appraisal data from HCAD, the central tax authority for Harris County. Specifically, we exploit reappraisals conducted by HCAD 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.[25] We compute d_j as the percentage change in the establishment's building value between January 1st, 2017 and its post-Harvey reappraisal.[26]

$$d_j = \frac{V_{b(j),post} - V_{b(j),pre}}{V_{b(j),pre}} \tag{7}$$

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, such as the building's quality and type. Further details are in Supplemental Appendix H.

Figure 8a reports the predicted $\hat{d}_j$ 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. The figure 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 the entry game.

Parameterization. We make several parametric assumptions to estimate the model. We assume that store margins (ζ_k^{NE} and ζ_j^{RE}) and fixed costs of entry (C_k^{NE} and C_j^{RE}) are constant within a NAICS category. New entrant mean utilities and profit shocks are distributed

[25] 12% of commercial properties appraised by HCAD were located in reappraisal districts. In Supplemental Appendix H.3, we find that flood exposure for properties in reappraisal and non-reappraisal districts was largely similar.

[26] 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 receives the same percentage of damage, d_j.

joint normally:

$$\begin{pmatrix} \delta^{NE} \\ \varepsilon^{NE} \end{pmatrix} \sim \mathcal{N}\left[\begin{pmatrix} \mu_\delta^{NE} \\ 0 \end{pmatrix}, \begin{pmatrix} (\sigma_\delta^{NE})^2 & 0 \\ 0 & (\sigma_\varepsilon^{NE})^2 \end{pmatrix} \right] \tag{8}$$

Re-entrant profit shocks are also distributed normally:[27]

$$\varepsilon^{RE} \sim \mathcal{N}\big(0, (\sigma_\varepsilon^{RE})^2\big) .$$

Given these assumptions and equations (3) and (5), we can express the probability of re-entry as:

$$\mathbb{P}(\iota_j = 1) = \Phi(\log E[s_j] + \alpha_n^{RE} + \beta \log X_j) \tag{9}$$

and the probability of new entry as:

$$\mathbb{P}(\iota_k = 1) = \Phi(\log E[s_k] + \alpha_n^{NE}) \tag{10}$$

where α_n^{NE} and α_n^{RE} are NAICS-specific intercepts and Φ is the normal cumulative distribution function. We show the full derivation and likelihood in Appendix G.

Identification. The parameters of the entry game are identified from cross-sectional variation in entry and re-entry decisions, combined with distributional assumptions and equilibrium restrictions. The probabilities specified in equations (9) and (10) correspond to standard probit specifications. For re-entrants, this specification considers regressors $\log E[s_j]$ and X_j (e.g., storm damage d_j, store size, chain-size indicators). The parameters α_n^{RE} and β are identified from cross-sectional variation in these regressors and re-entry decisions. Importantly, damage d_j enters exclusively through re-entry costs, but not through demand. In other words, mean utilities δ_j, which are computed through the demand model, are unaffected by storm damage, which provides the variation necessary to identify the effect of storm damage on re-entry decisions.

In the case of new entrants, mean utilities δ_k are only observed for stores that actually enter. The distribution parameters $(\mu_\delta^{NE}, \sigma_\delta^{NE})$ are therefore identified from the observed distribution of these mean utilities, which represent a selected sample from the unconditional distribution. Because we make a parametric assumption (i.e., joint normality), the shape of this truncated distribution is what pins down the unconditional mean and variance. The

[27]Re-entrant mean utilities are estimated from pre-Harvey data and treated as observed, so we do not parameterize their distribution.

variance of the new-entrant profit shock σ_ε^{NE} is not separately identified, and we normalize it as we discuss below. Given this normalization, which we show does not materially impact our estimates, and the assumed size of the potential entrant pool, the NAICS-specific intercepts α_n^{NE} are pinned down by the observed number of entrants in each NAICS.

Finally, the model is based on a double fixed point on beliefs B^{RE} and B^{NE}, which links parameters across the two stages of the game. Thus, the model must rationalize the observed entry and re-entry rates, providing additional discipline beyond what each stage's likelihood would impose on its own.

Estimation. The model is estimated by Simulated Maximum Likelihood, with a nested fixed point for beliefs B^{NE} and B^{RE}. We describe key aspects of the estimation here and defer details to Appendix G.

First, we define the market for each NAICS category as all stores in Harris County, with an outside option consisting of stores in the same category located outside the county. Using the demand system estimated in Section 5, we compute predicted consumer-level choice probabilities and aggregate them to obtain each store's implied county-level market share. We then invert these shares to recover mean utilities $\{\delta_j\}$ that rationalize the aggregate shares within the stylized logit setting used in the entry game.

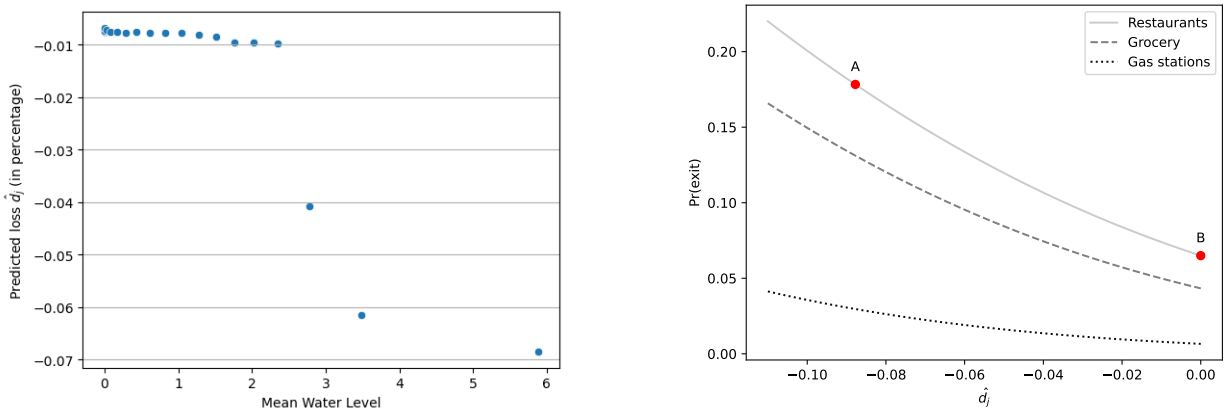
Second, the number of potential new entrants is not observed. Following common practice in the entry literature, we assume that the pool of potential entrants in each NAICS category is proportional to realized entry, and set the number of potential entrants to 1.5 times the observed number of entrants in that category. In Appendix G, we describe how this assumption enters the simulation routine and assess sensitivity to alternative values.

Third, because we observe δ only for potential entrants who actually enter, the variance of the profit shock is not identified. We therefore normalize the variance of the entrant shock and report robustness to alternative normalizations. Across reasonable values of this variance, the remaining parameter estimates and counterfactual implications are stable.

Parameter estimates. We report the estimated parameters of the entry model in Table H.1.[28] Each panel in the table reports coefficients for each NAICS in our sample and shows that, across columns, the signs of the estimated parameters are the expected ones: the coefficient on damage d_j is positive, implying that stores with more storm damage are more likely to exit.

In Figure 8b, we plot the implied relationship between $\hat{d}_j$ and the probability of exit using the predicted values from Table H.1 panel A for three NAICS: restaurants, grocery stores,

[28]Each panel in Table H.1 reports the estimated parameters for a given value of σ_ε^{NE}.



(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 equations (9) and (10) in Table H.1 panel A. 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.

and gas stations. Conditional on temporarily closing, an establishment with no damage is between 3 percentage points (gas stations) and 12 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.

Estimates of σ_δ^{NE} determine the variance in profits for potential new entrants and therefore the extent to which greater re-entry from temporarily exiting establishments will crowd out new establishment entry. Our estimates imply that a 20% increase in re-entry (due to increasing δ_j for all temporarily exiting stores) only reduces new entry by 0.01 new stores in expectation. In other words, the variance in profits for potential new entrants is large, so that only a minuscule fraction of potential new entrants are marginal and crowded out by increased re-entry.

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, first calculating the effect of aid on re-entry probabilities and then comparing 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 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).

Importantly, because the aid programs that we consider effectively reverse the damage suffered by existing establishments, this increases their expected profits (Equation 5), which increases their probability of re-entry (Equation 9). This increase in the probability of re-entry has the potential of crowding out new entry, through its impact on the potential entrants' beliefs about the intensity of future competition B^{NE}. More precisely, aid changes beliefs about the intensity of competition, B^{NE} and B^{RE}. For this reason, in the exercises that follow, we recompute beliefs to reflect the higher re-entry probabilities of firms that receive aid, as well as the potential for crowding out new entry. Because, in practice, we find that the crowding-out effect is of second order, we focus our discussion on re-entry.

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, we transform percent damage $\hat{d}_j$ to a dollar damage D_j as shown in equation 11. Store j's losses come from both damage to real estate value $V_{b(j)}$ and to establishment personal property (e.g., equipment and inventory) K_j. We assume real estate loss is proportional to the square feet the store occupies. We measure equipment and inventory value $K_{j,pre}$ using HCAD tax data on the assessed value of the business's personal property prior to the storm. Because we do not have post-storm damage estimates $K_{j,post}$, we assume that percent damage to K_j is equal to $\hat{d}_j \cdot \kappa$. We explore two scenarios for κ. First, we set $\kappa = 1$, which assumes that the share of damaged personal property 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. Second, we set $\kappa = 8.98$ such that a store that receives the maximum predicted real estate damage ($\hat{d}_j = 1/8.98$) experiences a 100% personal property loss.

$$D_j = \hat{d}_j \times \left[V_{b(j),pre} \times \frac{sqft_j}{sqft_{b(j)}} + \kappa \times K_{j,pre} \right] \tag{11}$$

We show summary statistics of the different components of D_j in Supplemental Appendix Table I.1. For establishments with more than 4 feet of flooding exposure, the average es-

timated 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.

