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COVID-19 to go? The role of disasters and evacuation in the COVID-19 pandemic

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ABSTRACT

Since the start of the pandemic, some U.S. communities have faced record storms, fires, and floods. Communities have confronted the increased challenge of curbing the spread of COVID-19 amid evacuation orders and short-term displacement that result from hazards. This raises the question of whether disasters, evacuations, and displacements have resulted in above-average infection rates during the COVID-19 pandemic. This study investigates the relationship between disaster intensity, sheltering-in-place, evacuation-related mobility, and contagion following Hurricane Zeta in Southeastern Louisiana and The Wildfires in Napa and Sonoma Counties, California, known as the Glass Fire. We draw on data from the county subdivision level and mapped and aggregated tallies of Facebook user movement from the Facebook Data for Good program’s GeoInsights Portal. We test the effects of disasters, evacuation, and shelter-in-place behaviors on COVID-19 spread using panel data models, matched panel models, and synthetic control experiments. Our findings suggest associations between disaster intensity and higher rates of COVID-19 cases. We also find that while sheltering-in-place led to decreases in the spread of COVID-19, evacuation-related mobility did not result in our hypothesized surge of cases immediately after the disasters. The findings from this study aim to inform policymakers and scholars about how to better respond to disasters during multi-crisis events, such as offering hotel accommodations to evacuees instead of mass shelters and updating intake and accommodation procedures at shelters, such as administration temperature screenings, offering hand sanitizing stations, and providing isolated areas for ill evacuees.

1. Introduction

Since the start of the COVID-19 pandemic, some U.S. communities have faced record storms, fires, and floods. In parts of California, over 9,000 fires over varying scales broke out and burned 4,257,800 acres and damaged 10,488 buildings (State of California, 2021). In Louisiana, storms Cristobal, Marco, Laura, Sally, Beta, Delta, and Zeta, varying in intensity and classification, all took aim at the Gulf Coast, but namely Louisiana. Responding to a disaster in 2020 presented unique challenges for individuals and households affected by them and the first responders deployed to them. Residents, first responders, and local officials were faced with responding to an emergency, managing evacuation, and providing aid while simultaneously trying to adhere to non-pharmaceutical interventions, such as physical distancing, masking, handwashing, and crowd avoidance promoted by the Centers for Disease Control and Prevention to curb the spread of COVID-19.

However, an unavoidable consequence of storms, fires, and floods is evacuation, producing considerable movement of residents within and outside county lines. This movement amid a pandemic raises the question of whether evacuation might have led to the increased spread of COVID-19 in communities when staying home and distancing was the most effective method of containment of the novel coronavirus. In late 2020, researchers (Pei et al., 2020) modeled a hypothetical hurricane evacuation from four counties in the State of Florida and concluded that such an event would result in increases in cases in the host and home cities of evacuees. Our study advances this work with two cases of evacuation from late 2020. We use spatial and statistical analytical approaches to study disaster intensity and population movement to estimate evacuation across regions in great detail. This study relies on data from Facebook’s Data for Good Program, which estimates mobility before, during, and after a crisis with geolocation. With this data, we construct mobility networks of aggregated Facebook user movement to test the degree to which evacuation affected the spread of COVID-19 after a crisis, drawing on the cases of Hurricane Zeta in Southeastern
Louisiana taking place in late September of 2020 and the Wildfires in Napa and Sonoma Counties, California, also known as the Glass Fire, taking place in late October of 2020.

2. Background

The Federal Emergency Management Agency (FEMA) defines an evacuation as “organized, phased, and supervised withdrawal, dispersal, or removal of civilians from dangerous or potentially dangerous areas and their reception and care in safe areas (FEMA, 2021, p3).” Evacuations can occur spontaneously, voluntarily, or by mandate. Spontaneous evacuations, also referred to as “shadow evacuations,” are unorganized and unsupervised and occur when individuals choose to flee a situation they consider dangerous without instruction to do so (FEMA, 2021, p3). Voluntary evacuations occur when a threat to life or property exists in the immediate future and individuals are advised to leave, but are not required to do so (FEMA, 2021, p4). Mandatory or directed evacuation occurs when individuals are required to leave according to local officials’ directives when there is an imminent threat to loss of life or property (FEMA, 2021, p4). Natural disasters, slow-onset environmental changes, accidental disruptions or industrial accidents, and conflict and warfare (Lonergan, 1994) are common disruptions that result in spontaneous, voluntary, or mandated evacuation.

The majority of evacuations involve the egress of 5,000 individuals (FEMA, 2021). Large-scale, mass evacuations involving the dispersal of 100,000 individuals account for less than 10% of all evacuations in the United States (Dotson and Jones, 2005). Examples of large-scale, mass evacuations include Hurricane Frances (2004), calling for the evacuation of 2.8 million people (Hurricane Frances & Hurricane Jeanne, 2004); Hurricane Katrina (2005), calling for the egress of 1.5 million people (Groen & Polivka, 2008); and Hurricane Matthew (2016), forcing 2.5 million residents across the state of Florida to flee (Hernández & Berman, 2016). Warnings to evacuate can come from three primary sources: warning by authority, warning by friend or family, or warning by mass media, and individuals can respond by leaving immediately, delaying action before confirming the threat, or ignoring the warning entirely and resuming normal activities (Drabek, 1969).

