Where Do People Go After the Storm?

An Analysis of Migration Following Tropical Storms in the United States between 1990 and 2010

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Introduction

In 2017, the United States set a new record for damage costs accrued from weather and climate events with a staggering $340.2 billion figure. Tropical storms alone were responsible for 86% of the damage.[2] Along several dimensions, tropical storms consistently do more damage in dollar terms than any other type of climate event and will likely become even more destructive in the future (NOAA, 2021). Not only is their magnitude projected to increase as a result of global climate change (Emanuel, 2005, 2013; Knutson et al., 2010), but development along the US coastal areas continues, placing more people and property in harm's way each year (NOAA, 2020). Given the increasing threat of tropical storms, and the large costs associated with their recovery, it is increasingly important to understand the demographic consequences of these climate events.

Yet migration following tropical storms remains poorly understood. While policy-makers often see migration as a failure to recover or adjust in the face of acute events (natural hazards) and a changing environment, recent scholarship has portrayed it as an adaptation process with the potential to reduce vulnerability to climate change and natural disasters (Black, Bennett, et al., 2011; Gemenne & Blocher, 2017; Hino et al., 2017; McLeman & Smit, 2006). The rationale for seeing migration as adaptation is that relocating allows residents of areas affected by environmental degradation or exposed to natural hazards to lower their individual and collective risk by moving to safer places. In contrast, when some populations are unable to relocate, they might become "trapped in place", unable to move away from environmental threats, but also lacking the resources to make their lives and properties more resilient (Black, Adger, et al., 2011).

Understanding migration as adaptation implicitly relies on the idea that individuals leaving vulnerable areas will settle in places with lower overall vulnerability. However, this assumption contrasts with two frequent findings of the literature on environmental and disaster-induced migration (Findlay, 2011). First, most individuals do not move when faced by environmental degradation or after they have been hit by a disaster. Second, the individuals who migrate usually travel short distances, often not enough to substantially reduce their risk level. Additionally, residents who leave disaster-prone areas will often be replaced by new ones (Dacy & Kunreuther, 1969; Fussell, 2009b), and it is unclear whether these new residents will come from areas with higher or lower risk.

Although a body of recent works has emerged to update our understanding of the demographic consequences of natural disasters from a theoretical (Olshansky et al., 2012; Pais & Elliott, 2008) and empirical perspective (Elliott & Pais, 2010; Fussell et al., 2017; Logan et al., 2016; Raker, 2020; Schultz & Elliott, 2013), several gaps still remain. In particular, most studies rely on population change as the primary outcome of interest, rather than migration itself, despite the theoretical understanding of population recovery as a migration process. This choice limits one's ability to separately model the contributions of in-migration and out-migration. Second, no prior studies have examined where the "lost" population is moving to and where the "gained" population is coming from, an important aspect if one wishes to understand the impact of post-disaster migration on the vulnerability at the origin and at the destination. Finally, although often discussed as an important determinant of recovery, the role of post-disaster relief from the federal government has rarely been included as an explanatory variable, an important omission given the size of the financial flows involved.

This study estimates the impact of experiencing a tropical storm on migration to and from affected counties, introducing new data sources and methods to address these important gaps in the

[2] Henceforth, I will use the terms tropical storm and hurricane interchangeably.

literature. Using Bayesian hierarchical spatial models, I estimate expected migration rates in the absence of tropical storms and compare them with the observed rates to compute *excess migration*. This novel methodology has the advantage of requiring no parametric assumption on the migration impact of tropical storms. It also produces county-year specific estimates of excess migration, allowing for spatial as well as temporal heterogeneity while also producing consistent uncertainty intervals for all estimated quantities.

This study also advances the existing literature by looking at inflows and outflows separately, allowing for different effects on these two components of population change. I further decompose inflows by risk level of the origin and outflows by risk level of the destination. This decomposition allows me to investigate whether individuals moving out from areas recently affected by a tropical storm resettle in areas with lower or higher risk and whether individuals moving to the recently affected areas come from more or rather less risky ones. Finally, I explore the role of damage, disaster relief from FEMA programs, insurance payments from the NFIP, and pre-disaster social vulnerability as moderators.

Although this question has received surprisingly little attention in the literature, it is crucial to our understanding of environmental migration as a force to reduce or rather increase vulnerability to natural hazards.

Background

In his 1945 dissertation, "Human Adjustment to Floods," Gilbert White states: "floods are 'acts of god,' but flood losses are largely acts of man." In doing so, White was the first to recognize that natural disasters are not simply unfortunate outcomes of biophysical conditions but rather complex processes in which formal and informal policy decisions and organizational practices interact with natural processes (Kates, 2011). A hurricane making landfall along an uninhabited coast would not produce a natural disaster. Similarly, recovery from natural disasters does not depend exclusively on the characteristics of the disaster (how many houses were destroyed, how many people displaced) but also on the ability of the affected communities to muster the resources needed to achieve recovery (Wright et al., 1979).

In the United States, the primary governmental body tasked with assisting in this recovery process is the Federal Emergency Management Agency (FEMA), which has established a variety of policies and programs aimed at channeling aid to areas affected by climate disasters. During the late 1980s, federal and state sponsored buyout programs rose in prominence, with the idea that it might be more cost effective to buy repeatedly flooded properties rather than insuring them. FEMA's Hazard Mitigation Grant Program (HMGP) funded 43,633 voluntary buyouts of flood-prone properties between 1989 and 2017 (Mach et al., 2019). This program is an implementation of managed retreat, the idea that in some cases the best long-term solution to natural disasters is relocation (Hino et al., 2017). This idea of managed retreat relies on the notion that individuals and households that decide or are forced to relocate will both move to areas exposed to lower levels of risk and will not be replaced.

However, in the years since, the effectiveness of these buyout programs have been called into question (Mach et al., 2019; McGhee, 2017). McGhee (2017) found that, in the case of Staten Island, many residents whose homes were bought out as part of a statewide program, relocated to areas as flood prone as those that they had left. Indeed, while FEMA ensures that the properties acquired as part of the buyouts program cannot be rebuilt, it does not impose any requirements on the destination of those relocating. This is not an issue limited to publicly sponsored programs.

Even when individuals decide to leave a flood-prone area without assistance, they might relocate in another flood-prone area which just happened not to suffer any major events in the recent period. At the same time, it is also likely that individuals leaving areas affected by tropical storms will be replaced by new ones (Fussell, 2009a). Positive net-migration has been documented after many natural disasters, from the Great Alaska Earthquake (Dacy & Kunreuther, 1969) to Hurricane Katrina (Frey & Singer, 2006; Fussell, 2009b, 2009a). These new residents, often attracted by the economic opportunities generated by the recovery process, may come from lower risk areas, possibly compensating any risk-reduction effects due to out-migration.

An analysis of the migration patterns following natural disasters reveals that the idea of managed retreat may be problematic on three levels, limiting the effectiveness of these buyout programs. First, while some areas experience population declines after natural hazards, this is not a general phenomenon, and the literature has documented several cases where the population of affected areas increased after the event (Elliott & Pais, 2010; Frey & Singer, 2006; Kates et al., 2006; Schultz & Elliott, 2013).

Second, the literature on environmental migration and disaster-induced migration (summarized in Findlay, 2011) has consistently documented that: 1) most people do not move following natural disasters or other acute environmental phenomena; 2) When they do move, they rarely travel long distances. These two empirical regularities coupled with the notion that hazards are geographically clustered, imply that even in the presence of significant post-disaster migration, neither the vulnerability for the individuals who relocate, nor the overall vulnerability of the origin-destination pair will decrease.

Third, individuals do not randomly choose where to live. In particular, low-income individuals will prioritize affordability in their search for housing and will be constrained by the availability of jobs in the area. Higher risk of experiencing a natural hazard tends, net of other factors, to reduce property values, thus making homes located in hazardous areas more affordable (Bin et al., 2008; Harrison et al., 2001; Kousky, 2017). The vulnerability of a place to natural disasters is the product of both its biophysical vulnerability - the risk of experiencing a disaster - and its social vulnerability - the ability of its residents to prepare for and recover from the disaster (Cutter et al., 2000, 2003). Failing to understand this intersectionality means not recognizing that the forces that make certain groups more vulnerable to disasters will also act when individuals from these groups decide or are forced to relocate (Tierney, 2006).

Theoretical Perspectives

Homogeneous Recovery

The homogeneous recovery hypothesis, usually traced back to work of Haas et al. (1977), posits that, in a relatively short amount of time, communities struck by natural disasters can recover from it, and do not experience long-term population or economic loss because of the disaster.

