Political Storms:
Emergent Partisan Skepticism of Hurricane Risks

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Abstract

The 2017 hurricane season devastated the U.S. gulf coast with two of the worst hurricanes in history: Harvey (107 deaths, \$125B in damages) and Irma (134 deaths, \$50B in damages). Despite extensive warnings, most affected residents did not evacuate their homes before the storms hit, complicating rescue and recovery efforts. Combining a large GPS dataset for 2.7 million smartphone users in Florida and Texas with U.S. Census demographic data and 2016 U.S. Presidential election precinct-level results, we empirically examine hurricane evacuation behavior. A difference-in-differences analysis demonstrates that Trump/Clinton vote share strongly predicts evacuation rates, but only after the emergence of conservative-media dismissals of hurricane warnings in September 2017, just before Irma made landfall in Florida. Following this viral "hurricane trutherism", we estimate that Trump-voting Florida residents were 10-11% less likely to evacuate Irma than Clinton-voters (34% vs. 45%) after controlling for key demographic and geographic covariates, highlighting one consequence of political polarization. This effect size is similar in magnitude to that of an official hurricane watch. We confirm the causal impact of hurricane advisories using a spatial regression-discontinuity design that compares evacuation rates for residents living just on opposite sides of county boundaries who received differential alerts. A hurricane watch *causally* increases rapid evacuations (within 24 hours) by 6 percentage-points compared to no watch, and by 4 percentage-points compared to a tropical storm watch.

Keywords: hurricane evacuations, fake news, political polarization, regression discontinuity

Introduction

The 2017 Atlantic hurricane season was the costliest on record, with damages exceeding \$125 billion following Harvey, \$50 billion following Irma, and \$90 billion following Maria [1]. These storms directly caused hundreds of deaths and, indirectly, thousands more due to slow recovery efforts, lack of sanitation, and reduced access to medical services. Increasingly destructive storms highlight the importance of public confidence in—and responsiveness to—advance warning systems [2].

Hurricanes range in strength from category 1 (winds speeds of 74-95 mph) to 5 (>156 mph), with lower grade cyclones considered "tropical storms". The National Hurricane Center (NHC), a branch of the U.S. National Oceanic and Atmospheric Administration (NOAA), provides forecasts to the public and issues "watches" (48 hours before *possible* landfall) and "warnings" (36 hours before *expected* landfall). Alerts are occasionally accompanied by state or local evacuation orders for specific populations (e.g., residents of coastal or low-lying areas, or those living in mobile homes) given the elevated risks of storm surge, flooding, and wind-related damages.

Survey evidence highlights several factors that contribute to low evacuation rates, even during Category 4 and 5 hurricanes [3]. At-risk residents may be unable to evacuate due to limited mobility, lack of transportation or shelter access, or misinformation about storm severity. Others choose to stay because of a mistrust of storm reporting, the need to care for pets, or fear of property damage or looting [4]. Advance stockpiling of bottled water and emergency supplies as part of hurricane preparedness is not common, particularly among lower income and less-educated populations, and most at-risk residents purchase supplies after hurricane landfall, contrary to expert recommendations [5]. Further complicating disaster management, in 2017 the political polarization of hurricanes spiked, with conservative news outlets claiming that hurricane warnings were another example of liberal "fake news. On September 5, 2017, conservative radio host Rush Limbaugh, the most popular talk radio host in America [6], publicly questioned the severity of Hurricane Irma and motivation behind government advisories, despite recent deaths from Hurricane Harvey in Texas and Louisiana.

> *...So there is a desire to advance this climate change agenda, and hurricanes are one of the fastest and best ways to do it... You don't need a hurricane to hit anywhere. All you need is to create the fear and panic accompanied by talk that climate change is causing hurricanes to become more frequent and bigger and more dangerous, and you create the panic, and it's mission accomplished... I've lived here since 1997, and I have developed a system that I trust, my own analysis of the data.*
>
> -Rush Limbaugh, September 5, 2017 [7]

While Limbaugh evacuated his Palm Beach-Florida home three days later, his dismissal of hurricane risks represented a discrete change in the politicization of storm warnings. Shortly after his show aired, conservative commentator Ann Coulter also questioned the reported severity of Hurricane Irma, sparking thousands of both supportive and outraged comments on Twitter [8]. Reporting on both Limbaugh and Coulter reached several "mainstream" news outlets, extending awareness of the controversy beyond Limbaugh's regular listeners [9, 10, 11]. Before this, only occasional instances of "hurricane trutherism" occurred on right-wing blogs, making comparisons before and after Limbaugh's statements a useful difference-in-differences measure of partisan evacuation behavior. Google Trends over a five-year period confirms both the novelty and virality of this hurricane skepticism, peaking just before Irma made Florida landfall (Appendix Figure S1).

We compute differences in evacuation rates between Trump and Clinton voters—both before and after the politicization of hurricane risk assessment—to measure a potentially life-threatening consequence of partisan distrust in news. We use a similar approach as [12], who estimate the cost of political polarization through abbreviated Thanksgiving dinners among cross-party families following the divisive 2016 election.

Our study adds to the growing literature on the role partisanship plays in news receptivity and biased belief formation. Allcott and Gentzkow find that both Democrats and Republicans were more likely to believe "fake news" stories about the 2016 election if the stories matched their own political views [13]. Kahan *et al.* find that the divide widens among those measuring high in science literary and numerical ability, suggesting that partisan disagreements might persist even as scientific evidence accumulates [14]. Whether this stems from motivated reasoning or a lack of critical thinking is under debate [15]. Other research suggests that reducing susceptibility to polarizing misinformation may be possible with low-cost, crowd-sourced flagging of low-quality news sources [16].

Surveys show that beliefs about climate change—and its effect on strengthening hurricane intensity—display a political ideological divide: 60% of liberal Democrats but only 19% of conservative Republicans believe that climate change will produce more severe storms [17]. Even among those with more science education [18] or meteorological experts [19], views on the existence and causes of climate change differ along political lines. Parallel divides appear in hypothetical responses to a warning of an impending hurricane [20], or a government evacuation order [21]. Official warnings have been shown to consistently correlate with stated evacuation intentions [3]. These studies, however, rely either on questions about a hypothetical hurricane, or on post-landfall surveys months or years after the storm, and thus potentially suffer from survivorship bias, imperfect recall of evacuation timing, or ex-post rationalization of critical decisions [22].

In this paper, we study evacuation patterns for Hurricanes Matthew, Harvey, and Irma using GPS location data for more than 30 million U.S. smartphone users. Our study is the first to observe actual evacuation behavior for millions of residents hit by at least one major hurricane. Beyond simply altering stated beliefs about climate change, partisan skepticism shifts people's choice to evacuate an oncoming storm, a personally consequential decision. To our knowledge, no prior study has empirically estimated the *causal* effect of advance hurricane warnings on evacuations, despite the central role such advisories play in mitigating loss of life. We do so here by exploiting spatial boundaries in the roll out of hurricane watches and warnings, using a regression-discontinuity (RD) design to estimate the direct causal effect of a hurricane alert on evacuation behavior [23].

Methods

Data Summary

Our primary dataset consists of anonymized smartphone location data for more than 30 million U.S. residents, from the data firm SafeGraph. Each observation ("ping") includes an anonymous phone ID, date, time, latitude and longitude coordinates, and location accuracy. Smartphone typically ping every ten minutes, with more frequent pings (approximately every 5 seconds) when driving.

Dates and times of hurricane alerts come from the National Hurricane Center (Appendix Tables S3-S5) [24]. Demographic data at the census tract and block group level is from the 2012-16 American Community Survey while block data is from the 2010 U.S. Census. Variables include residential density, median age, median household income, fraction with a college degree or higher, employment rate, and race/ethnicity. Geographic variables include distance to the coast [25] and elevation above sea-level [26]. Voting data comes from the 2016 U.S. Presidential election precinct-level results (the finest granularity legally permitted), specified as the two-party vote share won by Donald Trump [27]. All variables are summarized in Table 1.

Definitions

We examine smartphone data over a three-week period for each hurricane. To estimate a user's home location, we examine pings over one week, beginning 10 days before their state's first hurricane alert (September 7, 2017 for Irma). We define a user's "home area" as their modal location between 10:00 pm and 6:00 am over this period, aggregated to the geohash-7 to preserve anonymity. For Hurricanes Irma and Matthew, we include all smartphone users in Florida; for Hurricane Harvey, we exclude users in Texas who live more than 300 km from the coast, as they did not receive any hurricane alerts and were not in the path of the storm.

A hurricane "evacuation" is defined as a smartphone user spending >24 continuous hours at least 100 meters away from their home area, over a period beginning four days before the first alert until four days after all alerts were discontinued (September 3-15, 2017 for Irma). This definition captures both early evacuees and evacuations to nearby shelters, and uses a consistent window across the state of Florida. As a robustness exercise we consider a >48-hour definition, summarized in Appendix Table S2. The smartphone data is similarly processed for Hurricane Matthew in Florida ($n = 378,248$, first alert on October 4, 2016) and Hurricane Harvey in Texas ($n = 1,032,525$, first alert on August 23, 2017). Maps depicting >24-hour evacuations by voting precinct are shown in Figure 1.

Difference-in-Differences Specification

We examine whether evacuation behavior differs by likely political affiliation post-Limbaugh (our diff-in-diff analysis) using the following linear probability model:

$$\begin{aligned} Evac24h_i = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 TrumpShare_i + \boldsymbol{\beta}_2 TrumpShare_i \times AfterLimbaugh_i \\ + \alpha HurricaneAlert_i + \boldsymbol{\gamma}_0 \mathbf{X}_i + \boldsymbol{\gamma}_1 \mathbf{F}_i + \varepsilon_i \end{aligned} \tag{1}$$

where $Evac24h_i$ refers to a >24-hour evacuation during the hurricane. $TrumpShare_i$ is the 2016 Presidential election precinct-level two-party vote share won by Donald Trump, and $TrumpShare_i \times AfterLimbaugh_i$ is our main diff-in-diff variable ($TrumpShare_i$ times an indicator variable for post-Limbaugh's statements). $HurricaneAlert_i$ indicates whether individual i resides in a county that received a hurricane watch and/or warning. The vector $\mathbf{F}_i$ is a set of fixed effects for hurricanes and sub-state geographical units such as counties. The vector $\mathbf{X}_i$ includes demographic, geographic, and census controls for individual i (Table 1).

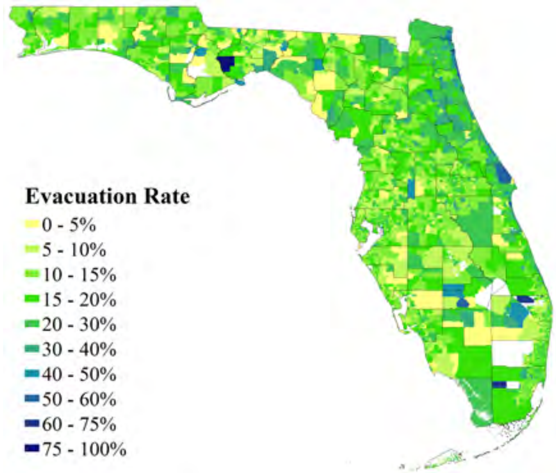
Robustness Tests

Our diff-in-diff coefficient $\boldsymbol{\beta}_2$ estimates the partisan effect of Limbaugh's statements on evacuation behavior. As tests of this coefficient's estimating assumptions, we perform three robustness exercises.

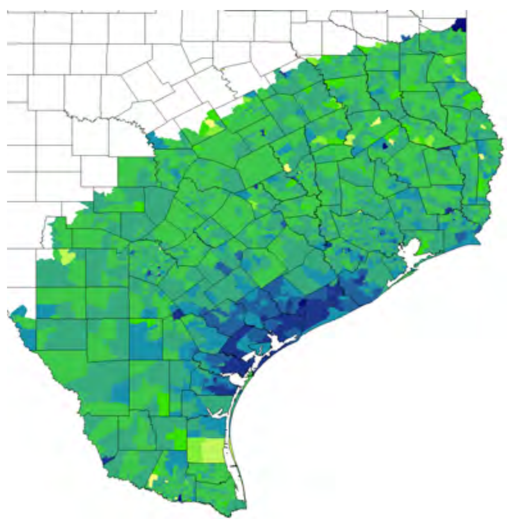
First, we vary the geographical level of both the fixed effects and corresponding clustering of

Figure 1: Proportion of residents (by voting precinct) with >24-hour evacuation from home during hurricane.