3. Evacuation

Researchers of disasters and evacuation have previously investigated the factors associated with evacuation behavior. Common determinants of household evacuation include spatial proximity to the disaster (Cutter & Barnes, 1982; Yun and Hamada, 2015), possessing a pre-existing plan (Perry, 1979), belief that the threat is imminent and real (Cutter and Barnes, 1982; Perry, 1979; Riad et al., 1999; Sugiuira et al., 2019), previously experiencing a disaster (Riad et al., 1999; Hasan et al., 2011); messaging (Cuite et al., 2017; Quarantelli, 1990); message credibility (Cohn et al., 2006; Quarantelli, 1990); perception of personal risk (Perry 1979; Cutter & Barnes, 1982; Sugiuira et al., 2019), close social ties and increased participation in the community (Cutter and Barnes, 1982; Perry, 1979; Riad et al., 1999; Metaxa-Kakavouli et al., 2018; Do, 2019), environmental and social cues (Fujimi and Fujimura, 2020); and demographic factors. Factors such as age (Cutter and Barnes, 1982; Perry, 1979; Thompson et al., 2017) and household size (Cutter & Barnes, 1982; Hasan et al., 2011), education (Yang et al., 2016), gender (Cahyawanto & Pennington-Gray, 2015; Meyer et al., 2018), presence of children (Dixit et al., 2012; Yin et al., 2014), race and ethnicity (Meyer et al., 2018), homeownership (Meyer et al., 2018), and income (Meyer et al., 2018) have been found to be important factors that explain evacuation behavior. Most of these common determinants have a positive effect on evacuation, increasing the likelihood that individuals will flee dangerous situations. However, there are several factors that explain non-evacuee behavior. Studies that explain why individuals stay, even when a threat of life or property loss is imminent, have found factors such as elderly age (Cutter and Barnes, 1982; Yun and Hamada, 2015), caring for an infirmed loved one (Yun and Hamada, 2015), physical health concerns (Yun and Hamada, 2015), staying to protect property (Baker, 1991; Riad et al., 1999; McGee et al., 2019), a tolerance for risk (McAfee et al., 2018), employment constraints (Baker, 1991; Cutter and Barnes, 1982; Hasan et al., 2011; Yun and Hamada, 2015), a lack of a formalized evacuation mandate (Cutter & Barnes, 1982), a lack of financial or social resources to mobilize (Cutter & Barnes, 1982; Riad et al., 1999), a lack of sheltering options for household pets (Farmer et al., 2016; Farmer and DeYoung, 2019; Taylor et al., 2015; Yin et al., 2014), and not knowing where to go (Yun and Hamada, 2015) can predict when individuals will stay behind. For example, only 37% of individuals over the age of 60 evacuated in response to the 2011 Tohoku earthquake and tsunami. Elderly in the Iwate and Miyagi Prefectures who refused to evacuate cited challenges with the care for others, the long distance to travel to safety, traffic congestion or rough roads, physical health concerns, and not knowing where to go when they considered evacuation (Yun and Hamada, 2015).

4. Evacuation and health outcomes

Previous research on the health outcomes of evacuation predominately explores mental and psychological consequences (Uscher-Pines, 2009), such as the prevalence of symptoms of depression, anxiety, and post-traumatic stress disorder (PTSD) following an evacuation. Studies of individuals forced to evacuate and who were displaced for some time in response to the 1983 to 1984 Bradyseism Earthquake (Bland et al., 1997), 2013 and 2014 floods in England (Murro et al., 2017), and Hurricane Sandy (Schwarz et al., 2018; Taioli et al., 2018) reveal higher measures of depression, anxiety, PTSD, among other mental health issues. For example, a cross-sectional study (Murro et al., 2017) of Gloucestershire, Wiltshire, Surrey, Somerset, and Kent counties in England in 2013 and 2014 found that individuals who were forced to evacuate and were displaced in response to flooding in the region scored much higher for measures of depression, anxiety, and PTSD compared to those who had not been displaced. This effect was even more significant among displaced individuals who received little or no warning before having to flee rising floodwaters.

In 1983 and 1984, 25,000 residents from the Italian city Pozzuoli were evacuated in response to the Bradyseism Earthquakes. In a longitudinal study of evacuees and non-evacuees of male factory workers who worked for the Olivetti Factory in Naples, Italy, researchers assessed nine different dimensions of psychological distress and sleep disturbances, measuring levels of depression, anxiety, interpersonal sensitivity, and hostility, among other symptoms, following the earthquakes. Researchers found (Bland et al., 1997) those who permanently relocated and remained isolated from their social networks reported higher distress scores on all symptoms measured, compared to those who returned to their social networks soon after leaving and those who chose to stay and shelter-in-place with their family during the earthquakes.

Physical health outcomes related to evacuation, such as disease and infections, have been understudied by disaster scholars (Uscher-Pines, 2009) compared to mental health outcomes and illnesses. A recent study (Loebach & Korinek, 2019) recently explored acute respiratory disease spread in a Nicaragua municipality following Hurricane Mitch. From a survey of 3,474 evacuees, 322 indicated they had evacuated to a temporary shelter. Among individuals in shelters and interim housing arrangements, there was a 31% increase in the probability of having diarrheal disease symptoms. Among those who stayed in a temporary shelter, there was a 14.78% increase in the probability of contracting a respiratory disease, compared to a 16.04% decrease among those staying in interim housing, suggesting that those who had nowhere to go were placed at higher risk of infection.