While most natural disasters cause a significant amount of losses to selected groups of individuals or families, even the most destructive ones only affect a relatively small part of the entire community. For example, Wright and colleagues report that between 1960 and 1970 hurricanes, arguably the most destructive of natural hazards, caused major damage to an average of 125 houses for every 10,000 in affected counties (Wright et al., 1979). At the same time, relief resources are often mobilized in response to natural disasters and rapidly employed to facilitate recovery. At the community level it thus seems unlikely that significant long-term effects of natural disasters could be detected. This hypothesis was well supported by the first empirical investigations of the impact of natural disasters in the United States. Studying how Cameron Parish recovered from Hurricane Audrey in 1957, Bates and colleagues formulated and found support for the hypothesis that natural disasters accelerate pre-disaster processes, promoting growth in expanding communities but possibly hastening decline where it was already under way (F. L. Bates et al., 1963). Conducting a case study on the Great Alaska Earthquake of 1964, Dacy and Kunreuther found that post-disaster growth was not limited to communities that were already successful before the event but extended to those that were declining (Dacy & Kunreuther, 1969).

In an attempt to generalize the conclusions drawn from single case studies, Haas, Kates, and Bowden (1977) examined four different events: the catastrophic 1972 flood in Rapid City, South Dakota; the 1972 earthquake in Managua, Nicaragua; the Great Alaska Earthquake of 1964; and the 1906 earthquake in San Francisco (Haas et al., 1977). Despite the heterogeneity of the cases, the authors find results remarkably consistent with the previous literature. The post-disaster period saw an acceleration of pre-disaster trends and recovery was achieved within 3 years for Alaska and Rapid City, and within 9 years for Managua and San Francisco. The authors portray the recovery process as "ordered, knowable, and predictable." Despite differences in the duration of the recovery process across the four locations, Haas and coauthors find that all areas were able to achieve "functional recovery," or a return to pre-disaster population, housing stock, and level of economic activity. The same conclusion was reached by Friesema and colleagues in their investigation of recovery in four communities hit by natural disasters (Friesema et al., 1979).

Case studies, while useful to establish plausible hypotheses regarding the general mechanisms driving post-disaster recovery, have methodological limitations. First, by focusing on a specific event and area, they are of limited utility when wishing to make general claims that could be applied to different disasters in different places. Second, the cases are not randomly selected from the population of natural disasters. From the viewpoint of destructiveness, the Great Alaska Earthquake, Hurricane Audrey, and the Rapid City flood were all extreme events in the right tail of the respective distributions of earthquakes, hurricanes, and floods. To remedy these two methodological limitations, Wright and colleagues conducted a systematic study of all major tornadoes, floods, and hurricanes that occurred in the US from 1960 to 1970 (Wright et al., 1979). Comparing demographic and economic indicators at the county and census tract level between 1960 and 1970, the authors conclude that no practically or statistically significant effects of natural disasters on the housing stock, the population size, and other county characteristics persist over the long term.

The implication of homogeneous recovery for post-disaster migration is that we should expect no permanent effect. Some residents will be leaving the affected area temporarily but then return once the emergency phase is complete. Some residents will instead relocate permanently but will be replaced by new residents attracted by the economic opportunities generated by the recovery effort. In the span of about three years, areas hit by a natural disaster should be unrecognizable migration-wise from areas that were never hit (net of other factors).

Segmented Recovery

The segmented recovery hypothesis originated as a critique of the homogeneous recovery approach and the desire to formulate a more nuanced understanding of recovery after natural disasters. Taken together, the work of (F. L. Bates et al., 1963; Dacy & Kunreuther, 1969; Friesema et al., 1979; Haas et al., 1977; Wright et al., 1979) paint recovery as a remarkably regular and uniform process. This characterization, and the implication that disaster relief might not be needed after most average disasters, were rejected by many, who argued that Wright et al. (1979)'s approach of estimating average effects hid underlying heterogeneity (Mileti, 1980; Rubin et al., 1985).

In one of the first studies to shed light on the distributive effects of natural disasters, Cochrane found that low income groups are exposed to higher risk of damage by living in low-quality buildings, consistently bear a disproportionate share of the losses, and receive a smaller proportion of disaster relief compared to high and medium income groups (Cochrane, 1975). In a similar vein, Rubin and coauthors (1985) question the idea that an overall rapid recovery can be taken to imply that all communities recover at the same pace or to the same level, and that public policies and programs do not matter (Rubin et al., 1985). In their analysis of 14 FEMA declared disasters that occurred between 1980 and 1985, Rubin and coauthors find that the process of recovery can be very heterogeneous and is rarely independent from the post-disaster policies and programs. They also investigate the factors responsible for accelerating or slowing recovery and argue that the ability of local administrators to effectively plan for natural disasters both before (in the form of mitigation) and after (in the form of reconstruction) are crucial.

Comerio (1998) reaches similar conclusions investigating four destructive disasters that followed a long period of quiet from 1972 to 1989: Hurricane Hugo and the Loma Prieta Earthquake in 1989, Hurricane Andrew in 1992, and the Northridge Earthquake in 1994 (Comerio, 1998). She finds a level of heterogeneity in recovery trajectories similar to the one described by Rubin and coauthors but also identifies a set of empirical regularities. First, rural areas usually recover at a slower pace compared to urban areas, a finding consistent with some of the results in Wright et al. (1979). Comerio links this delay, or absence of recovery in some cases, to higher vulnerability of rural areas to the disasters because of lower quality buildings and infrastructure, and, at the same time, to the absence of state help and the inability of rural counties to provide adequate planning and resources. Second, she finds that while the recovery of single family homes moved ahead quickly, the supply of multifamily housing and rental units sharply declined, especially low-cost ones.

The implication of segmented recovery for post-disaster migration is that while most areas will follow the homogeneous recovery pathway, communities that sustained more damage as a consequence of higher pre-disaster vulnerability may see negative post-disaster net migration, resulting in long-term population decline.

The Stimulus Hypothesis and Segmented Withdrawal

The debate between homogeneous functional recovery and segmented recovery gave way in the late 1990s and 2000s to a series of case studies more focused on understanding the impact of specific events on population change and migration than in building an overarching theory of recovery. These case studies included Hurricane Andrew (Elliott & Pais, 2010; Smith, 1996; Zhang & Peacock, 2009), Hurricanes Katrina and Rita (Curtis et al., 2015; Elliott & Pais, 2006; Frey & Singer, 2006; Fussell, 2009a; Fussell et al., 2010; Groen & Polivka, 2010; Horowitz, 2020; Kates et al., 2006), and Hurricane Sandy (Binder et al., 2015, 2019; Binder & Greer, 2016; Bukvic et al., 2015; Bukvic & Owen, 2017; Koslov, 2016). More recently, Hurricane Maria has attracted new interest to this field (Alexander et al., 2019; Santos-Lozada et al., 2020).

Although this vast body of work improved our understanding of recovery following natural disasters, all of these case studies focused on the most extreme events in terms of damage, limiting the ability to generalize the findings to a wider range of natural disasters. For example, the extensive change in migration patterns documented after Hurricanes Katrina and Rita which led, in some instances, such as in Baton Rouge (Frey & Singer, 2006), to positive net-migration and in others, like the city of New Orleans (Fussell, 2015), to long-term population loss, may not be found after less devastating events. This limitation stems from the fact that extreme natural disasters are, by definition, very rare, and their impact is difficult to disentangle from the context in which they occur (Gutmann & Field, 2010).

In an attempt to build a general theory that could apply to a wider range of events, a new literature analyzing the impact of multiple disasters has emerged in the last decade. Pais and Elliot (2008) formulated the concept of "recovery machines", coalitions of politicians and developers that encourage a rapid recovery in the aftermath of natural disasters, pushing aside concerns for long-term resilience and equity in the distribution of resources (Pais & Elliott, 2008). Investigating demographic change after Hurricanes Bob (1991), Andrew (1992), and Opal (1994), Pais and Elliott find that the affected area gained about 1.4 million additional residents and 600,000 new housing units. However, coastal neighborhoods, more exposed to the damage, tended to become smaller, whiter, and older while the surrounding neighborhoods experienced intense growth, with a significant expansion of the Black and Latino population.