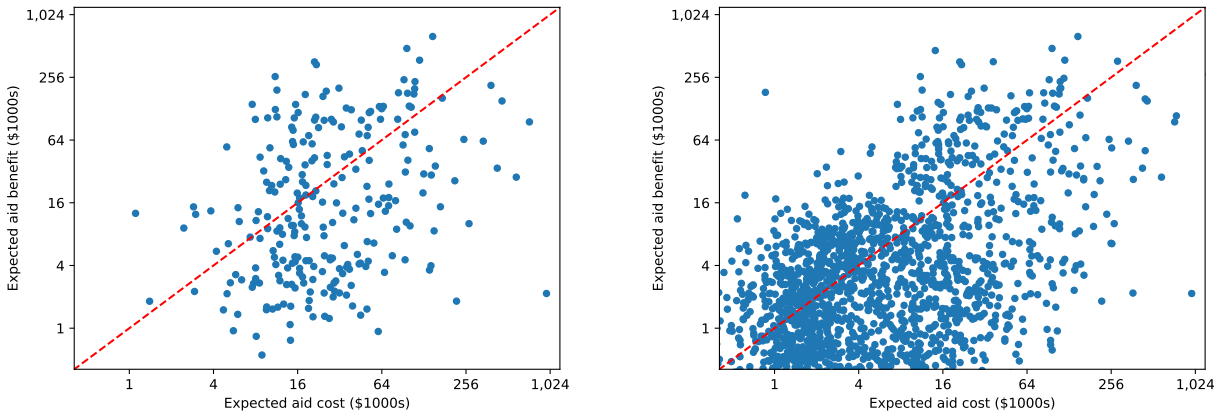
We compute the effect of a hypothetical aid program that gives a grant of size D_j to a damaged store, effectively reducing its exit probability by moving it along the damage curve in Figure 8b from the observed $\hat{d}_j$ to $\hat{d}_j = 0$. In doing so, we abstract from several practical issues related to aid disbursement 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 proportionally 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).[29]

Consumer and employment benefits: We compute the benefits to consumers from store re-entry using 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 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%.[30]

A store that re-enters also prevents the job loss associated with closure. To approximate these employment benefits, we compute the predicted unemployment insurance bene-

[29]For establishments with more than 4 feet of flooding, we estimate that aid decreases average exit probability by 6.2pp (relative to a base rate 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 (relative to a base rate of 21% over the first three years after a disaster).

[30]We calibrate this discount rate to 2.1%, which reflects the probability of establishment survival as well as the 3% annual discount rate (converted 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%.



(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) considers only establishments with 4 or more feet of flooding; panel (B) includes all establishments.

fits employees would receive. We take establishment-level employment 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.[31] Further details on this calculation are in Supplemental Appendix I.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, measured as the change in exit probability multiplied by the sum of the consumer surplus and employment benefits created by the store. We perform analyses across four scenarios to illustrate the sensitivity of aid efficacy 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 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 its expected benefit on the vertical axis. The 45-degree line plots the break-even point where benefits

[31] 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).

equal costs. The figure shows that relatively few businesses (31% of establishments) would justify an aid program based on their contribution to consumer welfare. 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.[32] 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 5, where the first column shows results from our baseline scenario. Under these assumptions, the total cost of such a program is about $41M, which generates only about $24M in benefits, resulting in a net loss of $17M. 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. Only in column 3, where we assume small capital decay and long-lived consumer benefits, do we find that a blanket aid program would pass a cost-benefit analysis. We find crowd out of new-entry is minimal, with expected reduction of new entrants less than 0.01 establishments in all four scenarios. The reason for this is that our estimates of σ_δ^{NE} are large, implying few marginal new entrants that would be crowded out by aid.

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 5. In our baseline scenario, this aid would benefit 664 establishments, costing about $6.1M and generating nearly $18.2M in expected benefits ($2.98 per dollar of aid), resulting in a net gain of nearly $12M. The net value is positive by construction in each of the four scenarios we consider, ranging from $5.7M (247 establishments) to $50.5M (1,024 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

[32]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 5: 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 benefit ($M)s duration	End of 2018	End of 2018	Inf. discounted	Inf. discounted
Aid to all damaged firms				
Cost ($M)	41.2	177.7	41.2	177.7
Benefit ($M)	24.0	24.0	68.9	68.9
CS benefit ($M)	20.6	20.6	65.5	65.5
# jobs	601	601	601	601
Net Value ($M)	-17.2	-153.6	27.7	-108.8
% firms positive value	25.3%	9.4%	39.0%	24.1%
# subsidized firms	2,625	2,625	2,625	2,625
Aid only to firms with positive net value				
Cost ($M)	6.1	5.3	10.1	16.9
Benefit ($M)	18.2	11.0	60.6	53.6
CS benefit ($M)	16.3	9.9	58.4	51.9
# jobs	351	212	426	336
Net Value ($M)	12.0	5.7	50.5	36.7
% firms positive value	100.0%	100.0%	100.0%	100.0%
# subsidized firms	664	247	1,024	633
Aid only to firms with predicted positive net value				
Cost ($M)	7.7	4.1	9.7	24.5
Benefit ($M)	18.5	7.7	58.5	55.2
CS benefit ($M)	16.6	7.1	56.4	53.3
# jobs	358	121	420	367
Net Value ($M)	10.8	3.5	48.8	30.7
% firms positive value	80.8%	78.3%	88.2%	78.7%
# subsidized firms	691	120	978	672

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 11), 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).

an indicator variable for whether an establishment has a 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 Supplemental Appendix Table I.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 5. In our baseline scenario, this program provides subsidies to 691 establishments (26% of the total), of which 80.8% have positive net value. These subsidies generate a total net value of about \$10.8M (\$2.40 in benefits for each dollar spent) and achieve 90% of the net gain from perfect targeting. The total net value is positive across all four scenarios, although the number of establishments receiving subsidies varies with assumptions about the costs and benefits of aid.

A key finding is that although few establishments generate sufficient benefits to justify the cost of aid, the right tail of exiting stores creates substantial welfare gains. We find that under most scenarios, 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.

Finally, we examine the cost and benefits of business aid programs designed to cover the expenses associated with a business' storm damage. Because aid reduces the likelihood that a business exits following a natural disaster, it also has the potential to crowd-out new entry. We consider this in the context of an entry game of incomplete information, in which businesses impacted by Hurricane Harvey decide whether to re-enter. We show that in our setting, aid has minimal impacts on crowd out of new entrants. We also show that blanket aid programs that provide aid to all impacted businesses are inefficient, but programs that target aid based on a business's observable characteristics are able to achieve about 90% of the gains achieved by an (infeasible) perfect targeting program.

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Supplemental Appendix: Not For Publication

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

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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.

    (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.

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

3. **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 **??** in Table **??**.

4. **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.

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

6. **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 Supplemental 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/`.

7. **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 Supplemental Appendix E.

8. **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 Supplemental Appendix E.

9. **NielsenIQ Kilts data.** We use the household panel data from 2016 and 2017, located in the following counties: Harris, Dallas, Tarrant, Bexar, Collin, Denton, Travis, Fort Bend, Montgomery, Williamson, Hidalgo, El Paso, Jefferson, and Nueces. Of these, Harris, Fort Bend, Mongomery, Jefferson, and Nueces correspond to counties that were on the path of Hurricane Harvey. We consider these to be "treated" counties. In terms of product categories, we consider all products sold through the channels of Grocery,

Discount Store, Drug Store, Quick Serve Restaurants, Warehouse Club, Dollar Stores, Service Stations, Hardware/Home Improvement, Restaurants, Department Stores, All Other Stores, Apparel Stores, Pet Store, Convenience Store, and Craft Stores. We do impose, however, the restriction that for a UPC to be considered in the analysis, it had to be purchased at least 10 times between 2016 and 2017.

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 Supplemental 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

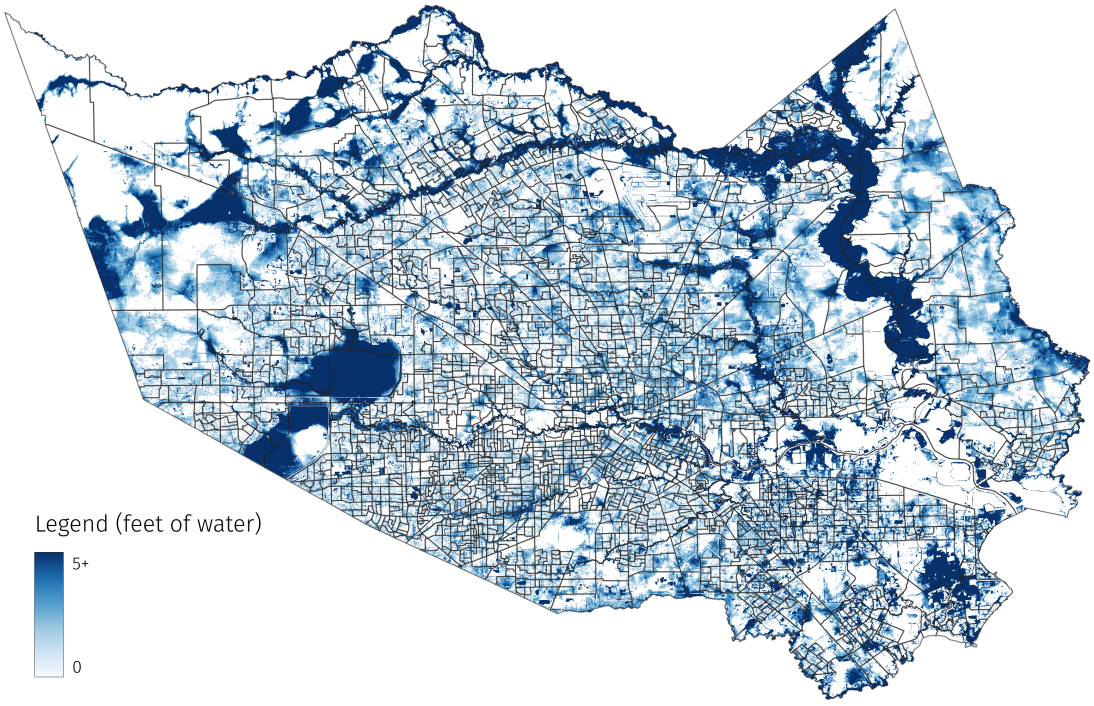
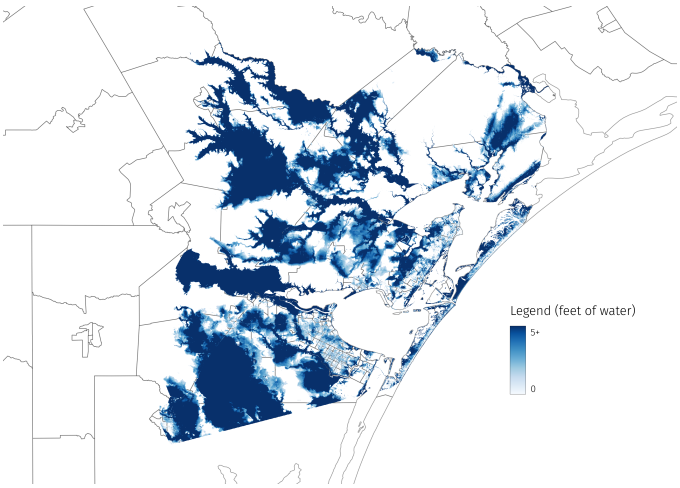
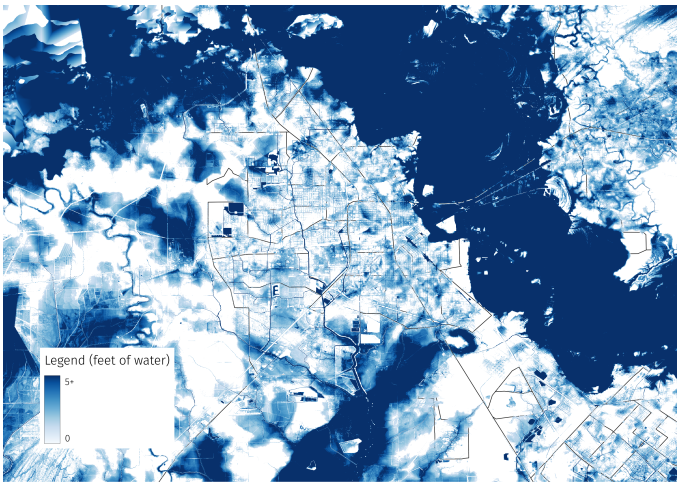


FIGURE B.1: Flooding level caused by Hurricane Harvey in Harris County.



