The Effect of Disaster-induced Displacement on Social Behaviour: The Case of Hurricane Harvey*

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Abstract

Natural disasters have deleterious effects on public health and individual behaviors. Disaster-induced displacement of individuals, in particular, is associated with psychological morbidity and trauma. Differential exposure to such a disaster and variation in vulnerability to individual stressors help to explain these individual health and behavioral outcomes. However, these relationships are not uniform between different groups of individuals. Drawing upon public health studies and individual accounts of disaster experience, we argue that differential experiences related to variation in group-level social context (e.g., ethnicity) during and after displacement is an important factor that remains understudied. Theoretically, we focus on differences in how physical displacement disrupts individuals' social networks, which in turn can have an adverse effect on mental health. Hurricane Harvey, which brought unprecedented levels of flooding, property damage, and displacement to the greater Houston area in late summer 2017, allows us to study pre- and post disaster behaviors of affected individuals. Specifically, we use tweeting patterns as a measure of individual-level behaviour that is deeply tied to social network engagement because social networking services are increasingly integrated into individuals' daily lives and they allow individuals to share information and perform social functions. Thus, disruptions to individuals' social networks will manifest in their social media behaviour. In order to compare pre- and post-displacement behaviour, we use a variety of measures to capture social and political engagement, starting with tweeting frequency. We expect that individuals subject to physical displacement will demonstrate abnormalities in their tweeting behaviour, and that these effects differ across ethnic groups, with visible minorities most substantially affected.

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1 Introduction

Hurricane Harvey made landfall in Texas in late August 2017. Before moving to the east, it poured a record-breaking 60 inches of rain over parts of Southeast Texas, with the Houston metropolitan statistical area receiving between 36 and 48 inches. This unprecedented amount of rain rapidly overwhelmed Houston's water control infrastructure, resulting in massive flooding throughout the metropolitan area and beyond. In total, Harvey directly caused 63 storm-related deaths, over 40000 displaced individuals, and an estimated $125 billion in damages including over 300000 structures (Blake and Zelinsky 2018). As the flooding destroyed thousands of homes, many of these dislocations are permanent. While Hurricane Harvey was record-setting in many ways, similar events have happened in the recent past, with Hurricanes Katrina in 2005 being the costliest hurricane in U.S. history. More importantly, it is unlikely to be the last. A recent study finds that tropical storms have become slower since the 1950s (Kossin 2018), which exacerbates the increasingly moist atmosphere caused by rising sea surface temperatures (Trenberth, Fasullo and Shepherd 2015), leading to expectations of greater rainfall and flooding in areas afflicted by storms. More generally, natural disasters routinely impact the lives of individuals around the world through destroyed properties, displacement, and death.

Natural disasters compel research. In addition to their high material costs, their toll on human well-being both physical and mental is widely documented. A particularly important focus in the public health literature is the persistent, deleterious relationship between exposure to disasters and long term mental health outcomes such as posttraumatic stress disorder (PTSD) and depression (Ivey 2017; Shultz and Galea 2017*a*). This relationship has further been found to differ between individuals from different ethnic groups. Specifically, blacks and Spanish-preferring Hispanics are more vulnerable than whites (Alexander et al. 2017; Ali et al. 2017; Davis et al. 2012; Perilla, Norris and Lavizzo 2002). Attempts to explain the source of this group-level variation has yielded mixed evidence, with some studies finding that adjusting for factors related to ethnicity attenuates inter-group variation, while others find that it does not.

