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Effects of income inequality on evacuation, reentry and segregation after disasters

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ABSTRACT

Large-scale disasters often trigger mass evacuation due to significant damages to urban systems. Understanding the evacuation and reentry (return) process of affected individuals is crucial for disaster management. Moreover, measuring the heterogeneity in the individuals' post-disaster behavior with respect to their socio-economic characteristics is essential for policy making. Recent studies have used large-scale location datasets collected from mobile devices to analyze post-disaster mobility patterns. Despite the availability of such data and the societal importance of the problem, no studies have focused on how income inequality affects the equity in post-disaster mobility. To overcome these research gaps, we overlay mobility data with income information from census to quantify the effects of income inequality on evacuation and reentry behavior after disasters, and the resulting spatial income segregation. Spatio-temporal analysis using location data of more than 1.7 million mobile phone users from Florida affected by Hurricane Irma reveal significant effects of income inequality on evacuation behavior. Evacuees with higher income were more likely to evacuate from affected areas and reach safer locations with less damage on housing and infrastructure. These differences were common among evacuees from both inside and outside mandatory evacuation zones. As a result of such effects of inequality, significant spatial income segregation was observed in the affected areas. Insights on the effects of income inequality on post-disaster mobility and spatial segregation could contribute to policies that better address social equity in pre-disaster preparation and post-disaster relief.

1. Introduction

The rise in both the frequency and intensity of natural disasters in recent years have significantly impacted human lives and has caused massive economic losses (Unisdr, 2005). Such large-scale disasters often trigger mass evacuation activities of people from the affected areas due to various factors including significant structural damages to buildings and infrastructure systems, risks due to flooding, and severe wind shear. For example, Hurricane Irma which made landfall in September 2017 caused one of the largest mass evacuation events in the history of the country, where over 6 million people were ordered to evacuate in Florida (Cangialosi et al., 2018). To implement effective traffic management strategies that allow efficient and safe mass evacuation from affected regions, evacuation behaviors of individuals have been studied extensively, and is also currently an active field of research (for a recent review on evacuation modeling, see Murray-Tuite and Wolshon (2013)). Studies have revealed the high complexity of evacuation decision making mechanisms, where the outcomes are affected by various critical factors such as race and ethnicity, gender, income levels, risk perception, and social ties (Dash and Gladwin, 2007). Such insights are often applied to construct agent-based evacuation models

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that are used to simulate spatio-temporal mobility patterns of mass evacuation (e.g. Ukkusuri et al., 2017), which may be used for transportation management and urban planning.

Among the various dimensions of disaster management, social equity (Guy and McCandless, 2012) is understood to be an important concept that needs to be addressed for effective disaster relief and recovery (Burton and Cutter, 2008). Social equity during a disaster is defined as the state where all affected people are given equal access to resources and opportunities that enable them to meet their needs for safe evacuation and recovery (Emrich et al., 2019). In the context of social equity in disaster evacuation and reentry, it is essential to quantify and understand the effects of inequality that exist between socio-economic groups using observations from past disasters. More specifically, quantifying how the evacuation rates and destination characteristics differ across different income groups is crucial for addressing policies that enhance social equity. Although findings differ across disasters, in general, past studies have used survey data collected after disasters to show that higher income households are able to evacuate more and further away compared to low income households (e.g. Whitehead et al., 2000). Such effects of inequality on evacuation behavior could allow higher income households to evacuate to safer locations compared to lower income households, which would increase the social inequity across population groups after disasters, leading to depletion of social resilience of communities (Doorn et al., 2019). A quantitative understanding of the effects of socio-economic inequality on evacuation and reentry behavior are needed, however, such efforts have been hindered by the low spatio-temporal resolution and limited scale of data collected from household surveys.

The recent availability of large-scale mobility data collected from mobile devices and online platforms (e.g. mobile phones, social media) have allowed us to observe and analyze the mobility patterns of individuals at an unprecedented scale and spatio-temporal granularity (Blondel et al., 2015). Such large-scale datasets have been applied in various domains and have revolutionalized the ways we tackle and solve urban challenges, such as preventing the spread of diseases (Bengtsson et al., 2015), estimating traffic demand (Iqbal et al., 2014), and estimating poverty (Blumenstock et al., 2015). Furthermore, merging mobility data with socio-demographic information (e.g. income data) collected from external sources such as national census has enabled us to analyze and quantify the differences (or similarities) in behavior and mobility patterns across different socio-economic population groups (Moro et al., 2019). In the context of natural hazards, studies have leveraged large-scale mobility data sources to understand the evacuation behavior after disasters including hurricanes, earthquakes, and other anomalous events (e.g. Lu et al., 2012). Despite such efforts, no studies have attempted to understand the effects of income inequality during mass disaster evacuation and reentry movements using large scale mobility data.

While there are various socio-economic characteristics that affect social equity, we focus on the effects of income inequality in this study. In this study, we aim to overcome the aforementioned research gaps by answering the following research questions using large scale mobility data of affected individuals observed before, during, and after a severe disaster.

i. Do the dynamic patterns of evacuation and reentry rates differ across income groups? If so, by how much?
ii. Do the effects of income inequality hold under various settings, including evacuation from inside and outside mandatory evacuation zones?
iii. How do the effects of income inequality on evacuation behavior result in macroscopic spatial segregation of income groups over time after the disaster?
iv. Are there differences in evacuation destination characteristics across income groups?

To answer these research questions, we analyze mobility data collected from more than 1.7 million mobile phone users in Florida affected by Hurricane Irma. The income level of each mobile phone user is estimated by spatially overlaying census-block level median income information obtained from national census with the estimated home locations of mobile phone users. The spatio-temporal movement trajectories of individual mobile phone users attributed with estimated income values are tracked over a 3 month period from the landfall of the hurricane. The presented results on the effects of income inequality on social equity in disaster evacuation and reentry behavior provide insights that could contribute to policies that better address social equity in pre-disaster preparation and post-disaster relief.

2. Literature review

Household surveys and interviews have been the primary data sources to understand post-disaster evacuation behavior for the past several decades (Baker, 1991). Surveys conducted after various disasters and events have revealed the high complexity of evacuation decision making processes (Dash and Gladwin, 2007). Previous works have studied the effects of various factors on the evacuation process (for a review on this topic, see Murray-Tuite and Wolshon, 2013). Although findings vary across disaster events due to the differences in social context and the hazard characteristics, personal and household characteristics such as ethnicity, gender and race (Peacock et al., 2012), as well as storm intensity (Whitehead et al., 2000) have been understood to affect evacuation decisions. Moreover, risk perception (Riad et al., 1999) and past disaster experiences (Demuth et al., 2016) affect how individuals and households react to disasters. In addition to such individual-level characteristics, how evacuation orders are delivered to households during evacuation (Fischer et al., 1995) and also the type of sources the information is disseminated through are also known to be important factors (Lindell et al., 2005). Also, recent studies have revealed the significant effect of social influences (Lovreglio et al., 2016) through connected peers in their social networks (Sadri et al., 2017). A study in rural Indiana showed the importance of social capital, personal networks, and emergency responders in evacuation decision making (Sadri et al., 2018). Studies have also used survey data to understand evacuation activities after no notice disasters (Golshani et al., 2019). In terms of Hurricane Irma, a study analyzed survey data collected from surveys to show the importance of social connections on evacuation behavior (Collins et al., 2018). Similar to evacuation behavior, the effect of various features on reentry behavior has been analyzed using data collected via household surveys (Siebeneck et al., 2013). Another study analyzed the evacuation behavior after Hurricane Irma using discrete choice models based on data collected from surveys, with 645 respondents (Wong et al., 2018).