(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 Supplemental Appendix section, 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.

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.1: Exit rates by business characteristics

Dep. Var.	(1) 1(Perm. exit)	(2) 1(Temp. Closure)	(3) 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.

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.

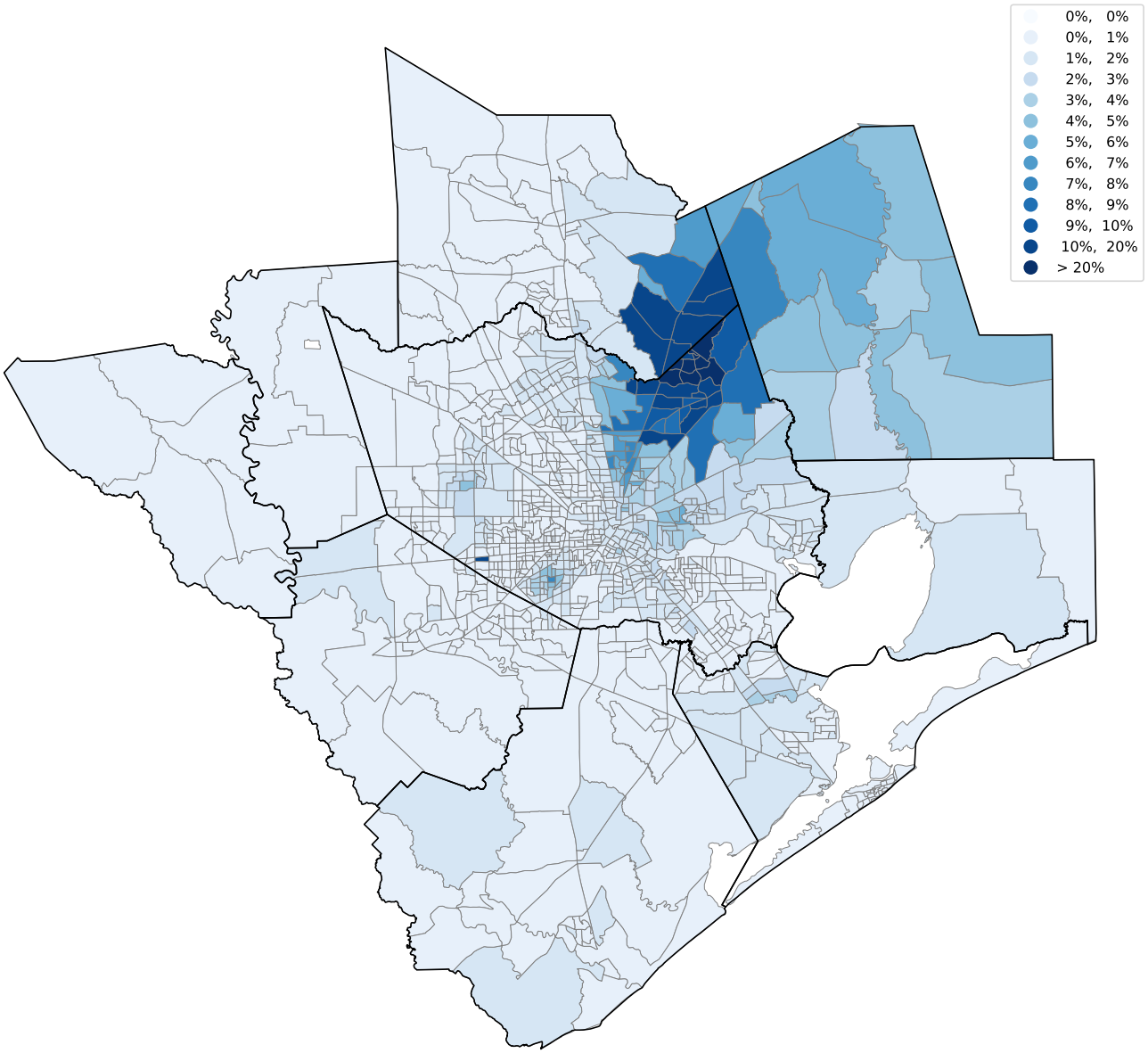
5. Our card data cleaning procedure also excludes stores that use third-party payment processors. Our card data does not record accurate name, location, nor NAICS information for such stores.

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.

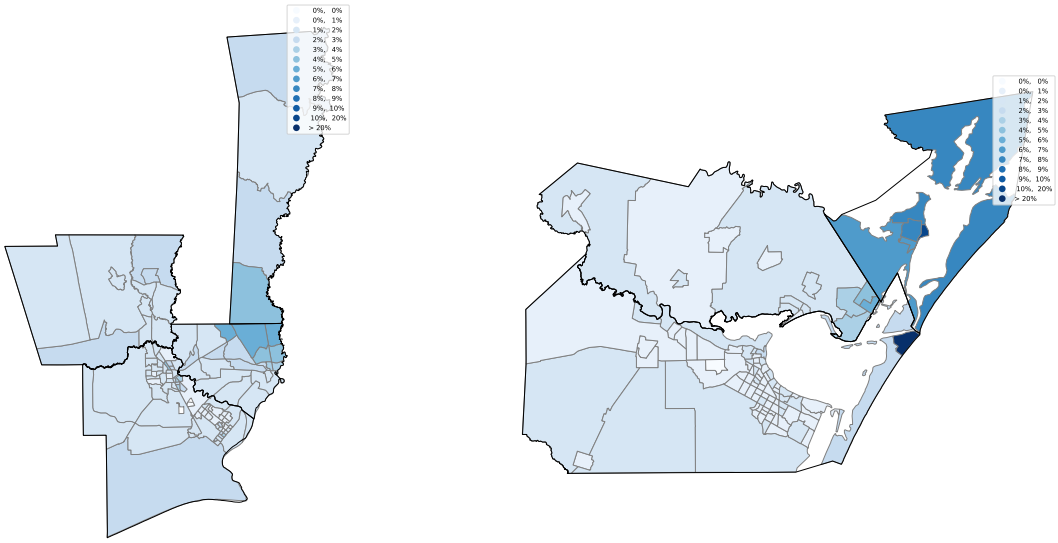
C.3 Share of pre-Harvey spending at closed stores

In this Online 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.

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.

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.

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.

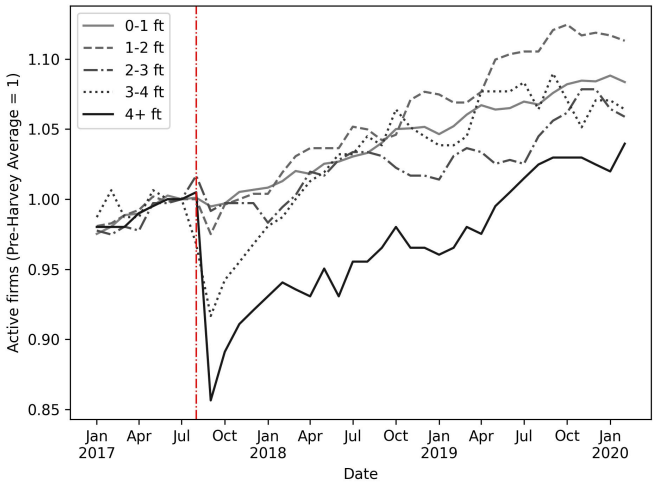


FIGURE C.3: Normalized count of establishments in MBGRT by Harvey flood level and month.

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.

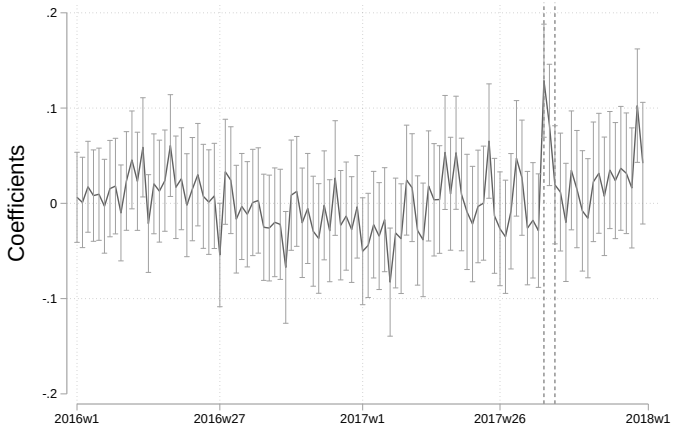
D Examining price responses to Hurricane Harvey

In this Supplemental Appendix section, we examine the extent to which retail prices changed during and after Hurricane Harvey. We do this by exploiting the NielsenIQ Homescan Consumer Panel, accessed through the Kilts Center at the University of Chicago.

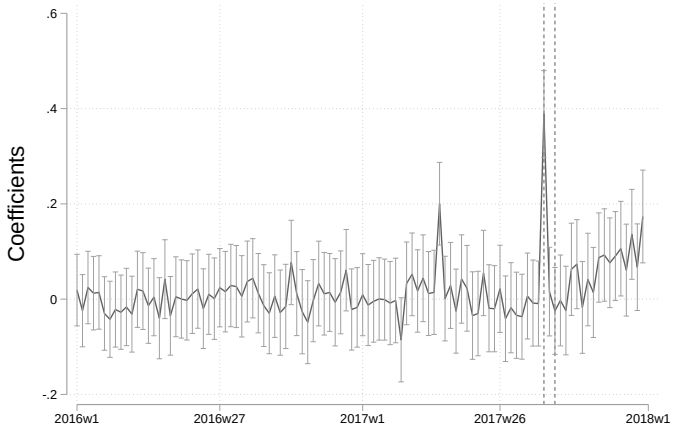
In our analyses, we restrict attention to the State of Texas between 2016 and 2017, and we focus on the largest counties contained in the data, such as Harris County (which contains the City of Houston and the surrounding areas). In addition to the largest counties, we include smaller counties that were impacted by Hurricane Harvey. These counties include Fort Bend County (the area to the southwest of Harris County), Montgomery County (the area to the north of Harris County), Jefferson County (which includes the City of Beaumont and the surrounding areas), and Nueces County (which contains the City of Corpus Christi, City of Port Aransas, and the surrounding areas). We labeled all the stores in these counties as stores located in affected (treated) areas. The remaining stores, located in the counties of Tarrant, Dallas, Bexar, Collin, Denton, Williamson, El Paso, and Hidalgo, are labeled as located in untreated areas.

