

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

Ben Klopock, Eric Lewis, Fernando Luco^a

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^a Texas A&M University.

“Researcher(s)’ own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business.”

“The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.”

Motivation

- Negative shocks (e.g., recessions, natural disasters) impact firm survival and consumers.
 - Cleansing: Shocks may induce the exit of inefficient firms.
 - Scarring: Exit of high-value firms and slow entry.
- This paper: study firm entry and exit in the context of Hurricane Harvey.
 - \approx \$125B in damages
 - Heterogenous impact over space
 - Temporary shock
- Natural disasters:
 - More frequent and costly:
 - \$201B/year in 1980s \rightarrow \$919B/year in 2010s (NOAA, 2022)
 - Potentially large impacts on firms, but sparse empirical work.
 - Firm closures \rightarrow consumer welfare \rightarrow distributional consequences

Motivation

- Welfare impact of closures caused by negative shocks depends on the value that consumers assign to the stores that close.
- Market frictions and externalities may induce exit of high-value firms or delay entry.
- Potential scope for policy intervention: Grant based aid program.
Value depends on:
 - Consumers' valuation of exiting stores
 - Efficacy of aid in reducing exit
 - Cost of aid
- Existing aid policy: Mostly for households (FEMA), or loans (SBA). Grants (through HUD) are not available until years later, conditional on business survival.

This paper

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 - Significant entry but worst-hit areas have net decrease in # of firms.

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- Evaluate the benefits of a grant-based aid program
 - Few stores contribute more to consumer welfare than the cost of aid.
 - But positive welfare gains from targeting on observables (\$1.73 per dollar of aid).

An illustrative example



HEB in Kingwood, August 2017 (average flooding level \approx 6ft)

An illustrative example

H-E-B sets reopening date for Kingwood store flooded by Hurricane Harvey

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H-E-B's newest store in Kingwood, at 4317 Kingwood Drive, opens Oct. 26. It spreads out over 103,000 square feet.

HEB in Kingwood, January 2018

- **Effect of entry and exit on allocative efficiency**

Olley and Pakes (1996), Foster et al. (2008), Caballero and Hammour (1994), Barlevy (2002)

- Quantify each establishment's contribution to consumer welfare.

- **The impact of natural disasters on firms**

Basker and Miranda (2018), Cole et al. (2019), Collier et al. (2024)

- High frequency data allow us to distinguish between temporary and permanent closures.

- **Welfare and distributional effects of changing retail environments.**

Allcott et al. (2019a,b), Dubois et al. (2014, 2020), Handbury (2021), Klopck (2024)

- Study impacts of natural disasters from consumer welfare perspective at localized levels.

- **Aid allocation and program design**

Brown et al. (2018), Alatas et al. (2012), Gordon et al. (2023), Fu and Gregory (2019)

- Combine program evaluation with structural model to conduct welfare analysis

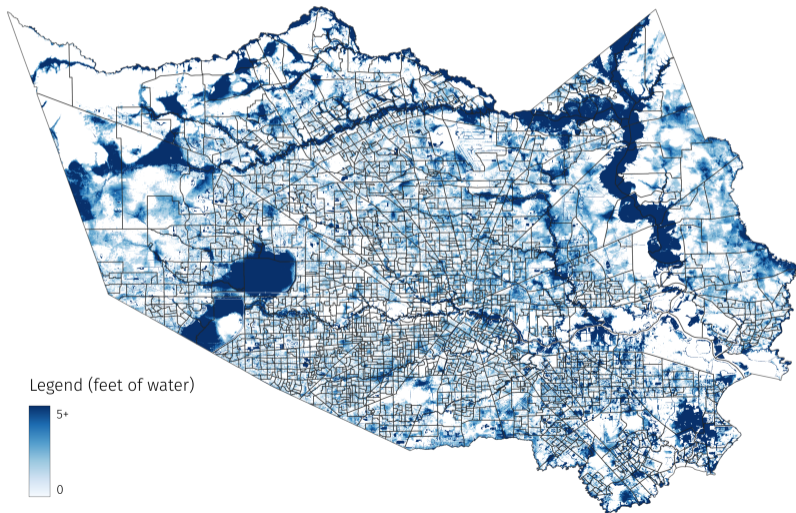
Data

- Transaction-level payment card data¹
 - Consumer purchases by credit/debit cards from major payments card provider
 - \approx 20% of US consumption in 2017
 - Each row is a transaction between consumer and merchant
 - Merchant: chain ID, name, NAICS, address
 - Card: observe history of past purchases.
 - For 70% of credit cards: home billing zip code (ZIP +4) + income
 - Primary sample: Houston, Corpus Christi, Beaumont MSAs between January 2017-December 2018

¹Data has been de-identified to remove account numbers and other PII

- Scraped business characteristics and reviews from Yelp and Google Maps
 - Use review dates to verify exits and entries [▶ More](#)
- Peak water levels: FEMA flooding depth (3m×3m grid)
 - Compute flooding exposure for businesses
- Property re-appraisal records from Harris county
- Kilts Center NielsenIQ Household Panel
- Auxiliary data:
 - Data Axle
 - SBA loan applicants and recipients
 - ACS and jurisdictional databases on state, county, census tract, census block group, and superneighborhood boundaries, as well as landcover data from the National Land Cover Database, and flood zone designations from FEMA

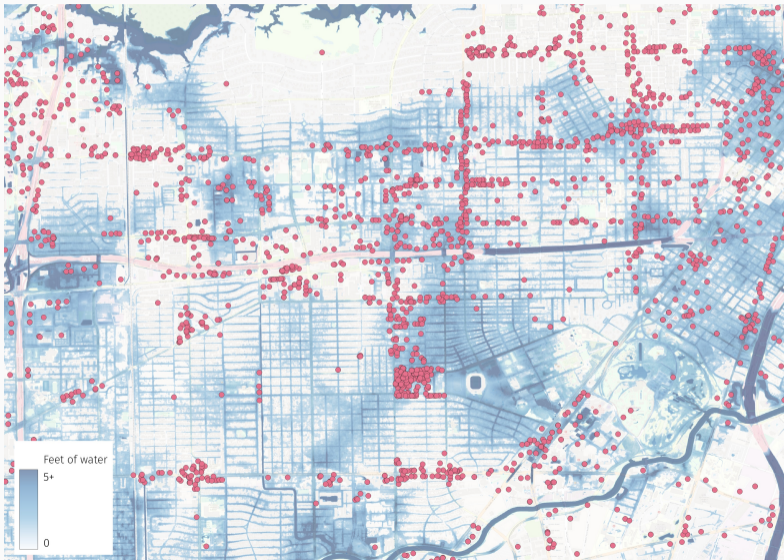
Which areas were flooded?



