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

Ben Klopack, Eric Lewis, Fernando Luco

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Citation/Disclaimer

"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."

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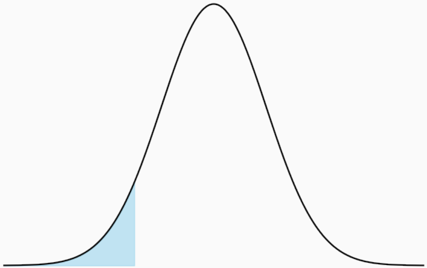

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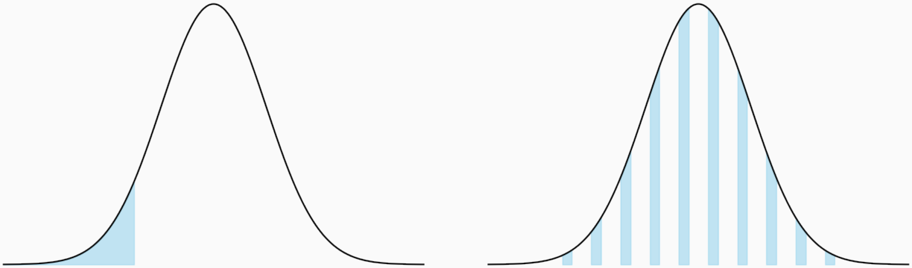

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  - Cost and efficacy of aid in reducing exit
- Big picture about natural disasters:
  - More frequent and costly: $201B in the 80s → $919B in the 2010s (NOAA, 2022)
  - Potentially large impacts on firms; sparse empirical work.
  - Firm closures → consumer welfare → distributional consequences
- Current policy: household grants (FEMA), business loans (SBA) — no timely business grants

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  - Low-income consumers bear up to 7x larger losses
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- Evaluate a grant-based aid program
  - Untargeted aid fails cost-benefit test
  - Targeting on observables: \$1.88 return per dollar of aid
    - 76% of what (infeasible) perfect targeting generates

An illustrative example of flooding and reopening

HEB in Kingwood, August 2017 (average flooding level $\approx$ 6ft). Note: The picture is illustrative only, meant to show what 6ft of flooding look like, **and** it is not linked to any retailer-specific analyses (and results) in the paper. Source: H-E-B Careers.

An illustrative example of flooding and reopening

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 4517 Kingwood Drive, opens Oct. 26. It spreads out over 105,000 square feet.

HEB in Kingwood, January 2018. Note: The pictures are illustrative only, meant to show what 6ft of flooding look like, **and** are not linked to any retailer-specific analyses (and results) in the paper. Sources: H-E-B Careers, Houston Business Journal. ▸ Ex: firm dynamics

Related literature

- **Welfare effects and distributional consequences of changes in retail environments**
  Cao et al. (2024), Allcott et al. (2019a,b), Dubois et al. (2014, 2020), Handbury (2021), Klopack (2024)
  - We: localized consumer welfare impacts of a natural disaster
- **Entry, exit, and allocative efficiency**
  Olley and Pakes (1996), Foster et al. (2008), Collard-Wexler and De Loecker (2015), Igami (2017), Caballero and Hammour (1994), Barlevy (2002, 2003)
  - We: consumer welfare contribution of each establishment
- **Natural disasters and firms**
  Basker and Miranda (2018), Cole et al. (2019), Collier et al. (2024)
  - We: high-frequency data $\rightarrow$ separate temporary vs. permanent closures
- **Aid allocation and program design**
  Brown et al. (2018), Gordon et al. (2023), Fu and Gregory (2019)
  - We: structural model + cost-benefit analysis of business aid

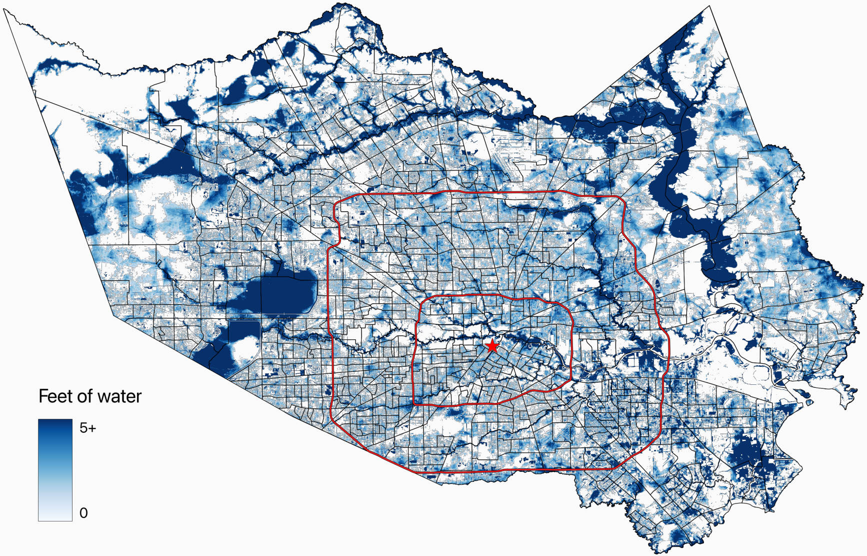
Data

Data

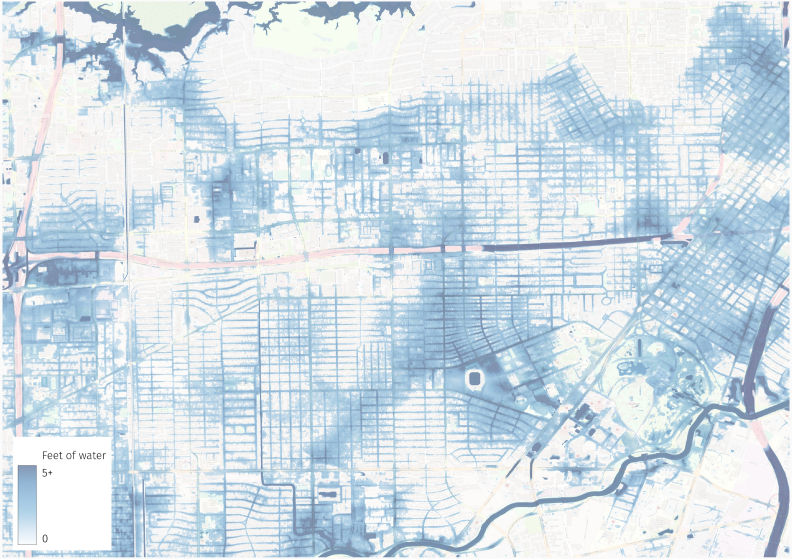
- Transaction-level payment card data[1]
  - $\approx$ 20% of US consumption (2017)
  - Observe: merchant (chain, NAICS, location) + card purchase history
  - 70% of credit cards: home ZIP+4 and income
  - Sample: Houston, Corpus Christi, Beaumont MSAs, Jan 2017–Dec 2018
- Yelp and Google Maps: verify exits/entries using review dates
- FEMA flood depth grids (3m$\times$3m): flooding exposure for firms and consumers
- Property re-appraisal records from Harris County ▸ Other data

[1] De-identified; no account numbers or PII

Which areas were flooded?