Recently, researchers explored the challenges in implementing infectious disease surveillance. Following Hurricane Sandy (2012) in New York and New Jersey, 73 temporary evacuation shelters were opened in...
anticipated the storm (Ridpath et al., 2015). Within a few days, several reports of gastrointestinal illnesses (i.e., one episode of vomiting or diarrhea) among evacuees in shelters emerged, compelling the NYC Department of Health and Mental Hygiene (DOHMH) to make regular visits to temporary shelters and instituting a system of daily logs of illnesses and instances when individuals were sent to a local emergency room.

5. Current study

In 2020, the COVID-19 pandemic presented unique challenges to individuals and emergency responders responding to disasters, especially when non-pharmaceutical interventions, such as physical distancing, masking, handwashing, and avoiding crowds were the only way to curt the spread of the virus. On Dec. 31 of 2019, officials in Wuhan, China, reported a cluster of pneumonia cases with an unknown cause (WHO, 2020). On Jan. 9, 2020, 59 cases were reported, and by Jan. 23, the case count rose to 300, resulting in an unprecedented decision to close off the city of Wuhan to the rest of China. On Jan. 31, the WHO declared a Global Health Emergency as cases jumped to 9,800 and deaths of 200. The virus would continue to escalate and reach all corners of the world, resulting in the first global pandemic of the modern era, halting travel and global commerce. Its spread, more efficient than influenza but less than measles, occurs from close person-to-person contact via tiny aerosolized droplets produced when someone with the virus coughs, sneezes, sings, talks, or breathes (CDC, 2020a).

Few studies have explored communicable diseases and evacuation, and this research fills that critical gap in the literature. This study is the first of its kind, to our knowledge, to explore the effect of evacuation on rates of COVID-19 following a disaster outside of recent hypothetical models (Pei et al., 2020). From the early months of the pandemic, physical distancing and crowd avoidance, among other things, were some of the best measures to prevent the spread of the virus (CDC, 2021); however, evacuations may present challenges to these safety measures. In this study, we explore this further with data on mobility related to two disasters, Hurricane Zeta and the Glass Fire, and rates of COVID-19 in select communities.

6. Methods and data

This study investigates whether disasters and evacuation might have led to the increased spread of COVID-19 in 2020. We hypothesize that (H1) disaster intensity and (H2) increased movement from evacuation orders led to higher disease transmission rates of COVID-19. These two hypotheses allow us to test, first, the effect a disaster had on COVID-19 case rates, and second the effect a disaster plus an evacuation had on COVID-19 case rates. An important distinction here is that not all disaster victims are asked or required to evacuate in response to a disaster, so testing these two hypotheses separately allows us to examine the health outcomes of the two events. We also hypothesize that (H3) sheltering-in-place led to decreased transmission rates, as this behavior is best aligned with the CDC’s guidelines to distance and avoid large crowds and mass gatherings to prevent the spread of COVID-19.

We draw on two unique cases from 2020: Hurricane Zeta and The Glass Fire (see Table 1). These two disasters share essential characteristics for this analysis: both were shocks to local and regional geographies, and both resulted in mandatory and voluntary evacuations. Estimates of mandatory evacuations place 70,000 people displaced due to the Glass Fire (Glass Fire updates, 2020) and 1,400 people from Grand Isle, alone from Hurricane Zeta (Brackett, 2020). The Glass Fire, wildfires occurring in Napa and Sonoma Counties, California, started on Sept. 27, 2020, and remained active for 23 days. It destroyed 67,484 acres, destroyed 1,555 structures, damaged 252 more structures (Glass Fire updates, 2020), and resulted in evacuation orders that mobilized an estimated 70,000 Napa and Sonoma County residents (Glass Fire: Blaze in Napa, 2020). Hurricane Zeta arrived at the end of a historically active hurricane season, forming on Oct. 24, dissipated on Oct. 30, 2020, and spanning Louisiana, Mississippi, and Alabama. Evacuations were mandated for areas of Jefferson, Lafourche, Orleans, and Terrebonne Parishes in Louisiana and Hancock County in Mississippi. Officials called for voluntary evacuations in Plaquemines Parish in Louisiana, Baldwin and Mobile Counties in Alabama, and Harrison and Jackson Counties in Mississippi (TWC, 2020). All told, Zeta caused $3.5 billion in damages.

This study measures COVID-19 transmission as its dependent variable, using available local level COVID-19 metrics reported to city or county health departments between August and December 2020. For California’s Glass Fire, we relied on rates of confirmed cases of COVID-19 per 100,000 residents per zipcode per week, assembled and reported by the Los Angeles Times (2021). In Louisiana, we relied on test positivity rates per census tract, measuring the percentage of COVID-19 tests which came back positive per week, out of all tests conducted, reported by the Louisiana Department of Health (2021). Where possible (Louisiana), we use test positivity rates, because this captures COVID-19 spread while controlling for variation in testing capacity through the denominator. Validation tests in Figures C1 and C2 show that test positivity rates and case rates track closely during the study period, indicating that results from either measure are largely comparable. Further, testing was not generally interrupted during the disaster, according to state-level validation tests in Figure C3, and testing capacity actually increased during the study period. We aggregated both measures from the zipcode or census tract level to the county subdivision level, a close proxy for cities.

Then, we zoomed into all county subdivisions in counties containing neighborhoods where aggregated Facebook user movement data indicated that Facebook users in the disaster zone had either moved to or from. We examine 181 county subdivisions in California in 32 counties, where 351 neighborhoods with affected Facebook users were located (mapped in Fig. 2 left panel), and 176 county subdivisions in 21 counties in Louisiana, where 102 neighborhoods with affected Facebook users were located (mapped in Fig. 2 right panel). We discuss the details of this Facebook user movement data further in the Variables section, and its representativeness in the Limitations section.

