Missed Opportunities for Resilient (De)Growth: Evidence from Post-Disaster Migration

Abstract

This working paper utilizes data acquired from the credit agency TransUnion to look at post-disaster migration in the state of North Carolina. TransUnion data is distinctive in that it includes de-identified individual-level addresses and dates of initial occupancy, providing millions of data points to use in creating an address-to-address dataset. Specifically, our paper tracks over 500,000 individuals who moved from or within the coastal plains of eastern North Carolina in the aftermath of Hurricanes Matthew (2016) and Florence (2018). We find that individuals who were exposed to a hurricane, or who lived in vulnerable areas were more likely than counterfactual groups to migrate *into* new residences within floodplains. However, the co-location of both exposure and vulnerability is associated with more resilient migration patterns, where individuals, on average, were less likely than counterfactual groups to move into new residences in floodplains within our study area. Despite these migration patterns, state-level vulnerability remained constant as migration into hurricane-affected areas and floodplains occurred at approximately the same rate as out-migration. This “vulnerability replacement” dynamic represents a missed opportunity to capitalize on the organic and voluntary post-hurricane process of individual flood vulnerability reduction, to develop regional resiliency.

Currently, our study period focuses on the 18 months after Hurricanes Matthew and Florence. Prior to PAA, we intend to extend our analysis to analyze migration patterns in the 18-months prior to Hurricane Matthew. This will help establish the degree to which post-disaster migration patterns mirror, interrupt, or accelerate pre-existing patterns of movement.

Keywords: Hazards, Disasters, Hurricanes, Migration, Vulnerability

1. Introduction

Anthropogenic climate change introduces a number of stressors that undermine the viability of a multitude of highly populated regions across the United States (Hauer et al., 2016). While federal, state, and local governments support relocation from at risk areas, current programs do not have the scale to adequately address the full extent of these problems (Song & Shaw, 2017). Over the past three decades, the US Federal Emergency Management Agency (FEMA) has provided funding for nearly 44,000 properties (A. Weber & Moore, 2019), with the number of properties decreasing over time (Mach et al., 2019). This is an impressive volume of buyouts, but, considering the scale of the problem, most individuals and households are still left to manage retreat on their own.

There has been a growing interest in studying environmental migration (Black et al., 2011a; Fussell et al., 2014), specifically in the post-disaster context in the aftermath of natural hazards (Dewaard, Johnson, et al., 2020; Elliott et al., 2021; Fussell et al., 2017; L. Weber & Peek, 2012). However, barriers to analysis in these settings persist because of the unique stressors caused by hazard conditions, where the disruption of the event impedes the collection of individual and longitudinal data. Additionally, the limited predictability of disasters (Zhang et al., 2019), and the acceleration of post-disaster activities (Olshansky et al., 2012), compound problems of low resolution in traditional migration data sources, where coarse-scale data are infrequently collected at set intervals (Dewaard et al., 2019).

To address this gap, this paper uses a novel data source whose fine temporal scale, small units of observation, and broad geographic coverage may reduce or eliminate these problems. Specifically, we employ data acquired from TransUnion, Inc., one of the three major credit reporting agencies in the United States. Their role in society is to report scores on credit worthiness of average citizens (Fair Credit Reporting Act, 2018), derived from information provided to them by banks, finance companies, retailers, landlords, loan providers, public records and other sources (TransUnion, 2022). These data include residential addresses, and corresponding dates of residence, of all adults with credit records that have, at some point, lived in North Carolina. While TransUnion has sold their data products for years, this is – to our knowledge – the first application of their data to the study of migration.

Utilizing these data, this paper analyzes migration patterns as they are influenced by the geographic overlap of flood *vulnerability*, which we represent as residence within the 100-year floodplain[1], and *exposure*, which we measure by experienced hurricane-driven flood damage[2]. We examine migration outcomes in the aftermath of Hurricanes Matthew (2016) and Florence (2018), for a period of 18 months after each event, across the coastal plain of North Carolina (comprising the 41 counties in the eastern third of the state). Specifically, we use survival analyses to address the questions: (1) how do hurricane exposure and flood vulnerability differentially and synergistically affect individual patterns of out-migration? (2) Do post-disaster migration patterns lead to increased or decreased vulnerability (i.e., lower rates of residence in floodplains)? In this study, we use "out-migration" to signify migration away from a referenced point of origin and focus on the next new address as the destination.

Respective to our research questions, our hypotheses are that (1) exposure to disasters will increase rates of out-migration; and (2) that exposure to disasters will increase the likelihood that individuals will migrate to areas that are less vulnerable to floods. While this may seem intuitive, and is, in fact, theorized in the literature (Black et al., 2013; McLeman & Smit, 2006), it is not yet proven by the

[1]We acknowledge that floodplains are not perfect proxies for flood vulnerability, however this is the geographic boundary we use to demarcate floodplain vulnerability within this chapter. The reason for this decision is fully laid out in section 4.2

[2]We acknowledge that other forms of vulnerability exist, and that decreasing one's flood vulnerability does not mean that one's overall vulnerability has decreased (e.g., a person could move from an area of mild flood vulnerability to an area that is highly vulnerable to wildfires, increasing their overall vulnerability to hazards). However, this paper focuses on physical flood vulnerability.

literature (Fussell et al., 2017; Logan et al., 2016), which has traditionally been limited to analysis of post-disaster migration at the county-to-county scale (Dewaard, Johnson, et al., 2020), or for limited samples (Elliott et al., 2021).

We find that, among those individuals who migrate during our study period, those who were exposed to a hurricane, or who lived in vulnerable areas were more likely than counterfactual groups (i.e., those not in floodplains or exposed to hurricane-induced flooding) to migrate *into* new residences within floodplains. However, the co-location of both exposure and vulnerability is associated with more resilient migration patterns, where individuals, on average, were less likely than counterfactual groups to move into new residences in floodplains within our study area. Similarly, exposure to *both* Hurricane Matthew and Hurricane Florence was associated with more resilient migration. This suggests that compounding disasters are related to vulnerability reduction on the part of individuals. Through these patterns, around 57% of individuals migrating from floodplains move to upland areas within the study area; and more than 32% move outside the study area.

However, we also found that, despite these migration patterns, state-level vulnerability remained constant as migration into hurricane-affected areas and floodplains occurred at approximately the same rate as out-migration. This “vulnerability replacement” dynamic represents a missed opportunity on the part of governments and civil society organizations – either through incentives or regulatory intervention – to capitalize on the organic and voluntary post-hurricane process of flood vulnerability reduction, observed on the part of those moving out of floodplains.

2. Background

2.1 Flood Exposure and Protective Action

Flood exposure can act as a risk signaling event that leads to some individuals adopting flood risk mitigation measures. In response to flood exposure, some flood-prone residents will change their behavior to decrease their vulnerability. Actions may include preparing their homes shortly before major storms (Siegrist & Gutscher, 2008), reducing liability by purchasing insurance (Bubeck et al., 2012; Gallagher, 2014), or implementing structural changes to their homes (Kreibich et al., 2005; Siegrist & Gutscher, 2008), among other strategies. However, the effect of flood exposure on protective action is not consistent, and many individuals still do not take protective action. Additionally, residents show considerably more reluctance to engage in permanent and high-investment strategies than temporary and low-investment strategies (Siegrist & Gutscher, 2008).

However, as disasters tend to act as a risk signal (Siegrist & Gutscher, 2008), and some individuals are spurred to action in response to that increased awareness (Kreibich et al., 2011), it would be intuitive to assume that hurricanes and resulting floods would prompt shifts in coping appraisals, resulting in increased net out-migration from high risk areas. However, it is not clear that this is the consistent effect of major flood and storm events (Fussell et al., 2017). Rather, studies on domestic migration after disasters find different, and at times conflicting, outcomes for both short-term displacement behaviors (Black et al., 2013) and long-term migration outcomes (Pais & Elliott, 2008).

2.2 Exposure and Migration

The current literature shows that the impact of hurricanes on an area's population growth is variable and associated with county-level population factors. For example, Pais and Elliott (2008) and Schultz and Elliott (Schultz & Elliott, 2013) show that counties encountering "billion dollar" storms during the 1990s experienced higher population growth compared to similar, unaffected counties (counterfactual observations). Both studies contend that this behavior is a product of the influx of private and public resources made available during the disaster recovery processes, which unintentionally encourages growth and investment in at-risk areas. Building from this work, Howell and Elliott (2018) analyzed the relationship between post-disaster funding and socio-economic factors, and found that post-disaster recoveries can increase economic polarization and inequality (Howell & Elliott, 2018).

Additionally, Logan et al. (2016) studied county-level disasters and population dynamics, nationwide from 1970 to 2005, determining that, in general, population growth was suppressed for up to three years in low-poverty counties (but not in high-poverty counties) that experienced wind damage and/or storm surges. Fussell et al. (Fussell et al., 2017) also analyzed all U.S. counties that experienced hurricanes and/or tropical storms between 1980 and 2012, and found that impacts on population change within a three-year period varied based on the pre-storm population density and growth rate of the county. Specifically, with some caveats, they noted that hurricanes and tropical storms only depressed future population growth in the two percent of all counties that were *both* growing prior to the disaster and had high population densities.

Focusing on destinations, Eyer et al. (2018) used data on county-to-county migration flows, made publicly available by the IRS, to study migration preferences from New Orleans in the aftermath of Hurricane Katrina. They found that individuals preferred closer destinations to distant ones. Because the counties[3] surrounding Orleans Parish are also highly vulnerable to disasters, the authors concluded that post-disaster migration is not certain to reduce exposure and vulnerability. However, as landscapes can be highly variable within a county, whether individuals are vulnerable is dependent on geographies that are only visible at a sub-county level. This requires studies operating at a finer geographic scale.

[3]In Louisiana, counties are called parishes. With the exception of proper nouns, we use the term counties to represent both counties and parishes. New Orleans is a consolidated city-parish, termed as Orleans Parish when referenced as a parish.

2.3 The Case for Finer-Scale Analyses

The relationship between environmental conditions and migration varies depending on the scale of analysis (Hunter et al., 2015). Migration analyses that take place at a larger scale can obscure patterns that exist at smaller scales. To better understand how migration patterns are playing out at finer geographies, migration studies have had great success using carefully curated datasets that are resource intensive to produce. For example, post-disaster migration studies derived from surveys and interviews show that white, affluent individuals often have more choice in post-disaster migration. Using a stratified, area-based sample of pre-Katrina New Orleans households to collect 147 interviews, Sastry (2009) and Fussell et al. (2011) found that more affluent, white residents were able to return in greater numbers compared to less affluent, black residents. These findings elucidate trends noted in county-level studies. For example, Pais and Elliott's (2008) and Schultz and Elliott's (2013) studies on population increases in counties experiencing "billion dollar" storms during the 1990s also show that greater federal funding increased inequity. The studies from Sastry (2009) and Fussell et al. (2011) that show how white and affluent residents have more capacity to recover may help explain the process by which post-disaster areas become more segregated, as seen in the county-level studies.

To better connect broad geographic extent with fine temporal and analytic scales, post-disaster migration researchers have increasingly turned to non-traditional migration sources that are collected for other purposes. In a particularly applicable example, DeWaard et al. (2020) used individual-level data at quarterly time intervals acquired from the Federal Reserve Bank of New York and the Equifax Consumer Credit Panel to study post-disaster migration from Puerto Rico in the aftermath of Hurricane Maria (2017) With these data, they were able to look at out-migration trends at the US Census tract-level, a scale which allowed for the incorporation of geospatially specific data about storm surges.

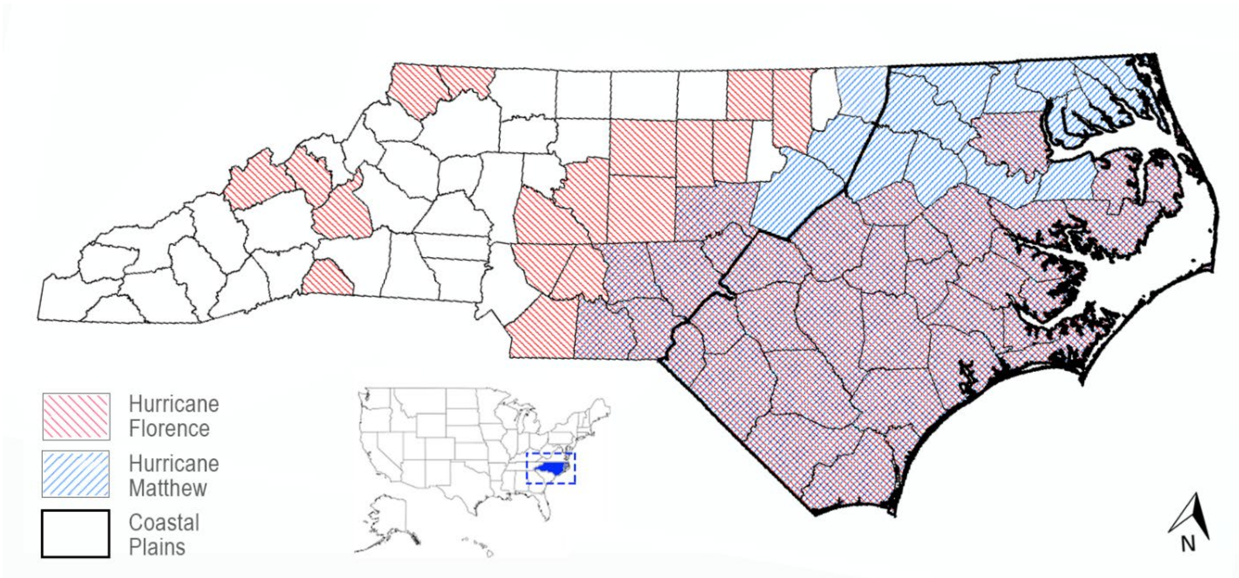
In this paper, we seek to go a step further to understand how individual residents affected by hurricanes manage their post-disaster housing and adaptation decisions through migration. Most importantly, our data source makes it possible to assess the specific geographic characteristics (i.e., hurricane exposure and flood vulnerability) at the household level for both migration origins and destinations, allowing for a fine-grained analysis of changing vulnerability for hundreds of thousands of individuals.