Flooding exposure for businesses



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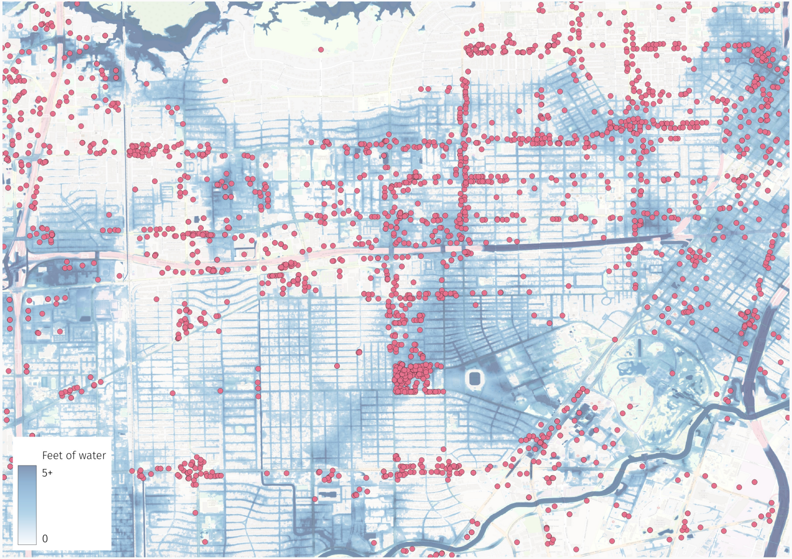

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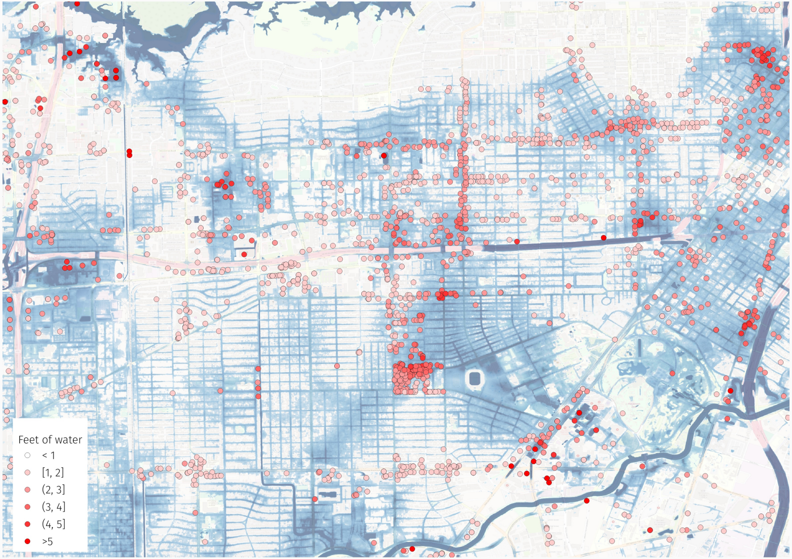
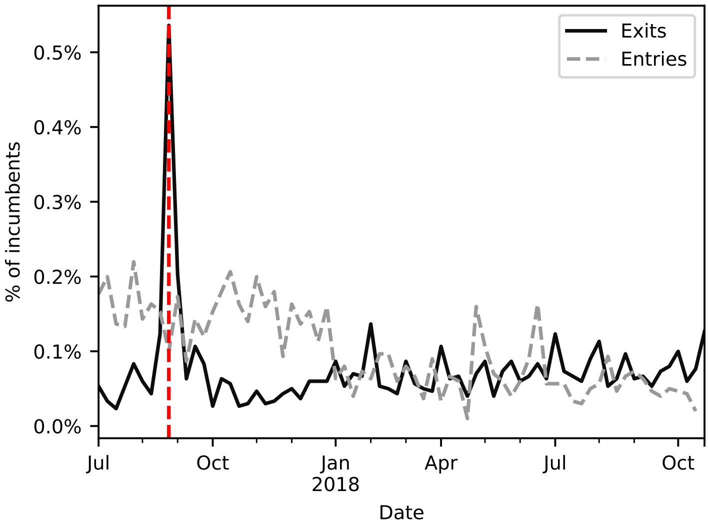


Measuring exit in the data

- Infer closures from gaps in transaction data
  - Permanent exit: last transaction within one month of Harvey
  - Temporary closure: stops transacting after Harvey, restarts before Dec 2018
- Verify all exits/entries with Yelp and Google Maps reviews
  - Require external confirmation for exits and entries
- Final sample: 56% of establishments (88% of transactions)
  - 43% of exits, 35% of entries

Descriptive evidence

Exit and entry rate over time

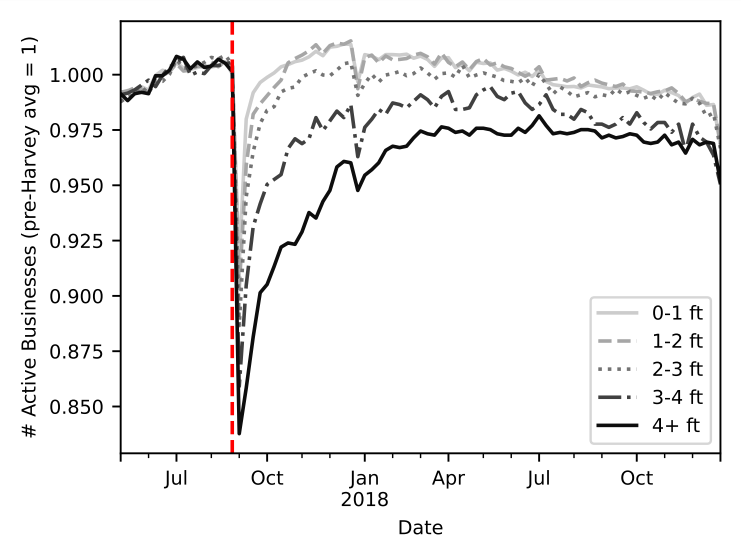


Rates of exit and temporary closure

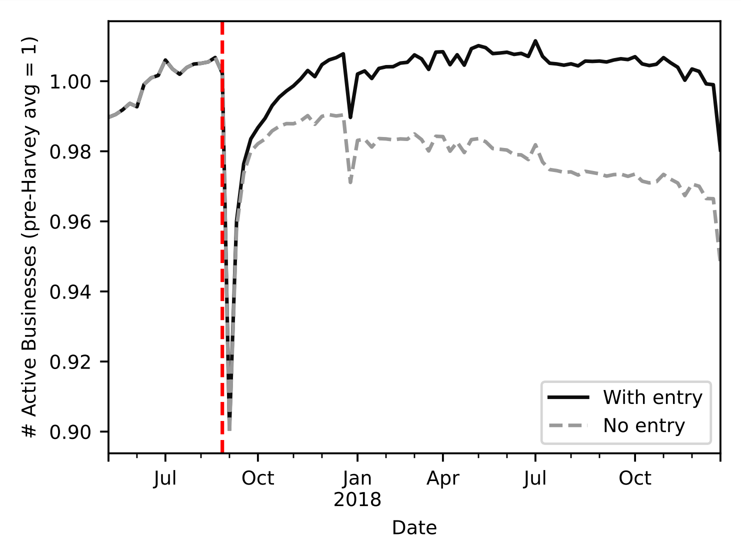
City	No closure	1-3 weeks	4-8 weeks	8+ weeks	Exit
Houston	81.9%	13.5%	1.5%	2.0%	1.1%
Beaumont	53.4%	38.3%	3.2%	3.8%	1.2%
Corpus Christi	76.1%	11.2%	4.3%	5.7%	2.7%
NAICS	No closure	1-3 weeks	4-8 weeks	8+ weeks	Exit
Restaurants	81.3%	13.0%	1.5%	2.2%	2.0%
Groceries	87.1%	7.8%	1.8%	2.6%	0.8%
Gasoline	91.0%	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%
Total	79.9%	14.8%	1.8%	2.3%	1.3%