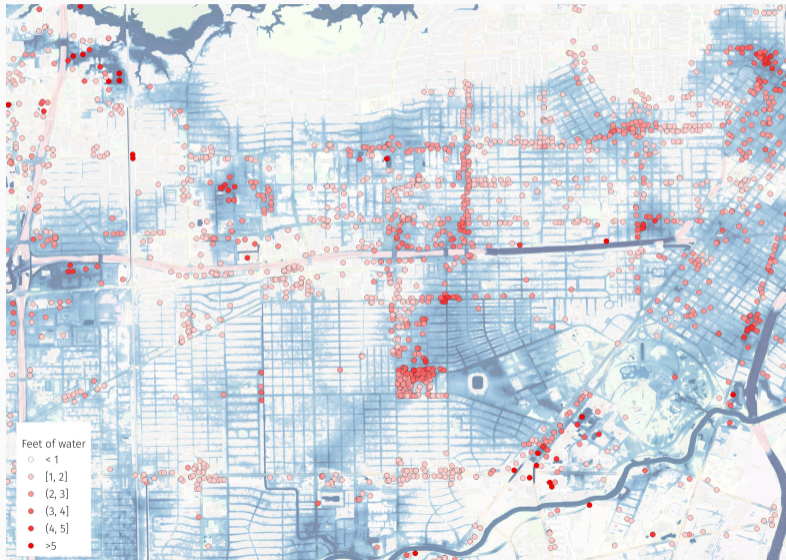
Flooding exposure for businesses



Flooding exposure for businesses



Flooding exposure for businesses



Measuring exit in the data

- Infer store closures from periods with no transactions
 - Permanent exit: store is open prior to Harvey but processes last transaction within one month of storm (August 2017)
 - Temporary closure: open before Harvey, stops processing transactions within one month of storm, but restarts before December 2018
- Issue: merchant identifiers in credit card data are imperfect.
- Verify all permanent exits with external data
 - Keep stores that permanently exit only if they are marked closed on Google or Yelp or had last review within 6 months of Harvey
 - Keep all stores that did not close or closed temporarily (even if not on Yelp)
- Keeps 56% all establishments (accounting for 88% of offline transactions)
 - 31,087 establishments between May and July 2017
 - 43% of exits and 35% of entries

Descriptive evidence

Rates of exit and temporary closure

NAICS	No closure	1-3 weeks	4-8 weeks	8+ weeks	Exit
Restaurants	81.3%	13.0%	1.5%	2.2%	2.0%
Groceries	87.1%	7.8%	1.8%	2.6%	0.8%
Gasoline	91.0%	5.0%	1.3%	2.4%	0.2%
Gen. Merch.	87.2%	8.4%	1.2%	2.8%	0.5%
Pharmacy	78.7%	18.3%	1.0%	1.5%	0.6%
Clothing	64.9%	29.2%	2.2%	2.7%	1.0%
Building supply	79.6%	16.1%	2.9%	1.1%	0.2%
Misc. retail	70.3%	22.6%	2.7%	3.2%	1.2%
Sports, books, hobby	69.7%	22.7%	3.0%	3.1%	1.4%
Auto parts	84.3%	12.3%	1.5%	1.5%	0.4%
Furniture	70.7%	23.5%	2.2%	2.5%	1.1%
Electronics	79.4%	15.1%	1.5%	2.6%	1.5%
Total	79.9%	14.8%	1.8%	2.3%	1.3%

► Closure time conditional on closure

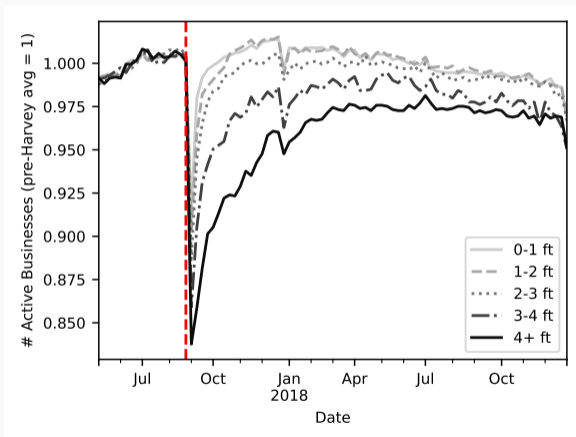
► Exit and entry over time

Rates of exit and temporary closure

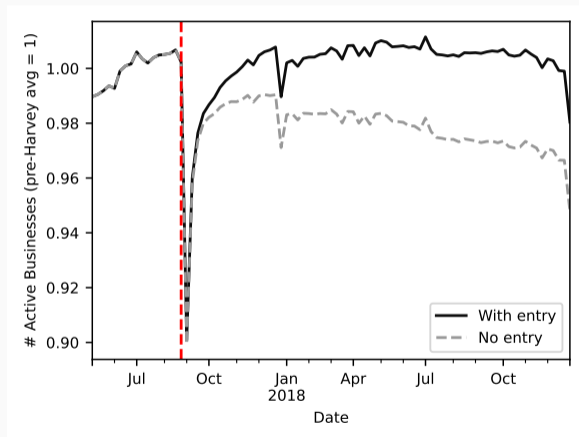
Closure status	Houston	Beaumont	Corpus Christi
No closure	81.9%	53.4%	76.1%
Temporary closure			
1-3 weeks	13.5%	38.3%	11.2%
4-8 weeks	1.5%	3.2%	4.3%
8+ weeks	2.0%	3.8%	5.7%
Perm closure	1.1%	1.2%	2.7%

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

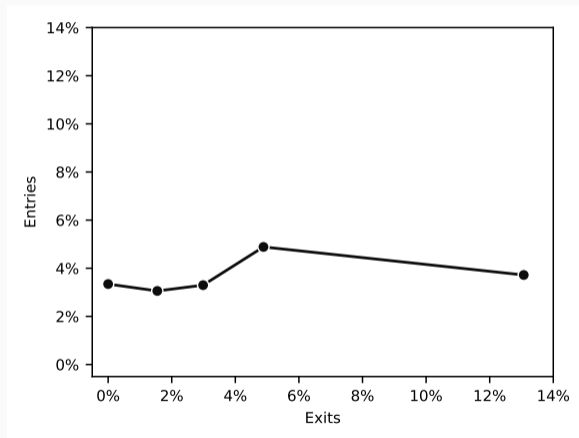
Likelihood of exit increases with flooding



New entrants eventually replace exiting firms...