We begin our analyses considering purchases in the following channels: groceries, discount stores, drug stores, quick-serve restaurants, warehouse clubs, dollar stores, service stations, hardware/home improvement, restaurants, department stores, online shopping, apparel stores, pet stores, convenience stores, craft stores, and All Other Stores.

To examine the extent of price changes during and after Hurricane Harvey, we estimate regressions of prices (at the product–store–week level) on the interaction of week fixed effects and an indicator that is equal to one for the affected areas (before and after the hurricane). We also include store and product fixed effects. In Figure D.1a, we report the estimated coefficients of the interaction of the week fixed effects and the indicator that identifies treated areas. We find that there is a one-week effect, at the time of the hurricane, during which prices were higher in impacted areas relative to untreated. Importantly, this effect is temporary, and it lasts for only one week. Further examination reveals that this one-week price effect is entirely driven by prices of stores in the Discount Store channel, located in impacted areas (D.1b). Again, we find that there were no long-lasting price effects in impacted areas.



(A) All stores and products



(B) Discount stores

FIGURE D.1: Estimates of week-level price effects

E Demand response evidence

In this Supplemental 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

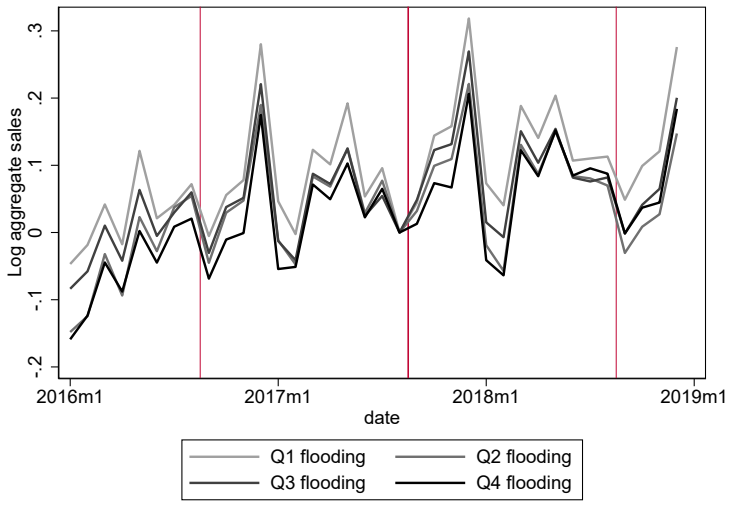


FIGURE E.1: Aggregate monthly spending by month x region

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.

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 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.[33] 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.

[33]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.

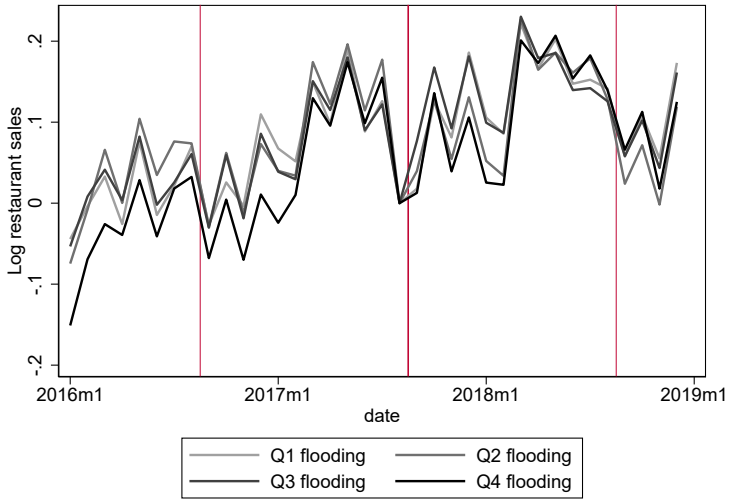


FIGURE E.2: Aggregate restaurant monthly spending by month x region

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.

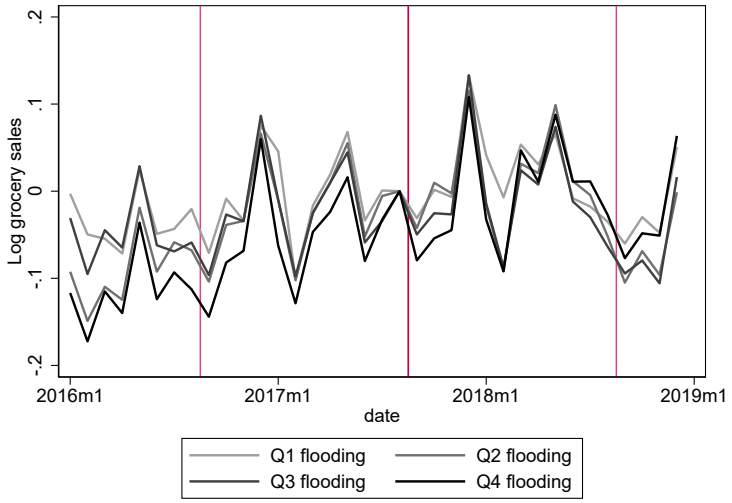


FIGURE E.3: Aggregate grocery monthly spending by month x region

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.

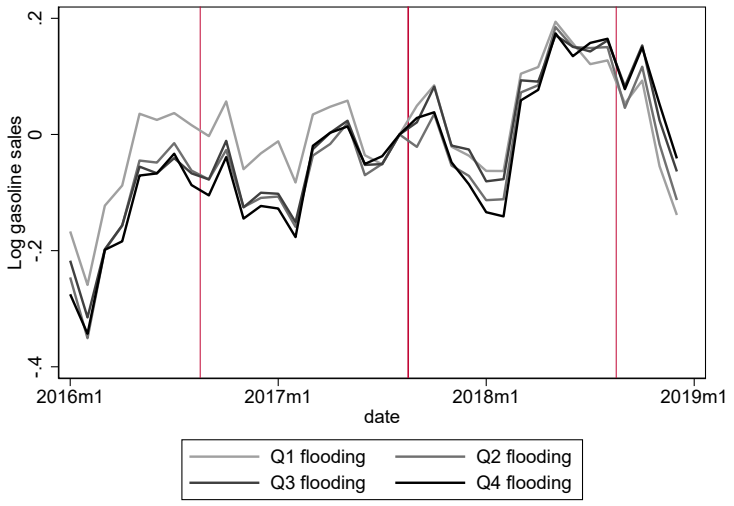


FIGURE E.4: Aggregate gasoline monthly spending by month x region

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[34]

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

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.

[34] 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.

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.

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 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.

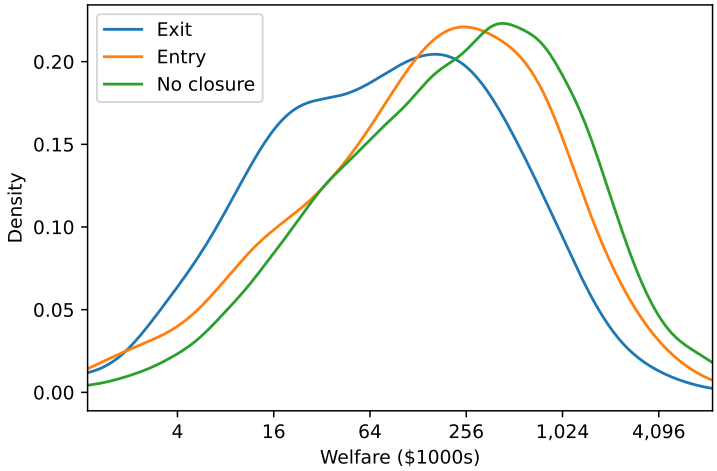
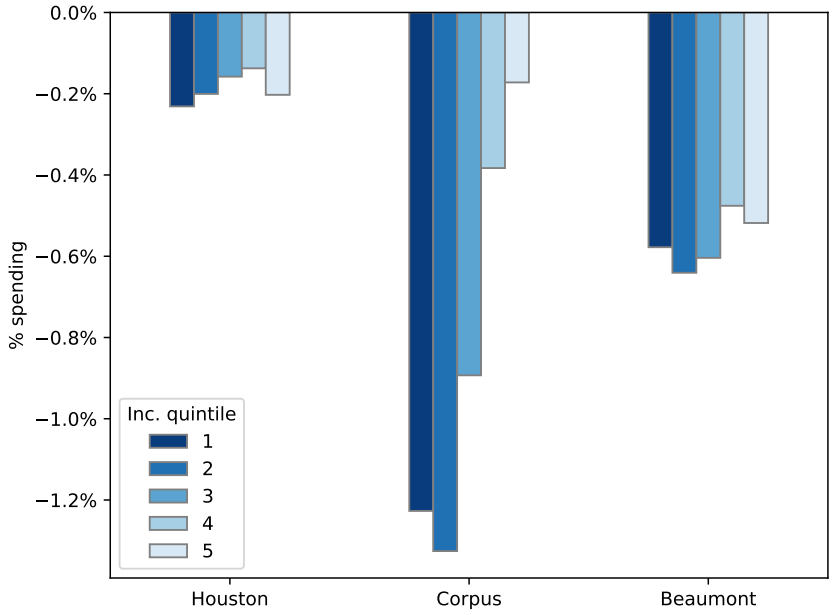


FIGURE F.1: Store-level consumer welfare contribution (pre-Harvey J).

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.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.

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 from the demand model - Corpus Christi

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

Notes: Demand model estimated separately for each NAICS by MSA. Table shows estimated parameters for Corpus Christi over all NAICS ranked by transaction volume with bootstrapped standard errors in parentheses. 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.

TABLE F.4: Parameter estimates from the demand model - Beaumont

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

Notes: Demand model estimated separately for each NAICS by MSA. Table shows estimated parameters for Beaumont over all NAICS ranked by transaction volume with bootstrapped standard errors in parentheses. 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.

G Entry model: Implementation details

In this section, we present the implementation details of the model that we introduced in Section 6.1.

G.1 Model primitives

In the model, the set of potential re-entrants who decide to re-enter is $N^{RE} \subset J^{RE}$, the set of incumbents who never close is N^I, and the set of potential entrants who decide to enter is $N^{NE} \subset J^{NE}$. Each NAICS category is assumed to be a separate market.

G.2 Mapping the demand model to δ_j used in the entry game

In Section 5, we estimate a random-coefficients demand model with spatial differentiation and rich consumer heterogeneity. To make the entry game computationally tractable, we summarize demand within each NAICS category using store-level mean utilities δ_j in a stylized logit environment.

Market definition and aggregate shares. For each NAICS category n, we define the market as all stores located in Harris County (where we have property tax appraisal data, described in Section 6.1) that operate in category n. The outside option consists of all stores in category n located outside of Harris County. The demand model delivers predicted choice probabilities at the consumer level. We aggregate these predicted probabilities across consumers (and neighborhoods) to construct each store's predicted aggregate market share, denoted $\hat{s}_j$, and the predicted outside share, denoted $\hat{s}_0$.