3. Study Area

The State of North Carolina (NC) is one of the most hurricane-prone states in the United States (Blake et al., 2005; North Carolina Climate Office, 2019). This vulnerability became particularly palpable in the past decade, which saw two of the deadliest and costliest hurricanes in the state's history strike within two years: Hurricane Matthew in October, 2016, and Hurricane Florence in September, 2018 (NCEM, 2022). The close spatial and temporal clustering of these storm events create a novel avenue for evaluating hurricane impacts on migratory patterns in areas of non-, single-, and repetitive-flood exposure.

Our analysis will focus on NC's coastal plain (Figure 1), a geographic area that can be roughly approximated as the 41 low-lying counties between the Atlantic Ocean and the geomorphic discontinuity that distinguishes the easily eroded sediments of the coastal plain from Piedmont's rocky foothills to the west (NCDPI, 2012; Negm et al., 2016). As reflected in its concentration of disaster declarations (Figure 1), the coastal plains bore the brunt of the hurricane damage for these two storms; all counties in the coastal plains received public assistance disaster declarations in the aftermath of Hurricane Matthew (FEMA, 2016), and an 28 additionally received public assistance disaster declarations in the aftermath of Hurricane Florence (FEMA, 2018).

__Figure 1:__ North Carolina coastal plain study area. Map shows counties with FEMA disaster declarations for public assistance for Hurricanes Matthew (2016) and Florence (2018). Data derived from FEMA disaster declarations (FEMA, 2016, 2018)*.*



4. Data

To analyze migration at the individual and/or household level, we collected datasets concerning individual-level address history (units of analysis), floodplains (vulnerability), hurricane-induced flood damage (exposure), and tract-level socio-economic variables (controls). Using these data, we flagged geocoded name-address pairs to indicate (a) whether they were exposed to Hurricane Matthew and/or Hurricane Florence; (b) whether they are in a floodplain; and (c) whether a move occurred within 18 months of the respective disaster event. For those who did move and remained within the study area, their next destination address was also flagged further flagged as to whether the new residence was (a) exposed to either storm and/or (b) in a floodplain.

4.1 Individual-Level Address Data

To our knowledge, this is the first-time data from TransUnion, Inc. has been used to study domestic migration, although other credit agency data from Equifax has been successfully used to study post-disaster migration on a quarterly basis (Dewaard, Johnson, et al., 2020). Transunion's TLOxp® (2022) data includes information for all individuals, with credit records, who have ever had an address in the State of North Carolina. The obtained data includes each individual's name, a person-specific identifying code, age, street addresses for all residences associated with the individual (including addresses from outside of the state), and dates for the first time they were observed at a given address, and the date that TransUnion received affirmative information that the individual had left an address, which could lag the actual date a person was last at an address considerably. Notably, as person-address pairs are not duplicated, returning to a previously lived at address does not generate new observations. This means that any individuals who move out of a floodplain into a previous residence (e.g., relocating to a family home) cannot be tracked with this data. However, we contend that this will only have a minor impact on our study: previous research undertaken in the aftermath of Hurricane Harvey (2017) shows that relatively few individuals (1.38%) were residing with "friends or family" three months after Hurricane Harvey (Rivera, 2020).

We created an extensive data cleaning and quality assurance process, detailed in the Supplemental Materials, which included removing data with errors and duplicated addresses, among other considerations. This process yielded a final dataset that includes 13,889,090 unique individuals, associated with between 1 and 20 addresses, representing a total of 76,751,394 person-address pairs (observations), with information up to June 2020. To justify its applicability to this research, we validated TransUnion's data through comparisons to more traditional sources of migration data. In our comparisons, TransUnion's county-to-county migration sums had Pearson's correlation coefficient of

0.97 (p<0.001) with the Internal Revenue Service's (IRS, 2010) county-to-county migration data. TransUnion's tract-level population counts had a Pearson's correlation coefficient of 0.88 (p<0.001) with tract-level population counts from the US Decennial Census (Manson et al., 2021; U.S. Census Bureau, 2010b). And, in a comparison to individual-level house sale data from Durham County, NC (Durham County, 2022), the TransUnion data successfully matched 74% of cleaned Durham County records on names and addresses, with closely aligned dates on over 80% of those matches.

We focus this study on the 18-month period after each storm. The literature suggests that this time frame is adequate for our purposes. For example, using a variety of non-traditional data sources, Acosta et al. (Acosta et al., 2020) showed that, in the aftermath of Hurricane Maria, migration from Puerto Rico to the mainland was accelerated for a period of four to six months, and then stabilized. Looking at return migration, Fussell et al. (2011) analyzed survey responses from individuals displaced from New Orleans in the aftermath of Hurricane Katrina. They showed that a quarter of their study population had returned by the two-months after the storm, half by seven months, and then return rates declined dramatically for the remaining fourteen months of the study. These analyses suggest that an 18-month post-hurricane period would capture the bulk of the migration linked to disaster exposure.

4.3 Exposure to Hurricane-Indued Flooding

Considering the aforementioned problems with how floodplain maps approximate vulnerability, large gaps exist between what we predict will become inundated (floodplain maps) and what specific, real-world storms *actually* inundate. Mapping *actual* flood inundation is a fraught process that has spawned dozens of models and algorithms designed to estimate historic and projected flood extents (Afshari et al., 2018; Merwade et al., 2008; Shen et al., 2019), which have varying ranges of accuracy (see, for example: Chen et al., 2021), and whose validation remains difficult.

For our analysis, we used inundation maps produced by North Carolina Department of Emergency Management (NCDEM, 2020), which have been used in a prior analysis of community flood vulnerability and risk assessment by Wang and Sebastian (2021). These maps had full spatial coverage of eastern North Carolina and were created through a uniform process for both storms, making the results for each storm more directly comparable. Specifically, storm surges were estimated using the Sea Lake and Overland Surges from Hurricanes (SLOSH) model provided by the National Oceanic and Atmospheric Administration (NOAA, 2022b), and fluvial and pluvial flooding were estimated using the Rapid Inundation Flood Tool (RIFT) from the Pacific Northwest National Laboratory (GeoPlatform, 2019).

Due to the inherent uncertainty in inundation mapping, we validated our results by using the NCDEM maps in conjunction with another set of inundation maps developed by Schafer-Smith et al. (2020). More details on our selection of the NCDEM map for this analysis and the relationship between the NCDEM (2020) maps and the Schafer-Smith et al. (2020) maps are in the Supplemental Materials. This includes additional robustness checks for the central analysis using the NCDEM maps in conjuncture with the Schafer-Smith maps.

4.4 Socio-Economic Controls

Numerous socio-economic variables have been found to influence post-disaster migration patterns and population change (Fussell et al., 2011; Sastry, 2009). To further contextualize migration patterns, and to control for the relative conditions at the residents' points of origin, we rely on tract-level socio-economic data from the U.S. Census' American Community Survey's 5-year sample for 2011-2015 (U.S. Census Bureau, 2010a). To measure population growth, we additionally use information from the U.S. Census' American Community Survey's 5-year sample for 2006-2010 (U.S. Census Bureau, 2010a). Specifically, we draw on per-capita income and employment rates, economic factors that were shown to influence post-disaster population growth in Logan et al. (2016). We also draw on population changes (between 2006-2010 and 2011-2015 data) and population density, as these factors were shown to be influential in Fussell et al. (Fussell et al., 2017). Finally, we controlled for the proportion of renter-occupied households, a factor that we were concerned could introduce additional noise as individuals who own but do not live in properties would still be linked to those properties in the TransUnion dataset (refer to the Supplemental Materials for further discussion). While these socioeconomic factors were not the focus of our analyses, they were important controls that allowed us to focus on the roles of hurricane exposure and flood vulnerability, the factors of interest central to this paper.

5. Methods

Our analysis was designed to address two specific research questions: (1) how do hurricane exposure and flood vulnerability differentially and synergistically affect individual patterns of out-migration? (2) Do post-disaster migration patterns lead to increased or decreased vulnerability? Because these questions imply a time-to-event framework, we employ a series of survival analyses.

Survival analyses are statistical models that were popularized in medical and ecological studies, where they are still commonly used. Traditionally, survival analyses are used (A) to measure the percent of individuals who live for given periods after a treatment, (B) to measure the longevity of different subsets of individuals who received different treatments, or (C) to compare *efficacy*, or the bifurcation of longevity between control groups (who receive a placebo) and treatment groups (Clark et al., 2003; Jenkins, 2005). Survival analyses are typically right censored, for those participants who did not experience the event, which in medical studies is often death, prior to the end of the study period

(Kishore et al., 2010). For the subset of total individuals (n) experiencing death (n_d) the survival probability (p) is estimated at any particular time (t) as:

$$p_t = \frac{n - n_d}{n}$$

Survival analyses are also common in the migration literature, including in studies of migration in the aftermath of hazard events (e.g., Fussell et al., 2011). In these studies, survival analyses are often reconceptualized with the hazard as the treatment, and migration as the event (instead of death). In the period between a hurricane (treatment) and eventual migration (event), individuals are in a state of being "at risk" of migrating (Fussell et al., 2014). The main advantage provided by survival models is that they allow for censoring cases where no migration occurs by the end of the study period (which, in our case, is 18-months after each hurricane), as survival analyses consider the analytical unit (the individual) through units of continuous time, or the period of "risk exposure" (Yamaguchi, 1991).

Our analyses consider (1) whether an individual moved, and (2) the characteristics of the location of their next address. For this, we employ three types of survival analyses, all implemented in the R statistical software (R 4.1.2; R Core Team, 2022). First, we use a Kaplan-Meier plot (Clark et al., 2003; Kaplan & Meier, 1958) to estimate the probability of survival in a given length of time. These plots allow us to visually compare "survival" curves (or "non-migration" curves) for different subjects, grouped by their exposure to each hurricane and disaggregated by their vulnerability (i.e., residence inside vs. outside of a floodplain).

Second, we use a Cox proportional-hazards regression model, which makes it possible to control for the impact of multiple covariates (i.e., socio-economic conditions, exposure, and vulnerability) on survival (Bradburn et al., 2003; Cox, 1972). Our results from the Cox proportional-hazards regression are provided as hazard ratios. The hazard ratio (HR) can be interpreted – similarly to odds ratio effects of logistic regressions – as the effect size of the exponentiated single unit of a covariate (i.e., e^{1*b}) on the outcome variable (Bradburn et al., 2003; Clark et al., 2003). Together, these two analyses allow us to address our first research question by indicating how exposure and vulnerability influence the likelihood of migration.

Our third, and final, analysis is designed to better address our second question by investigating likelihood of movement into a new residence within a floodplain, based on each individual's starting position (within or outside of floodplains) and their hurricane exposure. Individuals are considered to experience the event in question if they move and their next address is in a floodplain within our study period. Because individuals can also move outside of floodplains, we have a condition with competing risks. That is to say, these individuals moving to an upland residence or outside of the study area neither "survived" (e.g., did not migrate), nor did they experience the event (migration to a floodplain residence).

To address this, we use a cause-specific hazard regression model fit with a Cox proportional-hazards regression (Kalbfleisch & Prentice, 2011). This differs from the Cox proportional-hazards model we described previously because it only considers moves to residences within floodplains as experiencing the event, while individuals who move to upland locations (or beyond the study area), are censored at the time of migration as they are no longer at risk for "failure" (i.e., moving into the floodplain as their next residence from their pre-hurricane residence). This model has been shown to reflect the influence of the covariates on the specified event (Dignam et al., 2012). While bias may be introduced through dependencies between failure outcomes (e.g., unobserved dependence may exist between migrating to floodplains, which is isolated as a condition of interest, and migrating upland, which is censored), in reviews of this method using simulated data, the biases were shown to be minor compared to other competing hazard models (Allison, 2018).

Another model that addresses competing risks is the Fine-Gray model (Fine & Gray, 1999). This calculates the relative magnitude of change associated with a one-unit increase in a given covariate on the sub-distribution of competing risk (Austin & Fine, 2017). It is one of the most popular methods for survival regression analyses involving competing risks (Allison, 2018), however, there are considerable limitations. Interpretation can be un-intuitive (Austin & Fine, 2017), estimating absolute probability of competing events can violate fundamental assumptions of probability (Austin et al., 2021), and it is not appropriate for causal inference (Allison, 2018). However, as it has recently become the de facto "…standard method for analyzing competing risks" (Allison, 2018, p. n.p.), and to answer recent calls to include both models for completeness (Latouche et al., 2013), we included results from a Fine-Gray model in the Supplemental Materials.

6. Results

6.1 Descriptive Analysis

In Table 1, we see that, within flooded areas (i.e., areas exposed to hurricanes), the proportion of the population that moved was greater compared to non-flooded areas, regardless if residents lived in floodplains or upland areas, although individuals in upland areas moved more often than those in floodplains. In the aftermath of Hurricane Matthew, 11.01% of the inundated floodplain population moved within 18 months, compared with 9.93% of non-flooded floodplain population ($p<0.001$; proportional z-test). Similarly, 14.42% of the flooded upland population moved, compared to just 11.34% of the non-flooded upland residents moved in this period ($p<0.001$). Likewise, in the aftermath of Hurricane Florence, 8.03% of the inundated floodplain population moved within the study period, which was higher when compared with 7.57% of non-flooded floodplain population ($p<0.05$). Similarly, 8.81% of the flooded upland population moved, compared to 8.25% of the non-flooded upland residents ($p<0.001$).

There are a few more key details shown in Table 1. Comparing upland to floodplain population groups, we can see that the upland population had a greater percent of their population move during the study period. However, residents who originated in floodplains also moved at fairly high rates. After Hurricane Matthew, 10.81% of the original floodplain population moved within an 18-month period, and 7.98% in the aftermath of Hurricane Florence. Additionally, in the aftermath of Hurricane Matthew, roughly half of moves from individuals who originated in the floodplains remained within their origin county (intra-county moves), which holds true for Hurricane Florence as well. These moves would have been unobserved in analyses relying purely on inter-county migration data.