Earlier attempts at explaining inter-group differences in post-disaster mental health outcomes focused on factors associated with characteristics of the ethnic cultures or with exposure to the event itself (e.g. Perilla, Norris and Lavizzo 2002). More recently, researchers have looked toward disruptions in social networks and support as an alternative explanation (Alexander et al. 2017). This latter explanation fits well with our understanding that physical displacement of individuals during disasters is highly traumatic (Mills, Edmondson and Park 2007). In the short term, individuals facing imminent extreme weather must undertake a series of highly consequential decisions related to evacuation in what are often stressful and contentious settings (Weick 1988). In the medium term and beyond, evacuation efforts force individuals into new locales and, at the same time, force these individuals on preexisting populations. Continued coexistence of these often disparate groups requires almost immediate mutual adaptation to the suddenly-changed material resource levels and unfamiliar cultural practices (Oliver-Smith 2016). Under these conditions, preexisting cleavages that run along socioeconomic, and race and ethnic lines can become exacerbated, rendering what is already a difficult process even more stressful (Hopkins 2012). At the extreme, there is evidence that resource competition is related to inter-ethnic conflict (Ghimire, Ferreira and Dorfman 2015).

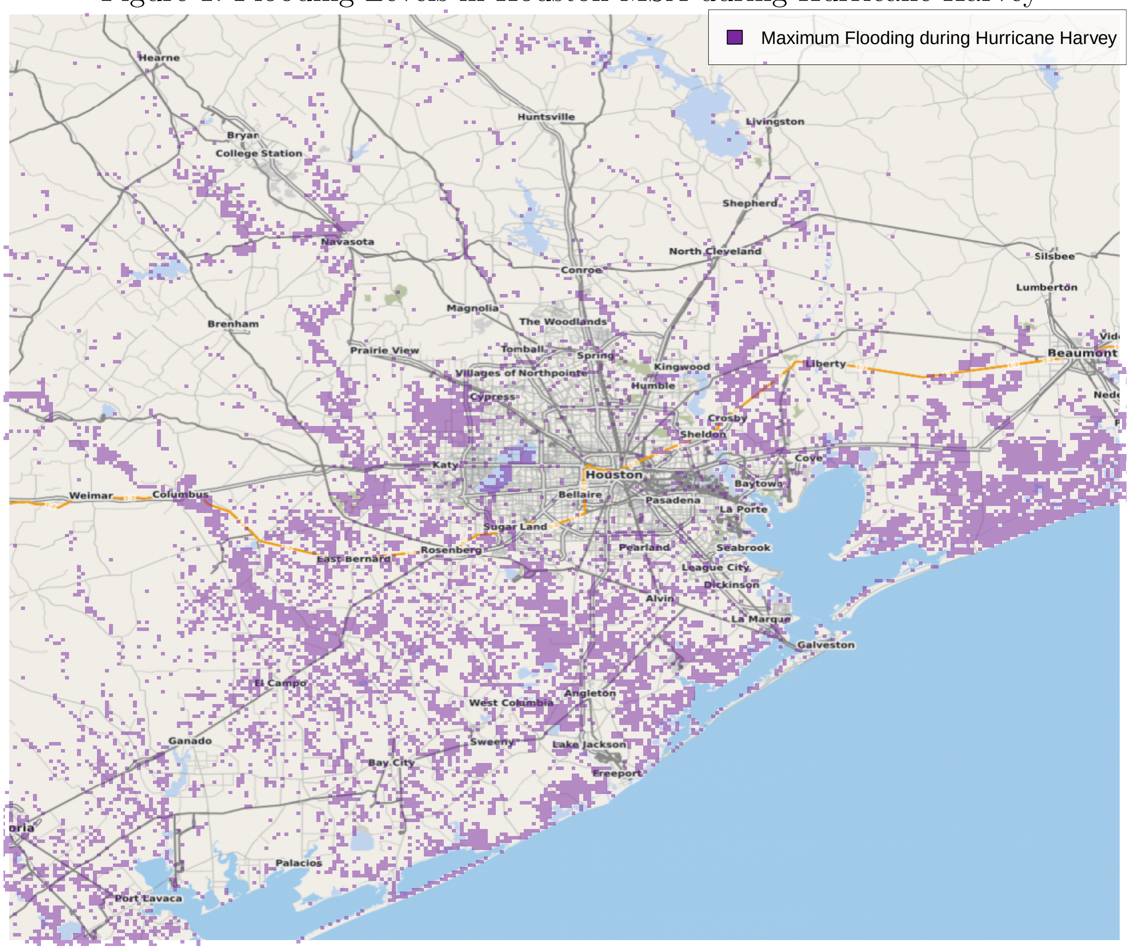
Factors associated with social networks are important predictors of individuals' mental health and behaviour more generally (Bond et al. 2012), often with greater impact on ethnic minorities (Plant and Sachs-Ericsson 2004). The greater reliance of minorities on their social networks and support structures, which tend to be disrupted during natural disasters especially through physical displacement, explains the inter-ethnic variation in observed mental health outcomes. In our project, we explore this issue using individual-level social network engagement before and after Hurricane Harvey.

