

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

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Abstract

We examine how adverse shocks impact firm dynamics and consumer welfare, using Hurricane Harvey as a case study. Based on data for consumer purchases in 12 large store categories, we estimate consumer demand and show that exiting stores contribute 43 percent less to consumer surplus than entrants and 55 percent less than surviving incumbents. Despite this, some exiting businesses provide significant welfare gains; but entry often occurs far from the most affected neighborhoods, leading to substantial localized welfare losses. Counterfactual simulations reveal that subsidizing all damaged businesses is inefficient, with costs outweighing consumer benefits, but targeted aid can deliver substantial net gains.

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1 Introduction

Negative economic shocks, such as recessions, natural disasters, and 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 makes new firms 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 struck the Gulf Coast in 2017. Harvey created an ideal laboratory to study these issues; it caused over \$125B in damage (National Hurricane Center, 2018), with substantial heterogeneity over space, resulting in wide variation in impact across firms. Additionally, 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 research area 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).

Our contributions are threefold. First, we document the entry and exit process after a large natural disaster and quantify its welfare impacts for consumers. We find that exiting establishments are, on average, worth less to consumers than both surviving incumbents and new entrants. Second, we show that modest aggregate effects can mask large distributional ones, primarily because entry and exit happen in different locations. This pattern results in welfare losses concentrated in neighborhoods with higher flooding exposure and lower income, providing evidence that large shocks can widen welfare inequality. Third, we examine the design of disaster aid for damaged stores. We show that blanket grant-based aid programs that compensate businesses for disaster damage are generally inefficient, as few damaged

¹Scarring mechanisms, such as 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).

businesses contribute more to welfare than the cost of the damage they suffered. However, we also show that programs that target aid based on business characteristics that are observable to policymakers at the time of a natural disaster can generate substantial welfare gains.

To quantify how Hurricane Harvey impacted store 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 enables 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 aid program on reentry 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 Harvey’s impact on local retail establishments and consumers. A unique strength of our dataset 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 the storm caused a large fraction of exits. Overall, we find that about 1.2 percent of stores (390 stores) exited permanently in the month after Harvey’s landing and 2.8 percent of stores (863) closed temporarily for two months or more.² We find that exits were geographically concentrated, with 7 percent of the Census tracts accounting for nearly 40 percent of permanent closures despite containing just 4 percent 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 such closures. Further, consumers may benefit if higher-value entrants replace low-value options. We identify 1,109 entrants (3.6 percent 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

²The monthly baseline exit rate was 0.16 percent 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.

³A third channel through which natural disasters may impact consumers is through changes in retail

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 percent. This increase in distance traveled was driven by transactions at the same chain as the closure, where distance traveled increased by about 50 percent, 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

We use the demand model to quantify each store’s contribution to consumer welfare. We find that the median exiting establishment would create about \$68,000 of surplus over the 16-month post-storm period, relative to \$119,000 for the median entrant and \$152,000 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; for example, the 90th percentile exiting store creates nearly \$900,000 in surplus over the same period.

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 impact of entry and exit. We find that welfare impacts are highly heterogeneous across Census tracts, with some neighborhoods experiencing no welfare loss and others losing nearly 10 percent of pre-storm consumption through December 2018. Although new entry provides significant welfare benefits, entrants tend to locate far from the hardest-hit areas, leaving consumers in these neighborhoods with large welfare losses.

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 lowest-income quintile of tracts suffered larger welfare losses than the highest quintile in each MSA, with the gap ranging from roughly 25 percent in Beaumont to seven-fold in Corpus Christi. This differential impact is driven partially by more limited access to retail options in low-income neighborhoods than in higher-income ones, increasing the welfare

prices. In Supplemental Appendix D, we show that Hurricane Harvey did not cause medium- to long-term price changes.

⁴Our 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 percent of brick-and-mortar payment card spending.

⁵In comparison, median store revenues over 16 months would be about \$264,000 for post-storm exiting stores, relative to \$557,000 for entrants and \$693,000 for surviving incumbents.

impact of closures. Our findings highlight the potential for shocks to disproportionately impact smaller and lower-income neighborhoods.

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 reentry decision for stores that closed temporarily after the storm. The model exploits the relationship between reentry decisions and monetized storm damage, which we measure 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 causes 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 18 percent 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 aid program. Under perfect targeting—where policymakers can identify establishments with positive net value—each dollar of aid generates \$2.48 in benefits. Under a feasible alternative where targeting is based on observable characteristics, a policymaker achieves about 76 percent of this gain, equivalent to \$1.88 per dollar spent.

Overall, our results illustrate that many of the stores that closed after Harvey have only 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 larger than aid costs, implying targeted subsidies could create substantial welfare gains.

1.1 Related literature

Our paper relates to a large literature on measuring the welfare effects and distributional consequences of changes in retail environments. For example, Cao et al. (2024) examines the impact of entry of dollar and discount stores, while Allcott et al. (2019a) focuses on the impact of food deserts. Other examples include Allcott et al. (2019b), Cao (2023), Dolfen et al. (2023), Dubois et al. (2014, 2020), Handbury (2021), Handbury and Moshary (2021), and Klopach (2024). We contribute to this literature by studying how a large and spatially concentrated shock to the retail environment—the exit and entry of establishments triggered by a natural disaster—affects consumer welfare. Using tools from this literature to estimate consumer demand, we show that exiting establishments contribute less to consumers on average than surviving incumbents and entrants, and that the resulting welfare losses fall disproportionately on the hardest-hit and lower-income neighborhoods.

Our work is also 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. Some 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). While this literature studies turnover through the lens of firm productivity, we measure its consequences for consumers, applying the distinction between cleansing and scarring to consumer welfare. We find a partial cleansing effect in the aggregate, but localized scarring in the hardest-hit neighborhoods.

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), for example, 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. To our knowledge, ours is the first paper to study the consumer welfare consequences of firm turnover following a natural disaster. Our work complements Collier et al. (2024) in that we also estimate the effectiveness of aid for firms; but we adopt a distinct modeling approach by focusing on the relationship between establishments’ exit decisions and a monetized measure

⁶Other 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).

of storm damage, and we explicitly account for how aid to damaged stores may crowd out new entry.

Finally, our paper relates to the literature on the optimal allocation of aid resources, including Brown et al. (2018), Gordon et al. (2023), and Fu and Gregory (2019). We contribute to this literature by showing that the welfare impact of business aid hinges on how well policymakers can target the most valuable establishments: a blanket program that compensates all damaged businesses is generally inefficient, but a program that targets aid using characteristics observable to policymakers at the time of the disaster realizes about three-quarters of the gains available under perfect, but infeasible, targeting.

2 Background

Hurricane Harvey made landfall in Texas on August 25, 2017, producing the highest recorded rainfall event in U.S. history (NOAA, 2022, National Weather Service, 2017). Harvey provides a useful research setting because flooding was largely unanticipated—the majority of flooded structures were outside the pre-storm FEMA 100-year flood plain, and observable characteristics (e.g., geospatial and socio-demographic characteristics) explain only 7 percent of the variation in flooding across Census blocks (Billings et al., 2022). Moreover, there was little outmigration or change in post-storm consumption (Supplemental Appendix E), so we interpret Harvey as a temporary shock to supply infrastructure rather than 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 annually on average since 2010 (NOAA, 2022), with hurricanes accounting for a large, growing fraction of that figure (rising from 21 percent in the 1980s to 54 percent 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 can firms access to respond to natural disasters? The primary federal aid channels, SBA disaster loans and HUD CDBG-DR grants, reach relatively few affected firms: many firms do not apply, so as to avoid taking on additional debt, and SBA has historically approved only 40 percent of applications (Collier et al., 2022b), and CDBG-DR grants are often disbursed years after the disaster (Jaroscak, 2020, Gimont, 2022).⁷ Private insurance plays a minor role: only 15 percent of firms affected by Harvey used it to cover

⁷For 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).

losses (Collier et al., 2022b). These limitations motivate our analysis of a more generous aid program.

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, then 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).

Credit and debit transaction data. Our primary data source on local stores and consumer purchases is provided by 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, 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 percent of credit cards (but none of the debit cards), we also observe the card’s home billing ZIP+4 location and the cardholder’s estimated income.⁸ We are unable to link multiple accounts to the same individual, and thus treat each credit account as a separate consumer. Our sample includes transactions in the Houston, Corpus Christi, and Beaumont MSAs between January 2017 and December 2018. Our analysis focuses on the transactions categorized as offline (as opposed to online transactions).

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

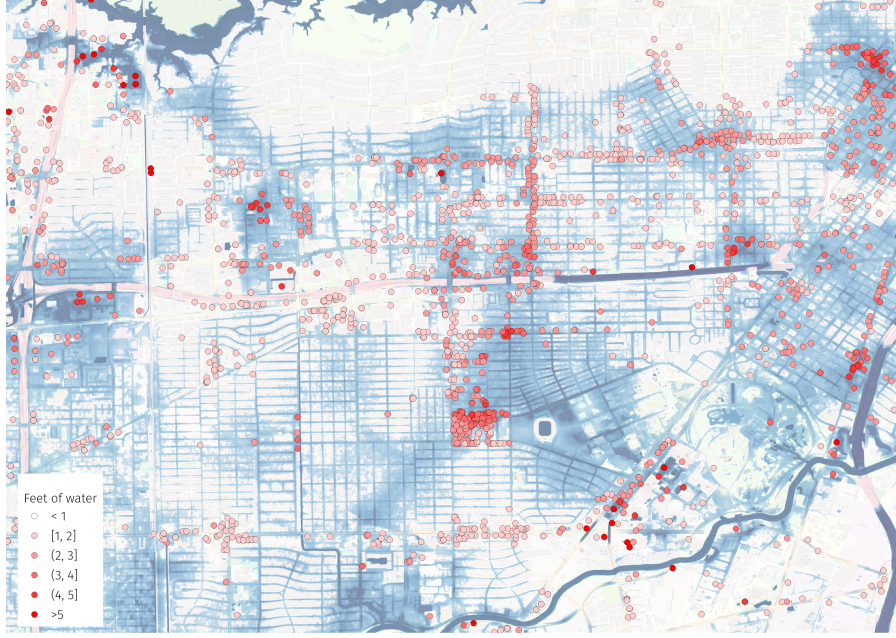


FIGURE 1: Businesses' exposure to flooding in central Houston.

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

The payment card data have two key advantages. First, our data provider covers about 20 percent of U.S. consumption and 43 percent of all retail spending in the United States, providing a significant share of economic activity across multiple categories (Dolfen et al., 2023, McCann, 2022). Second, transaction-level records with precise location and date information enable us to measure both the exact timing of closures and the spatial distribution of welfare losses across neighborhoods with different demographic profiles. Importantly, 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.

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 assesses real property at the parcel level (land and buildings) and personal property at the establishment level (e.g., inventory, equipment, vehicles, and other property owned by the retail establishment). HCAD also collects data on the square footage occupied by the business. Values of properties were assessed as of January 1st of each year, including in 2017 (pre-Harvey) and 2018 (post-Harvey). In addition, a subset of tax jurisdictions, which we refer to as “reappraisal districts,”

had real property value reassessments performed shortly after Hurricane Harvey based on surveys and inspections of damaged buildings.⁹

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 5-year 2012-2016 American Community Survey (ACS) at the census tract and block group levels, as well as 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 county-level average wages by NAICS. Fifth, we use data on Small Business Administration (SBA) loan applicants and recipients. Sixth, we use a variety of jurisdictional databases for state, county, census tract, census block group, and superneighborhood boundaries, as well as spatial Land Cover data from the National Land Cover Database. 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. Specifically, 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 code. We also use this location to define a consumer’s home Census tract.

We use the payment card data to construct several brand-level characteristics that affect a store’s demand. We count the nationwide locations with the same brand identifier to identify whether a store is part of a chain.¹⁰ 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.

⁹Reappraisals took place between September 22nd and October 16th of 2017. Source: Private communication with HCAD officials.

¹⁰The data do not allow us to distinguish between franchised and company-owned outlets.

Measuring entry and exit. We first construct a panel of stores by week in our three MSAs, subject to a modest size threshold.¹¹ 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 within one month of the hurricane. Some of these stores later reopened and resumed processing transactions; we code these as temporary closures and measure the length of closure by the number of weeks with few or no transactions.¹² 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 count it as a new entrant and record its opening date as the first week it begins processing transactions.

A key challenge is that merchant identifiers can change, generating spurious entries and exits. For this reason, we verify each entry and exit event using Yelp and Google data (e.g., checking whether the firm is marked as closed and the date of its last review). We verify 43 percent of potential exits and 35 percent of entries, and we drop unverified exits and entries. 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 722). These 12 categories account for 88 percent of offline transactions and 56 percent 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

¹¹We 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.

¹²Some stores continued to process a very small number of transactions even while closed (possibly due to offline transactions being misclassified as online). We count a store as open in a given week if, in that week, it recorded at least 10 percent of its average pre-Harvey transaction volume.

of long-term and permanent closures than Beaumont and Corpus Christi. The share of stores that permanently exit varies from 1.1 percent in Houston to about 2.7 percent 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 percent, as shown in Figure 2a.¹³ A higher share of establishments closed temporarily for at least a month, ranging from 3.5 percent in Houston to 10.0 percent 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—likely because Corpus Christi experienced significant wind damage in addition to flooding, and smaller metro areas may have less resilient firms.

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 percent of the pre-storm value. The solid black line includes post-Harvey entries, and shows that the aggregate number of stores fully recovered to its pre-Harvey level by the end of 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 percent fewer stores than their pre-storm average. By the end of our sample, these areas remained about 3 percent 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 depend directly on whether a given exit is caused by

¹³Our 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 percent. 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 higher exit rate than those 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

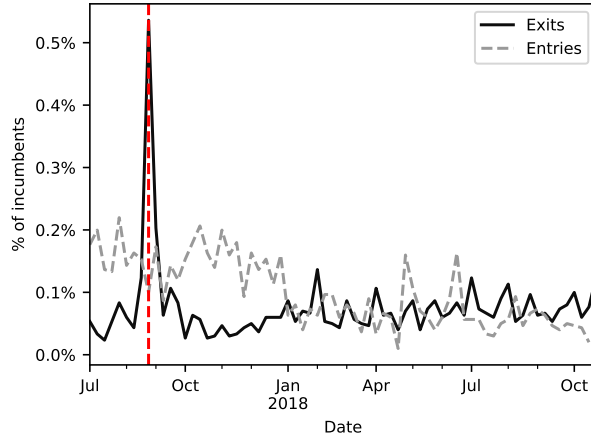
Notes: The top panel of the table shows the share of stores that closed temporarily and permanently in each of the three sample MSAs. The bottom panel shows the distribution of stores by their degree of flooding exposure, measured in feet. The table includes all stores that were active prior to Hurricane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

Harvey. We take firm turnover in the post-Harvey period as given and measure the net impact for consumers.

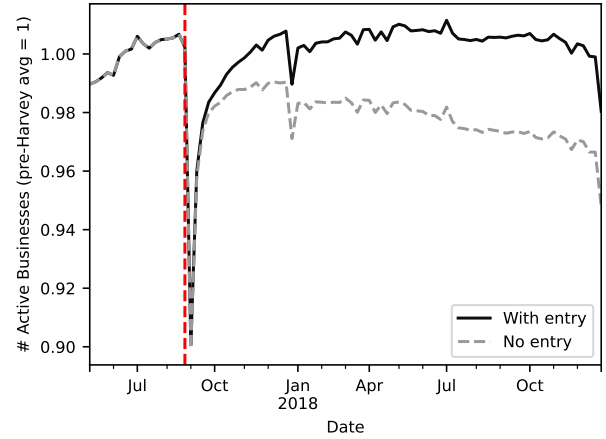
Table 2 shows the rates of temporary and permanent closures for the 12 store categories in our data, which reveal significant heterogeneity. Among these categories, gasoline stations have the fewest closures, with 91.0 percent never closing and only 0.2 percent of establishments exiting permanently. In contrast, only 81.3 percent of restaurants and 64.9 percent of clothing stores never close. Conditional on closing for at least four weeks, 35 percent of restaurants never reopen, and 17 percent of clothing stores never reopen.

4.2 New entry

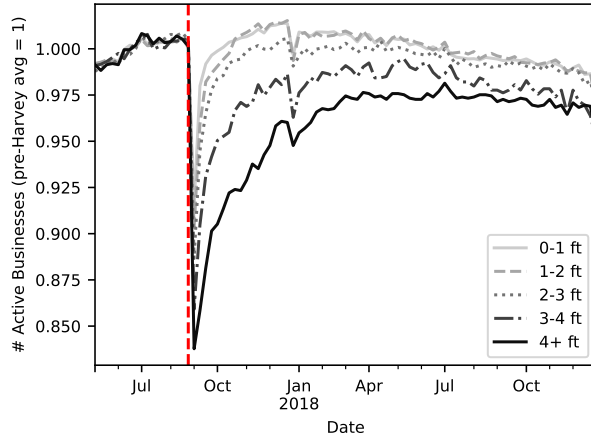
To what extent did entry replace exits? In the Houston MSA, we observe 307 permanent exits one month after Harvey and 1,006 new entrants in the 16 months after Harvey. Replacement rates were relatively lower in Beaumont and Corpus Christi, with 22 permanent exits and 37 entrants in Beaumont, and 61 permanent 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-



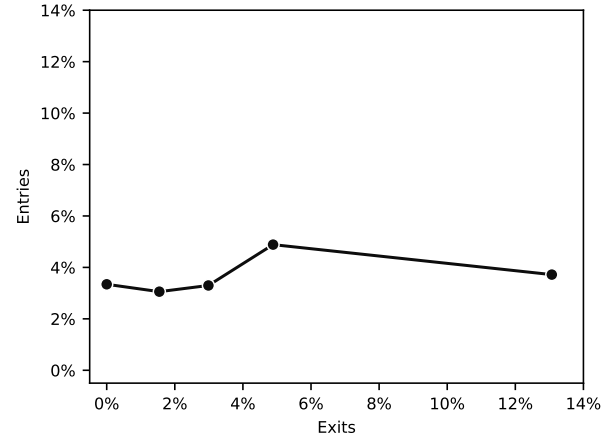
(A) Weekly exits and entries over time



(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.