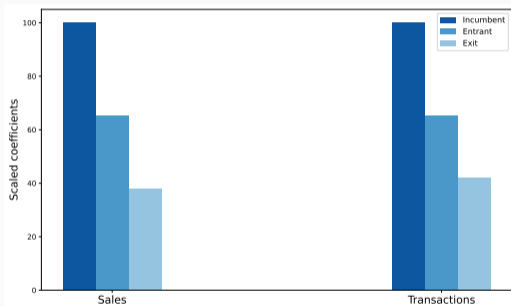
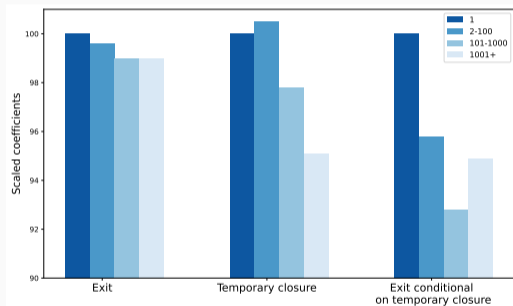
But there is a net decrease in # firms in most affected Census tracts



Average post-Harvey entry rates by quintile of Harvey exit rate.

▶ Long-run recovery

Who exits?



► Determinants of exits

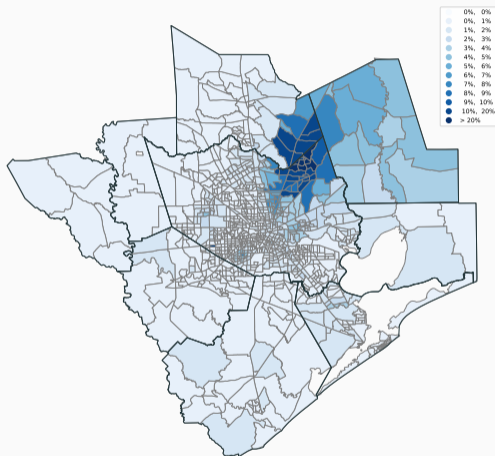
► Comparing entrants, incumbents and exiters

Summary of descriptive findings

1. Overall exit rates are low, but with significant heterogeneity across locations
2. Spatial reallocation: neighborhoods with most exits suffered a net loss in stores, while least affected neighborhoods gained stores
3. The exit rates are higher in smaller cities and among independent stores
4. On average, new entrants have more transactions and sales than firms that exit

Approximating welfare effects

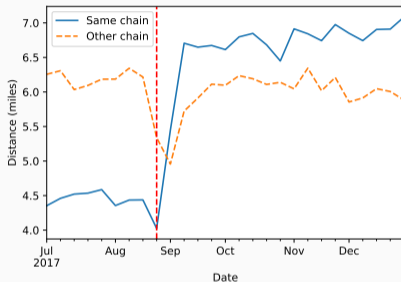
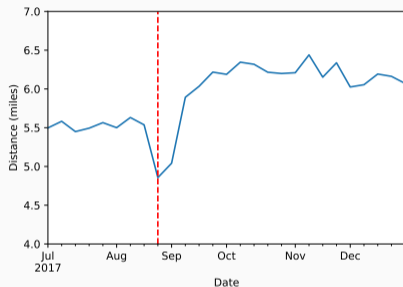
Where are consumers most affected?



Share of spending at stores that exit or close 8+ weeks

► Beaumont and Corpus Christi

Travel distance following store closures (top 20 store closures)



- One-way travel distance increased 15%, \$2.72 per trip \implies \$2M in four months, or \$50 per card
- Driven entirely by increase in travel distance to stores of same chain

► No effect on retail prices

Welfare effects of closures

Quantifying welfare effects of closures

- Estimate discrete choice model of demand using pre-Harvey data
 - Assume demand is separable across store categories
 - Consumers choose between stores within a category
 - Flexible demand model that leverages panel structure of data
 - Simulated maximum likelihood with repeated choices (Revelt and Train 1998)
 - Allows for rich preference heterogeneity *across* and *within* neighborhoods
- Sample for demand estimation
 - Consumer choice data for three months before Harvey (May-July 2017)
 - 11 retail NAICS + restaurants (89% of transactions)
 - Each consumer lives in neighborhood (Census tract)
 - Baseline: credit cards with matched income and home location data

Starting point: consumer preferences

We assume that utility is given by

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

- Consumer i , who lives in neighborhood n and visits store j at date t
- $\xi_{j,n}$: neighborhood x store fixed effect
- $d_{i_{(n)},j}$: Distance between a card's home and the store
- $x_{i_{(n)},j}$ includes:
 - Consumer income \times distance
 - Consumer income \times indicator for large chain
 - Consumer income \times "affluence" of store
 - Affluence = average card spend of its customers
- Correlated random coefficients on distance, store affluence
- $\varepsilon_{i_{(n)},j,t}$ and $\varepsilon_{i_{(n)},0,t}$ are i.i.d. type-1 extreme value distribution [▶ More](#)

Parameter estimates from the demand model (Houston)

NAICS	μ^d	$\sigma_{\theta^d}^2$	$\sigma_{\theta^a}^2$	ρ	$\theta^{\text{inc x dist}}$	$\theta^{\text{inc x aff}}$	$\theta^{\text{inc x chain}}$
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)