Finally, we examined our COVID-19 spread outcomes in these county subdivisions over 19 weeks between Aug. 17 to Dec. 23, 2020, excluding movement during the holiday period due to the known spike in COVID-19 cases during this period. (In contrast, we keep the post-Thanksgiving surge because it occurs so closely after our disasters on Sept. 27 and Oct. 28, and our models control for the outcome lagged by two weeks to account for path dependence in virus spread, as discussed below.) We paired these weekly observations with tallies of Facebook user movement data to approximate the evacuation behavior of residents.

Together, these produced two time-series datasets tracking COVID-19 outcomes by county subdivisions from the third week of August (using the first two for lagged data) until Dec. 23, just before a wave of holiday-related mobility. These included 176 county subdivision observations over 19 weeks (n = 3,344) for Hurricane Zeta in Southeastern Louisiana from Aug. 19, 2020 and 181 county subdivisions over 19 weeks (n = 3,439) for the Glass Fire in California. This study period

Table 1
Disaster and Evacuation Events captured by Facebook Disaster Maps after COVID-19.

| Disaster                             | Type     | Date         | Country | Region     | Format   | Period |
|--------------------------------------|----------|--------------|---------|------------|----------|--------|
| Wildfires in Napa and Sonoma Counties| Fire      | Sept. 27, 2020| U.S.    | California| Temporal | Every  |
| Hurricane Zeta in Southeastern Louisiana| Storm    | Oct. 28, 2020| U.S.    | Louisiana | Network  | 8-hours|
began on Aug. 17, rather than Aug. 1, to account for a two-week lag in evacuation, disaster, and general mobility controls to account for the incubation period of COVID-19, which lasts anywhere from 2 to 11 days (95% confidence interval). Fig. 1 visualizes the change in our outcome variables among county subdivisions in our two cases, highlighting both the incidence of the disaster and the date of potential onset of new cases two weeks later. Within the overall pattern, we see considerable variation among cities week to week, motivating our study, to investigate whether disaster conditions and disaster mobility exacerbated changes in COVID-19 spread during the study period.

7. **Variables**

This study used a series of variables to assess the effect of disaster intensity and evacuation behavior on COVID-19 spread. First, to represent disaster intensity, this study used two measures. In California, we calculated the projected percentage of land area burned that week, based on the number of fires, length of fire, and total burn area of fires, and spatially interpolated that from the county level to the county subdivision level using inverse distance weighting. In Louisiana, we calculated the total weekly rainfall in tenths of a millimeter, calculated by spatially interpolating data from 727 rain stations across the state (mapped in Figure B1). As shown in Figure B2, Louisiana suffered several major hurricanes during Fall 2020, just as California suffered many wildfires, making it especially important to adjust for rainfall and burn rates throughout the entire study period. We lagged both variables by two weeks to show the delayed effect of disasters on COVID-19 spread two weeks later.

Second, to measure evacuation behavior, this study relies on data from Facebook’s Data for Good Program, which estimates evacuation after a crisis by geolocating Facebook users in the region in the weeks prior to the crisis, and tallies of how many of these users move from one neighborhood to another after the crisis. Facebook provides these neighborhood-aggregated tallies to humanitarian NGOs and disaster researchers for disaster response and analysis while preserving user privacy (Maas et al., 2019).

We use this data to approximate six kinds of evacuation behavior. These included (1) overall evacuation, represented by increased mobility compared to pre-disaster baseline levels; (2) local evacuation, represented by increased mobility within the same city (county subdivision); (3) long-distance evacuation, represented by increased mobility between cities. These also included (4) sheltering in place, represented by decreased mobility compared to pre-disaster baseline levels; (5) reductions in local movement, represented by decreased mobility within the same city; and (6) reductions in long-distance movement, represented by decreased mobility between different cities. (1) Overall evacuation represents the sum of (2) local and (3) long-distance evacuation per 1,000 residents, while (4) overall sheltering in place represents the sum of (5) reductions in local movement and (6) reductions in long-distance movement per 1,000 residents. We lagged each of these variables by two weeks to show the delayed effect of evacuation behavior on COVID-19 spread two weeks later. Below, Fig. 3 maps the evacuation pathways of Facebook users among cities, comparing evacuation against the distribution of damage as estimated by our damage proxies. These lines connect cities that users evacuated between. The size of points shows estimated evacuation away from each city.

Third, we added two key time-variant controls. First, we controlled for the rates of COVID-19 spread in each county subdivision two weeks prior, to account for the tendency of COVID-19 cases to beget new cases. Second, we controlled for overall mobility levels in each county subdivision, using percent changes in workplace mobility according to Google Mobility Reports, which tally the mobility of Android phone users (39% of U.S. smartphone users) (used regularly to study mobility and COVID-19; eg. Borgonovi & Andrieu 2020; Basellini et al. 2021). To get county-subdivision measures, we spatially interpolated county-level observations of the weekly averages of daily percent changes in workplace mobility. Like with Facebook user data, these do not capture the movement of every person, especially children and the elderly, but they do capture aggregate surges in movement in a community. In this case, to be certain that the evacuation behavior of residents in the weeks around the disaster impacted COVID-19 spread, it is important to account for the ordinary mobility of residents across the months before and after the disaster.