Despite the various advantages of survey data (e.g. qualitative details on individual experiences), such data have several drawbacks that limit our analysis on the evacuation behavior of the affected individuals. The main limitations are the number of samples (number of respondents were 645 in Wong et al. (2018a)) and the coarse spatio-temporal granularity in which we are able to track the movements of people. The recent spread in mobile devices allow us to observe and analyze the individual mobility patterns of people at an unprecedented granularity and scale (Blondel et al., 2015). During the last decade, location data collected from mobile phones have become one of the primary data sources for analyzing human mobility patterns on the urban scale (Calabrese et al., 2011). Analysis of such large scale datasets have deepened our understandings of basic laws in human mobility patterns (Gonzalez et al., 2008), enabled dynamic and spatially detailed estimations of population distributions (Deville et al., 2014; Jiang et al., 2016) and macroscopic migration patterns (Blumenstock, 2012; Lai, 2019). Moreover, these datasets have been applied to solve various urban problems such as preventing disease spread (Finger et al., 2016; Wesolowski et al., 2012), estimating traffic flow (Iqbal et al., 2014; Alexander et al., 2015; Bachir et al., 2019), and estimating economic shocks (Toole et al., 2015).

In the context of disasters, studies have used mobile phone location data to analyze population displacement patterns (Wilson, et al., 2016; Lu et al., 2016). Lu et al. (2012) revealed the predictability of displacement destinations from pre-disaster behavioral patterns in Haiti. Other studies have used a more online machine learning approach to predict the population flow after disasters using real time location data in an online manner (Song et al., 2014; Sudo et al., 2016). More recently, a study revealed universal patterns in reentry dynamics after evacuation across disasters in various regions including Florida, Puerto Rico, and the Tohoku region in Japan (Yabe et al., 2019). Despite the increasing number of studies using large scale mobility data sources for evacuation and reentry behavior, none of the studies have focused on quantitatively understanding the effects of income inequality on evacuation and reentry patterns after disasters.

Social equity is an important concept in disaster management that addresses the fair treatment of all individuals in the face of disaster situations (Emrich et al., 2019). It is now understood that social equity plays an important role in the social resilience of communities after disasters (Doorn et al., 2019). Dash and Gladwin (2007) found that higher income households were able to evacuate with a higher rate after disasters, and Kettl (2006) found that households with higher income were able to evacuate further distances after Hurricane Katrina. Moreover, income segregation and fractionalization are known to have negative impacts on the economic performance of cities and communities (Alesina et al., 2003). As a result, many efforts have been allocated to promote integration and diversity within communities. Recent studies have quantified income segregation in cities and communities on usual days, by combining large scale mobility data (e.g. mobile phone data) with income information obtained from economic census (Moro et al., 2019). In the disaster context, studies have assessed the effect of natural hazards on the dynamics of income distributions (Shaughnessy et al., 2010), and a cross-comparative study on disasters across 73 countries for a period of 22 years showed that higher income inequality leads to more deaths due to disasters on the national scale (Kahn, 2005). To overcome the issues regarding social equity during evacuation after disasters, studies have focused on the evacuation of disadvantaged population groups such as older people (Gibson and Hayunga, 2006). Studies have been conducted in the transportation engineering domain to assess the effectiveness of carsharing (Renne et al., 2011; Renne and Mayorga, 2018) and bus-based evacuation (Bish, 2011) as potential solutions to issues in social equity after disasters (Litman, 2006). To assess the impact of such solutions for disaster social equity, a quantitative understanding of the effects of income inequality on evacuation and reentry behavior is needed.

3. Data

3.1. Mobile phone location data

Mobile phone location data used in this study were provided by Safegraph, a data company that aggregates anonymized location data from numerous applications in order to provide insights about physical places. To enhance privacy, SafeGraph excludes census block group information if fewer than five devices visited an establishment in a month from a given census block group. Each observation in the dataset contains the user ID, timestamp, longitude, latitude of mobile phones measured via the Global Positioning Satellite (GPS) system, with the agreement of individuals to provide their location data for research purposes. All user IDs were anonymized and other demographic information were not collected to protect the privacy of the users. In total, mobile phone data of 1,730,326 unique users who were observed in Florida at least once with in the period between 10 days before the landfall of Hurricane Irma (August 31st) and landfall (September 10th) were collected. The location data of these users were collected from 2 weeks before the landfall of Hurricane Irma, until 3 months after the landfall date. Each user was observed at high frequency with 97 observations on average per day, which is temporally granular enough to capture the date the users evacuated from their home locations, where they evacuated to, how long they were evacuated for, and where they stayed the night each day.

The mobile phone data contains several limitations. The first limitation is that the data does not include the exact demographic characteristics of the individual users. Such demographic characteristics include information such as age, gender, and occupation. This is a disadvantage compared to survey based data, however, we use mobile phone data for this study because of the advantages in the number of samples (over 1.7 million versus several hundreds), and also because such demographic data are not required for our objective of the study. The second limitation is the potential bias in the user samples. People who do not own mobile phones are more likely to have a lower income, which could skew the income distribution upwards. The third limitation is that we are not able to

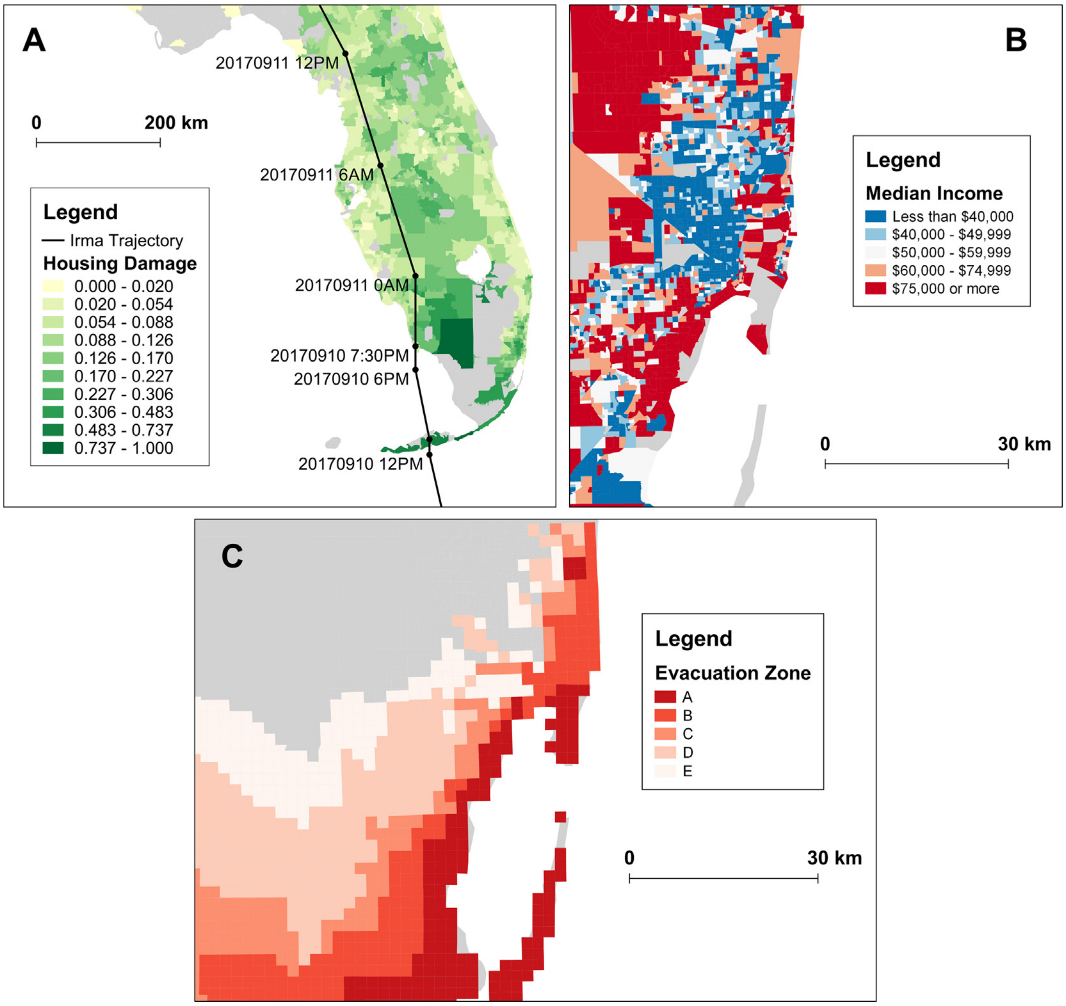


Fig. 1. (A) Trajectory of Hurricane Irma and housing damage rates in each zip code. (B) Median income of all census blocks in Miami-Dade County. Miami-Dade County has the largest income inequality among all counties in Florida State. (C) Hurricane evacuation zones in Miami-Dade County.

completely exclude the non-residents (e.g. tourists and transients) from the dataset. However, we overcome this issue through the preprocessing of mobile phone data in Section 4.1. We find that the estimated number of mobile phone users in each census block agrees well with actual census population data (shown in Fig. 2).