Estimates for ▶ Corpus Christi and ▶ Beaumont MSAs are similar

Welfare analysis

- Use post-Harvey data to estimate $\xi_{j,n}$ for new entrants [▶ Details](#)
- Compute consumer surplus using logit inclusive value for each consumer:

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

- The impact of closures on welfare is therefore

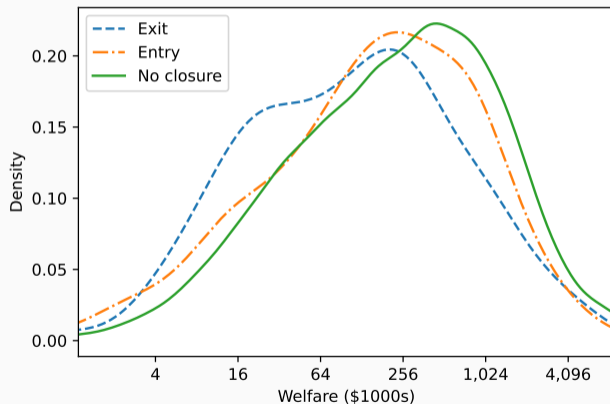
$$\Delta CS_{i(n),t} = \$3.44 \cdot \frac{1}{E[\theta_{i(n)}^d]} \left(IV_{i(n)}(\tilde{J}_{n,t}) - IV_{i(n)}(J_{n,t}) \right)$$

where $\tilde{J}_{n,t}$ is the observed choice set and $J_{n,t}$ is the counterfactual one.

- Compute $\Delta CS_{i(n)}$ as sum of $\Delta CS_{i(n),t}$ for each post-storm week t in 2017-2018.

Store-level consumer welfare contribution $\Delta CS_{i(n)}$

Conditional on set of stores open post-Harvey:



Similar when conditional on set of stores open pre-Harvey [▶ More](#)

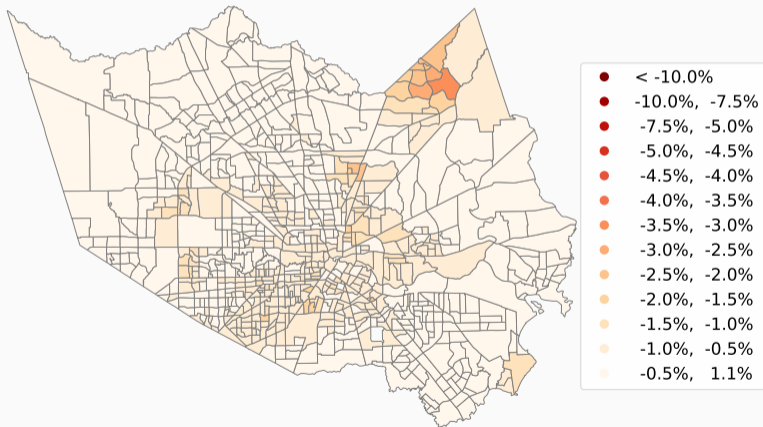
Distribution of welfare effects by neighborhood and NAICS: Houston

Change in consumer surplus as share of pre-storm expenditure:

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

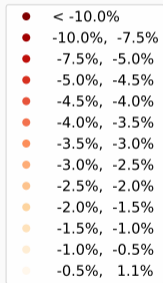
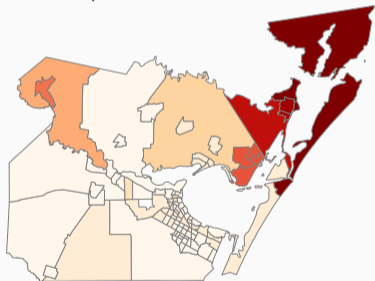
Distribution of welfare effects for **Corpus** and **Beaumont**

Distribution of aggregate welfare effects by neighborhood: Houston – Harris county

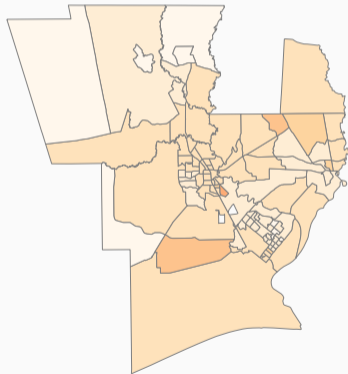


Distribution of aggregate welfare effects by neighborhood: Corpus and Beaumont

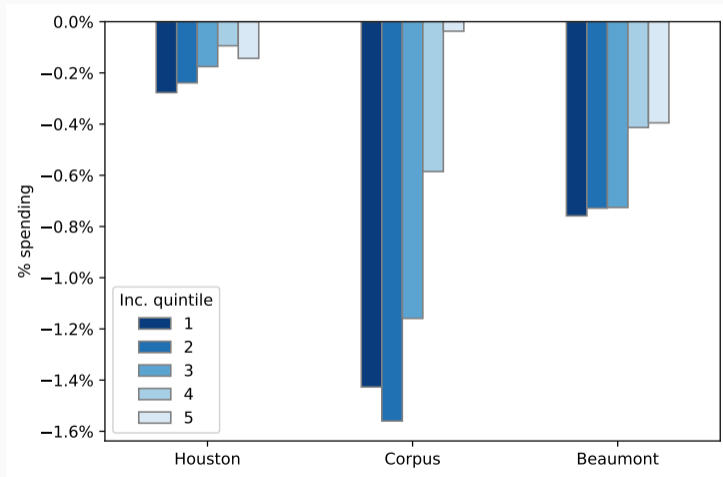
Corpus Christi:



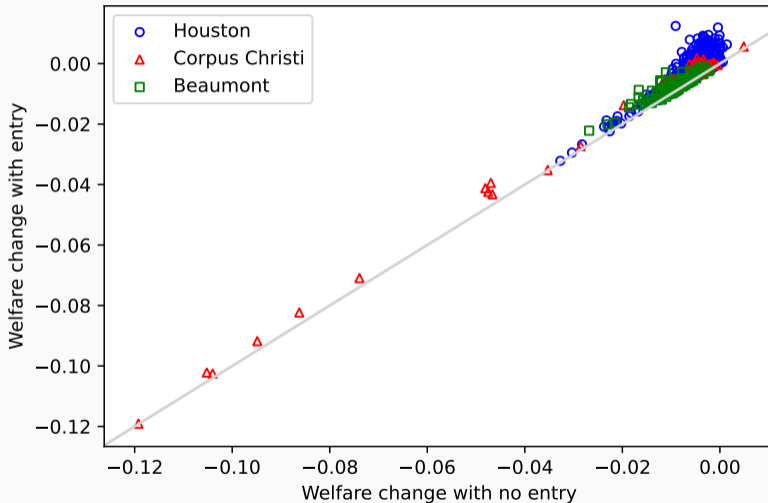
Beaumont:



Welfare losses by tract-level income



Welfare effects with and without new entry



Quantifying welfare losses

- Mean welfare loss over all consumers Sep 2017 - Dec 2018
 - Houston MSA: 0.28% of pre-storm expenditure (About \$200M)
 - Corpus MSA: 0.88%
 - Beaumont MSA: 0.85%
- Why bigger losses in Corpus and Beaumont?
 - Greater damage.
 - Fewer total options to start with.
- Correlation in CS loss over industries:
 - 0.7 for grocery and restaurants.
 - 0.63 for grocery and general merchandise.
- Distance traveled explains only about 40% of welfare loss [▶ Details](#)

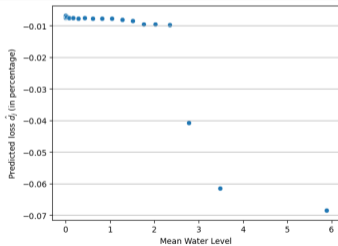
The impact of business aid programs

The impact of business aid programs

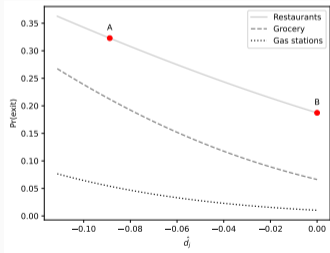
- Cost-benefit analysis for a (hypothetical) grant-based aid program.
- Aid given shortly after storm:
 - Aid provider can only observe current exit status
 - Cannot identify who will re-enter versus exit permanently
- How does aid increase probability of re-entry?
- Benefit of aid:
 - ⇒ Consumer surplus
 - ⇒ Employment benefits
- Cost: Dollar cost of grant

3-step approach:

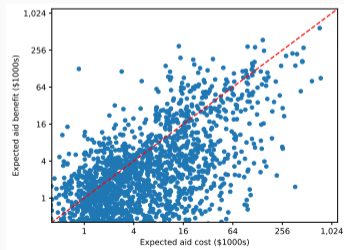
1. Machine learning to predict damage:



2. Re-enter or exit permanently:



3. Benefit and cost of aid:



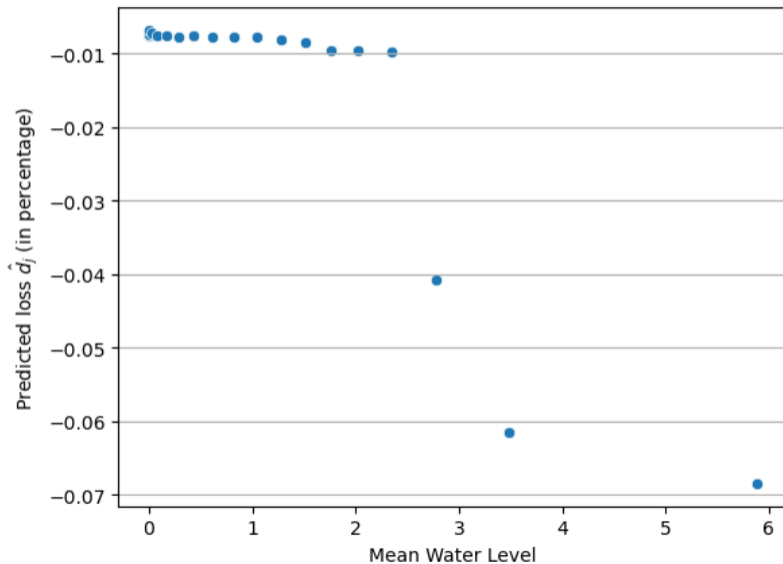
Step 1: Predicting damage using machine learning

- Few measures of storm damage for businesses
- Real property values assessed only annually, typically only in January
- Some retail real properties re-appraised shortly after Harvey
 - Only in “reappraisal districts”
 - Reappraisal and non-reappraisal properties had similar flood exposure [▶ Details](#)
- Construct measure of percent damage:

$$d_j = \frac{V_{post} - V_{pre}}{V_{pre}}$$

- Use random forest algorithm to predict \hat{d}_j for all retail real properties in Harris County

Step 1: Predicting damage using random forest



Step 2: Predicting probability permanently exits

$$\mathbb{P}(j \text{ exits}) = \mathbb{P} \left(\mathbb{E} \sum_{t=0}^{\infty} \delta_j^t R_{jt} \cdot m_j - F_j(\hat{d}_j) < 0 \right)$$

Step 2: Predicting probability permanently exits

$$\begin{aligned}\mathbb{P}(j \text{ exits}) &= \mathbb{P} \left(\mathbb{E} \sum_{t=0}^{\infty} \delta_j^t R_{jt} \cdot m_j - F_j(\hat{d}_j) < 0 \right) \\ &= \mathbb{P} \left(\log \left(\frac{1}{1 - \delta_n} \right) + \log(R_j) + \log(m_j) < \log \left(F_j(\hat{d}_j) \right) \right)\end{aligned}$$

Step 2: Predicting probability permanently exits

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

Determinants of profits:

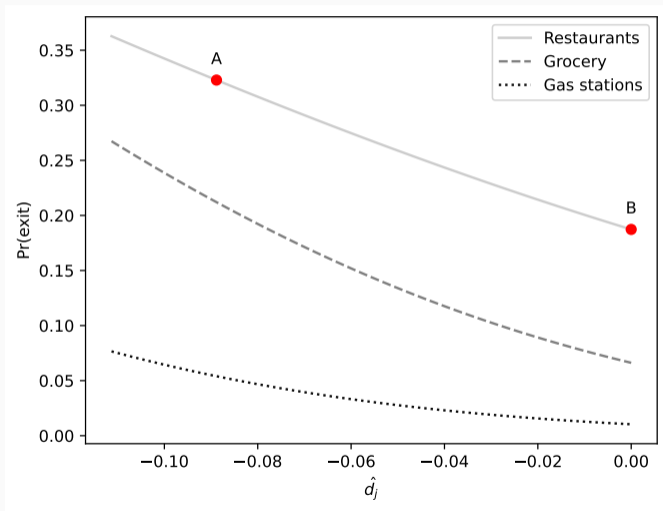
- Industry FE β_n^0
- Monthly pre-storm revenue R_j
- Chain size FE, FEMA flood plain x_j

Determinants of cost:

- Damage \hat{d}_j
- Square footage $sqft_j$
- β_n^0, x_j

Normal distribution for $\psi_j \Rightarrow$ estimated via probit [▶ More](#)

Step 2: Predicting probability permanently exits



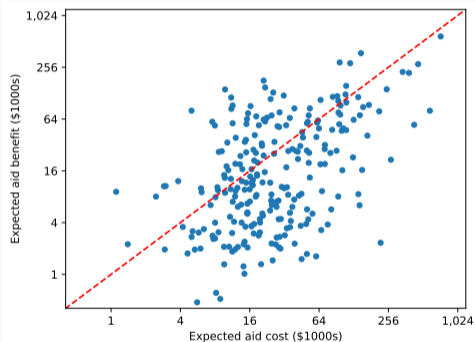
Step 3: Benefits and costs of aid

Additional modeling assumptions:

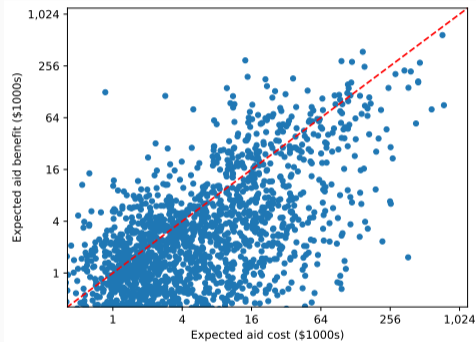
- Focus on aid sufficient to move \hat{d}_j to zero
- Back out damage in dollars [▶ Details](#)
 - Capital losses may be large or small
- Consumer benefits from store re-entry may be long- or short-lived [▶ Details](#)
- Employment benefits are UI payments [▶ Details](#)
- Marginal cost of public funds equal to 1.3 (Poterba, 1996)

Step 3: Benefits and costs of aid

4+ feet of water:



All:



- Aid to some firms does pass cost-benefit test
- Giving aid to all establishments does *not* pass cost-benefit test

Step 3: Benefits and costs of aid (in millions of \$)

	Baseline	Variation 1	Variation 2	Variation 3
Aid to all damaged firms:				
Cost	\$40.6			
Benefit	\$21.5			
% firms positive value	20%			
# subsidized firms	3,108			
Aid only to firms with positive net value:				
Cost	\$5.3			
Benefit	\$11.8			
% firms positive value	100%			
# subsidized firms	619			
Aid only to firms with predicted positive net value:				
Cost	\$6.3			
Benefit	\$10.9			
% firms positive value	71%			
# subsidized firms	529			

Targeting
details

► More

Step 3: Benefits and costs of aid (in millions of \$)

	Baseline	Variation 1	Variation 2	Variation 3
Aid to all damaged firms:				
Cost	\$40.6	\$171.3	\$40.6	\$171.3
Benefit	\$21.5	\$21.5	\$61.0	\$61.0
% firms positive value	20%	5%	40%	20%
# subsidized firms	3,108	3,108	3,108	3,108
Aid only to firms with positive net value:				
Cost	\$5.3	\$3.6	\$16.4	\$13.5
Benefit	\$11.8	\$6.1	\$54.0	\$33.7
% firms positive value	100%	100%	100%	100%
# subsidized firms	619	168	1,252	613
Aid only to firms with predicted positive net value:				
Cost	\$6.3	\$1.1	\$16.0	\$16.5
Benefit	\$10.9	\$1.9	\$46.5	\$30.7
% firms positive value	71%	60%	81%	70%
# subsidized firms	529	35	1,253	535

Targeting
details

► More

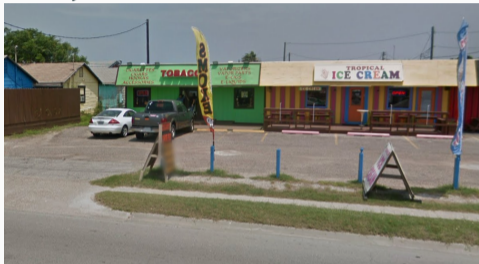
- Natural disasters are adverse shocks leading to firm turnover
- Cleansing or scarring?
 - New entrants contribute more to consumer surplus than exiting establishments
 - But new entry is not in places with most exit
- Average welfare effects are moderate but there is long right tail of harm
- Business aid must be targeted to pass cost-benefit test