Building on their previous work, Elliott and Pais (2010) compare the impact of Hurricane Andrew in Miami and in rural Louisiana (Elliott & Pais, 2010). They observe two directionally opposite processes of segmentation. In rural areas, disadvantaged residents became more concentrated as more advantaged residents left after the hurricane. The authors label this process the "concentration hypothesis." In urban areas, disadvantaged residents were instead more likely to be displaced as they often suffered more damage (as a consequence of lower quality housing) and had less resources to recover in place. The authors label this process the "displacement hypothesis."

In a more systematic study building methodologically on Wright et al. (1979), Schultz and Elliott (2013) regress population change between 1990 and 2000 on damage from natural disasters, finding a positive correlation and offering support for a "stimulus hypothesis" whereby counties experiencing a disaster not only are able to recover but experience enhanced growth (Schultz & Elliott, 2013). No strong support emerges in the study for either the concentration or the displacement hypothesis. The authors find that counties hit by a natural disaster experience an increase in median income but no change in poverty, suggesting that individuals below the median saw their incomes increase on average but those at the very bottom did not experience major gains.

Logan et al. (2016) build on the "concentration hypothesis" and, analyzing the demographic impact of tropical storms hitting the Gulf Coast over the 1970-2005 period, find that damage from tropical storms reduces population growth for up to three years following the event (Logan et al., 2016). They also show that the population loss is concentrated among high-income White residents, as predicted by the concentration hypothesis, labeling this phenomenon "segmented withdrawal." Finally, Fussell et al. 2017, investigating the impact of damage from hurricanes on population growth between 1980 and 2012, find that damage affects population growth only in high-density counties whose population was growing before the event (Fussell et al., 2017). Current year damage suppresses population growth, however, cumulative damage is associated with increased growth. Because high-density counties with a growing population are only 2% of all counties in the US, Fussell and colleagues interpret these findings as consistent with the idea of functional recovery and the absence of long term effects for most natural disasters.

To summarize, the most recent developments in the literature suggest that while most tropical storms do not cause population loss or gain through migration, some of the most destructive ones can trigger substantial population change. If the recovery machines hypothesis is correct, areas hit by a tropical storm should experience positive net migration for some years following the storm, either as a result of increased inmigration or as a consequence of reduced outmigration.

Conversely, if segmented withdrawal provides a better description of reality, we would expect tropical storms to cause population loss, especially in areas with a high proportion of high-income White residents.

Summary and Hypotheses

Based on my review of the literature, I test four hypotheses corresponding to the four theories I illustrated in the review:

1. Homogeneous recovery hypothesis: little impact on net migration in the aftermath of tropical storms.
2. Segmented recovery hypothesis: negative impact on net migration but only for socially vulnerable areas sustaining heavy damage.
3. Stimulus hypothesis: population growth through positive net migration in areas affected by tropical storms.
4. Segmented withdrawal hypothesis: negative impact on net migration leading to population loss. Magnitude of the impact is stronger in areas with high income and majority White.

Regarding the risk dimension of migration, the empirical regularities regarding environmental migration summarized by Findlay (2011), suggest that outmigration generated by tropical storms will move individuals from disaster affected areas to nearby regions, likely sharing a similar level of risk. The literature offers less guidance regarding the characteristics of migrants flowing into disaster affected areas, and I thus have no strong expectations about whether they will be coming from equally risky or less risky areas.

Data

Yearly county-to-county migration flows for the period 1990-2010 come from the Internal Revenue Service Statistics of Income Division (IRS-SOI). The IRS data captures individuals who changed tax address from one year to the next and as such does not capture individuals who only temporarily moved out of county. While IRS data only captures taxpayers, an analysis by Molloy and coauthors showed that over 87% of the population is represented (Molloy et al., 2011). Concerns have been raised over the data quality of IRS estimates after a change in the methodology used to produce the estimates in 2010 (Pierce, 2015). Therefore, I limit my analysis to data collected before 2011.[3]

Population counts by race, origin, and age for the period 1987-2010 come from the SEER database, which is in turn based on Census data. Through the OpenFEMA portal, I obtained data on claims to the National Flood Insurance Program (NFIP) for the 1987-2010 period (FEMA, 2021b), data on applications to the Individual Assistance (IA) and Public Assistance (PA) programs for the 2002-2010 period (FEMA, 2021c, 2021d), and data on disaster declarations for the period 1987-2010 (FEMA, 2021a). Data on direct and indirect damage from all natural disasters and tropical storms alone for the period 1987-2020 comes from SHELDUS (ASU, 2021).[4] Finally, I obtained

[3] I believe that the issues with post-2010 IRS data first identified by (Stone, 2016) and then investigated in depth by (DeWaard et al., 2021) could be made less serious with the use of calibration methods developed for digital traces data (Zagheni et al., 2014, 2017; Zagheni & Weber, 2012) but, to avoid complicating my analysis, I will only use data up to 2010.

[4] I've made an effort to ensure that all the data used in this project is publicly available with no paywalls. I think this is an important aspect which should be given more attention in order to simplify the process of replication, thus increasing the collective confidence in the results. The only exception is the SHELDUS

the Social Vulnerability Index at the county level for 2014 from the (CDC, 2022). Table 1 summarizes sample characteristics.

Methods

My main goal is to model migration from and to coastal counties in the counterfactual scenario where no to tropical storms occurred. I then compare expected migration in the absence of tropical storms with the observed value and define the difference as excess migration associated with tropical storms. To investigate the geographical patterns of migration with respect to the risk of experiencing natural disasters, I further decompose flows by the level of exposure to natural disasters in the origin or destination counties. In this paper, I define coastal counties starting from the definition adopted by NOAA[5] and removing counties outside of the contiguous United States, those located on the West Coast, and those situated on a lake. Finally, I include all the excluded counties that are surrounded exclusively by coastal counties. To measure risk of experiencing a natural disaster, I compute the total per capita damage from natural disasters over the period 1987-2020 using data from SHELDUS and divide US counties into 5 quintiles (or levels of risk). Counties in the top quintile (high-risk counties) experienced an average of 56.1 of damage from natural disasters per capita every three years, while those in the bottom quintile (low-risk counties) experienced less than \$1. Decomposing migration flows by risk level allows me to investigate whether excess migrants associated with tropical storms come from or move to safer or rather riskier counties. Figure 1 shows how all counties in the US score on the risk scale and clarifies which counties I define as coastal[6].

I use Bayesian hierarchical models to predict yearly migration in the counterfactual scenario of no tropical storms hitting a given county. Let y_{tsr} be the flow of migrants between spatial unit s and other counties with risk level r at time t. I keep the direction of the flow unspecified to use a common notation for the models for in- and out-migration. Let P_{ts} be the population of spatial unit s at time t. I assume a Poisson distribution for the number of migrants y_{tsr} and model the risk r_{tsr} of migrating using the following specification:

$$y_{tsr} = Poisson(r_{tsr} \cdot P_{ts})$$
$$\log(r_{tsr}) = \beta_{0t} + f(Time_{ts}) + b\_s$$

Where β_{0t} is the year specific intercept given by $\beta_{0t} = \beta_0 + \varepsilon_t$, with β_0 being the global intercept and $\varepsilon_t \sim Normal(0, \tau_\varepsilon^{-1})$ an unstructured random effect representing the deviation of each year from the global intercept. The parameter τ_ε indicates the precision of ε_t. The linear predictor also includes a non-linear effect $f(\cdot)$ of time (in years) since the start of the period ($t = 1, 2, \ldots$ with time 1 corresponding to 1990); in particular, I assume the following first-order random walk (RW1) model:

$$Time_{ts} \mid Time_{t-1,s}, \tau_t \sim Normal(Time_{t-1,s}, \tau_t^{-1})$$

I fit a separate random walk for each county to allow for county-specific time trends but let all the random walks share the same hyperparameter τ_t^{-1}. I model county-level intercepts using the

database for which I was unable to find an open-access alternative. Interested readers might want to look into the National Center for Environmental Information (NCEI, 2021) database on natural disasters which, however, goes back only until 1996 and does not include all types of natural disasters. All the codes to produce the results of this paper can be accessed here [LINK TO GITHUB REPOSITORY].