Table 1: *Study area population migration summary. Table shows proportion of the study area population that moved to a novel address within 18 months of Hurricanes Matthew (2016) and Florence (2018), categorized by their vulnerability (residence in floodplain) and exposure*

	Floodplain			Upland		
	Flooded	Non-Flooded	Sub-total	Flooded	Non-Flooded	Sub-total
Hurricane Matthew						
Initial population	118,415	27,156	145,571	9,461	2,328,313	2,337,774
Total moves	13,041	2,697	15,738	1,364	264,008	265,372
% of initial population	11.01%	9.93%	10.81%	14.42%	11.34%	11.35%
Intra-county moves	6,568	1,141	7,709	778	125,852	126,630
% of total moves	50.36%	42.31%	48.98%	57.04%	47.67%	47.72%
Hurricane Florence						
Initial population	129,685	16,515	146,200	56,341	2,322,093	2,378,434
Total moves	10,419	1,250	11,669	4,964	191,621	196,585
% of initial population	8.03%	7.57%	7.98%	8.81%	8.25%	8.27%
Intra-county moves	4,949	680	5,629	2,379	89,661	92,040

% of total moves	47.50%	54.40%	48.24%	47.93%	46.79%	46.82%

Next, we looked at how individuals moved between different areas as categorized by vulnerability and exposure within the 18-month period after Hurricanes Matthew (Figure 2) and Florence (Figure 3). With these figures, we narrow our focus to look at a pattern of vulnerability replacement. For this purpose, these figures only include individuals who originated in the floodplain at the time of the respective storm or who moved into the floodplain within the 18-month period of the study. More details on patterns of movement between other areas (e.g., upland to upland moves) are included in the Supplemental Materials.

The main feature of Figure 2 and Figure 3 is that they graphically show how gross populations within the floodplains are largely retained in the aftermath of Hurricanes Matthew and Florence. While 14,182 individuals moved out of the floodplains in eastern North Carolina within 18 months of Hurricane Matthew, and 10,529 did the same after Hurricane Florence, they were largely replaced. After Hurricane Matthew, 13,395 individuals moved into these same floodplains from either upland areas in eastern North Carolina or from outside of the study area (an additional 1,556 individuals moved from one floodplain residence to another), and 9,157 individuals did the same after Hurricane Florence (an additional 1,140 individuals moved from one floodplain residence to another).

These shifts work to retain populations within the floodplains: at the time of Hurricane Matthew, we identified 145,571 individuals in the floodplains, 18 months later, the number of individuals in the floodplain had dropped by less than 1,000 residents to 144,784. By the time Hurricane Florence hit, that number had grown and, we identified 146,200 individuals in the floodplains, which was reduced to 144,828 at the end of the study period even though more than 10,000 people moved away from these highly vulnerable residences after each event. Notably, these estimates do not include return migration, which likely increases the total number of individuals in the floodplain at the end of the study period.

Figure 2: *Sankey diagram of post-Hurricane Matthew floodplain moves*

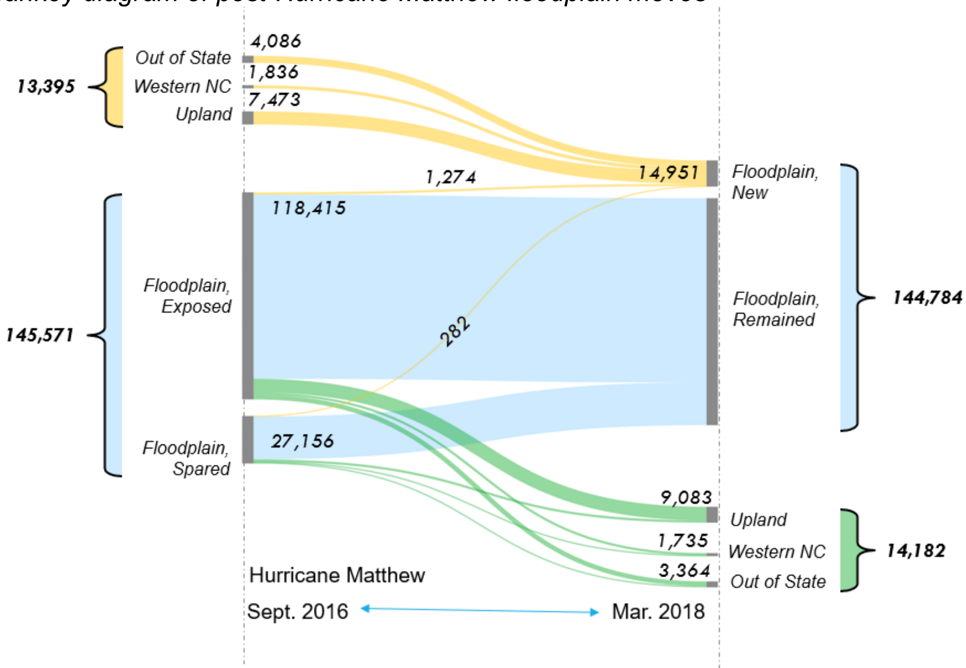
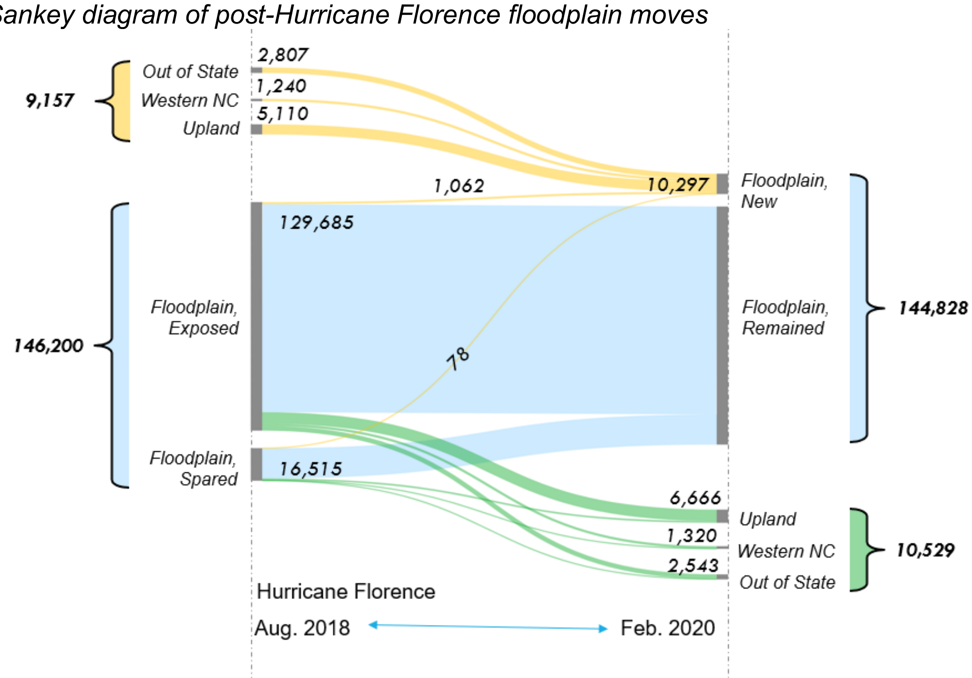


Figure 3: *Sankey diagram of post-Hurricane Florence floodplain moves*

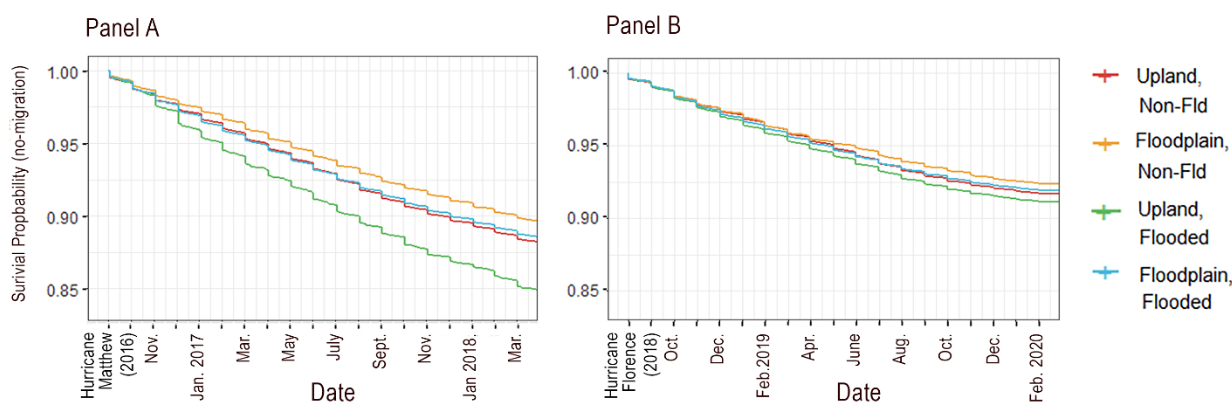


6.2 Likelihood of Out-Migration

Our survival analyses employed the '*survival*' R package (Therneau et al., 2022) to produce Kaplan-Meier plots, comparing four different groups disaggregating hurricane exposure and floodplain vulnerability.

As Figure 4 shows, upland areas that were flooded had lower survival probabilities (i.e., individuals in these areas were more likely to migrate) compared to upland areas that were not; similarly, individuals residing in floodplains that experienced hurricane-related floods also had lower survival probabilities than those in floodplains who were not flooded. These patterns hold true for both storms, although the differences between categories is larger in the aftermath of Hurricane Matthew (Panel A), compared to the survival probabilities estimated in the aftermath of Hurricane Florence (Panel B). A post-estimation log-rank test (Clark et al., 2003) confirms that the survival rates for the different groups have statistically significant differences (p <0.001).

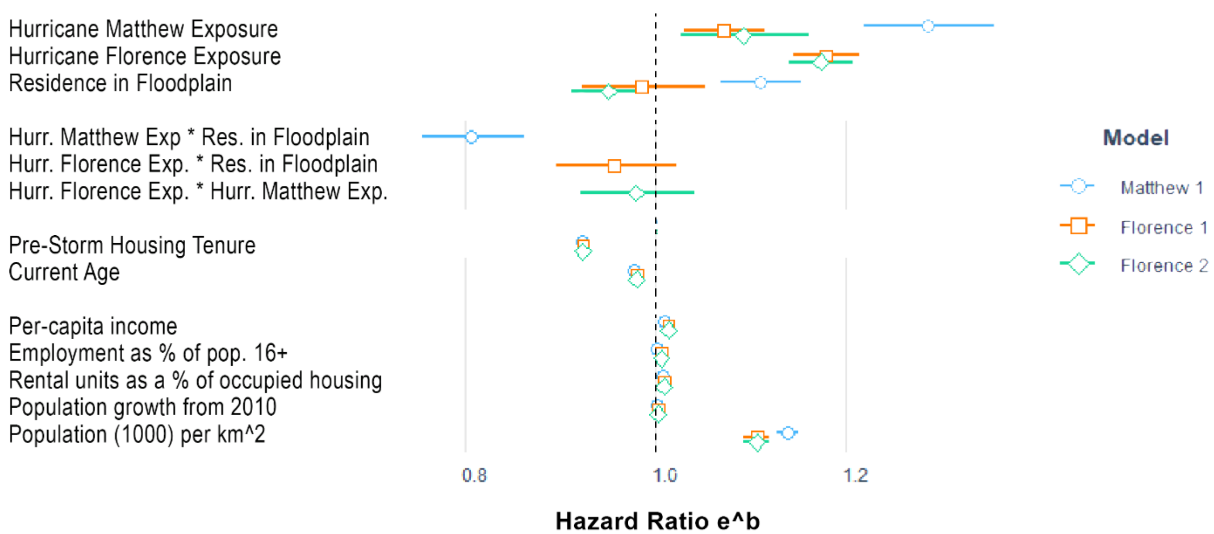
Figure 4 *Kaplan-Meier plots estimating the risks of experiencing migration. Survival curves are shown for a period of 18 months following (Panel A) Hurricane Matthew (2016) and (Panel B) Hurricane Florence (2018)*



In our second analysis, we interrogated these trends further using a series of Cox proportional-hazards regression to create three models (see Table 2 and Figure 5). The first model, Matthew 1, is indexed to Hurricane Matthew and includes an interaction between exposure to Hurricane Matthew and floodplain vulnerability; the following two, are indexed to Hurricane Florence and show interaction terms between exposure to Hurricane Matthew and floodplain vulnerability (Florence 1), and between exposure to

Hurricane Matthew and Hurricane Florence. Additional model testing is included in the Supplemental Materials. The goodness of fit is analyzed using a c-index statistic representing the probability that the observed and predicted survival times are concordant, with a value of 0.743 – 0.746 (Harrell et al., 2005; Therneau & Atkinson, 2022).

Figure 5: *Exponentiated coefficient plots. Plot shows effects on hazard ratios with error bars for three Cox proportional-hazards regressions detailed in Table 2*



Across these regression models, hurricane exposure has significant effects on out-migration in the direct aftermath of the disaster, although those effects were greater for Hurricane Matthew than for Hurricane Florence. Exposure to Hurricane Matthew increased an individual's risk of moving by 28.7% (HR=1.287; p<0.01), and exposure to Hurricane Florence increased an individuals risk of moving by 17.6% - 18.0% (HR=1.175 – 1.180; p<0.01) compared to those not innundated by each hurricane, respectively. The effects of residence in a floodplain were inconsistent between the two hurricanes; they were significantly associated with an 11% increase (HR=1.110, p<0.01) in the risk of moving in the aftermath of Hurricane Matthew. However, after Hurricane Florence, residents in floodplains had a slightly decreased likelihood (4.9%; HR =0.951; p<0.1) of moving, an effect that was only detectable in the wake of controlling for flood exposure to both hurricanes (an effect that, itself, had no significant relationship with move probability).

Interestingly, in the aftermath of Hurricane Matthew, residents of floodplains that also experienced flooding were actually 19% less likely to move (HR=0.806; p<0.01). This verifies a pattern observed in Panel A of Figure 4, which showed that individuals who were both in the floodplain and innundated by Hurricane Matthew had higher moving risks (i.e., lower “survival probabilities”) than those who were in the floodplain but not innundated, but lower moving risks than those who experienced flooding in upland areas. The interaction between flood exposure from Hurricane Florence and residence in the floodplain, as well as for exposure from both Hurricane Florence and Hurricane Matthew, did not have singificant impacts on the risk of migration.

Additionally, we controlled for other variables that were associated with changes in post-disaster migration patterns in other studies (Fussell et al., 2017; Logan et al., 2014). Per-capita income, employment, renter population, and recent population change (2010 – 2015) and density were all significantly (but mostly weakly, given their measurement units) associated (p<0.01) with a higher probability of moves after both storms. Population density, however, was more strongly correlated with higher move likelihood (HR=1.107-1.140; p<0.01).

