Abstract

Tropical Storms are among the most devastating natural disasters in the United States. Climate change is projected to make them even more destructive, and the number of people and properties at risk has steadily increased. Migration is often seen by scholars as an adaptation strategy to the risk posed by natural disasters. However, studies of migration after tropical storms have led to inconsistent results and have not analysed post-storm migration from the viewpoint of risk. This paper uses an innovative approach based on estimating "excess migration" associated with tropical storms with Bayesian hierarchical models, and decomposes migration by risk level of the origin and destination to understand whether migrants move to safer areas or rather riskier ones. It finds that excess migration after tropical storms is rare and does not usually reduce the number of people at risk. Only the most destructive tropical storms are associated with significant excess migration. Neither the amount of post-disaster assistance nor the socio-demographic characteristics of the affected counties are strongly associated with excess migration.

Introduction

Given the increasing threat posed by tropical storms in the United States (Emanuel, 2013; Knutson et al., 2010), and the large costs associated with their recovery (NOAA, 2021), it is increasingly important to understand the impact of these events on American communities. An important but understudied dimension is how population responds to these environmental shocks, particularly through migration.

Recent scholarship has portrayed migration following tropical storms as an adaptation process with the potential to reduce exposure to some of the negative effects of climate change and environmental 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" (Logan et al., 2016), 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 areas exposed to frequent and damaging environmental disasters will settle in places with lower exposure. However, more recent conceptual frameworks recognize that migration can also lead to an increase in the risk faced by the individuals who move (Cissé et al., 2022; McLeman et al., 2021). Additionally, substantial evidence in the migration literature suggests that most environmental migrants move over relatively short distances and that migration is considered as an option only once other adaptation strategies are no longer available (Cattaneo et al., 2019; Findlay, 2011; McLeman et al., 2021).

Although a body of recent works has emerged to update our understanding of the demographic consequences of environmental disasters from a theoretical (McLeman et al., 2021; 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 large scale 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 (Elliott & Pais, 2010; Fussell et al., 2017; Pais & Elliott, 2008; Raker, 2020). This choice limits one's ability to separately model the contributions of in-migration and out-migration. Second, few prior studies have examined where the "lost" population is moving to and where the "gained" population is coming from (see (DeWaard et al., 2016; Fussell et al., 2014) for two exceptions). Finally, 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 literature. Using Bayesian hierarchical spatial models, I estimate expected in-migration and out-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 along with consistent uncertainty intervals for all estimated quantities. 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 recently affected areas come from more or rather less risky ones. Finally, I explore the role of damage, disaster relief from Federal Emergency Management Agency (FEMA) programs, insurance payments from the National Flood Insurance Program (NFIP), and social vulnerability as moderators.

Background

Population Recovery from Environmental disasters

Homogeneous Recovery

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

While most environmental disasters cause significant 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 environmental disasters and are rapidly employed to facilitate recovery. At the community level it thus seemed unlikely that significant long-term effects of environmental disasters could be detected. This hypothesis was well supported by the first empirical investigations of the impact of environmental disasters in the United States. Studying how Cameron Parish recovered from Hurricane Audrey in 1957, Bates and colleagues (1963) formulated and found support for the hypothesis that environmental 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 (1969) 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 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. 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 size, housing stock, and level of economic activity. The same conclusion was reached by Friesema and colleagues (1979) in their investigation of recovery in four communities hit by environmental disasters between 1955 and 1966 (Friesema et al., 1979).

Another confirmation came from the landmark study of Wright and colleagues who investigated the impact 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 failed to detect any long-term practically or statistically significant impact of environmental disasters on the housing stock, the population size, and other county characteristics.

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 an environmental 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 environmental disasters. Despite the heterogeineity observed for some subpopulations, 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) paints 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 environmental disasters, Cochrane (1975) 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 environmental 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: 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 because of higher pre-disaster vulnerability may see negative post-disaster net migration, resulting in long-term population decline.

Recent Developments

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, 2009; 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; West, 2023).

Although this vast body of work improved our understanding of recovery following environmental disasters, all 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 environmental disasters. This limitation stems from the fact that extreme environmental disasters are, by definition, very rare, and their impact is difficult to disentangle from the context in which they occur (Gutmann & Field, 2010).