Harvey, entry rates remain either slightly higher than or equal to exit rates throughout the rest of our sample period.

We find, moreover, 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

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%
Gen. Merch.	87.2%	8.4%	1.2%	2.8%	0.5%
Gasoline	91.0%	5.0%	1.3%	2.4%	0.2%
Clothing	64.9%	29.2%	2.2%	2.7%	1.0%
Hardware	79.6%	16.1%	2.9%	1.1%	0.2%
Auto parts	84.3%	12.3%	1.5%	1.5%	0.4%
Sporting Goods	69.7%	22.7%	3.0%	3.1%	1.4%
Pharmacy	78.7%	18.3%	1.0%	1.5%	0.6%
Misc. retail	70.3%	22.6%	2.7%	3.2%	1.2%
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 never. Categories are ranked by transaction volume.

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.

How did new entrants compare to incumbents? Table C.2 in Supplemental Appendix C shows the results of regressing the log of transactions on establishment characteristics and closure dummies. The table shows that relative to incumbent firms that did not close, new entrants had about 29 percent fewer transactions ($\exp(-0.347) - 1 \approx -29\%$). In contrast, exiting stores had about 44 percent fewer transactions. We find similar results when examining sales.

The pattern reported in Figure 2d implies a net decrease in the number of stores in the hardest-hit areas within our sample period. One potential impact of Hurricane Harvey is a permanent decrease in retail establishments in the most flooded areas. This could be due, for example, to updated beliefs about future flood risk or to new regulations prohibiting rebuilding in the most flooded areas. To examine this, we use a longer panel of data on establishment-level alcohol sales as a proxy for establishment activity.¹⁴ Figure C.3 shows

¹⁴Available from the Texas Comptroller of Public Accounts and previously used by Goldfarb and Xiao, 2024.

a steep post-Harvey dip in establishment presence in the most flooded areas, but the total number of establishments recovers to pre-Harvey levels by late 2019, suggesting no persistent long-run reduction in business activity in high flood-risk locations.

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 lasting 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 percent 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.¹⁵ 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 percent, while we observe no persistent change for trips to other chains. The fact that some consumers drive much farther to visit the same chain suggests that accounting for brand preferences is crucial to understanding the welfare effects of store closures, which are not captured by travel distance alone.

The increase in travel distance shown in Figure 3 is likely 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 figures also show 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.

¹⁵Following 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.

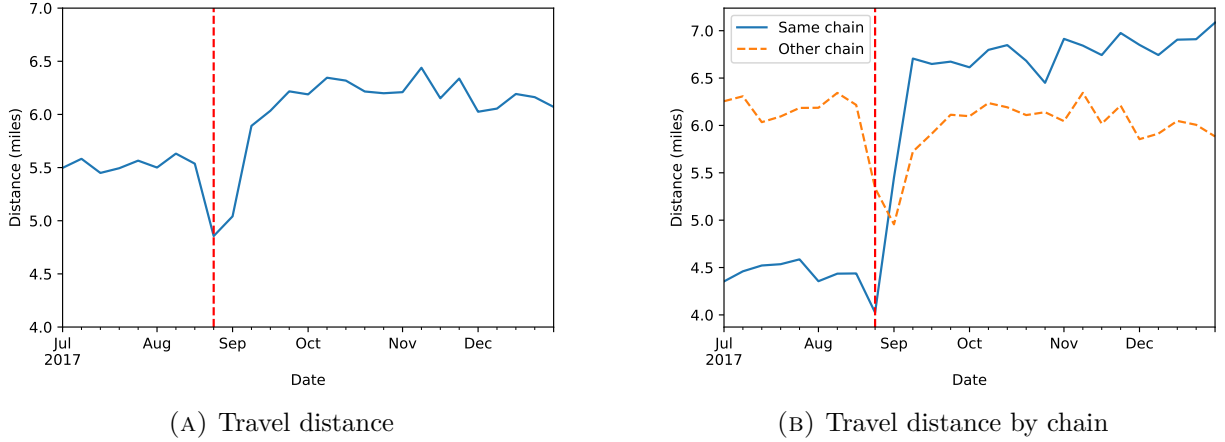


FIGURE 3: Average travel distance following store closures

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 closed either permanently or temporarily. The sample of consumers used to create this figure includes only credit cards with a valid billing ZIP+4 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.

In addition to damaging businesses, Harvey 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 those in other areas in Texas. We find no meaningful price effects other than a one-week price 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 enables 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 for purchase trip t within quarter $q(t)$ is given by:

$$u_{i(n),j,t} = x_{i(n),j} \cdot \theta_{i(n)} - \theta_{i(n)}^{dist} \cdot dist_{i(n),j} + \xi_{j,n,q(t)} + \varepsilon_{i(n),j,t} \quad (1)$$

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. $dist_{i(n),j}$ denotes the distance between consumer i ’s home (identified by the ZIP+4 code) and store j . In the vector $x_{i(n),j}$, we include a store’s consumers’ “affluence,” distance interacted with the consumer’s income, income interacted with 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:

$$\begin{pmatrix} \theta_{i(n)}^a \\ \log \theta_{i(n)}^{dist} \end{pmatrix} \sim \mathcal{N} \left[\begin{pmatrix} 0 \\ \mu_{\theta^{dist}} \end{pmatrix}, \begin{pmatrix} \sigma_{\theta^a}^2 & \rho \\ \rho & \sigma_{\theta^{dist}}^2 \end{pmatrix} \right]$$

The inclusion of $x_{i(n),j} \cdot \theta_{i(n)}$ 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 versus 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 $\xi_{j,n,q(t)}$ 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, utilizing 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.¹⁶ We compute standard errors using a block bootstrap procedure that samples consumers with replacement from each neighborhood. We report technical details of the 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+4 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, which we denote as $q = 0$. We use this sample to estimate NAICS-specific parameters θ and store-neighborhood values of $\xi_{j,n,q=0}$ for the stores open before Harvey. However, for counterfactuals, we also need measures of $\xi_{j,n,q=0}$ for new entrants. To capture these, we also estimate demand for the five post-storm quarters q after Harvey—2017Q4 to 2018Q4—where we hold estimated demand parameters θ fixed from our May-July 2017 sample but estimate new values of $\xi_{j,n,q}$ for all of the stores operating post-Harvey. We then use a linear projection based on our pre- and post-storm estimates of $\xi_{j,n,q}$ to predict what pre-storm values of $\xi_{j,n,q=0}$ would be for new entrants. We provide further details 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.2-F.3). Consistent with estimates from existing literature (Klopach, 2024, among others), we find that consumers are sensitive to distance. The average distance sensitivity conditional on income is equal to $\exp(\mu_{\theta^{dist}} + 0.5 \cdot \sigma_{\theta^{dist}}^2) - inc \cdot \theta^{inc \times dist}$, which averaged over NAICS is equal to 0.532 for the lowest income consumers and 0.521 for the highest-income consumers.¹⁷ This implies that moving a store one mile further away decreases the probability that it is chosen by 41.3

¹⁶We exclude Electronics (NAICS 443) in Corpus Christi and Beaumont because our sample contains many neighborhoods that purchase from only one or two stores.

¹⁷Consumer 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 the income variable ranges between 0 and 0.25.

percent (40.6 percent) for the lowest-income (highest-income) consumers.¹⁸

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.¹⁹ The highest-income consumer in our sample in Houston is 66.2 percent more likely to go to a store with a 90th percentile affluence level than the lowest-income consumer.²⁰ 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.²¹ 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 tend to prefer low-affluence stores, conditional on income.

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. All welfare aggregates use a weighting procedure that corrects for our sampling of cards and reweights NAICS categories so that the implied spending distribution matches that reported in U.S. Census Bureau (2017). We describe this procedure in Supplemental Appendix F.3. We measure consumer welfare associated with a specific choice set using the logit inclusive value

$$IV_{i(n)}(J_n) \equiv E \log \left(1 + \sum_{j \in J_n} \exp \left(x_{i(n),j} \cdot \theta_{i(n)} - \theta_{i(n)}^{dist} dist_{i(n),j} + \xi_{j,n,q=0} \right) \right) + C$$

¹⁸The percentage decrease in the probability of choosing store j when it moves one mile further away is $1 - \exp(-E[\theta_{i(n)}^{dist}] + inc \cdot \theta^{inc \times dist})$, which follows from the ratio of choice probabilities $P_{ijt}/P_{ij't} = \exp(E[\theta_{i(n)}^{dist}] - inc \cdot \theta^{inc \times dist})$ for identical j and j' , except that j' is one mile further away. The means of $E[\theta_{i(n)}^{dist}]$ and $\theta^{inc \times dist}$ across all Houston NAICS are 0.532 and 0.044, implying a ratio of $\exp(0.532) = 1.702$ and a percentage decrease of $1 - 1/1.702 = 41.3\%$ for a consumer with zero income, and a ratio of $\exp(0.532 - 0.044 \times 0.25) = 1.684$ and a percentage decrease of $1 - 1/1.684 = 40.6\%$ for a consumer with annual income of \$250k.

¹⁹Store affluence is top-coded at \$5,000 and divided by \$1,000, so this variable ranges between 0 and 5.

²⁰The 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 $P_{ijt}/P_{i'jt} \approx \exp(0.683 \times 0.25 \times 2.976) / \exp(0) = 1.662$.

²¹The variance of $\theta_{i(n)}^{dist}$ is $\text{Var}(\theta_{i(n)}^{dist}) = [\exp(\sigma_{\theta^{dist}}^2) - 1] \cdot \exp(2\mu_{\theta^{dist}} + \sigma_{\theta^{dist}}^2)$, which in Houston ranges between 0.054 (restaurants) and 0.706 (pharmacy).

TABLE 3: Parameter estimates from the demand model – Houston

NAICS	$\mu^{\theta^{dist}}$	$\sigma_{\theta^{dist}}^2$	$\sigma_{\theta^a}^2$	ρ	$\theta^{inc \times dist}$	$\theta^{inc \times aff}$	$\theta^{inc \times chain}$
Restaurants	-1.068 (0.007)	0.292 (0.004)	1.012 (0.006)	0.250 (0.004)	0.089 (0.009)	0.282 (0.056)	-0.532 (0.040)
Groceries	-0.653 (0.006)	0.540 (0.007)	2.208 (0.017)	0.478 (0.008)	0.096 (0.013)	0.659 (0.074)	-0.447 (0.073)
Gasoline	-0.887 (0.007)	0.760 (0.014)	2.605 (0.021)	0.859 (0.012)	0.000 (0.011)	0.274 (0.089)	-0.255 (0.138)
Gen. Merch.	-0.686 (0.006)	0.585 (0.007)	3.370 (0.025)	0.723 (0.009)	0.284 (0.009)	1.260 (0.081)	-3.793 (0.165)
Pharmacy	-0.616 (0.007)	0.758 (0.011)	3.200 (0.039)	0.866 (0.012)	0.031 (0.011)	0.324 (0.078)	-0.248 (0.102)
Clothing	-1.248 (0.011)	0.525 (0.012)	1.073 (0.010)	0.331 (0.008)	0.052 (0.008)	1.097 (0.035)	-1.580 (0.061)
Misc. retail	-1.028 (0.011)	0.840 (0.020)	1.519 (0.014)	0.443 (0.013)	-0.055 (0.012)	1.051 (0.054)	-0.262 (0.061)
Sporting Goods	-1.242 (0.011)	0.562 (0.015)	0.818 (0.010)	0.405 (0.010)	0.002 (0.009)	0.650 (0.040)	-0.872 (0.071)
Hardware	-0.840 (0.008)	0.467 (0.009)	0.863 (0.011)	0.325 (0.008)	0.037 (0.011)	0.303 (0.049)	-0.463 (0.084)
Auto parts	-1.226 (0.016)	0.761 (0.031)	0.712 (0.014)	0.348 (0.016)	-0.031 (0.012)	0.588 (0.045)	-0.375 (0.076)
Furniture	-1.207 (0.021)	0.772 (0.033)	1.120 (0.022)	0.492 (0.023)	-0.034 (0.015)	1.087 (0.063)	-0.903 (0.141)
Electronics	-1.017 (0.022)	0.743 (0.041)	2.471 (0.077)	0.809 (0.049)	0.052 (0.020)	0.622 (0.126)	-0.450 (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 1,000,000 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.2-F.3.

where $i_{(n)}$ denotes a consumer in neighborhood n , J_n is the choice set for neighborhood n , C is Euler’s constant, and the expectation is taken over the distribution of $\theta_{i_{(n)}}$ and $\theta_{i_{(n)}}^{dist}$ (McFadden, 1978). The impact in dollars of a change in choice set from J_n to $\tilde{J}_n$ is then:

$$\Delta CS_{i_{(n)}}(J_n, \tilde{J}_n) = \$3.44 \cdot \frac{1}{E[\theta_{i_{(n)}}^{dist}]} (IV_{i_{(n)}}(\tilde{J}_n) - IV_{i_{(n)}}(J_n)) \quad (2)$$

where $E[\theta_{i_{(n)}}^{dist}]$ is the (NAICS-specific) mean sensitivity to distance and \$3.44 is the cost of traveling one mile (Dolfen et al., 2023).²²

We present estimates of each store’s contribution to consumer welfare. Classical models

²²To aggregate monetized welfare across NAICS, we construct NAICS weights using U.S. Census Bureau (2017) - see Supplemental Appendix F.3.

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 $\Delta CS_j(J, \tilde{J}) = \sum_i \Delta CS_{i(n)}(J, \tilde{J})$ for each establishment j using equation 2, where we define J as the choice set excluding j and $\tilde{J}$ as the choice set including j . We sum the change in surplus consumers receive from the availability of j across all sample consumers and scale up to match aggregate retail spending from September 2017 to December 2018 (see Supplemental Appendix F.3 for details).

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 \$68,000 of consumer surplus evaluated at the post-storm choice set, compared to \$119,000 for entrants and \$152,000 for surviving incumbents. In comparison, the median of store revenues over a 16-month period is \$264,000 for post-storm exiting stores but is \$557,000 for entrants and \$693,000 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).

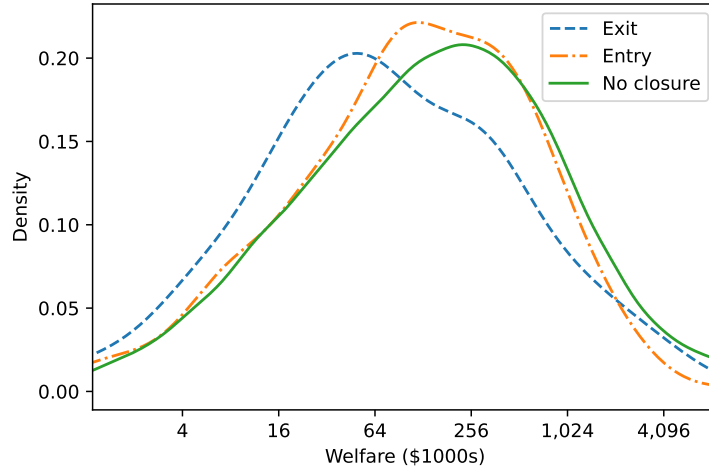


FIGURE 4: Store-level consumer welfare contribution.

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

By itself, this pattern may suggest creative destruction, whereby lower-quality establishments exit and are replaced by new, more valuable entrants, which may make consumers

better off. However, Figure 4 also shows significant dispersion in store values among the exiting group; the 90th percentile exit, for example, creates nearly \$900,000 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 results in a net increase in the number of stores in less affected areas and a net decrease in more 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.²³ Our data are well-suited to measure distributional effects, as we can compute surplus at a very fine level of aggregation (down to the consumer) across a large sample. Again, using equation 2, we compute the change in welfare for each consumer $i_{(n)}$ in each week $w(t)$ in the post-storm period, and then aggregate over time (September 2017 to December 2018). In each week, we define $\tilde{J}_{n,w}$ to be the set of stores that are open in post-storm week w (which includes entrants and incumbents that had reopened by that point) and $J_{n,w}$ to be the set of stores open prior to Harvey. Aggregate welfare effects for each week w are the sum over all individuals and all purchase events within each post-storm week w . To isolate the welfare impact of new entry, we also present a version of the calculation in which we exclude entrants from $\tilde{J}_{n,w}$. 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 0.03 percent (electronics) and 0.39 percent (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 0.21 percent, the worst hit neighborhood lost 11.72 percent. On average, across all NAICS in Houston, the estimated mean welfare loss is 0.25 percent. This represents a consumer welfare loss of approximately \$183 million between September 2017 and December 2018.

Consumer welfare losses in Corpus Christi and Beaumont are somewhat larger (as a share of expenditures) but vary significantly across NAICS. For example, the mean welfare loss for

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

restaurants was 1.53 percent in Corpus Christi and Beaumont (relative to 0.38 percent in Houston). Aggregated across NAICS, the worst-hit neighborhoods experienced particularly large welfare losses in Corpus Christi, where the maximum loss reached over 9 percent 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. 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. Beaumont had less geographic heterogeneity in welfare effects overall.

We find that welfare losses are spatially concentrated because store closures are correlated across NAICS. For example, the correlation between grocery- and restaurant-closure-driven losses is 0.70; the correlation between grocery- and general-merchandise-closure-driven losses is 0.63.