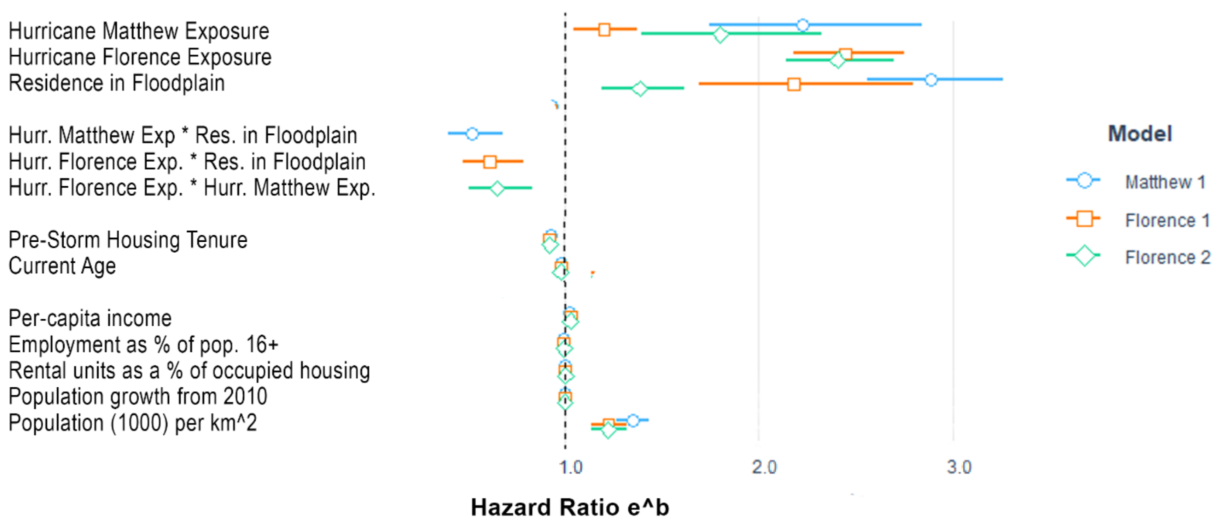
Table 2: *Cox proportional-hazards model of migration risk. Effects on hazard ratios (e^b) reported with 95% standard errors in parentheses; *p < 0.1, **p < 0.05, ***p < 0.01.*

		Matthew 1	Florence 1	Florence 2
Exposure and Vulnerability	Hurricane Matthew Exposure(binary)	1.287 ***	1.072 ***	1.093 **
		[1.220-1.357]	[1.031-1.115]	[1.027-1.163]
	Hurricane Florence Exposure (binary)	-	1.180 ***	1.175 ***
		-	[1.147-1.215]	[1.142-1.209]
	Residence in Floodplain (binary)	1.110 ***	0.985	0.951 *
		[1.068-1.153]	[0.923-1.052]	[0.912-0.991]
Exposure / Vulnerability Interactions	Hurricane Matthew Exposure * Residence in Floodplain	0.806 ***	-	-
		[0.754-0.863]	-	-
	Hurricane Florence Exposure * Residence in Floodplain	-	0.957	-
		-	[0.896-1.022]	-
	Hurricane Florence exposure * Hurricane Matthew exposure	-	-	0.979
		-	-	[0.921-1.042]
Individual Factors	Pre-Storm Housing Tenure (Years)	0.923 ***	0.924 ***	0.924 ***
		[0.922-0.924]	[0.923-0.924]	[0.923-0.924]
	Current Age (in 2020; years)	0.977 ***	0.981 ***	0.981 ***
		[0.977-0.978]	[0.980-0.981]	[0.980-0.981]
Census Tract Demographics	Per-capita Income (annual USD $100s)	1.010 ***	1.014 ***	1.014 ***
		[1.009-1.010]	[1.013-1.014]	[1.013-1.014]
	Employment as a % of population aged 16+	1.002 ***	1.007 ***	1.007 ***
		[1.002-1.003]	[1.006-1.007]	[1.006-1.007]
	Rental units as a % of total occupied housing units	1.008 ***	1.009 ***	1.009 ***
		[1.008-1.009]	[1.009-1.010]	[1.009-1.010]
	Population growth from 2010	1.001 ***	1.003 ***	1.003 ***
		[1.001-1.002]	[1.003-1.003]	[1.003-1.003]
	Population (1000) per km^2	1.140 ***	1.107 ***	1.107 ***
		[1.128-1.152]	[1.094-1.121]	[1.094-1.121]
Model Details	Observations	2,482,803	2,524,162	2,524,162
	Events	281,028	208,213	208,213
	C-Index	0.746	0.743	0.743
	Likelihood Ratio Test	219,866.40	158,819.10	158,817.80

6.3 Likelihood of Out-Migration to Floodplains

Our final analysis uses a Cox proportional-hazards regression fit with a cause-specific hazard approach (Dignam et al., 2012; Kalbfleisch & Prentice, 2011) to explore which individuals were moving into floodplains in our study area (Figure 6 and Table 3). We again use three models that mirror the analysis in the prior regression example. As in the previous set of regression models, additional models, and robustness checks for a number of conditions are available in the Supplemental Materials. Our c-index gives an indicator of model fit with a value of 0.747-0.760 (Harrell et al., 2005; Therneau & Atkinson, 2022).

Figure 6: *Exponentiated coefficient plots (effects on hazard ratios with error bars) for three Cox proportional-hazards cause-specific regressions detailed in Table 3*



The models in this section reveal that both hurricanes had consistent positive effects on resident migration into floodplains (a finding consistent across the three models). Individuals exposed to inundation by Hurricane Matthew had, on average, a 122.6% (HR = 2.226; p<0.01) increase in their risk of moving into a floodplain in the direct aftermath of the storm, compared to those who did not experience flooding. This effect continued in the aftermath of Hurricane Florence: those who had experienced flooding during Hurricane Matthew experienced an increased risk between 19.8% (HR = 1.198; p<0.05) and 80.0% (HR=1.800; p<0.01) of moving into a floodplain. Similarly, exposure to flooding from Hurricane Florence increased the risk of migrating to a floodplain by 140.5% (HR=2.405; p<0.01) to 144.8% (HR=2.448; p<0.01).

Starting in a floodplain also increased the risk of migrating into a floodplain; after Hurricanes Matthew and Florence, those residing in floodplains experienced 188.9% (HR=2.889; p<0.01) and 38.4-117.8% (HR=1.384-2.178; p<0.01) increases in their risk of moving into a floodplain, respectively. However, the co-location (interaction) of vulnerability and exposure reversed this effect; those who experienced flooding from Hurricane Matthew within a floodplain were 48.5% less likely (HR=0.515; p<0.01) to migrate into a floodplain, and those who experienced flooding from Hurricane Florence within a floodplain were 35.4%-39.5% (HR=0646-0.605; p<0.01) to move to a floodplain. The same holds true for those experiencing flooding during both Hurricanes Matthew and Florence, who had a 35.4% lower risk (HR=0.646; p<0.01) of moving into a floodplain.

Like our previous regression models, we controlled for US Census tract-level socio-economic variables that have been shown to influence post-disaster migration in previous studies. As before, nearly all of these variables had relatively small effects on the likelihood of movement into floodplains, with effects that ranged from a 1.4% decrease in the hazard ratio, to a 2.7% increase in the hazard ratio. The exception is the variable for population per km^2, which increased the hazard ratio by 22.1%-34.7% (HR=1.221-1.347; p<0.01), which is a similar trend to our previous set of models.

Table 3: *Cox proportional-hazards fit to a cause-specific hazard regression model of "risk" of migration into floodplains. Effects on hazard ratios (e^b) reported with 95% standard errors in parentheses; *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.*

		Matthew 1	Florence 1	Florence 2
Exposure and Vulnerability	Hurricane Matthew	2.226 ***	1.198 **	1.800 ***
	Exposure(binary)	[1.743-2.842]	[1.046-1.374]	[1.394-2.324]
	Hurricane Florence Exposure	-	2.448 ***	2.405 ***
	(binary)	-	[2.180-2.749]	[2.144-2.698]
	Residence in Floodplain (binary)	2.889 ***	2.178 ***	1.384 ***
		[2.561-3.260]	[1.694-2.800]	[1.188-1.613]
Exposure / Vulnerability Interactions	Hurricane Matthew Exposure *	0.515 ***	-	-
	Residence in Floodplain	[0.391-0.678]	-	-
	Hurricane Florence Exposure *	-	0.605 ***	-
	Residence in Floodplain	-	[0.469-0.782]	-
	Hurricane Florence exposure *	-	-	0.646 ***
	Hurricane Matthew exposure	-	-	[0.503-0.829]
Individual Factors	Pre-Storm Housing Tenure	0.927 ***	0.922 ***	0.922 ***
	(Years)	[0.923-0.930]	[0.918-0.926]	[0.918-0.926]
	Current Age (in 2020; years)	0.980 ***	0.981 ***	0.981 ***
		[0.979-0.981]	[0.980-0.983]	[0.980-0.983]
Census Tract Demographics	Per-capita Income (annual USD	1.023 ***	1.027 ***	1.027 ***
	$100s)	[1.021-1.026]	[1.024-1.030]	[1.024-1.030]
	Employment as a % of	0.986 ***	0.990 ***	0.989 ***
	population aged 16+	[0.984-0.988]	[0.987-0.992]	[0.987-0.992]
	Rental units as a % of total	0.998 *	1.000	1.000
	occupied housing units	[0.996-1.000]	[0.997-1.002]	[0.997-1.002]
	Population growth from 2010	0.995 ***	0.997 ***	0.997 ***
		[0.994-0.997]	[0.995-0.998]	[0.995-0.998]
	Population (1000) per km^2	1.347 ***	1.222 ***	1.221 ***
		[1.266-1.433]	[1.132-1.319]	[1.131-1.318]
Model Details	Observations	2,482,803	2,524,162	2,524,162
	Events	9,293	6,425	6,425
	C-Index	0.747	0.760	0.760
	Likelihood Ratio Test	7482.07	6101.14	6098.48

7. Discussion

7.1 Vulnerability Replacement Dynamics

Our first research question asked: how do hurricane exposure and flood vulnerability differentially and synergistically affect individual patterns of out-migration? And our hypothesis was that we would see increased rates of out-migration in areas exposed to flooding. Our results suggest several clear patterns: first, Hurricanes Matthew and Florence have had a relatively consistent, but mild, impact on the propensity for study area residents to move, generally (Table 2). This makes intuitive sense; disasters at the scale of Hurricanes Matthew or Florence will effectively force migration (Black et al., 2011b). This finding also aligns with the literature on disasters as risk signals that can trigger adaptive behavior (Kreibich et al., 2011; Siegrist & Gutscher, 2008). Comparatively, residence within the floodplain has a minor and inconsistent impact on gross out-migration patterns (Table 3). This may indicate a selection bias, where individuals who self-select into floodplains are more resistant to the risk signals that the floodplains represent (Dynes, 1993).

When we narrow our focus to migration specifically into floodplains (Table 3), additional patterns emerge. Our results show that individuals who are in residences within floodplains or who are exposed to hurricanes at the start of our analysis have a greater risk of moving into new residences in floodplains compared to individuals who reside in upland areas or who spared from hurricane exposure, respectively. This does not align with our hypothesis, where we posited that individuals exposed to disasters would move in more resilient patterns. We have two theories on why this may be the case. The first theory is that this pattern shows a consistent prioritization of a set of preferences; individuals who live in flood prone areas may do so because of the amenities they provide (e.g., close to waterways or the ocean). This preference may inform subsequent moves. Our second theory is that living in the floodplain creates a biased set of nearby available properties. If individuals wish to remain in close proximity to their communities from the start of the study period, then those who live in floodplains, or who were flooded during the recent hurricanes, are likely to be closer to a greater number of floodplain properties, increasing their likelihood of moving into one with a short-distance post-disaster move. Future qualitative work could help shed light as to the reasons that individuals give when moving to flood-vulnerable properties.

However, there are two important caveats to the finding regarding the proclivity of vulnerable individuals to relocate within vulnerable areas. First, these patterns are reversed with compounding conditions of vulnerability and exposure. Individuals who had their vulnerability realized (e.g., individuals who lived in floodplains and were exposed to either Hurricane Matthew or Hurricane Florence) were less likely to migrate to new floodplain residences compared to others. Similarly, if individuals were exposed to both Hurricane Florence and Hurricane Matthew, then their risk of migrating to floodplain properties decreases. As individuals who were exposed to hurricanes have greater rates of migration than individuals who were spared from flooding (Table 1), our findings suggest that the co-location of vulnerability and exposure results in more resilient migration overall. Our interpretation of these patterns is that, in the absence of compounding factors of vulnerability and exposure, individuals may view their vulnerability as tolerable, or view the hazard as an aberration. However, when these factors coincide, the risk signal becomes strong enough to prompt individuals to employ vulnerability reduction using migration as adaptation.

Our second caveat notes that even if individuals who reside in floodplains are more likely than individuals in upland areas to move into floodplain residences, they make up a minority of individuals who move into the floodplains in the aggregate. Floodplains make up a relatively small portion of area within the state; at the time of both Hurricane Matthew and Hurricane Florence, within our study area, there were over 145,000 residents within the floodplain, compared to over 2 million residents in upland areas (Table 1). Therefore, even with comparable rates of migration across vulnerable and non-vulnerable groups, the quantities are notably different. Because there were close to 200,000 more upland movers in each study period, more upland residents moved into floodplains than floodplain residents, even though they were individually less likely to do so. This creates a pattern of vulnerability replacement (see Figure 2 and Figure 3).

The patterns of who moves into floodplains provides an answer to our second question: do post-disaster migration patterns lead to increased or decreased vulnerability? Individuals in floodplains are at a high risk of replicating their vulnerability through migration (Table 3), however, the majority of floodplain movers leave floodplains in eastern North Carolina (Figure 2 and Figure 3). We believe that this represents an overall pattern of decreased individual vulnerability through adaptive migration, however, it remains possible that these individuals are simply moving to vulnerable locations further away (e.g., to coastal Florida), and more work is needed to further evaluate whether destination for long-distance movers vary by the vulnerability and exposure of their origins. This pattern is enhanced with the colocation of exposure and vulnerability or the colocation of multiple exposures. However, individuals who leave floodplains are largely replaced by new in-migration. Therefore, while individuals are often able to decrease their vulnerability, the overall state of vulnerability remains constant within our study area. This finding is a function of our data revealing patterns that are not always visible at the scale of traditional county-to-county migration analyses (e.g., see disaggregation in Table 1).