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 environmental 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 populations.

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 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 environmental 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.

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 environmental 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 in-migration or as a consequence of reduced out-migration. 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.

The Role of Insurance and Disaster-Aid

Disaster aid in the United States provides substantial funds to counties affected by tropical storms. Three main agencies are involved: the US Department of Housing and Urban Development (HUD), the Small Business Administration (SBA), and the Federal Emergency Management Agency (FEMA) (Olshansky & Johnson, 2014). Deryugina (2017) estimates that while the per-capita cost of a major hurricane averages $700, direct disaster aid for tropical storms averages $155–$160 per capita and additional transfers from non-disaster social security programs contribute an additional $780–$1,150, implying that post-disaster funds might exceed the initial damage (Deryugina, 2017). However, despite the substantial amount of public funds involved, there is limited research on the role of disaster-aid in increasing or reducing post-disaster migration. Looking at tornadoes and business survival, Gallagher and colleagues find that average-damage neighborhoods receiving Individual Assistance funds from FEMA retain more businesses and employees compared to neighborhoods that received no assistance (Gallagher et al., 2023). Similarly, Colby and Zipp (2021) estimate that flood insurance subsidies contribute to substantially increase the number of houses in flood-prone counties (Colby & Zipp, 2021). Indeed, while approximately 80% of NFIP policies have premiums designed to be actuarially fair, the remaining 20% of policies pay discounted premiums (Kousky, 2018). This imbalance between premiums and expected costs has led the NFIP to accumulate $20.5 billion in debt by 2021 despite receiving $16 billion debt relief from Congress in 2017 (Colby & Zipp, 2021). It thus appears likely that both FEMA assistance and the NFIP could be increasing the number of properties and people facing exposure to natural hazards as well as discouraging out-migration (Colby & Zipp, 2021; Gaul, 2019; Patsch et al., 2023). A positive connection between the influx of resources in the post-disaster phase and in-migration is indeed part of the recovery machines framework (Pais & Elliott, 2008) and would also result from the use of the more general New Economics of Labor Migration framework (Stark & Bloom, 1985). Both theories would predict that, net of damage, a larger influx of disaster-aid and insurance payments has the potential to increase in-migration into the affected areas by strengthening their recovery.

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 of tropical storms on net migration leading to population loss. The 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 suggest that outmigration generated by tropical storms will move individuals from disaster affected areas to nearby regions, likely sharing a similar level of risk (Adger et al., 2018; Cattaneo et al., 2019; Findlay, 2011; McLeman et al., 2021). 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. Financial assistance in the aftermath of a storm can be expected to lower out-migration and increase in-migration.

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 a county. While IRS data only captures taxpayers, an analysis by Molloy and coauthors showed that over 87% of the US population is represented (Molloy et al., 2011). Serious concerns have been raised over the data quality of IRS estimates after a change in the methodology used to produce the estimates in 2010 (DeWaard et al., 2021) (see (Pierce, 2015) for a description of the changes). Therefore, I limit my analysis to data collected before 2011.

Population counts by race, origin, and age for the period 1987-2010 come from the SEER database. 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 environmental disasters and tropical storms alone for the period 1987-2020 comes from SHELDUS (ASU, 2021).[1] Finally, I obtained the Social Vulnerability Index at the county level for 2000 from the CDC (CDC, 2022), this is the earliest year for which this index was available at the county level. 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 environmental disasters, I further decompose flows by the level of exposure to environmental disasters in the origin or destination counties. In this paper, I define coastal counties

[1] I've made an effort to ensure that all the data used in this project is publicly available with no paywalls. The only exception is the SHELDUS 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.

starting from the definition adopted by NOAA[2] 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 border exclusively with coastal counties. To measure risk of experiencing an environmental disaster, I compute the total per capita damage from environmental 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 environmental disasters per capita every three years, while those in the bottom quintile (low-risk counties) experienced less than $1. Using a longer time-period to assess exposure to natural hazards ensures a more precise estimation. 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 are defined as coastal[3].