2 Case Background

Several characteristics of Hurricane Harvey make it a suitable case for exploring the impact of disaster-induced displacement on social and political behaviour. First, Hurricane Harvey was unprecedented in many ways, including in terms of how much flooding and flood-induced damages and displacement that resulted. Figure 1 shows the extent to which the Greater Houston metropolitan statistical area (MSA) was flooded in the two week period during and after the storm. This unprecedented flooding displaced more than 30000 individuals (Bauerlein 2017).

Second, compared to previous large-scale disasters, social media data is becoming increasingly abundant. The availability of social media history allows us to establish with relative ease and granularity a baseline to assess disaster-induced changes with, which has so far been a hurdle in this area of research (Shultz and Galea 2017*b*). Additionally, using observational data such as this avoids concerns with some of the measures previously employed, such as medical records which tend to underrepresent the extent to which blacks are affected by mental health disorders (Alexander et al. 2017),

Figure 1: Flooding Levels in Houston MSA during Hurricane Harvey



3 Empirical Approach

Our aim is to examine whether individuals' social and political behaviours are influenced by having been displaced. To do so, we compare the behaviour of individuals before and after Harvey started using a difference-in-difference framework. Harvey officially became a hurricane on August 17, but its effects, which we capture using a continuous measure of flooding, were not felt in the Houston area until August 25, which we designate as the first day of our Harvey period. Using our data, described below, we fit the regression model

$$Y_{i,t} = \alpha + \beta * Flood_i + \tau * Harvey_t + \gamma(Flood_i * Harvey_t) + \epsilon_{i,t}, \tag{1}$$

where $Y_{i,t}$ is a behavioural outcome of interest of individual i at time t (which in our first examination is volume of tweets), $Flood_i$ is a continuous measure of how much flooding individual i experienced, and $Harvey_t$ is an indicator for days on or after August 25. γ is the DID effect we are interested in.