7.2 Relationship to Prior Scholarship

As noted in the literature section, current post-disaster migration scholarship primarily relies on county-to-county datasets. The result of studies relying on these data have shown that population growth at the county level was suppressed in only limited circumstances, with Logan et al. (2016) showing that growth was suppressed for up to three years in low-poverty counties, and Fussell et al. (Fussell et al., 2017) finding that county-level growth was only surprised in counties that were both growing prior to disasters and that had high population densities. Our findings, where we see population churn in the floodplains but not population loss, does not dispute this prior work. What we add is greater nuance on how many people leave even as the overall population remains fairly constant. This helps to align post-disaster migration studies that have not found wide-spread settlement abandonment, with theories that posit that this is, in fact, what we *should* find.

Specifically, work by Black, McLemen, and their colleagues have theorized that global environmental change related to climate change will lead to major changes to population settlement patterns. McLeman (2017) has theorized that we should see thresholds where environmental degradation would reach progressive tipping points shifting out-migration from a linear to exponential pattern. Black et al. (2013) theorized that major disaster events would lead to three outcomes: migration, displacement, and immobility. In this framework, the authors assumed that those with the ability to move would do so as conditions deteriorated, largely leaving behind a 'trapped' population of the most vulnerable individuals least able to move to safer ground. These theories are reflected in future migration models. Hauer (Hauer, 2017; Hauer et al., 2016) projects that millions of Americans living along the coasts could be displaced by the end of the century.

This analysis bridges the differences in the prior work, which on one hand shows limited changes to population growth in areas subjected to extreme events (Fussell et al., 2017; Logan et al., 2016), and on the other hand theorizes that we should see population loss in these same places (Black et al., 2011b; McLeman, 2017). What we show is that there is population loss, but that loss is rapidly replaced with new in-migration. Further work is planned to better analyze who is moving into these vulnerable areas, to better understand the forces encouraging replication of vulnerabilities.

7.3 Caveats and Limitations

There are two main caveats to our findings, which each indicate areas where further research is necessary: First, our data and findings do not consider return migration or the duration that individuals stay in their post-migration residences. As a result, it is likely that a percentage of the individuals exposed to Hurricanes Matthew or Florence relocated temporarily, and then returned to their original residences when they were able to do so. This suggests that the population who continue to be vulnerable within floodplains is larger than shown. To further understand how return migration factors into replicated pre-existing vulnerability, more research on return migration to floodplains in conjuncture with new in-migration to floodplains is necessary. That said, our focus is on the destination outcomes considering the next address after a storm. Even if further patterns beyond the scope of this study shows a greater number of individuals returning to vulnerable positions, the fact that they move from vulnerable areas at any point creates an opportunity to capitalize on that vulnerability reduction and extend it into a permanent condition.

Second, our analysis does not consider prior patterns of migration. This means that our analysis is limited in its ability to consider the effect of endogenous conditions specific to floodplains or upland areas. That is to say, it is possible that some of the patterns we see in our analysis are not driven by the treatment of hurricane exposure but are instead reflective of pre-existing migration patterns. Future work is needed to compare pre- and post-disaster migration patterns in floodplain and upland areas to better understand if pre-existing patterns continue irrespective to the hurricanes, if the hurricanes accelerate pre-existing patterns, or if they interrupt pre-existing patterns, leading to the generation of new migration networks. Currently, we have plans to expand this study to address this question. However, we argue that the fact that we see different patterns emerge in the aftermath of compounding disasters compared to conditions where individuals are exposed to only one disaster, and, similarly, that we see different patterns within floodplains dependent on whether or not the individuals were exposed to either storm suggest that we are picking up on a causal mechanism as driven by experienced flooding.

8. Conclusion

This study has aimed to complement existing literature on post-disaster migration, which has largely drawn on either county-level data on migration flows, or high-resolution data with small population samples. We have engaged with a novel migration dataset, set in a large-scale study area, that tracks individual level population movements. Compared to county-level migration studies (Fussell et al., 2017), our approach can identify individuals residing within, or outside of floodplains, and offer perspectives on intra-county population movements, which makes up nearly half (47.8% after Hurricane Matthew, and 46.9% after Hurricane Florence) of the moves tracked in this study. Contrasting recent studies that draw on small samples of high-resolution data across temporal and geographic scales (e.g., Graif, 2016), our analysis includes millions of individuals migrating over three years, facilitating a broad assessment of the roles of flood vulnerability, disaster exposure, and socio-economic factors. Additionally, our study also complements recent, exciting studies (Acosta et al., 2020; Dewaard et al., 2019) that also rely on non-traditional data sets to study post-disaster migration, through our relatively novel effort to analyze the effects of temporally-clustered, repeated storm events.

Our analysis shows that floodplains, like upland areas, are the source of considerable, post-disaster migration. However, while individuals who originated in floodplains often mitigate their individual or household vulnerability through out-migration, the lack of controls to limit new in-migration retains larger patterns of vulnerability. Hurricanes, and associated flooding, can accelerate migration, maximizing opportunities for intervention. However, these patterns of churn within the floodplains are ongoing in floodplains spared from exposure from Hurricanes Matthew and Florence, suggesting interventions at other times would be successful as well.

As climate change continues to impact flooding frequencies and magnitudes, it will become increasingly essential to reverse our national trend of increased flood vulnerability (Hauer et al., 2016; Wing et al., 2018). The patterns of migratory replacement into floodplains that we observe suggest (1) that policy changes – at the local, state, and federal levels –are necessary for disincentivizing (or preventing) movement of new migrants into floodplains; (2) that such policies should capitalize on observed patterns of post-disaster population migration away from floodplains; and (3) that, while disaster events are not necessary to operationalize out-migration support, policy changes should consider how such events may accelerate a de-growth process.

However, it is not easy to determine how such a policy shift should take shape. Simply restricting floodplain in-migration would inevitably (and inequitably) erase the considerable value that has been amassed and locked up in the floodplain housing market. This would create perverse effects, limiting current residents' ability to out-migrate, and impact the national housing market (Bakkensen & Barrage, 2021). Additionally, such a federal-scale proposal would have little local and state-level support, as it would directly reduce the tax base of affected jurisdictions.

However, policy inaction does remedy the continuing reality that a significant portion of the country's housing stock is within flood-prone areas, and this stock – and its associated financial and public safety liabilities – continues to grow year after year (Wing et al., 2018). Certain programs show promise and should be explored further. For example, floodplain buyouts with rentbacks, where properties could be purchased in anticipation of hazard exposure and eventual relocation, could ease the relocation transition to upland areas (Keeler et al., 2022). Likewise, transfer of development rights, a tool that has been used historically to achieve land preservation in historical or environmentally important areas, could help shift value out of the floodplains in exchange for additional development rights on a less vulnerable parcel (ULI, 2017). These, and other policy solutions, need further analysis in the context of interrupting the patterns of vulnerability replacement.

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Supplemental Materials

S1. Cleaning and Validating Address Data

The TLOxp® data acquired from TransUnion (2022) include information on all adult individuals who have had a residential address in North Carolina (within their 20 last addresses). For each individual, the data contains a unique identification key, their full names, age, phone number, up to 20 of their most recent addresses, and the first and last time seen at each address. New individuals are included in the data as they develop credit histories and are dropped from the sample if TransUnion receives information that they are deceased. The raw dataset included 116,851,482 person-address observations, with 15,530,926 unique individuals.

TransUnion's data has a few known limitations regarding the sample population. First, credit data is not recorded for individuals under the age of 18; as such, our data does not include any information on minors. Additionally, it does not pick up on young adults until they develop credit information, for example, through background checks for employment opportunities or rental properties, or by opening a credit card. Therefore, there is a lag in the introduction of young adults into the data set. As a result, we expect young adults to be underrepresented and older adults to be overrepresented. In a comparative analysis of quarterly panel data based on credit information acquired through the Federal Reserve Bank of New York to information from the American Community Survey (ACS), Lee and van der Klaauw (2010) found that those under the age of 25 were underrepresented, and those over 85 were over represented.

Second, the data is more robust for those with regular interactions within the formal economy. In a different comparative analysis of quarterly credit information from Equifax acquired through the Federal Reserve Bank of New York to information from the ACS, Wardrip and Hunt (2013) suggest that there may be more noise or loss of data in low-income neighborhoods compared to high-income neighborhoods.

In terms of its application to migration studies, there are additional limitations. First, individuals who own multiple properties will be associated with all of them from the initial time of association. That is to say, if Person 1 owns and lives in Property A, and then buys and rents out Property B, they will be associated with Property A at the time of purchase, and Property B at the time of purchase as well. This introduces a degree of noise into the data that tracks with changes in the number of renter-occupied households. Second, person-address pair is a unique observation within the dataset with a single date entry. This makes it impossible to track migration to a house that a person had previously lived in. This would occur in instances of return migration, or, for example, an individual relocated to a parent's home in the aftermath of a disaster event which they had already been associated with. While this would greatly limit a study on return migration, the impact on this study focused on out-migration from and in-migration to the floodplains is smaller. Related to the possibility that individuals will temporarily relocate to houses they had already had a history in, we believe the impact will be minor: a recent study by Rivera (2020) using survey data of a random sample of 798 participants in south-eastern Texas, found that three months after Hurricane Harvey, only 1.38% were living with "friends or family". The impact of this missing data on final estimations for floodplain repopulation are covered in further detail in the discussion section.

These limitations make the TransUnion data much like other forms of non-traditional data. There is a tradeoff between the specificity of the data (individual level observation, and daily information for new associations with addresses), the relative ease of acquisition, and the amount of noise that is introduced. The following subsections will detail our cleaning efforts and will attempt to quantify where these data are robust, and where there are limitations through a series of comparative analyses.

Prior to using the TransUnion data, we interrogated the dataset and removed person-address pairings that were suspect, using the following steps:

1. Standardization: We standardized the addresses using the US Postal Service's National Change of Address Database (NCOA), through a contracted provider, Accuzip, Inc. (USPS, 2021)
2. Removing bad dates: Entries were flagged and dropped if the recorded date first seen is prior to the birth of the individual (approximated to the year based on age values). This dropped 3,576,157 person-address observations (3.1% of observations). Based on conversations with TransUnion representatives, it appears this happens with data entry errors (by those giving the credit bureau data) and may represent missing data.
3. Removing bad durations: Entries were flagged and dropped if the duration between TransUnion's first seen and last seen fields were less than 1 day. This dropped an additional 21,975,183 person-address observations (19.3% of remaining observations). Based on conversation with TransUnion representatives, it appears this happens when an address is misattributed to an individual and is simply excess noise in the data.
4. Removing PO boxes: person-address pairs where the address was a PO box were dropped. This dropped an additional 8,297,814 entries (9.1% of remaining observations).
5. Removing duplicate addresses: If we presumed that addresses were duplicates created by data entry errors, we removed them from the data set. This dropped an additional 6,970,934 person-address observations (8.3% of the remaining observations). We identified addresses as duplicates if:
    a. They were subsequent chronological observations from an individual which were fuzzy matched as replicated addresses, represented by a Levenshtein distance of 10% or less. A

Levenshtein distance is calculated by the number of deletions, insertions, and substitutions separating one character string from another. The threshold is calculated as the distance as a percentage of the pattern length rounded to the nearest whole number. E.g., if we have a person moving from “123 Adams St” to “123 Adam St”, the string distance is one (deletion of *s*) for a pattern length of 12, and the second observation would be dropped. However, “123 Jackson St” to “123 Jackie St” has a string distance of 3 (two substitutions and one deletion) for a string length of 14 and would be retained. We confirmed this threshold as acceptable by reviewing 100 entries selected for deletion through this process and found the assumptions to be reasonable.

b. Or if subsequent addresses for the same individual that were the same except for a unit or apartment number (which were not consistently provided). E.g., if we had a person moving from “123 Adams St, unit J” to “123 Adams St”, the second observation was dropped.

In summation, the number of person-address observations were reduced from 116,851,482 observations (raw data) to 76,751,394 observations (dropping 34.3% of observations), with a parallel reduction in unique person IDs from 15,530,926 to 13,889,090 unique person ID’s (dropping 10.6% of unique individuals). This changes the mean number of moves from 11.5 to 8.1, and removes the far-right skew for number of addresses seen in Figure S.1 and Table S.1:

Figure S1: *Number of addresses per individual Panel A shows the frequency of different address counts by individual for the raw data; Panel B shows the same information for the cleaned data.*

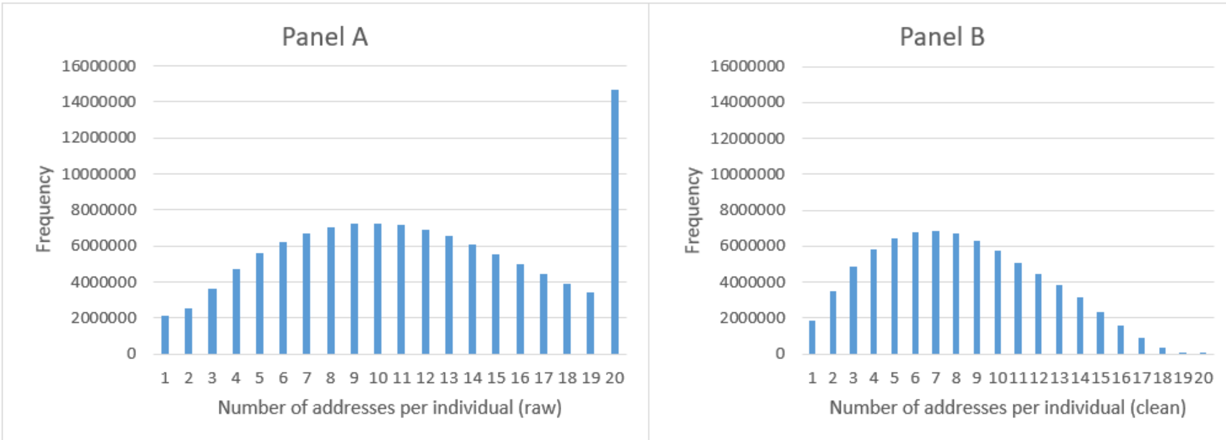


__Table S1:__ Number of addresses per person in TransUnion dataset

	Number of Moves per Person				
Addresses	**1**	**2**	**3**	**4**	**5**
Raw data	2,102,885	2,545,192	3,610,728	4,699,916	5,601,420
Cleaned	1,860,697	3,491,988	4,869,957	5,825,664	6,458,570
Addresses	**6**	**7**	**8**	**9**	**10**
Raw data	6,254,544	6,710,102	7,021,248	7,218,747	7,271,370
Cleaned	6,782,130	6,863,311	6,683,496	6,291,936	5,732,550
Addresses	**11**	**12**	**13**	**14**	**15**
Raw data	7,185,288	6,928,956	6,567,002	6,102,992	5,571,840
Cleaned	5,100,513	4,477,344	3,825,627	3,138,268	2,371,050
Addresses	**16**	**17**	**18**	**19**	**20**
Raw data	5,013,488	4,450,957	3,907,728	3,399,879	14,687,200
Cleaned	1,596,880	880,651	376,290	107,692	16,780

Following the cleaning process, we performed two tasks to enhance the data: geocoding and identifying the next address. First, we geocoded all of the addresses using a standalone address database covering the United States using ArcMap Desktop: Release 10.5 (ESRI, 2022a). The cleaned dataset described above had 24,100,259 unique addresses, including 4,871,294 in the state of North Carolina. Of these, over 99% (n = 24,077,983) were successfully geocoded, and 80% (n = 19,478,008) had a "PointAddress" match, defined as “a street address based on points that represent house and building locations” (ESRI, 2022b). Other matches were less precise, and identified the address to the specific street, or parcel, for example. In our analyses, we ran robustness checks where we subset the data to include only the addresses with PointAddress matches and found no meaningful differences in regression outcomes (see Figures S.5 through S.8).