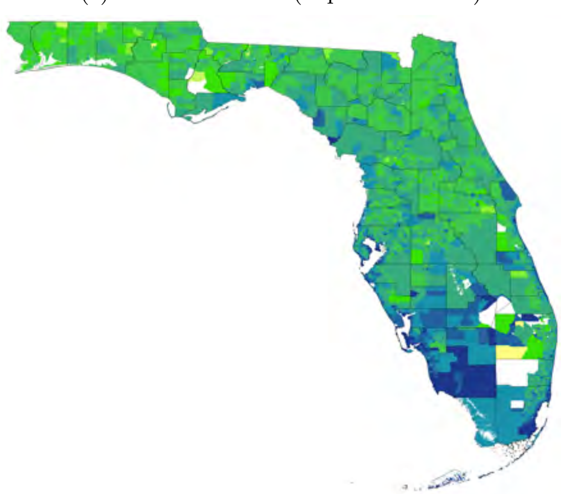
(a) Hurricane Matthew (October 2016)



(b) Hurricane Harvey (August 2017)



(c) Hurricane Irma (September 2017)



standard errors (Table 2). This examines whether the evacuation wedge between likely Trump and Clinton voters during Hurricane Irma can be explained by spatial autocorrelation in hurricane intensity.

Second, we replicate our main diff-in-diff regressions using a stricter, >48-hour definition of evacuation (Appendix Table S2). This tests whether our results are sensitive to the cut-off used to define a hurricane evacuation.

Finally, we test our main coefficient's stability to unobservable selection as developed in [28] and recently updated in [29]. This procedure adjusts the main coefficient on $TrumpShare \times AfterLimbaugh$ to remove the effect of selection on unobservables, and further calculates how strong the selection on unobservables would need to be for the causal effect to be zero.

Regression Discontinuity Specification

Estimating the effect of a hurricane watch on evacuation behavior poses challenges due to endogeneity (e.g., strong winds or precipitation are correlated with the NHC's timing and targeting of alerts and may themselves trigger an evacuation) and omitted variable bias (e.g., news coverage, social media, and peer-to-peer communication may spike concurrently with NHC alerts, and may also directly affect evacuations). To address these issues, we propose a spatial regression discontinuity (RD) design, exploiting the fact that NHC alerts are typically issued at the county-level. Conceptually, suppose two individuals reside within a few blocks of one another—but in different counties—such that one receives a hurricane watch in advance of the other. We examine the extent to which the earlier alert triggers rapid evacuation (i.e., within 24 hours) in the focal county. We focus on rapid evacuation because the NHC typically upgrades hurricane watches to hurricane warnings within 12 to 24 hours, and we aim to estimate the causal effect of the initial watch.

We estimate the following local-linear RD model:

$$\begin{aligned} Rapid_i = {} & \tau HurricaneWatch_i + \beta_0 + \beta_1(X_i - X_c) \\ & + \beta_2 HurricaneWatch_i \times (X_i - X_c) + \beta_3 TrumpShare_i + \varepsilon_i \end{aligned} \tag{2}$$

where $Rapid_i$ corresponds to individual i evacuating within 24 hours of the hurricane watch, X_c refers to the cut-off (i.e., the county border), X_i is the running variable (i.e., individual i's home area), so $X_i - X_c$ represents the distance between individual i's home and the county border, and $TrumpShare_i$ is as specified previously. $HurricaneWatch_i$ is a binary variable indicating whether individual i resides in a county that received a hurricane watch:

$$HurricaneWatch_i = \begin{cases} 1 & \text{if } X_i > X_c \quad \text{(hurricane watch occurs)} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

The coefficient τ represents the local average treatment effect (of a hurricane watch versus no watch) at the cut-off. The coefficients, β_0, β_1, and β_2 represent the intercept, slope before the cut-off, and slope after the cut-off, respectively. We follow the approach in [30] to estimate a covariate-adjusted local-linear RD design, in which $TrumpShare_i$ is controlled for but β_3 is not directly estimated. While controlling for covariates is not strictly necessary, it is prudent to control for vote share because our spatial discontinuities occur at political boundaries; our results do not substantively change if this covariate is removed. Our RD estimator includes individuals living within a "bandwidth" of the border, where bandwidth selection is based on MSE-optimal point estimation, and linearly weights observations using a triangular kernel.

We employ this RD specification for Hurricane Irma, using the border between Martin ($n = 11,208$) and Palm Beach ($n = 83,707$) counties in Florida (Appendix Figure S5). We consider other potential RD sites, but these are either too sparsely populated (e.g., Dixie and Levy counties) or have large geographic or demographic jumps at the border (e.g., Pinellas and Manatee counties are separated by Tampa Bay and the 7 km long Sunshine Skyway Bridge, and display different demographics on either side of the bridge).

We use a similar specification for Hurricane Harvey in Texas (Appendix Figure S6). On August 23, 2017 at 10:00 am, Brazoria County ($n = 26,510$) received a hurricane watch and neighboring Galveston County ($n = 28,437$) received a tropical storm watch. Here, the local average treatment effect is the difference in rapid evacuations following a hurricane watch versus tropical storm watch.

Robustness Tests

We run placebo RD regressions for both RD analyses, replacing $Rapid_i$ with $Evac24h_i$, which includes *any* 24-hour evacuation over the hurricane's duration, not just evacuations immediately following an official alert. In both placebo regressions, the MSE-optimal bandwidth is re-estimated using the same procedure as our main RD specifications.

Table 1: Variable definitions and hurricane statistics.

Variable	Matthew	Harvey	Irma
Trump Vote Share by Precinct	49.2%	52.3%	49.4%
Duration of Evacuation from Home			
>24 Hours	16.4%	32.7%	37.2%
>48 Hours	13.4%	27.2%	31.1%
Highest Alert Received			
Hurricane Watch/Warning	34.6%	8.8%	73.1%
Tropical Storm Watch/Warning	34.7%	31.7%	1.3%
Flood Risk			
Distance to Nearest Coast (km)	22.7	116.7	20.8
Elevation (m)	3.9	33.4	3.6
Residential Density			
Urban	88.4%	74.3%	88.0%
Suburban	3.4%	7.6%	3.4%
Rural	8.2%	18.0%	8.5%
Census Demographics			
Median Age	41.0	35.8	41.9
Median Household Income ($ 000s)	56.4	67.2	57.6
College Degree	28.6%	30.7%	30.2%
Employment Rate	55.6%	60.7%	55.3%
Race/Ethnicity			
Black	14.0%	9.4%	11.7%
Asian	2.8%	4.2%	2.7%
Hispanic	23.7%	34.7%	24.9%
White	58.4%	50.9%	59.7%

Mean values reported by hurricane: n=378,248 (Matthew), n=1,032,525 (Harvey), and n=1,321,571 (Irma).

Results

Evacuation Rates

Of the 1.3 million smartphone users in our 2017 Florida sample, 37% evacuated their home for >24 hours during Irma and 31% evacuated for >48 hours (Table 1). Approximately 73% reside in counties receiving hurricane watches, which were all subsequently escalated to hurricane warnings 12-24 hours later. Hurricane Harvey saw similar rates: 33% evacuated for >24 hours and 27% evacuated for >48 hours. Only 9% of the 1.0 million Texas users in our dataset received a hurricane watch or warning, and 44% of these residents evacuated. Among Texas residents who live within 300 km of the coast but did not receive any official storm alerts, 30% still chose to evacuate, potentially contributing to traffic congestion and shelter capacity shortages. During Hurricane Matthew, only 16% of the 378,000 Florida residents in our dataset evacuated for >24 hours, in part because fewer residents (35%) received a hurricane alert.

Substantial variation exists in evacuation rates across all three hurricanes, even among geographically proximate regions (Figure 1). During Irma, for example, evacuation rates in Broward County averaged 40% among the 141,092 individuals in our sample, yet ranged from 20% to 78% among precincts within 5 km of the coast, an area at high-risk of storm surge and flooding (Appendix Figure S2).

Difference-in-Differences of Partisan Evacuation Behavior

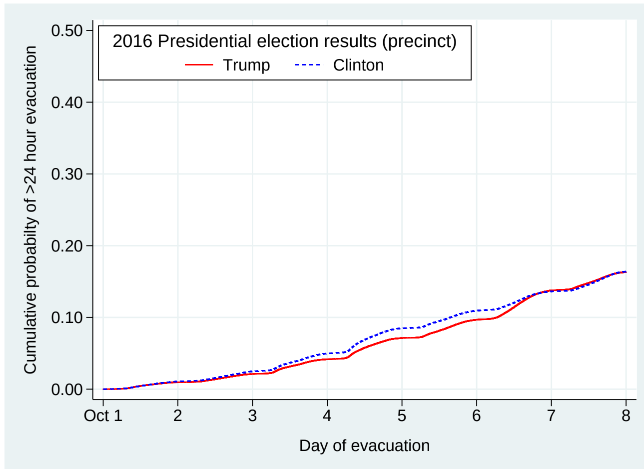
Using precinct-level vote share as a proxy for likely political affiliation, Figure 2 illustrates the raw differences in evacuation behavior between residents of Trump- and Clinton-majority precincts across these three hurricanes. Trump voters evacuated at substantially lower rates during Irma—consistent with Republican-leaning skepticism of hurricane risks—but at similar rates during both Harvey and Matthew.

Our main diff-in-diff analysis (Table 2) estimates the coefficient on $TrumpShare \times AfterLimbaugh$, suggesting that Trump voters were approximately 10 percentage-points less likely to evacuate during Irma—after Limbaugh denounced hurricane preparedness—than comparable Clinton voters, relative to Hurricanes Matthew and Harvey. Differences in evacuation rates are not explained by obvious spatial or demographic covariates, and are significant at the 0.001-level, even when clustering adjusts for spatial autocorrelation within counties.

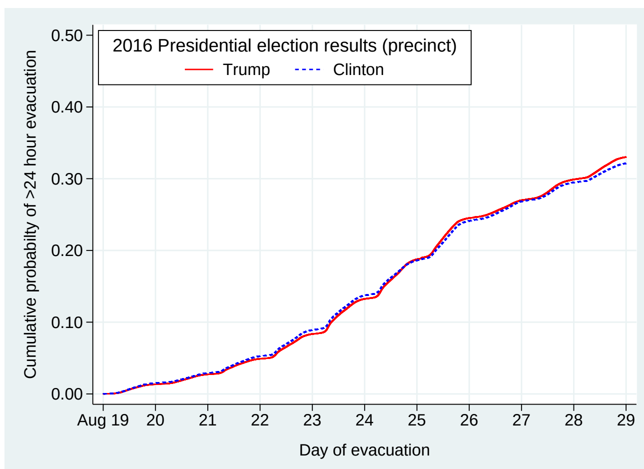
One threat to our identification strategy is whether Irma disproportionately hit Clinton-majority precincts, compared to Matthew and Harvey, beyond geographical variation captured by county-level hurricane alerts. To exclude this possible explanation for the observed partisan effect, we add progressively finer spatial fixed effects (Table 2, columns 3-4); the evacuation wedge between likely Trump and Clinton voters persists even when comparing residents less than 20 km apart (i.e., within the same geohash-4). With hurricane-force winds reaching more than 100 km in diameter, it is unlikely that Hurricane Irma systematically hit Clinton precincts more severely than Trump precincts less than 20 km away. With these additional fixed effects, our diff-in-diff estimates a 10 percentage-point causal effect of partisan skepticism on hurricane evacuations. In our sample, we estimate that 34% of likely Trump voters evacuated during Irma, compared to 45% of Clinton voters.

Figure 2: Kaplan-Meier failure curves for probability of any >24-hour evacuation from home during hurricane.