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 resilience of nearby businesses, and access to alternative stores. We compute average welfare losses by city and tract-level median income quintile, which we display in Figure 6. The figure shows that lower-income neighborhoods suffered larger impacts in all three MSAs. In a regression specification that additionally conditions on tract-level flooding exposure, NAICS fixed effects, and card-level income, we see even sharper effects of neighborhood income (Appendix Table F.4), suggesting that differential flooding exposure is not driving this result. The regression also reveals that the income gradient operates primarily through neighborhood income rather than individual cardholder income: conditional on both, the tract-level income coefficients are 2.5–4 times larger than the card-level coefficients across the three MSAs. This is consistent with welfare losses being driven by the local retail environment a consumer faces, not by the consumer’s own income. Because lower-income neighborhoods have fewer nearby retail options, each closure has a larger welfare impact—even when flooding exposure is relatively uniform across income groups.

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 $\tilde{J}_{n,w(t)}$ includes only incumbent stores (including temporary closures that reopen) and excludes new entrants. In Figure 7, we graph

TABLE 4: Distribution of welfare effects by neighborhood and NAICS

Houston					
NAICS	Avg.	P10	P50	P90	Min
Restaurants	-0.38%	-1.10%	-0.42%	0.39%	-4.31%
Groceries	-0.21%	-0.72%	-0.19%	-0.00%	-11.72%
Gen. Merch.	-0.15%	-0.57%	-0.11%	-0.02%	-2.63%
Gasoline	-0.37%	-0.76%	-0.34%	-0.08%	-4.79%
Clothing	-0.11%	-0.49%	-0.19%	0.06%	-1.96%
Hardware	-0.22%	-0.47%	-0.25%	-0.04%	-1.93%
Auto parts	-0.06%	-0.15%	-0.07%	-0.03%	-0.66%
Sporting Goods	-0.39%	-0.84%	-0.35%	-0.07%	-2.00%
Pharmacy	-0.35%	-0.50%	-0.18%	-0.02%	-18.52%
Misc. retail	-0.23%	-0.82%	-0.24%	0.06%	-2.56%
Furniture	-0.16%	-0.30%	-0.04%	-0.01%	-7.26%
Electronics	-0.03%	-0.06%	-0.01%	0.00%	-0.92%
Total	-0.25%	-0.60%	-0.26%	-0.03%	-2.68%

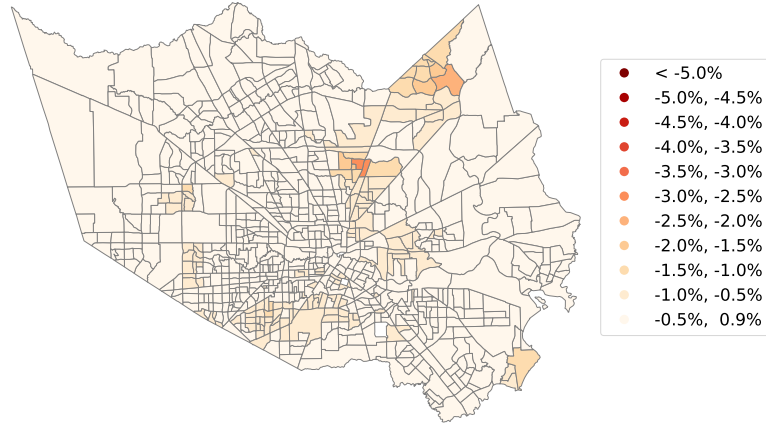
Corpus Christi					
NAICS	Avg.	P10	P50	P90	Min
Restaurants	-1.53%	-2.01%	-0.34%	0.03%	-15.89%
Groceries	-0.12%	-0.30%	-0.08%	-0.00%	-1.17%
Gen. Merch.	-0.33%	-0.60%	-0.08%	-0.04%	-2.81%
Gasoline	-2.63%	-4.26%	-1.02%	-0.35%	-28.36%
Clothing	-0.91%	-1.34%	-0.62%	-0.05%	-11.30%
Hardware	-0.37%	-0.75%	-0.06%	0.06%	-12.59%
Auto parts	-0.18%	-0.34%	-0.10%	-0.04%	-1.85%
Sporting Goods	-0.90%	-1.53%	-0.82%	-0.03%	-5.02%
Pharmacy	-1.29%	-0.61%	-0.12%	-0.03%	-33.74%
Misc. retail	-1.50%	-4.04%	-0.94%	-0.40%	-8.75%
Furniture	-0.38%	-1.03%	-0.28%	-0.05%	-3.29%
Total	-0.95%	-2.44%	-0.36%	-0.24%	-9.19%

Beaumont					
NAICS	Avg.	P10	P50	P90	Min
Restaurants	-1.53%	-2.23%	-1.46%	-0.72%	-3.71%
Groceries	-0.41%	-1.43%	-0.26%	-0.07%	-6.04%
Gen. Merch.	-0.31%	-0.67%	-0.34%	-0.17%	-2.19%
Gasoline	-0.43%	-0.86%	-0.38%	-0.12%	-2.99%
Clothing	-1.16%	-1.94%	-1.16%	-0.40%	-2.99%
Hardware	-0.19%	-0.58%	-0.16%	0.40%	-2.02%
Auto parts	-0.18%	-0.34%	-0.13%	-0.02%	-2.18%
Sporting Goods	-1.80%	-3.01%	-0.47%	-0.14%	-6.72%
Pharmacy	-0.33%	-0.87%	-0.32%	-0.11%	-1.26%
Misc. retail	-0.54%	-1.45%	-0.51%	-0.21%	-9.35%
Furniture	-0.26%	-0.63%	-0.22%	-0.02%	-1.68%
Total	-0.64%	-1.07%	-0.67%	-0.34%	-2.47%

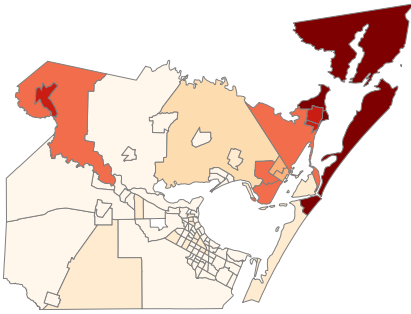
Note: The table shows the distribution of welfare effects across Census tracts by store category. We compute consumer welfare losses (as a share of spending) for each consumer and each NAICS category between September 2017 and December 2018. We then aggregate by the residential Census tract of consumers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

FIGURE 5: Distribution of aggregate welfare effects by neighborhood

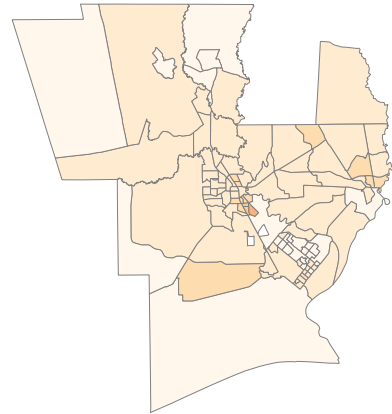
(A) Houston



(B) Corpus Christi

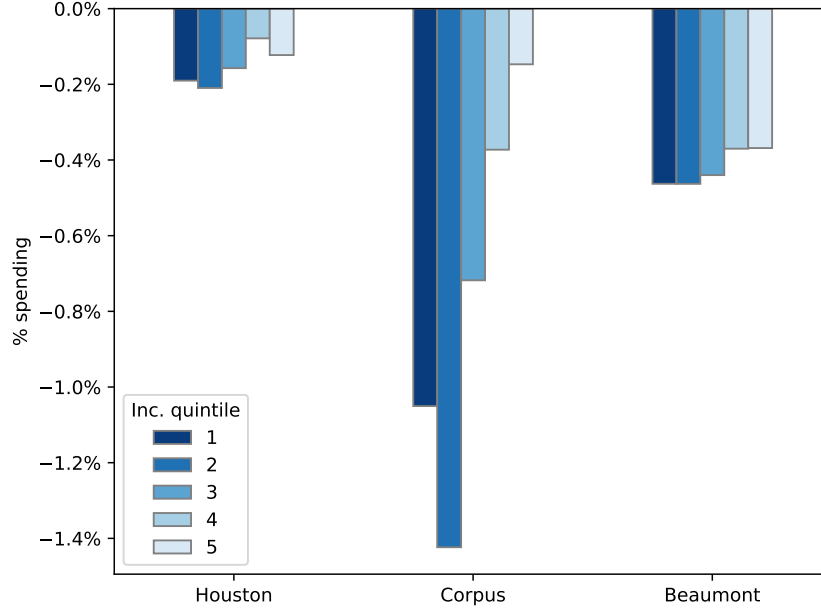


(C) Beaumont



The figure shows the percent welfare loss (as a share of spending) for each Census tract. Welfare losses are first computed for each consumer and each NAICS category between September 2017 and December 2018. We then aggregate by the residential Census tract of consumers and then by NAICS.

FIGURE 6: Welfare effects by tract-level income

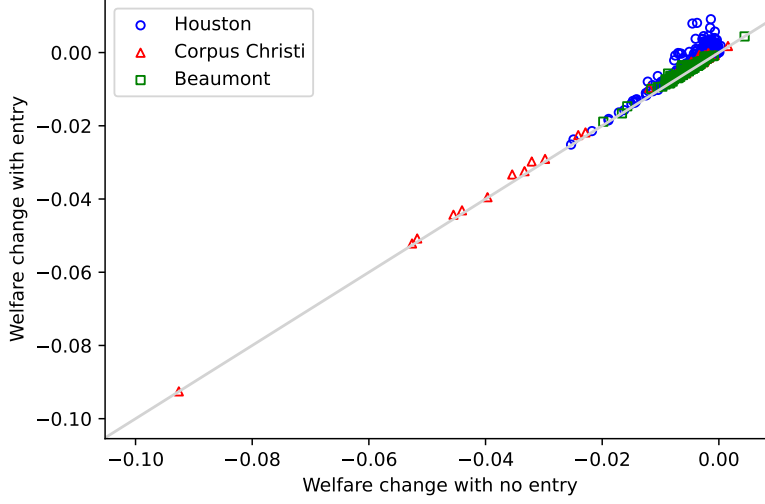


Note: The figure shows welfare losses as a share of total spending through December 2018 by quintiles of tract-level median household income for the three MSAs in our sample. To produce the figure, we compute welfare changes (net of entry) at the card-NAICS level and aggregate them by MSA and income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

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 line (in grey). However, the plot highlights the limited impact of new stores for the most affected places; in the neighborhoods with the largest welfare losses, the points lie close to the diagonal. Instead, it is the relatively less affected neighborhoods in which entry has the largest impacts. This finding is driven by the spatial mismatch between the locations of exits and entries, quantifying the impact of the pattern in Figure 2d on consumer welfare.

Finally, we examine the extent to which welfare losses are explained by changes in travel distance vs. substitution to less preferred stores. Using the estimated parameters of the model, we predict the probability that each card i will visit each store within the choice sets $J_{n,w}$ and $\tilde{J}_{n,w}$ for each post-storm week w and then use the store-card distance to compute the difference in expected travel distance between the choice sets $J_{n,w(t)}$ and $\tilde{J}_{n,w(t)}$. 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 percent 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 significantly.

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 $J_{n,w(t)}$ includes new entrants. The horizontal axis graphs the change in welfare when $J_{n,w(t)}$ does not include new entrants. Welfare losses are calculated between September 2017 and December 2018 and are aggregated across store categories.

6 Efficacy of aid and aid targeting

In the previous section, we showed that Harvey-induced store closures were geographically concentrated and were not fully replaced by new entrants, resulting in significant consumer harm. We next consider the welfare impacts of a business aid program. If private closure decisions differ from those of a social planner—for example, because of consumer surplus externalities or credit market frictions—business aid may be desirable. Whether providing such aid is justified depends on the consumer welfare benefits of the store, the 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 post-Harvey entry and reentry decisions, which we refer to as the entry model. The model uses novel property tax appraisal data from Harris County to construct a store-level measure of physical damage, and exploits the relationship between monetized damage and reentry decisions to estimate how a given dollar of aid affects the probability that a temporarily closed store reopens. We quantify the welfare benefits of aid as the change in reentry probability multiplied by the store’s consumer surplus and employment contributions.

The model also accounts for how a given dollar of aid crowds out entry of new stores. Aid is more likely to crowd out new entry when the distribution of new-entrant profits is tightly distributed around zero. In practice, we find a wide distribution of new-entrant profits,

implying quantitatively small crowd-out of new entry and that the consumer welfare impact of aid is driven primarily through increased reentry of 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. The game is played separately within each NAICS category g . To keep notation concise, we suppress NAICS subscripts throughout. We describe the key features of the model in this section, and refer the reader to Supplemental Appendix G for implementation details.

6.1.1 Model description

Let J^{RE} denote the set of temporarily closed stores that may reenter with $N^{RE} \subset J^{RE}$ the subset that choose to reenter. 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, let δ_l denote the mean utility for any store $l \in J^{RE} \cup J^{NE} \cup N^I$ and let ε_l denote the profit shock for any store $l \in J^{RE} \cup J^{NE}$.

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 reentrants) 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 reentrant mean utilities $\{\delta_m : m \in J^{RE}\}$. Each reentrant 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 reentry decisions of temporarily closed stores and the mean utilities of all incumbents (N^I) and reentrants (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 reentry decisions are made, incumbents, reentrants, 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 is large, estimating a full equilibrium entry model with the rich demand system from Section 5 is computationally infeasible. We therefore make two simplifying assumptions. First, we adopt a stylized demand environment in which consumer utility from

store j is $u_{ij} = \delta_j + \nu_{ij}$. We discipline the $\{\delta_j\}$ using the random-coefficients model that we presented above and compute each store's implied aggregate market share, and invert it to recover the 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 intensity of competition. We describe each stage of the game.

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

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

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 equation 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. Formally, B^{NE} is the expectation of the inverse market share denominator (equation 4), where ι_k indicates that potential new entrant k has positive profits. Under the oblivious equilibrium assumption, each store takes an expectation over all potential entrants' decisions (including its own) rather than internalizing its effect on the denominator. We solve for B^{NE} as a nested fixed point: given the distribution of $(\delta_k, \varepsilon_k)$, the value of B^{NE} rationalizes observed entry.

$$B^{NE} = \mathbb{E} \left[1 / \left(1 + \sum_{k \in J^{NE}} \iota_k \cdot \exp(\delta_k) + \sum_{j \in N^{RE}} \exp(\delta_j) + \sum_{l \in N^I} \exp(\delta_l) \right) \right]. \quad (4)$$

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

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

with $\log(F_j(X_j)) = \log(C_j^{RE}) - \beta X_j$, where $F(X_j)$ is the fixed cost of reentry which depends on a vector of covariates including physical damage to the building (which we discuss below), the log square footage 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 reentrants 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. B^{RE} is defined analogously as the expectation of the inverse market share denominator (equation 6), where ι_k and ι_m indicate positive profits for potential new entrants and reentrants, respectively. We apply the same oblivious equilibrium assumption and nested fixed-point approach, solving for the value of B^{RE} that rationalizes observed reentry rates.

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

6.1.2 Identification, estimation, and results

Measuring damage. Estimating the entry game requires a store-level measure of storm damage, d_j . We construct d_j by combining flood-exposure data with novel property-tax appraisal data from HCAD, the central tax authority for Harris County. After Hurricane Harvey, HCAD conducted reappraisals in a subset of tax districts during fall 2017. Properties within these districts were physically inspected and assigned new assessed values reflecting storm damage.²⁴ We therefore compute d_j as the percentage change in the establishment's building value between January 1st, 2017, and its post-Harvey reappraisal.²⁵

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

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 flood exposure (in feet of water) and building characteristics, such as building quality and type. Further details are in Supplemental Appendix H.

Figure 8a plots predicted d_j against flood exposure in a binscatter plot. The figure shows that flooding below 2.5 feet causes a drop in value of 1 percent or less, but damage increases sharply 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

²⁴12 percent of commercial properties appraised by HCAD were located in reappraisal districts. In Supplemental Appendix H.3, we show that flood exposure for properties in reappraisal and non-reappraisal districts was largely similar.

²⁵Real 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 .

change in building value, $\hat{d}_j$, as our measure of d_j when 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 joint normally:

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

Reentrant profit shocks are also distributed normally:²⁶

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

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

$$\mathbb{P}(\iota_j = 1 | \delta_j) = \Phi \left(\frac{\delta_j + \log(B^{RE}) + \alpha^{RE} + \beta X_j}{\sigma_\varepsilon^{RE}} \right) \quad (9)$$

and the probability of new entry as:

$$\mathbb{P}(\iota_k = 1 | \delta_k) = \Phi \left(\frac{\delta_k + \log(B^{NE}) + \alpha^{NE}}{\sigma_\varepsilon^{NE}} \right) \quad (10)$$

where α^{NE} and α^{RE} are intercepts and Φ is the normal cumulative distribution function. In our estimation, we allow all parameters to vary across NAICS, except for the parameter vector β , which we impose to be constant across industries. We show the full derivation and likelihood in Supplemental Appendix G.

Identification. We identify the parameters of the entry game from cross-sectional variation in entry and reentry decisions, combined with distributional assumptions and equilibrium restrictions. The probabilities specified in equations (9) and (10) correspond to standard probit specifications. For reentrants, this specification includes the mean utilities δ_j and beliefs B^{RE} (which define the expected market share), NAICS-specific intercepts α^{RE} , and X_j (e.g., storm damage d_j , store size, chain-size indicators). Beliefs B^{RE} and B^{NE} jointly rationalize entry decisions across both reentry and new entry stages. The parameter α_g^{RE} is identified by NAICS-level reentry rate conditional on beliefs and covariates, while

²⁶Reentrant mean utilities are estimated from pre-Harvey data and treated as observed, so we do not parameterize their distribution.

the vector β is identified from cross-sectional variation in those covariates X_j . Importantly, damage d_j enters exclusively through reentry costs ($X_j\beta$), but not through demand. Therefore, 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 reentry decisions.