Bonus slides

Using Google Maps to study firm dynamics

◀ Back

1. May 2016



2. Jan 2018



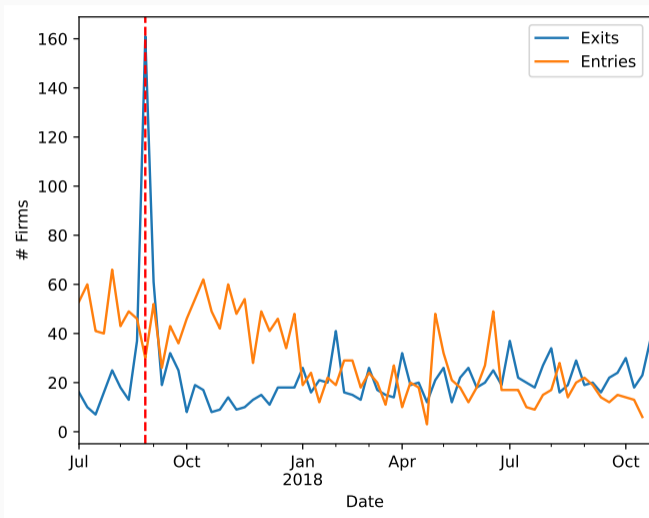
3. Mar 2019



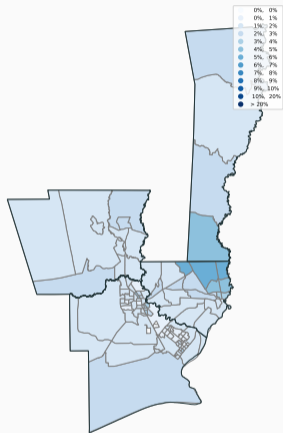
4. Jan 2022



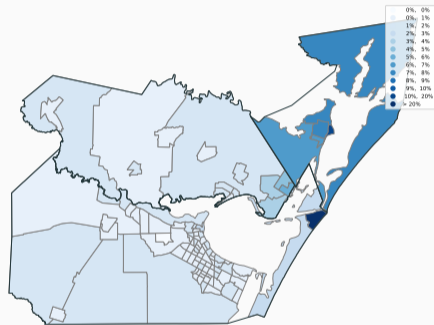
Exit and entry rates over time



Where are consumers most affected? Corpus Christi and Beaumont



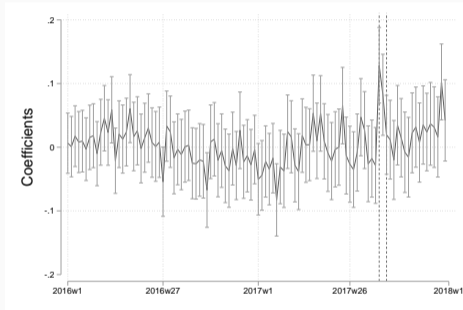
Beaumont



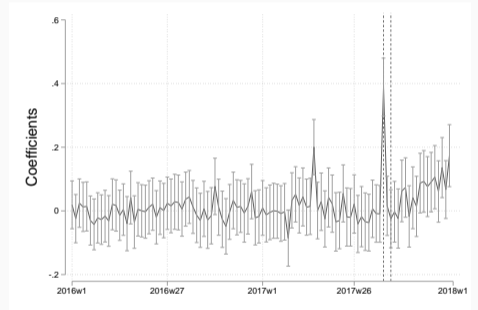
Corpus Christi

◀ Houston MSA

No price responses in the medium- and long-run



All channels



Discount stores

← Event study

Summary statistics for top 6 categories in the estimation sample

NAICS	Census Tracts	Consumers	Stores	Transactions	Dollars
Restaurants	1267	635,551	12,034	6,100,044	150,754,698
Groceries	1267	655,535	3,183	5,069,143	204,634,570
Gasoline	1267	733,493	2,031	3,453,678	83,577,392
Gen. Merch.	1267	780,572	993	3,579,117	226,934,858
Pharmacy	1267	600,959	1,280	1,802,785	68,503,099
Clothing	1267	604,601	2,662	1,754,111	163,919,199
Total	1267	1,774,852	29,249	26,223,051	1,378,599,013

How long-lasting are the effects?

Share of stores by reopening date for stores closed 4+ weeks

NAICS	10/2017	11/2017	12/2017	2018	Exit
Restaurants	49.1%	7.4%	4.0%	12.1%	27.4%
Groceries	70.2%	4.8%	2.9%	12.5%	9.6%
Gasoline	69.1%	7.4%	4.3%	13.8%	5.3%
Gen. Merch.	50.0%	17.6%	8.8%	14.7%	8.8%
Pharmacy	54.3%	6.5%	6.5%	19.6%	13.0%
Clothing	68.5%	9.4%	4.4%	6.6%	11.0%
Total	64.8%	8.3%	3.4%	11.0%	12.5%

What determines whether a firm exits?

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

Entrants have higher weekly transactions and sales than exiters

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

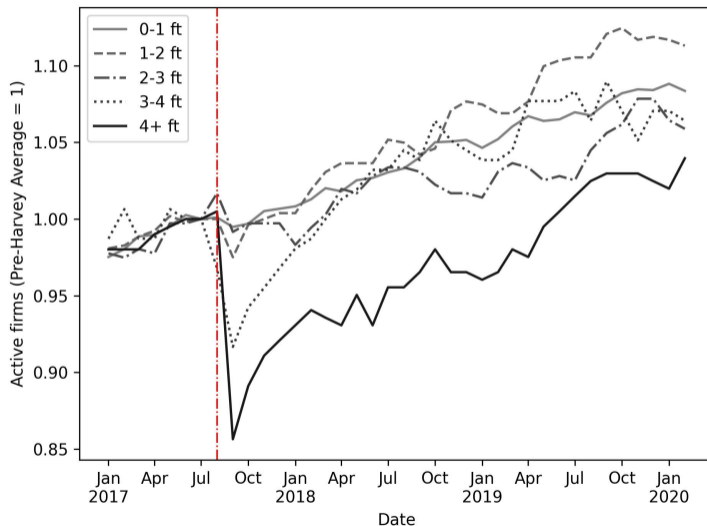
More details on consumer preferences

- Choice set: All retail options within 15 mile buffer of Census Tract:
 - Outside option: Retail visits to outlets outside of choice set
- Random coefficients:

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

- Affluence:
 - Average customer spending of a store (computed at the chain level)
 - Measured in dollars divided by 1,000, ranges from 0 to 5
- Distance: Measured in miles, ranges from 0 to 15.
- Consumer income: Measured in annual dollars divided by \$100,000 and top coded → ranges from 0 to 0.25

Long-run recovery



Estimation results: Corpus Christi

NAICS	μ^d	$\sigma_{\theta^d}^2$	$\sigma_{\theta^a}^2$	ρ	$\theta^{\text{inc} \times \text{dist}}$	$\theta^{\text{inc} \times \text{aff}}$	$\theta^{\text{inc} \times \text{chain}}$
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)

