Imminent Natural Disaster and Price Gouging? Evidence from Hurricane Harvey in the U.S.

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Background

Price gouging on necessity and emergency goods is often decried by the public in times of catastrophe.

Price gouging laws in most states explicitly forbid **excessive** increases in the price of necessity goods during declared disasters (ABA, 2020). But the lack of clarity about what constitutes an excessive price makes law enforcement difficult (FTC, 2006).

Determining **appropriate** price changes for essential and emergency goods during a disaster is crucial for distinguishing among efficient price dynamics that reflect changing underlying conditions (production costs or increased demand) and opportunistic rent-seeking on the part of retailers.

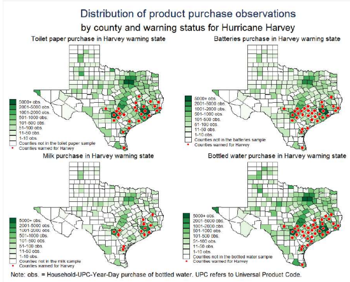


Figure 4: Map for product purchase

Data sources

- Consumer-level scanner data, aggregated at the store level, sourced from the Nielsen Company (US), LLC
- Hurricane warning data sourced from the National Centers for Environmental Information (NCEI) of the National Oceanic and Atmospheric Administration (NOAA)
  - Supplemented by NOAA way back machine data and Google search with date range customized to the hurricane season
- Applications to individual assistance (IA) programs and applications reporting needs sourced from the Federal Emergency Management Agency (FEMA)

Table 4: Assessment of price changes due to warning for Harvey, during landfall, and after strike - Coastal counties in the state of Texas

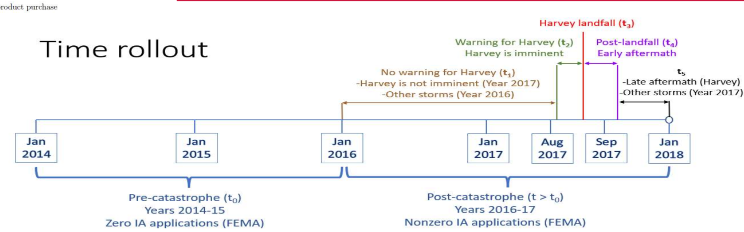
VARIABLES	(1) TP	(2) BT	(3) MK	(4) BW
Post-catastrophe year (ℓ)	0.012***	-0.005*	0.012***	0.012***
	(0.001)	(0.003)	(0.003)	(0.001)
Warning for actual Harvey (ϖ)	-0.010	0.010	0.037	0.011
	(0.013)	(0.013)	(0.029)	(0.012)
During actual Harvey landfall ($\hbar$)	0.108***	0.061**	0.073	-0.025
	(0.031)	(0.028)	(0.072)	(0.015)
After actual Harvey strike (1-3 weeks) (§)	-0.010	0.103**	0.062	-0.018
	(0.020)	(0.041)	(0.045)	(0.018)
Applications to Housing Programs (IHP/HA) (%)	-0.001	-0.001	-0.025	0.006
	(0.005)	(0.006)	(0.016)	(0.004)
Applications reporting a need for shelter (%)	-0.011	0.003	0.065***	-0.004
	(0.008)	(0.009)	(0.023)	(0.004)
Applications reporting a need for special accommodations (%)	0.020	-0.054	-0.235	0.161***
	(0.083)	(0.094)	(0.274)	(0.047)
Applications reporting a need for emergency items or food (%)	0.003	0.002	0.021	-0.015***
	(0.006)	(0.009)	(0.020)	(0.005)
Hurricane Hermine period (28 Aug 2016 - 3 Sep 2016)	-0.007	-0.009	-0.016	-0.006
	(0.010)	(0.018)	(0.021)	(0.007)
Hurricane Matthew period (28 Sep 2016 - 9 Oct 2016)	-0.008	0.007	-0.003	0.001
	(0.010)	(0.017)	(0.019)	(0.006)
Hurricane Irma period (30 Aug 2017 - 12 Sep 2017)	0.010	-0.000	-0.051*	0.017*
	(0.010)	(0.011)	(0.028)	(0.009)
Hurricane Maria period (16 - 30 Sep 2017)	-0.004	0.001	0.050**	0.005
	(0.007)	(0.015)	(0.022)	(0.006)
Constant	0.988***	1.005***	0.982***	0.985***
	(0.001)	(0.002)	(0.002)	(0.001)
Observations	24,148	11,041	5,023	31,417
R-squared	0.008	0.006	0.037	0.009
Counties	Coastal	Coastal	Coastal	Coastal
Price index winsorized at the 2nd and 98th percentiles	Yes	Yes	Yes	Yes
Store fixed effects and sampling weights	Yes	Yes	Yes	Yes
Efficient price change at warning (λ^{ϖ})=	0.000	0.000	0.000	0.000
Observed price change at warning ($\varpi + \ell$)=	0.002	0.005	0.049	0.024
Testing observed price change at warning ($\varpi + \ell$) = λ^{ϖ}, p-value=	0.848	0.705	0.091	0.046
Efficient price change at landfall ($\lambda^{\hbar}$)=	0.000	0.000	0.859	0.792
Observed price change at landfall ($\hbar + \ell$)=	0.120	0.056	0.084	-0.013
Testing observed price change at landfall ($\hbar + \ell$) = $\lambda^{\hbar}$, p-value=	0.000	0.043	0.000	0.000
Efficient change after strike ($\lambda^{§}$)=	0.000	0.000	0.000	1.274
Observed price change after strike (§ + ℓ)=	0.003	0.098	0.073	-0.005
Testing observed price change after strike (§ + ℓ) = $\lambda^{§}$, p-value=	0.898	0.017	0.104	0.000