Figure 2: Tweeting Trends over Time, by Flooding in Home Census Tract

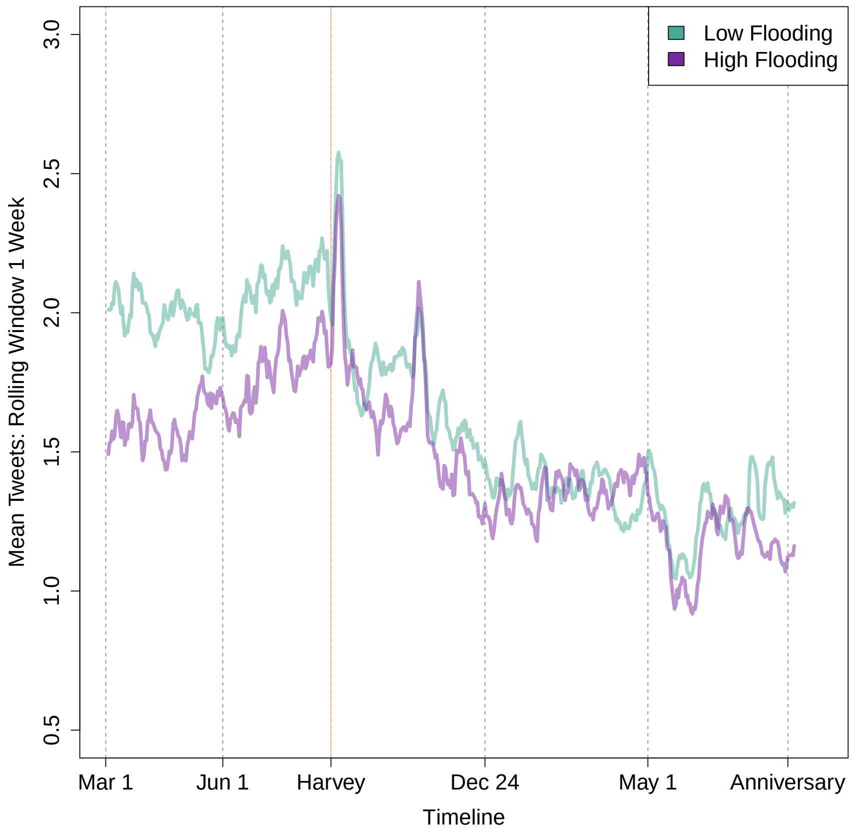


Figure 2 shows a rolling average of mean tweets over time, with two groups differentiated by how much they were exposed to flooding. We describe our measures in detail below, but for now, it is apparent that there is a common trend prior to the onset of Harvey flood. While there is a gap in how much the groups tweeted, it does not appear to differ in trend, captured by the slope of the lines. Harvey witnessed a tremendous spike in tweeting levels, which is expected given the abundance of anecdotal evidence suggesting the extent to which social media platforms such as Twitter were used during disaster response efforts (Aisch et al. 2017). After that spike, it appear that the two trends converged, suggesting that there is an effect of flooding in increasing tweeting behaviour.

3.1 Sample

Our target population are all individuals potentially displaced by the Harvey floods, which we specify as those who lived in the Houston area prior to August 2017. Our initial sample is the subpopulation of all Twitter users who tweeted at least once between the period of August 3rd, 2017 and September 18, 2017, with a tweet that 1) was geolocated to be in the greater Houston Metro Area or 2) tagged in one of twenty-one cities or census designated places in Greater Houston with population of at least 25000. These political boundaries are summarized in Table 1. These users are identified through tweets licensed from Twitter via Texifter on April 30, 2018.[1]

Table 1: Houston Area Political Boundaries Used for Sampling

Houston MSA 2010 Counties		Communities in Greater Houston (2010 Pop.: 25000+)			
Brazoria	Waller	Houston	Channelview	Atascocita	Rosenberg
Galveston	Liberty	Pearland	League City	Mission Bend	Kingwood
Fort Bend	Montgomery	Baytown	Sugar Land	Pasadena	Spring
Chambers		Friendswood	Conroe	The Woodlands	
Austin		La Porte	Galveston	Deer Park	
Harris		Texas City	Missouri City	Lake Jackson	