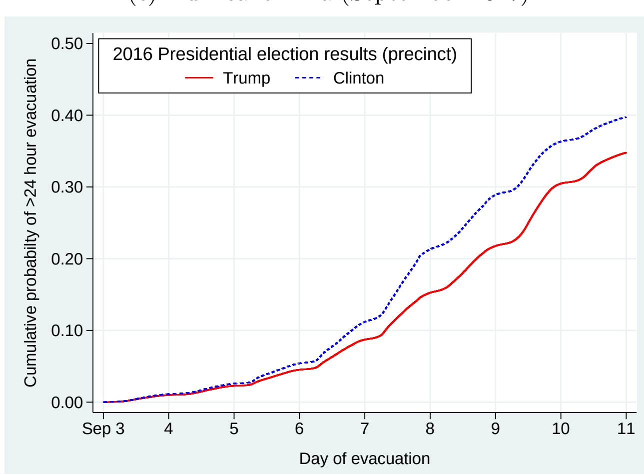
(a) Hurricane Matthew (October 2016)



(b) Hurricane Harvey (August 2017)



(c) Hurricane Irma (September 2017)



An advantage of using geohash (a rectangular grid) fixed effects is their independence from political, geographic, and demographic boundaries. As a robustness check, we vary the level of fixed effects using regions 150 km (geohash-3) to 0.15 km (geohash-7) in width (Appendix Figures S3-S4), and find a consistent diff-in-diff estimate of approximately 10 percentage-points. This coefficient stability across the scale of geographic controls suggests that spatially correlated omitted variables are unlikely to drive our results. Further, we cluster all regressions at the highest level possible given the fixed effects, and find our results are robust to spatial autocorrelation. We also consider a narrower definition of "evacuation" as leaving home for >48 hours during a hurricane. Although 3-7% fewer people evacuate under this definition, our general findings are unchanged with Trump voters 11-12 percentage-points ($p < 0.0001$) less likely to evacuate (Appendix Table S2).

As a final robustness test, we adjust for unobservable variable selection based on the approach outlined in [29], which generates a significantly stronger estimate than our original regression ($\delta = -0.003, z = -28.19, p < 0.0001$). This indicates that residents of more Trump-voting precincts in Florida have, on average, observable demographics associated with *higher* predicted evacuation rates, yet their actual evacuation rates during Irma are lower than their Clinton-voting counterparts. In other words, partisan evacuation differences post-Limbaugh are unlikely to be explained by omitted variable bias and, if anything, underestimate the true causal effect size.

Causal Effect of Hurricane Alerts

To interpret the size of our measured partisan effect, note that in Table 2, the coefficient on $TrumpShare \times AfterLimbaugh$ is generally larger than the effect of receiving a government hurricane alert. The presence of spatial fixed-effects in columns 3-4 complicates this comparison, as the coefficient on $HurricaneAlert$ mixes both the direct effect of receiving an alert and the greater evacuation rate during Irma from areas of Florida that did not receive an alert during less-widespread Matthew. In our next analysis, we isolate the causal effect of NHC hurricane alerts, as a basis of comparison to our main partisan effect. Moreover, this quantity may be of interest to the government agencies that set and implement such alerts.

We employ an RD analysis of hurricane alerts by examining neighboring counties that share a densely populated boundary but received different alerts, a situation that occurred once during Irma. On September 7, 2017 at 11:00 am, residents of coastal Palm Beach County, Florida received the first hurricane watch for Irma, while neighboring coastal Martin County had not yet received any alerts (Appendix Figure S5). Following [30], we estimate the optimal RD bandwidth to include

Table 2: Difference-in-differences regression model for any >24-hour evacuation before or during the hurricane.

Independent Variable	Evac24h (1)	Evac24h (2)	Evac24h (3)	Evac24h (4)
Trump Share	0.0115	-0.00626	-0.00998	0.00659
	(0.0144)	(0.0200)	(0.0293)	(0.0197)
Trump x Limbaugh	-0.117*	-0.130**	-0.0959***	-0.104***
	(0.0454)	(0.0364)	(0.0177)	(0.0207)
Hurricane Alert	0.107***	0.0727***	0.144***	0.0870***
	(0.0139)	(0.0134)	(0.0220)	(0.0153)
Geographic Controls	No	Yes	Yes	Yes
Demographic Controls	No	Yes	Yes	Yes
Fixed Effects (# units)	Hurricane (3)	Hurricane (3)	Hurricane (3) and County (166)	Hurricane (3) and Geo-4 (708)
Clustering	County	County	County	Geo-4
Observations	2,727,999	2,677,181	2,677,181	2,677,175
Adjusted R^2	0.031	0.035	0.043	0.044

$^{***}p < 0.0001$, $^{**}p < 0.001$, $^{*}p < 0.01$. Clustered standard errors in parentheses. Geographic controls include polynomials for distance to coast and elevation. Demographic controls include residential density, median age, median household income, college graduation rate, employment, and race/ethnicity. Full results in Appendix Table S1.

residents living within 7.8 km of the county border. Within this sample, a hurricane watch causally increases the probability of evacuating by nearly 6 percentage-points ($p = 0.000064$) (Table 3). That is, Palm Beach residents were discontinuously more likely to evacuate in the 24 hours following their county's hurricane watch, compared to their geographically proximate Martin County neighbors. A similar discontinuity occurred before Hurricane Harvey made landfall in Texas. On August 23, 2017 at 10:00 am, residents of coastal Brazoria County received a hurricane watch, while neighboring Galveston County received a lower-grade tropical storm watch at the exact same time (Appendix Figure S6). Using a similar RD approach, we estimate that a hurricane watch increases the probability of rapid evacuation by nearly 4 percentage-points, vis-à-vis a tropical storm watch ($p = 0.013$).

The key identifying assumption of these analyses is that besides differential hurricane alerts, no other significant drivers of evacuation behavior vary discontinuously at the county boundary. Although evacuations are measured at the individual level in our data, demographics and vote-share vary at the census tract and precinct levels, respectively, precluding us from directly testing for

Table 3: Spatial regression discontinuity to estimate causal effect of hurricane watch on evacuation probability.

	Harvey		Irma	
	RapidEvac	Evac24h	RapidEvac	Evac24h
RD Treatment Effect	0.038	-0.0092	0.058	-0.018
	(0.015)	(0.020)	(0.015)	(0.029)
	p = 0.013	*p = 0.644*	*p = 0.000064*	*p = 0.952*
Trump Vote Share Control	Yes	Yes	Yes	Yes
Bandwidth (km)				
Treated	2.6	8.4	7.8	10.4
Untreated	2.6	8.4	7.8	10.4
Observations Included				
Treated	1,489	6,782	6,178	7,498
Untreated	1,722	5,706	518	789
First Alert Time and Type	Aug 23, 2017 10:00 am		Sep 7, 2017 11:00 am	
Treated	Hurricane Watch		Hurricane Watch	
Untreated	Tropical Storm Watch		None	
Location of First Alert				
Treated	Brazoria County, TX		Palm Beach County, FL	
Untreated	Galveston County, TX		Martin County, FL	

Standard errors in parentheses and p-values in *italics*. Dependent variable is probability of evacuation immediately following alert (RapidEvac) or a placebo test on the probability of any >24-hour evacuation during hurricane (Evac24h). Bandwidth selection based on MSE-optimal point estimation. Coefficients are covariate-adjusted for precinct-level vote share, and bias-corrected with a conventional variance estimator [30].

demographic discontinuities. However, we run placebo RD analyses using *any* evacuation during the hurricane (Table 3). During Irma, Martin County eventually received a hurricane watch and subsequent warning 12-18 hours after the same alerts were issued in Palm Beach County (Appendix Figure S7). Thus, we do not expect an overall evacuation discontinuity at the Palm Beach-Martin boundary, unless driven by discontinuous demographic differences. Neither placebo regression finds evidence of jumps in overall evacuation rates, suggesting that our RD approach is sound. Finally, while Hurricane alert status changes discontinuously at county boundaries, news reporting and social spillovers from evacuating neighbors likely make our estimates lower bounds of the true causal effect of alerts.

Discussion

Rising ocean temperatures are expected to increase the frequency and intensity of hurricanes—a longstanding scientific consensus [31, 32]—and record rainfall, flooding, and wind speeds have characterized recent storm seasons [33]. Partisan skepticism of climate science, hurricane risks, and official alerts drove an evacuation wedge between Trump and Clinton voters during Hurricane Irma, larger than most demographic predictors, and similar in magnitude to the direct effect of receiving a hurricane watch.

The vast majority of residents in our sample stay home during a hurricane. Among those who do evacuate, however, one-third depart *before* an NHC watch is issued, two-thirds evacuate within 24 hours, and nearly 90% leave within 48 hours of the issued watch (Appendix Figure S8), with the observed partisan evacuation wedge arising even before the earliest official alerts (Figure 2). By casting doubt on the severity of Hurricane Irma, government advisories and concomitant news reporting, partisan media outlets negated a large share of precautionary evacuations. Immediately following Limbaugh's and Coulter's original statements, reporting by traditional news outlets greatly expanded awareness of these partisan claims (Appendix Figure S1). Altogether, this news coverage appears to have led to an immediate and high-stake schism in evacuation behavior, complicating the ability of scientific and government agencies to mitigate storm risks.

Post-Irma, the political polarization of hurricanes has persisted, as illustrated by Limbaugh's recent assertions:

> *[M]any people in government or government-related jobs are totally now invested in this whole idea that human beings in the United States are causing climate change and causing these hurricanes... But for people that don't have any history knowledge or perspective, theyre gonna fall into the trap of thinking that these things are bigger and worse than they've ever been so it must be climate change, and nothing could be further from the truth.*
>
> -Rush Limbaugh, September 3, 2019 [34]

Federal agencies, including NOAA and the Federal Emergency Management Agency (FEMA) are increasingly investing in efforts to counter hurricane rumors and fake news, diverting limited resources and personnel from more critical tasks and reporting [35, 36]. Although the politicization of hurricane warnings shows no signs of abating [37], a remaining question is whether its impact on actual evacuation behavior is durable.

Our study has several limitations. Although our dataset includes movement patterns for millions of residents in Florida and Texas, we only observe smartphone users, likely under-weighting some populations (e.g., older residents). We define an "evacuation" as departing one's home for >24 hours during the storm, but it is possible that someone left their home yet remained in a high-risk area. Repeating our analysis with a >48-hour definition does not meaningfully change any results.

While it is beyond the scope of our analysis to determine optimal evacuation behavior for every resident at risk of hurricane harm, the arrival of partisan differences in evacuation rates is alarming. Our study cannot delineate *why* political affiliation has come to affect evacuation decision-making. Have beliefs about the likelihood of hurricane harm diverged, or is media-fueled partisanship shifting behavior, independent of beliefs?

Reaching the majority of residents who stay behind despite extensive warnings—and targeting those most vulnerable to storm harm—will require improvement in the public's trust of vital hurricane information. In the current era of "fake news" dominating headlines and the widening politicization of shared risks, finding credible, nonpartisan ways of communicating the potential dangers of hurricanes are warranted.

Acknowledgments

The authors thank SafeGraph for providing the dataset, and Kevin Oswald for research assistance.

References

[1] CNN. Hurricane Statistics Fast Facts. `https://www.cnn.com/2013/05/31/world/americas/hurricane-statistics-fast-facts/index.html`, 2018. Accessed October 1, 2019.

[2] World Meteorological Organization (WMO). Caribbean 2017 Hurricane Season: An Evidence-Based Assessment of the Early Warning System. `https://library.wmo.int/doc_num.php?explnum_id=5459`, 2018. Accessed October 1, 2019.

[3] Shih-Kai Huang, Michael K Lindell, and Carla S Prater. Who Leaves and Who Stays? A Review and Statistical Meta-Analysis of Hurricane Evacuation Studies. *Environment and Behavior*, 48(8):991–1029, 2016.

[4] Stanley K Smith and Chris McCarty. Fleeing the Storm(s): An Examination of Evacuation Behavior during Florida's 2004 Hurricane Season. *Demography*, 46(1):127–145, 2009.

[5] Timothy KM Beatty, Jay P Shimshack, and Richard J Volpe. Disaster Preparedness and Disaster Response: Evidence from Sales of Emergency Supplies Before and After Hurricanes. *Journal of the Association of Environmental and Resource Economists*, 6(4):633–668, 2019.

[6] Talkers Magazine. Top Talk Audiences. `https://web.archive.org/web/20170906064456/http://www.talkers.com/top-talk-audiences/`, 2017. Accessed October 1, 2019.

[7] Rush Limbaugh. My Analysis of the Hurricane Irma Panic. `https://www.rushlimbaugh.com/daily/2017/09/05/my-analysis-of-the-hurricane-irma-panic/`, 2017. Accessed October 1, 2019.

[8] Ann Coulter. HURRICANE UPDATE FROM MIAMI: LIGHT RAIN; RESIDENTS AT RISK OF DYING FROM BOREDOM. `https://twitter.com/AnnCoulter/status/906876843667619840`, 2017. Accessed October 1, 2019.

[9] Avi Selk. Rush Limbaughs hurricane survival guide: Stop buying water and dont listen to the news. *The Washington Post*, 2017. Accessed October 1, 2019.