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 rate of migration γ_{tsr} using the following specification:

$$y_{tsr} \sim Poisson(\gamma_{tsr} \cdot P_{ts})$$

[2] https://coast.noaa.gov/data/digitalcoast/pdf/defining-coastal-counties.pdf
[3] I tested different definitions of coastal counties as well as different measures of exposure to natural hazards and found that the results were not sensitive to these choices.

$$\log(\gamma_{tsr}) \sim \; Normal(\beta^0 + \beta_s^{county} + \beta_{t,s}^{time:county}, \sigma)$$

Where β^0 is the global intercept, β_s^{county} is the county-specific intercept for county s, $\beta_{ts}^{time:county}$ is the county-specific time effect for county s and time t, and σ is the standard deviation of $\log(\gamma_{tsr})$. All county-specific time effects are modeled as random walks of first order (RW1):

$$\beta_{t,s}^{time:county} \sim Normal(\beta_{t-1,s}^{time:county}, \sigma^{time})$$

Notice that the variance of the RW1 processes is shared among counties but the time-effects are different for each county in the sample. The choice of an RW1 model for the time effects relaxes functional assumptions on the effect of time and effectively performs linear interpolation between points when data is missing. Similar models have recently been used to model mortality rates and estimate excess mortality during the COVID-19 pandemic (Davies et al., 2021; Konstantinoudis et al., 2022). Bryant and Zhang (2020) develop a similar, although more complex, model for internal migration in Iceland (Bryant & Zhang, 2020). I experimented with alternative specifications substituting an autoregressive process of order 1 (AR1) to the RW1 processes as in (Paglino et al., 2023) and obtained results similar to those of the RW1 model. Similarly, adding parametric time trends to the model did not substantially change the estimates.

I model county-level intercepts using the modified Besag, York and Mollie spatial model proposed by (Riebler et al., 2016) (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. β_s^{county} is defined as:

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

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 use default minimally informative prior distributions for the global intercept 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). 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 β_s^{county}. The choice of priors for σ_b and ϕ follows established practices (Davies et al., 2021; Konstantinoudis et al., 2022; Paglino et al., 2023). For the precision of the RW1 process, I adopt the recommended regularizing PC prior that expresses the belief that $\Pr\left(\sigma^{time} > 1\right) = 0.01$.

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 county-years for which no tropical storm causing more than the median amount of per capita damage[4] occurred in the previous three years[5]. 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 environmental disasters that I've discussed in the background section. Examples of the model fit and more details are presented in the Methodological Appendix.

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. To ensure consistency between risk-specific estimates and total estimates, expected outflows to all destinations and inflows from all origins are obtained by aggregating estimates from the risk-specific models.

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. 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

[4] About \$5.

[5] 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.

of compliance (ICC). Finally, I compute the total 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 (Davies et al., 2021). For each of these 250 analyses, I fit the following hierarchical model:

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

$$\pi_{0s} \sim N(\gamma_{0S}, \sigma_{0S}^2)$$

$$\pi_{0y} \sim N(\gamma_{0Y}, \sigma_{0Y}^2)$$

$$\varepsilon_{tsr} \sim N(0, \sigma_{\varepsilon}^2)$$

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 j^{th} 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 not well captured when using quintiles. For all variables, I use the first quintile 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 95% confidence intervals by computing the mean, the 2.5th, and the 97.5th percentiles of each sample. All the stage 2 models are estimated in R with the lme4 package (D. Bates et al., 2015)[6].

Results[7]

Spatial and Temporal Patterns of Excess Migration

Table 2 summarizes the results at the county-year level. Of the 1909 county-years for which a tropical storm caused more than the median amount of damage in the last three years, only 2.35% percent had out-migration exceeding the lower bound of expected migration (negative and significant excess out-migration), and only 3.42% had an out-migration exceeding the upper bound (positive and significant excess out-migration). The corresponding figures for in-migration are

[6] 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.

[7] 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 (10^{th} posterior percentile – 90^{th} posterior percentile).

4.22% and 6.35%. The balance of excess migration was negative and significant in 3.74% of the county-years and positive in 5.34%. 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.