[5] https://coast.noaa.gov/data/digitalcoast/pdf/defining-coastal-counties.pdf

[6] I tested different definitions of coastal counties, and the results were not sensitive to the different criteria.

modified Besag, York and Mollie spatial model proposed by 10/7/22 10:53:00 AM (BYM2 model). This model is the sum of a spatially unstructured random effect, $v_s \sim Normal(0, \tau_v^{-1})$ and spatially structured effects u_s. b_s is defined as:

$$b_s = \frac{1}{\sqrt{\tau_b}} \left(\sqrt{1-\phi}\, v_s^\star + \sqrt{\phi}\, u_s^\star \right)$$

where $u_s^\star$ and $v_s^\star$ are standardized versions of u_s and v_s to have variance equal to 1. The term $0 \leq \phi \leq 1$ is a mixing parameter which measures the proportion of the marginal variance explained by the spatially structured effect.

I specify minimally informative prior distributions for the fixed effects β_0. For the hyperparameters of the BYM2 model, ϕ and τ_b, I adopt priors that tend to regularize inference while not providing too strong information, the so-called penalized complexity (PC) priors introduced in Simpson et al. (2017). In particular, for the standard deviation $\sigma_b = \sqrt{\tau_b^{-1}}$ I select a prior so that $\Pr(\sigma_b > 1) = 0.01$, implying that it is unlikely to have a spatial relative risk higher than $\exp(2)$ based solely on spatial or temporal variation. For ϕ I set $\Pr(\phi < 0.5) = 0.5$ reflecting our lack of knowledge about which spatial component, the unstructured or structured, should dominate the spatial term b_s. Finally, I also adopt PC priors for all the remaining standard deviations $\sigma_y = \sqrt{\tau_y^{-1}}$, $\sigma_\varepsilon = \sqrt{\tau_\varepsilon^{-1}}$, and $\sigma_t = \sqrt{\tau_t^{-1}}$ such that for each hyperparameter $\Pr(\sigma > 1) = 0.01$.

I fit the models using the Integrated Nested Laplace Approximation (INLA) method, through the R-INLA software package (Rue et al., 2009). To model migration in the absence of tropical storms, I trained the models on data points, i.e. county-years, for which no tropical storm causing more than the median amount of per capita damage[7] occurred in the previous three years. Excluding all county-years for which a tropical storm occurred in the previous three years, irrespective of damage, led to very similar results but made the estimates less stable as it significantly reduced the number of observations on which the model could be trained. The decision of setting three years after the hurricane as the threshold for return to normality is based both on a preliminary exploration of the data, and on the literature on recovery after natural disasters that I've discussed in the background section.

I compare the expected migration counts with the observed ones to compute the number of excess in-migrants and excess out-migrants for each county-year and each level of risk of the destination/origin. I denote this variable by e_{tsr}. I use the posterior samples from the model to obtain posterior intervals on all estimated quantities.

As a second part of the analysis, I investigate possible determinants of excess migration associated with tropical storms. I explore the role of NFIP insurance payments, FEMA IHP and PA payments, total damage, social vulnerability, and selected population characteristics. For damage, FEMA assistance, and NFIP payments, I compute the total amount per-capita received in the last three years to better capture the medium-term effect. I compute damage from tropical storms using the values reported in the SHELDUS database. While necessarily imperfect, these figures are, to my knowledge, the best available estimates which are consistent over time and space. I compute the total amount of money paid by NFIP for a given county-year as the sum of payments for claims on buildings, content, and increased cost of compliance (ICC). Finally, I compute the total

[7] About $5.

payments by FEMA IHP and PA by summing payments for Public and Individual Assistance. I adjust all monetary amounts for inflation.

To ensure uncertainty in the estimation of e_{tsr} is expressed in the second stage of analysis, I drew 250 samples from the posterior distribution of each e_{tsr} and ran a stage 2 analysis fixing e_{tsr} to each of these values in turn. For each of these 250 analyses, I fit the following hierarchical model:

$$e_{tsr} = \pi_{0s} + \pi_{0y} + \varepsilon_{tsr}$$

$$\pi_{0c} \sim N(\gamma_{0C}, \sigma^2{}_{0C})$$
$$\pi_{0y} \sim N(\gamma_{0Y}, \sigma^2{}_{0Y})$$
$$\varepsilon_{tsr} \sim N(0, \sigma^2{}_{\varepsilon})$$

For the univariate analysis I added the term $\delta_q X_{qst}$ where X_{qst} is the qth quantile of the variable in spatial unit s at time t. Similarly, for the full multivariate model evaluating the joint effect of all variables, I added the term $\sum_j \delta_{j,q} X_{j,qst}$, where j represents the jth explanatory variable. I used quintiles for population size, population density, percentage of the population identifying as Black, and percentage of the population aged 65 or older. I instead used quartiles dividing the last one into three partitions (75th percentile to 90th percentile, 90th percentile to 95th percentile, and above 95th percentile) for damage, FEMA assistance, and NFIP payments. The decision to use this more granular partition for these three variables was motivated by their highly non-linear effect which was well not captured when using quintiles. For all variables, I use the first quantile as the reference category. Because FEMA assistance is only available from 2002 onwards, the univariate coefficients for this variable use only observations after this year. This is also the reason why I did not include FEMA assistance in the multivariate analysis.

The product of the stage 2 analysis are 250 vectors of coefficients for each model with their corresponding 250 vectors of standard errors. I then sample 250 vectors for each model, each using a different coefficient-standard error pair. The result is a sample of 250 values for each coefficient reflecting its distribution. I obtained the mean of the coefficients and their confidence intervals by computing the mean, the 2.5th, and the 97.5th percentiles of each sample. The choice of the number of samples followed analyses using a range of different sample sizes. I ensured the stability of the estimates while minimizing unnecessary computational burden.

All the stage 2 models are estimated in R with the lme4 package (D. Bates et al., 2015). While employing a Bayesian framework in both stages of the analysis would have been preferred, the additional computational burden for estimating the stage 2 models in INLA made it impractical. As a robustness check, I replicated a subset of the stage 2 analysis using INLA and found no significant differences either in the coefficients' means or in their confidence intervals.

Results[8]

Spatial and Temporal Patterns of Excess Migration

[8] Where not otherwise specified, all intervals presented in this section and all statements referring to statistical significance refer to 80% symmetric posterior intervals. All figures for which posterior intervals are reported follow the schema: median value (10th posterior percentile – 90th posterior percentile).

Table 2a and Table 2b report the estimated number of excess out-migrants, in-migrants, and net-migrants by year and state, respectively. My analysis finds that tropical storms are associated with a total of 271,232 (107,350 - 437,778) excess out-migrants and a total of 221,022 (72,921 - 366,283) excess in-migrants. In terms of net excess migration, I find a negative net balance -52,160 (-275,528 - 184,193) but not statistically significant. At the national level, we can thus conclude that while tropical storms increase geographical mobility in the affected counties, excess out-migration is compensated, on average, by excess in-migration and the net balance is not statistically different from zero.

Of the 1909 county-years for which a tropical storm had caused more than the median amount of damage in the last three years, only 5% percent had a negative out-migration exceeding the lower bound of expected migration, and only 4.7% had a positive out-migration. The corresponding figures for in-migration are 8.2% and 10.9%. The balance of excess migration was negative and significant in 5.6% of the county-years and positive in 8.3%. Overall, only in a minority of cases experiencing a tropical storm causes changes in migration large enough to be incompatible with expected migration in the absence of a tropical storm.

Interestingly, in-migration seems to be more sensible to tropical storms than out-migration. Only in 11.3% of the county-years affected by a tropical storm migration, migration led to a significant population loss or gain. These figures confirm the overall finding that while tropical storms are associated with increases in geographical mobility, they seldom cause population gain or loss at the county level. These findings offer support for the homogeneous recovery hypothesis, in most cases migration has not net effect, but partially contradict both the stimulus hypothesis and the segmented withdrawal hypothesis, as I find little evidence that either positive or negative net migration is strongly associated with tropical storms.

Figure 2 presents the median estimate of excess in- and out-migration by state, year, and risk level of the origin (for in-migration) or the destination (for out-migration). The figure reveals that large numbers of excess in-migrants or out-migrants are rare and confined to few state-years. Except for 1990, when in-migration in counties affected by tropical storms was significantly lower than expected, in- and out-migration significantly exceed their predicted values only after 2005 and remain higher than expected for six consecutive years (in-migration) and three consecutive years (out-migration). Those familiar with the chronology of US hurricanes will recognize the exceptionality of the 2005 hurricane season when Hurricane Katrina struck the Gulf Coast in August, causing an estimated $186.3 billion[9] damage. If we remove the 2005 season, and even then, only in Louisiana, we find little evidence that tropical storms are associated with excess migration at the state level.