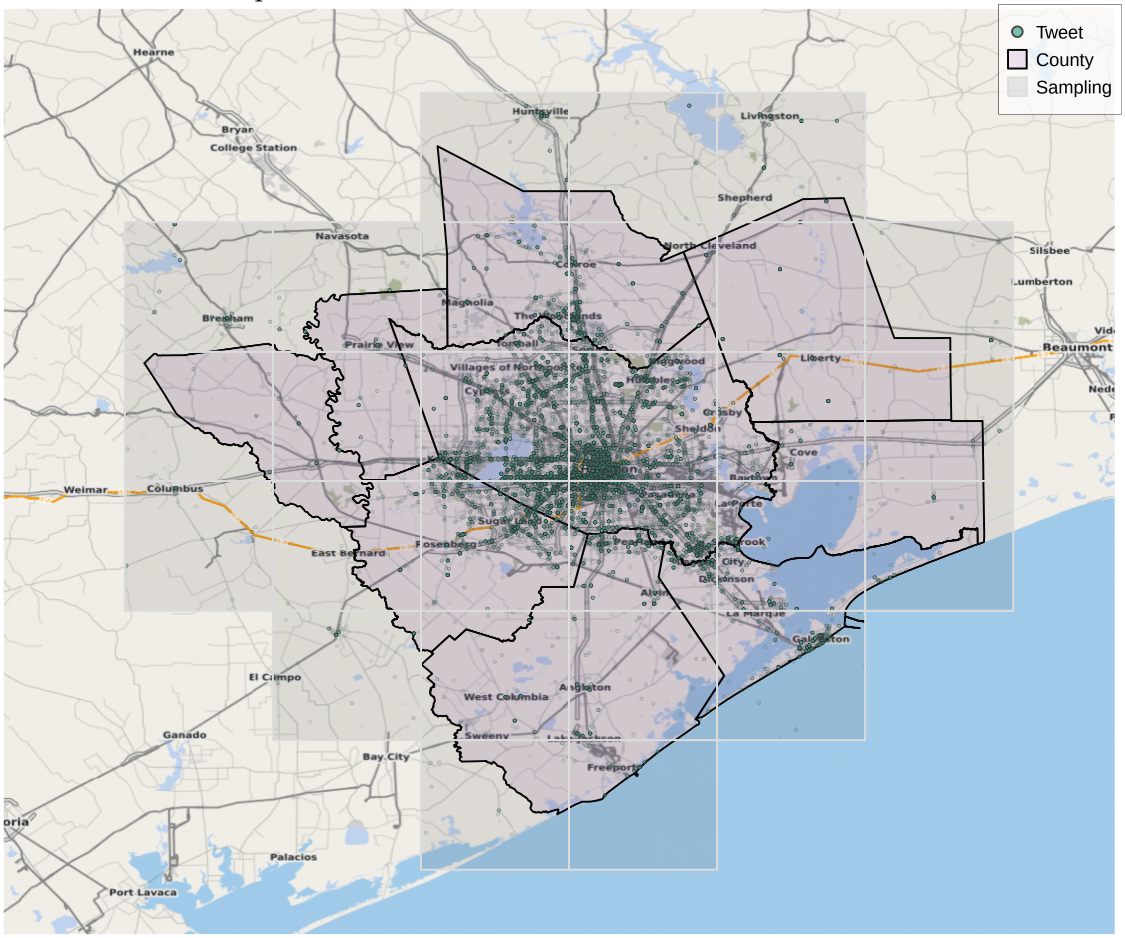
In the present analysis, only users with geolocated tweets are included. Figure 3 presents the geographical distribution of each of these tweets. This sample initially includes 16050 unique users. The sample is reduced as described below. First, we use Twitter's API to obtain timelines, or tweet histories, of these users up to one year prior to Harvey forming (i.e. August 16, 2016 onward). Calls to the Twitter API were made between Sept. 5, 2018 and Sept 10, 2018. From this, we obtained timelines of 15698 users. This procedure removed 352 users whose accounts were deleted or set to private during the period we accessed the API. Next, in order to ensure a balanced panel of tweeting patterns with enough time before and after Harvey, we removed accounts that were created fewer than six months before Harvey formed (February 25, 2017). Fifty-eight users were removed this way. Finally, we use geographical information from each user's timeline to estimate their home location. We only kept users who we were able to obtain an estimate we are comfortable with, and if the estimated location falls into the greater Houston Metropolitan Statistical Area. This procedure, described below, reduced our sample to 1398.

3.2 Measurement

Our study generally looks at the relationship between individuals' displacement from their *homes* due to *flooding* and changes in their *socioipolitical behaviours*. We discuss each of the three measures in turn.

[1] https://texifter.com/about/

Figure 3: Licensed Sample of Geolocated Tweets in Relation to Houston Political Boundaries



3.2.1 Home Location

We use two sources of information to estimate an individual's home location. First, we use the account's self-identified "location" field. Second, for users who do not volunteer that information, we take their homes as the locations where they tweet from the most between 10pm and 8am in the year prior to when Hurricane Harvey first formed. This procedure is summarized is as follows. Results of our home location estimation are presented in Figure 4.