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, jointly with Table 3 presenting estimates of excess migration by year, reveals that large numbers of excess in-migrants or out-migrants are rare and confined to few state-years. In-migration is significantly lower than expected in 1991, 1995, and 2000, and significantly higher than expected in 2004, 2005, 2006, and 2007. Out-migration is significantly lower than expected in 1990 and 1991, and significantly higher in 1992, 2004, 2005 and 2006. Overall, only 2004, 2005, 2006, and 2007 exhibit large deviations from the expected values, and only in 2004 (positive) and 2005 (negative) we observe significant excess net 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[8] damage. If we were to remove the 2005 season in Louisiana, we would find little evidence that tropical storms are associated with excess migration.

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

[8] Adjusted to 2022 values

representing the destination of the relative 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. Overall, we can conclude that excess migration does not have, on average, an adaptive character.

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 migrants 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 for the period 2005-2010. 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.

Factors Associated with Excess Migration

The second part of my analysis explores the role of NFIP insurance payments, FEMA assistance, damage, social vulnerability, and population characteristics. The results are presented in Figure 4. 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 instead are all positively correlated with the number of excess out-migrants and in-migrants. Once I include all variables simultaneously, damage appears to be the only significant predictor. Even then, only counties in or above the 95th percentile (more than $1,003 in damage per capita) have significantly more excess migrants compared to counties with lower damage. This key finding suggests that only devastating tropical storms have a strong effect on 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 results for in-migration are not clear-cut. The relationship between damage and excess in-migration appears to be stronger in counties in the middle of the distribution of social vulnerability and proportion of Black residents.

This could mean that the new residents moving to areas recently affected by a tropical storm tend to settle in counties which are neither the most advantaged nor the most disadvantaged.

The findings on out-migration are easier to interpret in relation to the hypotheses formulated in the paper. 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 a steeper rise 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. Net population change due to excess migration associated with tropical storms is equally 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 either 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 environmental disasters. I argued that the migration as adaptation framework assumes that environmental change and natural disasters will move people from high-risk areas towards low-risk ones. This assumption, while seemingly intuitive, is problematic considering 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 limited 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.

While excess migration associated with tropical storms is not adaptative in absolute terms, my analysis of relative excess migration shows 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.

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 both excess out-migration and in-migration. However, the effect disappears when controlling for damage, challenging the idea that post-disaster assistance is a crucial driver of post disaster migration.

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 environmental disasters are available for the period under examination below the county level. Additionally, no origin-destination migration data for the period under consideration is made publicly available for administrative units smaller than counties (though digital traces offer hope for more granular data becoming available in the future (Kang et al., 2020)).

Despite these limitations, the present work is an important first step in moving from the analysis of population change in the aftermath of environmental 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.

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Tables and Figures

Table 1: Descriptive Statistics

Characteristic	N = 9,009[1]	Percentiles						
		20th	40th	50th	60th	80th	90th	95th
Tropical Storm Damage Per Capita in the Last 3 Years	405.75 (4,459.53)	1.36	4.72	8.60	16.0	86.4	339	1,003
FEMA Assistance Per Capita in the Last 3 Years	110.27 (892.86)	0.368	1.70	3.13	5.50	32.3	107	252
(Missing)	6,006							
NFIP Payments Per Capita in the Last 3 Years	33.10 (420.25)	0.376	0.649	1.02	1.71	6.71	20.6	55.2
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	0.60 (0.31)	0.259	0.561	0.678	0.773	0.899	0.941	0.970

[1] Mean (SD)