Inversion to mean utilities. In the entry model, preferences within category n are summarized by a multinomial logit with mean utilities $\{\delta_j\}_{j \in \mathcal{J}_n}$ and an outside option:

$$u_{ij} = \delta_j + \nu_{ij}, \qquad u_{i0} = \nu_{i0},$$

where ν_{ij} is i.i.d. Type I Extreme Value. This implies market shares

$$s_j = \frac{\exp(\delta_j)}{1 + \sum_{k \in \mathcal{J}_n} \exp(\delta_k)}, \qquad s_0 = \frac{1}{1 + \sum_{k \in \mathcal{J}_n} \exp(\delta_k)}.$$

Given predicted aggregate shares $(\hat{s}_j, \hat{s}_0)$ from the demand model, the implied mean utilities are recovered by the standard logit inversion

$$\delta_j = \log(\hat{s}_j) - \log(\hat{s}_0). \tag{12}$$

We use these inverted values δ_j as the mean utilities that enter the entry and re-entry model for each store category.

G.3 Second stage

In the second stage, potential new entrants form beliefs about the degree of competition and enter if expected profits are nonnegative. As described in the main text, each potential entrant observes its own δ_k and ε_k, as well as the entry decisions and mean utilities of all re-entrants, but not the mean utilities or profit shocks of other potential entrants. Therefore, potential entrant k uses the known joint distribution of δ and ε to compute this expectation. However, we assume that k does not take into account its own mean utility and profit shock in the calculation of the *degree of competition*. This assumption is required because it yields symmetric beliefs among stores, greatly simplifying the computation of the equilibrium. Further, it is important to note that, because of the large number of stores, the impact of using draws from the distribution of mean utilities and profit shocks, rather than the realization of these, is minor.

In practice, we proceed as follows. Given the observed entry decisions and mean utilities of the re-entrants $\{(\iota_m, \delta_m)\}_{m \in J^{RE}}$, as well as a parameter vector θ, which includes entry costs and the mean and variance of δ and ε, draw R_1 realizations of the unobservables for each potential entrant $k \in J^{NE}$. Fix an initial guess for beliefs about competition, B_0^{NE}. For each draw $s \in \{1, \ldots, R_1\}$ and each potential entrant k, evaluate expected profits implied by θ_0 and beliefs B_i^{NE},

$$\mathbb{E}[\pi_k^{NE,s} \mid B_i^{NE}, \theta_0],$$

and set the entry decision

$$\iota_k^s(B_i^{NE}) = \mathbf{1}\Big(\mathbb{E}[\pi_k^{NE,s} \mid B_i^{NE}, \theta_0] \geq 0\Big).$$

Given the resulting entry decisions, compute the draw-specific implied degree of competition,

$$\bar{B}^s(B_i^{NE}) \equiv \left(\sum_{k \in J^{NE}} \iota_k^s(B_i^{NE}) \exp(\delta_k^s) \; + \sum_{m \in J^{RE}} \iota_m \exp(\delta_m) \; + \sum_{l \in J^I} \exp(\delta_l) \right)^{-1},$$

and average across simulation draws,

$$\mathbb{E}[\bar{B}(B_i^{NE})] \equiv \frac{1}{R_1}\sum_{s=1}^{R_1}\bar{B}^s(B_i^{NE}).$$

We then update beliefs according to

$$B_{i+1}^{NE} = \mathbb{E}[\bar{B}(B_i^{NE})],$$

and iterate until convergence. Denote the converged belief by B^{*NE}. This fixed point condition ensures that the belief B^{*NE} is consistent with the set of entrants implied by B^{*NE}.

G.4 First stage

The first stage corresponds to the re-entry decision of temporarily closed establishments. In this stage, mean utilities for potential re-entrants, $\{\delta_m\}_{m\in J^{RE}}$, are treated as observed (estimated from the pre-Harvey data), while re-entry profit shocks are unobserved. We compute an equilibrium belief about competition for re-entrants, B^{*RE}, by fixed-point iteration. Each candidate belief B^{RE} implies a set of re-entry decisions, which in turn determines the equilibrium of the second-stage new entry subgame and the implied degree of competition faced by re-entrants.

We begin with a parameter vector θ governing re-entry costs and the distribution of re-entry shocks, and a vector of re-entrant mean utilities $\{\delta_m\}_{m\in J^{RE}}$. Draw R_2 realizations of re-entry profit shocks $\varepsilon_m^{RE,r}$ for each potential re-entrant $m \in J^{RE}$, for $r \in \{1,\ldots,R_2\}$. Fix an initial guess for beliefs about competition faced by re-entrants, B_0^{RE}.

For each iteration i and each draw r, evaluate expected profits for each potential re-entrant m implied by θ_0 and beliefs B_i^{RE} and set the draw-specific re-entry decision

$$\iota_m^r(B_i^{RE}) = \mathbf{1}\big(\mathbb{E}[\pi_m^{RE,r} \mid B_i^{RE}, \theta_0] \geq 0\big).$$

Nested second stage. Given the re-entry decisions $\{\iota_m^r(B_i^{RE})\}_{m\in J^{RE}}$, solve the second-stage new-entry subgame using the procedure in the previous subsection. This yields the draw-specific equilibrium belief for new entrants, denoted $B_r^{*NE}(B_i^{RE})$, and the implied entry decisions for potential new entrants under that subgame. (Equivalently, this step maps a candidate re-entry outcome into the equilibrium degree of competition generated after new entry.)

Using the implied re-entry and new-entry outcomes, compute the draw-specific implied

degree of competition relevant for re-entrants,

$$\tilde{B}^r(B_i^{RE}) \equiv \left(\sum_{k \in J^{NE}} \iota_k^{rs}\big(B_r^{*NE}(B_i^{RE})\big) \exp(\delta_k^s) \; + \sum_{m \in J^{RE}} \iota_m^r(B_i^{RE}) \exp(\delta_m) \; + \sum_{l \in J^I} \exp(\delta_l) \right)^{-1},$$

where $\iota_k^{rs}(\cdot)$ denotes the entry decision for potential entrant k under draw (r, s) in the nested second-stage simulation, and δ_k^s denotes the simulated mean utility draw for potential entrant k used in that second-stage computation.

Finally, average across draws to obtain the implied belief update,

$$\tilde{B}^r(B_i^{RE}) \equiv \frac{1}{R_1} \sum_{s=1}^{R_1} \left(\sum_{k \in J^{NE}} \iota_k^{rs}\big(B_r^{*NE}(B_i^{RE})\big) \exp(\delta_k^s) + \sum_{m \in J^{RE}} \iota_m^r(B_i^{RE}) \exp(\delta_m) + \sum_{l \in J^I} \exp(\delta_l) \right)^{-1}.$$

$$\mathbb{E}[\tilde{B}(B_i^{RE})] \equiv \frac{1}{R_2} \sum_{r=1}^{R_2} \tilde{B}^r(B_i^{RE})$$

and update beliefs according to

$$B_{i+1}^{RE} = \mathbb{E}[\tilde{B}(B_i^{RE})].$$

We iterate until convergence, i.e., until $\left|B_{i+1}^{RE} - B_i^{RE}\right|$ is below a prespecified tolerance. Denote the converged belief by B^{*RE}. This fixed point condition ensures that B^{*RE} is consistent with the set of re-entrants implied by B^{*RE}, taking into account equilibrium new entry in the second-stage subgame.

G.5 Likelihood function and estimation

This subsection derives the likelihood implied by the profit functions in equations (3) and (5).

Deriving choice probabilities. New entrants. For a potential new entrant $k \in J^{NE}$ in NAICS n, profits are

$$\mathbb{E}[\pi_k] = M \cdot \mathbb{E}[s_k] \cdot \zeta_{n(k)}^{NE} - C_{n(k)}^{NE} \cdot \exp(\varepsilon_k).$$

Entry occurs when $\mathbb{E}[\pi_k] \geq 0$, which is equivalent to

$$M \cdot \mathbb{E}[s_k] \cdot \zeta_{n(k)}^{NE} \geq C_{n(k)}^{NE} \cdot \exp(\varepsilon_k)$$
$$\log M + \log \mathbb{E}[s_k] + \log \zeta_{n(k)}^{NE} - \log C_{n(k)}^{NE} \geq \varepsilon_k.$$

Define the NAICS-specific intercept

$$\alpha_n^{NE} \equiv \log M + \log \zeta_n^{NE} - \log C_n^{NE}.$$

Then the entry condition can be written as

$$\varepsilon_k \leq \log \mathbb{E}[s_k] + \alpha_{n(k)}^{NE}.$$

If $\varepsilon_k \sim \mathcal{N}(0, (\sigma_\varepsilon^{NE})^2)$, the conditional entry probability is

$$\mathbb{P}(\iota_k = 1 \mid \delta_k, B^{*NE}) = \Phi\left(\frac{\log \mathbb{E}[s_k] + \alpha_{n(k)}^{NE}}{\sigma_\varepsilon^{NE}}\right), \tag{13}$$

where $\log \mathbb{E}[s_k] = \delta_k + \log B^{*NE}$.

Re-entrants. For a potential re-entrant $j \in J^{RE}$, profits are

$$\mathbb{E}[\pi_j] = M \cdot \mathbb{E}[s_j] \cdot \zeta_{n(j)}^{RE} - F_j(X_j) \cdot \exp(\varepsilon_j).$$

We parameterize the re-entry cost as

$$F_j(X_j) = C_{n(j)}^{RE} \cdot X_j^{\beta}, \quad \text{so that} \quad \log F_j(X_j) = \log C_{n(j)}^{RE} + \beta \log X_j.$$

Re-entry occurs when $\mathbb{E}[\pi_j] \geq 0$, which is equivalent to

$$\log M + \log \mathbb{E}[s_j] + \log \zeta_{n(j)}^{RE} - \log C_{n(j)}^{RE} - \beta \log X_j \geq \varepsilon_j.$$

Define

$$\alpha_n^{RE} \equiv \log M + \log \zeta_n^{RE} - \log C_n^{RE}.$$

Then the re-entry condition is

$$\varepsilon_j \leq \log \mathbb{E}[s_j] + \alpha_{n(j)}^{RE} - \beta \log X_j.$$

If $\varepsilon_j \sim \mathcal{N}(0, (\sigma_\varepsilon^{RE})^2)$, the conditional re-entry probability is

$$\mathbb{P}(\iota_j = 1 \mid \delta_j, B^{*RE}) = \Phi\left(\frac{\log \mathbb{E}[s_j] + \alpha_{n(j)}^{RE} - \beta \log X_j}{\sigma_\varepsilon^{RE}}\right), \tag{14}$$

where $\log \mathbb{E}[s_j] = \delta_j + \log B^{*RE}$.