Estimation results: Beaumont

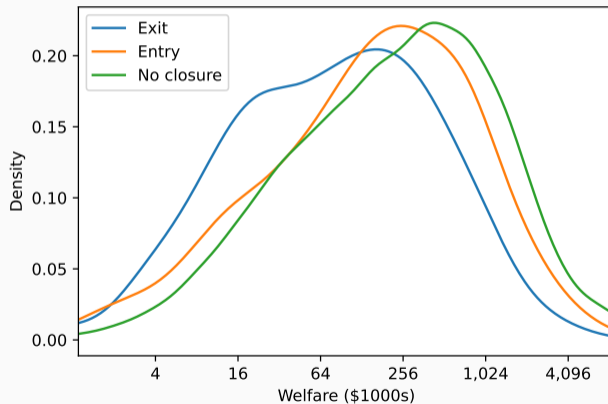
NAICS	μ^d	$\sigma_{\theta^d}^2$	$\sigma_{\theta^a}^2$	ρ	$\theta^{\text{inc} \times \text{dist}}$	$\theta^{\text{inc} \times \text{aff}}$	$\theta^{\text{inc} \times \text{chain}}$
Restaurants	-1.478 (0.030)	0.438 (0.024)	2.183 (0.064)	0.467 (0.025)	0.094 (0.042)	1.681 (0.397)	-0.521 (0.191)
Groceries	-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)

Accounting for entry

- Need $\xi_{j,n}$ values for stores that enter post-Harvey
- Main estimation sample is pre-storm ($t_0 = \text{May-July 2007}$).
 - Use this sample to estimate θ and $\xi_{j,n}$ for stores open pre-storm.
- Estimating ξ_{j,n,t_0} for stores that open post-storm
 - Use data from each post-storm quarter: $t = 17Q4, 18Q1, 18Q2, 18Q3,$ and $18Q4$
 - Hold fixed estimated θ from pre-storm
 - Estimate $\xi_{j,n,t}$ for each post-storm quarter t
 - Project all $\xi_{j,n,t}$ on store-neighborhood FE ($\alpha_{j,n}$) and quarter-neighborhood FE ($\alpha_{t,n}$)
- For new entrants: $\xi_{j,n} = \widehat{\alpha}_{j,n} + \widehat{\alpha}_{t_0,n}$

Store-level consumer welfare contribution $\Delta CS_{i(n)}$

Conditional on set of stores open pre-Harvey:



Distribution of welfare effects by neighborhood and NAICS: Corpus

Change in consumer surplus as share of pre-storm expenditure:

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

Distribution of welfare effects by neighborhood and NAICS: Beaumont

Change in consumer surplus as share of pre-storm expenditure:

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

Decomposing welfare effects

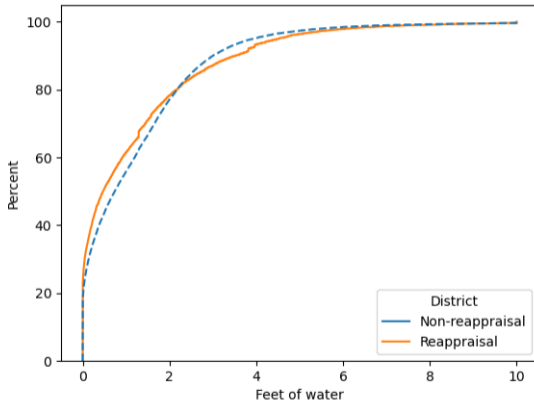
$$\Delta CS_{i_n,t} = -\$3.44 \cdot \Delta E[\text{distance}_{i_n,t}] + \text{Remainder}_{i_n,t}$$

where

$$E[\text{distance}_{i_n,t}] = \sum_j \text{distance}_{ij} \cdot \text{probability}_{ijt}$$

- Disutility caused by increased travel distance is 39% of the total welfare effect

Similarity of reappraisal and non-reappraisal properties



◀ Back

Parameter estimates from re-entry / exit permanently estimation

Sample	Dependent variable: 1(Exit)		
	(1) All stores	(2) Restaurants	(3) Retail
$\hat{\alpha}_i$	-6.293 (1.245)	-4.822 (1.698)	-7.941 (1.838)
Log(weekly rev.)	-0.129 (0.030)	-0.147 (0.038)	-0.098 (0.047)
Log(sqft)	0.100 (0.051)	0.091 (0.080)	0.065 (0.066)
2-100 locations	0.105 (0.088)	0.189 (0.113)	-0.030 (0.145)
101-1000 locations	-0.232 (0.145)	-0.386 (0.229)	-0.127 (0.192)
1001+ locations	-0.108 (0.140)	-0.432 (0.215)	0.211 (0.194)
1(Flood plain)	-0.029 (0.103)	-0.045 (0.138)	-0.016 (0.156)
Observations	3030	1199	1831
Pseudo R^2	0.082	0.054	0.058

Dollars of damage

- Task: Convert \hat{d}_j (as percent) to dollar damages D_j

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

where:

[◀ Back](#)

- $V_{b(j),pre}$ is real property assessed value Jan 2017
- $sqft_j/sqft_{b(j)}$ is establishment j 's share of real property
- $K_{j,pre}$ is establishment personal property (capital, inventory, etc.) Jan 2017
- κ is rate of decay of personal property
 - $\kappa = 1$: Share of damaged capital is same as that of real property.
⇒ Baseline and Variation 2
 - $\kappa = 8.98$: Calibrated so that store with max \hat{d}_j experiences 100% capital loss.
⇒ Variations 1 and 3

How long-lived are consumer welfare benefits?

- Consumer benefits last for length of sample:
 - 16 months
 - No discounting
 - ⇒ Baseline and Variation 1
- Infinitely discounted consumer surplus:
 - Monthly discount rate of 2.1%
 - Accounts for firm survival rate (Luo and Stark, 2014)
 - ⇒ Variations 2 and 3

Employment benefits

Approximated using Unemployment Insurance (UI) benefits:

- Data Axle: Count of total employees per establishment
- Bureau of Labor Statistics: County by NAICS average wages
- UI benefit rules for Texas in 2017
- Average resulting benefit is \$5,994 per employee

Targeting details

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