In the case of new entrants, mean utilities δ_k are observed only 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 variance of the new-entrant profit shock σ_ε^{NE} is not separately identified. In estimation, we normalize it to different values, which we show do not materially impact our estimates.²⁷ Given this normalization and the assumed size of the potential entrant pool, the NAICS-specific intercepts α_g^{NE} are pinned down by the observed number of entrants in each NAICS.

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 Supplemental Appendix G.

First, we define the market for each NAICS category g 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, we do not observe the number of potential new entrants. 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 Supplemental Appendix G, we describe how this assumption enters the simulation routine, and assess sensitivity to alternative values.

Parameter estimates. We report the estimated parameters of the entry model in Table I.1.²⁸ Each panel in the table reports coefficients and finds that the signs of the estimated parameters are as expected: the coefficient on damage $\hat{d}_j$ is positive, implying that stores

²⁷See Supplemental Appendix I for the full set of estimates under the various values of σ_ε^{NE} .

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

with more storm damage (more negative value of $\hat{d}_j$) are less likely to reenter, while the coefficient on store size is negative, suggesting that conditional on δ_j , bigger stores are less likely to reenter, though this coefficient is insignificant.

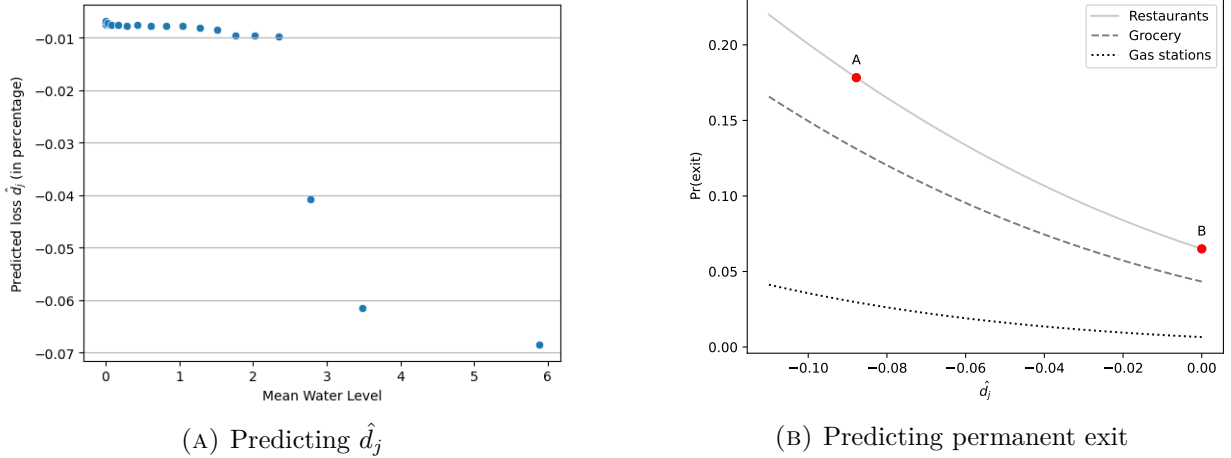


FIGURE 8: Predicting damage d_j and predicting permanent exit.

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 I.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.

In Figure 8b, we plot the implied relationship between $\hat{d}_j$ and the probability of exit using the predicted values from Table I.1 panel A for three NAICS: restaurants, grocery stores, and gas stations. Conditional on temporarily closing, the gap in exit probability between an undamaged store and one with the maximum observed damage ranges from 3 percentage points (gas stations) to 15 percentage points (restaurants), consistent with the heterogeneity across categories shown in Table 2.

Our estimates of σ_δ^{NE} determine the variance in profits for potential new entrants and therefore the extent to which greater reentry from temporarily exiting establishments will crowd out new establishment entry. Our estimates of σ_δ^{NE} are large, such that only a small fraction of potential new entrants are marginal and crowded out by the increased reentry of damaged stores in our aid counterfactuals, as we discuss below.

6.2 Cost-benefit analysis of aid

We now consider the effect of a grant-based aid program through the lens of our reentry model, first calculating the effect of aid on reentry probabilities and then comparing the expected benefits of aid to its cost.

Effect of aid on reentry 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 reverses the damage suffered by existing establishments, which increases their expected profits (Equation 5) and their probability of reentry (Equation 9). In our counterfactuals, we recompute equilibrium beliefs about the intensity of competition, B^{NE} and B^{RE} , under the different aid scenarios.

To evaluate the effect of an aid package measured in dollars, we transform the 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 the 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 the 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.²⁹ Second, we set $\kappa = 8.98$ such that a store that receives the maximum predicted real estate damage experiences a 100 percent personal property loss.

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

We show summary statistics of the different components of D_j in Supplemental Appendix Table J.1. For establishments with more than four feet of flooding exposure, the average estimated damage is approximately \$55K in our baseline case ($\kappa = 1$), where real estate damage accounts for 57 percent of that cost. If we use $\kappa = 8.98$, real estate damage accounts for 13 percent of total damage, and the average total damage is \$243K. To compute the total cost of aid, we multiply damage by 1.3 to account for the marginal cost of public funds (Poterba, 1996), resulting in an average aid cost of \$72K in the baseline scenario.

We consider a hypothetical program that gives each damaged store a grant equal to D_j , moving it to $d_j = 0$. This abstracts from several frictions we cannot model: contracting issues between establishment and building owners, liquidity constraints that may make a dollar of aid more effective than a dollar reduction in damage, and moral hazard in damage prevention. Despite these simplifications, the implied changes in reentry probabilities are consistent with quasi-experimental estimates from Collier et al. (2024).³⁰

²⁹This 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.

³⁰For establishments with more than four feet of flooding, we estimate that aid decreases average exit probability by 6.6 percentage points (relative to a base rate of 10.9 percent). Collier et al. (2024) find that

Consumer and employment benefits. We compute consumer benefits using each store’s monthly consumer surplus contribution under two scenarios for the duration of benefits. The first sums consumer surplus through December 2018 (the end of our sample) with no discounting, providing a likely lower bound as establishments persist beyond our sample period. The second sums an infinite discounted stream using a monthly discount rate of approximately 2 percent.³¹

A store that reenters also prevents job losses. We approximate employment benefits as the maximum Texas unemployment insurance payout per worker, using establishment-level employment from Data Axle and NAICS-by-county wages from the BLS. The average benefit is \$5,994 per employee.³² Further details on this calculation are in Supplemental Appendix J.1.

Results. We compare the cost of a grant equal to D_j against its expected benefit – the change in exit probability times the store’s consumer surplus and employment contributions – across four scenarios that vary the time horizon of consumer benefits (through 2018 vs. infinite discounted) and capital decay ($\kappa = 1$ vs. 8.98).

Figure 9 plots the costs and benefits of aid in our baseline scenario; establishments above the 45-degree line have benefits that exceed costs. Among stores exposed to four or more feet of water (Panel A), few businesses (29 percent of establishments) would justify an aid program based on their contribution to consumer welfare. When considering the entire sample of damaged stores, only 18 percent 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 \$18M in benefits, resulting in a net loss of \$23M. 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

receiving an SBA loan reduces an applicant firm’s exit probability in the year in which a disaster occurs by approximately 8-9 percentage points (relative to a base rate of 21 percent over the first three years after a disaster).

³¹We calibrate this discount rate to 2.1 percent, which reflects the probability of establishment survival as well as the 3 percent annual discount rate (converted to a monthly rate of 0.25 percent) 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 percent.

³²We 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).

TABLE 5: Cost-benefit analysis for establishment subsidies with targeting

	(1)	(2)	(3)	(4)
	Baseline	Variation 1	Variation 2	Variation 3
Assumptions				
Rate of capital destruction	$\kappa = 1$	$\kappa = 8.98$	$\kappa = 1$	$\kappa = 8.98$
CS benefits duration	End of 2018	End of 2018	Inf. discounted	Inf. discounted
Aid to all damaged stores				
Cost (\$M)	41.2	177.7	41.2	177.7
Benefit (\$M)	18.0	18.0	49.9	49.9
CS benefit (\$M)	14.6	14.6	46.5	46.5
# jobs	599	599	599	599
Net Value (\$M)	-23.2	-159.6	8.7	-127.8
% stores positive value	17.5%	5.5%	31.5%	16.5%
# subsidized stores	2,625	2,625	2,625	2,625
Aid only to stores with positive net value				
Cost (\$M)	4.6	2.9	11.3	11.8
Benefit (\$M)	11.4	5.8	44.0	31.8
CS benefit (\$M)	9.9	5.1	41.8	30.4
# jobs	286	135	408	274
Net Value (\$M)	6.8	2.9	32.7	20.1
% stores positive value	100.0%	100.0%	100.0%	100.0%
# subsidized stores	459	144	826	432
Aid only to stores with predicted positive net value				
Cost (\$M)	5.9	0.5	9.0	20.6
Benefit (\$M)	11.1	1.5	38.3	33.6
CS benefit (\$M)	9.6	1.5	36.3	32.0
# jobs	298	12	382	312
Net Value (\$M)	5.2	1.0	29.3	13.0
% stores positive value	66.3%	73.9%	83.2%	64.3%
# subsidized stores	489	23	792	476

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 \$5,994 per job).

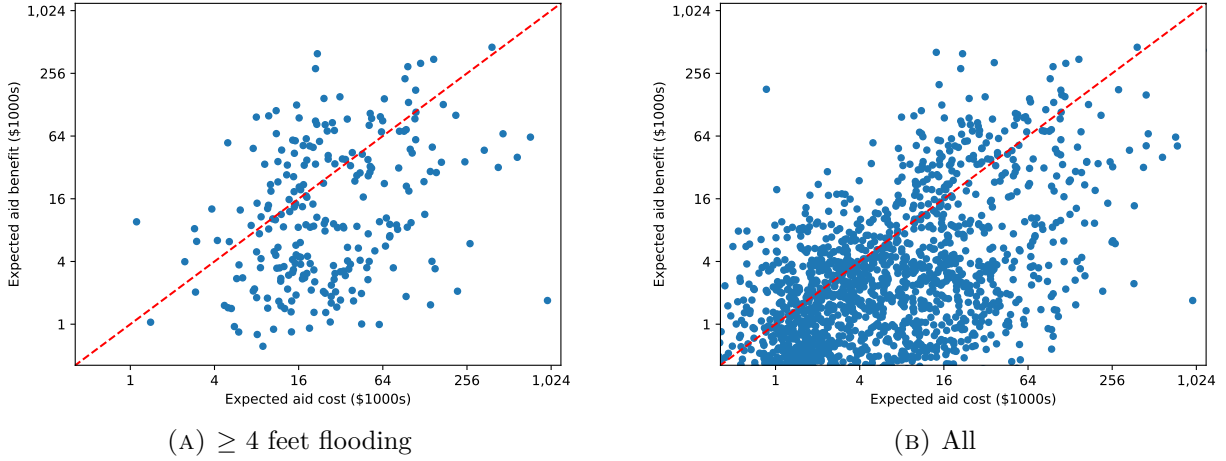


FIGURE 9: Benefits and costs of business aid

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 four or more feet of flooding; panel (B) includes all establishments.

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 0.5 establishments.³³ 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 459 establishments, costing about \$4.6M and generating about \$11.4M in expected benefits (\$2.48 per dollar of aid), resulting in a net gain of about \$6.8M. The net value is positive by construction in each of the four scenarios we consider, ranging from \$2.9M (144 establishments) to \$32M (826 establishments).

Perfect targeting is infeasible in practice: policymakers cannot precisely measure each store’s consumer surplus. We therefore consider targeting based on observables. We estimate a logit regression of an indicator that identifies establishments that have a positive expected net value on sales, store size, NAICS category, chain affiliation, flood exposure, and the number of nearby competitors at various radii. We report the results in Supplemental

³³When estimating using $\sigma_{\varepsilon}^{NE} = 1$ (Table I.1, Panel A), we find that aid to all damaged firms in the baseline scenario of Table 5 crowds out 0.44 new entrants in expectation. Expected crowd-out drops to 0.02 new entrants when using $\sigma_{\varepsilon}^{NE} = 10$ (Table I.1, Panel F).

Appendix Table J.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 489 establishments (18.6 percent of the total), of which 66 percent have positive net value. These subsidies generate a total net value of about \$5.2M (\$1.88 in benefits for each dollar spent) and achieve 76 percent of the net gain from perfect targeting (\$5.2M relative to \$6.8M in the middle panel). 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.

In sum, few establishments generate sufficient benefits to justify the cost of aid, making blanket aid programs inefficient. Crucially, however, we also show that targeting on observable business characteristics identifies a substantial fraction of the establishments that would receive aid under perfect targeting, which allows such a program to achieve a substantial share of the gains that could be achieved under perfect targeting. Finally, we also show that even under the most generous assumptions ($\kappa = 1$ and infinite horizon in column 3 of Table 5), targeting on observables still outperforms a blanket aid program.

7 Conclusion

How do adverse shocks to firms affect firm entry, exit, and consumer welfare? A large literature has explored the impact 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 creative destruction: lower-value stores tend to exit and be replaced by more productive entrants, which might suggest intervention is unnecessary. However, we note two important caveats. First, because of spatial mismatch between entries and exits, firm turnover generates large distributional consequences, with the largest losses

in smaller MSAs and lower-income neighborhoods. Second, while the average exiting store is marginal for consumer welfare, a right tail of high-value exits means 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 reenter. 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 three-quarters 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

Ben Klopach Eric Lewis Fernando Luco

A Data sources and data processing

We use data from the following sources:

1. **Card data.** Our main dataset to identify business exit and reentry comes from a payment card company that represents about 20 percent of U.S. consumption. The data include information on credit and debit card expenditures. We identify whether a business location is open by observing 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 percent of its pre-storm weekly average transaction volume. We also use these data to construct information on consumer expenditures. The data include both debit and credit cards. For about 70 percent of the credit cards (and none of the debit cards), the home location of the card is identified at the ZIP+4 code 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.

We use Yelp and Google to verify the timing of entry and exit using the following steps:

- (a) Using the Yelp API, we search for each business in the card data within Yelp. We use the Jaro-Winkler similarity score to measure the distance between two strings, the business name in the card data, and that in Yelp.
- (b) The Yelp API only returns businesses currently operating at the time of search using the API. To find the Yelp pages of closed businesses, we use a Google Custom Search Engine to find old Yelp records. Specifically, for businesses in the card data that cannot be matched to Yelp data in the previous step, we search for them using a custom Google search with the search terms consisting of establishment name, establishment address, and the word “Yelp”. This returns search results from Yelp.
- (c) We search establishments not found in the previous two steps 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 six months prior to its first transaction.

- (e) Finally, we hired research assistants 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 research assistants who checked its status independently.

2. **FEMA flood depth data.** We used raster data of FEMA estimates of flood depth (in feet) at the 3-meter-by 3-meter level.

3. **Harris Central 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 include the square footage of the establishment and the property’s assessed value such as inventory, capital equipment, vehicles, and others. 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 based on 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 in which corresponding real

property each card-level establishment is located. 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.

4. **American Community Survey.** We use the 5-year 2012-2016 ACS estimates of demographic characteristics at the Census block group level.
5. **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/>.
6. **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.
7. **National Land Cover Database (NLCD).** NLCD data include information on land cover, 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.
8. **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, Montgomery, Jefferson, and Nueces correspond to counties that were in Hurricane Harvey’s path. 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 must have been purchased at least 10 times between 2016 and 2017.

9. **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 contain 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.