Likelihood contributions. After solving for equilibrium beliefs (B^{*NE}, B^{*RE}) for a candidate parameter vector θ, we compute the likelihood contributions of each type of player.

Potential new entrants. We assume δ_k is observed when k enters, but not observed when k does not enter (as in the main text). When k does not enter, the likelihood contribution integrates over the distribution of δ:

$$\begin{aligned} L_{\text{k does not enter}}^{NE} &= \mathbb{P}(\iota_k = 0) \\ &= \int_{-\infty}^{\infty} \left[1 - \Phi\left(\frac{\log \mathbb{E}[s_k(x)] + \alpha_{n(k)}^{NE}}{\sigma_\varepsilon^{NE}}\right)\right] f_\delta(x)\, dx, \end{aligned}$$

where $\log \mathbb{E}[s_k(x)] = x + \log B^{*NE}$ and f_δ is the normal density implied by (8).

When k enters and δ_k is observed at value x, the likelihood contribution is

$$\begin{aligned} L_{\text{k enters}}^{NE} &= \mathbb{P}(\iota_k = 1 \;\&\; \delta_k = x) \\ &= f_\delta(x) \times \Phi\left(\frac{\log \mathbb{E}[s_k(x)] + \alpha_{n(k)}^{NE}}{\sigma_\varepsilon^{NE}}\right). \end{aligned}$$

Potential re-entrants. For re-entrants, we observe δ_j for all $j \in J^{RE}$ regardless of whether they re-enter. Let $\delta_j = x$ denote the observed value. If j does not re-enter,

$$\begin{aligned} L_{\text{j does not reenter}}^{RE} &= \mathbb{P}(\iota_j = 0 \;\&\; \delta_j = x) \\ &= f_\delta^{RE}(x) \times \left[1 - \Phi\left(\frac{\log \mathbb{E}[s_j(x)] + \alpha_{n(j)}^{RE} - \beta \log X_j}{\sigma_\varepsilon^{RE}}\right)\right], \end{aligned}$$

and if j re-enters,

$$\begin{aligned} L_{\text{j reenters}}^{RE} &= \mathbb{P}(\iota_j = 1 \;\&\; \delta_j = x) \\ &= f_\delta^{RE}(x) \times \Phi\left(\frac{\log \mathbb{E}[s_j(x)] + \alpha_{n(j)}^{RE} - \beta \log X_j}{\sigma_\varepsilon^{RE}}\right), \end{aligned}$$

where $\log \mathbb{E}[s_j(x)] = x + \log B^{*RE}$ and f_δ^{RE} denotes the density of re-entrant mean utilities (or an empirical distribution if δ_j is treated as fixed after first-stage estimation).

Log-likelihood and estimation. Let L_k^{NE} and L_j^{RE} denote the appropriate likelihood contribution given each store's observed decision. The log-likelihood is

$$LL(\theta) \equiv \sum_{k \in J^{NE}} \log L_k^{NE}(\theta) + \sum_{j \in J^{RE}} \log L_j^{RE}(\theta). \tag{15}$$

We maximize $LL(\theta)$ over θ by numerical optimization. Each evaluation of $LL(\theta)$ solves for equilibrium beliefs (B^{*NE}, B^{*RE}) using the fixed point procedures described above.

H Measuring building damage with HCAD data

H.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 consists of payment card data, which serves as the core dataset of the paper. This dataset identifies businesses by name and address 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) and 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 identified in the data. We then match the card data to the real property data based on addresses. For records we cannot match by address, we match them to the record with the shortest distance.

H.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 **??**.

In the Fall of 2017, soon after Hurricane Harvey made landfall, ten districts in Harris

County conducted a reappraisal. 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 occurred soon after Harvey landed, we can interpret the implied change in value as the storm's damage.

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 reappraisal in the Fall of 2017. Because the reappraisal considers properties only in the reappraisal districts, we train our model on data from these districts.

We train the model on HCAD data. Specifically, in our model, we include variables measuring flood exposure and building characteristics. Among these, we include the building's age, 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, and 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 model's generalizability 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 were 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 5.

H.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 H.1.

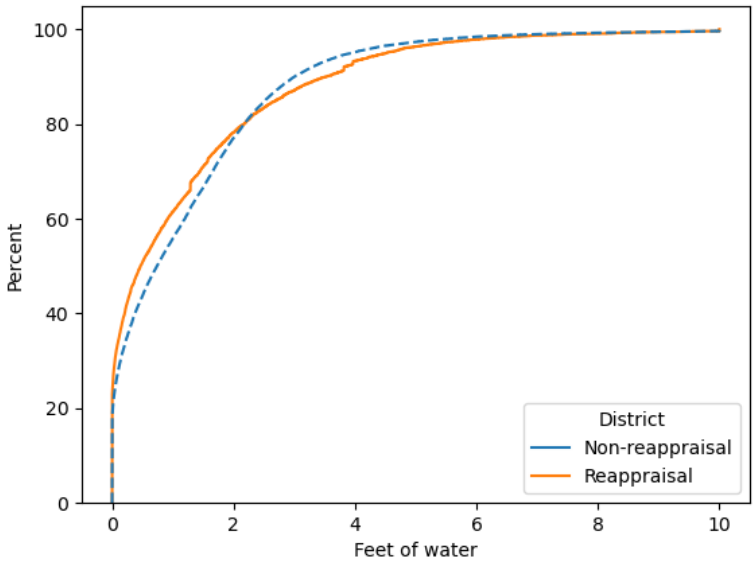


FIGURE H.1: CDF of flood exposure for reappraisal and non-reappraisal districts

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

TABLE H.1: Parameter estimates from entry model

Panel A: $\sigma_{\varepsilon}^{NE} = 1$

NAICS	Industry	α^{RE}	α^{NE}	μ_{ξ}^{NE}	σ_{ξ}^{NE}	$\sigma_{\varepsilon}^{\text{NE}}$	$\sigma_{\varepsilon}^{\text{RE}}$	β^{flood}	β^{sqft}	$\beta^{\text{chains 2-100}}$	$\beta^{\text{chains 101-1000}}$	$\beta^{\text{chains 1001+}}$
441	Auto parts	-31.43	-2.459	-6.550	1.399	1.000	12.95	83.40	-0.394	-1.160	1.946	3.181
		(9.847)	(0.183)	(0.220)	(0.157)	(–)	(4.117)	(28.87)	(0.657)	(1.189)	(2.209)	(2.522)
442	Furniture	-35.48	-2.336	-6.182	1.088	1.000	12.95	83.40	-0.394	-1.160	1.946	3.181
		(11.64)	(0.272)	(0.251)	(0.180)	(–)	(4.117)	(28.87)	(0.657)	(1.189)	(2.209)	(2.522)
443	Electronics	-48.11	-2.815	-6.131	0.856	1.000	12.95	83.40	-0.394	-1.160	1.946	3.181
		(27.06)	(0.609)	(0.448)	(0.324)	(–)	(4.117)	(28.87)	(0.657)	(1.189)	(2.209)	(2.522)
444	Building materials	-57.12	-3.195	-6.405	2.142	1.000	12.95	83.40	-0.394	-1.160	1.946	3.181
		(37.00)	(0.269)	(0.461)	(0.325)	(–)	(4.117)	(28.87)	(0.657)	(1.189)	(2.209)	(2.522)
445	Groceries	-29.28	-2.245	-6.926	2.054	1.000	12.95	83.40	-0.394	-1.160	1.946	3.181
		(8.930)	(0.108)	(0.183)	(0.129)	(–)	(4.117)	(28.87)	(0.657)	(1.189)	(2.209)	(2.522)
446	Pharmacy	-32.37	-3.314	-6.316	1.481	1.000	12.95	83.40	-0.394	-1.160	1.946	3.181
		(9.789)	(0.194)	(0.239)	(0.169)	(–)	(4.117)	(28.87)	(0.657)	(1.189)	(2.209)	(2.522)
447	Gasoline	-38.02	-2.175	-6.806	1.575	1.000	12.95	83.40	-0.394	-1.160	1.946	3.181
		(12.30)	(0.157)	(0.217)	(0.155)	(–)	(4.117)	(28.87)	(0.657)	(1.189)	(2.209)	(2.522)
448	Clothing	-34.62	-2.036	-6.743	1.796	1.000	12.95	83.40	-0.394	-1.160	1.946	3.181
		(10.43)	(0.114)	(0.170)	(0.121)	(–)	(4.117)	(28.87)	(0.657)	(1.189)	(2.209)	(2.522)
451	Sporting goods	-33.64	-2.710	-6.581	1.500	1.000	12.95	83.40	-0.394	-1.160	1.946	3.181
		(10.59)	(0.188)	(0.241)	(0.171)	(–)	(4.117)	(28.87)	(0.657)	(1.189)	(2.209)	(2.522)
452	Gen. Merch.	-29.40	-2.139	-6.347	1.558	1.000	12.95	83.40	-0.394	-1.160	1.946	3.181
		(9.686)	(0.196)	(0.257)	(0.182)	(–)	(4.117)	(28.87)	(0.657)	(1.189)	(2.209)	(2.522)
453	Misc. retail	-33.16	-3.011	-6.586	1.448	1.000	12.95	83.40	-0.394	-1.160	1.946	3.181
		(9.857)	(0.101)	(0.125)	(0.089)	(–)	(4.117)	(28.87)	(0.657)	(1.189)	(2.209)	(2.522)
722	Restaurants	-25.05	-1.582	-7.390	2.031	1.000	12.95	83.40	-0.394	-1.160	1.946	3.181
		(7.884)	(0.066)	(0.068)	(0.048)	(–)	(4.117)	(28.87)	(0.657)	(1.189)	(2.209)	(2.522)

Notes: This table presents parameter estimates for the structural entry model described in Section 6.1, estimated via Simulated Maximum Likelihood. The parameters α^{RE} and α^{NE} are NAICS-specific intercepts. μ_{δ}^{NE} and σ_{δ}^{NE} represent the mean and standard deviation of the mean utility distribution for new entrants, respectively. $\sigma_{\varepsilon}^{RE}$ is the standard deviation of the re-entrant profit shock. The vector X includes store-specific characteristics: X^{flood} measures flooding exposure via building damage; X^{sqft} is the log of store square footage; and the remaining X variables are dummies for chain size (2–100, 101–1000, and 1001+ locations), with single-location stores as the omitted category. Because the variance of the new entrant profit shock ($\sigma_{\varepsilon}^{NE}$) is not separately identified from the mean utility parameters, it is normalized to a fixed value in each specification. Standard errors are reported in parentheses. Panels B-F report estimates for alternative values of $\sigma_{\varepsilon}^{NE}$.