We begin by subsetting all tweets prior to August 17, 2017 from our licensed sample, which begins in August 3, 2017. Each entry contains information from the originating user's profile, which sometimes includes a "location" supplied by the user. This location is a text field, and can contain a geographical area (e.g. "Houston, TX" or "Texas"), street address, geocoordinates, or something unrelated to geography.[2] We obtained the location text from

[2]We are limited to data from the licensed tweets for this task because the user meta data differs depending on the way a tweet was obtained. If licensed through the historical powertrack, then it is at the time of posting. If through the search api, it is at time of api access, which in this case is after Hurricane Harvey. See: `https://`

all users in this subset, and determined which locations are precise enough (i.e. street addresses, landmarks, and geocoordinates). Street addresses and landmarks are converted to geocoordinates using the Google Geocoding API.[3] Finally, we identified the census tract for each geocoordinate, and set that as the user's home location. This first step returned home locations for 182 users, with 132 of them residing in a greater Houston MSA census tract.

We estimate the home locations of each remaining user by identifying the census tract they tweeted from the most at night, in the year prior to Hurricane Harvey. Specifically, for each account, we subset tweets falling between August 17, 2016 and August 16, 2017. This set of tweets is further reduced to those falling between 10pm and 8am (UTC-5). Next, we identified the census tract of tweets in this subset that has a geocoordinate (14.3% of these tweets), and obtained each user's modal census tract as an estimate of their home location.[4] To raise our confidence in these estimates, we discard modal estimates where the modal census tract is observed fewer than five times. This procedure returns home locations for 1279 users. Twenty-five of these accounts had two modes and one account had three; for these users, one of the multiple tracts were randomly selected. Our final sample contains 1398 users.

Of the 1398 individuals, 1161 are estimated to be in Hariss County, which at 83% of the sample, is an overestimate compared to Houston MSA residents living in Hariss County at the population level (68%). However, the overall distribution between counties, shown in Table 2, appears to be a reasonable approximation of the population.

A more granular examination of these estimates raises cause for concern. Figure 4 shows the 1161 individual estimated to be Harris County residents in their estimated census tracts. Within each census tract, locations are randomly distributed for visualization purposes. The purple shading represents for each census tract its population sorted by deciles. From the figure, we see that while the population in Harris County tends to be distributed more around the periphery of the county, the estimated locations are heavily distributed in the center census tracts. These results suggest that the location estimation procedure is capturing individual activity rather than residence, even after subsetting to nighttime tweets. It is especially telling that there is a high number of estimated homes in the census tract to the north (30.0,-94.3) that has no actual population; this is the location of the Houston International Airport. Further work is required in this area.

developer.twitter.com/en/docs/tweets/data-dictionary/guides/tweet-timeline#key_concepts.