With the addresses located, we identified the migration path for individuals. The TransUnion data has both dates first seen at addresses and dates last seen. Through discussions with TransUnion representatives, we came to understand that the date last seen lags the last time a person was at an address, oftentimes by considerable margins. This is because TransUnion waits for positive information that a person has left a residence (e.g., a lack of further association with the property is not sufficient for TransUnion to record a data last seen). Therefore, we sorted the date first seen variable chronologically, and used this to approximate if, and when, a person moved.

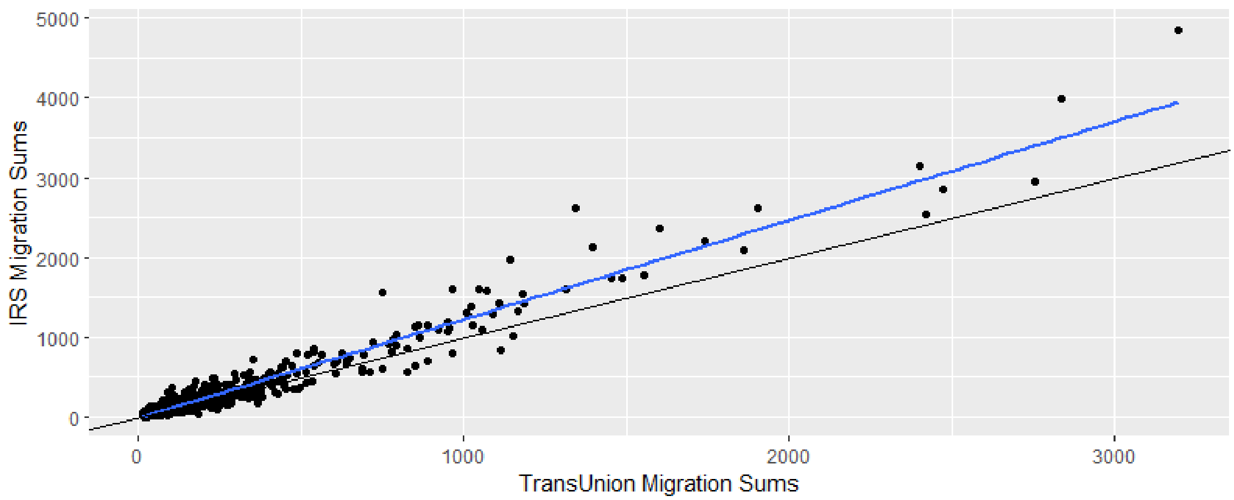
After cleaning the data and understanding the limitations that we expect from it, we wanted to confirm that the migration patterns we were approximating were reflective of other, more traditional, sources of migration data. We did this across three scales: the county-, tract-, and household-level. For county-level comparisons, we compared the TransUnion to IRS migration data (IRS, 2010), which have been used in previous post-disaster migration studies such as Curtis et al. (2019) and Eyer et al. (2018). For tract-level comparisons, we used population counts from the decennial census (Manson et al., 2021; U.S. Census Bureau, 2010b), which have been used in previous post-disaster migration studies such as Logan et al. (2016). And, for individual-level comparisons we used property data from Durham County, NC (Durham County, 2022); similar property data have been used in post-disaster migration studies such as Elliott et al. (2021) and Loughran et al. (2019).

For the county-level comparison, we aggregated TransUnion's migration patterns to create county-county migration flows for given years. This was compared to county-county migration data made publicly available through the IRS (2010). We used 2010 data because the IRS changed the process that they use to prepare county-county migration estimates in 2011 (Pierce, 2015), and concerns have been raised about the consistency of the data from that point onward (Dewaard, Hauer, et al., 2020).

To prepare the TransUnion data for this analysis, we aggregated new address changes in 2010 by origin and destination counties, within North Carolina, so that each county-county pair had a summary of migration counts moving between them. Any county-to-county pair with sums below 10 were dropped from the dataset to mirror the process used by the IRS (2010). We used a Pearson's correlation test (Artusi et al., 2002) to measure the relationship between the two variables, which had a coefficient estimate of 0.973 ($p<0.001$).

We also looked at this relationship graphically (Figure S.2, using scatter plots with logged scales on the x and y axes to visually understand the relationship between the TransUnion and IRS county-count migration sums. The graph shows that the TransUnion data tracks well with the IRS data, although, TransUnion underestimated migration in counties with greater migration sums. However, overall, we feel that this demonstrates that the TransUnion migration data is approximating real-world movement in line with more established sources of migration data.

Figure S.2: *Scatter plot of county-county migration sums for TransUnion and IRS migration data using logged scales*



For tract level comparisons, we took TransUnion population estimates in 2010 and compared them to population and age data from the decennial census (U.S. Census Bureau, 2010b). We used 2010 data to better align with the county-to-county comparisons above. To prepare the TransUnion data for this analysis, we subset the data relevant to the 2010 decennial census. This was done by selecting all cases where the date first seen was prior to 04/01/2010, and the date next seen was after 03/31/2010 (census day for 2010 was April 1, U.S. Census Bureau, 2021). These selected observations were aggregated into population counts for their respective census tracts, bifurcated by age using 10-year intervals. We used a Pearson's correlation test (Artusi et al., 2002) to measure the relationship between the two datasets, which had a coefficient estimate of 0.880 ($p<0.001$).

We also looked at this relationship graphically (Figure S.3), using scatter plots with logged scales on the x and y axes to visually understand the relationship between the TransUnion and census population sum. TransUnion underestimates the population for those aged 20-29; this aligns with our assumptions about the data because we know that it can take some time before individuals develop a credit history and engage with the economy in a manner that would be picked up by TransUnion (e.g., getting credit cards, taking out mortgages, etc.). After this age group, the TransUnion tracks the census data accurately from ages 30-59, which makes up the bulk of the population. After age 60, TransUnion begins to overestimate the population compared to the census data, although the data still tracks well until the population is in the 90s, after which, the overestimation becomes more dramatic. This also aligns with what we would expect from the data: it is probable that deceased individuals are more likely to remain in the TransUnion dataset for a period after their passing, while they would never be included in a census count.

Figure S.3: *TransUnion and 2010 Decennial Census comparison by age*

Based on what these analyses tells us about the relationship between age and the quality of the data, we ran robustness checks on our analyses that dropped observations outside of the 30-79 population range and found no noticeable differences in our results.

For household level comparisons, we used Durham County's property database (Durham County, 2022), which includes the real estate billing files for the entire county. This dataset includes information, property addresses, and date sold for 121,194 properties. Like the TransUnion data, addresses were standardized using the US Postal Service's National Change of Address Database (NCOA), through a contracted provider, Accuzip, Inc. (USPS, 2021). Our intent was to match names and dates between the TransUnion data and the data provided by Durham County, NC. To clean the Durham County data for comparison, we took the following steps per Table S.2:

Table S.2 *Durham County property cleaning process*

Step		Count	Percent of Total
-	Initial properties	121,194	100.00%
1	Dropped non-residential properties and vacant lots	94,018	77.58%
2	Dropped properties without purchase date	62,927	51.92%
3	Dropped presumed rental properties based on owner name	56,697	46.78%
4	Dropped properties with purchase date after June 26, 2020	50,670	41.81%

We were able to find 49,191 of the relevant Durham County addresses within the TransUnion data (97%). Durham County has only one field for the full owners' names (compared to TransUnion, which has separate fields for first, middle, and last names). We used a process which matched the data between the data sets if the first and last name from TransUnion were found within the owners' name field in the Durham County data. Using this process, we were able to match 36,391 (74%) of the Durham County addresses, with 1,833 matching to two names in the TransUnion data (for example, this occurred when both a husband and wife were listed as owners within the Durham County dataset).

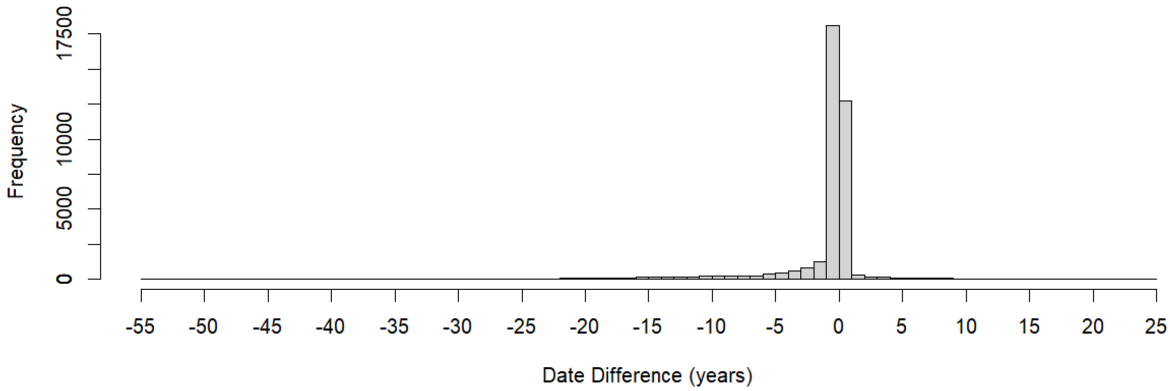
Next, we compared the date first seen from the TransUnion data with the purchase date in the Durham County data. Of the 38,224 address-name matches, 30,885 had dates within one year of each other (81%), and the majority were within one month: per Appendix Table 3.3, the first quintile for the date difference (in years) is -0.07, and the third quintile is 0.04, meaning that half the matched data has date differences between -25 and 13 days. This is also represented graphically in Figure S.4.

Table S.3: *Summary data for Durham County validation check*

Date First Seen (TU) – Purchase Date (Durham) in Years					
Min.	1st Quintile	Median	Mean	3rd Quintile	Max.
-50.38	-0.07	0.00	-1.10	0.04	21.91

There are multiple reasons why the date first seen from TransUnion and the Durham County purchase date may be far apart: individuals may inherit a house that they had lived at prior to gaining ownership, common names may have made incorrect matches, or there may be error in the data (either on the Durham County side, or in the TransUnion data). However, we feel that the results of this validation check and the prior ones demonstrate the TransUnion data is firmly based in real world conditions and reflects reasonably accurate dates and locations.

Figure S.4: *Histogram for Durham County validation check*


Frequency
0
5000
10000
17500
-55
-50
-45
-40
-35
-30
-25
-20
-15
-10
-5
0
5
10
15
20
25
Date Difference (years)

S2. Comparing Hurricane Inundation Maps

For our analysis, we tried to source flood inundation maps for both Hurricane Florence and Matthew that met two requirements: 1) the maps were established in the literature for understanding vulnerability and 2) they were created through a uniform process for both storms, so that the results for each storm are more directly comparable. We found two sets of maps that met these requirements: the maps produced by NCDEM (2020) and the maps developed by Danica Schaffer-Smith (2020).

The NCDEM maps estimated storm surges using the Sea Lake and Overland Surges from Hurricanes (SLOSH) model provided by the National Oceanic and Atmospheric Administration (NOAA, 2022b), and fluvial and pluvial flooding were estimated using the Rapid Inundation Flood Tool (RIFT) from the Pacific Northwest National Laboratory (GeoPlatform, 2019). The maps produced by Shaffer-Smith (2020) were developed using a supervised random forest classification model to delineate flooded and non-flooded areas. Their model incorporated pre- and post- storm synthetic aperture radar imagery from the European Space Agency's Sentinel-1 satellite with a 10-meter resolution and state-wide geomorphological features; and trained the model NOAA's high-resolution aerial photos (NOAA, 2022a), and high-water marks recorded by the United States Geological Survey (USGS, 2022) and NCDEM. As reported in their study detailing the development and use of this data (Schaffer-Smith et al., 2020).

As these maps were generated through different processes, they produced different estimates of flood inundation. To provide a robustness check, we compared these maps to flood insurance claims (FEMA, 2020) from the National Flood Insurance Program (NFIP), provided by FEMA. According to the model analysis (see Table S.4 and Table S.5), NCDEM better predicts the NFIP claims, and is therefore used for the analyses presented in the main portion of this article. However, for robustness checks, we performed additional regressions using information derived from both the NCDEM and TNC maps. These robustness check analyses are included in section S4 and show limited differences from the original model used in the main body of the chapter.