3.2. Hurricane damage data

Hurricane Irma made landfall on Florida on September 10th as a category 4 hurricane and traversed through the Florida peninsula, spawning storm surge and causing major inland flooding. Especially in the Florida Keys, 25 percent of the homes were destroyed and 65 percent were damaged. Many homes and businesses suffered damage or destruction, with more than 65,000 structures damaged to some degree in West Central and Southwest Florida alone. The hurricane caused more than 7.7 million homes and businesses to be out of power in the entire state of Florida, and at least 134 fatalities were confirmed (Cangialosi et al., 2018). The total economic losses caused by the hurricane is estimated to be $50 billion (Smith, 2018).

To understand the spatial distribution of hurricane damage, we use the housing damage rates in each zip code. The housing damage rate of a given zip code area refers to the rate of houses approved for the Individuals and Households Program of FEMA in each zip code. This dataset is publicly accessible from the FEMA website (FEMA). Fig. 1A shows the housing damage rates in all zip codes in Florida. Out of all the counties, 6 of them experienced extensive damage, with housing damage rates of more than 10%. In particular, Miami-Dade County experienced the largest number of affected households (179,069), which was 25% of all of the affected households (Table 1). In addition to the housing damage rate data, we also used the power outage data provided by the Florida Division of Emergency Management. This data contains the percentage of power outages in each county every six hours between September 9th and 28th. The floodzone map of Miami-Dade County (Fig. 1C) was obtained from the Open Data Hub of Miami-Dade County (Hub). In Miami-Dade County, mandatory evacuation orders were issued to residents in evacuation zones A and

Table 1
Miami-Dade county had largest hurricane damage and income inequality in Florida.

Rank in State	Households affected by Hurricane Irma			Income inequality	
	County	Number of Households	Percentage	County	Gini Index
1	**Miami-Dade**	179,069	25.0%	**Miami-Dade**	0.5256
2	Broward	86,811	12.1%	Lafayette	0.5248
3	Pinellas	44,603	6.2%	Collier	0.5237
4	Orange	43,685	6.1%	Martin	0.5219
5	Lee	39,423	5.5%	Palm Beach	0.5197
	(State Total)	715,679	100.0%	(State Average)	0.4858

a portion of B that covers barrier islands between Biscayne Bay and the ocean on September 6th at around 6AM, and were expanded to zones A, B, and C on September 7th at around 2:15PM.

3.3. Socio-economic data

Out of all the counties in Florida, Miami-Dade County has the largest Gini Index, meaning that the income inequality is highest among all counties (Table 1). The Gini index, or Gini coefficient, is a metric that quantifies the degree of inequality in a distribution (Sen and Foster, 1997). Given a set of values x_i ($i = 1, \ldots, n$), the Gini index G is calculated as:

$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}|x_i - x_j|}{2n^2\bar{x}} \tag{1}$$

where $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$. The Gini Index takes a value between 0 and 1, where 0 indicates perfect equality and 1 indicates maximal inequality where one individual owns all income and all others own nothing. Considering that Miami-Dade County also had the largest number of affected households due to Hurricane Irma (Table 1), we focus our analysis on the residents of Miami-Dade County in this study. Population data, median income data, and Gini Index data on the census block, census tract, and county level were all obtained from the American Community Survey (Bureau, a). Income ranges used commonly by the United States Census Bureau (less than \$40,000, \$40,000 to \$49,999, \$50,000 to \$59,999, \$60,000 to \$74,999, more than \$75,000) were used in the analysis (e.g. Bureau, b). To perform spatial analysis including geographical extraction and labeling, we used the Shapefile data of Florida provided by the National Census (Bureau, c).

4. Methods

4.1. Preprocessing of mobile phone data

The dataset includes location data of all users who were observed at least once in Florida between the 2 weeks before the hurricane. In this study we focus on the evacuation behavior of the residents in the state. Thus, we exclude observed location data of all non-resident users (e.g. tourists and visitors) by first selecting the users whose home locations were estimated to be inside Florida, and then selecting those who were observed to be staying more than 6 nights out of the 7 nights in his/her estimated home location between August 31st and September 6th. We selected September 6th as the threshold date since only a small fraction of people (4.4%) had evacuated before this date (Wong et al., 2018a). The dataset may still include visitors if they stayed in Florida during more than 6 days between August 31st and September 6th, however we assume that this is a small portion of the population.

4.2. Home location and income estimation

Home locations of all users were estimated using the collected mobile phone location dataset. It is well known that human trajectories show a high degree of temporal and spatial regularity, each individual having a significant probability to return to a few highly frequented locations, including his/her home location (Gonzalez et al., 2008). Due to this characteristic, past works have shown that home locations of individuals can be detected with high accuracy by clustering the individual's stay point locations during the night (Calabrese et al., 2011). We assume that each individual has one main home location in this study. The home location of each individual user was detected by applying the mean-shift clustering algorithm (Cheng, 1995) to the nighttime stay points (observed between 8PM and 6AM), weighted by the duration of stays in each location. Mean-shift clustering is a clustering procedure for locating the mode of a density function given discrete data sampled from the target function. In our problem setting, the discrete data are the observed night-time location data points of a given user, and our goal is to estimate the true mode (which is the home location) of that user. The algorithm is an iterative method, where we start with an initial estimate and iteratively shift our point estimate based on the density of surrounding points. During each iteration, the point estimate gradually shifts towards regions with higher density of observations, and finally converges when the estimate point reaches the mode of the underlying density function. Each mobile phone user's income is estimated by spatially matching his/her estimated home location with the census-block based median income data obtained from the American Community Survey (Fig. 1B).

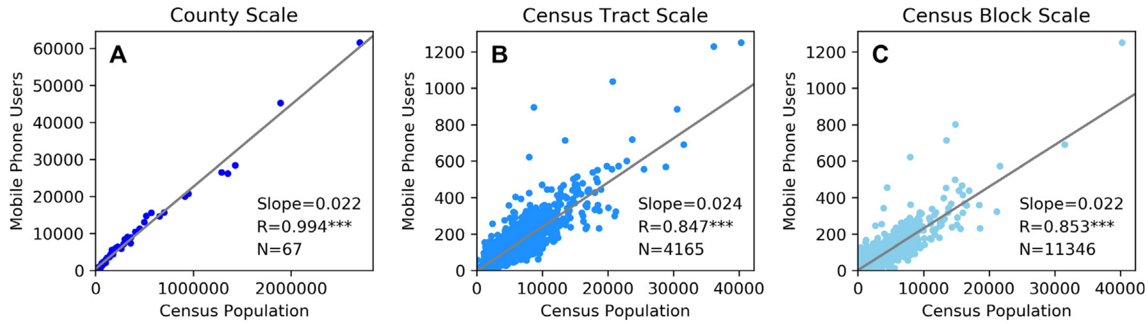


Fig. 2. Comparison between census population and mobile phone users in (A) county scale, (B) census tract scale, and (C) census block scale.