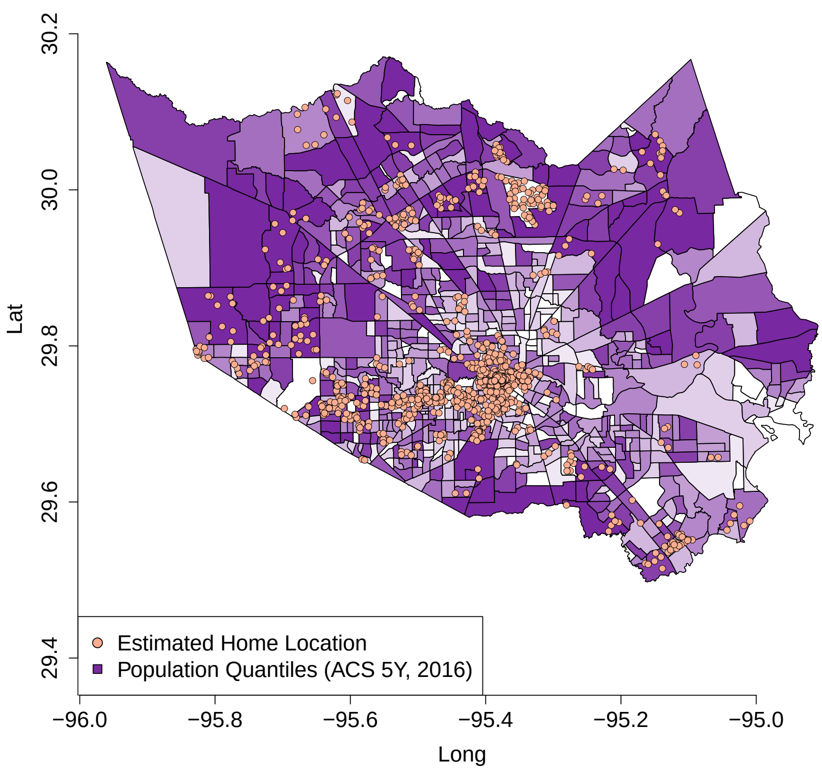
[3] https://developers.google.com/maps/documentation/geocoding/

[4] Tweets that do not have geocoordinates can contain a "place" identifier, which can further be parsed to obtain geocoordinates. An additional 12.3% of total tweets have a place identifier. In future iterations of this paper we will use this information, but for now, rate limits associated with Twitter's API prevent us from doing so.

Table 2: Distribution of Estimated Home Locations, by County

County	Users	Prop.	Census Prop.
Austin	1	0.00	0.00
Brazoria	47	0.03	0.05
Chambers	1	0.00	0.01
Fort Bend	73	0.05	0.11
Galveston	50	0.04	0.05
Harris	1161	0.83	0.68
Liberty	2	0.00	0.01
Montgomery	53	0.04	0.08
Waller	10	0.01	0.01

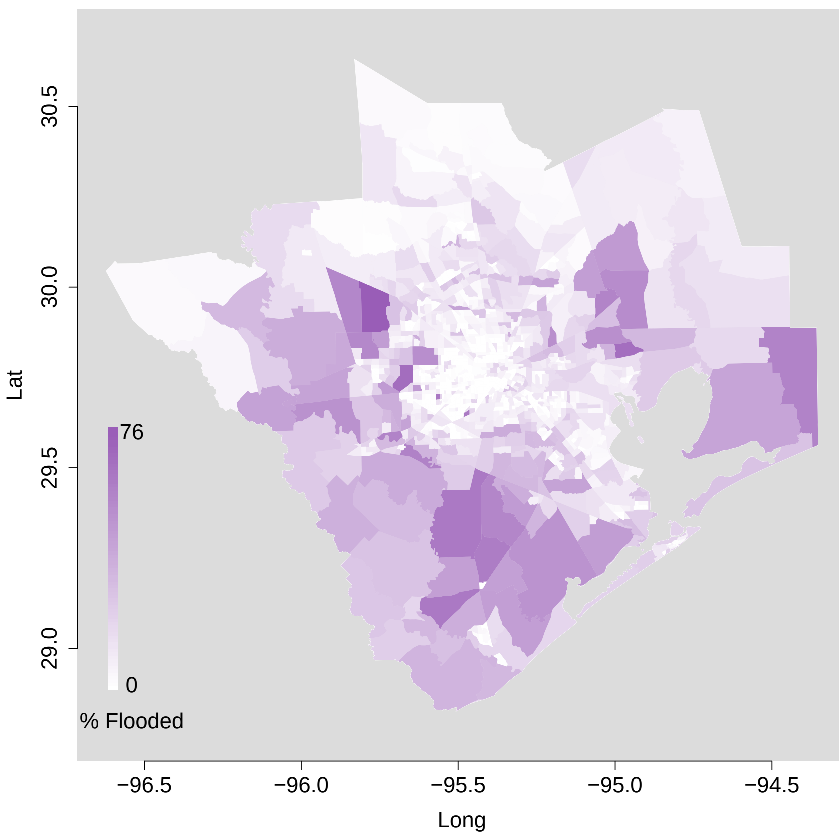
Figure 4: Estimated Home Locations in Relation to Population Data