10. **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.
11. **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.
12. **Mixed Beverage Gross Receipts Tax data.** These data comes from the Texas Comptroller of Public Accounts. The data include 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

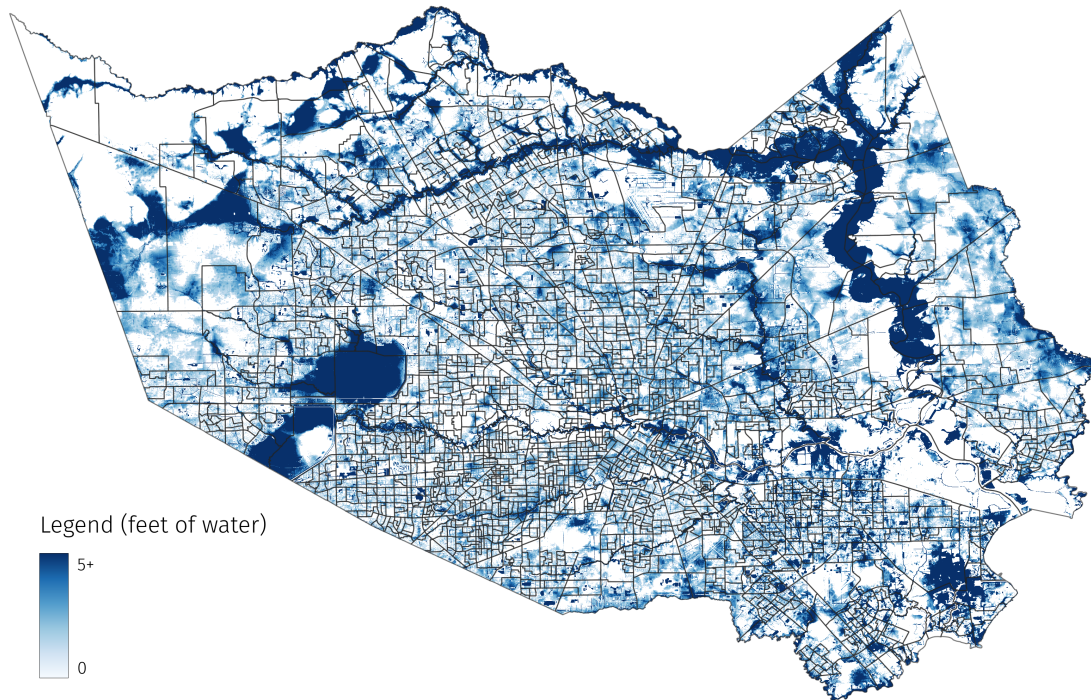
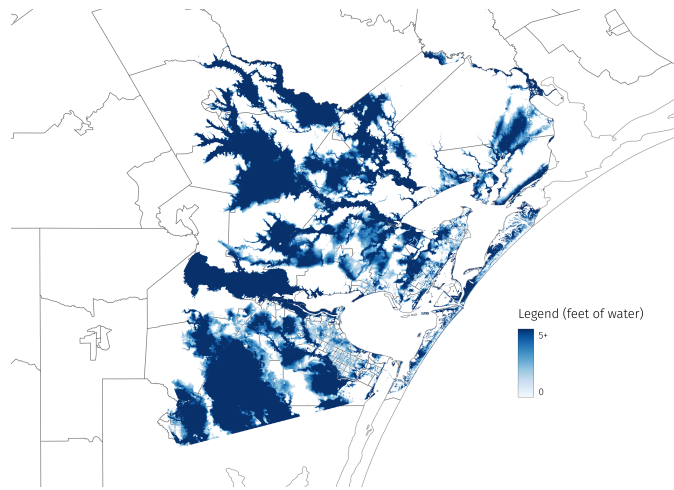
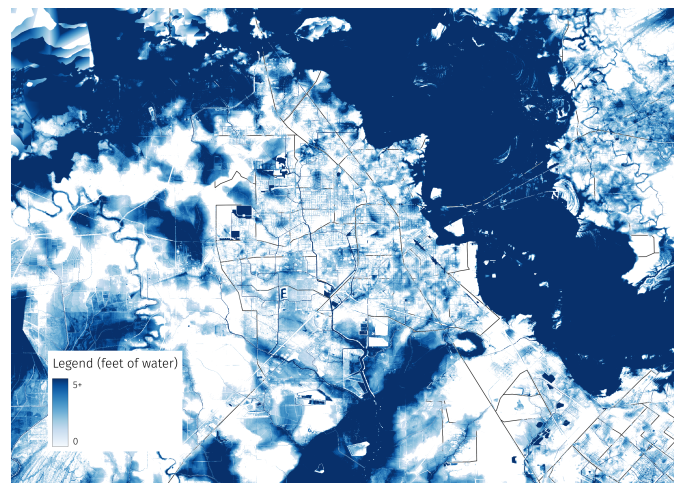


FIGURE B.1: Flooding level caused by Hurricane Harvey in Harris County.



(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 four weeks, stores that belong to large chains are less likely to permanently exit.

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 $\log(\text{transactions})$ and $\log(\text{sales})$ on indicators for whether the store is a new entrant post-Harvey, exits temporarily at the time of Harvey but reenters, 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 44 percent fewer transactions, with similar numbers for stores that closed temporarily and reopened. In contrast, new entrants had about 29 percent 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)	0.008 (0.006)	0.007 (0.006)	0.140 (0.073)
1(Houston)	0.003 (0.003)	-0.012 (0.010)	0.248 (0.120)
Locations - 1001+	-0.011 (0.004)	-0.018 (0.002)	-0.046 (0.050)
Locations - 101-1000	-0.011 (0.003)	-0.015 (0.002)	-0.006 (0.029)
Locations - 2-100	-0.004 (0.001)	-0.008 (0.002)	0.024 (0.011)
1(Beaumont) x Flood	0.006 (0.004)	0.011 (0.007)	0.097 (0.059)
1(Corpus) x Flood	0.017 (0.005)	0.043 (0.008)	-0.001 (0.029)
1(Houston) x Flood	0.003 (0.001)	0.010 (0.001)	-0.028 (0.020)
1(Beaumont) x Flood sq	0.000 (0.001)	0.000 (0.001)	-0.010 (0.008)
1(Corpus) x Flood sq	-0.001 (0.001)	-0.003 (0.001)	0.004 (0.005)
1(Houston) x Flood sq	-0.000 (0.000)	-0.001 (0.000)	0.002 (0.002)
NAICS FEs	x	x	x
R2	0.010	0.020	0.066
Observations	28587	28587	1439

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 four or more weeks (column (2)), and an indicator for whether a store permanently exited conditional on being closed for four or more weeks (column (3)). The sample in column (3) is smaller than the total number of stores that temporarily closed for four or more weeks because flood exposure data are missing for some stores. 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 (0.037)	-0.345 (0.039)
1(exit)	-0.578 (0.069)	-0.619 (0.071)
1(temp. closure 1-3 weeks)	-0.479 (0.111)	-0.443 (0.055)
1(temp. closure 4-8 weeks)	-0.803 (0.065)	-0.817 (0.068)
1(temp. closure 8+ weeks)	-0.580 (0.112)	-0.589 (0.132)
1(1001+ locations)	1.668 (0.148)	1.122 (0.253)
1(101-1000 locations)	1.391 (0.153)	1.167 (0.244)
1(2-100 locations)	0.363 (0.046)	0.333 (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 monthly baseline exit rate equal to 0.16 percent 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 percent. Within Texas in particular, monthly exit rates from March 2016 to March 2017 were 0.66 percent for NAICS codes beginning with 44 and 45, and 0.74 percent for NAICS codes beginning with 72. The discrepancy is likely due to several factors:

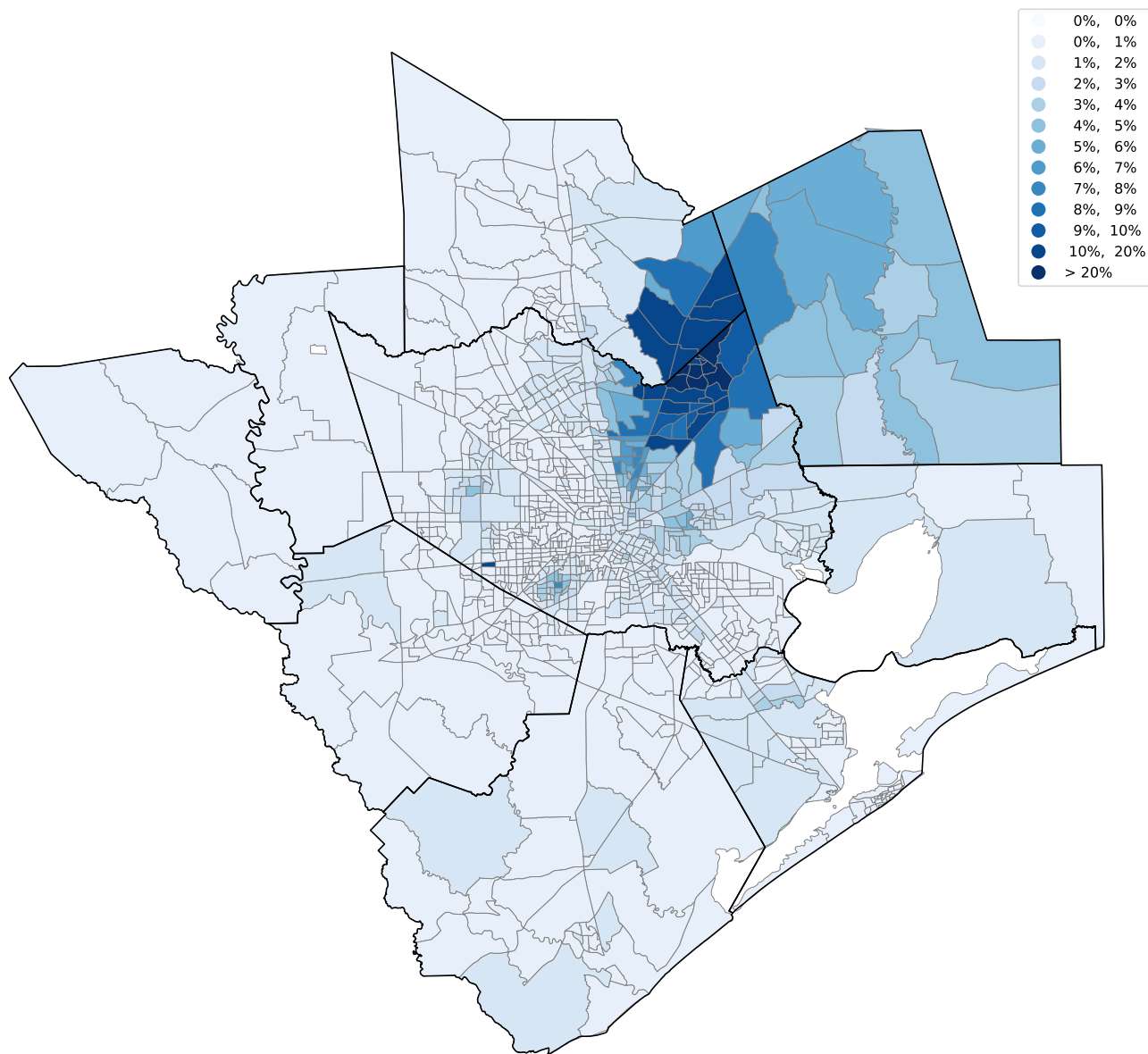
1. In the case of long temporary exit and reentry (for example, an establishment that closed in September 2017 and reopened in May 2018), we classify this as a temporary exit whereas BDS would likely classify this as a permanent exit and a new entry.
2. Because we aggregate data to the brand-ZIP code 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), along with 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 do 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.

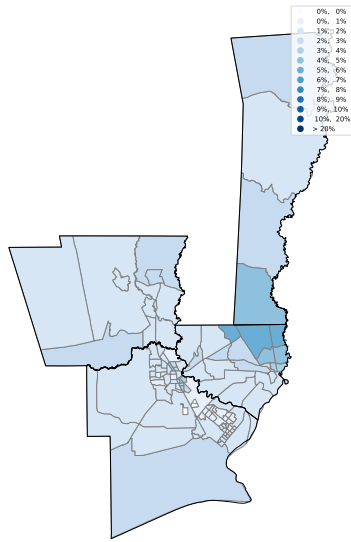
C.3 Share of pre-Harvey spending at closed stores

In this Supplemental 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.

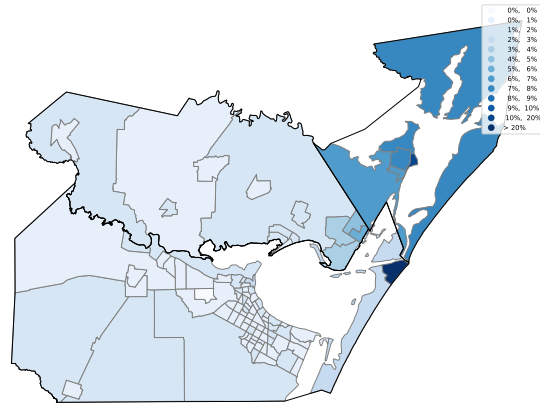
FIGURE C.1: Share of pre-Harvey spending at stores that closed for eight or more weeks in Houston



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 2017 that took place at establishments that later closed for eight 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 eight 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 allow us to measure entry only through the end of 2018. To study longer-run business recovery, we examine data from the Mixed Beverage Gross Receipts Tax (MB-GRT) data from the Texas Comptroller of Public Accounts. The data report 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.

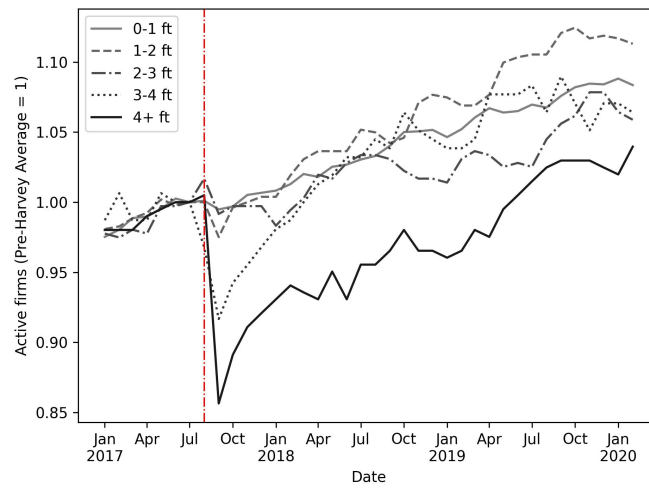


FIGURE C.3: Normalized count of establishments in MBGRT by Harvey flood level and month.

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

D Examining price responses to Hurricane Harvey

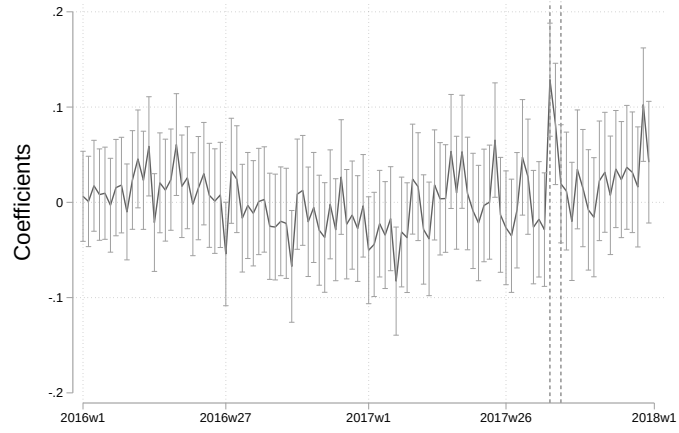
In this Supplemental Appendix section, we examine the extent to which retail prices changed during and after Hurricane Harvey. We do this by exploiting the NielsenIQ Homescan Consumer Panel, accessed through the Kilts Center at the University of Chicago.

In our analyses, we restrict attention to the State of Texas between 2016 and 2017, and focus on the largest counties in the data, such as Harris County (which includes the City of Houston and surrounding areas). In addition to the largest counties, we include smaller counties affected 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.

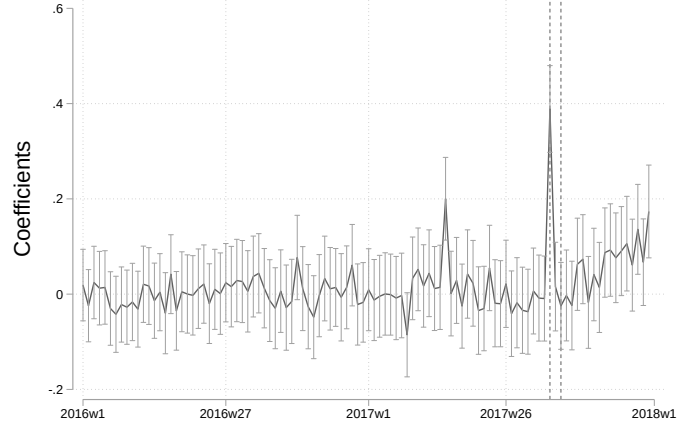
We begin our analyses considering purchases in the following channels: groceries, discount stores, drug stores, quick-serve restaurants, warehouse clubs, dollar stores, service stations, hardware/home improvement, restaurants, department stores, online shopping, apparel stores, pet stores, convenience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

To examine the extent of price changes during and after Hurricane Harvey, we estimate regressions of log prices (at the product–store–week level) on week fixed effects and the interaction of week fixed effects with an indicator equal to one for affected areas. 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. The dashed lines indicate the hurricane period.³⁴ We find that there is a one-week effect, at the time of Harvey’s landfall, 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.

³⁴Harvey made landfall on August 25th, 2017, a Friday, so the dashed lines identify a two-week period in the figures.



(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 related to 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 Harvey’s landfall. 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 percent from 2016 to 2017 but a 7.0 percent decrease 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 study 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

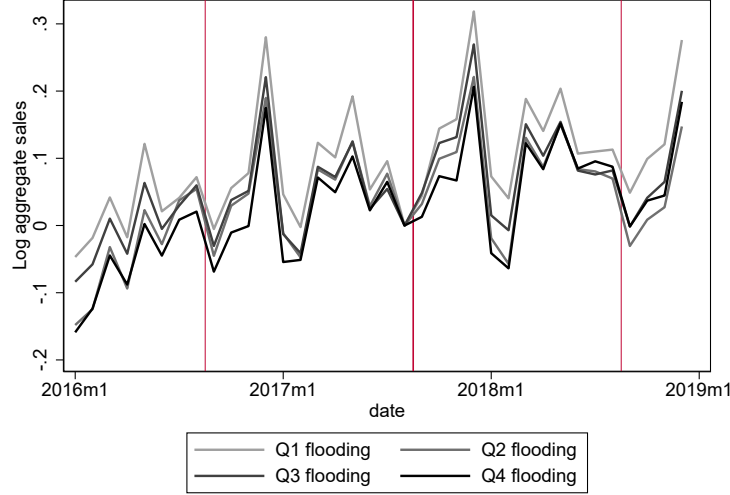


FIGURE E.1: Aggregate monthly spending by month x region

Note: Region is defined as a Houston superneighborhood 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, others). 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). Overall, 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.³⁵ 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.

³⁵The 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.