Fourth, we adjusted for several key county-subdivision level controls. To control for social ties, established as an important determinant in evacuation behavior (Perry, 1979; Cutter & Barnes, 1982; Baker, 1991; Riad et al., 1999; Hasan et al., 2011; Metaxa-Kakavouli et al., 2018) and disaster outcomes (Aldrich, 2012, 2019), we relied on the three categories of social capital: bonding social capital (in-group ties), bridging social capital (inter-group ties), and linking social capital...
(vertical ties to authorities), using county-subdivision level indices developed by Fraser, Page-Tan, & Aldrich (2021) based off the validated county-level indices by Kyne & Aldrich (2020). The bonding social capital index uses measures of how similar residents in each community are in terms of race, ethnicity, gender, age, income, and employment, among others, because homophilous communities tend to have stronger bonding, in-group ties (McPherson et al., 2001; Moww, 2006). The bridging social capital index uses measures of associational membership in unions, civic associations, fraternal associations, charitable associations, and more, because associations tend to build bridging ties across different social cleavages (Putnam, 2000, Varshney, 2001). Finally, the linking social capital index uses 5 measures of representation and political linkages to represent linking ties to local, state, and federal authorities, which help residents obtain public goods in times of need (Tsai 2007; Aldrich, 2017). These each measure social capital on a scale from 0 (weakest) to 1 (strongest).

Next, we controlled for social vulnerability, characteristics that have previously been established as important factors of disease spread after a disaster (Loebach & Korinek, 2019). We used data from the Centers for Disease Control and Prevention’s Social Vulnerability Index, broken into four types, including (1) socioeconomic status, (2) household composition & disability, (3) minority status & language, and (4) housing type.
and transportation (Flanagan et al., 2011). These each measure vulnerability to hazards on a scale from 0 (least vulnerable) to 1 (most vulnerable). These were averaged upwards from the census tract level to the county subdivision level.

Fifth, we measured several county-level traits, spatially interpolating each down to the county subdivision level: To represent health care capacity, we used a simple index averaging two indicators as Z-scores, including the number of primary care physicians (Baicker & Chandra, 2004) and the inverse of the number of preventable hospital stays (Brumley et al., 2007), both per 100,000 residents in 2017. To represent the overall quality of health, we averaged seven indicators, rescaled as Z-scores. These included the share of residents who reported currently smoking in 2017, drinking excessively in 2017, being physically inactive in 2016, had diabetes in 2016, being obese in 2016, experiencing poor physical health over two weeks in a month in 2017, as well as the age-adjusted premature mortality rate between 2016 and 2018. These health indicators were compiled by the County Health Rankings (University of Wisconsin Population Health Institute, 2019). Finally, we also controlled for governance capacity, measured using the number of municipal employees per capita, as well as for partisanship, measured using the percentage of voters who voted for Hillary Clinton in the 2016 presidential election (MIT Election Data and Science Lab, 2018).

8. Modeling

We used three methods to model this data, including (1) panel data models, (2) coarsened exact matching, and (3) synthetic control experiments. First, we used panel data models to assess the effect of disasters and evacuation behavior on COVID-19 spread outcomes while controlling for all other variables. We used annual fixed effects to adjust for weekly variation, and compared them with random effects models. Statistically significant Hausman tests found that fixed effects fit better than random effects models in Louisiana (p < 0.05) and California (p = 0.01). We present our fixed effects models in Table A1; random effects are available in the replication code. All models in this study involved log-transformed outcome variables, to account for heteroskedasticity common in right-skewed rates; likelihood ratio tests indicated these log-transformed outcomes produced better fitting models than ordinal models (p < 0.001).

This study accounts for four types of extenuating circumstances that might change the community transmission rate. First, we examine a study period (Aug. 17 - Dec. 23, 2020) which predates vaccines and the Alpha variant, which constituted just 76 known cases by Jan. 13, 2021 (Galloway et al., 2021). Second, all models control for COVID rates two weeks prior, to account for surges. Third, weekly fixed effects control for any such change in the virus over time. Fourth, our evacuation/disaster covariates are expected to absorb any change due to protective measures implemented during the crisis, as well as any protective measures that residents could not maintain during crisis. Otherwise, we assume the virus’ infectiousness remains constant during the study period. Temperature and humidity also affect the virus’s spread, but are highly correlated with weekly fixed effects, as shown in Figure C4. We use weekly fixed effects to capture the changing effects of temperature and humidity on transmission.

9. Matching

Second, we zoomed into a subset of cities as similar as possible using coarsened exact matching (CEM). This matching method has been widely used in economics (Azulay et al., 2011) and health care research (King et al., 2011) to make better causal inference by improving the balance between treatment and control groups in terms of several key matching covariates (Jacus et al., 2012). Further, CEM has been shown to produce less bias than propensity score matching (King et al., 2011; King et al., 2011b). For each disaster, we created three matched datasets as similar as possible in terms of (a) population density, (b) overall social capital (averaging bonding, bridging, and linking social capital), (c) social vulnerability (overall index), and (d) governance capacity, except for one key difference in each case: (1) some experienced higher levels of disaster intensity while others did not, represented by any active fires or rainfall above the median, (2) some faced any increased movement from Facebook users during disaster while others did not, and (3) some faced any decreased movement from Facebook users during disaster while others did not. We highlight the names of cities in these three matched samples in Appendix Figure A2.