Figure 2 also decomposes flows by risk level and reveals that, at the national level, most excess migrants from counties affected by a tropical storm move between high-risk counties. The only exception to this pattern seems to be the 2005 hurricane season, when, despite high-risk counties representing the destination of the majority of excess outmigrants, counties with lower risk represent a significant share of the total. It is likely that the exceptional devastation caused by Hurricane Katrina (especially in Louisiana) proved to be a large enough shock to permanently displace a sizeable portion of the resident population. Some of these migrants (possibly those having enough resources to do so) decided to relocate in other states with lower natural disaster risk. Overall, we can conclude that excess migration does not have, on average, an adaptive character. At least at the county level, we have no indication that excess out-migrants move to

[9] Adjusted to 2022 values

safer areas. At the same time, excess in-migrants are likely to come from areas with high natural disaster risk, thus not changing the level of risk they face.

By construction, counties struck by a tropical storm will tend to have higher risk scores and so will nearby counties (many of which will also be hit). The geographical clustering of risk combined with the inverse relationship between distance and migration is thus clearly an important factor in explaining why most excess migrant move between high-risk counties. To understand how much distance plays a role, we can look at the ratio between excess migrants and expected migrants (relative excess). Figure 3 presents the estimates of relative excess by state, year, and risk level. It reveals that while most excess migrants move between high-risk counties, this pattern is mostly driven by pre-storm migration patterns. Once these patterns are accounted for by expressing excess as a percentage of expected migration, we see that low-risk counties are the destinations that experience the largest relative increase in migration from counties affected by a tropical storm. Conversely, the largest relative increases in in-migration to counties that experienced a tropical storm come from low-risk counties. Overall, these findings signify that excess out-migration associated with tropical storms is unusually adaptive when compared with baseline migration. However, the migration system of counties exposed to tropical storms is so strongly skewed towards high-risk destinations that the overall effect of tropical storms is to move individuals from high-risk counties to other high-risk counties. Conversely, excess in-migration associated with tropical storms attracts more individuals from low-risk counties compared to baseline migration patterns (it is thus less adaptive). However, because in-migrants from low-risk counties are usually a small fraction of those coming to coastal counties, the overall effect is negligible.

Determinants of Excess Migration

The second part of my analysis explores the moderating role of NFIP insurance payments, FEMA assistance, damage, social vulnerability, and population characteristics. The results are presented in Figure 4. Contrary to my expectations, neither populations characteristics nor the Social Vulnerability Index appear to be related to the number of excess migrants, not even in the univariate analysis. FEMA assistance, NFIP payments, and damage are all positively correlated with the number of excess migrants. The relationship holds even when all variables are included in the same model (multivariate analysis). The fact that only counties in or above the 95th percentile (more than \$2187.80 in damage per capita) have significantly more excess migrants compared to counties with lower damage suggests, however, that only devastating tropical storms have a strong effect on migration.

The positive effect of NFIP payments persists even when controlling for damage. This finding suggests that higher insurance payouts and higher assistance for a given level of damage increase excess migration, providing some evidence that having the resources to recouple from tropical storm damage enables individuals who wish to do so to relocate. Because the positive relationship between NFIP payments and migration holds even when controlling for SVI (which would be higher in high income counties), higher NFIP payments are likely the result of higher insurance rates. It is thus likely higher insurance rates that are associated with more intense post-storm migration. Overall, the effect of both damage and insurance is stronger for outmigration than it is for in-migration, suggesting that more devastating tropical storms will likely see negative net migration.

I found no association between SVI or population characteristics and the number of excess migrants. This result suggests that more socially vulnerable areas are not more likely to see higher or lower excess migration conditional on having experienced a tropical storm. In a further analysis presented in Figure 5, I looked at the interaction of SVI and percentage of the population identifying as White and Black with damage from tropical storms. The findings suggest that counties with an SVI falling in the 3rd and 4th quintiles, those with a proportion of the population Black in the top 2 quintiles, and those with a proportion of the population White in the bottom quintile see a steeper increase in out-migration as damage increases compared to other counties. In other words, counties in the top half of the SVI distribution, which are thus comparatively less socially vulnerable (but not those at the top), those with a high proportion of Black population, and those with a low proportion of White population will be particularly affected by high-damage tropical storms and will likely see more negative net migration. These findings are inconsistent with the segmented withdrawal hypothesis, as lower vulnerability majority White counties are not more likely to see negative net migration as damage increases compared to other counties. However, the fact that less vulnerable counties do see migration increase more steeply as damage increases, suggests that lower vulnerability does increase post-storm mobility, although race does not seem to be an important factor. On the contrary, the results in this section offer some support for the segmented recovery hypothesis. Counties with a sizeable Black minority are, even controlling for social vulnerability, more likely to see steeper rises in out-migration as damage from tropical storms increases.

Discussion and Conclusion

This study makes three key contributions to our understanding of post-disaster migration patterns. First, I show that experiencing a tropical storm has large effects on migration only in the presence of catastrophic tropical storms (such as Hurricane Katrina). Net population change due to excess migration associated with tropical storms is also rare. Both findings offer strong support for the homogeneous recovery hypothesis. While post-disaster migration is more likely to lead to population gains, population loss is also common, thus offering limited evidence to support wither the stimulus hypothesis of tropical storms as growth machines or the segmented withdrawal hypothesis of tropical storms as causes of population decline.

A second question I wanted to explore concerns the redistributive effect of post-disaster migration from the viewpoint of vulnerability to all natural disasters. Strategies of managed retreat and public buyout programs rely on the idea that migration in response to environmental change and natural disasters will move people from high-risk areas towards low-risk ones. I argued that this assumption, while seemingly intuitive, is problematic in light of two broad regularities observed in many studies of environmental migration: 1) most individuals do not move, 2) when they move, they do not travel long distances. Furthermore, I maintained that what we know about the intersection of social and biophysical vulnerability should lead us to think that the factors that pushed certain groups to live in areas prone to hazards will also play a role in their relocation decisions, pushing them to other risky areas. I show that there is little evidence that migration following tropical storms reduces the vulnerability of the individuals involved. Residents who leave areas just hit by a tropical storm are likely to move to similarly risky areas while the new residents replacing them come, in part, from areas with lower risk. By comparing absolute and relative excess migration, I show that excess out-migration is comparatively more adaptive than pre-storm migration. In other words, the relative increase in migration towards counties with low risk is larger than that towards counties with high risk. However, the pre-storm migration system is so biased towards other (nearby) high-risk counties that the net effect is to move individuals from one risky area to another. This finding should be concerning for proponents of buyout programs and has clear implications for disaster assistance programs more in general. Without specific interventions, voluntary, involuntary, or assisted relocation after tropical storms will not reduce the risk faced by the individuals moving.

The third question I set out to explore concerned the role of NFIP insurance payments, FEMA assistance, damage, social vulnerability, and population characteristics as determinants of excess migration associated with tropical storms. I find that higher insurance payments and FEMA assistance increase excess out-migration and in-migration. This finding suggests that, on the one hand, more post-disaster financial assistance allows some residents to leave the disaster-affected area. On the other hand, assistance also increases the flow of new residents moving into the area, likely following the economic opportunities generated by the reconstruction process. Consistently with the idea that areas receiving more disaster relief experience heightened mobility, I showed that, controlling for damage, areas that receive less disaster relief see less mobility.

I find no relationship between social vulnerability or demographic characteristics and excess migration. However, I uncovered a moderation effect of SVI and racial composition on the effect of damage. Less vulnerable counties and those with a high proportion of Black residents and a low proportion of White residents see a steeper relationship between damage and excess out-migration. These findings are not fully compatible with any of the theories I examined but support a model in which very vulnerable communities are trapped in place, high-income least socially vulnerable communities can easily recover from storms, and those with average to low vulnerability, especially if they have a high proportion of Black residents, are more likely to see high excess out-migration as damage increases.

While I believe this paper to be a valuable advancement over the existing literature, I need to acknowledge some limitations. Due to issues with migration data from the IRS after 2010, I was not able to capture the most recent tropical storms in my analysis. There are several major storms that occurred after 2010 that my analysis misses, from Hurricane Sandy to the record hurricane season of 2017. However, recent work on Hurricane Maria, which struck Puerto Rico in 2017, led to findings consistent with those in the present work, showing that net migration from Puerto Rico was not influenced, in the long term, by the hurricane (Alexander et al., 2019; Santos-Lozada et al., 2020).