TABLE H.1: Parameter estimates from entry model (continued)

Panel B: $\sigma_{\varepsilon}^{NE} = 2$

NAICS	Industry	α^{RE}	α^{NE}	μ_{ξ}^{NE}	σ_{ξ}^{NE}	$\sigma_{\varepsilon}^{\text{NE}}$	$\sigma_{\varepsilon}^{\text{RE}}$	β^{flood}	β^{sqft}	$\beta^{\text{chains 2-100}}$	$\beta^{\text{chains 101-1000}}$	$\beta^{\text{chains 1001+}}$
441	Auto parts	-31.20	-2.273	-6.389	1.553	2.000	13.40	90.97	-0.249	-1.202	2.082	3.226
		(10.02)	(0.370)	(0.252)	(0.186)	(–)	(4.519)	(33.89)	(0.682)	(1.236)	(2.332)	(2.614)
442	Furniture	-35.16	-2.163	-6.052	1.201	2.000	13.40	90.97	-0.249	-1.202	2.082	3.226
		(11.82)	(0.546)	(0.289)	(0.215)	(–)	(4.519)	(33.89)	(0.682)	(1.236)	(2.332)	(2.614)
443	Electronics	-52.76	-2.719	-6.023	0.954	2.000	13.40	90.97	-0.249	-1.202	2.082	3.226
		(40.79)	(1.222)	(0.522)	(0.399)	(–)	(4.519)	(33.89)	(0.682)	(1.236)	(2.332)	(2.614)
444	Building materials	-61.14	-2.860	-6.164	2.293	2.000	13.40	90.97	-0.249	-1.202	2.082	3.226
		(56.13)	(0.528)	(0.505)	(0.357)	(–)	(4.519)	(33.89)	(0.682)	(1.236)	(2.332)	(2.614)
445	Groceries	-29.10	-2.023	-6.715	2.237	2.000	13.40	90.97	-0.249	-1.202	2.082	3.226
		(9.079)	(0.213)	(0.203)	(0.146)	(–)	(4.519)	(33.89)	(0.682)	(1.236)	(2.332)	(2.614)
446	Pharmacy	-32.21	-3.074	-6.138	1.622	2.000	13.40	90.97	-0.249	-1.202	2.082	3.226
		(9.992)	(0.386)	(0.270)	(0.195)	(–)	(4.519)	(33.89)	(0.682)	(1.236)	(2.332)	(2.614)
447	Gasoline	-37.34	-1.997	-6.635	1.749	2.000	13.40	90.97	-0.249	-1.202	2.082	3.226
		(12.20)	(0.322)	(0.248)	(0.183)	(–)	(4.519)	(33.89)	(0.682)	(1.236)	(2.332)	(2.614)
448	Clothing	-34.57	-1.859	-6.544	1.967	2.000	13.40	90.97	-0.249	-1.202	2.082	3.226
		(10.66)	(0.227)	(0.191)	(0.138)	(–)	(4.519)	(33.89)	(0.682)	(1.236)	(2.332)	(2.614)
451	Sporting goods	-33.40	-2.504	-6.413	1.659	2.000	13.40	90.97	-0.249	-1.202	2.082	3.226
		(10.77)	(0.379)	(0.274)	(0.202)	(–)	(4.519)	(33.89)	(0.682)	(1.236)	(2.332)	(2.614)
452	Gen. Merch.	-29.33	-1.892	-6.160	1.706	2.000	13.40	90.97	-0.249	-1.202	2.082	3.226
		(9.961)	(0.395)	(0.290)	(0.210)	(–)	(4.519)	(33.89)	(0.682)	(1.236)	(2.332)	(2.614)
453	Misc. retail	-33.16	-2.832	-6.420	1.606	2.000	13.40	90.97	-0.249	-1.202	2.082	3.226
		(10.13)	(0.203)	(0.143)	(0.106)	(–)	(4.519)	(33.89)	(0.682)	(1.236)	(2.332)	(2.614)
722	Restaurants	-24.98	-1.703	-7.197	2.234	2.000	13.40	90.97	-0.249	-1.202	2.082	3.226
		(7.935)	(0.113)	(0.076)	(0.055)	(–)	(4.519)	(33.89)	(0.682)	(1.236)	(2.332)	(2.614)

Notes: This table replicates the results from Table H.1 assuming a normalization of $\sigma_{\varepsilon}^{NE} = 2$. All other estimation procedures and data remain identical.

TABLE H.1: Parameter estimates from entry model (continued)

Panel C: $\sigma_{\varepsilon}^{NE} = 3$

NAICS	Industry	α^{RE}	α^{NE}	μ_{ξ}^{NE}	σ_{ξ}^{NE}	$\sigma_{\varepsilon}^{\text{NE}}$	$\sigma_{\varepsilon}^{\text{RE}}$	β^{flood}	β^{sqft}	$\beta^{\text{chains 2-100}}$	$\beta^{\text{chains 101-1000}}$	$\beta^{\text{chains 1001+}}$
441	Auto parts	-33.58	-2.167	-6.289	1.657	3.000	14.29	96.05	-0.333	-1.288	2.274	3.574
		(12.12)	(0.558)	(0.275)	(0.211)	(–)	(5.485)	(39.55)	(0.724)	(1.332)	(2.569)	(2.957)
442	Furniture	-37.71	-2.092	-5.979	1.271	3.000	14.29	96.05	-0.333	-1.288	2.274	3.574
		(14.13)	(0.821)	(0.314)	(0.241)	(–)	(5.485)	(39.55)	(0.724)	(1.332)	(2.569)	(2.957)
443	Electronics	-56.57	-2.654	-5.977	1.004	3.000	14.29	96.05	-0.333	-1.288	2.274	3.574
		(44.59)	(1.839)	(0.564)	(0.445)	(–)	(5.485)	(39.55)	(0.724)	(1.332)	(2.569)	(2.957)
444	Building materials	-67.18	-2.676	-6.005	2.423	3.000	14.29	96.05	-0.333	-1.288	2.274	3.574
		(74.03)	(0.786)	(0.546)	(0.393)	(–)	(5.485)	(39.55)	(0.724)	(1.332)	(2.569)	(2.957)
445	Groceries	-31.36	-1.903	-6.564	2.382	3.000	14.29	96.05	-0.333	-1.288	2.274	3.574
		(11.01)	(0.320)	(0.221)	(0.163)	(–)	(5.485)	(39.55)	(0.724)	(1.332)	(2.569)	(2.957)
446	Pharmacy	-34.56	-2.942	-6.029	1.725	3.000	14.29	96.05	-0.333	-1.288	2.274	3.574
		(12.10)	(0.579)	(0.294)	(0.220)	(–)	(5.485)	(39.55)	(0.724)	(1.332)	(2.569)	(2.957)
447	Gasoline	-40.65	-1.888	-6.524	1.872	3.000	14.29	96.05	-0.333	-1.288	2.274	3.574
		(15.08)	(0.487)	(0.271)	(0.207)	(–)	(5.485)	(39.55)	(0.724)	(1.332)	(2.569)	(2.957)
448	Clothing	-37.19	-1.773	-6.414	2.095	3.000	14.29	96.05	-0.333	-1.288	2.274	3.574
		(13.03)	(0.341)	(0.208)	(0.155)	(–)	(5.485)	(39.55)	(0.724)	(1.332)	(2.569)	(2.957)
451	Sporting goods	-36.04	-2.390	-6.302	1.770	3.000	14.29	96.05	-0.333	-1.288	2.274	3.574
		(13.11)	(0.572)	(0.300)	(0.228)	(–)	(5.485)	(39.55)	(0.724)	(1.332)	(2.569)	(2.957)
452	Gen. Merch.	-31.75	-1.752	-6.046	1.811	3.000	14.29	96.05	-0.333	-1.288	2.274	3.574
		(11.96)	(0.594)	(0.316)	(0.235)	(–)	(5.485)	(39.55)	(0.724)	(1.332)	(2.569)	(2.957)
453	Misc. retail	-35.52	-2.733	-6.318	1.714	3.000	14.29	96.05	-0.333	-1.288	2.274	3.574
		(12.31)	(0.307)	(0.157)	(0.120)	(–)	(5.485)	(39.55)	(0.724)	(1.332)	(2.569)	(2.957)
722	Restaurants	-27.20	-1.858	-7.053	2.393	3.000	14.29	96.05	-0.333	-1.288	2.274	3.574
		(9.559)	(0.161)	(0.083)	(0.062)	(–)	(5.485)	(39.55)	(0.724)	(1.332)	(2.569)	(2.957)

Notes: This table replicates the results from Table H.1 assuming a normalization of $\sigma_{\varepsilon}^{NE} = 3$. All other estimation procedures and data remain identical.

TABLE H.1: Parameter estimates from entry model (continued)

Panel D: $\sigma_{\varepsilon}^{NE} = 4$

NAICS	Industry	α^{RE}	α^{NE}	μ_{ξ}^{NE}	σ_{ξ}^{NE}	$\sigma_{\varepsilon}^{\text{NE}}$	$\sigma_{\varepsilon}^{\text{RE}}$	β^{flood}	β^{sqft}	$\beta^{\text{chains 2-100}}$	$\beta^{\text{chains 101-1000}}$	$\beta^{\text{chains 1001+}}$
441	Auto parts	-30.60	-2.103	-6.223	1.728	4.000	13.01	86.82	-0.264	-1.204	1.868	3.111
		(9.449)	(0.748)	(0.292)	(0.230)	(–)	(4.153)	(30.69)	(0.662)	(1.201)	(2.188)	(2.500)
442	Furniture	-34.27	-2.048	-5.934	1.317	4.000	13.01	86.82	-0.264	-1.204	1.868	3.111
		(11.05)	(1.097)	(0.331)	(0.261)	(–)	(4.153)	(30.69)	(0.662)	(1.201)	(2.188)	(2.500)
443	Electronics	-51.44	-2.625	-5.946	1.034	4.000	13.01	86.82	-0.264	-1.204	1.868	3.111
		(39.25)	(2.459)	(0.591)	(0.475)	(–)	(4.153)	(30.69)	(0.662)	(1.201)	(2.188)	(2.500)
444	Building materials	-58.13	-2.544	-5.881	2.524	4.000	13.01	86.82	-0.264	-1.204	1.868	3.111
		(44.88)	(1.045)	(0.579)	(0.424)	(–)	(4.153)	(30.69)	(0.662)	(1.201)	(2.188)	(2.500)
445	Groceries	-28.68	-1.832	-6.455	2.495	4.000	13.01	86.82	-0.264	-1.204	1.868	3.111
		(8.571)	(0.428)	(0.235)	(0.178)	(–)	(4.153)	(30.69)	(0.662)	(1.201)	(2.188)	(2.500)
446	Pharmacy	-31.55	-2.858	-5.956	1.794	4.000	13.01	86.82	-0.264	-1.204	1.868	3.111
		(9.378)	(0.774)	(0.312)	(0.238)	(–)	(4.153)	(30.69)	(0.662)	(1.201)	(2.188)	(2.500)
447	Gasoline	-37.23	-1.821	-6.446	1.959	4.000	13.01	86.82	-0.264	-1.204	1.868	3.111
		(11.88)	(0.654)	(0.289)	(0.226)	(–)	(4.153)	(30.69)	(0.662)	(1.201)	(2.188)	(2.500)
448	Clothing	-33.99	-1.727	-6.322	2.191	4.000	13.01	86.82	-0.264	-1.204	1.868	3.111
		(9.995)	(0.456)	(0.221)	(0.169)	(–)	(4.153)	(30.69)	(0.662)	(1.201)	(2.188)	(2.500)
451	Sporting goods	-32.82	-2.315	-6.228	1.848	4.000	13.01	86.82	-0.264	-1.204	1.868	3.111
		(10.18)	(0.766)	(0.319)	(0.248)	(–)	(4.153)	(30.69)	(0.662)	(1.201)	(2.188)	(2.500)
452	Gen. Merch.	-28.89	-1.662	-5.966	1.887	4.000	13.01	86.82	-0.264	-1.204	1.868	3.111
		(9.495)	(0.793)	(0.336)	(0.255)	(–)	(4.153)	(30.69)	(0.662)	(1.201)	(2.188)	(2.500)
453	Misc. retail	-32.44	-2.667	-6.247	1.789	4.000	13.01	86.82	-0.264	-1.204	1.868	3.111
		(9.460)	(0.411)	(0.167)	(0.130)	(–)	(4.153)	(30.69)	(0.662)	(1.201)	(2.188)	(2.500)
722	Restaurants	-25.10	-2.005	-6.948	2.516	4.000	13.01	86.82	-0.264	-1.204	1.868	3.111
		(7.510)	(0.206)	(0.088)	(0.068)	(–)	(4.153)	(30.69)	(0.662)	(1.201)	(2.188)	(2.500)