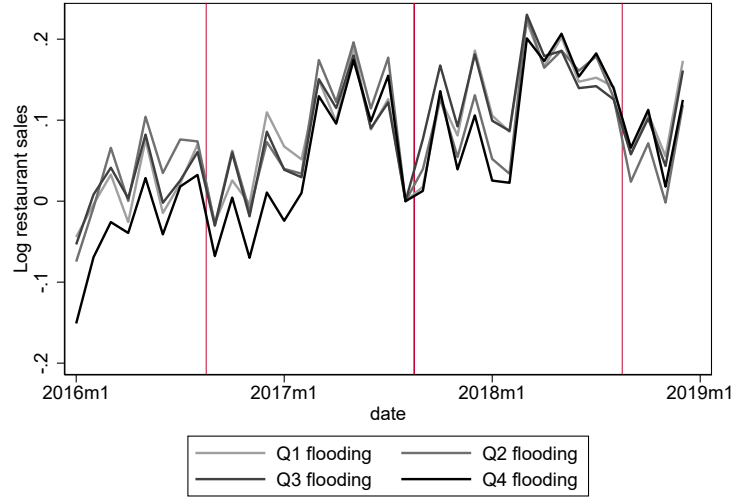


FIGURE E.2: Aggregate restaurant monthly spending by month x region

Note: Region is defined as a Houston superneighborhood 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.

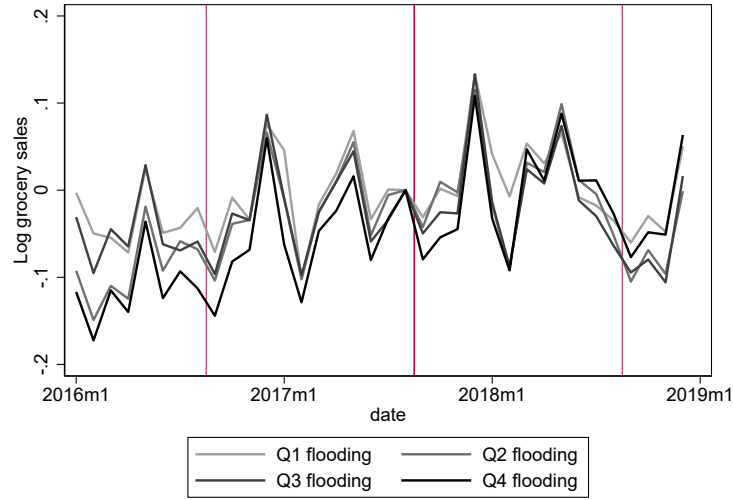


FIGURE E.3: Aggregate grocery monthly spending by month x region

Note: Region is defined as a Houston superneighborhood 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.

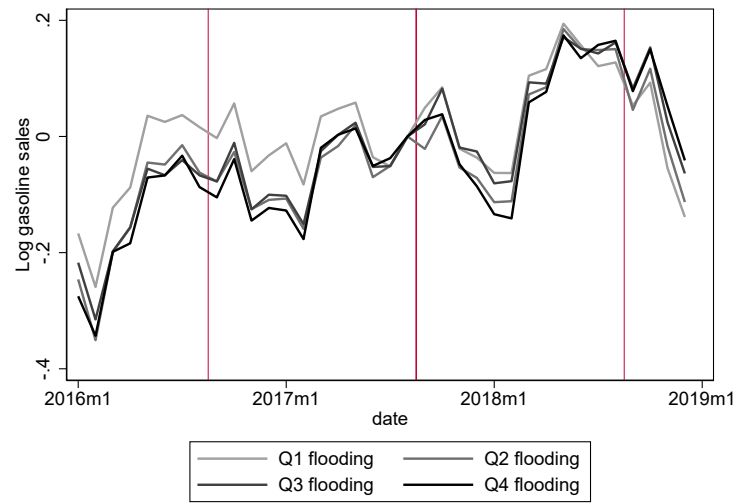


FIGURE E.4: Aggregate gasoline monthly spending by month x region

Note: Region is defined as a Houston superneighborhood 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 ZIP code. 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 that these 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 on a given purchase trip t as³⁶

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

where v_i denotes the random components of the utility function.

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

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

where $\mathbf{m}_i = m_{1i}, \dots, m_{Ti}$ denotes the observed sequence of store choices by i and the product Π_t is taken over all purchase trips t by consumer i .

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

$$L_{im} = \int P_{im}(v_i) f(v_i) dv_i.$$

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 $\xi_{j,n,q}$. We implement our estimation routine using Jax (Bradbury et al., 2018) and GPU-specific tools that enable us to accelerate estimation. Finally, we approximate the integral that defines the unconditional probability of the sequence using 50 scrambled Halton

³⁶Recall 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.

draws.

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

F.2 Estimating $\xi_{j,n,q=0}$ 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 $\xi_{j,n,q=0}$ for the pre-storm quarter $q = 0$. This estimation sample does not allow us to estimate $\xi_{j,n,q=0}$ for entrants that enter post-Harvey. Therefore, we use the following steps to estimate $\xi_{j,n,q=0}$ 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 $\xi_{j,n,q}$. This results in a maximum of 6 different $\xi_{j,n,q}$ 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 ($q = 0$) values of $\xi_{j,n,q=0}$ would be for new entrants by taking all estimated values of $\xi_{j,n,q}$ and projecting them on store fixed effects and time fixed effects:

$$\xi_{j,n,q} = \alpha_n + \alpha_j + \alpha_q + \varepsilon_{j,n,q}$$

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 $\hat{\xi}_{j,n,q=0} = \alpha_n + \alpha_j + \alpha_{q=0}$.

F.3 Weighting estimation-sample welfare to representative populations

The welfare changes we estimate are defined at the level of the demand-estimation sample, a random sample of matched credit cards drawn from within each (NAICS, neighborhood) cell. To aggregate these welfare changes to representative populations, we use a sequence of three weights, defined with respect to the following nested populations: the *all-retail*

population of spending in our sample cities across all payment methods; the *all-payment card population* of all credit- and debit-card spending on the data provider’s network in the same cities and NAICS; the *estimation population* of credit cards on the provider’s network for which we observe cardholder demographics; and the *estimation sample* of cards drawn from the estimation population for the structural estimation.

Weight 1: estimation sample to estimation population. For each NAICS g and neighborhood n , let $S_{g,n}^{\text{samp}}$ denote total estimation-sample spending and $S_{g,n}^{\text{est}}$ denote total estimation-population spending. Define $w_{g,n}^{\text{est}} = S_{g,n}^{\text{est}}/S_{g,n}^{\text{samp}}$. Multiplying any sample-level dollar magnitude by $w_{g,n}^{\text{est}}$ recovers the corresponding estimation-population magnitude.

Weight 2: estimation population to all-payment card population. For each city c and NAICS g , let $\rho_{c,g}$ denote the share of spending by all payment cards on the data provider’s network that is included in the estimation population in that (city, NAICS) cell. Dividing an estimation-population dollar magnitude by $\rho_{c,g}$ scales it to the all-payment card population.

Weight 3: all-payment card to all-retail, with Census NAICS-mix correction. The all-payment card NAICS basket differs from the U.S. retail NAICS basket, and the all-payment card population accounts for a fraction of all retail spending. We bundle both corrections into a single NAICS-level weight,

$$\omega_g = \frac{s_g^{\text{Census}}}{s_g^{\text{card}}} \cdot \frac{1}{0.53} \cdot \frac{1}{0.79},$$

where s_g^{Census} is NAICS g ’s share of total U.S. retail spending in the 2017 Census of Retail Trade (U.S. Census Bureau, 2017), s_g^{card} is NAICS g ’s share of all-payment card spending in our sample cities and time window, 0.53 is the card provider’s share of U.S. card spending (McCann, 2022), and 0.79 is the share of U.S. retail spending across all payment card networks (Klopach and Luco, 2025). The ratio $s_g^{\text{Census}}/s_g^{\text{card}}$ reweights each NAICS so the implied basket matches Census expenditure shares; the constant $1/(0.53 \cdot 0.79)$ scales all-payment card magnitudes up to total retail.

Application. For a dollar magnitude of welfare change (e.g., the per-store welfare contributions in Figure 4), the sample change in consumer surplus is scaled to a population-

representative change in consumer surplus using the three weights as follows:

$$\Delta CS_j^{\text{representative}} = \Delta CS_j^{\text{samp}} \cdot w_{g,n}^{\text{est}} \cdot \rho_{c,g}^{-1} \cdot \omega_g.$$

For a share-of-spending outcome aggregated across NAICS (e.g., the choropleth map in Figure 5 and the income-quintile bar chart in Figure 6), we first scale sample dollar magnitudes by $w_{g,j}^{\text{est}}$ within each (NAICS, neighborhood) and form per-NAICS share-of-spending ratios r_g . We then take a Census-share-weighted average across NAICS, $\hat{Y} = (\sum_g s_g^{\text{Census}} r_g) / (\sum_g s_g^{\text{Census}})$. The factors $\rho_{c,g}^{-1}$ and $1/(0.53 \cdot 0.79)$ appear identically in numerator and denominator of each r_g and therefore cancel.

F.4 Store-level consumer welfare contribution

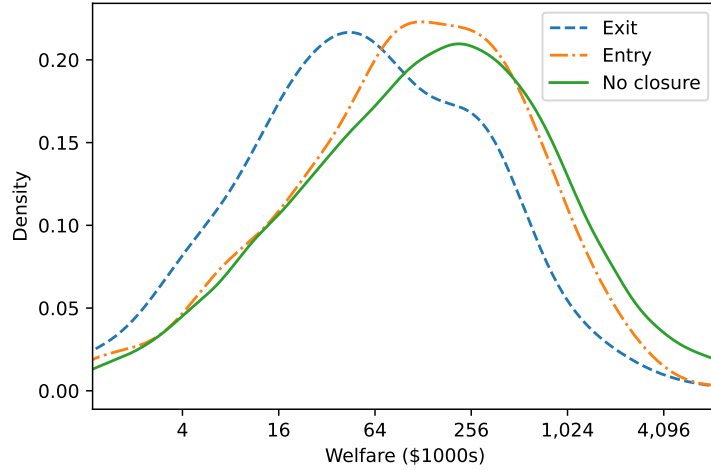


FIGURE F.1: Store-level consumer welfare contribution (pre-Harvey J).

Note: Density plots of the marginal welfare contribution of each store (the axis is on a 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 Harvey's landing.

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

TABLE F.1: Summary statistics for estimation sample

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

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

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

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

TABLE F.2: Parameter estimates from the demand model – Corpus Christi

NAICS	$\mu^{\theta^{dist}}$	$\sigma_{\theta^{dist}}^2$	$\sigma_{\theta^a}^2$	ρ	$\theta^{inc \times dist}$	$\theta^{inc \times aff}$	$\theta^{inc \times chain}$
Restaurants	-1.386 (0.027)	0.429 (0.021)	1.535 (0.034)	0.324 (0.018)	0.191 (0.038)	0.974 (0.253)	-0.488 (0.182)
Groceries	-0.661 (0.025)	0.540 (0.021)	2.962 (0.094)	0.529 (0.034)	0.251 (0.058)	0.415 (0.365)	-0.878 (0.236)
Gasoline	-1.204 (0.038)	1.111 (0.069)	4.256 (0.179)	1.159 (0.074)	0.359 (0.058)	-0.948 (0.534)	-0.881 (0.720)
Gen. Merch.	-0.926 (0.045)	0.566 (0.038)	3.897 (0.137)	0.634 (0.050)	0.116 (0.063)	2.431 (0.420)	-4.640 (0.731)
Pharmacy	-0.604 (0.055)	0.808 (0.074)	6.955 (0.654)	1.257 (0.131)	0.156 (0.082)	0.790 (0.659)	-1.588 (0.740)
Clothing	-2.203 (0.132)	0.892 (0.174)	1.802 (0.099)	0.723 (0.109)	0.005 (0.062)	1.365 (0.328)	-2.218 (0.487)
Misc. retail	-1.641 (0.111)	1.348 (0.169)	2.506 (0.165)	0.847 (0.140)	0.030 (0.068)	0.357 (0.362)	-0.099 (0.501)
Sporting Goods	-1.963 (0.116)	0.758 (0.125)	1.593 (0.101)	0.575 (0.099)	0.132 (0.053)	0.840 (0.337)	-1.165 (0.407)
Hardware	-1.465 (0.066)	0.612 (0.078)	0.684 (0.039)	0.240 (0.044)	-0.055 (0.061)	0.719 (0.206)	-0.389 (0.478)
Auto parts	-1.434 (0.095)	0.623 (0.095)	1.074 (0.086)	0.376 (0.088)	-0.034 (0.067)	0.495 (0.307)	-1.109 (0.483)
Furniture	-2.675 (2.872)	0.647 (5.728)	0.820 (0.217)	0.236 (0.699)	0.186 (0.154)	-0.020 (0.602)	-1.307 (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 1,000,000 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 at 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.3: Parameter estimates from the demand model – Beaumont

NAICS	$\mu^{\theta^{dist}}$	$\sigma_{\theta^{dist}}^2$	$\sigma_{\theta^a}^2$	ρ	$\theta^{inc \times dist}$	$\theta^{inc \times aff}$	$\theta^{inc \times chain}$
Restaurants	-1.478 (0.030)	0.438 (0.024)	2.183 (0.064)	0.467 (0.025)	0.094 (0.042)	1.681 (0.397)	-0.521 (0.191)
Groceries	-0.800 (0.031)	0.692 (0.038)	4.331 (0.135)	0.656 (0.061)	0.201 (0.082)	0.123 (0.575)	-0.663 (0.401)
Gasoline	-1.189 (0.030)	0.959 (0.053)	3.720 (0.154)	0.962 (0.052)	0.014 (0.047)	1.419 (0.563)	-1.627 (0.772)
Gen. Merch.	-1.181 (0.034)	0.729 (0.043)	3.318 (0.115)	0.684 (0.052)	0.366 (0.048)	3.741 (0.468)	-7.668 (0.863)
Pharmacy	-0.944 (0.060)	0.803 (0.076)	7.302 (0.542)	1.231 (0.137)	0.192 (0.109)	0.663 (0.939)	-0.498 (0.714)
Clothing	-1.842 (0.147)	0.586 (0.117)	1.735 (0.104)	0.416 (0.108)	0.047 (0.072)	2.497 (0.383)	-2.908 (0.466)
Misc. retail	-1.373 (0.114)	0.891 (0.154)	2.530 (0.232)	0.540 (0.108)	0.082 (0.089)	2.786 (0.470)	-2.642 (0.474)
Sporting Goods	-1.629 (0.113)	0.584 (0.098)	1.652 (0.154)	0.639 (0.101)	0.090 (0.069)	0.637 (0.566)	-1.864 (1.097)
Hardware	-1.527 (0.069)	0.556 (0.074)	0.787 (0.052)	0.327 (0.050)	0.142 (0.062)	0.422 (0.296)	-0.830 (0.772)
Auto parts	-1.446 (0.071)	0.650 (0.074)	0.765 (0.101)	0.319 (0.070)	0.131 (0.071)	0.281 (0.290)	-1.183 (0.445)
Furniture	-1.664 (0.344)	0.346 (0.255)	1.586 (0.647)	0.459 (0.259)	-0.238 (0.213)	-0.111 (0.837)	-1.197 (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 1,000,000 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: Welfare changes by income group

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

G Entry model: Implementation details

In this section, we present the implementation details of the model that we introduced in Section 6.1. Unlike that section, this appendix section does not suppress the NAICS subscript g .

G.1 Model primitives

For each industry g , the set of potential reentrants who decide to reenter is $N_g^{RE} \subset J_g^{RE}$, the set of incumbents who never close is N_g^I , and the set of potential entrants who decide to enter is $N_g^{NE} \subset J_g^{NE}$. Each store j maps to only one NAICS g , meaning we can write a function $g(j)$.

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 retail 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) within Harris County to construct each store’s predicted aggregate market share within industry n , denoted $\hat{s}_j$, and the predicted outside share, denoted $\hat{s}_0$.

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

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

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

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

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

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

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

G.3 Second stage

In the second stage, potential new entrants (the set J_g^{NE}) 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 reentrants, 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 δ_k and profit shock ε_k in the calculation of the *degree of competition* B_g^{NE} . 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 reentrants $\{(\iota_m, \delta_m)\}_{m \in J_g^{RE}}$, 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 $k \in J_g^{NE}$. Fix an initial guess for beliefs about competition, $B_{i=0,g}^{NE}$. For each draw $s \in \{1, \dots, R_1\}$ and each potential entrant k , evaluate expected profits implied by θ_0 and beliefs $B_{i,g}^{NE}$,

$$\mathbb{E}[\pi_k^{NE,s} \mid B_{i,g}^{NE}, \theta_0],$$

and set the entry decision

$$\iota_k^s(B_{i,g}^{NE}) = \mathbf{1}\left(\mathbb{E}[\pi_k^{NE,s} \mid B_{i,g}^{NE}, \theta_0] \geq 0\right).$$

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

tition,

$$\bar{B}^s(B_{i,g}^{NE}) \equiv \left(1 + \sum_{k \in J_g^{NE}} \iota_k^s(B_{i,g}^{NE}) \exp(\delta_k^s) + \sum_{m \in J_g^{RE}} \iota_m \exp(\delta_m) + \sum_{l \in N_g^I} \exp(\delta_l) \right)^{-1},$$

and average across simulation draws,

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

We then update beliefs according to

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

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

G.4 First stage

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

We begin with a parameter vector θ governing reentry costs and the distribution of reentry shocks, and a vector of reentrant mean utilities $\{\delta_m\}_{m \in J_g^{RE}}$. Draw R_2 realizations of reentry profit shocks $\varepsilon_m^{RE,r}$ for each potential reentrant $m \in J_g^{RE}$, for $r \in \{1, \dots, R_2\}$. Fix an initial guess for beliefs about competition faced by reentrants, $B_{i=0,g}^{RE}$.

For each iteration i and each draw r , evaluate expected profits for each potential reentrant m implied by θ_0 and beliefs $B_{i,g}^{RE}$ and set the draw-specific reentry decision

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

Nested second stage. Given the reentry decisions $\{\iota_m^r(B_{i,g}^{RE})\}_{m \in J_g^{RE}}$, 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 $B_r^{*NE}(B_{i,g}^{RE})$, and the implied entry

decisions for potential new entrants under that subgame. Equivalently, this step maps a candidate reentry outcome into the equilibrium degree of competition generated after new entry.