A second limitation comes from the use of counties as the geographical unit of analysis. This choice, motivated by data availability, is not completely satisfactory from a theoretical point of view. Damage from tropical storms, disaster relief, social vulnerability, and population are likely to be heterogeneously distributed within counties. Using county-level indicators thus masks potentially interesting within-county variation. Unfortunately, no nation-wide estimates of damage from natural disasters are available below the county level. Additionally, no origin-destination migration data is made publicly available at the census-tract level, thus making it impossible to assess the impact of tropical storms on migration at that scale.

Despite these limitations, the present work is an important first step in moving from the analysis of population change in the aftermath of natural disasters to the examination of its implications for the vulnerability of individuals contributing to this change. I find that migration in the aftermath of tropical storms does not in itself reduce the vulnerability of the individuals involved. I suspect that underlying this finding is the lack of adequate public policies aimed at incentivizing individuals to move away from risk. In the absence of such policies, the current economic environment acts as a strong factor pushing new residents to hazardous areas. To be ready to face the challenges that climate changes will pose in the coming decades, we need more robust strategies grounded in an holistic understanding of the determinants of population distribution. Buyout programs and other strategies for reducing the nation's vulnerability to natural hazards should be redesigned to encompass both the area individuals leave behind and the one they move to. These programs should be designed in such a way that individuals are not only incentivized to move away from risky areas but also to move to less risky ones. This can be accomplished by combining mitigation policies with other social policies, for example by pairing buyout programs with affordable housing initiatives. Making sure that new residents are informed on the risk of experiencing a natural disaster is also crucial and an effort should be made to ensure that the information provided takes into account climate change. Finally, more stringent regulations on where and how to build in areas vulnerable to natural disasters should be implemented nationwide. Only in this way can we make the nation more resilient and contribute to reducing the number of people and properties at risk.

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Tables and Figures

Table 1: Descriptive Statistics

		Percentiles						
Characteristic	**N = 9,009**[1]	20th	40th	50th	60th	80th	90th	95th
Tropical Storm Damage Per Capita in the Last 3 Years	348.89 (4,157.64)	0.827	2.81	5.08	9.71	56.1	240	804
FEMA Assistance Per Capita in the Last 3 Years	104.67 (902.89)	0.368	0.930	2.08	4.22	21.2	90.4	234
(Missing)	5,802							
NFIP Payments Per Capita in the Last 3 Years	33.10 (430.52)	0.368	0.574	0.871	1.47	6.15	18.9	51.0
Population (Thousands)	71.43 (131.04)	7.25	13.6	20.2	34.8	100	191	304
Population Density (per Square Kilometer)	135.22 (611.30)	5.40	10.4	15.0	25.8	86.8	224	431
Proportion Aged 65+	0.19 (0.05)	0.149	0.170	0.179	0.188	0.218	0.250	0.288
Proportion Black	0.21 (0.16)	0.055	0.127	0.162	0.210	0.348	0.439	0.525
Proportion White	0.77 (0.16)	0.633	0.755	0.809	0.846	0.923	0.961	0.981
SVI	0.58 (0.30)	0.257	0.517	0.633	0.732	0.893	0.958	0.982

[1] Mean (SD)

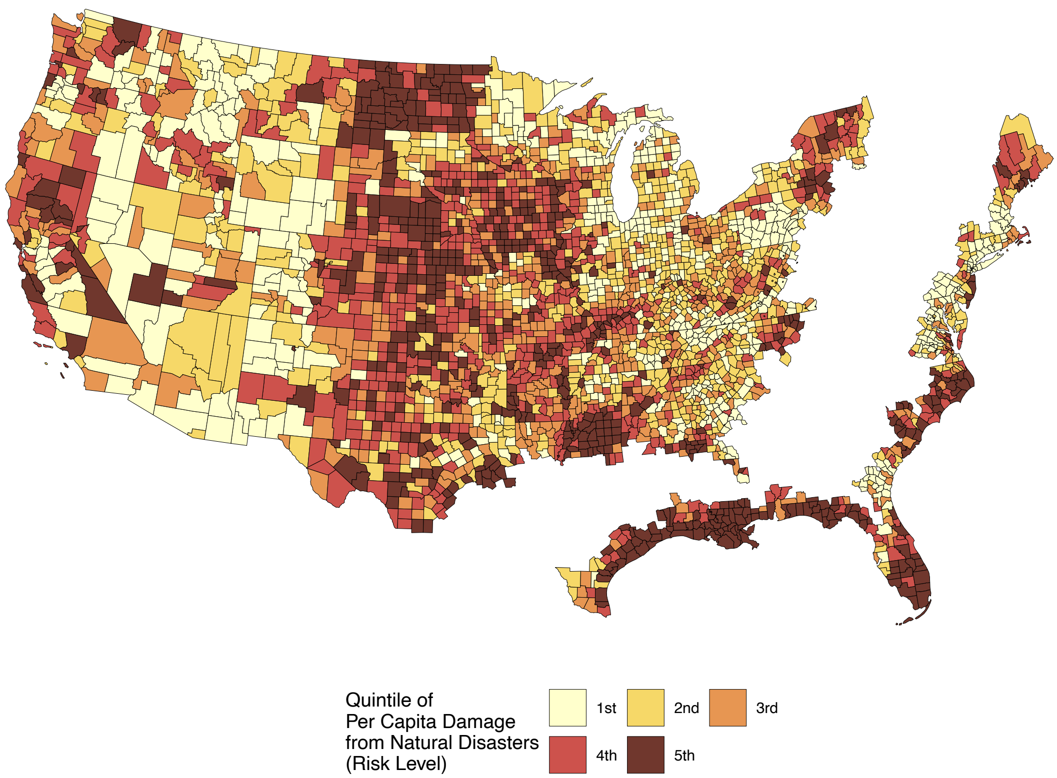
Table 2a: Estimates of Excess In-Migration, Out-Migration, and Net Migration by Year.

Excess Migration by Year									
	Excess In-Migrants			Excess Out-Migrants			Excess Migrants (Net)		
Year	Median	10th Percentile	90th Percentile	Median	10th Percentile	90th Percentile	Median	10th Percentile	90th Percentile
1990	−6,281	−12,070	−579	−572	−6,538	5,419	−5,659	−13,787	2,241
1991	−6,337	−14,151	1,545	−5,574	−16,574	5,269	−332	−14,486	12,640
1992	−10,028	−28,656	7,634	8,318	−15,797	30,909	−18,596	−47,988	10,662
1993	3,054	−12,016	17,068	−5,788	−24,089	10,936	9,309	−13,812	31,708
1994	−4,791	−18,831	7,168	−1,138	−15,810	12,596	−4,156	−23,579	15,856
1995	−1,490	−10,813	7,990	3,428	−5,904	13,014	−4,821	−18,684	8,963
1996	1,016	−5,886	7,912	−4,390	−12,150	1,916	5,876	−3,911	15,659
1997	−434	−6,953	5,884	741	−5,494	7,361	−1,227	−10,707	8,229
1998	−6,403	−15,450	2,588	−9,643	−19,475	790	3,122	−10,378	16,958
1999	−13,077	−36,843	9,866	−8,471	−38,523	19,196	−4,329	−39,993	33,994
2000	−3,452	−28,932	20,457	−18,599	−49,458	12,001	13,877	−24,380	54,834
2001	−3,716	−29,661	18,729	−6,326	−39,387	23,289	2,886	−38,506	43,040
2002	−11,131	−30,981	8,739	7,652	−18,656	33,087	−19,293	−51,530	14,937
2003	−2,887	−21,031	14,498	−14,446	−36,379	7,072	12,961	−15,128	40,071
2004	27,395	−2,718	59,376	−16,088	−53,876	20,768	43,964	−3,098	91,731
2005	115,884	78,326	147,241	214,782	174,073	255,871	−101,100	−154,694	−45,586
2006	44,510	18,431	72,344	84,735	51,092	115,924	−40,484	−79,693	1,594
2007	25,391	9,537	39,975	27,680	11,122	42,557	−1,874	−24,804	19,333
2008	36,815	15,413	57,193	10,816	−14,802	33,735	25,702	−4,552	58,902
2009	26,509	7,316	45,795	9,867	−12,965	31,691	17,654	−13,942	47,933
2010	17,463	2,911	29,837	4,642	−11,912	19,743	12,666	−9,079	34,151
Total	221,022	72,921	366,283	271,232	107,350	437,778	−52,160	−275,528	184,193

Table 2b: Estimates of Excess In-Migration, Out-Migration, and Net Migration by State.