[10] Oliver Darcy. Rush Limbaugh evacuates Florida home after floating unfounded theories about Hurricane Irma. *CNN*, 2017. Accessed October 1, 2019.

[11] Mike Snider. Rush Limbaugh, Ann Coulter facing blowback on Hurricane Irma comments. *USA Today*, 2017. Accessed October 1, 2019.

[12] M Keith Chen and Ryne Rohla. The Effect of Partisanship and Political Advertising on Close Family Ties. *Science*, 360(6392):1020–1024, 2018.

[13] Hunt Allcott and Matthew Gentzkow. Social Media and Fake News in the 2016 Election. *Journal of Economic Perspectives*, 31(2):211–36, 2017.

[14] Dan M Kahan, Ellen Peters, Maggie Wittlin, Paul Slovic, Lisa Larrimore Ouellette, Donald Braman, and Gregory Mandel. The Polarizing Impact of Science Literacy and Numeracy on Perceived Climate Change Risks. *Nature Climate Change*, 2(10):732, 2012.

[15] Gordon Pennycook and David G Rand. Lazy, Not Biased: Susceptibility to Partisan Fake News is Better Explained by Lack of Reasoning than by Motivated Reasoning. *Cognition*, 188:39–50, 2019.

[16] Gordon Pennycook and David G Rand. Fighting Misinformation on Social Media using Crowdsourced Judgments of News Source Quality. *Proceedings of the National Academy of Sciences*, 116(7):2521–2526, 2019.

[17] Pew Research Center. The Politics of Climate. https://www.pewresearch.org/science/2016/10/04/the-politics-of-climate/, 2016. Accessed October 1, 2019.

[18] Caitlin Drummond and Baruch Fischhoff. Individuals with Greater Science Literacy and Education have More Polarized Beliefs on Controversial Science Topics. *Proceedings of the National Academy of Sciences*, 114(36):9587–9592, 2017.

[19] Neil Stenhouse, Edward Maibach, Sara Cobb, Ray Ban, Andrea Bleistein, Paul Croft, Eugene Bierly, Keith Seitter, Gary Rasmussen, and Anthony Leiserowitz. Meteorologists' Views About Global Warming: A Survey of American Meteorological Society Professional Members. *Bulletin of the American Meteorological Society*, 95(7):1029–1040, 2014.

[20] Rebecca E Morss, Julie L Demuth, Jeffrey K Lazo, Katherine Dickinson, Heather Lazrus, and Betty H Morrow. Understanding Public Hurricane Evacuation Decisions and Responses to Forecast and Warning Messages. *Weather and Forecasting*, 31(2):395–417, 2016.

[21] Jeffrey K Lazo, Ann Bostrom, Rebecca E Morss, Julie L Demuth, and Heather Lazrus. Factors Affecting Hurricane Evacuation Intentions. *Risk analysis*, 35(10):1837–1857, 2015.

[22] Nicole M Stephens, MarYam G Hamedani, Hazel Rose Markus, Hilary B Bergsieker, and Liyam Eloul. Why Did They "Choose" to Stay? Perspectives of Hurricane Katrina Observers and Survivors. *Psychological Science*, 20(7):878–886, 2009.

[23] David S Lee and Thomas Lemieux. Regression Discontinuity Designs in Economics. *Journal of Economic Literature*, 48(2):281–355, 2010.

[24] National Hurricane Center (NHC). Data Archive. https://www.nhc.noaa.gov/data/, 2019. Accessed October 1, 2019.

[25] National Aeronautics and Space Administration (NASA). Ocean Biology Processing Group: Distance to the Nearest Coast. https://oceancolor.gsfc.nasa.gov/docs/distfromcoast/, 2009. Accessed October 1, 2019.

[26] United States Geological Survey (USGS). The National Map - Data Delivery. https://www.usgs.gov/core-science-systems/ngp/tnm-delivery/, 2018. Accessed October 1, 2019.

[27] Ryne Rohla. 2016 Presidential General Election Maps. http://rynerohla.com/index.html/election-maps/2016-presidential-general-election-maps/, 2018. Accessed October 1, 2019.

[28] Joseph G Altonji, Todd E Elder, and Christopher R Taber. Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools. *Journal of Political Economy*, 113(1):151–184, 2005.

[29] Emily Oster. Unobservable Selection and Coefficient Stability: Theory and Evidence. *Journal of Business & Economic Statistics*, 37(2):187–204, 2019.

[30] Sebastian Calonico, Matias D Cattaneo, Max H Farrell, and Rocio Titiunik. Regression Discontinuity Designs using Covariates. *Review of Economics and Statistics*, 101(3):442–451, 2019.

[31] Peter J Webster, Greg J Holland, Judith A Curry, and H-R Chang. Changes in Tropical Cyclone Number, Duration, and Intensity in a Warming Environment. *Science*, 309(5742):1844–1846, 2005.

[32] Kevin Trenberth. Uncertainty in Hurricanes and Global Warming. *Science*, 308(5729):1753–1754, 2005.

[33] Christina M Patricola and Michael F Wehner. Anthropogenic Influences on Major Tropical Cyclone Events. *Nature*, 563(7731):339–346, 2018.

[34] Rush Limbaugh. Politics Has Forever Changed Hurricane Coverage. https://www.rushlimbaugh.com/daily/2019/09/03/hurricane-dorian/, 2019. Accessed October 1, 2019.

[35] National Oceanic and Atmospheric Administration (NOAA). FAQ: Why don't we try to destroy tropical cyclones by nuking them? https://www.aoml.noaa.gov/hrd/tcfaq/C5c.html, 2018. Accessed October 1, 2019.

[36] Federal Emergency Management Agency (FEMA). Hurricane Florence Rumor Control. https://www.fema.gov/florence-rumors, 2018. Accessed October 1, 2019.

[37] Abby Ohlheiser. Sharks, dishwashers and guns: A running list of viral hoaxes about Hurricane Florence. *The Washington Post*, 2018. Accessed October 1, 2019.

Appendix

Figure S1: News interest in public comments made by Rush Limbaugh and Ann Coulter before Hurricane Irma.

(a) The Rush Limbaugh Show (September 5, 2017)

My Analysis of the Hurricane Irma Panic

Sep 5, 2017

RUSH: The hurricane is what I want to lead off with, folks. And I've gotta be very careful here because I am not a meteorologist, and nothing I say today should be considered to be a forecast or a prediction. I am not the National Hurricane Center. I am not a climatologist or meteorologist. All I do is analyze the data that they publish. Just as I am the go-to tech guy in my family and here on the staff, when it comes to a hurricane bearing down on south Florida, I'm the go-to guy.

Everybody says, "What do you think is going to happen?" The reason for that is that I'm not biased and I have no agenda with my analysis of the data. The data is what it is. But — and I don't want to overdo this — but I do want to share with you the way I react to and listen. Do you realize here in south Florida, from where we are all the way down to Miami, you cannot buy bottled water. This hurricane, if it hits us, is not supposed to hit us until Sunday. It was never going to hit us before Sunday.

(b) Washington Post (September 6, 2017)

The Washington Post
Democracy Dies in Darkness

Health

Rush Limbaugh's hurricane survival guide: Stop buying water and don't listen to the news

By **Avi Selk**
September 6, 2017

Conservative talk show host Rush Limbaugh (Ron Edmonds/Associated Press)

"I am not the National Hurricane Center," Rush Limbaugh told his millions of listeners, by way of modest disclaimer.

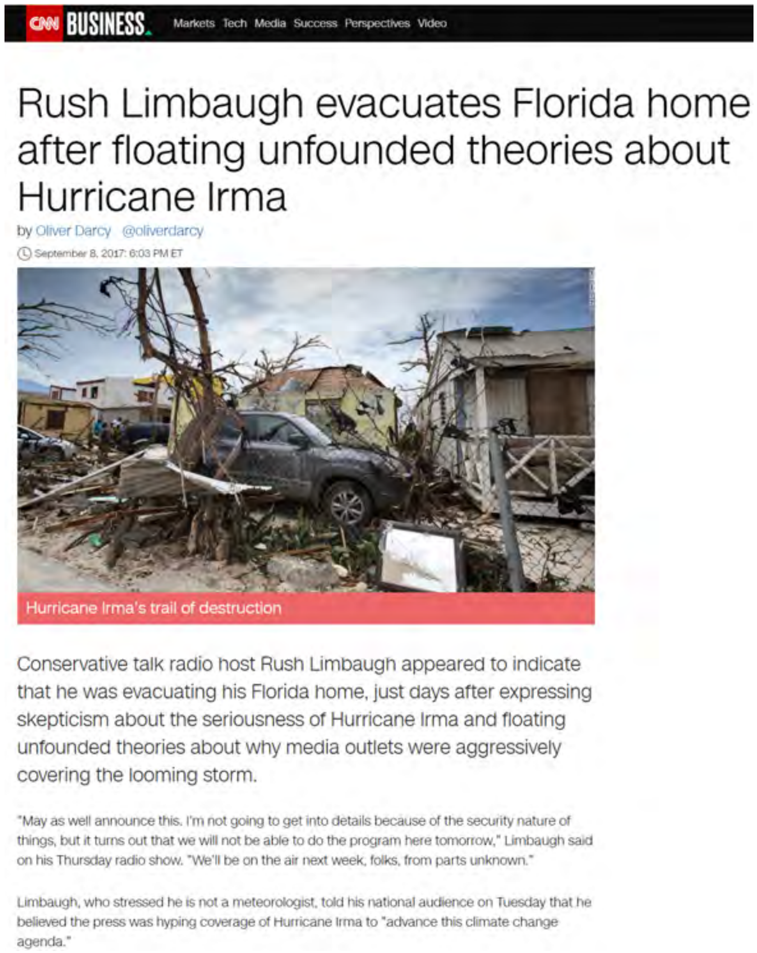
"I am not a climatologist, a meteorologist," he added, now 25 seconds into Tuesday's radio show, which had so far been accurate.

But, Limbaugh continued, he was something of a hurricane analyst, having lived and broadcast for 20 years in Palm Beach County, Fla., a perennial target of sea storms, now directly in the predicted path of Hurricane Irma.

"When it comes to a hurricane bearing down on South Florida, I'm the go-to guy," Limbaugh said, and then spent the next 24 minutes dispensing hurricane advice that no meteorologist or federal agency would likely dare utter.

[The Fix: Limbaugh's dangerous suggestion that Hurricane Irma is fake news]

(c) CNN (September 8, 2017)


CNN BUSINESS Markets Tech Media Success Perspectives Video

Rush Limbaugh evacuates Florida home after floating unfounded theories about Hurricane Irma

by Oliver Darcy @oliverdarcy

September 8, 2017: 6:03 PM ET

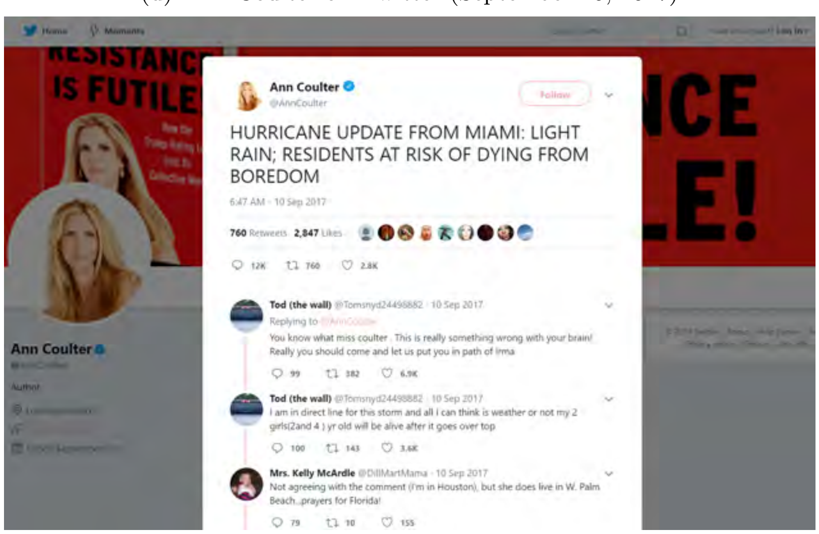
Hurricane Irma's trail of destruction

Conservative talk radio host Rush Limbaugh appeared to indicate that he was evacuating his Florida home, just days after expressing skepticism about the seriousness of Hurricane Irma and floating unfounded theories about why media outlets were aggressively covering the looming storm.