3.2.2 Displacement

It is difficult to obtain a direct measure of displacement, as even observed movement patterns can result from other reasons. A potential solution is to obtain survey data, which will also help with location estimation. For now, we use flooding as an indirect measure of displacement. We obtain flooding data for Hurricane Harvey from the Dartmouth Flood Observatory (Brakenridge and Kettner N.d.). Specifically, this geographical data, used to plot Figure 1, shows the maximum observed flooding during Hurricane Harvey, from August 28 until September 8, 2017. The data is created by comparing pre- and post-flood satellite images to identify water-covered areas at various points during the hurricane that are not existing bodies of water pre-flooding.[5] Using this data, we calculated the proportion each census tract within the Greater Houston MSA flooded during Hurricane Harvey. We use this value as our measure of displacement. Figure 5 shows the proportion flooded for all census tracts.

Figure 5: Distribution of Proportion Flooded in Houston MSA, by Census Tract



[5]For an exact description of the data and methodology, see `http://floodobservatory.colorado.edu/Events/2017USA4510/2017USA4510.html`.

3.2.3 Social and Political Behaviours

We intend to examine various sociopolitical outcomes, including political participation and indicators of mental health, which tend to be related (Ojeda 2015; Ojeda and Pacheco 2017). Recent advancements in computational algorithms have increased our ability to study these phenomenon through observable social media data (Kaur and Singh 2016; Kandias et al. 2017; Joshi et al. 2017). In this study we begin by examining individuals' social media engagement, which we operationalize as the frequency with which an individual tweets in a day. Tweeting, and social media engagement more generally, is an important behavioural outcome. It is tied to self expression, identity, and social and political participation (Chen 2011). Increasingly, for certain segments of the population, social network activities are routinized parts of life (Smith and Anderson 2018). We expect large-scale disruptions in individuals' social networks and lives in general to have an impact on their tweeting frequency.

4 Results

Using the measures presented above, we fit Equation 1 with and without day-fixed effects. The two fitted models are presented in Table 3. The substantive conclusion that can be drawn from the models are effectively the same. The effect of having experienced flooding is increase in tweeting behaviour. At this time, we forgo further discussion of these results as we are working to improve our estimates for individuals' home locations.

Table 3: Models for Tweeting Behaviour

	Pooled		Fixed Effects	
	Coefficient	s.e.	Coefficient	s.e.
Harvey × Flooding	0.669*	0.081	0.669*	0.081
Flooding	−0.849*	0.067	−0.849*	0.066
Harvey	−0.547*	0.011	−0.673*	0.125
Intercept	1.960*	0.009	1.913*	0.089
			(Day Fixed Effects)	

$n = 1398, t = 546$; $* = p < 0.05$

5 Discussion

The materials presented in this paper is a preliminary look at the question of whether physical displacement caused by natural disasters disrupts an individual's social network, thereby influencing their social network engagement. Because we are not confident in our home location estimation, this paper primarily serves to illustrate our approach to studying this topic. In future iterations of this paper, we seek to make a number of improvements.

First, we are only using the geolocated subset of our initial sample of licensed tweets. While this sample contains 16050 users, approximately 60000 more remain. The addition of these users affords us greater flexibility in constructing our measures. Most immediately, for home estimation, we can further subset the tweets to only weeknights, hopefully reducing nighttime activities outside the home.

Second, while we discussed issues of social cleavage and disruptions to social networks as an explanation for variation between ethnic groups in observed mental health outcomes after disasters, the present study does not address this issue. In addition to the larger sample size, we plan to determine the user's ethnicity. The initial approach would likely be to determine the language of tweets (i.e. English and Spanish), then proceed further from there.

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