For our study, it is important to evaluate the spatial bias in the number of observed mobile phone users before conducting the analysis. To evaluate spatial bias of the data, the correlation between the number of mobile phone users and census populations in each county, census tract, and census block were calculated. Home locations of all mobile phone users were estimated using the aforementioned home location estimation methods. As shown in Fig. 2, the number of mobile phone samples were highly correlated with census population for each county, with Pearson's correlation coefficient of 0.994 ($p < 0.001$). Furthermore, even for small spatial scales, the correlations are very high ($R = 0.847$ for census tracts and $R = 0.853$ for census blocks, both statistically significant), indicating that the differences in sample rates across census blocks are minimal in our dataset. Moreover, the correlation stays high for all days within the observation period even after the disaster when mobile phone towers are damaged. This is because the mobile phone apps store the location information within the device until the mobile phone towers recover, and uploads the information afterwards. Due to the consistent sample rates of mobile phone users across all census blocks, census tracts and counties, we use the mobile phone data users as accurate approximations of the entire population.

For each day, each mobile phone user's nighttime staying location is estimated by applying the mean shift clustering algorithm on the location data points observed during nighttime (8 PM to 6 AM). A user is determined to be evacuated if the nighttime staying location was outside his/her home county. The evacuation rate of each income group for each day are defined as the rate of evacuated users on that day out of the total number of observed users in the target population group.

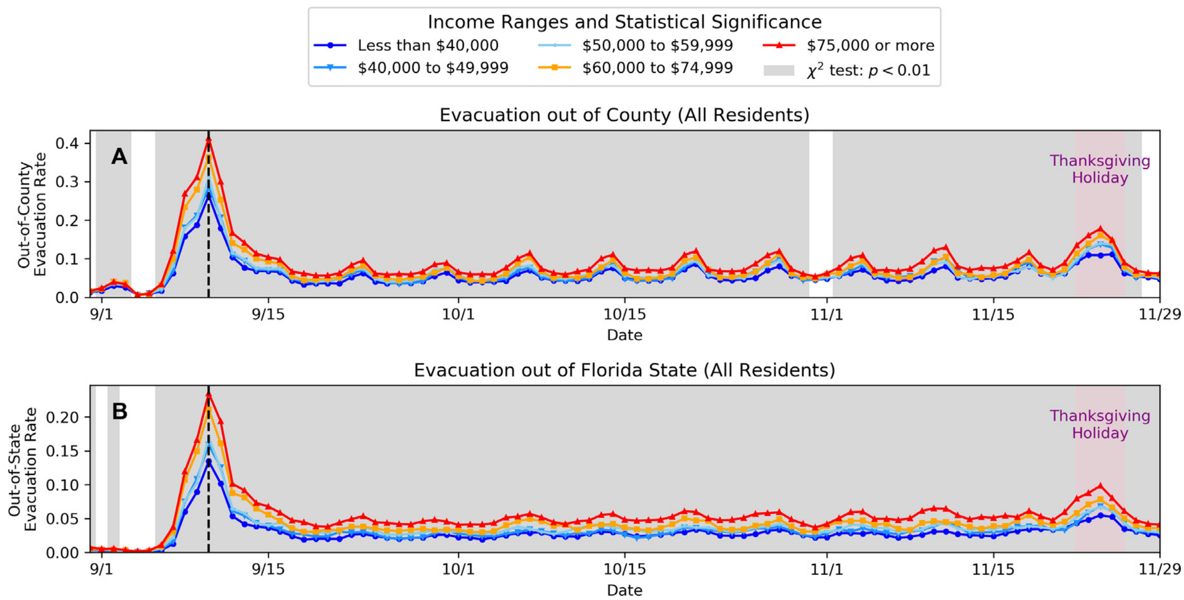


Fig. 3. Out-of-county and out-of-state evacuation rates of Miami-Dade residents. Higher income residents were more likely to evacuate than low income residents, and were also able to stay away from the affected areas for a longer duration. Gray shades indicate days where differences in evacuation rates were statistically significant between income groups.

Table 2
Daily evacuation rates (and differences) of evacuation from Miami-Dade County from September 6th to September 15th across different income groups.

Income range	Evacuation rate on each day (difference from day before) (%)				
	Sep 6th	7th	8th	9th	10th
All income groups	2.5	8.7 (+6.2)	21.0 (+12.3)	24.6 (+3.6)	33.6 (+9.0)
Less than $40,000	1.6	5.3 (+3.7)	13.1 (+7.8)	15.8 (+2.7)	21.7 (+5.9)
$40,000 to $49,999	1.8	5.9 (+4.1)	15.9 (+10.0)	19.0 (+3.0)	25.1 (+6.1)
$50,000 to $59,999	2.1	6.8 (+4.7)	15.4 (+8.6)	18.2 (+2.8)	26.4 (+8.1)
$60,000 to $74,999	2.8	8.6 (+5.8)	20.6 (+12.0)	24.9 (+4.3)	31.9 (+7.0)
$75,000 or more	3.1	11.3 (+8.2)	25.4 (+14.1)	29.8 (+4.4)	38.6 (+8.8)

Income range	Evacuation rate on each day (difference from day before) (%)					
	Sep 10th	11th	12th	13th	14th	15th
All income groups	33.6	23.6 (−10.0)	13.0 (−10.6)	10.9 (−2.1)	8.8 (−2.1)	8.4 (−0.4)
Less than $40,000	21.7	15.0 (−6.7)	9.2 (−5.8)	7.0 (−1.2)	6.3 (−0.7)	6.3 (±0.0)
$40,000 to $49,999	25.1	18.0 (−7.1)	9.9 (−8.1)	8.7 (−1.2)	7.0 (−1.7)	7.0 (±0.0)
$50,000 to $59,999	26.4	17.5 (−8.9)	10.3 (−7.2)	9.0 (−1.3)	7.2 (−1.8)	7.3 (+0.1)
$60,000 to $74,999	31.9	22.4 (−9.5)	12.4 (−10.0)	10.8 (−1.6)	8.9 (−1.9)	8.5 (−0.4)
$75,000 or more	38.6	28.3 (−10.3)	15.7 (−12.6)	13.1 (−2.6)	10.5 (−2.6)	9.9 (−0.6)

5. Results

5.1. *Effects of income inequality on evacuation and reentry*

5.1.1. *All residents of Miami-Dade County*

We first quantify the evacuation and reentry rates of Miami-Dade County residents on each day during the observation period. Fig. 3 shows the net evacuation rates of the Miami-Dade County residents on each day before, during and after Hurricane Irma. The upper panel (A) shows the rate of evacuees who evacuated outside Miami-Dade County, and the lower panel (B) shows the rate of evacuees who went outside the State of Florida. The net evacuation rates of different income groups are shown in color in each panel. The Thanksgiving Holidays (around November 23rd to 26th) are highlighted as unusual periods. Table 2 shows the numerical values of net evacuation rates of all income groups between September 6th and 15th, where the dynamics are most significant. The table also shows the differences in net evacuation rates from the day before to better capture the daily dynamics of evacuation and reentry activities. Several observations can be made from the analysis results. First, we observe a sharp increase in the net evacuation rates in both panels until September 10th, which is the date of hurricane landfall. The daily differences of the net evacuation rates in Table 2 show that most evacuation occurred on September 8th (+12.3% for all income groups aggregated together), which was a day after the evacuation orders were issued. We also observe a large portion of evacuation on September 10th, which was the day of the landfall (+9.0% for all income groups aggregated together). After September 10th, the evacuation rates gradually decrease and by around September 18th, the rates stabilize. Most evacuees returned and reentered Miami-Dade County on September 11th and 12th, shortly after the hurricane struck the peninsula. Second, we observe a significant difference in evacuation rates across income groups, where higher income population groups had higher evacuation rates, both in terms of out-of-county evacuation and out-of-state evacuation rates. This difference was verified to be statistically significant ($p < 0.01$) in most days (shaded in gray) using a Chi-Squared test. Table 2 shows that 38.6% of high income ($75,000 or more) residents were able to evacuate from Miami-Dade County, compared to 21.7% of low income residents ($40,000 or less). The differences between income groups are larger in out-of-state evacuation rates, indicating that higher income groups were more likely to travel further away from Miami-Dade when evacuating. Third, the evacuation rates stayed significantly larger than pre-disaster (August 31st to September 5th) levels for a long duration after the hurricane (around 10% for high income groups on November 15th). Similar to short term evacuation rates, the high income population groups had higher long term evacuation rates, indicating that these people were able to find places to stay for long durations outside Miami-Dade County. Fourth, we see weekly fluctuations in evacuation rates after the hurricane in both panels, where evacuation rates are higher on Fridays and Saturdays compared to weekdays. This pattern indicates that a fraction of the people traveled outside the county or state on weekends. This weekly increase in evacuation rates may be due to actual evacuation, or it may contain non-evacuation trips going outside of the county or state since we are not capable of identifying trip purposes from mobile phone trajectories, which is one limitation of our analysis.