"May as well announce this. I'm not going to get into details because of the security nature of things, but it turns out that we will not be able to do the program here tomorrow," Limbaugh said on his Thursday radio show. "We'll be on the air next week, folks, from parts unknown."

Limbaugh, who stressed he is not a meteorologist, told his national audience on Tuesday that he believed the press was hyping coverage of Hurricane Irma to "advance this climate change agenda."

(d) Ann Coulter on Twitter (September 10, 2017)


Ann Coulter
@AnnCoulter

HURRICANE UPDATE FROM MIAMI: LIGHT RAIN; RESIDENTS AT RISK OF DYING FROM BOREDOM

6:47 AM - 10 Sep 2017

760 Retweets 2,847 Likes

12K 760 2.8K

Tod (the wall) @Tomsnyd24498882 · 10 Sep 2017
Replying to @AnnCoulter
You know what miss coulter . This is really something wrong with your brain! Really you should come and let us put you in path of Irma

99 382 6.9K

Tod (the wall) @Tomsnyd24498882 · 10 Sep 2017
I am in direct line for this storm and all I can think is weather or not my 2 girls(2and 4) yr old will be alive after it goes over top

100 143 3.6K

Mrs. Kelly McArdle @DillMartMama · 10 Sep 2017
Not agreeing with the comment (I'm in Houston), but she does live in W. Palm Beach...prayers for Florida!

79 10 155

(e) USA Today (September 13, 2017)

USA TODAY MONEY Home Markets Business Personal Finance USA & Main Subscribe

Rush Limbaugh, Ann Coulter facing blowback on Hurricane Irma comments

MIKE SNIDER | USA TODAY
Updated 6:21 a.m. PDT Sep. 13, 2017

Limbaugh: Hurricane Irma coverage is part of 'deep state' conspiracy

Conservative radio host Rush Limbaugh put a surprising twist on the Hurricane Irma that appears to be on its way to Florida. Josh King has the story (@abridgetoland).
BUZZ60

Hurricane Irma may have passed but the blowback on two conservative pundits' skepticism about the hurricanes' danger continues to swirl.

As Irma barreled into Florida over the weekend, columnist Ann Coulter and talk radio host Rush Limbaugh were making an unusual — some said dangerous — counterpoint to the blunt warnings booming out of the state's official offices to "get out now."

Ann Coulter
CLIFF OWEN, AP

(f) Google Trends over 5 years (January 2013-December 2017)

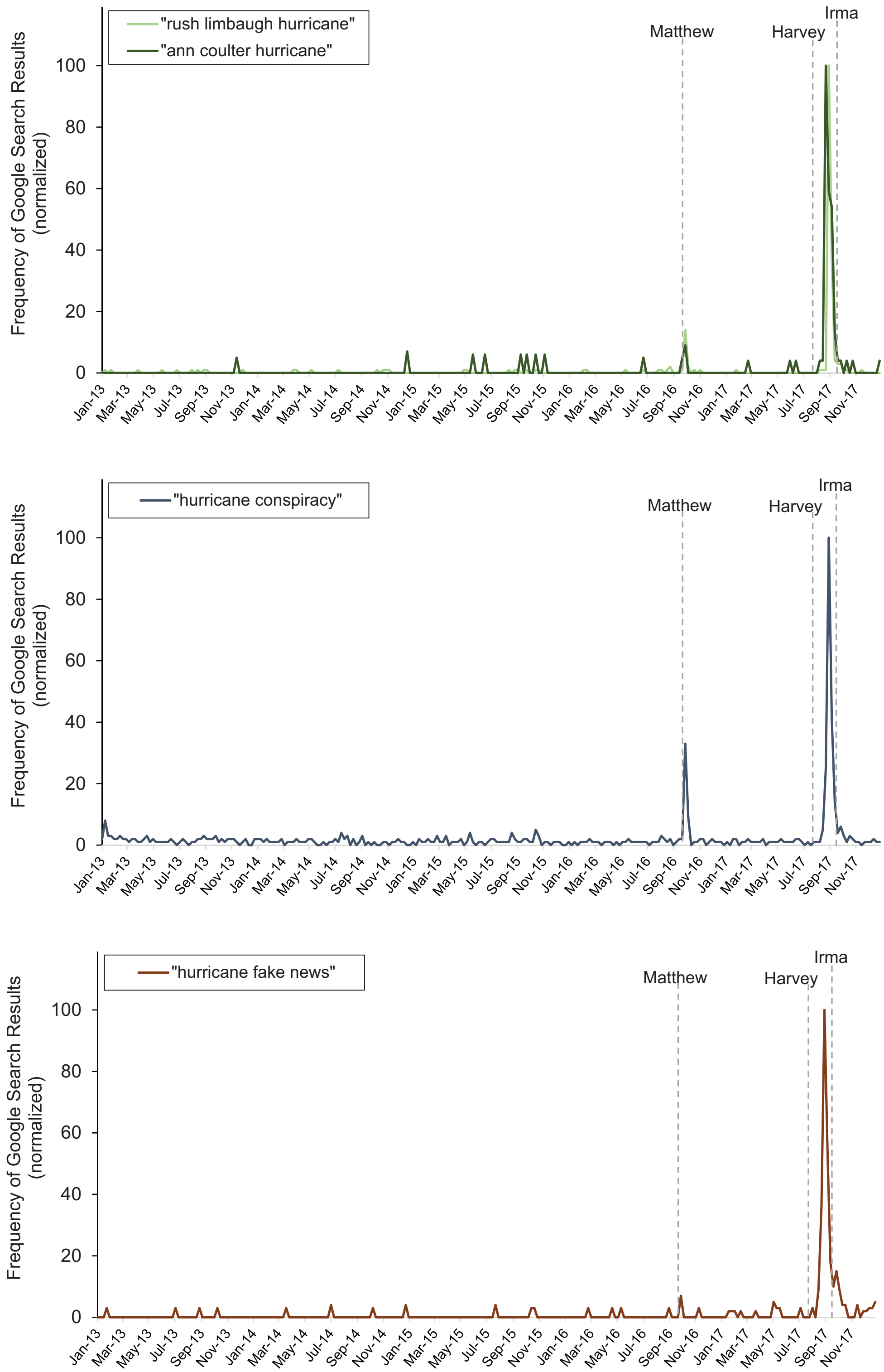
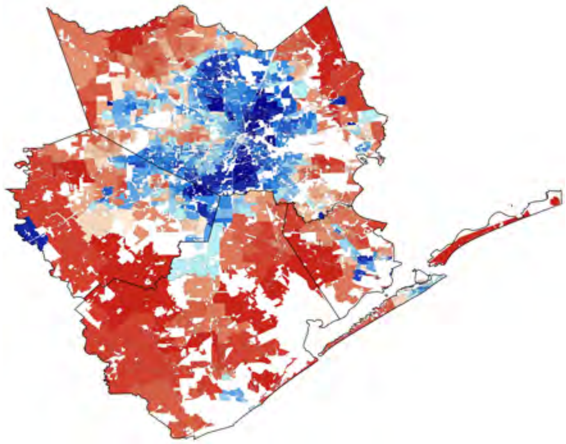
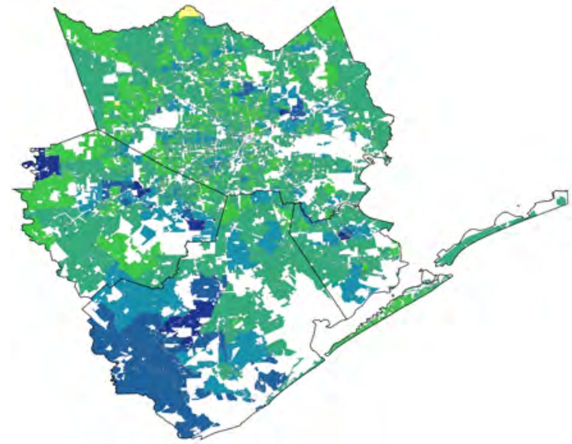


Figure S2: Evacuation rates and voting results in major metropolitan areas.

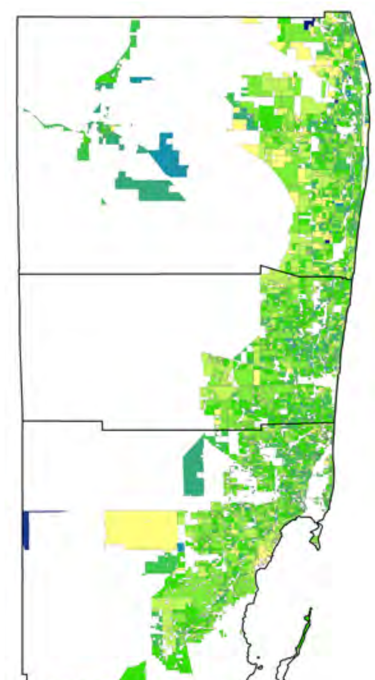
(a) 2016 Trump/Clinton vote share in Houston, Texas



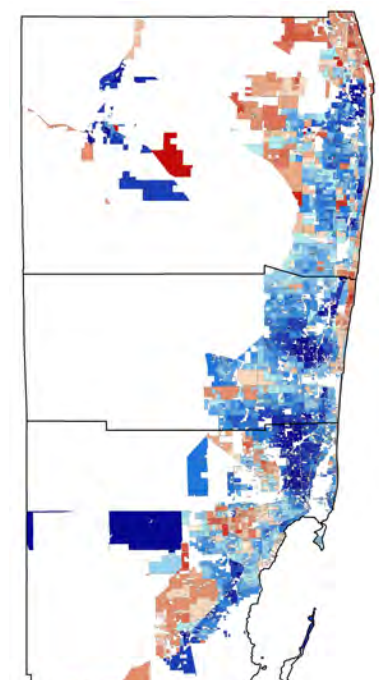
(b) Hurricane Harvey evacuations in Houston, Texas



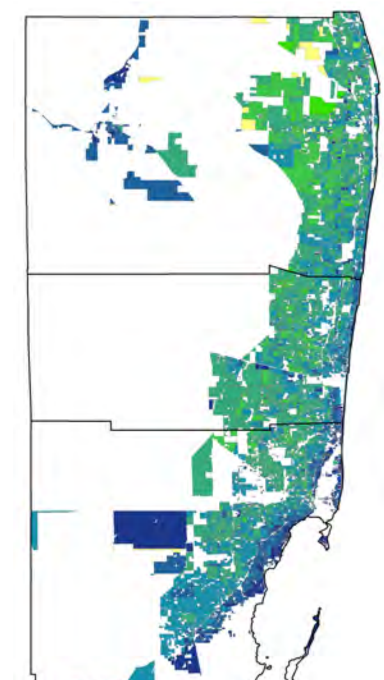
(c) Hurricane Matthew evacuations in Miami, Broward, and Palm Beach, Florida



(d) 2016 Trump/Clinton vote share in Miami, Broward, and Palm Beach, Florida



(e) Hurricane Irma evacuations in Miami, Broward, and Palm Beach, Florida



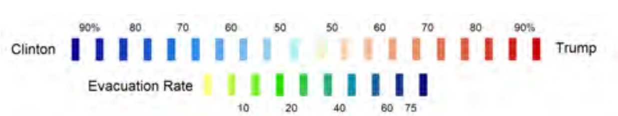
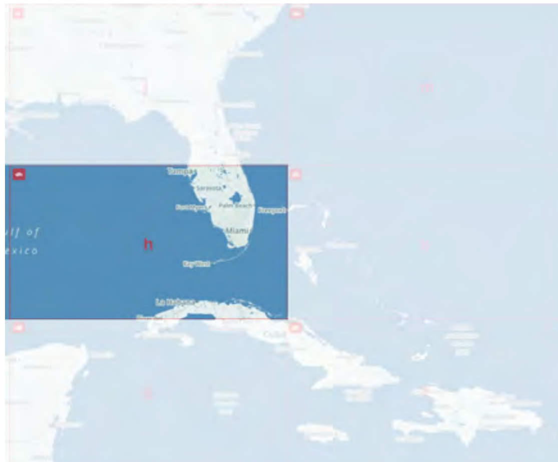
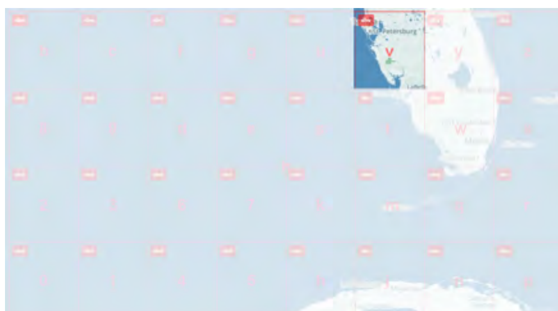


Figure S3: Geohash maps with approximate dimensions in (a)-(f) Florida and (g)-(l) Texas (*source*: Mapzen).