Matching greatly improved the balance among matching covariates, as shown in Appendix Figure A1. This method allowed us to more directly test the effect of our two overall treatment variables (disasters vs. evacuation behavior) while eliminating major confounding variables. After matching, we fitted fixed effects models for all matched datasets due to statistically significant Hausman test statistics (p < 0.001), except for California matched evacuation models, for which random effects fit better.

These original and matched models both explained considerable amounts of variation in COVID-19 spread rates, ranging from 30 to 43% for original models, to 20–52% for matched models. Finally, the final models did not suffer from any problematic collinearity. To reduce collinearity in California models, we split up socioeconomic status, minority status, health care capacity, and health quality indices, into four quartiles each. In our Californian matched models, we removed minority status, health care capacity, and health care quality indices, which were extremely correlated with socioeconomic status and bonding social capital, and we split socioeconomic status into 4 quartiles. All final models had variance inflation factors (VIF) below 10, the threshold for problematic multicollinearity, typically near 2. These matched model tables are listed in Appendix Tables A2-A4.

10. Difference-in-Differences

Third, to triangulate these findings, we applied difference in differences experiments on our matched datasets. Difference-in-differences (DiD) models are a quasi-experimental technique that uses interaction effects between our key treatment variables to illustrate whether disaster intensity, evacuation, or shelter-in-place behavior creates not just direct, constant effects on COVID-19 spread, but also multiplicative effects over time. Each DiD model also controlled for weekly fixed effects to account for the independent effect of each time period.

DiD models have been used to study public health outcomes not well suited to randomized control trials for decades (Angrist & Pischke, 2008; Wing et al., 2018), with simpler versions dating back to John Snow’s natural experiment on London’s Cholera outbreak (Snow, 1855). Recent innovations on the technique, including synthetic control experiments, have been used to study the effects of rare treatments over time like tobacco policies (Abadie et al., 2010), nuclear power plants (Ando, 2015), and terrorism on communities over time, by creating a synthetic control group composed of weighted communities that did not receive the treatment (Abadie et al., 2015). However, this technique, typically applied with two-way fixed effects, can only adjust for time-variant controls (Xu, 2017). Our study, however, contains time-variant controls, such as disaster intensity and overall mobility, as well as time-invariant controls, such as social capital and social vulnerability. This study pairs difference in differences models with our matched panel datasets to test for multiplicative effect over time among communities as similar as possible. This quasi-experiment gives us a close glimpse at what COVID-19 spread might have looked like had the disaster not occurred.

11. Results

This study examined why some communities experienced higher rates of COVID-19 than others in Southeastern Louisiana and Central California, testing the effects of disasters, evacuation, and shelter-in-
place behaviors using panel data models, matched panel models, and synthetic control experiments.

12. Panel & matched panel model results

First, we tested the effect of disaster intensity on COVID-19 spread. While our overall panel data models suggest that greater disaster intensity was related to less COVID-19 spread (significant in California, $p < 0.10$), our matched models tell a different story. After zooming into comparable cities, we found that disaster intensity was in fact associated with greater COVID-19 spread, at highly statistically significant levels for the Glass Fire ($\beta = 0.44$, $p < 0.01$), allowing us to reject the null hypothesis ($H_0$). After adjusting for each type of evacuation in Louisiana, this effect was also positive but not statistically significant. This implies that disasters do logically increase the vulnerability of communities, altering routines and behaviors that kept residents safe pre-disasters, and leading to a general increase in COVID-19 spread. The difference between our matching experiment and panel models highlights the importance of comparing like cases in disaster studies, as in our matched samples (Dunning, 2012; Iacus et al., 2012).

Second, we tested the effect of evacuation behavior on COVID-19 spread. We found no statistically significant evidence of a relationship between increased evacuation mobility and infection rates in our overall panel models. When we zoomed into matched models, we found that evacuation still was unrelated to infection in Louisiana, but in California, increased disaster-related mobility was related to decreases in case rates, both for evacuation overall ($\beta = 0.43$, $p < 0.05$) and within cities ($\beta = 0.49$, $p < 0.10$). This implies that contrary to our hypothesis ($H_2$), increased mobility from evacuation need not lead to spikes in COVID-19; residents can practice social distancing and masking. One reason this effect was especially strong in California may have been due to increased rates of using masks during the fire season, as poor air quality related to wildfires led many residents to have to wear respirator masks that limited inhalation of harmful air pollutants in wildfire smoke (CDC, 2020b).

Third, we tested the effect of shelter-in-place behavior on COVID-19 spread. Our overall panel models show that decreased mobility was associated with lower rates of COVID-19 spread. Our matched models confirmed these results, showing strong, statistically significant decreases in COVID-19 spread for every additional person who sheltered-in-place rather than going out, both in Louisiana ($\beta = -0.04$, $p < 0.001$) and in California ($\beta = -0.15$, $p < 0.05$), allowing us to reject our null hypothesis ($H_3$). This effect persisted (and grew stronger) for decreases in movement within cities in Louisiana ($\beta = -0.14$, $p < 0.001$) and California ($\beta = -0.25$, $p < 0.01$). However, decreases in mobility between cities were related to increased COVID-19 spread in Louisiana ($\beta = 0.17$, $p < 0.001$) and California ($\beta = 0.12$, not significant).