Using the implied reentry and new-entry outcomes, compute the draw-specific implied degree of competition relevant for reentrants,

$$\tilde{B}^{r,s}(B_{i,g}^{RE}) \equiv \left(1 + \sum_{k \in J_g^{NE}} \iota_k^{rs}(B_{r,g}^{*NE}(B_{i,g}^{RE})) \exp(\delta_k^s) + \sum_{m \in J_g^{RE}} \iota_m^r(B_{i,g}^{RE}) \exp(\delta_m) + \sum_{l \in N_g^I} \exp(\delta_l) \right)^{-1},$$

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.

Averaging over the R_1 inner draws yields the implied belief for outer draw r ,

$$\tilde{B}^r(B_{i,g}^{RE}) \equiv \frac{1}{R_1} \sum_{s=1}^{R_1} \tilde{B}^{r,s}(B_{i,g}^{RE}).$$

Averaging over the R_2 outer draws then gives the belief update,

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

and update beliefs according to

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

We iterate until convergence, i.e., until $|B_{i+1,g}^{RE} - B_{i,g}^{RE}|$ is below a prespecified tolerance. Denote the converged belief by B_g^{*RE} . This fixed-point condition ensures that B_g^{*RE} is consistent with the set of reentrants implied by B_g^{*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 g , profits are given by equation 3, which we restate below as equation 13.

$$\mathbb{E}[\pi_k] = M_g \cdot \exp(\delta_k) \cdot B_g^{NE} \cdot \zeta_k^{NE} - C_k^{NE} \cdot \exp(\varepsilon_k) \quad (13)$$

According to the oblivious equilibrium concept, the expected market share for a new entrant k given mean utility δ_k is $\mathbb{E}[s_k] \equiv \exp(\delta_k) \cdot B_g^{NE}$.

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

$$\begin{aligned} M_g \cdot \mathbb{E}[s_k] \cdot \zeta_g^{NE} &\geq C_g^{NE} \cdot \exp(\varepsilon_k) \\ \log M_g + \log \mathbb{E}[s_k] + \log \zeta_g^{NE} - \log C_g^{NE} &\geq \varepsilon_k. \end{aligned}$$

Define the NAICS-specific intercept

$$\alpha_g^{NE} \equiv \log M_g + \log \zeta_g^{NE} - \log C_g^{NE}.$$

Then the entry condition can be written as

$$\varepsilon_k \leq \log \mathbb{E}[s_k] + \alpha_g^{NE}.$$

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

$$\mathbb{P}(\iota_k = 1 \mid \delta_k, B_g^{*NE}) = \Phi\left(\frac{\log \mathbb{E}[s_k] + \alpha_g^{NE}}{\sigma_{\varepsilon,g}^{NE}}\right), \quad (14)$$

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

Reentrants. For a potential reentrant $j \in J^{RE}$, profits are given by equation 5, which we restate below in equation 15:

$$\mathbb{E}[\pi_j] = M_g \cdot \exp(\delta_j) \cdot B_g^{RE} \cdot \zeta_j^{RE} - F_j(X_j) \cdot \exp(\varepsilon_j), \quad (15)$$

According to the oblivious equilibrium concept, expected market share for a reentrant j given mean utility δ_j and reentry is $\mathbb{E}[s_j] \equiv \exp(\delta_j) \cdot B_g^{RE}$. We parameterize the reentry cost as

$$F_j(X_j) = C_g^{RE} \cdot \exp(-\beta X_j), \quad \text{so that} \quad \log(F_j(X_j)) = \log C_g^{RE} - \beta X_j.$$

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

$$\log M_g + \log \mathbb{E}[s_j] + \log \zeta_g^{RE} - \log C_g^{RE} + \beta X_j \geq \varepsilon_j.$$

Define

$$\alpha_g^{RE} \equiv \log M_g + \log \zeta_g^{RE} - \log C_g^{RE}.$$

Then the reentry condition is

$$\varepsilon_j \leq \log \mathbb{E}[s_j] + \alpha_g^{RE} + \beta X_j.$$

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

$$\mathbb{P}(\iota_j = 1 \mid \delta_j) = \Phi\left(\frac{\log \mathbb{E}[s_j] + \alpha_g^{RE} + \beta X_j}{\sigma_{\varepsilon,g}^{RE}}\right), \quad (16)$$

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

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

- **Potential new entrants.** For new entrants, we observe δ_k only if potential new entrant k enters. When k does not enter, the likelihood contribution integrates over the distribution of δ :

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

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

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

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

- **Potential reentrants.** For reentrants, we observe δ_j for all $j \in J^{RE}$ regardless of

whether they reenter. Let $\delta_j = x$ denote the observed value. If j does not reenter,

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

and if j reenters,

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

where $\log \mathbb{E}[s_j(x)] = x + \log B_g^{*RE}$ and $f_{\delta,g}^{RE}$ denotes the density of reentrant 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

$$LL(\theta) \equiv \sum_g \left[\sum_{k \in J_g^{NE}} \log L_k^{NE}(\theta) + \sum_{j \in J_g^{RE}} \log L_j^{RE}(\theta) \right]. \quad (17)$$

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

H Measuring building damage with HCAD data

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

We use the HCAD data to measure the damage caused by Hurricane Harvey to 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 real property data.

The HCAD Personal Property data are 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. We match records we cannot match by address 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 we maximize the Log-likelihood given by equation 17.

In fall 2017, soon after Hurricane Harvey made landfall, 10 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 caused by 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 fall 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, our model includes variables measuring flood exposure and building characteristics. Among these are the building’s age, building type, replacement cost, various measures of the area covered by the building (e.g., actual, improved, heated), 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 hyperparameter grid and performed a randomized search to tune the hyperparameters. 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.

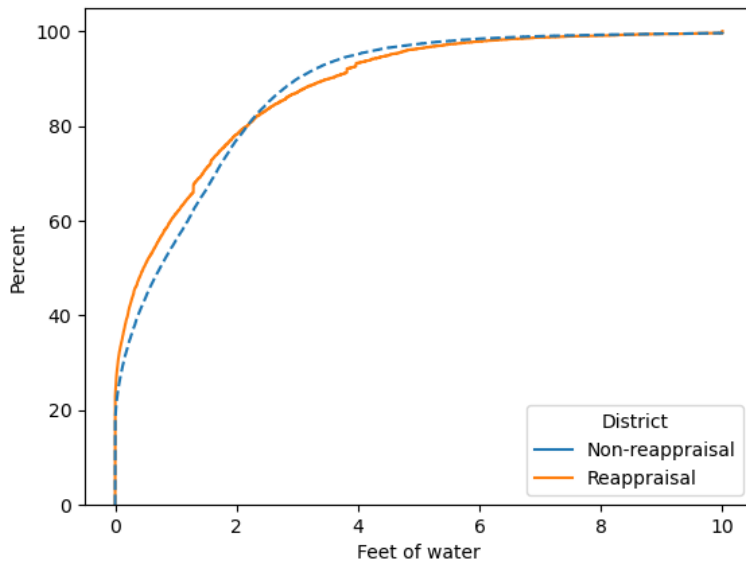


FIGURE H.1: CDF of flood exposure for reappraisal and non-reappraisal districts

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

I Parameter estimates of the entry model

In this appendix, we report the full set of estimates of our entry model, estimated under different values for σ_ε^{NE} . We report six sets of estimates, with σ_ε^{NE} ranging from 1 to 10, and show that the choice of this value has only a minor effect on the remaining model parameters.

TABLE I.1: Parameter estimates from entry model

Panel A: $\sigma_{\varepsilon}^{NE} = 1$												
NAICS	Industry	α^{RE}	α^{NE}	μ_{δ}^{NE}	σ_{δ}^{NE}	$\sigma_{\varepsilon}^{RE}$	$\sigma_{\varepsilon}^{NE}$	$\beta^{\hat{d}}$	$\beta^{\log(\text{sqft})}$	$\beta^{\text{chains 2-100}}$	$\beta^{\text{chains 101-1000}}$	$\beta^{\text{chains 1001+}}$
441	Auto parts	-28.29 (9.237)	-0.771 (0.183)	-6.549 (0.220)	1.399 (0.157)	13.12 (4.259)	1.000 (-)	89.72 (32.55)	-0.166 (0.675)	-1.214 (1.212)	1.907 (2.222)	3.175 (2.547)
442	Furniture	-31.94 (10.83)	-0.648 (0.273)	-6.180 (0.251)	1.085 (0.179)	13.12 (4.259)	1.000 (-)	89.72 (32.55)	-0.166 (0.675)	-1.214 (1.212)	1.907 (2.222)	3.175 (2.547)
443	Electronics	-48.61 (36.26)	-1.137 (0.610)	-6.122 (0.450)	0.859 (0.325)	13.12 (4.259)	1.000 (-)	89.72 (32.55)	-0.166 (0.675)	-1.214 (1.212)	1.907 (2.222)	3.175 (2.547)
444	Building materials	-59.51 (69.36)	-1.516 (0.269)	-6.406 (0.461)	2.141 (0.325)	13.12 (4.259)	1.000 (-)	89.72 (32.55)	-0.166 (0.675)	-1.214 (1.212)	1.907 (2.222)	3.175 (2.547)
445	Groceries	-26.27 (8.379)	-0.557 (0.108)	-6.926 (0.183)	2.055 (0.130)	13.12 (4.259)	1.000 (-)	89.72 (32.55)	-0.166 (0.675)	-1.214 (1.212)	1.907 (2.222)	3.175 (2.547)
446	Pharmacy	-29.39 (9.231)	-1.626 (0.194)	-6.316 (0.238)	1.480 (0.169)	13.12 (4.259)	1.000 (-)	89.72 (32.55)	-0.166 (0.675)	-1.214 (1.212)	1.907 (2.222)	3.175 (2.547)
447	Gasoline	-34.94 (11.70)	-0.486 (0.158)	-6.808 (0.217)	1.577 (0.155)	13.12 (4.259)	1.000 (-)	89.72 (32.55)	-0.166 (0.675)	-1.214 (1.212)	1.907 (2.222)	3.175 (2.547)
448	Clothing	-31.63 (9.831)	-0.346 (0.115)	-6.741 (0.170)	1.794 (0.120)	13.12 (4.259)	1.000 (-)	89.72 (32.55)	-0.166 (0.675)	-1.214 (1.212)	1.907 (2.222)	3.175 (2.547)
451	Sporting goods	-30.53 (9.982)	-1.023 (0.189)	-6.581 (0.241)	1.500 (0.172)	13.12 (4.259)	1.000 (-)	89.72 (32.55)	-0.166 (0.675)	-1.214 (1.212)	1.907 (2.222)	3.175 (2.547)
452	Gen. Merch.	-26.52 (9.285)	-0.452 (0.196)	-6.347 (0.257)	1.558 (0.182)	13.12 (4.259)	1.000 (-)	89.72 (32.55)	-0.166 (0.675)	-1.214 (1.212)	1.907 (2.222)	3.175 (2.547)
453	Misc. retail	-30.21 (9.290)	-1.323 (0.101)	-6.587 (0.125)	1.448 (0.089)	13.12 (4.259)	1.000 (-)	89.72 (32.55)	-0.166 (0.675)	-1.214 (1.212)	1.907 (2.222)	3.175 (2.547)
722	Restaurants	-21.95 (7.316)	0.106 (0.067)	-7.390 (0.068)	2.031 (0.048)	13.12 (4.259)	1.000 (-)	89.72 (32.55)	-0.166 (0.675)	-1.214 (1.212)	1.907 (2.222)	3.175 (2.547)

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 reentrant profit shock. The vector X includes store-specific characteristics: building damage $\hat{d}$, log of store square footage, and 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 I.1: Parameter estimates from entry model (continued)

Panel B: $\sigma_{\varepsilon}^{NE} = 2$												
NAICS	Industry	α^{RE}	α^{NE}	μ_{δ}^{NE}	$\sigma_{\delta}^{\text{NE}}$	$\sigma_{\varepsilon}^{\text{RE}}$	$\sigma_{\varepsilon}^{\text{NE}}$	$\beta^{\hat{d}}$	$\beta^{\log(\text{sqft})}$	$\beta^{\text{chains 2-100}}$	$\beta^{\text{chains 101-1000}}$	$\beta^{\text{chains 1001+}}$
441	Auto parts	-29.50 (10.05)	-0.585 (0.371)	-6.388 (0.252)	1.553 (0.186)	13.45 (4.575)	2.000 (-)	91.14 (34.13)	-0.236 (0.686)	-1.228 (1.245)	2.038 (2.324)	3.275 (2.648)
442	Furniture	-33.30 (11.76)	-0.487 (0.547)	-6.050 (0.289)	1.201 (0.215)	13.45 (4.575)	2.000 (-)	91.14 (34.13)	-0.236 (0.686)	-1.228 (1.245)	2.038 (2.324)	3.275 (2.648)
443	Electronics	-50.71 (39.16)	-1.022 (1.223)	-6.027 (0.521)	0.953 (0.398)	13.45 (4.575)	2.000 (-)	91.14 (34.13)	-0.236 (0.686)	-1.228 (1.245)	2.038 (2.324)	3.275 (2.648)
444	Building materials	-62.14 (77.58)	-1.180 (0.528)	-6.170 (0.505)	2.293 (0.358)	13.45 (4.575)	2.000 (-)	91.14 (34.13)	-0.236 (0.686)	-1.228 (1.245)	2.038 (2.324)	3.275 (2.648)
445	Groceries	-27.43 (9.128)	-0.336 (0.214)	-6.715 (0.203)	2.237 (0.146)	13.45 (4.575)	2.000 (-)	91.14 (34.13)	-0.236 (0.686)	-1.228 (1.245)	2.038 (2.324)	3.275 (2.648)
446	Pharmacy	-30.55 (10.04)	-1.385 (0.387)	-6.137 (0.271)	1.625 (0.196)	13.45 (4.575)	2.000 (-)	91.14 (34.13)	-0.236 (0.686)	-1.228 (1.245)	2.038 (2.324)	3.275 (2.648)
447	Gasoline	-36.26 (12.65)	-0.310 (0.323)	-6.637 (0.248)	1.749 (0.183)	13.45 (4.575)	2.000 (-)	91.14 (34.13)	-0.236 (0.686)	-1.228 (1.245)	2.038 (2.324)	3.275 (2.648)
448	Clothing	-32.91 (10.72)	-0.172 (0.229)	-6.546 (0.191)	1.966 (0.138)	13.45 (4.575)	2.000 (-)	91.14 (34.13)	-0.236 (0.686)	-1.228 (1.245)	2.038 (2.324)	3.275 (2.648)
451	Sporting goods	-31.82 (10.87)	-0.819 (0.381)	-6.409 (0.275)	1.660 (0.202)	13.45 (4.575)	2.000 (-)	91.14 (34.13)	-0.236 (0.686)	-1.228 (1.245)	2.038 (2.324)	3.275 (2.648)
452	Gen. Merch.	-27.74 (10.05)	-0.206 (0.396)	-6.161 (0.290)	1.706 (0.210)	13.45 (4.575)	2.000 (-)	91.14 (34.13)	-0.236 (0.686)	-1.228 (1.245)	2.038 (2.324)	3.275 (2.648)
453	Misc. retail	-31.43 (10.15)	-1.144 (0.205)	-6.421 (0.143)	1.606 (0.106)	13.45 (4.575)	2.000 (-)	91.14 (34.13)	-0.236 (0.686)	-1.228 (1.245)	2.038 (2.324)	3.275 (2.648)
722	Restaurants	-23.27 (7.957)	-0.015 (0.116)	-7.196 (0.076)	2.234 (0.055)	13.45 (4.575)	2.000 (-)	91.14 (34.13)	-0.236 (0.686)	-1.228 (1.245)	2.038 (2.324)	3.275 (2.648)