(a) Geohash-2 (1,250 km × 625 km)

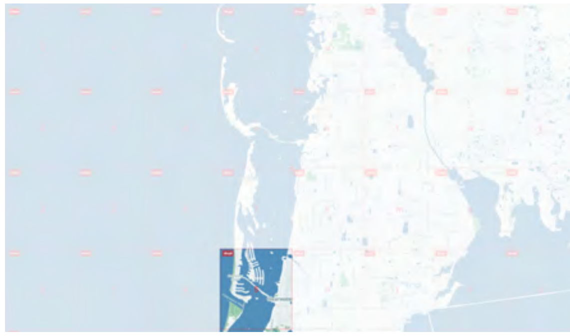


(b) Geohash-3 (156 km × 156 km)



(c) Geohash-4 (39 km × 19.5 km)

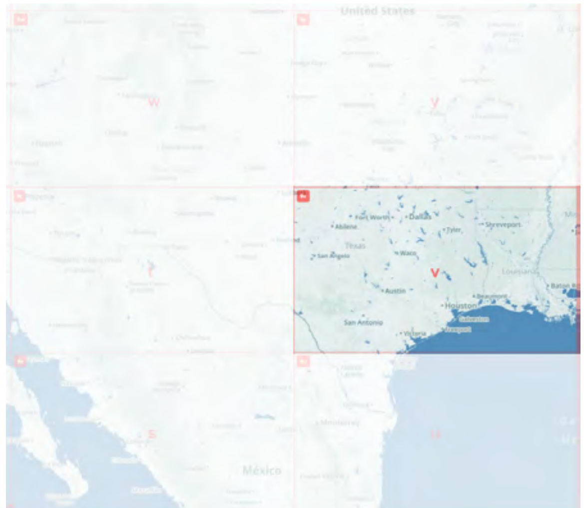
(d) Geohash-5 (4.9 km × 4.9 km)



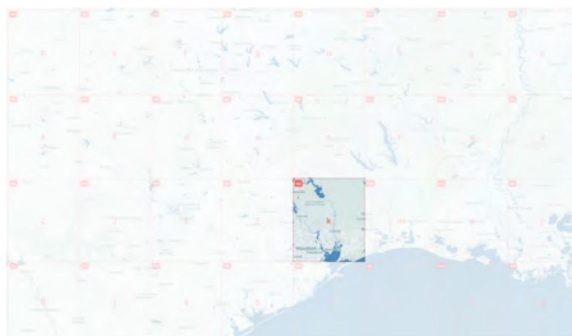
(e) Geohash-6 (1.2 km × 0.6 km)

(f) Geohash-7 (0.15 km × 0.15 km)

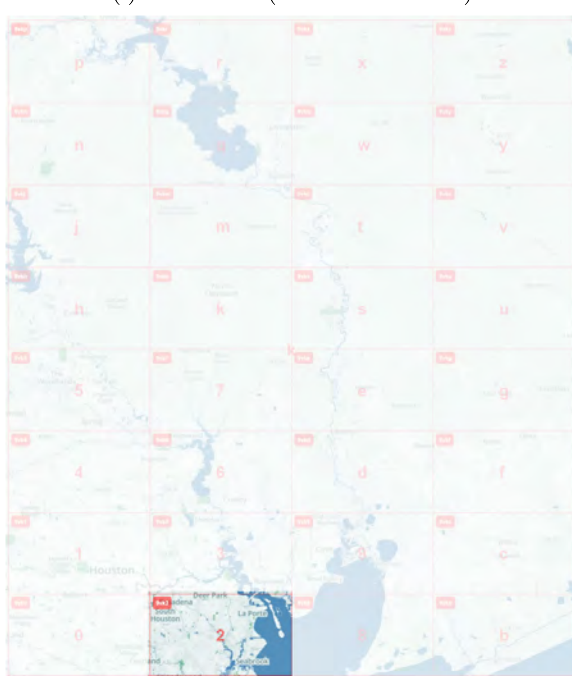
(g) Geohash-2 (1,250 km × 625 km)



(h) Geohash-3 (156 km × 156 km)



(i) Geohash-4 (39 km × 19.5 km)



(j) Geohash-5 (4.9 km × 4.9 km)

(k) Geohash-6 (1.2 km × 0.6 km)

(l) Geohash-7 (0.15 km × 0.15 km)

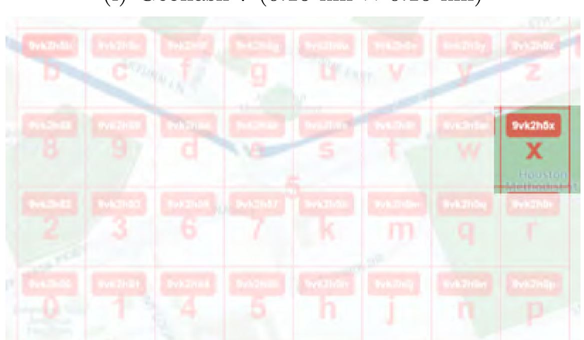


Figure S4: Difference-in-difference estimate by level of fixed effects and standard error clustering.

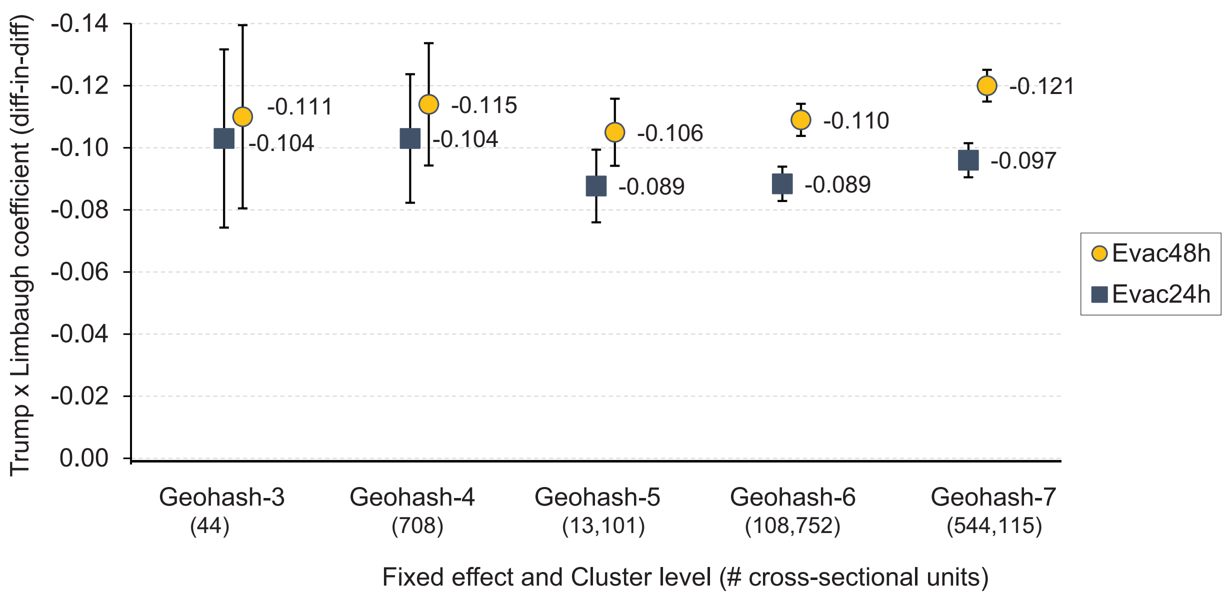
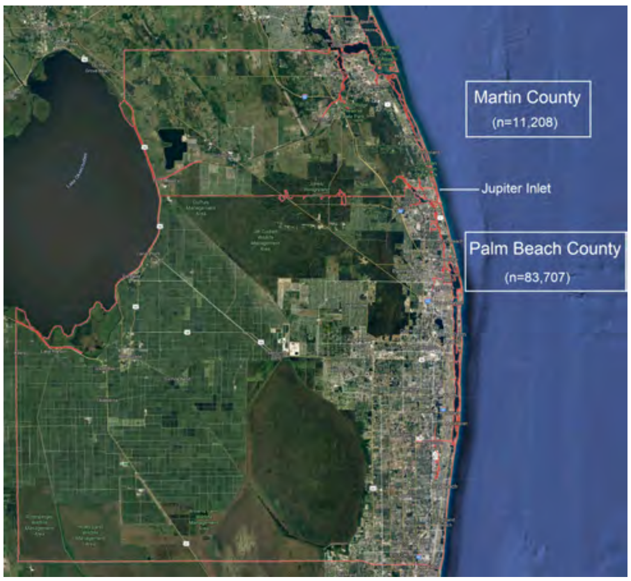
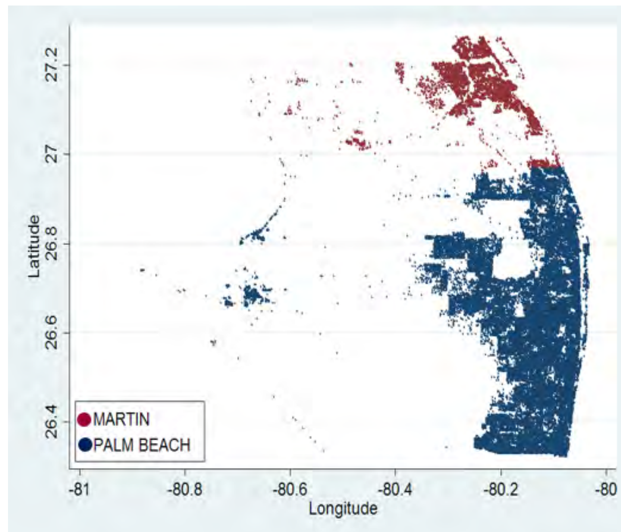


Figure S5: Spatial regression discontinuity design for Hurricane Irma (September 2017).

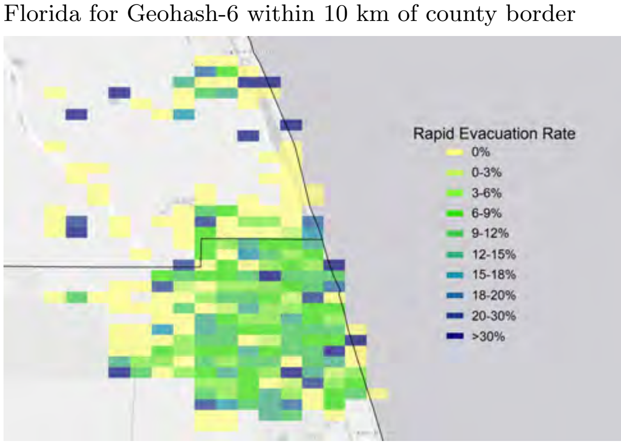
(a) Martin and Palm Beach counties, Florida (*source*: Google Maps)



(b) Residents in Martin and Palm Beach counties, Florida



(c) Rapid evacuations in Martin and Palm Beach counties, Florida for Geohash-6 within 10 km of county border



(d) Regression discontinuity for probability of rapid evacuation following hurricane watch

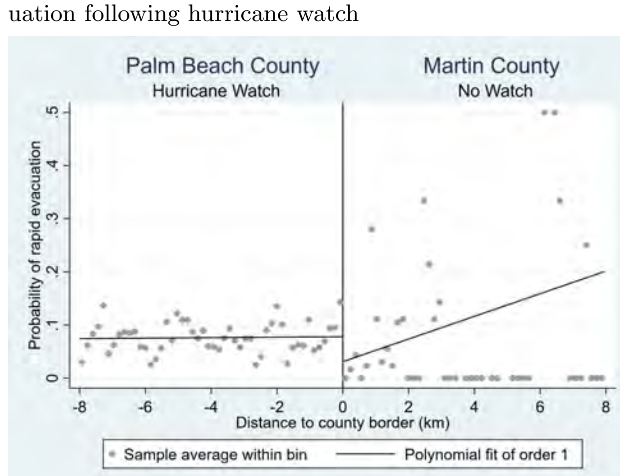
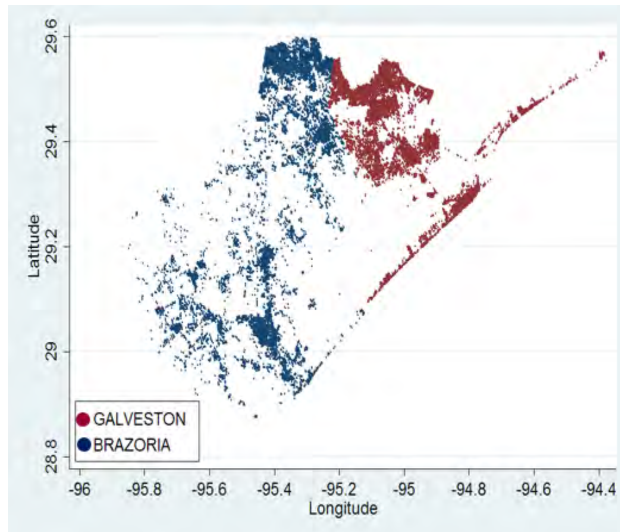