Notes: This table replicates the results from Table H.1 assuming a normalization of $\sigma_{\varepsilon}^{NE} = 4$. All other estimation procedures and data remain identical.

TABLE H.1: Parameter estimates from entry model (continued)

Panel E: $\sigma_{\varepsilon}^{NE} = 5$

NAICS	Industry	α^{RE}	α^{NE}	μ_{ξ}^{NE}	σ_{ξ}^{NE}	$\sigma_{\varepsilon}^{\text{NE}}$	$\sigma_{\varepsilon}^{\text{RE}}$	β^{flood}	β^{sqft}	$\beta^{\text{chains 2-100}}$	$\beta^{\text{chains 101-1000}}$	$\beta^{\text{chains 1001+}}$
441	Auto parts	-32.54	-2.048	-6.174	1.781	5.000	13.77	92.03	-0.331	-1.260	2.141	3.369
		(11.03)	(0.938)	(0.306)	(0.245)	(–)	(4.897)	(35.47)	(0.698)	(1.278)	(2.418)	(2.749)
442	Furniture	-36.55	-2.002	-5.904	1.350	5.000	13.77	92.03	-0.331	-1.260	2.141	3.369
		(12.90)	(1.374)	(0.344)	(0.276)	(–)	(4.897)	(35.47)	(0.698)	(1.278)	(2.418)	(2.749)
443	Electronics	-54.01	-2.475	-5.924	1.059	5.000	13.77	92.03	-0.331	-1.260	2.141	3.369
		(39.89)	(3.080)	(0.614)	(0.502)	(–)	(4.897)	(35.47)	(0.698)	(1.278)	(2.418)	(2.749)
444	Building materials	-63.46	-2.433	-5.790	2.609	5.000	13.77	92.03	-0.331	-1.260	2.141	3.369
		(58.89)	(1.305)	(0.608)	(0.453)	(–)	(4.897)	(35.47)	(0.698)	(1.278)	(2.418)	(2.749)
445	Groceries	-30.51	-1.785	-6.373	2.582	5.000	13.77	92.03	-0.331	-1.260	2.141	3.369
		(10.01)	(0.537)	(0.247)	(0.190)	(–)	(4.897)	(35.47)	(0.698)	(1.278)	(2.418)	(2.749)
446	Pharmacy	-33.54	-2.798	-5.902	1.847	5.000	13.77	92.03	-0.331	-1.260	2.141	3.369
		(11.01)	(0.969)	(0.326)	(0.253)	(–)	(4.897)	(35.47)	(0.698)	(1.278)	(2.418)	(2.749)
447	Gasoline	-39.49	-1.767	-6.388	2.025	5.000	13.77	92.03	-0.331	-1.260	2.141	3.369
		(13.79)	(0.821)	(0.303)	(0.243)	(–)	(4.897)	(35.47)	(0.698)	(1.278)	(2.418)	(2.749)
448	Clothing	-36.18	-1.659	-6.254	2.264	5.000	13.77	92.03	-0.331	-1.260	2.141	3.369
		(11.83)	(0.570)	(0.232)	(0.181)	(–)	(4.897)	(35.47)	(0.698)	(1.278)	(2.418)	(2.749)
451	Sporting goods	-34.87	-2.265	-6.170	1.908	5.000	13.77	92.03	-0.331	-1.260	2.141	3.369
		(11.88)	(0.961)	(0.335)	(0.265)	(–)	(4.897)	(35.47)	(0.698)	(1.278)	(2.418)	(2.749)
452	Gen. Merch.	-30.67	-1.601	-5.914	1.941	5.000	13.77	92.03	-0.331	-1.260	2.141	3.369
		(10.89)	(0.993)	(0.350)	(0.271)	(–)	(4.897)	(35.47)	(0.698)	(1.278)	(2.418)	(2.749)
453	Misc. retail	-34.50	-2.632	-6.198	1.844	5.000	13.77	92.03	-0.331	-1.260	2.141	3.369
		(11.17)	(0.516)	(0.174)	(0.139)	(–)	(4.897)	(35.47)	(0.698)	(1.278)	(2.418)	(2.749)
722	Restaurants	-26.91	-2.135	-6.868	2.612	5.000	13.77	92.03	-0.331	-1.260	2.141	3.369
		(8.755)	(0.250)	(0.093)	(0.073)	(–)	(4.897)	(35.47)	(0.698)	(1.278)	(2.418)	(2.749)

Notes: This table replicates the results from Table H.1 assuming a normalization of $\sigma_{\varepsilon}^{NE} = 5$. All other estimation procedures and data remain identical.

TABLE H.1: Parameter estimates from entry model (continued)

Panel F: $\sigma_\varepsilon^{NE} = 10$

NAICS	Industry	α^{RE}	α^{NE}	μ_ξ^{NE}	σ_ξ^{NE}	$\sigma_\varepsilon^{\text{NE}}$	$\sigma_\varepsilon^{\text{RE}}$	β^{flood}	β^{sqft}	$\beta^{\text{chains 2-100}}$	$\beta^{\text{chains 101-1000}}$	$\beta^{\text{chains 1001+}}$
441	Auto parts	-31.44	-1.935	-6.058	1.912	10.00	13.46	90.85	-0.260	-1.227	2.028	3.280
		(10.18)	(1.896)	(0.342)	(0.287)	(–)	(4.582)	(33.97)	(0.685)	(1.245)	(2.320)	(2.652)
442	Furniture	-35.28	-1.926	-5.831	1.423	10.00	13.46	90.85	-0.260	-1.227	2.028	3.280
		(11.92)	(2.767)	(0.376)	(0.312)	(–)	(4.582)	(33.97)	(0.685)	(1.245)	(2.320)	(2.652)
443	Electronics	-53.00	-2.466	-5.881	1.104	10.00	13.46	90.85	-0.260	-1.227	2.028	3.280
		(40.78)	(6.200)	(0.659)	(0.554)	(–)	(4.582)	(33.97)	(0.685)	(1.245)	(2.320)	(2.652)
444	Building materials	-61.37	-2.232	-5.567	2.824	10.00	13.46	90.85	-0.260	-1.227	2.028	3.280
		(55.14)	(2.620)	(0.688)	(0.538)	(–)	(4.582)	(33.97)	(0.685)	(1.245)	(2.320)	(2.652)
445	Groceries	-29.65	-1.683	-6.148	2.825	10.00	13.46	90.85	-0.260	-1.227	2.028	3.280
		(9.246)	(1.084)	(0.283)	(0.230)	(–)	(4.582)	(33.97)	(0.685)	(1.245)	(2.320)	(2.652)
446	Pharmacy	-32.47	-2.663	-5.775	1.978	10.00	13.46	90.85	-0.260	-1.227	2.028	3.280
		(10.16)	(1.949)	(0.364)	(0.296)	(–)	(4.582)	(33.97)	(0.685)	(1.245)	(2.320)	(2.652)
447	Gasoline	-38.15	-1.650	-6.243	2.193	10.00	13.46	90.85	-0.260	-1.227	2.028	3.280
		(12.71)	(1.664)	(0.342)	(0.289)	(–)	(4.582)	(33.97)	(0.685)	(1.245)	(2.320)	(2.652)
448	Clothing	-35.05	-1.566	-6.072	2.461	10.00	13.46	90.85	-0.260	-1.227	2.028	3.280
		(10.84)	(1.149)	(0.263)	(0.217)	(–)	(4.582)	(33.97)	(0.685)	(1.245)	(2.320)	(2.652)
451	Sporting goods	-33.78	-2.128	-6.041	2.053	10.00	13.46	90.85	-0.260	-1.227	2.028	3.280
		(11.00)	(1.941)	(0.375)	(0.313)	(–)	(4.582)	(33.97)	(0.685)	(1.245)	(2.320)	(2.652)
452	Gen. Merch.	-29.68	-1.449	-5.770	2.085	10.00	13.46	90.85	-0.260	-1.227	2.028	3.280
		(10.16)	(1.998)	(0.392)	(0.318)	(–)	(4.582)	(33.97)	(0.685)	(1.245)	(2.320)	(2.652)
453	Misc. retail	-33.38	-2.517	-6.072	1.985	10.00	13.46	90.85	-0.260	-1.227	2.028	3.280
		(10.26)	(1.044)	(0.195)	(0.164)	(–)	(4.582)	(33.97)	(0.685)	(1.245)	(2.320)	(2.652)
722	Restaurants	-26.51	-2.481	-6.646	2.879	10.00	13.46	90.85	-0.260	-1.227	2.028	3.280
		(8.060)	(0.450)	(0.107)	(0.090)	(–)	(4.582)	(33.97)	(0.685)	(1.245)	(2.320)	(2.652)

Notes: This table replicates the results from Table H.1 assuming a normalization of $\sigma_\varepsilon^{NE} = 10$. All other estimation procedures and data remain identical.

I Cost-benefit analysis of aid: Further details

I.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 Supplemental 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 reported in the BLS data and that the previous year was full employment. Denoting ww as the weekly wages for an individual, the weekly benefit amount wb and maximum UI benefits mb are calculated as:

$$wb = \max\{67, \min\{494, ww \cdot 13/25\}\} \tag{16}$$

$$mb = \min\{26 \cdot wb,\ 0.27 \cdot 13 \cdot ww\} \tag{17}$$

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

TABLE I.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 closed 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 I.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.