▸ Closure time conditional on closure ▸ Exit and entry over time ▸ By flooding ▸ By NAICS

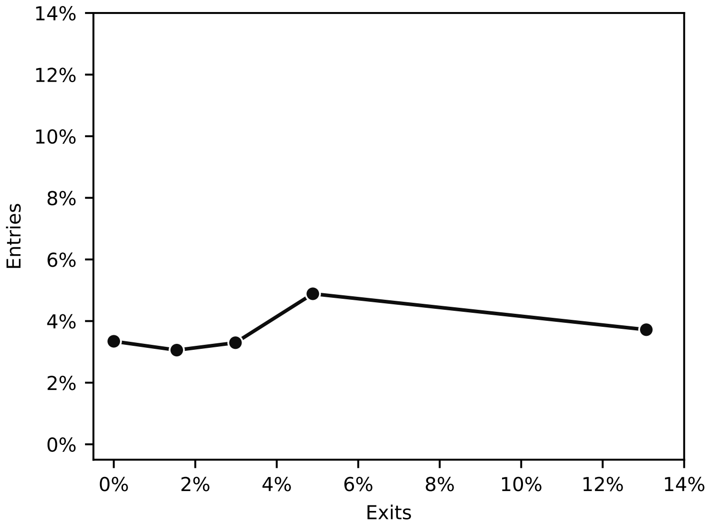
Likelihood of exit increases with flooding



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 ▸ Char. of exits

Entrants have higher weekly transactions and sales than exiters

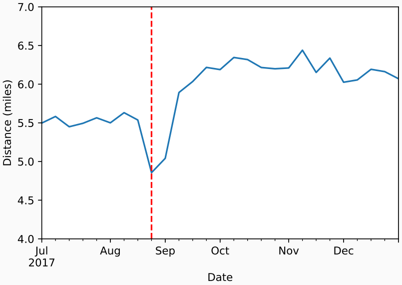
Dep. Var.	(1) Log(trans)	(2) Log(sales)
1(entry)	-0.347	-0.345
	(0.037)	(0.039)
1(exit)	-0.578	-0.619
	(0.069)	(0.071)
1(temp. closure 1-3 weeks)	-0.479	-0.443
	(0.111)	(0.055)
1(temp. closure 4-8 weeks)	-0.803	-0.817
	(0.065)	(0.068)
1(temp. closure 8+ weeks)	-0.580	-0.589
	(0.112)	(0.132)
1(1001+ locations)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

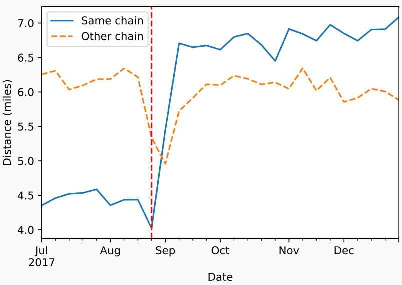
Summary of descriptive findings

1. Low exit rates, but higher among independents, restaurants, smaller cities
2. Spatial reallocation: worst-hit areas lose stores; least-hit areas gain
3. New entrants have more transactions and sales than exiters

Approximating welfare effects

A lower bound for welfare losses: increased travel distance

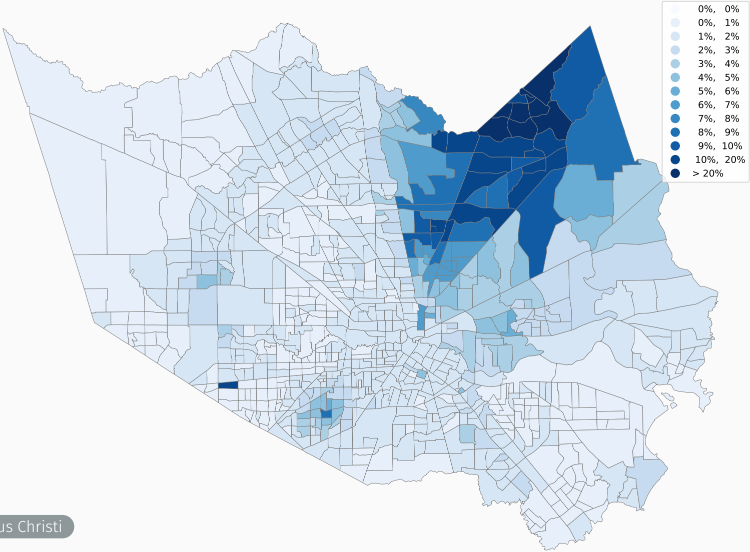




- One-way travel distance increased 15%
- Welfare loss of \$2.72 per trip $\Longrightarrow$ \$2M in four months; \$50 per card
- Driven by increased distance to same-chain stores

▸ No effect on retail prices ▸ Share of spending at closures

An upper bound for welfare losses: share of spending at long term closures



Beaumont and Corpus Christi

Welfare effects of closures

Quantifying welfare effects of closures

- Discrete choice demand model, estimated on pre-Harvey data
  - Separable across store categories (NAICS)
  - Simulated MLE with repeated choices (Revelt and Train 1998)
  - Rich preference heterogeneity across and within neighborhoods
- Estimation sample
  - May–July 2017 (three months pre-Harvey)
  - 11 retail NAICS + restaurants (88% of offline transactions)
  - Credit cards with matched income and home location

Consumer preferences

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

- $dist_{i(n),j}$: distance from card home to store
- $\xi_{j,n,q(t)}$: mean utility that store j provides to residents of neighborhood n in quarter $q(t)$
- $x_{i(n),j}$: income $\times$ distance, income $\times$ large chain, income $\times$ store affluence
  - Affluence $\equiv$ avg. card spend of store's customers
- Correlated random coefficients on distance (lognormal) and affluence
- ε: i.i.d. T1EV ▸ More

Parameter estimates from the demand model (Houston)