We visualize these trends in Fig. 4, depicting how rates of COVID-19 spread change as the number of Facebook users who shelter in place per 1,000 residents in a community increases from 0 to 10. We calculated these expected outcomes using 1,000 simulations from the Zelig package in R (Choirat et al., 2017) based on our matched models (California’s random effects lead to jagged edges, while Louisiana’s fixed effects lead to smoother confidence intervals). These highlight that sheltering-in-place and reducing movement within one’s city is related to a decrease in new cases, while reductions in movement between cities is sometimes related to an increase in new cases. This might be because disasters also disrupt individuals’ ordinary movement patterns, cutting off access to highways, grocery stores, or jobs, potentially forcing residents to go to new places in their community to get food or shelter, places where they may not have the same protections, masking, and social distancing practices.

We theorize that evacuation (increased movement) was not closely related to COVID-19 spread because its effect was largely captured by prior COVID-19 rates; in other words, it is not guaranteed that evacuation will lead to greater COVID-19 spread; that largely depends on whether COVID-19 rates were high in that community at the time. However, decreases in movement during a crisis generally lead to reduced COVID-19 spread, just like past studies on lockdowns have indicated (May 2020).

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**Fig. 4.** Local Sheltering-in-Place Decreases COVID-19 Spread Caption: Based on 1000 simulations run by the Zelig package in R, holding all other traits constant at their means, as the level of decreased mobility by type was varied from 0 to 10 users per 1000 residents. This range approximates the 20th to 80th percentiles for these variables.
We summarize main results from panel and matched models in Fig. 5, highlighting significant effects and using arrows to indicate significant effects found (see Tables A1-A7 for complete model results). When disputes arise between panel and matched models, we prioritize matched models, because these matching experiments facilitate better comparisons among more comparable cities than our unmatched panel models (Dunning, 2012; Iacus et al., 2012). The most consistent effects found are that decreases in mobility during the crisis, especially within cities, were linked to decreases in COVID-19 spread.

13. Difference in differences matched models

Finally, this study examined the changing effects of our key variables of interest over time using matched models, to identify whether the constant effects identified in our matched panel models were accompanied by multiplicative effects. We found no evidence of multiplicative effects for disaster intensity (Table A5), and limited evidence of these effects for evacuation (Table A6). We found that cities with increased mobility between cities saw rising test positivity rates in Louisiana, but this effect actually declined over time (beta = -0.18, p < 0.05); this was accompanied by the same effect in California, albeit statistically insignificant.

Instead, decreased mobility has strong effects over time. When examining cities as similar as possible except for their level of sheltering-in-place (Table A7), we found that cities that decreased their mobility saw much lower test positivity rates at face value (beta = -3.91, p < 0.10 in L.A., beta = -2.32, albeit p > 0.10 in C.A.), but these rates increase over time in Louisiana (beta = 0.25, p < 0.10) and in California (beta = 0.18, albeit p > 0.10), shown by the interaction between decreases mobility and our weekly counter. The same trends were found for

Fig. 5. Summary of Effects for Key Independent Variables (with Model Numbers) Caption: Cells depict standardized effects (beta coefficients) on logged outcomes from our models, shaded by strength of effect, with all controls, with model labels. Full model results reported in Appendix A. Statistically significance associations highlighted; insignificant associations transparent. Arrows indicate effects which demonstrated any statistically significant associations, while question marks indicate results that were inconclusive and insignificant.
reductions in mobility within tracts. Fig. 6 illustrates how the shelter-in-place phenomenon within cities led to an initial dip in COVID-19 spread rates, but was quickly followed by increases in subsequent weeks; that rise was stronger and more consistent for Hurricane Zeta than the Glass Fire. Why does sheltering-in-place become less effective at reducing COVID-19 spread with each passing week? We anticipate this is because COVID still circulates in households and neighborhoods during this period, even if mobility decreases hinder its spread in the city at large.

14. Discussion

In this study, we found mixed evidence disaster intensity led to higher transmission rates of COVID-19 in California, and strong evidence that sheltering-in-place led to decreased transmission rates in both Louisiana and California. Contrary to our hypothesis, we found no evidence that increased evacuation-related mobility led to increased cases of COVID-19. Our first finding reveals that the shock of a disaster may have led to an increase in COVID-19 cases in California, increasing community vulnerability by altering routines and behaviors that kept residents safe pre-disasters, leading to a general increase in COVID-19 spread.

Second, our findings suggest that sheltering-in-place can decrease the probability of high rates of infection immediately following a disaster. When safe, orders to shelter-in-place from local and state officials during a disaster could prevent a disaster within a disaster and potentially ease the case rate of a protracted health crisis.

Finally, we also found that contrary to our hypothesis and previous hypothetical evacuation models (Pei et al., 2020), our study did not reveal an association between increased evacuation mobility and increased infection rates. This may suggest that the forced egress doesn’t necessarily place individuals at immediate risk of contagion. This may be explained by established norms of personal protective equipment (PPE) use and distancing from the prolonged COVID-19 pandemic and changes in both evacuation behavior and sheltering procedures in California and Louisiana.

In advance of the Glass Fire, there were reports of groups and high-risk individuals seeking out shelter in hotels (Boone & Cline 2020) and California’s Governor, Gavin Newsom, calling for temperature checks of wildfire evacuees at hotels (Luna, 2020). In Louisiana, state-level officials booked thousands of hotel rooms for hurricane evacuees seeking government assistance following Hurricane Laura (Karlin & McAuley, 2020; Haines, 2020), occurring less than two months before Hurricane Zeta. Many of those same evacuees from Hurricane Laura stayed through Hurricane Zeta and returned home weeks after. Further, in advance of the record wildfire and hurricane season for California and Louisiana, respectively, the American Red Cross released a series of updated protocols for disaster shelters. These updated protocols included intake health screenings; space to isolate those who required additional care; mandates and provisioning for face coverings; guidelines for distancing, including staggered meal times and extra space between cots, chairs, and tables; additional handwashing stations; and enhanced cleaning and sanitation protocols (American Red Cross, 2020).