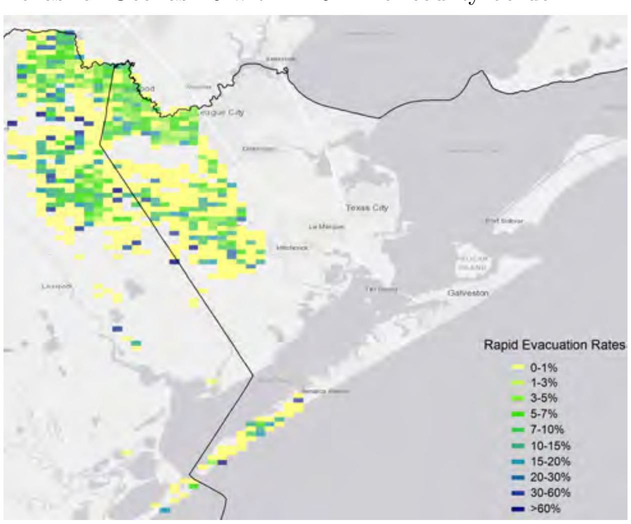
Figure S6: Spatial regression discontinuity design for Hurricane Harvey (August 2017).

(a) Galveston and Brazoria counties, Texas (*source*: Google Maps)

(b) Residents in Galveston and Brazoria counties, Texas



(c) Rapid evacuations in Galveston and Brazoria counties, Texas for Geohash-6 within 10 km of county border



(d) Regression discontinuity for probability of rapid evacuation following hurricane watch

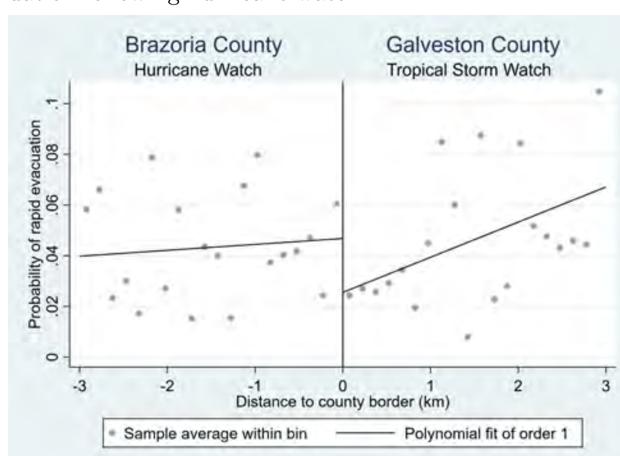
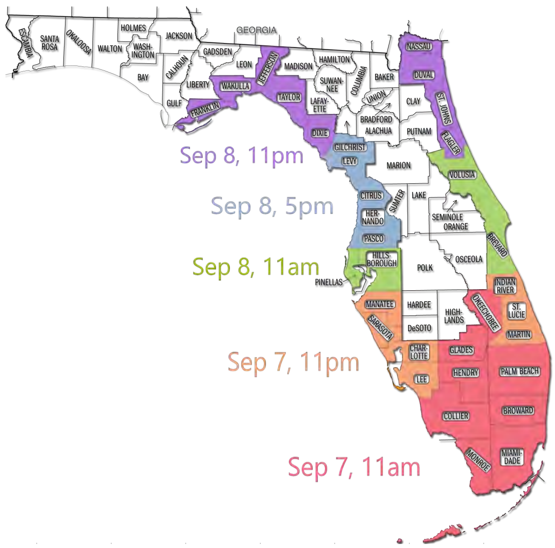
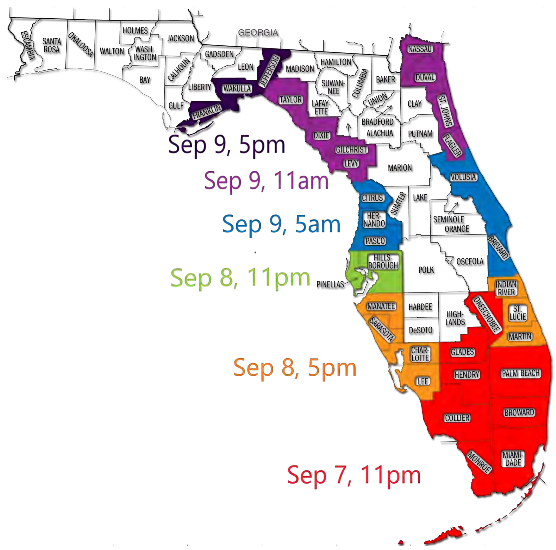


Figure S7: Dates and times of National Hurricane Center alerts for Hurricane Irma (September 2017) and Hurricane Harvey (August 2017).

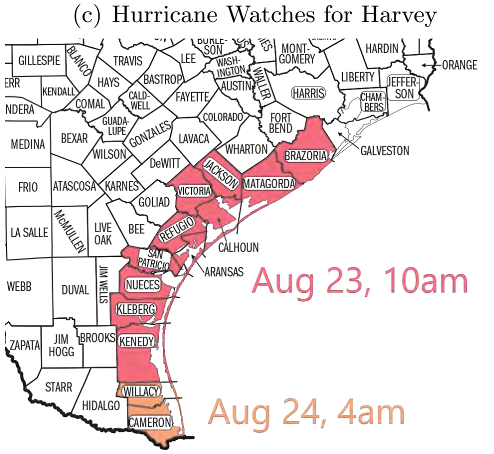
(a) Hurricane Watches for Irma



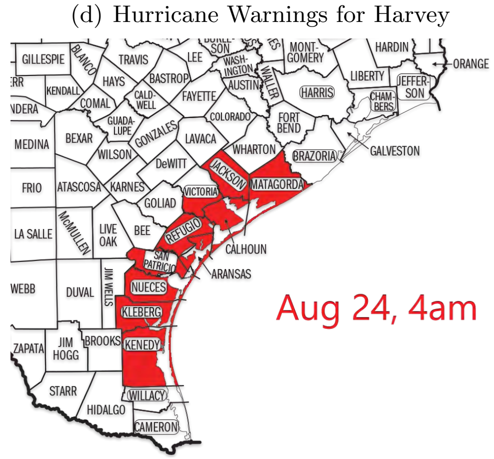
(b) Hurricane Warnings for Irma



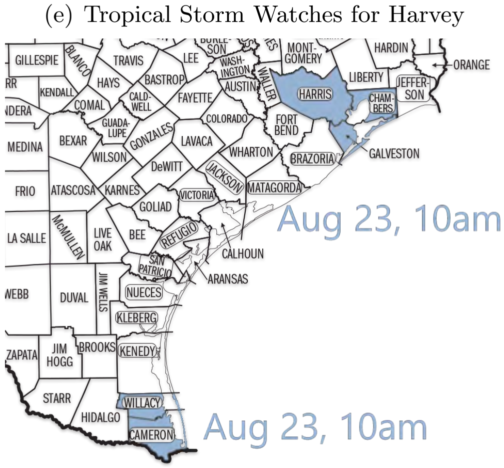
(c) Hurricane Watches for Harvey



(d) Hurricane Warnings for Harvey



(e) Tropical Storm Watches for Harvey



(f) Tropical Storm Warnings for Harvey

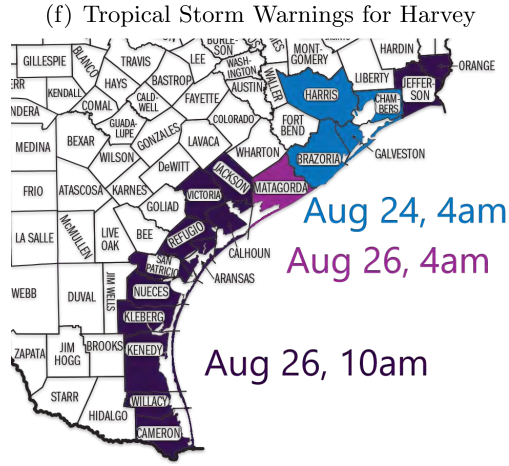


Figure S8: Histograms of hourly evacuation times by first hurricane alert during Hurricane Irma (September 2017).

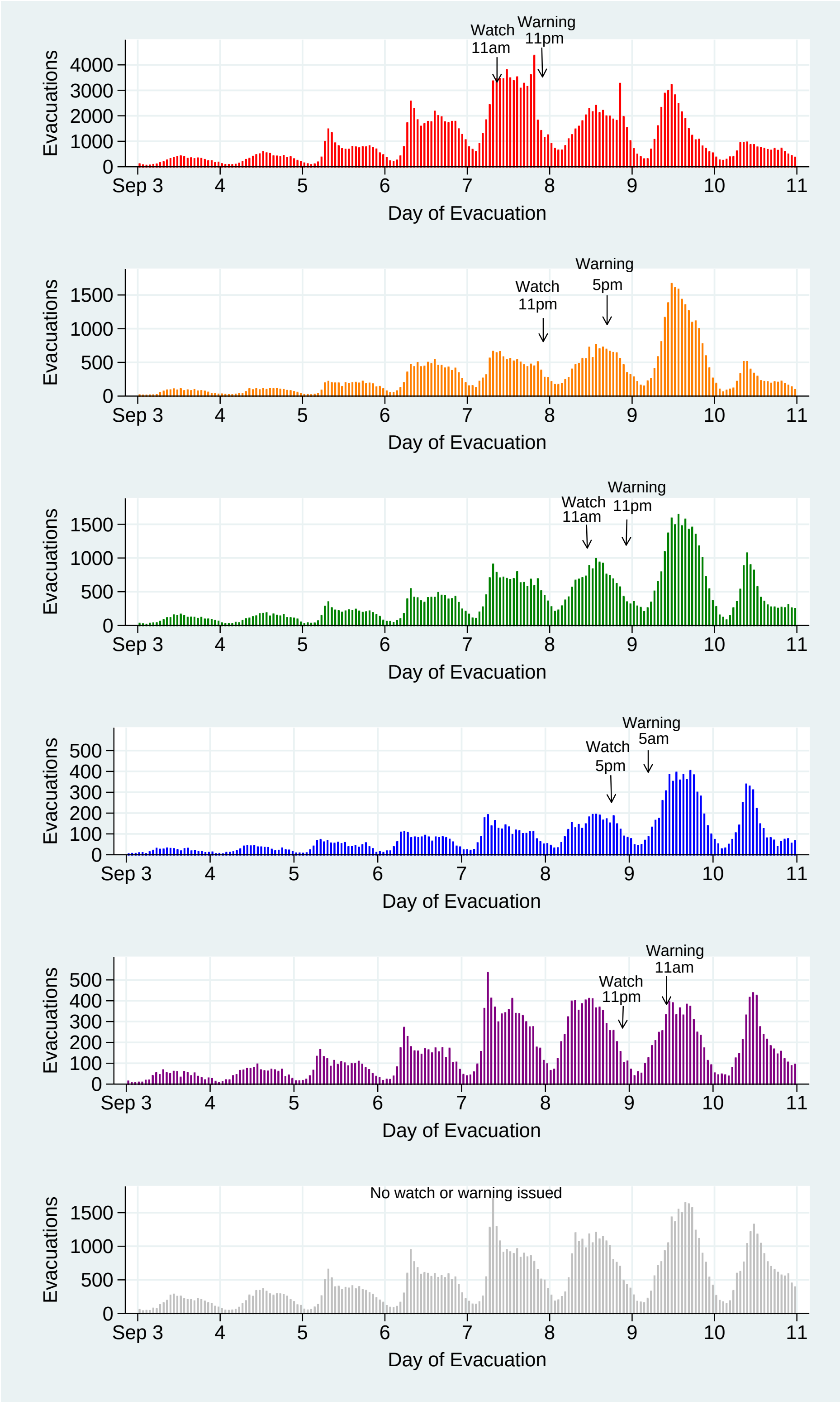


Table S1: Difference-in-difference regression model for any >24-hour evacuation before or during the hurricane.