NAICS	μ_{θ^d}	$\sigma^2_{\theta^d}$	$E[\theta_i^d]$	$\sigma^2_{\theta^a}$	ρ	$\theta^{\text{inc x dist}}$	$\theta^{\text{inc x aff}}$	$\theta^{\text{inc x chain}}$
Restaurants	-1.068	0.292	0.398	1.012	0.25	0.089	0.282	-0.532
	(0.007)	(0.004)	-	(0.006)	(0.004)	(0.009)	(0.056)	(0.040)
Groceries	-0.653	0.540	0.682	2.208	0.478	0.096	0.659	-0.447
	(0.006)	(0.007)	-	(0.017)	(0.008)	(0.013)	(0.074)	(0.073)
Gasoline	-0.887	0.760	0.602	2.605	0.859	0.000	0.274	-0.255
	(0.007)	(0.014)	-	(0.021)	(0.012)	(0.011)	(0.089)	(0.138)
Gen. Merch.	-0.686	0.585	0.675	3.370	0.723	0.284	1.260	-3.793
	(0.006)	(0.007)	-	(0.025)	(0.009)	(0.009)	(0.081)	(0.165)
Pharmacy	-0.616	0.758	0.789	3.200	0.866	0.031	0.324	-0.248
	(0.007)	(0.011)	-	(0.039)	(0.012)	(0.011)	(0.078)	(0.102)

▸ Corpus Christi and ▸ Beaumont

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- Moving store 1 mile further $\rightarrow \approx 41\%$ decrease in choice probability

Corpus Christi and Beaumont

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- Higher income groups prefer independents and more “affluent” stores (relative to low income)

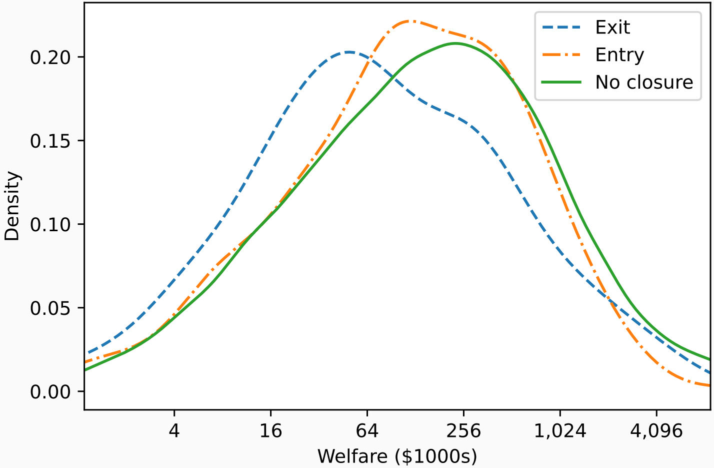
▸ Corpus Christi and ▸ Beaumont

Welfare analysis

- Monetize welfare using distance ▸ Details
  - $\Delta CS_{i_{(n)},t} = \$3.44 \cdot \frac{1}{E[\theta^{dist}_{i_{(n)}}]} \left(E[CS_{i_{(n)}}(\tilde{J}_{n,t})] - E[CS_{i_{(n)}}(J_{n,t})] \right)$
  - \$3.44 = cost of one mile (Dolfen et al 2023); $\tilde{J}$,J: observed, counterfactual ch. set
- Aggregate welfare impact in neighborhood n, week t: $\Delta CS_{nt} = \sum_{i \in n} \Delta CS_{i_{(n)},t}$
- Store j's welfare contribution: $\Delta CS_j = \sum_i \Delta CS_{i_{(n)},t}$ (with vs. without j)
- Estimate ξ's for new entrants from post-Harvey data ▸ Details

Store-level consumer welfare contribution ΔCS_j

Conditional on set of stores open post-Harvey:



Similar when conditional on set of stores open pre-Harvey ▸ More

Distribution of welfare effects (% of pre-storm expenditure) by Census tract

NAICS	Houston		Beaumont	Corpus Christi
	Avg.	Min.		
Restaurants	-0.38%	-4.31%		
Groceries	-0.21%	-11.72%		
Gasoline	-0.37%	-4.79%		
Gen. Merch.	-0.15%	-2.63%		
Pharmacy	-0.35%	-18.52%		
Clothing	-0.11%	-1.96%		
Misc retail	-0.23%	-2.56%		
Sporting Goods	-0.39%	-2.00%		
Hardware	-0.22%	-1.93%		
Auto parts	-0.06%	-0.66%		
Furniture	-0.16%	-7.26%		
Electronics	-0.03%	-0.92%		
Total	-0.25%	-2.68%		

- Total consumer harm ≈ \$183M in Houston (through Dec 2018)

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	Avg.	Min.	Avg.	Min.	Avg.	Min.
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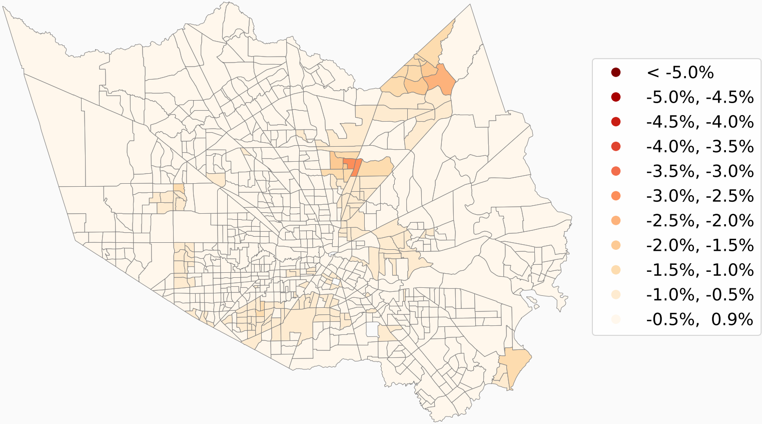
Groceries	-0.21%	-11.72%	-0.41%	-6.04%	-0.12%	-1.17%
Gasoline	-0.37%	-4.79%	-0.43%	-2.99%	-2.63%	-28.36%
Gen. Merch.	-0.15%	-2.63%	-0.31%	-2.19%	-0.33%	-2.81%
Pharmacy	-0.35%	-18.52%	-0.33%	-1.26%	-1.29%	-33.74%
Clothing	-0.11%	-1.96%	-1.16%	-2.99%	-0.91%	-11.30%
Misc retail	-0.23%	-2.56%	-0.54%	-9.35%	-1.50%	-8.75%
Sporting Goods	-0.39%	-2.00%	-1.80%	-6.72%	-0.90%	-5.02%
Hardware	-0.22%	-1.93%	-0.19%	-2.02%	-0.37%	-12.59%
Auto parts	-0.06%	-0.66%	-0.18%	-2.18%	-0.18%	-1.85%
Furniture	-0.16%	-7.26%	-0.26%	-1.68%	-0.38%	-3.29%
Electronics	-0.03%	-0.92%	-	-	-	-
Total	-0.25%	-2.68%	-0.64%	-2.47%	-0.95%	-9.19%

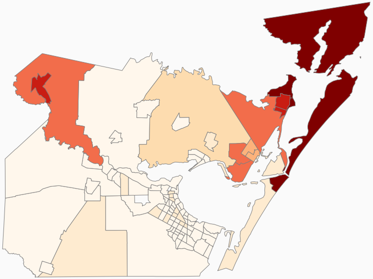
- Total consumer harm $\approx$ \$183M in Houston (through Dec 2018)
- Larger % losses in smaller MSAs: more damage, fewer options, less entry

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



Distribution of aggregate welfare effects by neighborhood: Corpus and Beaumont

Corpus Christi:



●	< -5.0%
●	-5.0%, -4.5%
●	-4.5%, -4.0%
●	-4.0%, -3.5%
●	-3.5%, -3.0%
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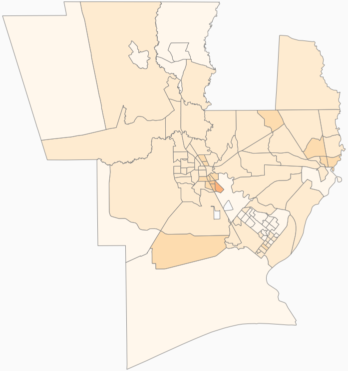
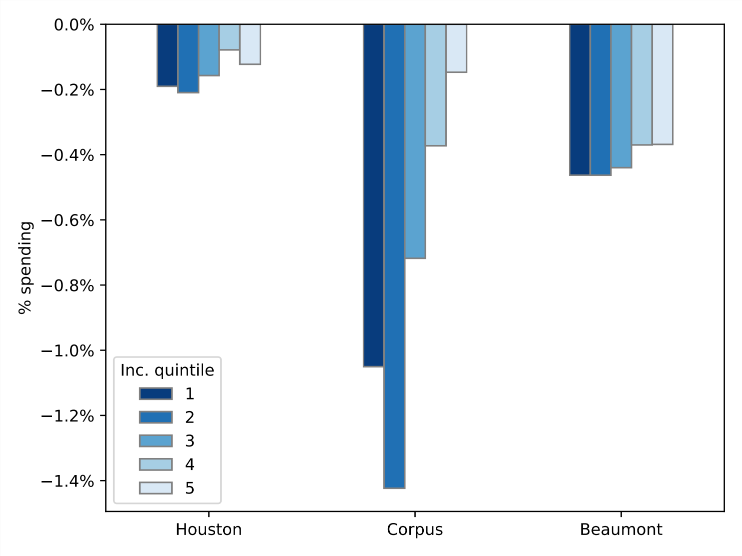
●	-2.0%, -1.5%
●	-1.5%, -1.0%
●	-1.0%, -0.5%
●	-0.5%, 0.9%

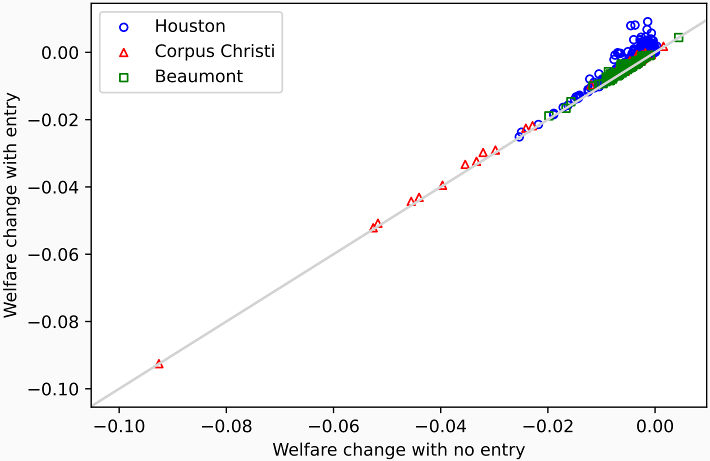
Beaumont:



Larger losses in lower-income Census tracts



Welfare effects with and without new entry



Quantifying welfare losses

- Mean welfare loss (Sep 2017 – Dec 2018, % of pre-storm expenditure):
  - Houston: 0.25% ($\approx$ \$183M)   Corpus Christi: 0.95%   Beaumont: 0.64%
  - Larger losses in smaller MSAs: more damage, fewer substitute options
- Welfare losses correlated across categories (grocery–restaurants: 0.7; grocery–general merch: 0.63)
- Distance traveled accounts for only $\approx$ 40% of welfare loss Details

The impact of business aid programs

The impact of business aid programs

- Cost-benefit analysis of a hypothetical grant-based aid program
- Setting: aid disbursed shortly after storm; cannot distinguish temporary vs. permanent exits ex ante
- Aid $\uparrow$ reentrant survival, but may crowd out new entry

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Benefits

- Consumer surplus from reentry
- Avoided unemployment

Costs

- Dollar cost of grants
- Crowd-out of new entry

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- Key variation: storm damage $\rightarrow$ exit probability

Two-stage entry model

Timing

1. Temporarily closed stores choose: reopen or exit permanently
2. Potential new entrants choose: enter or stay out
3. All active stores compete within NAICS

Each store knows δ's of others but not profit shocks ε. Enter if $E[\pi_j] \geq 0$:

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

Common beliefs B over competition:

$$E[s_j] = E\left[\frac{\exp\left(\delta_j\right)}{\sum_k \exp\left(\delta_k\right)}\right] = \exp(\delta_j) \cdot B$$

Oblivious equilibrium: stores do not internalize own entry on B

Entry model: new entrants

Stage 2: potential new entrants observe reentrants' δ's and own $(\delta_k, \varepsilon_k)$

- Other NEs' types drawn from:

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

- Equilibrium beliefs B^{NE}:

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

- Enter if $E[\pi_k] \geq 0$:

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

Entry model: reentrants

Stage 1: temporarily closed stores know own $(\delta_j, \varepsilon_j)$ and all other REs' δ's

- Beliefs B^{RE} over RE and NE entry:

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

- Re-enter if $\mathbb{E}[\pi_j] = M \cdot \exp(\delta_j) \cdot B^{RE} \cdot \zeta_j^{RE} - F_j(X_j) \cdot \exp(\varepsilon_j) \geq 0$
    - $\log(F_j(X_j)) = \log\left(C_j^{RE}\right) - \beta X_j$; X_j: building damage, log(sqft), chain indicator
- Estimated by MLE with nested fixed point for beliefs ▸▸ Details ▸▸ Estimates

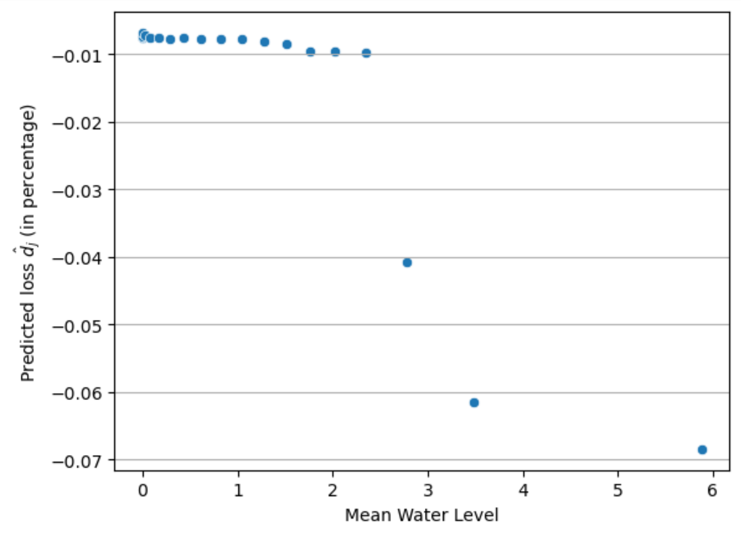
Measuring building damage

- Harris County reappraised some commercial properties shortly after Harvey
  - Only in "reappraisal districts" (similar flood exposure to non-reappraisal)
    ⏩ Balance ⏩ Data ⏩ Example
- Percent damage from change in assessed value:

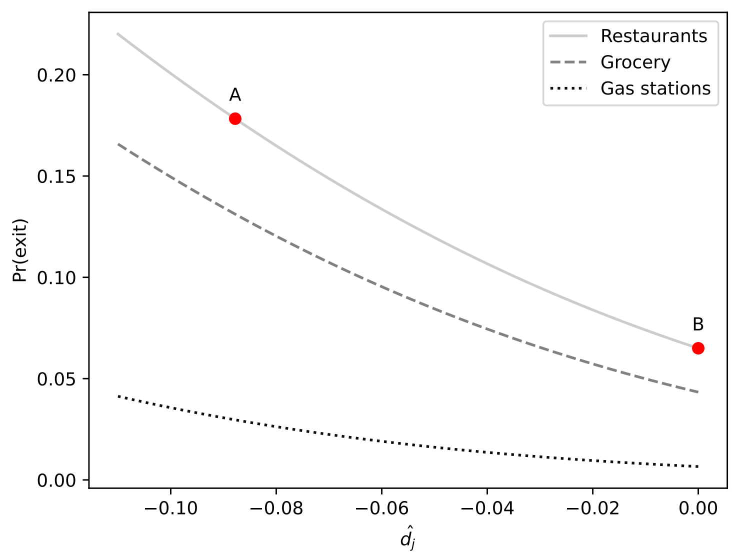
$$d_j = \frac{V_{post} - V_{pre}}{V_{pre}}$$

- Random forest to predict $\hat{d}_j$ for all properties in Harris County

Measuring building damage



Damage-exit curves

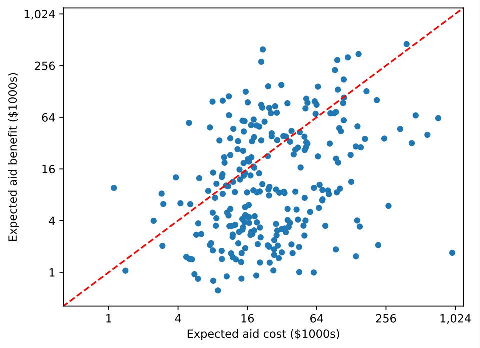


Benefits and costs of aid

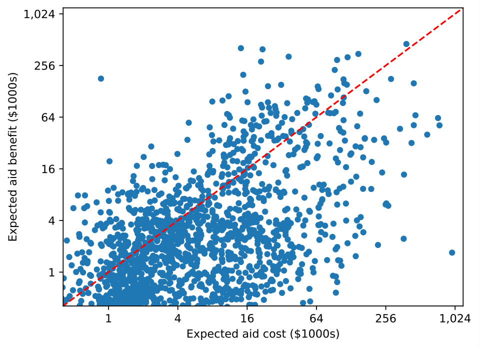
- Counterfactual: grant moves $\hat{d}_j \to 0$, solve for new equilibrium ⏩ Dollar conversion
- Crowd-out of new entry is negligible $\to$ action is on reentry margin
- Scenarios vary:
  - Capital loss rate ($\kappa = 1$ vs. $\kappa = 8.98$)
  - Duration of consumer benefits (sample period vs. infinite discounted) ⏩ Details
- Employment benefits $=$ UI payments ⏩ Details; MCPF $= 1.3$ (Poterba 1996)

Benefits and costs of aid

4+ feet of water:



All:



- Aid passes cost-benefit test for some firms, but *not* when given to all

Benefits and costs of aid (in millions of $)

	(1) Baseline	(2) Variation 1	(3) Variation 2	(4) Variation 3
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
% 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
% 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
% stores positive value	66.3%	73.9%	83.2%	64.3%
# subsidized stores	489	23	792	476

Targeting details

▸ More

Conclusion

- Evidence of both cleansing and scarring:
  - Entrants contribute more to surplus than exiters
  - But entry does not occur where exit is greatest
- Moderate average welfare losses, but long right tail of harm
- Harm is much higher in lower-income areas
- Targeted business aid passes cost-benefit test; blanket aid policies do not

Bonus slides

Firm dynamics

◂ Back ◂ Data

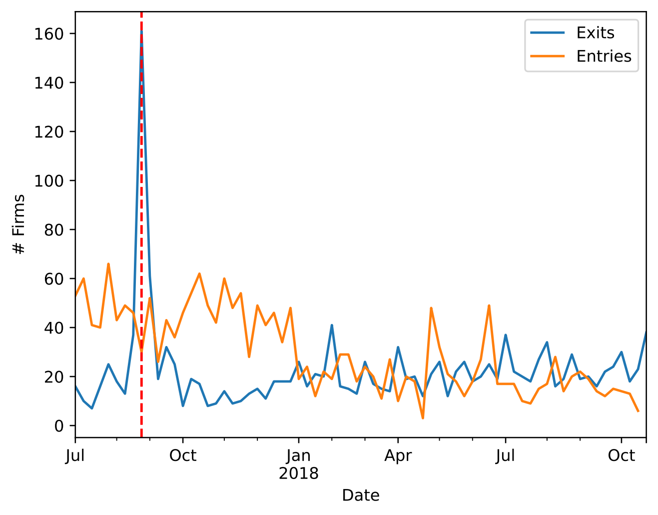
1. May 2016

2. Jan 2018

3. Mar 2019

4. Jan 2022

Exit and entry rates over time



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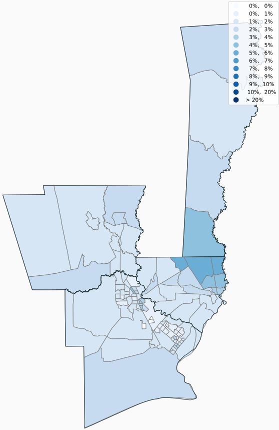
Data

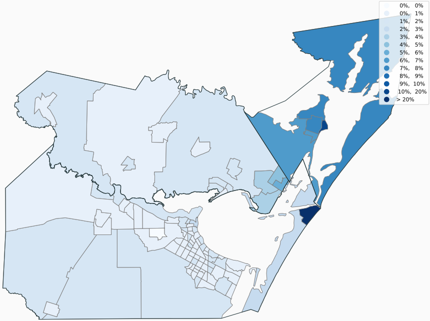
- Kilts Center NielsenIQ Household Panel
  - Pricing behavior
- Data Axle
  - Establishment level employment
- SBA loan applicants and recipients
- ACS: demographics by census tract
- Land cover data from the National Land Cover Database
- Flood zone designations from FEMA