5.1.2. *Mandatory and shadow evacuation*

The analysis presented in the previous section shows the rates of evacuation from all residential areas. In the following results (Fig. 4 and Table 3), we group the mobile phone users into residents of areas inside the mandatory evacuation zones (zones A, B, C in Fig. 1C), and residents outside the mandatory evacuation zones. Distinguishing between these two population groups is important from the viewpoint of disaster management officials, since they need to develop policies for future disasters based on how the

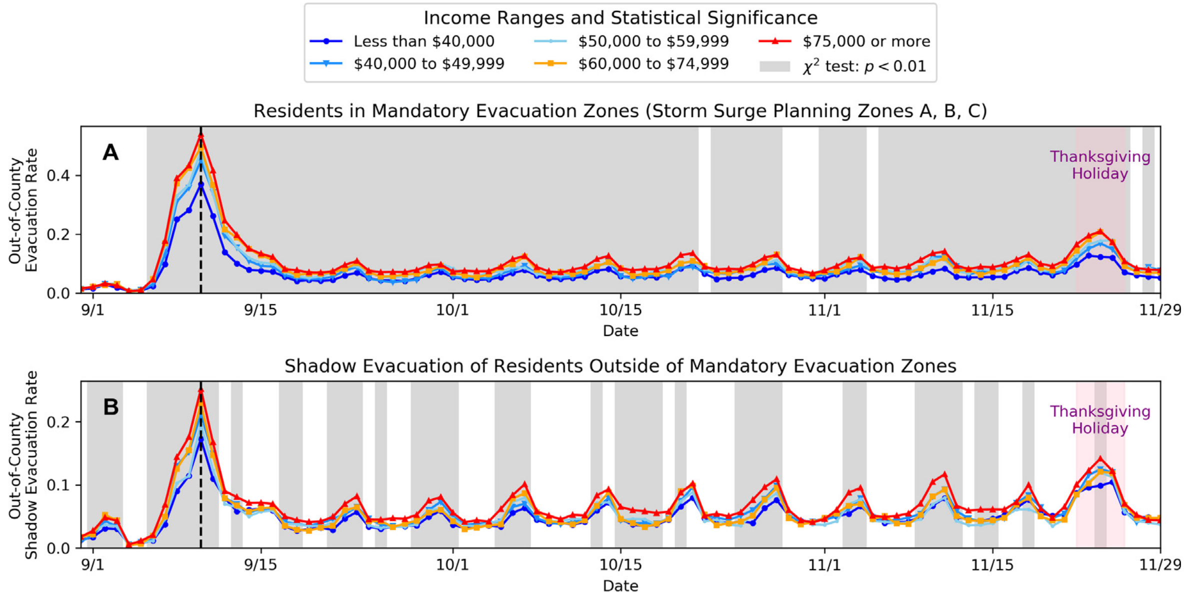


Fig. 4. Out-of-county evacuation rates of residents (A) living inside mandatory evacuation zones (zones A, B, C), and (B) living outside mandatory zones (shadow evacuation rates), across different income groups.

residents in the designated flood zones complied with the evacuation orders, and also by how much of the residents outside those regions evacuated ("shadow evacuation") despite receiving no evacuation orders.

Fig. 4 shows the (A) out-of-county net evacuation rates of residents in the mandatory evacuation zones (zones A, B, C) and (B) shadow net evacuation rates for residents outside the mandatory zones. Table 3 shows the detailed statistics of daily evacuation rates and differences for each income group in each zone type. We observe that the peak evacuation rate from the mandatory zones (47.5%) was around double of the shadow evacuation rates (21.3%). The effects of income inequality in evacuation rates for both zone types were strikingly similar, where we observe significant differences in both short term and long term evacuation rates across income groups. This difference was also verified to be statistically significant ($p < 0.01$) in most of the days (shaded in gray) using a Chi-Squared test. During the reentry phase, effects of income inequality were larger inside mandatory evacuation zones, where for example on September 15th, the evacuation rates of high income residents were around double (13.3%) compared to low income residents (7.5%). On the other hand, reentry patterns were similar across income groups outside of the mandatory evacuation zones, with less days with statistical significant differences across income groups.

Further correlation analysis revealed that higher income residents slightly tended to live more in the coastal areas of Florida ($R = -0.06$, $p < 0.05$). To verify whether the inequity in evacuation and reentry patterns exist because of income inequality and not the distance from the coastal areas, we performed a similar analysis for the population group living in the coastal areas (<3 km from closest coast) and the other population group. The results are shown in Fig. 5. Plots similar to Figs. 3 and 4 show that the differences in evacuation and reentry rates are indeed statistically significant across income groups in most of the days before and after the hurricane, conditioned on the distance from the coastline.

5.2. *Temporal variation of spatial income segregation*

As a result of the effects of income inequality on evacuation and reentry mobility patterns, we observe high spatial income segregation between people who stayed inside Miami-Dade County and people who moved to outside Miami-Dade County after the disaster. Fig. 6 shows the histograms of mobile phone users' income values for the two population groups: users who stayed inside Miami-Dade (gray color) and users who evacuated out of the county (green color), for each day between September 4th and 15th. Since previous studies have empirically shown that the income values of the majority (97–99%) of the population are distributed log-normally (Clementi and Gallegati, 2005), we fit the income values of the two groups with log normal distributions. The probability density function of the (2-parameter) log-normal distribution is

$$f(x) = \frac{1}{xs\sqrt{2\pi}}\exp\left\{-\frac{\left(\ln(\frac{x}{m})\right)^2}{2s^2}\right\} \tag{2}$$

where s is the shape parameter (and also is the standard deviation of the log of the distribution) and m is the scale parameter (which is also the median of the distribution). We may also have location parameter θ in the formulation, however this parameter does not appear in our formulation because we restrict this to $\theta = 0$. We assume that an income value of a resident who is *IN*side (or *OUT*side)

Table 3
Daily evacuation rates from Miami-Dade County from September 6th to September 15th across income groups, for residents inside and outside the mandatory evacuation zones.