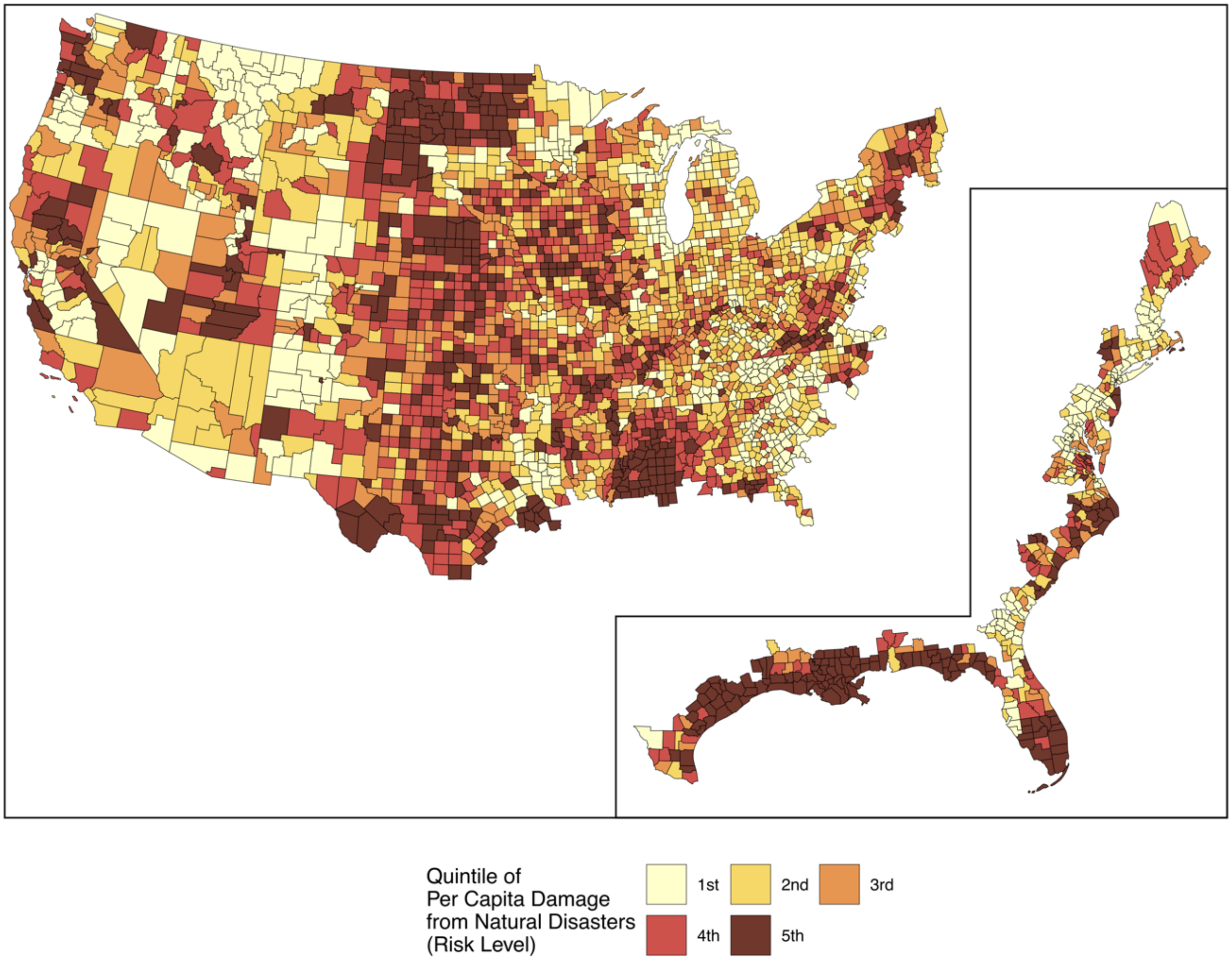
Table 2: Summary Results for County-Years

	Percentage of County-Years with Posterior Probability of Non-Zero Excess > 80%		Percentage of County-Years with Posterior Probability of Non-Zero Excess <=80%
	Negative Excess	Positive Excess	
Net-Migration	3.74	5.34	92.53
In-Migration	4.22	6.35	91.56
Out-Migration	2.35	3.42	95.30

Table 3: Estimates of Excess In-Migration, Out-Migration, and Net Migration by Year.