▸ Other data

Share of spending at long-term closures: Corpus Christi and Beaumont



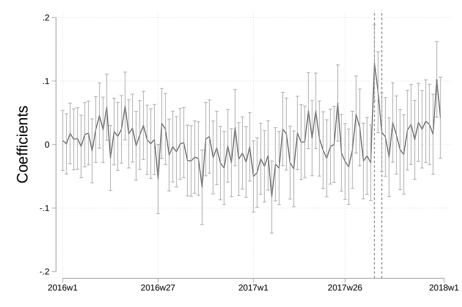
Beaumont



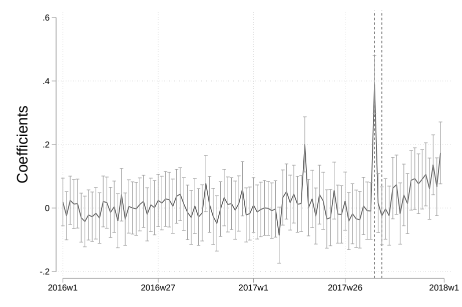
Corpus Christi

Back

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%

Back

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

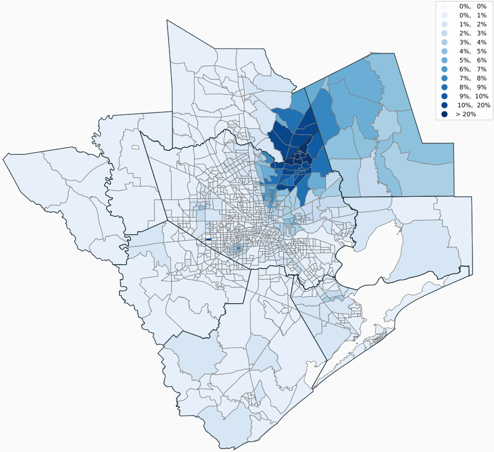
Back

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%
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%

Back

Where are consumers most affected?



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

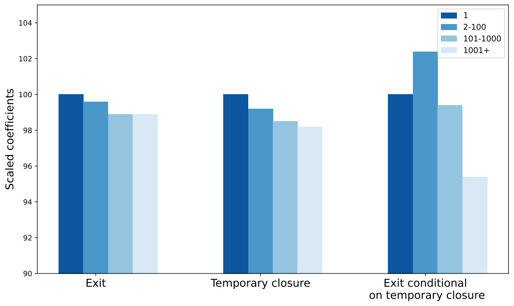
▸ Beaumont and Corpus Christi

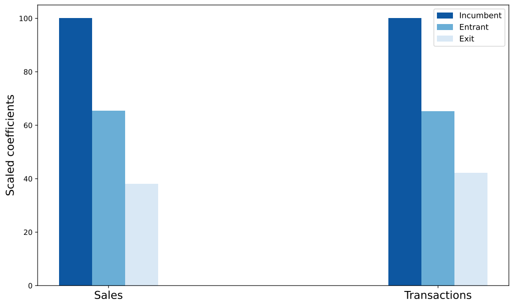
What determines whether a firm exits?

Dep. Var.	(1) 1(Perm. exit)	(2) 1(Temp. Closure)	(3) 1(Exit | Temp. closure)
1(Corpus)	0.008	0.007	0.140
	(0.006)	(0.006)	(0.073)
1(Houston)	0.003	-0.012	0.248
	(0.003)	(0.010)	(0.120)
Locations - 1001+	-0.011	-0.018	-0.046
	(0.004)	(0.002)	(0.050)
Locations - 101-1000	-0.011	-0.015	-0.006
	(0.003)	(0.002)	(0.029)
Locations - 2-100	-0.004	-0.008	0.024
	(0.001)	(0.002)	(0.011)
1(Beaumont) x Flood	0.006	0.011	0.097
	(0.004)	(0.007)	(0.059)
1(Corpus) x Flood	0.017	0.043	-0.001
	(0.005)	(0.008)	(0.029)
1(Houston) x Flood	0.003	0.010	-0.028
	(0.001)	(0.001)	(0.020)
1(Beaumont) x Flood sq	0.000	0.000	-0.010
	(0.001)	(0.001)	(0.008)
1(Corpus) x Flood sq	-0.001	-0.003	0.004
	(0.001)	(0.001)	(0.005)
1(Houston) x Flood sq	-0.000	-0.001	0.002
	(0.000)	(0.000)	(0.002)
NAICS FEs	x	x	x
R2	0.010	0.020	0.066
Observations	28587	28587	1439

◂ Back

Who exits?





▸ Back

More details on consumer preferences

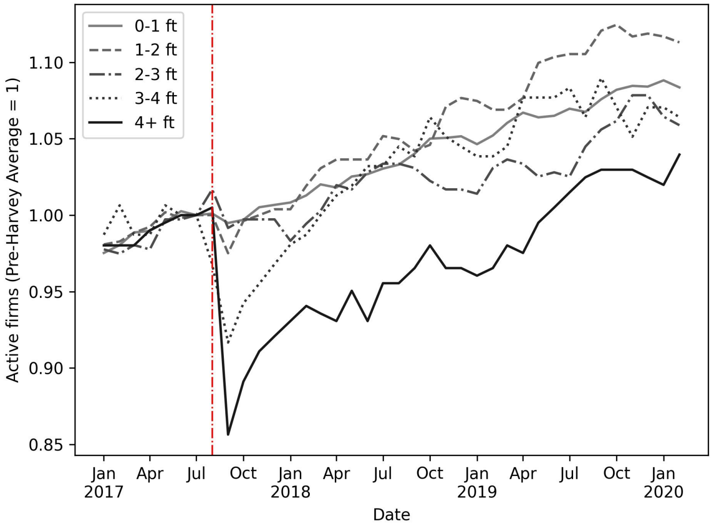
- Choice set: stores within 15 mi of Census tract; out. option: stores beyond
- Random coefficients:

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

- Variable scales:
  - Affluence: avg. customer spend at chain level (\$/1000, range 0–5)
  - Distance: miles (0–15)
  - Income: annual \$/1M, top-coded (range 0–0.25)

Back

Long-run recovery



Mixed Beverage Gross Receipts Tax (MBGRT) data, Texas Comptroller of Public Accounts

Back

Estimation results: Corpus Christi

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

◂ Back

Estimation results: Beaumont

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

Back

Accounting for entry

- Need $\xi_{j,n}$ for post-Harvey entrants (not in pre-storm sample)
- Approach: hold $\hat{\theta}$ fixed from pre-storm; estimate $\xi_{j,n,t}$ for each post-storm quarter
- Project $\xi_{j,n,t}$ on store-neighborhood FE ($\alpha_{j,n}$) + quarter-neighborhood FE ($\alpha_{t,n}$)
- New entrant value: $\xi_{j,n} = \widehat{\alpha_{j,n}} + \widehat{\alpha_{t_0,n}}$

◂ Back

Computing welfare

- Compute consumer surplus using logit inclusive value for each consumer:

$$IV_{i_{(n)}}(J_n) \equiv E \log \left(1 + \sum_{j \in J_n} \exp \left(x_{i_{(n)},j,t} \cdot \theta_{i_{(n)}} - \theta^{dist}_{i_{(n)}} dist_{i_{(n)},j} + \xi_{j,n,t} \right) \right) + C$$

- The impact of closures on welfare is therefore

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

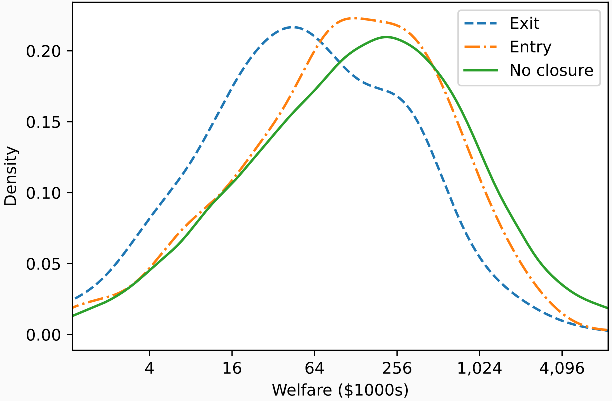
where $\tilde{J}_{n,t}$ is the observed choice set and $J_{n,t}$ is the counterfactual one.