Notes: This table reports the results from price estimations using Eq.6. The estimation sample covers all four years (2014-2017) and includes coastal counties in the state of Texas. As defined by FEMA, coastal counties (a) have a shoreline, or (b) contain velocity zones (V-zones) or coastal high hazard areas. Dependent variable is store-UPC-level price index winsorized at the 2nd and 98th percentiles: values smaller than the 2nd percentile are replaced by the 2nd percentile, and values higher than the 98th percentile are replaced by the 98th percentile. The product is toilet paper (TP) in column 1, batteries (BT) in column 2, milk (MK) in column 3, and bottled water (BW) in column 4. Applications to individual assistance programs and applications reporting needs are normalized by the total population (number of households) in the zipcode3 for the corresponding year and multiplied by 100. Timing of actual Harvey landfall in Texas is August 25-26th, 2017. Store fixed effects and sampling weights are used in all regressions. Robust standard errors are in parentheses below the coefficients. Significance levels: *** 1%, ** 5%, * 10%.

Research questions

Two-fold research question

1. Do market prices change in times of catastrophe?
2. Are the changes in prices efficient (in that they reflect changes in supply and demand)?



Optimal pricing and comparative statics

- Retailer r selling product j in its store s in period $t \in \{0,1,2,3,4,5\}$ chooses monopolistically competitive prices P_{rsjyw} in week w of year y
  - Profit maximization problem

$$\max_{P_{rsjyw}} \sum_{s,j} (P_{rsjyw} - c_j) * Q_{rsjyw}(P_{rsjyw}) - \sum_{s} C_{sj}. \qquad \text{(Eq.1)}$$

  - $Q_{rsjyw}(P_{rsjyw}) = k_{sj} e^{b_{sj}(t) * P_{rsjyw}}$: residual demand for product j in store s of retailer r in week w described by a semi-log function of price
  - F.O.C.

$$P^*_{rsjyw} = c_j - \frac{1}{b^*_{sj}(t)} \quad , \quad b^*_{sj}(t) \neq 0. \qquad \text{(Eq.2)}$$