To gain better insight into the accuracy of the flood extent maps, we compared the counts of exposed properties to the counts of NFIP claims data,[4] which is publicly available through FEMA's website (FEMA, 2020), and contains information on claims paid in response to flood losses. There are two issues with using this data. First, the data is redacted to remove personally identifiable information. As a result, the dataset only provides latitude and longitudinal values accurate to 1 decimal place. This provides an approximate rather than a precise location. To manage that reality, we summarized counts of NFIP claims from the year of the respective disaster by census tract, as well as the counts of exposed properties according to both the NCDEM and TNC maps. Second, the NFIP has notoriously low market penetration (Dixon et al., 2006). However, successful NFIP claims still depend on flood damage as a prerequisite. Therefore, it holds that there should be a relationship between accurate flood extent modeling and NFIP claims. For this reason, NFIP claims have been used as a validation tool for other flood maps (Chen et al., 2021).

We ran three models for each storm using Poisson regressions, see Table S.4 (Hurricane Matthew) and Table S.5 (Hurricane Florence). In Model 1, we analyzed counts of NFIP claims as a function of flooded properties identified through NCDEM; in Model 2 this process was repeated with the Schaffer-Smith model; in Model 3, counts from both maps were used to compare fits. Based on the regressions shown

[4]FEMA and the Federal Government cannot vouch for the data or analyses derived from these data after the data have been retrieved from the Agency's website(s) and/or Data.gov.

in, the NCDEM inundation map had a stronger relationship with the NFIP claims, and a better fit, for both storms.

Table S.4: *Hurricane Matthew: Poisson regression for NFIP claims as a function of flooded properties by census tract as a function of flooded properties (in the 100s) per the NCDEM and TNC flood extent maps. Effects on odds ratios reported (e^b), with 95% standard errors shown in parentheses; statistical signficance represented as *p < 0.1, **p < 0.05, ***p < 0.01.*

	Model 1	Model 2	Model 3
NCDEM (100)	0.114***	-	0.114***
	(0.00)	-	(0.00)
Schaffer-Smith (100)	-	0.057***	0.0003
	-	(0.00)	(0.00)
Constant	1.528***	1.760***	1.528***
	-0.016	-0.015	-0.017
N	789	789	789
AIC	16,272.14	19,219.84	16,274.11

Table S.5: *Hurricane Florence: Poisson regression for NFIP claims as a function of flooded properties by census tract as a function of flooded properties (in the 100s) per the NCDEM and TNC flood extent maps. Effects on odds ratios reported (e^b), with 95% standard errors shown in parentheses; statistical signficance represented as *p < 0.1, **p < 0.05, ***p < 0.01.*

	Model 1	Model 2	Model 3
NCDEM (100)	0.129***	-	0.121***
	(0.00)	-	(0.00)
Schaffer-Smith (100)	-	0.084***	0.020***
	-	(0.00)	(0.00)
Constant	1.891***	2.354***	1.868***
	-0.012	-0.01	-0.012
N	988	988	988
AIC	26,893.14	46,214.74	26,559.08

S3. Supplementary Analyses

Table S.6: *Post-Hurricane Matthew destinations (18mo). This table shows the population of eastern North Carolina who moved within 18 months of Hurricane Matthew, and how these movements changed an individual's vulnerability, with respect to recent hurricane exposure*

			Hurricane Matthew: Next Move (censored at 18 months)								
			Floodplain			Upland			Outside E.NC		
			Flooded	Non-Flooded	Total	Flooded	Non-Flooded	Total	Western NC	Out of State	Total
At Matthew	Floodplain	Flooded	1,120	154	1,274	73	7,686	7,759	1,318	2,690	4,008
		Non-Flooded	166	116	282	0	1,324	1,324	417	674	1,091
		Total	1,286	270	1,556	73	9,010	9,083	1,735	3,364	5,099
	Upland	Flooded	59	4	63	62	873	935	90	276	366
		Non-Flooded	6,076	1,334	7,410	598	164,647	165,245	27,661	63,692	91,353
		Total	6,135	1,338	7,473	660	165,520	166,180	27,751	63,968	91,719
	Out Eastern NC	Western NC	1,359	477	1,836	39	26,475	26,514			
		Out of State	3,158	928	4,086	248	71,180	71,428			
		Total	4,517	1,405	5,922	287	97,655	97,942			
		Total	11,938	3,013	14,951	1,020	272,185	273,205	29,486	67,332	96,818

Table S.7: *Post-Hurricane Florence destinations (18mo). This table shows the population of eastern North Carolina who moved within 18 months of Hurricane Florence, and how these movements changed an individual's vulnerability, with respect to recent hurricane exposure*

			Hurricane Florence: Next Move (censored at 18 months)								
		-	Floodplain			Upland			Outside E.NC		
			Flooded	Non-Flooded	Total	Flooded	Non-Flooded	Total	Western NC	Out of State	Total
At Florence	Floodplain	Flooded	1,025	37	1,062	380	5,411	5,791	1,205	2,361	3,566
		Non-Flooded	31	47	78	8	867	875	115	182	297
		Total	1,056	84	1,140	388	6,278	6,666	1,320	2,543	3,863

Upland	Flooded	300	13	313	324	2,644	2,968	457	1,226	1,683
	Non-Flooded	4,100	697	4,797	2,181	116,510	118,691	20,362	47,771	68,133
	Total	4,400	710	5,110	2,505	119,154	121,659	20,819	48,997	69,816
Out Eastern NC	Western NC	1,151	89	1,240	478	19,707	20,185			
	Out of State	2,649	158	2,807	1,289	53,489	54,778			
	Total	3,800	247	4,047	1,767	73,196	74,963			
	Total	9,256	1,041	10,297	4,660	198,628	203,288	22,139	51,540	73,679

Table S.8: *Expanded Cox proportional-hazards model (Hurricane Matthew) for "risk" of migration.*

*Coefficients reported as Hazards Ratios. 95% standard errors in parentheses; *p < 0.1, **p < 0.05, ***p < 0.01. Refer to Table 2*

		Matthew 0	Matthew 1
Exposure and Vulnerability	Hurr. Matthew Exposure(binary)	1.124 ***	1.287 ***
		[1.086-1.163]	[1.220-1.357]
	Hurr. Florence Exposure (binary)	-	-
		-	-
	Residence in Floodplain (binary)	1.038 *	1.110 ***
		[1.004-1.073]	[1.068-1.153]
Exposure / Vulnerability Interactions	Hurr. Matthew Exposure * Residence in Floodplain	-	0.806 ***
		-	[0.754-0.863]
	Hurr. Florence Exposure * Residence in Floodplain	-	-
		-	-
	Hurr. Florence exposure * Hurr. Matthew exposure	-	-
		-	-
Individual Factors	Pre-Storm Housing Tenure (Years)	0.923 ***	0.923 ***
		[0.922-0.924]	[0.922-0.924]
	Current Age (in 2020; years)	0.977 ***	0.977 ***
		[0.977-0.978]	[0.977-0.978]
Census Tract Demographics	Per-capita Income (annual USD $100s)	1.010 ***	1.010 ***
		[1.009-1.010]	[1.009-1.010]
	Employment as a % of population aged 16+	1.002 ***	1.002 ***
		[1.002-1.003]	[1.002-1.003]
	Rental units as a % of total occupied housing units	1.008 ***	1.008 ***
		[1.008-1.009]	[1.008-1.009]
	Population growth from 2010	1.001 ***	1.001 ***
		[1.001-1.002]	[1.001-1.002]
	Population (1000) per km2	1.139 ***	1.140 ***
		[1.127-1.151]	[1.128-1.152]
Model Details	Observations	2,482,803	2,482,803
	Events	281,028	281,028
	C-Index	0.746	0.746
	Likelihood Ratio Test	219,828.60	219,866.40

Table S.9: *Expanded Cox proportional-hazards model (Hurricane Florence) for "risk" of migration.*

*Coefficients reported as Hazards Ratios. 95% standard errors in parentheses; *p < 0.1, **p < 0.05, ***p < 0.01. Refer to Table 2*

		Florence 0	**Florence 1**	**Florence 2**	**Florence 3**
Exposure and Vulnerability	Hurr. Matthew Exposure(binary)	1.075 ***	1.072 ***	1.093 **	1.040
		[1.034-1.118]	[1.031-1.115]	[1.027-1.163]	[0.943-1.146]
	Hurr. Florence Exposure (binary)	1.170 ***	1.180 ***	1.175 ***	1.179 ***
		[1.140-1.201]	[1.147-1.215]	[1.142-1.209]	[1.146-1.214]
	Residence in Floodplain (binary)	0.952 *	0.985	0.951 *	1.013
		[0.914-0.992]	[0.923-1.052]	[0.912-0.991]	[0.914-1.123]
Exposure / Vulnerability Interactions	Hurr. Matthew Exposure * Residence in Floodplain	-	-	-	-
		-	-	-	-
	Hurr. Florence Exposure * Residence in Floodplain	-	0.957	-	0.927
		-	[0.896-1.022]	-	[0.829-1.038]
	Hurr. Florence exposure * Hurr. Matthew exposure	-	-	0.979	1.038
		-	-	[0.921-1.042]	[0.933-1.154]
Individual Factors	Pre-Storm Housing Tenure (Years)	0.924 ***	0.924 ***	0.924 ***	0.924 ***
		[0.923-0.924]	[0.923-0.924]	[0.923-0.924]	[0.923-0.924]
	Current Age (in 2020; years)	0.981 ***	0.981 ***	0.981 ***	0.981 ***
		[0.980-0.981]	[0.980-0.981]	[0.980-0.981]	[0.980-0.981]
Census Tract Demographics	Per-capita Income (annual USD $100s)	1.014 ***	1.014 ***	1.014 ***	1.014 ***
		[1.013-1.014]	[1.013-1.014]	[1.013-1.014]	[1.013-1.015]
	Employment as a % of population aged 16+	1.007 ***	1.007 ***	1.007 ***	1.007 ***
		[1.006-1.007]	[1.006-1.007]	[1.006-1.007]	[1.006-1.007]
	Rental units as a % of total occupied housing units	1.009 ***	1.009 ***	1.009 ***	1.009 ***
		[1.009-1.010]	[1.009-1.010]	[1.009-1.010]	[1.009-1.010]
	Population growth from 2010	1.003 ***	1.003 ***	1.003 ***	1.003 ***
		[1.003-1.003]	[1.003-1.003]	[1.003-1.003]	[1.003-1.003]
	Population (1000) per km2	1.107 ***	1.107 ***	1.107 ***	1.107 ***
		[1.094-1.121]	[1.094-1.121]	[1.094-1.121]	[1.094-1.121]
Model Details	Observations	2,524,162	2,524,162	2,524,162	2,524,162
	Events	208,213	208,213	208,213	208,213
	C-Index	0.743	0.743	0.743	0.743
	Likelihood Ratio Test	158,817.40	158,819.10	158,817.80	158,819.60

Table S.10: *Expanded cause-specific Cox proportional-hazards model (Hurricane Matthew) for "risk" of migration to floodplains. Coefficients reported as Hazards Ratios. 95% standard errors in parentheses; *p < 0.1, **p < 0.05, ***p < 0.01. Refer to Table 3*

		Matthew 0	**Matthew 1**
Exposure and Vulnerability	Hurr. Matthew	1.292 ***	2.226 ***
	Exposure(binary)	[1.142-1.463]	[1.743-2.842]
	Hurr. Florence Exposure	-	-
	(binary)	-	-
	Residence in Floodplain	2.603 ***	2.889 ***
	(binary)	[2.314-2.929]	[2.561-3.260]
Exposure / Vulnerability Interactions	Hurr. Matthew Exposure *	-	0.515 ***
	Residence in Floodplain	-	[0.391-0.678]
	Hurr. Florence Exposure *	-	-
	Residence in Floodplain	-	-
	Hurr. Florence exposure *	-	-
	Hurr. Matthew exposure	-	-
Individual Factors	Pre-Storm Housing Tenure	0.927 ***	0.927 ***
	(Years)	[0.923-0.930]	[0.923-0.930]
	Current Age (in 2020; years)	0.980 ***	0.980 ***
		[0.979-0.981]	[0.979-0.981]
Census Tract Demographics	Per-capita Income (annual	1.024 ***	1.023 ***
	USD $100s)	[1.021-1.026]	[1.021-1.026]
	Employment as a % of	0.986 ***	0.986 ***
	population aged 16+	[0.984-0.988]	[0.984-0.988]
	Rental units as a % of total	0.998 *	0.998 *
	occupied housing units	[0.996-1.000]	[0.996-1.000]
	Population growth from 2010	0.995 ***	0.995 ***
		[0.994-0.997]	[0.994-0.997]
	Population (1000) per km2	1.345 ***	1.347 ***
		[1.265-1.432]	[1.266-1.433]
Model Details	Observations	2,482,803	2,482,803
	Events	9,293	9,293
	C-Index	0.747	0.747
	Likelihood Ratio Test	7466.59	7482.07

Table S.11: *Expanded cause-specific Cox proportional-hazards model (Hurricane Florence for "risk" of migration to floodplains. Coefficients reported as Hazards Ratios. 95% standard errors in parentheses; *p < 0.1, **p < 0.05, ***p < 0.01. Refer to Table 3*