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

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

Panel C: $\sigma_\varepsilon^{NE} = 3$												
NAICS	Industry	α^{RE}	α^{NE}	μ_δ^{NE}	$\sigma_\delta^{\text{NE}}$	$\sigma_\varepsilon^{\text{RE}}$	$\sigma_\varepsilon^{\text{NE}}$	$\beta^{\hat{d}}$	$\beta^{\log(\text{sqft})}$	$\beta^{\text{chains 2-100}}$	$\beta^{\text{chains 101-1000}}$	$\beta^{\text{chains 1001+}}$
441	Auto parts	-30.56 (10.83)	-0.480 (0.560)	-6.288 (0.275)	1.657 (0.211)	13.74 (4.859)	3.000 (-)	92.34 (35.55)	-0.298 (0.697)	-1.245 (1.273)	2.104 (2.395)	3.374 (2.745)
442	Furniture	-34.48 (12.64)	-0.397 (0.823)	-5.979 (0.314)	1.271 (0.242)	13.74 (4.859)	3.000 (-)	92.34 (35.55)	-0.298 (0.697)	-1.245 (1.273)	2.104 (2.395)	3.374 (2.745)
443	Electronics	-59.94 (94.25)	-0.965 (1.840)	-5.978 (0.564)	1.005 (0.446)	13.74 (4.859)	3.000 (-)	92.34 (35.55)	-0.298 (0.697)	-1.245 (1.273)	2.104 (2.395)	3.374 (2.745)
444	Building materials	-62.35 (65.99)	-0.986 (0.787)	-6.007 (0.545)	2.421 (0.392)	13.74 (4.859)	3.000 (-)	92.34 (35.55)	-0.298 (0.697)	-1.245 (1.273)	2.104 (2.395)	3.374 (2.745)
445	Groceries	-28.47 (9.842)	-0.214 (0.323)	-6.564 (0.221)	2.382 (0.163)	13.74 (4.859)	3.000 (-)	92.34 (35.55)	-0.298 (0.697)	-1.245 (1.273)	2.104 (2.395)	3.374 (2.745)
446	Pharmacy	-31.59 (10.83)	-1.256 (0.581)	-6.029 (0.295)	1.725 (0.220)	13.74 (4.859)	3.000 (-)	92.34 (35.55)	-0.298 (0.697)	-1.245 (1.273)	2.104 (2.395)	3.374 (2.745)
447	Gasoline	-37.23 (13.41)	-0.202 (0.490)	-6.525 (0.271)	1.871 (0.207)	13.74 (4.859)	3.000 (-)	92.34 (35.55)	-0.298 (0.697)	-1.245 (1.273)	2.104 (2.395)	3.374 (2.745)
448	Clothing	-34.05 (11.57)	-0.083 (0.346)	-6.414 (0.208)	2.096 (0.155)	13.74 (4.859)	3.000 (-)	92.34 (35.55)	-0.298 (0.697)	-1.245 (1.273)	2.104 (2.395)	3.374 (2.745)
451	Sporting goods	-32.86 (11.66)	-0.702 (0.575)	-6.302 (0.300)	1.770 (0.228)	13.74 (4.859)	3.000 (-)	92.34 (35.55)	-0.298 (0.697)	-1.245 (1.273)	2.104 (2.395)	3.374 (2.745)
452	Gen. Merch.	-28.77 (10.77)	-0.062 (0.595)	-6.045 (0.316)	1.811 (0.235)	13.74 (4.859)	3.000 (-)	92.34 (35.55)	-0.298 (0.697)	-1.245 (1.273)	2.104 (2.395)	3.374 (2.745)
453	Misc. retail	-32.49 (10.96)	-1.045 (0.310)	-6.318 (0.157)	1.714 (0.120)	13.74 (4.859)	3.000 (-)	92.34 (35.55)	-0.298 (0.697)	-1.245 (1.273)	2.104 (2.395)	3.374 (2.745)
722	Restaurants	-24.45 (8.568)	-0.171 (0.165)	-7.053 (0.083)	2.394 (0.062)	13.74 (4.859)	3.000 (-)	92.34 (35.55)	-0.298 (0.697)	-1.245 (1.273)	2.104 (2.395)	3.374 (2.745)

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

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

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

NAICS	Industry	α^{RE}	α^{NE}	μ_δ^{NE}	$\sigma_\delta^{\text{NE}}$	$\sigma_\varepsilon^{\text{RE}}$	$\sigma_\varepsilon^{\text{NE}}$	$\beta^{\hat{d}}$	$\beta^{\log(\text{sqft})}$	$\beta^{\text{chains 2-100}}$	$\beta^{\text{chains 101-1000}}$	$\beta^{\text{chains 1001+}}$
441	Auto parts	-30.57 (10.92)	-0.411 (0.750)	-6.222 (0.293)	1.729 (0.230)	13.83 (4.962)	4.000 (-)	93.39 (36.47)	-0.280 (0.703)	-1.246 (1.282)	2.150 (2.432)	3.412 (2.782)
442	Furniture	-34.57 (12.79)	-0.351 (1.100)	-5.934 (0.331)	1.316 (0.261)	13.83 (4.962)	4.000 (-)	93.39 (36.47)	-0.280 (0.703)	-1.246 (1.282)	2.150 (2.432)	3.412 (2.782)
443	Electronics	-52.50 (41.18)	-0.926 (2.459)	-5.948 (0.591)	1.035 (0.476)	13.83 (4.962)	4.000 (-)	93.39 (36.47)	-0.280 (0.703)	-1.246 (1.282)	2.150 (2.432)	3.412 (2.782)
444	Building materials	-66.03 (102.31)	-0.858 (1.048)	-5.890 (0.578)	2.522 (0.424)	13.83 (4.962)	4.000 (-)	93.39 (36.47)	-0.280 (0.703)	-1.246 (1.282)	2.150 (2.432)	3.412 (2.782)
445	Groceries	-28.54 (9.923)	-0.143 (0.432)	-6.455 (0.235)	2.494 (0.178)	13.83 (4.962)	4.000 (-)	93.39 (36.47)	-0.280 (0.703)	-1.246 (1.282)	2.150 (2.432)	3.412 (2.782)
446	Pharmacy	-31.59 (10.90)	-1.171 (0.776)	-5.955 (0.313)	1.796 (0.238)	13.83 (4.962)	4.000 (-)	93.39 (36.47)	-0.280 (0.703)	-1.246 (1.282)	2.150 (2.432)	3.412 (2.782)
447	Gasoline	-37.54 (13.70)	-0.129 (0.659)	-6.446 (0.289)	1.959 (0.226)	13.83 (4.962)	4.000 (-)	93.39 (36.47)	-0.280 (0.703)	-1.246 (1.282)	2.150 (2.432)	3.412 (2.782)
448	Clothing	-34.17 (11.69)	-0.039 (0.463)	-6.321 (0.221)	2.192 (0.169)	13.83 (4.962)	4.000 (-)	93.39 (36.47)	-0.280 (0.703)	-1.246 (1.282)	2.150 (2.432)	3.412 (2.782)
451	Sporting goods	-32.99 (11.82)	-0.627 (0.771)	-6.228 (0.319)	1.848 (0.248)	13.83 (4.962)	4.000 (-)	93.39 (36.47)	-0.280 (0.703)	-1.246 (1.282)	2.150 (2.432)	3.412 (2.782)
452	Gen. Merch.	-28.76 (10.83)	0.026 (0.796)	-5.967 (0.336)	1.886 (0.255)	13.83 (4.962)	4.000 (-)	93.39 (36.47)	-0.280 (0.703)	-1.246 (1.282)	2.150 (2.432)	3.412 (2.782)
453	Misc. retail	-32.54 (11.06)	-0.981 (0.417)	-6.248 (0.167)	1.789 (0.130)	13.83 (4.962)	4.000 (-)	93.39 (36.47)	-0.280 (0.703)	-1.246 (1.282)	2.150 (2.432)	3.412 (2.782)
722	Restaurants	-24.71 (8.632)	-0.317 (0.216)	-6.948 (0.088)	2.516 (0.068)	13.83 (4.962)	4.000 (-)	93.39 (36.47)	-0.280 (0.703)	-1.246 (1.282)	2.150 (2.432)	3.412 (2.782)

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

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

Panel E: $\sigma_\varepsilon^{NE} = 5$												
NAICS	Industry	α^{RE}	α^{NE}	μ_δ^{NE}	$\sigma_\delta^{\text{NE}}$	$\sigma_\varepsilon^{\text{RE}}$	$\sigma_\varepsilon^{\text{NE}}$	$\beta^{\hat{d}}$	$\beta^{\log(\text{sqft})}$	$\beta^{\text{chains 2-100}}$	$\beta^{\text{chains 101-1000}}$	$\beta^{\text{chains 1001+}}$
441	Auto parts	-29.43 (9.868)	-0.365 (0.944)	-6.175 (0.306)	1.780 (0.245)	13.26 (4.378)	5.000 (-)	88.91 (32.37)	-0.272 (0.674)	-1.218 (1.225)	1.969 (2.263)	3.206 (2.581)
442	Furniture	-33.24 (11.57)	-0.318 (1.377)	-5.903 (0.344)	1.348 (0.275)	13.26 (4.378)	5.000 (-)	88.91 (32.37)	-0.272 (0.674)	-1.218 (1.225)	1.969 (2.263)	3.206 (2.581)
443	Electronics	-49.94 (37.33)	-0.902 (3.081)	-5.927 (0.612)	1.057 (0.499)	13.26 (4.378)	5.000 (-)	88.91 (32.37)	-0.272 (0.674)	-1.218 (1.225)	1.969 (2.263)	3.206 (2.581)
444	Building materials	-60.44 (65.38)	-0.766 (1.312)	-5.801 (0.606)	2.602 (0.451)	13.26 (4.378)	5.000 (-)	88.91 (32.37)	-0.272 (0.674)	-1.218 (1.225)	1.969 (2.263)	3.206 (2.581)
445	Groceries	-27.54 (8.960)	-0.103 (0.544)	-6.372 (0.247)	2.581 (0.190)	13.26 (4.378)	5.000 (-)	88.91 (32.37)	-0.272 (0.674)	-1.218 (1.225)	1.969 (2.263)	3.206 (2.581)
446	Pharmacy	-30.43 (9.832)	-1.114 (0.971)	-5.904 (0.326)	1.847 (0.253)	13.26 (4.378)	5.000 (-)	88.91 (32.37)	-0.272 (0.674)	-1.218 (1.225)	1.969 (2.263)	3.206 (2.581)
447	Gasoline	-36.03 (12.31)	-0.079 (0.825)	-6.389 (0.303)	2.024 (0.242)	13.26 (4.378)	5.000 (-)	88.91 (32.37)	-0.272 (0.674)	-1.218 (1.225)	1.969 (2.263)	3.206 (2.581)
448	Clothing	-32.89 (10.47)	0.020 (0.610)	-6.253 (0.232)	2.264 (0.180)	13.26 (4.378)	5.000 (-)	88.91 (32.37)	-0.272 (0.674)	-1.218 (1.225)	1.969 (2.263)	3.206 (2.581)
451	Sporting goods	-31.77 (10.68)	-0.574 (0.964)	-6.175 (0.334)	1.906 (0.265)	13.26 (4.378)	5.000 (-)	88.91 (32.37)	-0.272 (0.674)	-1.218 (1.225)	1.969 (2.263)	3.206 (2.581)
452	Gen. Merch.	-27.72 (9.894)	0.088 (0.996)	-5.910 (0.351)	1.942 (0.271)	13.26 (4.378)	5.000 (-)	88.91 (32.37)	-0.272 (0.674)	-1.218 (1.225)	1.969 (2.263)	3.206 (2.581)
453	Misc. retail	-31.32 (9.918)	-0.937 (0.523)	-6.198 (0.174)	1.844 (0.139)	13.26 (4.378)	5.000 (-)	88.91 (32.37)	-0.272 (0.674)	-1.218 (1.225)	1.969 (2.263)	3.206 (2.581)
722	Restaurants	-24.04 (7.835)	-0.447 (0.256)	-6.868 (0.093)	2.611 (0.073)	13.26 (4.378)	5.000 (-)	88.91 (32.37)	-0.272 (0.674)	-1.218 (1.225)	1.969 (2.263)	3.206 (2.581)

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

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

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

NAICS	Industry	α^{RE}	α^{NE}	μ_δ^{NE}	$\sigma_\delta^{\text{NE}}$	$\sigma_\varepsilon^{\text{RE}}$	$\sigma_\varepsilon^{\text{NE}}$	β^d	$\beta^{\log(\text{sqft})}$	$\beta^{\text{chains } 2-100}$	$\beta^{\text{chains } 101-1000}$	$\beta^{\text{chains } 1001+}$
441	Auto parts	-30.19 (10.49)	-0.251 (1.908)	-6.057 (0.342)	1.912 (0.287)	13.57 (4.692)	10.00 (-)	91.08 (34.38)	-0.289 (0.689)	-1.236 (1.257)	2.058 (2.350)	3.311 (2.686)
442	Furniture	-34.06 (12.27)	-0.237 (2.770)	-5.831 (0.376)	1.423 (0.312)	13.57 (4.692)	10.00 (-)	91.08 (34.38)	-0.289 (0.689)	-1.236 (1.257)	2.058 (2.350)	3.311 (2.686)
443	Electronics	-52.43 (43.41)	-0.867 (6.200)	-5.884 (0.657)	1.103 (0.552)	13.57 (4.692)	10.00 (-)	91.08 (34.38)	-0.289 (0.689)	-1.236 (1.257)	2.058 (2.350)	3.311 (2.686)
444	Building materials	-62.15 (68.94)	-0.533 (2.625)	-5.567 (0.688)	2.824 (0.538)	13.57 (4.692)	10.00 (-)	91.08 (34.38)	-0.289 (0.689)	-1.236 (1.257)	2.058 (2.350)	3.311 (2.686)
445	Groceries	-28.36 (9.530)	-9.93e-04 (1.121)	-6.148 (0.283)	2.825 (0.230)	13.57 (4.692)	10.00 (-)	91.08 (34.38)	-0.289 (0.689)	-1.236 (1.257)	2.058 (2.350)	3.311 (2.686)
446	Pharmacy	-31.19 (10.47)	-0.976 (1.957)	-5.775 (0.364)	1.978 (0.296)	13.57 (4.692)	10.00 (-)	91.08 (34.38)	-0.289 (0.689)	-1.236 (1.257)	2.058 (2.350)	3.311 (2.686)
447	Gasoline	-37.00 (13.11)	0.039 (1.673)	-6.243 (0.342)	2.194 (0.289)	13.57 (4.692)	10.00 (-)	91.08 (34.38)	-0.289 (0.689)	-1.236 (1.257)	2.058 (2.350)	3.311 (2.686)
448	Clothing	-33.82 (11.19)	0.125 (1.164)	-6.072 (0.263)	2.461 (0.217)	13.57 (4.692)	10.00 (-)	91.08 (34.38)	-0.289 (0.689)	-1.236 (1.257)	2.058 (2.350)	3.311 (2.686)
451	Sporting goods	-32.54 (11.33)	-0.440 (1.964)	-6.042 (0.375)	2.053 (0.312)	13.57 (4.692)	10.00 (-)	91.08 (34.38)	-0.289 (0.689)	-1.236 (1.257)	2.058 (2.350)	3.311 (2.686)
452	Gen. Merch.	-28.44 (10.46)	0.221 (2.000)	-5.770 (0.392)	2.085 (0.318)	13.57 (4.692)	10.00 (-)	91.08 (34.38)	-0.289 (0.689)	-1.236 (1.257)	2.058 (2.350)	3.311 (2.686)
453	Misc. retail	-32.12 (10.59)	-0.829 (1.056)	-6.072 (0.195)	1.985 (0.164)	13.57 (4.692)	10.00 (-)	91.08 (34.38)	-0.289 (0.689)	-1.236 (1.257)	2.058 (2.350)	3.311 (2.686)
722	Restaurants	-25.20 (8.315)	-0.793 (0.477)	-6.646 (0.107)	2.880 (0.090)	13.57 (4.692)	10.00 (-)	91.08 (34.38)	-0.289 (0.689)	-1.236 (1.257)	2.058 (2.350)	3.311 (2.686)

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

J Cost-benefit analysis of aid: Further details

J.1 Employment benefits

To compute the estimated impacts of business reentry 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 reentry (Texas Workforce Commission, 2024). We assume that the employee-specific benefits of establishment reentry 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:

$$wb = \max\{67, \min\{494, ww \cdot 13/25\}\} \quad (18)$$

$$mb = \min\{26 \cdot wb, 0.27 \cdot 13 \cdot ww\} \quad (19)$$

We assume that an establishment's total employment benefit of reentry 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 J.1: Damage estimates
Establishments with ≥ 4 feet of flooding

	Real estate damage	Capital damage - baseline	Total aid cost - baseline	Capital damage - larger κ	Total aid cost - larger κ
count	263	263	263	263	263
mean	31,536	23,506	71,555	211,158	315,501
50%	12,600	4,354	24,276	39,113	69,458
75%	25,491	14,526	52,587	130,485	195,926
90%	60,898	34,957	124,697	314,020	459,684
95%	90,651	87,724	235,630	788,030	1,100,321

All establishments

	Real estate damage	Capital damage - baseline	Total aid cost - baseline	Capital damage - larger κ	Total aid cost - larger κ
count	3,007	3,007	3,007	3,007	3,007
mean	6,166	4,373	13,700	39,281	59,082
50%	1,094	467	2,382	4,195	7,736
75%	3,326	1,824	7,294	16,381	27,000
90%	11,446	5,840	23,493	52,462	84,591
95%	22,367	13,990	50,406	125,674	187,273

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 four 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: $\hat{d}_j \times V_{b(j),pre} \times \frac{sfft_j}{sfft_{b(j)}}$. 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 J.2: Parameter estimates from targeting regression

Scenario	(1) Baseline	(2) Variant 1	(3) Variant 2	(4) Variant 3
Log(weekly rev.)	1.014 (0.069)	1.014 (0.101)	0.997 (0.062)	1.017 (0.070)
Log(sqft)	-1.785 (0.131)	-1.635 (0.174)	-1.409 (0.102)	-1.373 (0.124)
2-100 locations	0.298 (0.171)	0.311 (0.233)	0.372 (0.164)	0.293 (0.171)
101-1000 locations	0.497 (0.222)	-1.055 (0.391)	0.232 (0.222)	-0.155 (0.223)
1001+ locations	-0.325 (0.220)	-1.582 (0.401)	0.589 (0.243)	-1.219 (0.235)
Flood exposure (ft)	0.381 (0.084)	0.215 (0.120)	0.192 (0.086)	0.384 (0.085)
Flood exposure sq. (ft)	-0.023 (0.011)	-0.005 (0.014)	0.012 (0.013)	-0.028 (0.011)
log(comp. w/in 1 mile)	-0.291 (0.136)	-0.118 (0.198)	-0.096 (0.127)	-0.247 (0.139)
log(# comp. w/in 2 miles)	0.264 (0.211)	-0.521 (0.307)	-0.087 (0.194)	0.125 (0.216)
log(# comp. w/in 5 miles)	0.088 (0.271)	1.424 (0.437)	0.001 (0.243)	0.196 (0.280)
log(# comp. w/in 10 miles)	0.387 (0.244)	-0.296 (0.408)	0.356 (0.213)	0.335 (0.252)
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	2625	2625	2625	2625
Pseudo R^2	0.492	0.404	0.564	0.474

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. This table presents results from estimating the entry model with $\sigma_{\varepsilon}^{NE} = 10$. 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.