  - Result from the implicit function theorem

$$\frac{dP^*_{rsjyw}}{dt} = \frac{\frac{\partial b^*_{sj}(t)}{\partial t}}{\left(b^*_{sj}(t)\right)^2} \quad , \quad b^*_{sj}(t) \neq 0. \qquad \text{(Eq.3)}$$

  - Periods $t = 0$: non-catastrophe years; $t = 1$: before warning for the catastrophe; $t = 2$: warning for the catastrophe; $t = 3$: catastrophe hits; $t = 4$: short-term aftermath; $t = 5$: medium/long-term aftermath

Values of the pre-disaster parameter of the price elasticity of demand $b^*_{sj}(t = 0)$

Values of the change in the parameter of the price elasticity of demand $\frac{\partial b^*_{sj}(t)}{\partial t}$	-0.05	-0.10	-0.15	-0.20	-0.25	-0.30	-0.35	-0.40	-0.45	-0.50	-0.55	-0.60	-0.65	-0.70	-0.75	-0.80	-0.85	-0.90	-0.95
0.00	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
0.05	95%	45%	29%	21%	16%	13%	11%	9%	8%	7%	6%	5%	5%	4%	4%	3%	3%	3%	3%
0.10	190%	91%	58%	42%	32%	26%	21%	18%	15%	13%	12%	10%	9%	8%	8%	7%	6%	6%	5%
0.15	286%	136%	87%	63%	48%	38%	32%	27%	23%	20%	18%	16%	14%	13%	11%	10%	10%	9%	8%
0.20	381%	182%	116%	83%	64%	51%	42%	36%	31%	27%	23%	21%	19%	17%	15%	14%	13%	12%	11%
0.25	476%	227%	145%	104%	80%	64%	53%	45%	38%	33%	29%	26%	23%	21%	19%	17%	16%	15%	13%
0.30	571%	273%	174%	125%	96%	77%	63%	54%	46%	40%	35%	31%	28%	25%	23%	21%	19%	18%	16%
0.35	667%	318%	203%	146%	112%	90%	74%	63%	54%	47%	41%	36%	33%	29%	27%	24%	22%	20%	19%
0.40	762%	364%	232%	167%	128%	103%	85%	71%	61%	53%	47%	42%	37%	34%	30%	28%	25%	23%	22%
0.45	857%	409%	261%	188%	144%	115%	95%	80%	69%	60%	53%	47%	42%	38%	34%	31%	29%	26%	24%
0.50	952%	455%	290%	208%	160%	128%	106%	89%	77%	67%	59%	52%	47%	42%	38%	35%	32%	29%	27%
0.55	1048%	500%	319%	229%	176%	141%	116%	98%	84%	73%	65%	57%	51%	46%	42%	38%	35%	32%	30%
0.60	1143%	545%	348%	250%	192%	154%	127%	107%	92%	80%	70%	63%	56%	50%	46%	42%	38%	35%	32%
0.65	1238%	591%	377%	271%	208%	167%	138%	116%	100%	87%	76%	68%	61%	55%	50%	45%	41%	38%	35%
0.70	1333%	636%	406%	292%	224%	179%	148%	125%	107%	93%	82%	73%	65%	59%	53%	49%	45%	41%	38%
0.75	1429%	682%	435%	313%	240%	192%	159%	134%	115%	100%	88%	78%	70%	63%	57%	52%	48%	44%	40%
0.80	1524%	727%	464%	333%	256%	205%	169%	143%	123%	107%	94%	83%	75%	67%	61%	56%	51%	47%	43%
0.85	1619%	773%	493%	354%	272%	218%	180%	152%	130%	113%	100%	89%	79%	71%	65%	59%	54%	50%	46%
0.90	1714%	818%	522%	375%	288%	231%	190%	161%	138%	120%	106%	94%	84%	76%	69%	63%	57%	53%	49%
0.95	1810%	864%	551%	396%	304%	244%	201%	170%	146%	127%	111%	99%	89%	80%	72%	66%	60%	56%	51%
1.00	1905%	909%	580%	417%	320%	256%	212%	179%	153%	133%	117%	104%	93%	84%	76%	69%	64%	58%	54%