Excess Migration by State									
	Excess In-Migrants			Excess Out-Migrants			Excess Migrants (Net)		
State	Median	10th Percentile	90th Percentile	Median	10th Percentile	90th Percentile	Median	10th Percentile	90th Percentile
Alabama	7,230	743	13,452	−981	−10,037	6,466	8,606	−2,212	19,803
Connecticut	−34	−3,484	3,618	−562	−4,591	3,315	562	−4,798	6,190
Delaware	558	−3,937	4,981	−8	−5,141	4,370	920	−5,986	7,184
District of Columbia	−2,419	−16,717	10,210	−5,360	−25,251	12,679	2,906	−20,666	24,899
Florida	13,970	−68,022	93,217	57,151	−35,253	151,736	−44,273	−160,166	71,475
Georgia	−372	−1,896	985	−413	−1,835	993	−6	−2,028	1,941
Louisiana	204,594	120,743	279,099	274,057	175,160	364,674	−68,486	−193,002	54,502
Maine	−12,845	−19,079	−7,218	−9,280	−15,770	−2,870	−3,628	−12,429	4,763
Maryland	−5,614	−19,594	8,110	−9,188	−29,082	7,129	4,237	−17,348	27,584
Massachusetts	−1,808	−20,096	14,694	−13,090	−39,771	10,260	12,150	−19,217	41,820
Mississippi	12,144	−5,050	27,010	17,535	−5,659	34,026	−5,116	−29,345	21,427
New Hampshire	−86	−1,737	1,600	−102	−1,666	1,655	−22	−2,332	2,398
New Jersey	−4,844	−22,863	13,967	−4,311	−29,445	18,843	−242	−29,130	30,623
New York	2,714	−6,254	11,316	299	−9,695	10,136	2,576	−10,959	15,848
North Carolina	−10,212	−23,590	2,529	4,776	−11,112	20,123	−14,703	−35,389	5,244
Pennsylvania	−1,381	−29,629	25,827	893	−35,918	34,809	−1,108	−44,261	44,306
Rhode Island	−837	−4,669	3,163	−503	−7,595	5,729	−154	−7,662	7,513
South Carolina	−2,170	−10,341	4,698	−1,851	−9,259	5,507	−624	−11,505	9,342
Texas	51,694	5,002	94,118	834	−62,197	57,609	49,342	−27,832	128,589
Virginia	−19,255	−60,395	23,062	−19,690	−77,070	32,722	2,804	−62,905	70,918
Total	221,022	72,921	366,283	271,232	107,350	437,778	−52,160	−275,528	184,193

Figure 1: Ranking of Counties in the Contiguous United States in the Distribution of Per Capita Damage from Natural Disasters (1987-2020).



Notes: The counties separated from the rest on the right are those I classified as coastal and for which outflows and inflows were computed.

Figure 2: Number of Migrants in Excess of Prediction by State, Year, and Risk Level