		Florence 0	**Florence 1**	**Florence 2**	**Florence 3**
Exposure and Vulnerability	Hurr. Matthew	1.222 **	1.198 **	1.800 ***	1.294
	Exposure(binary)	[1.065-1.401]	[1.046-1.374]	[1.394-2.324]	[0.805-2.079]
	Hurr. Florence Exposure	2.236 ***	2.448 ***	2.405 ***	2.450 ***
	(binary)	[2.002-2.497]	[2.180-2.749]	[2.144-2.698]	[2.182-2.751]
	Residence in Floodplain	1.449 ***	2.178 ***	1.384 ***	2.035 **
	(binary)	[1.241-1.692]	[1.694-2.800]	[1.188-1.613]	[1.263-3.279]
Exposure / Vulnerability Interactions	Hurr. Matthew Exposure *	-	-	-	-
	Residence in Floodplain	-	-	-	-
	Hurr. Florence Exposure *	-	0.605 ***	-	0.651
	Residence in Floodplain	-	[0.469-0.782]	-	[0.393-1.078]
	Hurr. Florence exposure *	-	-	0.646 ***	0.920
	Hurr. Matthew exposure	-	-	[0.503-0.829]	[0.561-1.509]
Individual Factors	Pre-Storm Housing Tenure	0.922 ***	0.922 ***	0.922 ***	0.922 ***
	(Years)	[0.918-0.926]	[0.918-0.926]	[0.918-0.926]	[0.918-0.926]
	Current Age (in 2020; years)	0.981 ***	0.981 ***	0.981 ***	0.981 ***
		[0.980-0.983]	[0.980-0.983]	[0.980-0.983]	[0.980-0.983]
Census Tract Demographics	Per-capita Income (annual	1.027 ***	1.027 ***	1.027 ***	1.027 ***
	USD $100s)	[1.024-1.030]	[1.024-1.030]	[1.024-1.030]	[1.024-1.030]
	Employment as a % of	0.989 ***	0.990 ***	0.989 ***	0.990 ***
	population aged 16+	[0.987-0.992]	[0.987-0.992]	[0.987-0.992]	[0.987-0.992]
	Rental units as a % of total	1.000	1.000	1.000	1.000
	occupied housing units	[0.997-1.002]	[0.997-1.002]	[0.997-1.002]	[0.997-1.002]
	Population growth from	0.997 ***	0.997 ***	0.997 ***	0.997 ***
	2010	[0.995-0.998]	[0.995-0.998]	[0.995-0.998]	[0.995-0.998]
	Population (1000) per km2	1.219 ***	1.222 ***	1.221 ***	1.222 ***
		[1.129-1.316]	[1.132-1.319]	[1.131-1.318]	[1.132-1.319]
Model Details	Observations	2,524,162	2,524,162	2,524,162	2,524,162
	Events	6,425	6,425	6,425	6,425
	C-Index	0.760	0.760	0.760	0.760
	Likelihood Ratio Test	6033.60	6101.14	6098.48	6101.25

Table S.12*: Fine-Gray Model for the subdistribution of competing risk. This analysis was performed using R Studio version 4.1.2 for subdistribution analysis of competing risk* (Gray, 2021)*. It is analogous to the Cox proportional-hazards cause-specific analysis shown in Table 3*

		Matthew 1	Florence 1	Florence 2
Exposure and Vulnerability	Hurricane Matthew Exposure(binary)	2.184 ***	1.188 *	1.792 ***
		[1.710-2.789]	[1.041-1.357]	[1.392-2.307]
	Hurricane Florence Exposure (binary)	-	2.434 ***	2.392 ***
		-	[2.165-2.736]	[2.126-2.692]
	Residence in Floodplain (binary)	2.879 ***	2.197 ***	1.393 ***
		[2.547-3.254]	[1.709-2.824]	[1.200-1.618]
Exposure / Vulnerability Interactions	Hurricane Matthew Exposure * Residence in Floodplain	0.523 ***	-	-
		[0.397-0.689]	-	-
	Hurricane Florence Exposure * Residence in Floodplain	-	0.604 ***	-
		-	[0.467-0.781]	-
	Hurricane Florence exposure * Hurricane Matthew exposure	-	-	0.642 ***
		-	-	[0.500-0.826]
Individual Factors	Pre-Storm Housing Tenure (Years)	0.930 ***	0.925 ***	0.925 ***
		[0.926-0.934]	[0.920-0.929]	[0.920-0.929]
	Current Age (in 2020; years)	0.982 ***	0.982 ***	0.982 ***
		[0.980-0.983]	[0.981-0.983]	[0.981-0.983]
Census Tract Demographics	Per-capita Income (annual USD $100s)	1.023 ***	1.026 ***	1.026 ***
		[1.020-1.025]	[1.023-1.029]	[1.023-1.029]
	Employment as a % of population aged 16+	0.986 ***	0.989 ***	0.989 ***
		[0.984-0.988]	[0.987-0.992]	[0.987-0.992]
	Rental units as a % of total occupied housing units	0.997 **	0.999	0.999
		[0.995-0.999]	[0.996-1.001]	[0.997-1.001]
	Population growth from 2010	0.995 ***	0.997 ***	0.997 ***
		[0.994-0.997]	[0.995-0.998]	[0.995-0.998]
	Population (1000) per km^2	1.329 ***	1.212 ***	1.211 ***
		[1.254-1.409]	[1.124-1.306]	[1.124-1.305]
Model Details	Observations	2,482,803	2,524,162	2,524,162
	Events	9,293	6,425	6,425

S4. Robustness Checks for Analyses

Throughout this article and the Supplemental Materials, we have highlighted several limitations with the primary data. To address those, we have run a series of robustness analyses to confirm that the influences of those limitations do not significantly change our results. To that end, we have repeated the analyses in Table 2 and Table 3 using four different conditions. The relationship between the results from these robustness checks, and the results shown in the main body of the chapter, are shown graphically in the following exponentiated co-efficient plots, specifically for Model: Matthew 1 and Model: Florence 3 in their analogous tables. Full tables of the regression results underpinning these plots are available upon request.

The first robustness check, "Inundation" replaces the inundation values with more conservative estimations. More specifically, in our main model, we flag residences as being exposed to Hurricanes Matthew and Florence based on the NCDEM (2020) inundation maps. In our robustness check, we only consider a residence to be exposed if it is shown as flooded in both the NCDEM map and the Schaffer-Smith (2020) inundation maps, reviewed in Section S2. This changes the number of properties considered to be exposed from 127,641 to 55,200 during Hurricane Matthew, and from 186,020 to 61,207 during Hurricane Florence. As shown in Figure S5 and Figure S.6 (indexed to results shown in Table 2), we see that this change has a few material effects on the results, although some key variables have exaggerated coefficients compared to the original models. However, except for the floodplain variable in Figure S.6 (which changed from a non-significant negative value to a significant positive value) the direction of the results remains the same. The exaggerated influences are diminished in Figure S.7 and Figure S.8(indexed to results shown inTable 3), and both figures show results that track well with the original model.

We believe these changes to be the result of three processes. First, we believe that using a stricter definition of inundation reduces noise from potential false positives, albeit at the cost of introducing more false negatives. Second, most of the flooding happened in the floodplain, and reducing the number of properties considered exposed reduces the correlation between the floodplain variable and the exposure variable, resulting in greater influence for each variable. Third, we believe it biases the sample towards properties who were more significantly flooded (and were therefore readily determined as inundated in maps developed through two different processes). The resulting increased effect of Hurricane Matthew and Florence on the risk of migration may indicate that exposure and effect may scale with the degree of flooding experienced.

From the following models, “Age” and “Geocoding” robustness checks address issues highlighted in Section S1 about the generation and limitations of the TransUnion data. For “Age”, we limited the sample to individuals between the ages of 30 and 79. This was a response to how well the TransUnion data tracked against population estimates from the census across different age ranges (see Figure S.3, which showed that TransUnion slightly underestimated younger respondents, and overestimated older ones. For “Geocoding”, we limited the sample to person-address observations that had geocoding matches for PointAddresses, which are precise to the housing location on the street front (ESRI, 2022b). Other matches within our sample were less precise. In both cases and across all models, “Age” and “Geocoding” were effectively identical. The hazard ratios for the robustness check models mirrored the original model in directionality, degree, and significance for Figure S.5 through Figure S.8.

As a final robustness check, we used households, instead of individuals, as the unit of analysis and collapsed observations where the originating address and destination addresses were the same – suggesting a familial move. Similar to the “Age” and “Geocoding” models, the “Households” model results tracked with the original model for Figure S.5 through Figure S.8 for most variables. Specifically, the influence of our key variables for Hurricane Matthew, Hurricane Florence, and the Floodplains remained consistent with the original model results.

References

Figure S.5: *Robustness check for risk of migration (Hurricane Matthew). This graphic compares the original Cox proportional-hazards regressions (see Table 2, Model: Matthew 1) with results from robustness checks.*

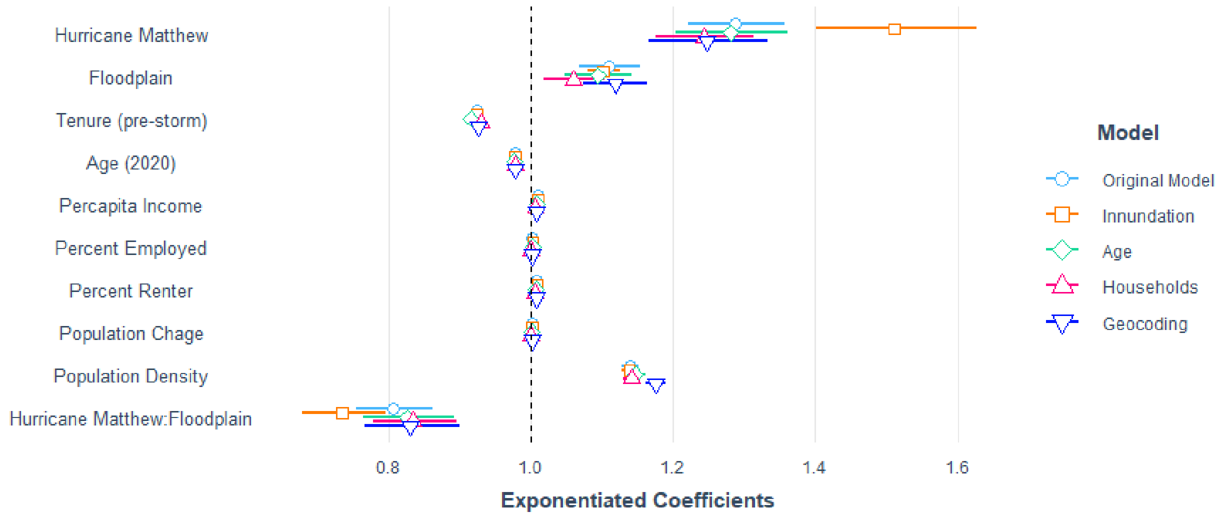


Figure S.6: *Robustness check for risk of migration (Hurricane Florence). This graphic compares the original Cox proportional-hazards regressions (see Table 2, Model: Florence 2) with results from robustness checks.*

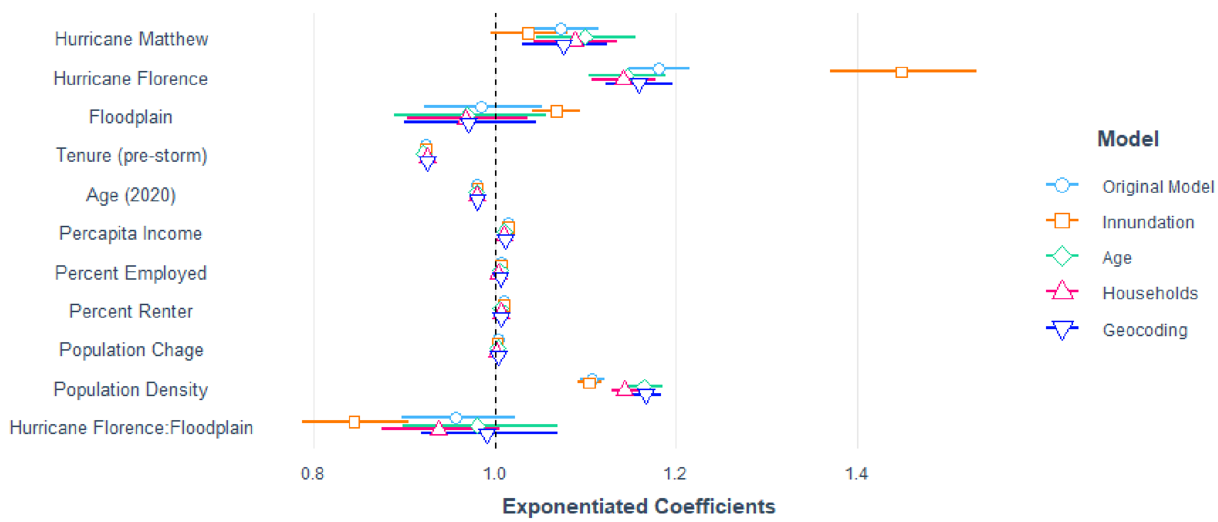


Figure S.7: *Robustness check for risk of migration to floodplains (Hurricane Matthew)..This graphic compares the original Cox proportional-hazards regressions (see Table 3, Model: Matthew 1) with results from robustness checks.*

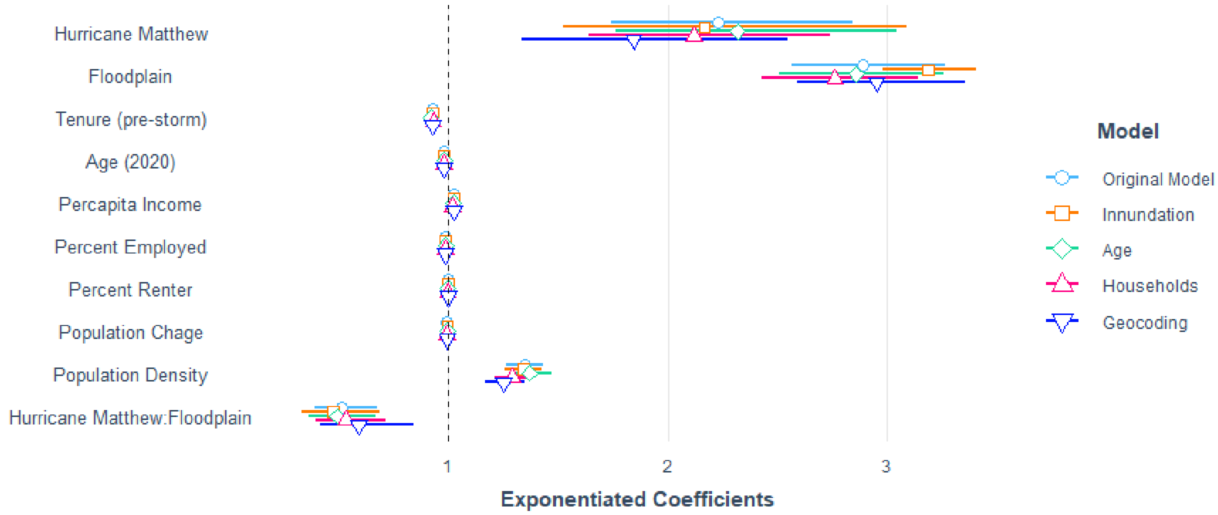


Figure S.8: *Robustness check for risk of migration to floodplains (Hurricane Florence). This graphic compares the original Cox proportional-hazards regressions (see Table 3, Model: Florence 2) with results from robustness checks.*