Independent Variable	Evac24h (1)	Evac24h (2)	Evac24h (3)	Evac24h (4)
Trump Share	0.0115	-0.00626	-0.00998	0.00659
	(0.0144)	(0.0200)	(0.0293)	(0.0197)
Trump x After Limbaugh	-0.117*	-0.130**	-0.0959***	-0.104***
	(0.0454)	(0.0364)	(0.0177)	(0.0207)
Hurricane Alert Received	0.107***	0.0727***	0.144***	0.0870***
	(0.0139)	(0.0134)	(0.0220)	(0.0153)
Distance to Coast		-0.00108*	-0.00180	-0.00200*
		(0.000351)	(0.000719)	(0.000742)
Distance to Coast^2		0.00000264*	0.00000720*	0.00000901**
		(0.000000961)	(0.00000265)	(0.00000259)
Elevation		0.000198	-0.00169	-0.00379**
		(0.000686)	(0.00121)	(0.000992)
Elevation^2		-0.00000116	0.00000546	0.0000186*
		(0.00000394)	(0.00000799)	(0.00000597)
Census Tract Suburb		0.0448	0.0126	0.00798
		(0.0179)	(0.0133)	(0.00742)
Census Tract Rural		0.0155	0.0102	0.00191
		(0.0125)	(0.0110)	(0.00799)
Census Median Age		0.000656	-0.000121	-0.000247
		(0.000381)	(0.000320)	(0.000217)
Census Median Income		-0.000451*	-0.000491**	-0.000429***
		(0.000151)	(0.000130)	(0.0000786)
Census College Grad		0.101***	0.0949***	0.0852***
		(0.0243)	(0.0175)	(0.0145)
Census Employment		-0.0298	-0.0403*	-0.0415*
		(0.0160)	(0.0149)	(0.0129)
Census Race Black		-0.0314	-0.0350	-0.0242*
		(0.0121)	(0.0146)	(0.00779)
Census Race Asian		-0.0227	-0.0338*	-0.0198
		(0.0217)	(0.0112)	(0.00983)
Census Race Hispanic		0.0265*	-0.0110	-0.00291
		(0.00863)	(0.0112)	(0.00651)
Constant	0.301	0.346***	0.388***	0.423***
	(0.0163)	(0.0263)	(0.0299)	(0.0235)
Fixed Effects (# units)	Hurricane (3)	Hurricane (3)	Hurricane (3) and County (166)	Hurricane (3) and Geo-4 (708)
Clustering	County	County	County	Geohash-4
Observations	2,727,999	2,677,181	2,677,181	2,677,175
Adjusted R^2	0.031	0.035	0.043	0.044

$^{***}p < 0.0001$, $^{**}p < 0.001$, $^{*}p < 0.01$. Clustered standard errors in parentheses.

Table S2: Difference-in-difference regression model for any >48-hour evacuation before or during the hurricane.

	Evac48h (1)	Evac48h (2)	Evac48h (3)	Evac48h (4)
Trump Share	0.00817	-0.00770	-0.0143	0.00425
	(0.0170)	(0.0182)	(0.0275)	(0.0183)
Trump x After Limbaugh	-0.140*	-0.147**	-0.107***	-0.115***
	(0.0483)	(0.0390)	(0.0162)	(0.0197)
Hurricane Alert Received	0.100***	0.0637***	0.122***	0.0715***
	(0.0135)	(0.0122)	(0.0247)	(0.0145)
Distance to Coast		-0.00107*	-0.00182	-0.00208*
		(0.000365)	(0.000742)	(0.000756)
Distance to Coast^2		0.00000255	0.00000714*	0.00000836*
		(0.00000101)	(0.00000270)	(0.00000262)
Elevation		0.0000231	-0.00109	-0.00253*
		(0.000720)	(0.00113)	(0.000846)
Elevation^2		9.81e-08	0.00000178	0.0000115
		(0.00000424)	(0.00000800)	(0.00000539)
Census Tract Suburb		0.0520	0.0173	0.00998
		(0.0214)	(0.0129)	(0.00720)
Census Tract Rural		0.0148	0.0121	0.00314
		(0.0129)	(0.0107)	(0.00734)
Census Median Age		0.000633	-0.000188	-0.000356
		(0.000351)	(0.000306)	(0.000211)
Census Median Income		-0.000421*	-0.000501***	-0.000431***
		(0.000137)	(0.000121)	(0.0000732)
Census College Grad		0.118***	0.113***	0.0999***
		(0.0263)	(0.0181)	(0.0150)
Census Employment		-0.0350	-0.0491*	-0.0522***
		(0.0164)	(0.0150)	(0.0124)
Census Race Black		-0.0229	-0.0319	-0.0200
		(0.0120)	(0.0152)	(0.00787)
Census Race Asian		-0.0174	-0.0291*	-0.0158
		(0.0178)	(0.00955)	(0.00846)
Census Race Hispanic		0.0290*	-0.0147	-0.00655
		(0.0103)	(0.0107)	(0.00650)
Constant	0.257***	0.297***	0.346***	0.383***
	(0.0177)	(0.0251)	(0.0263)	(0.0226)
Fixed Effects (# units)	Hurricane (3)	Hurricane (3)	Hurricane (3) and County (166)	Hurricane (3) and Geo-4 (708)
Clustering	County	County	County	Geohash-4
Observations	2,727,999	2,677,181	2,677,181	2,677,175
Adjusted R^2	0.027	0.032	0.041	0.043

$^{***}p < 0.0001$, $^{**}p < 0.001$, $^{*}p < 0.01$. Clustered standard errors in parentheses.

Table S3: Dates and times of National Hurricane Center alerts for Hurricane Matthew.

Florida County	Tropical Storm Watch	Tropical Storm Warning	Hurricane Watch	Hurricane Warning
BREVARD			10/4/16 11:00	10/5/16 11:00
BROWARD	10/4/16 11:00		10/4/16 17:00	10/4/16 23:00
CHARLOTTE	10/5/16 17:00			
CITRUS	10/5/16 17:00	10/6/16 11:00		
COLLIER		10/4/16 11:00		
DUVAL			10/5/16 05:00	10/5/16 23:00
FLAGLER			10/5/16 05:00	10/5/16 23:00
GLADES	10/4/16 11:00		10/4/16 19:45	10/4/16 23:00
HENDRY	10/4/16 11:00		10/4/16 19:45	10/4/16 23:00
HERNANDO	10/5/16 17:00	10/6/16 11:00		
HILLSBOROUGH	10/5/16 17:00			
INDIAN RIVER			10/4/16 11:00	10/4/16 23:00
LEE	10/5/16 17:00			
LEVY	10/5/16 17:00	10/6/16 11:00		
MANATEE	10/5/16 17:00			
MARTIN			10/4/16 11:00	10/4/16 23:00
MIAMI-DADE	10/4/16 11:00	10/4/16 23:00		
MONROE	10/4/16 11:00	10/4/16 23:00		
NASSAU			10/5/16 05:00	10/5/16 23:00
OKEECHOBEE	10/4/16 11:00		10/4/16 19:45	10/4/16 23:00
PALM BEACH			10/4/16 11:00	10/4/16 23:00
PASCO	10/5/16 17:00	10/6/16 11:00		
PINELLAS	10/5/16 17:00			
SARASOTA	10/5/16 17:00			
ST. JOHNS			10/5/16 05:00	10/5/16 23:00
ST. LUCIE			10/4/16 11:00	10/4/16 23:00
VOLUSIA			10/4/16 23:00	10/5/16 11:00

Table S4: Dates and times of National Hurricane Center alerts for Hurricane Harvey.

Texas County	Tropical Storm Watch	Tropical Storm Warning	Hurricane Watch	Hurricane Warning
ARANSAS			8/23/17 10:00	8/24/17 04:00
BRAZORIA		8/24/17 04:00	8/23/17 10:00	
CALHOUN			8/23/17 10:00	8/24/17 04:00
CAMERON	8/23/17 10:00	8/26/17 10:00	8/24/17 04:00	
CHAMBERS	8/23/17 10:00	8/24/17 04:00		
GALVESTON	8/23/17 10:00	8/24/17 04:00		
HARRIS	8/23/17 10:00	8/24/17 04:00		
JACKSON			8/23/17 10:00	8/24/17 04:00
JEFFERSON		8/26/17 10:00		
KENEDY			8/23/17 10:00	8/24/17 04:00
KLEBERG			8/23/17 10:00	8/24/17 04:00
MATAGORDA			8/23/17 10:00	8/24/17 04:00
NUECES			8/23/17 10:00	8/24/17 04:00
ORANGE		8/26/17 10:00		
REFUGIO			8/23/17 10:00	8/24/17 04:00
SAN PATRICIO			8/23/17 10:00	8/24/17 04:00
VICTORIA			8/23/17 10:00	8/24/17 04:00
WILLACY	8/23/17 10:00	8/26/17 10:00	8/24/17 04:00	

Table S5: Dates and times of National Hurricane Center alerts for Hurricane Irma.

Florida County	Tropical Storm Watch	Tropical Storm Warning	Hurricane Watch	Hurricane Warning
BAY	9/9/17 11:00	9/9/17 17:00		
BREVARD		9/11/17 08:00	9/8/17 11:00	9/9/17 05:00
BROWARD		9/10/17 23:00	9/7/17 11:00	9/7/17 23:00
CHARLOTTE		9/11/17 05:00	9/7/17 23:00	9/8/17 17:00
CITRUS		9/11/17 08:00	9/8/17 17:00	9/9/17 05:00
COLLIER		9/10/17 23:00	9/7/17 11:00	9/7/17 23:00
DIXIE		9/11/17 08:00	9/8/17 23:00	9/9/17 11:00
DUVAL		9/11/17 08:00	9/8/17 23:00	9/9/17 11:00
FLAGLER		9/11/17 08:00	9/8/17 23:00	9/9/17 11:00
FRANKLIN		9/11/17 08:00	9/8/17 23:00	9/9/17 17:00
GLADES		9/11/17 05:00	9/7/17 11:00	9/7/17 23:00
GULF	9/9/17 11:00	9/9/17 17:00		
HENDRY		9/11/17 05:00	9/7/17 11:00	9/7/17 23:00
HERNANDO		9/11/17 08:00	9/8/17 17:00	9/9/17 05:00
HILLSBOROUGH		9/11/17 05:00	9/8/17 11:00	9/8/17 23:00
INDIAN RIVER		9/11/17 05:00	9/7/17 23:00	9/8/17 17:00
JEFFERSON		9/11/17 08:00	9/8/17 23:00	9/9/17 17:00
LEE		9/11/17 05:00	9/7/17 23:00	9/8/17 17:00
LEVY		9/11/17 08:00	9/8/17 17:00	9/9/17 11:00
MANATEE		9/11/17 05:00	9/7/17 23:00	9/8/17 17:00
MARTIN		9/11/17 05:00	9/7/17 23:00	9/8/17 17:00
MIAMI-DADE		9/10/17 23:00	9/7/17 11:00	9/7/17 23:00
MONROE		9/10/17 23:00	9/7/17 11:00	9/7/17 23:00
NASSAU		9/11/17 08:00	9/8/17 23:00	9/9/17 11:00
OKEECHOBEE		9/11/17 05:00	9/7/17 11:00	9/7/17 23:00
PALM BEACH		9/10/17 23:00	9/7/17 11:00	9/7/17 23:00
PASCO		9/11/17 08:00	9/8/17 17:00	9/9/17 05:00
PINELLAS		9/11/17 05:00	9/8/17 11:00	9/8/17 23:00
SARASOTA		9/11/17 05:00	9/7/17 23:00	9/8/17 17:00
ST. JOHNS		9/11/17 08:00	9/8/17 23:00	9/9/17 11:00
ST. LUCIE		9/11/17 05:00	9/7/17 23:00	9/8/17 17:00
TAYLOR		9/11/17 08:00	9/8/17 23:00	9/9/17 11:00
VOLUSIA		9/11/17 08:00	9/8/17 11:00	9/9/17 05:00
WAKULLA		9/11/17 08:00	9/8/17 23:00	9/9/17 17:00
WALTON	9/9/17 11:00	9/9/17 17:00		