- Compute $\Delta CS_{i_{(n)}}$ as sum of $\Delta CS_{i_{(n)},t}$ for each post-storm week t in 2017-2018.
- Welfare loss as percent of pre-storm expenditure: $\Delta CS_{i_{(n)}} / PreExp_{i_{(n)}}$

Back

Store-level consumer welfare contribution ΔCS_j

Conditional on set of stores open pre-Harvey:



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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	-1.53%	-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%

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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	-1.53%	-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%

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Decomposing welfare effects

$$\Delta CS_{i_n,t} = -\$3.44 \cdot \Delta E[distance_{i_n,t}] + Remainder_{i_n,t}$$

where

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

- Disutility caused by increased travel distance about 40% of the total welfare effect

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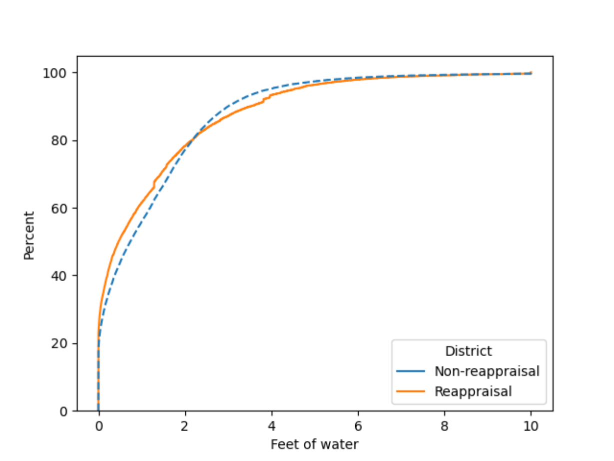
Similarity of reappraisal and non-reappraisal properties



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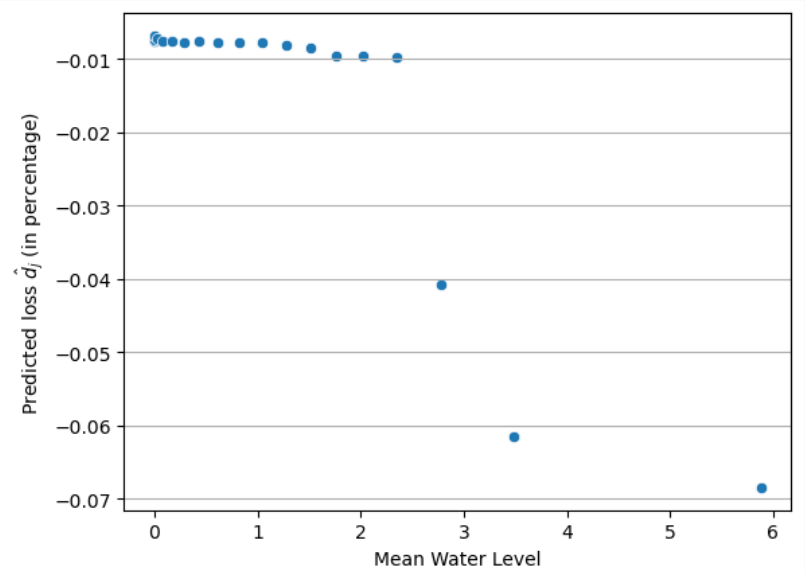
Predicting damage using random forest



Dollars of damage

- Convert percent damage $\hat{d}_j$ to dollars:

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

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- $V_{b(j),pre}$: real property value (Jan 2017); $sqft_j / sqft_{b(j)}$: store's share of property
- $K_{j,pre}$: personal property (capital, inventory); κ: capital decay rate
  - $\kappa = 1$: capital damaged at same rate as real property (Baseline, Var. 2)
  - $\kappa = 8.98$: max-damaged store loses 100% of capital (Var. 1, 3)

How long-lived are consumer welfare benefits?

- Consumer benefits last for length of sample:
  - 16 months
  - No discounting

  $\Rightarrow$ Baseline and Variation 1
- Infinitely discounted consumer surplus:
  - Monthly discount rate of 2.1%
  - Accounts for firm survival rate (Luo and Stark, 2014)

  $\Rightarrow$ Variations 2 and 3

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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

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Estimating the monetary impact of flooding

- Match card-data firms to HCAD assessed values (2016–2018)
- Real property (parcel level, e.g. shopping center):
  - Land + building values; total sqft
  - Damaged buildings inspected Sep 2017 – Jan 2018; depreciated 10–85%
- Personal property (store level):
  - Inventory, equipment, capital; store sqft

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Property tax data

Valuations		
	2016 Value	2017 Value
Total Appraised	13,186	13,199

Value Detail		
Category	2016 Value	2017 Value
Aircraft	0	0
Vessels	0	0
Inventory	776	789
Supplies	0	0
Raw Materials	0	0
Work In Progress	0	0
Furniture and Fixtures	1,801	1,801
Machinery and Other Equipment	10,609	10,609
Computers	0	0
Leasehold Improvements	0	0
Vehicles	0	0
Miscellaneous	0	0

Valuations					
Value as of January 1, 2017			Value as of January 1, 2018		
	Market	Appraised		Market	Appraised
Land	1,221,205		Land	976,964	
Improvement	4,908,700		Improvement	7,423,014	
Total	6,129,905	6,129,905	Total	8,399,978	8,399,978

5-Year Value History

Land

Market Value Land

Line	Land Use	Unit Type	Units	Size Factor	Site Factor	Appr O/R Factor	Appr O/R Reason	Total Adj	Unit Price	Adj Unit Price	Value
1	8004 -- Land Neighborhood Section 4 4343 -- Neighborhood Shopping Center	SF	244,241	1.00	1.00	1.00	--	1.00	4.00	4.00	976,964.00

Building

Building	Year Built	Type	Style	Quality	Impr Sq Ft	Building Details
1	1980	Neighborhood Shopping Center	8412 -- Neighborhood Shopping Ctr	Good	18,386	Displayed
2	1980	Neighborhood Shopping Center	8412 -- Neighborhood Shopping Ctr	Good	39,036	View

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Targeting details

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

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Estimation of entry model

- Mean utilities δ: predict shares from full demand system, invert in logit
- Simulated MLE with nested fixed point for beliefs
- Estimated separately for restaurants vs. all other categories
- $\sigma_{\varepsilon}^{NE}$ not identified $\rightarrow$ normalized; robust to alternative values
- $|J^{NE}| = 1.5\times$ realized entrants

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Parameter estimates from reentry / exit permanently estimation

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

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