Figure 1: Efficient price increases on necessity and emergency goods produced at a marginal cost of $1

Empirical framework

Step 1: Checking pre-catastrophe demand is elastic

$$log(Q_{rsjyw}) = \mu + \vartheta_{sj} P^{index}_{rsjyw} + \alpha_y + \gamma_w + \varepsilon_{rsjyw}. \qquad \text{(Eq.4)}$$

- Test the null hypothesis (inelastic demand): $\vartheta_{sj} = 0$ or $\eta_{sj} = 0$, $\eta_{sj} = \vartheta_{sj} * \overline{P^{index}_{rsjyw}}$.

Step 2: Assessing changes in price elasticity of demand due to Harvey

$$log(Q_{rsjyw}) = \mu + \vartheta^{pre}_{sj} P^{index}_{rsjyw} + \alpha_{sj} Post_y + \beta^{post}_{sj}(P^{index}_{rsjyw} \times Post_y) + \beta^{\varpi}_{sj}(P^{index}_{rsjyw} \times Warning_{rsyw})$$
$$+ \beta^{\hbar}_{sj}(P^{index}_{rsjyw} \times HarveyLandfall_{rsyw}) + \beta^{§}_{sj}(P^{index}_{rsjyw} \times AfterStrike_{rsyw}) + Confounders'_{rsyw}\Psi + \gamma_s + \varepsilon_{rsjyw}. \qquad \text{(Eq.5)}$$

- If $\vartheta^{pre}_{sj} \neq 0$, then expected price changes due to warning are $\lambda^{\varpi}_{sj} = \frac{\beta^{\varpi}_{sj} + \beta^{post}_{sj}}{(\vartheta^{pre}_{sj})^2}$, those during the landfall are $\lambda^{\hbar}_{sj} = \frac{\beta^{\hbar}_{sj} + \beta^{post}_{sj}}{(\vartheta^{pre}_{sj})^2}$, and those after the landfall are $\lambda^{§}_{sj} = \frac{\beta^{§}_{sj} + \beta^{post}_{sj}}{(\vartheta^{pre}_{sj})^2}$.

Step 3: Assessing changes in prices due to Harvey

$$P^{index}_{rsjyw} = \nu + \ell_{sj} Post_y + \varpi_{sj} Warning_{rsyw} + \hbar_{sj} HarveyLandfall_{rsyw}$$
$$+ §_{sj} AfterStrike_{rsyw} + Confounders'_{rsyw}\Upsilon + \gamma_s + \epsilon_{rsjyw}. \qquad \text{(Eq.6)}$$

- Observed changes in prices due to warning ($\varpi_{sj} + \ell_{sj}$), those during the landfall ($\hbar_{sj} + \ell_{sj}$), and those after the landfall ($§_{sj} + \ell_{sj}$)
- Conduct the efficiency test: $\lambda^T_{sj} = T + \ell_{sj}$, for $T = \varpi_{sj}, \hbar_{sj}, §_{sj}$.

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Findings

1. Do market prices change in times of catastrophe?
   - **Yes,** prices of the four products studied — toilet paper, batteries, milk, and bottled water — in coastal Texas change a little during Hurricane Harvey season
   - Modest price changes would have complied with a standard proportional price increase cap of 25%
2. Are the changes in prices efficient (in that they reflect changes in supply and demand)?
   - **Yes,** demand-driven price changes due to Harvey in the short run
   - Observed price changes mostly within the ranges of efficiency permitted by variations in the price elasticity of demand

Implications

- **Need to revise "price gouging" laws**, such as those applied in the state of Texas — Texas Business & Commerce Code Section §17.46 (2019) — setting a subjective price cap for necessity goods during a declared disaster
- **Theoretical suggestion** ⇒ Revise laws based on the optimal, short-term changes in demand for each target good in the affected locations relative to a period of absence of the disaster
- **Empirical suggestion** ⇒ zero-increase price cap for batteries and bottled water, but a cap of 22% for toilet paper and 86% for milk in coastal Texas