Decisions made by individuals to seek out hotel rooms as temporary shelters, as well as the government assistance to offer such accommodations to those who may not otherwise have the financial security to do so, likely curbed the spread of COVID-19. These temporary housing

**Fig. 6.** Sheltering-in-Place reduced COVID spread temporarily, but not permanently

Caption: Based on 1,000 simulations in the Zelig package in R, holding all other variables at their means. Solid grey line indicates date of disaster; purple band denotes post-treatment period. Treatment refers to the rate of additional people who sheltered-in-place, reducing movement within their city per 1,000 residents. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
arrangements provided individuals and families the ability to distance and isolate themselves during the pandemic. This finding is well-aligned with previous work (Loebach & Korinek, 2019) that found a 16% decrease in the probability of contracting a respiratory illness among evacuees staying in interim housing, compared to mass shelters following Hurricane Mitch in 1998. Finally, hotel arrangements also likely reduced the capacity of shelters in the surrounding areas in Louisiana and California, subsequently creating more space for those who sought out refuge in traditional mass shelters erected in churches and gymnasia.

15. Limitations

This study used several models to account for the disasters leading up to Hurricane Zeta and the Glass Fire from a historic hurricane and wildfire season. We also adjusted for variables that may otherwise explain rates of COVID-19. However, our study is limited by (1) a surge of cases following Thanksgiving, (2) the estimation of the data used in our models, and (3) the limitations of the data from a single social media platform.

First, the disasters under analysis closely preceded Thanksgiving, an American holiday that typically brings families and friends together. This holiday followed just weeks after, bringing a surge of cases for many states in the United States (Lazo, 2020; Stone, 2020). However, our models adjust for this with a lagged outcome. The differences in differences analysis reveals that the surge following Thanksgiving follows several weeks after the incubation period in our observational period; this makes it clearer that Thanksgiving spread did not affect our results.

Second, to conduct a spatial analysis of evacuation mobility, we interpolated key data points across geography to estimate values used in our analyses. However, in spatial analysis, these data methods are widely accepted to create new data (Burrough et al., 2015). Spatial interpolation allowed us to synthesize covariates from neighborhood, city, and county-level data. We used these techniques to measure disaster intensity and key county-level covariates like health care capacity, overall quality of health, and overall mobility, and then we controlled for these spatially smooth measures in our models.

Finally, we recognize that Facebook’s data does not capture all individuals, nor the mobility in the days and weeks prior to the two disasters in this study. To capture data on mobility before the disasters, we used data from Google Mobility Reports, which tally the mobility of Android phone users. Like with Facebook user data, these do not capture the movement of every person, but they do establish a general estimate of community mobility.

Further, these data are surprisingly more representative than commonly perceived. As of August 2020, 40% of the U.S. mobile phone market ran on Android (Stat Counter, 2021). And according to a Pew Research Study in June 2019, 69% of Americans use Facebook, 75% of whom used it on a daily basis (Perrin & Anderson 2019). Rates of use are very similar among Whites, Blacks, and Hispanics (69–70%) and among ages 18–29 (68%), ages 30–49 (79%), and ages 50–64 (68%) (the main exception being ages 65 + at 46%, still very high). Rates are also fairly similar among urban, suburban, and rural residents (66–73%), among residents with some college education (61%) vs. none (75%), and for residents with annual incomes below $30,000 (69%) as well as above that threshold (72–74%) (Perrin & Anderson 2019). This adds to our confidence that our measures are capturing a meaningful chunk of population mobility.

16. Conclusion

Ensuring the health and safety of disaster victims and evacuees is no easy task and this difficulty is further complicated during prolonged seasons of wildfires, hurricanes, and a pandemic. However, we find that contrary to our initial hypothesis, increased mobility that resulted from voluntary and mandatory evacuations from the Glass Fire in late September of 2020 and Hurricane Zeta in late October of 2020 did not necessarily result in higher rates of transmission of the novel coronavirus. Efforts to offer hotel accommodations to evacuees in California and Louisiana, instead of mass shelters, and updated protocols at shelters, such as intake health screenings, isolated areas to care for sick evacuees, distancing arrangements, and enhanced cleaning, likely curbed further spread of COVID-19. Further, sheltering-in-place is an ideal option for households, when safe, as it is associated with lower levels of COVID-19 case rates. Moving forward, future studies should aim to capture the stories of individuals displaced during the COVID-19 pandemic or other health crises to understand additional factors that explain associations between mobility, social ties, policy directives, and health-related outcomes following a disaster.

Data availability

Model data and code will be made available for replication on the Harvard Dataverse (https://doi.org/10.7910/DVN/QV9UYM). Due to data sharing agreements and privacy protections for Facebook users, the original aggregated neighborhood movement tallies used in this study cannot be shared directly, but derivatives like the county subdivision-level aggregated movement data used in our models can be shared.

Ethics & data privacy statement

This study never engaged with individual-level Facebook user data; only aggregate tallies were received, which are regularly shared with humanitarian NGOs, disaster management agencies, and researchers through Facebook’s Data for Good program. For more information or data access, please reach out the Facebook Data for Good program team.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gloenvcha.2022.102471.

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