In/Outside Flood Zones	Income range	Evacuation rate on each day (%)									
		6th	7th	8th	9th	10th	11th	12th	13th	14th	15th
Inside Mandatory Evacuation Zones (Zones A, B, C)	All income groups	3.7	14.4	33.5	37.8	47.5	35.2	20.1	16.2	12.4	11.0
	Less than $40,000	2.2	9.7	25.0	28.1	36.9	26.1	13.8	10.0	7.8	7.5
	$40,000 to $49,999	2.9	12.9	30.9	35.7	44.9	34.2	19.4	15.5	10.9	9.2
	$50,000 to $59,999	4.0	15.6	32.9	36.7	48.1	33.6	20.8	15.4	11.9	10.2
	$60,000 to $74,999	4.7	16.8	37.2	42.3	49.4	36.7	21.5	18.7	14.9	12.7
	$75,000 or more	4.5	17.6	38.9	43.2	53.9	41.5	24.6	19.6	15.0	13.3
Outside Mandatory Evacuation Zones, (Zones D, E, else), i.e. Shadow evacuation	All income groups	1.5	4.9	11.9	14.4	21.3	14.0	8.0	6.8	6.0	6.4
	Less than $40,000	1.1	3.7	8.9	11.4	17.2	10.9	7.8	5.8	6.0	6.2
	$40,000 to $49,999	1.4	4.6	12.9	15.1	21.1	14.9	7.9	6.9	5.5	6.1
	$50,000 to $59,999	1.1	4.6	10.2	11.4	19.6	12.3	6.9	6.4	5.0	5.7
	$60,000 to $74,999	1.9	4.9	12.5	15.5	22.8	14.6	7.9	6.7	5.7	6.2
	$75,000 or more	2.0	6.8	14.3	17.5	25.1	16.7	9.0	8.0	7.1	7.1

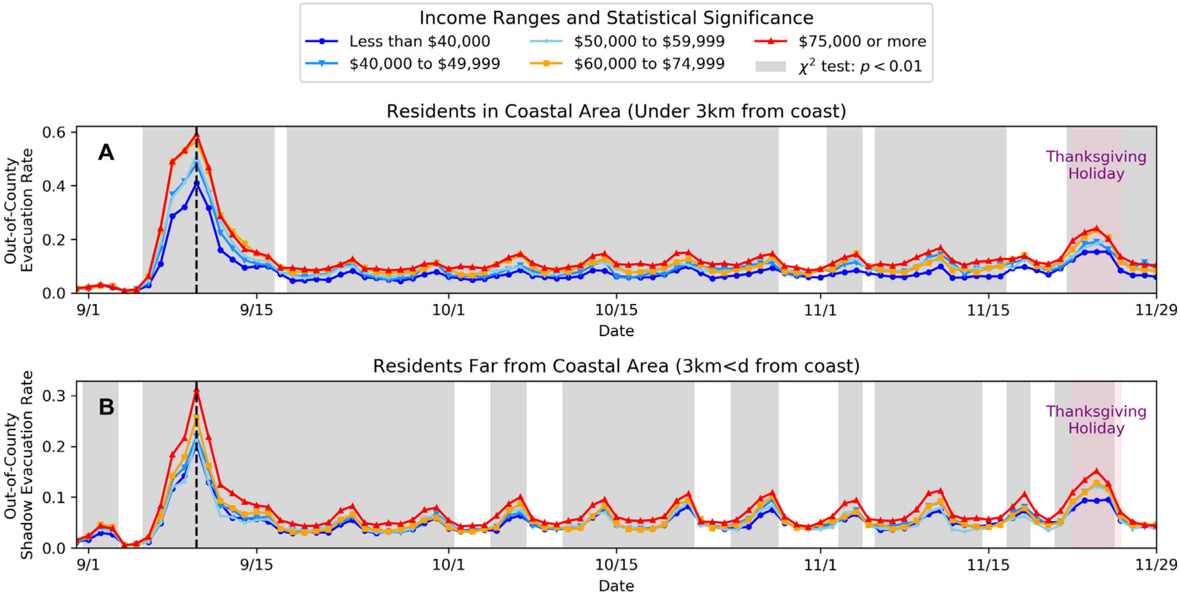


Fig. 5. Effects of income inequality on evacuation and reentry rates with respect to distance from coast. Chi-squared tests confirmed statistically significant differences in evacuation and reentry rates.

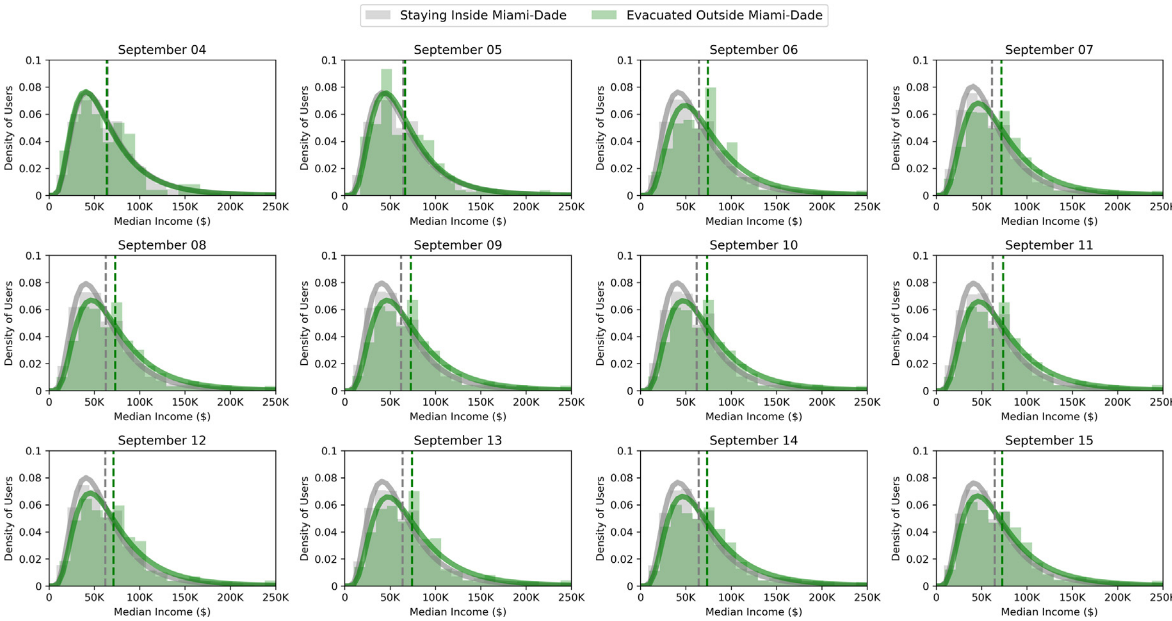


Fig. 6. Income distributions and fitted lognormal density functions of residents staying inside Miami-Dade County (in gray) and residents who evacuated outside Miami-Dade (in green) for all days between September 4th and 15th. Vertical dotted lines show the mean income values of the two population groups. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Miami-Dade County on day t, which is denoted as x_t^{IN} (or x_t^{OUT}) comes from a lognormal distribution with parameters (s_t^{IN}, m_t^{IN}) (or (s_t^{OUT}, m_t^{OUT})). All parameters for both *IN* and *OUT*, for all days t, are estimated using maximum likelihood estimation:

$$\widehat{m}_t^{IN} = \exp\{\widehat{\mu}_t^{IN}\} \tag{3}$$

$$\widehat{s}_t^{IN} = \sqrt{\frac{\sum_{i=1}^{N} (\ln(x_t^{IN})_i - \widehat{\mu}_t^{IN})^2}{N}} \tag{4}$$