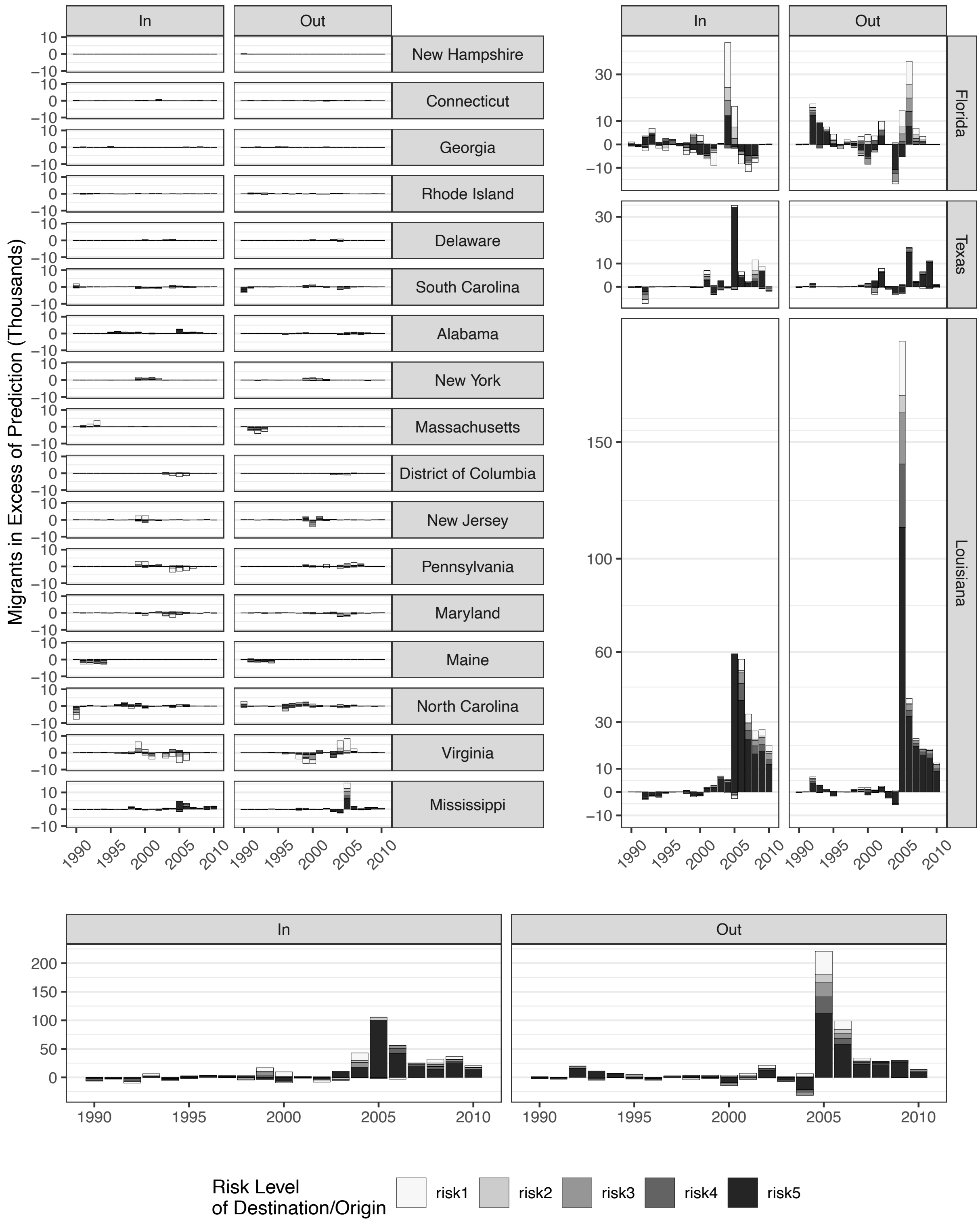


Figure 3: Relative Excess Migration by State, Year, and Risk Level

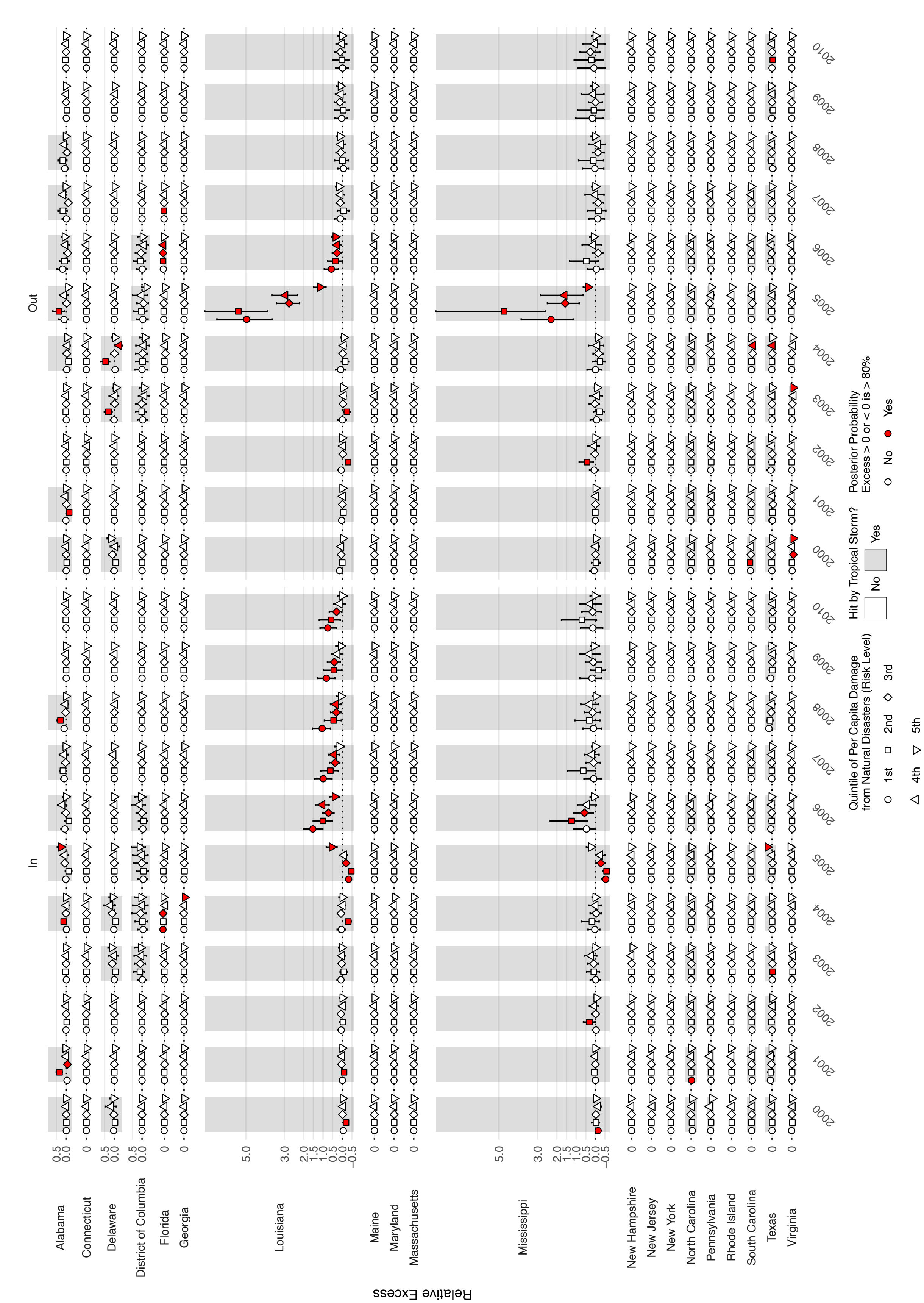


Figure 4: Determinants of Excess Migration

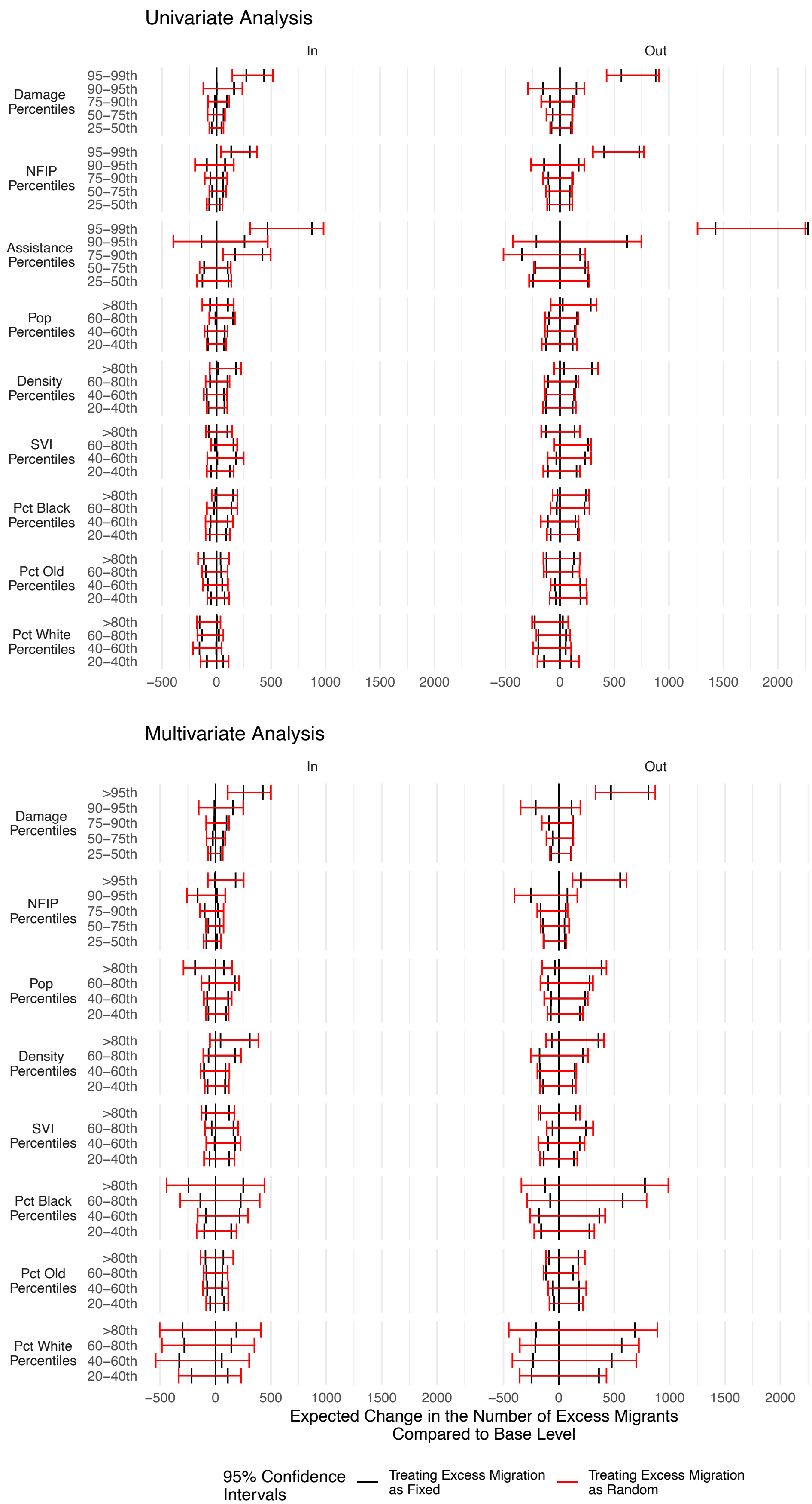
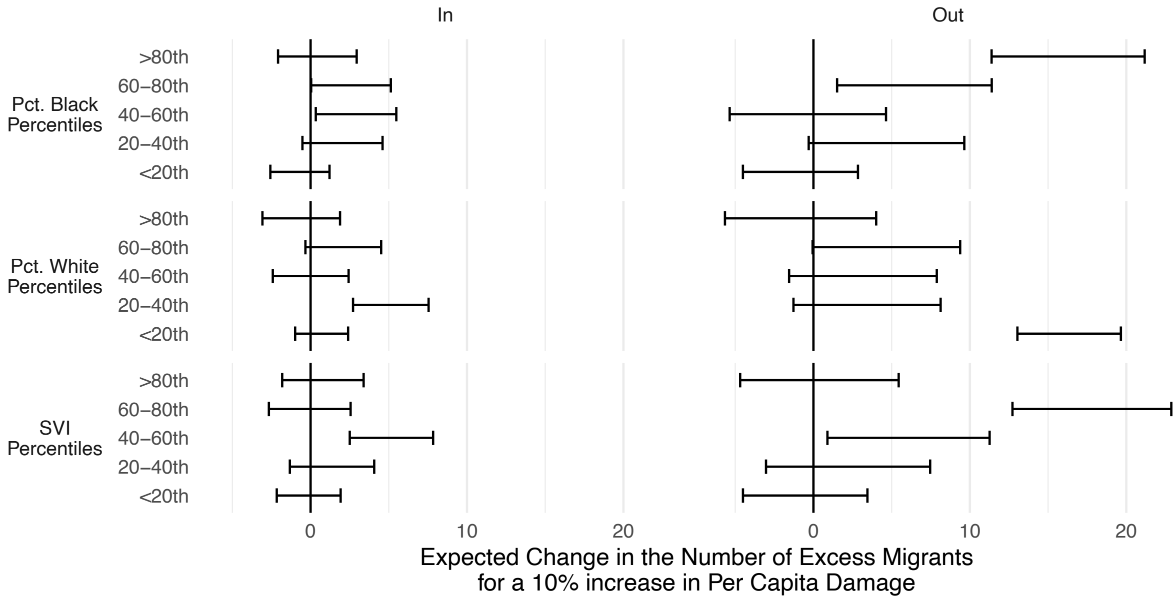


Figure 5: Moderators of the Impact of Damage on Excess Migration



Notes: The confidence intervals presented here are at the 95% level and are obtained by treating the number of excess migrants as fixed.