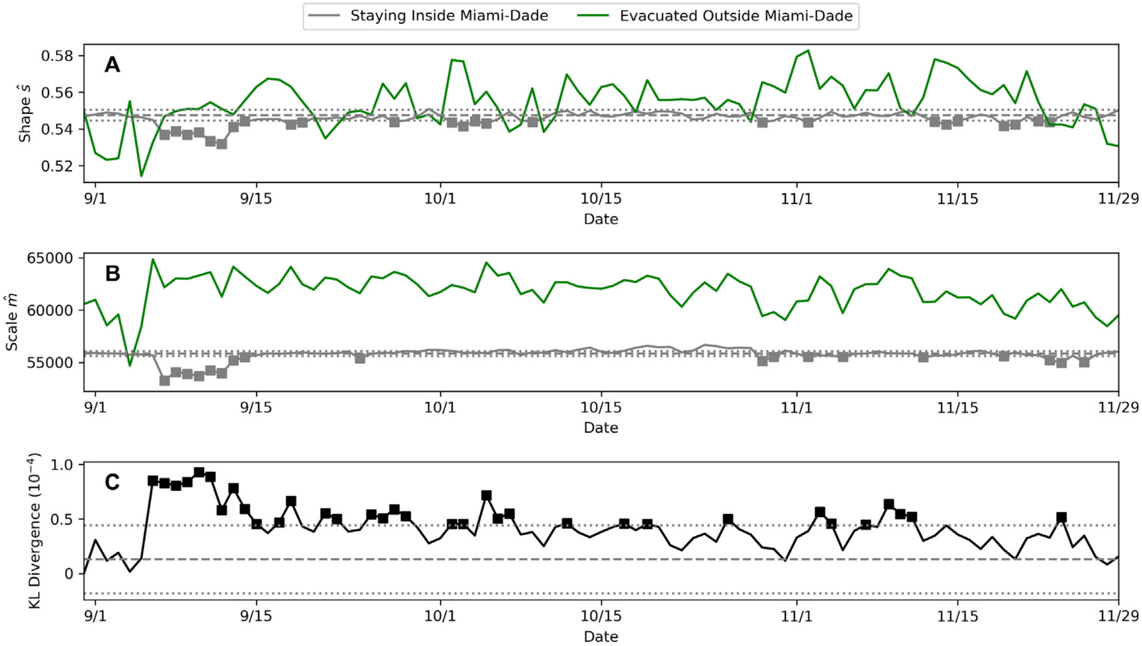


Fig. 7. Quantifying spatial segregation after disasters. (A) Shape parameter and (B) scale parameter estimates of income distributions of the 2 population groups over time. (C) Kullback-Leibler Divergence between the income distributions of the two population groups over time.

$$\text{where,} \quad \hat{\mu}_t^{IN} = \frac{\sum_{i=1}^{N} \ln(x_t^{IN})_i}{N} \tag{5}$$

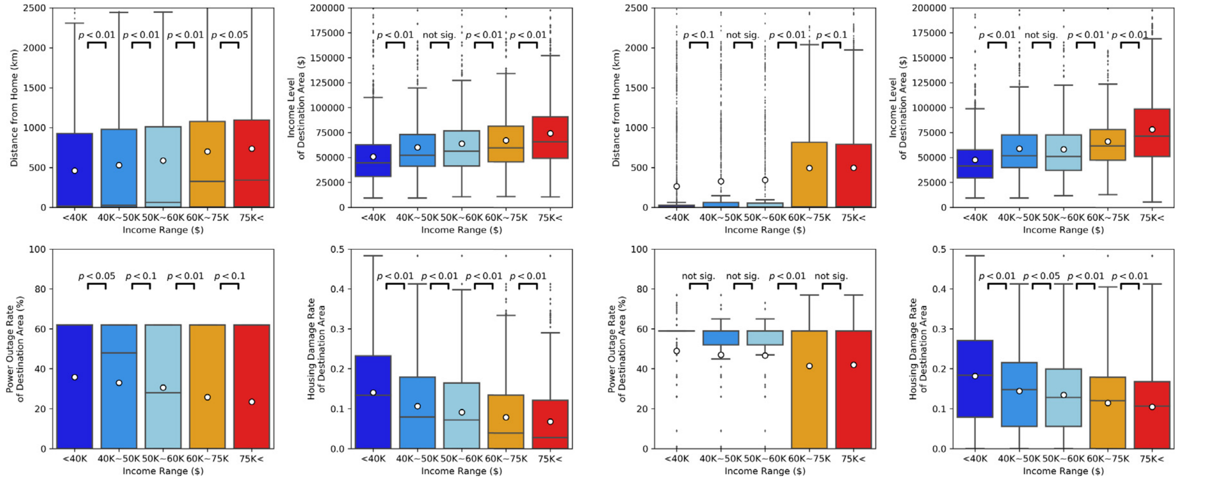
The above equations are applied to estimate parameters for all days of observation t and for both user groups inside (*IN*) and outside (*OUT*) Miami-Dade County. Fig. 6 shows the income distributions and fitted lognormal density functions of residents staying inside Miami-Dade County (in gray) and residents who evacuated outside Miami-Dade (in green) for all days between September 4th and 15th. Vertical dotted lines show the mean income values of the two population groups. We visually observe that the income distributions are very similar before the hurricane on September 4th and 5th. However, the the distributions of evacuated users diverge to the right, indicating that a larger fraction of the high income populations evacuated to outside the county, causing spatial income segregation.

The estimated parameter values of the lognormal distributions are shown in Fig. 7A (shape parameter s_t) and 7B. In Fig. 7A, the estimated $\hat{s}_t^{IN}$ and $\hat{s}_t^{OUT}$ are plotted in gray and green colors, respectively. The gray square scatter plots show the shape parameter values that are anomalous compared to usual values. Anomalies were detected using the 3-standard deviations rule. More specifically, the horizontal dashed gray line is the mean value of $\hat{s}_t^{IN}$ before the evacuation starts ($t \leq 6$), which is calculated by $\mu_s^{IN} = \frac{1}{6}\sum_{t=1}^{6} \hat{s}_t^{IN}$. The standard deviation of $\hat{s}_t^{IN}$ before the evacuation starts ($t \leq 6$), can be calculated by $\sigma_s^{IN} = \sqrt{\frac{1}{6}\sum_{t=1}^{6} (\hat{s}_t^{IN} - \mu_s^{IN})^2}$. The dotted lines above and below the mean horizontal line are $\mu_s^{IN} + 3\sigma_s^{IN}$ and $\mu_s^{IN} - 3\sigma_s^{IN}$, respectively. Similarly, in Fig. 7B, anomalous scale parameters were plotted with gray squares. We observe that in both panels A and B, the estimated parameters of the users inside Miami-Dade significantly (anomalously) decrease between September 7th and September 14th. Decrease in both of the parameters indicate that the income distribution shifts to the left (towards lower income), and that the distribution has less variance. On the other hand, both the shape and scale parameters of users who have evacuated outside of Miami-Dade County increase, indicating that the distribution shifts to the right and that the variance also increases. The shifts of the two distributions in sum indicate that the distributions are shifting away from each other, implying an increase in spatial income segregation.

Further, we quantify the magnitude of segregation by calculating the Kullback-Leibler Divergence (KL divergence) between the two income distribution functions. The KL divergence between 2 functions $P(x)$ and $Q(x)$ is formulated by the following equation:

$$D_{KL}(P||Q) = \int_{-\infty}^{\infty} P(x)\log\left\{\frac{Q(x)}{P(x)}\right\}dx \tag{6}$$

Fig. 7C plots the daily KL divergence between the income distributions of the two population groups (inside and outside Miami-Dade County). Similar to the previous analyses, the dashed and 2 dotted horizontal lines mark the mean, mean plus 3 standard deviations, mean minus 3 standard deviations, respectively, of the KL divergence values before the evacuation started on September 7th. The black square plots show the anomalous values of KL divergence, indicating that spatial segregation is occurring with statistical significance ($p < 0.01$). We observe significant spatial segregation in most of the days in September, and over a long period of time after the landfall even during November (2 months after landfall). To summarize, the analysis presented in this section using



(a) Results for September 10th (b) Results for September 12th

Fig. 8. Evacuees with higher income levels were able to evacuate further, to locations of higher income, lower power outages, and less housing damages due to the hurricane compared to lower income evacuees.

mobility data and income information shows that spatial income segregation does occur after disasters due to the effects of income inequality in post-disaster mobility patterns, and that it persists for a long period of time after the hurricane landfall.

5.3. Inequity in evacuation destination characteristics

In this section, in addition to quantifying the effects of income inequality on evacuation and reentry rates (Section 5.1) and spatial segregation (Section 5.2) after the hurricane, we further analyze the characteristics of evacuation destinations across different income groups. The box plots in the two panels (each consisting of 4 sub-panels) in Fig. 8 show the various characteristics of evacuation destinations of evacuees belonging to each of the 5 income groups (shown in blue to red colors). In each sub-panel, the horizontal line in each whisker plot shows the median value, and the white marker shows the mean value of each population group.

The left panel (Fig. 8(a)) shows the results for September 10th, which is the day of the landfall. The top left sub-panel shows the the distributions of evacuation distances of the five population groups. In addition to Figs. 3 and 4 where it was shown that people with higher income evacuate at a higher rate, it is shown here that people with higher income tend to evacuation longer distances. Since the mean distance is significantly greater than the median distance in low income groups, we can infer that the majority of the low-income evacuees traveled short distances (less than 10 km). Similar to how we estimated the income of evacuees based on their residential census block, we estimated the income level of the destination area of each individual using census block level income data. The top right sub-panel shows that people with higher income were more likely to evacuate to locations of high income. Moreover, using the power outage data, the distributions of the power outage rate of the destination locations were estimated for each income group. The bottom left sub-panel shows that the high-income evacuees were able to reach areas with less power outage rates compared to low income evacuees. Similarly, the bottom right sub-panel shows that high income evacuees were able to reach locations with lower housing damage rates compared to low income evacuees. These latter two results which indicate that higher income residents were able to reach safer locations than lower income residents, highlight the inequity in evacuation destinations across income groups. To test the statistical significance of these differences, Kolmogorov-Smirnov tests (KS-tests) were performed on the neighboring pairs of data in each of the panels in Fig. 8. The p-values of the KS-tests for the pair of data distributions of neighboring income groups are shown in the figures. For most neighboring pairs of income groups, the differences in the data distributions were significant with $p < 0.1$, often even with $p < 0.01$. The instances with no significant differences are observed mainly between the second group ($40 K~$50 K) and third group ($50 K~$60 K). However, in many of the income group pairs, significant differences in evacuation destination characteristics were observed. In summary, the more high income population groups were able to reach safer locations with less power outages and housing damages, whereas the lower income population groups had to stay in areas with more damage. These analyses were performed for all days after the hurricane, and these findings were found to be consistent over days after the hurricane until the end of September. Results for September 12th are shown in the right panel Fig. 8(b).

6. Discussion

In this study, we presented a data-driven method to (i) quantify the effects of income inequality on evacuation and reentry patterns after disasters, (ii) quantify the spatial income segregation in the affected regions, and to (iii) understand the inequity in evacuation destination characteristics across different income groups. The methods were empirically tested using mobility data collected from mobile phone users living in Miami-Dade County who were affected by Hurricane Irma, which were further integrated with household income data. The results highlight the significant effects of income inequality on evacuation and reentry behavior, where the high income population had higher likelihood of evacuating from the affected areas. This characteristic was common across evacuation from both mandatory evacuation zones and non-mandatory zones (i.e. shadow evacuation). Moreover, they were able to reach richer and safer areas with less power outages and housing damages compared to the lower income population groups. To the best of our knowledge, this is the first work to quantify the inequity in post-disaster mobility patterns across income groups and to also quantify the increase in spatial income segregation after disasters in the urban scale using large scale data.

The presented empirical results should be considered in the light of some limitations. First, due to the passive observational nature of the location data collected from mobile phones, unlike household surveys, we were not able to fully understand the trip purposes of each mobility trajectory. Thus, although home locations were estimated using a well established methodology, our sample may still include people who were just visiting Miami-Dade County just before the hurricane. The reliability of the analysis could improve if data from a longer period before the hurricane were available, however we were limited to 2 weeks of data before the hurricane landfall. Second, as noted in Section 3.1, mobile phone data does not include the demographic characteristics of the individual users due to privacy issues. We overcome this issue by overlaying census-block level household income data with the estimated home locations. However, in the analysis, we assigned median household income values of census blocks to each mobile phone user, based on the user's estimated home location. Thus, the estimated income values of the mobile phone users may contain estimation errors, which could not be addressed in our analysis since we do not know the true income values of the mobile phone users. In future studies, we may combine the results with survey based data to estimate socio-economic characteristics of mobile phone users more accurately, even though scalability would be an issue. Third, the analysis presented in this study was limited to Miami-Dade County due to its high degree of income inequality and hurricane damage. Moreover, although we were able to capture the macroscopic evacuation patterns outside the county, within-county evacuation was not analyzed in this paper. Therefore, we were not able to verify whether the findings in this study are common across different regions in Florida, as well as within the county. However, one of the advantages of using large scale mobility data is its scalability. The methodology can be easily extended to data collected from other counties. Increasing the number of disaster events and testing the generalizability of our conclusions would be an interesting path for future research. In particular, investigating the spatial segregation dynamics in other geographical settings such as islands (e.g. Hurricane Maria in Puerto Rico) would be an interesting comparative case study.

We finally discuss how the methods, analysis, and findings presented in this study may be applied in policy making to provide favorable and equitable outcomes after disasters. First, the analysis results may be used to monitor evacuation and reentry behavior for traffic congestion prediction. By aggregating the analysis results and multiplying them with actual regional populations, policy makers could grasp the evacuation traffic volume from each of the evacuation zones, including the non-mandatory zones to understand the magnitude of shadow evacuation activities. These estimates could be fed into evacuation traffic simulation frameworks (e.g. Ukkusuri et al., 2017) to predict the severity and spatial distributions of traffic congestion in the affected areas, which is an issue often seen in emergency situations (Maghelal et al., 2017). Moreover, our analysis on the effects of income inequality on evacuation rates across different income groups could allow policy makers to quantify the number of low income residents who are not able to evacuate from vulnerable (e.g. coastal) areas. Recently, various solutions are suggested to solve social inequity in disaster evacuation and reentry Feng et al., (2015). For example, studies have proposed bus and transit based evacuation (Bish, 2011; Bian and Wilmot, 2018; Zhang, 2014; Kim et al., 2013), evacuation via car sharing (Li et al., 2018; Borowski and Stathopoulos, 2020; Wong et al., 2018b; Wong and Shaheen, 2019), and use of autonomous vehicles for evacuation (Chang and Edara, 2018; Ivanov and Knyazkov, 2014; Yin et al., 2018). The estimations made in this study could be used as input data to assess the benefits and costs of these transportation solutions for equity in disaster evacuation.

7. Conclusion

The increase in frequency and intensity of large scale disasters pose significant urgency to cities to develop disaster management plans that can efficiently manage mass evacuation activities. Social equity among various population groups during the evacuation and reentry phases is an important concept that needs to be addressed for effective community recovery. In this study, we quantified the effects of income inequality on evacuation and reentry dynamics, and further quantified the magnitude of spatial segregation after disasters using mobile phone location data and income information collected from Hurricane Irma. Such findings can be used as empirical evidence to quantitatively assess the impacts of socio-economic inequality, or can be combined with evacuation simulation frameworks to simulate evacuation dynamics of different income groups, which could ultimately contribute to policies that better address social equity in disaster preparation and relief.

CRediT authorship contribution statement

Takahiro Yabe: Conceptualization, Methodology, Software, Validation, Investigation, Writing - original draft, Visualization. **Satish V. Ukkusuri:** Conceptualization, Methodology, Investigation, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition.

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Physical Networks.

Author contributions

The authors confirm contribution to the paper as follows: study conception and design: T. Yabe, S.V. Ukkusuri; analysis and interpretation of results: T. Yabe, S.V. Ukkusuri; draft manuscript preparation: T. Yabe, S.V. Ukkusuri. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Competing Interest

The authors declare that they have no competing interests.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2020.102260.

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