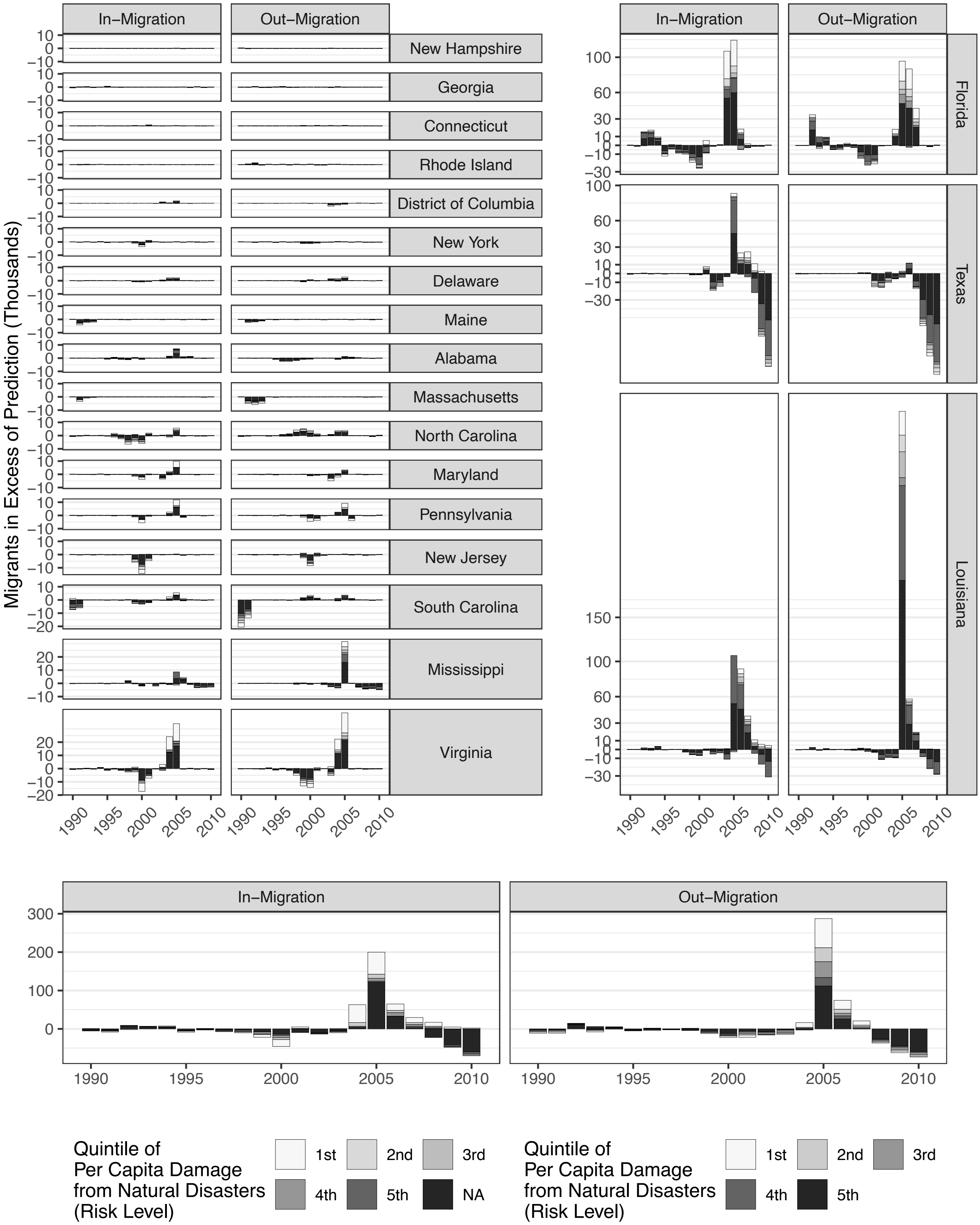
Excess Migration by Year									
	Excess In-Migrants			Excess Out-Migrants			Excess Migrants (Net)		
Year	Median	10th Percentile	90th Percentile	Median	10th Percentile	90th Percentile	Median	10th Percentile	90th Percentile
1990	−4,280	−10,335	1,447	−11,122	−17,200	−5,435	6,852	−1,360	14,384
1991	−8,166	−15,099	−1,694	−11,092	−17,592	−4,698	2,814	−6,799	11,883
1992	7,548	−6,726	20,978	15,238	1,698	26,546	−7,196	−25,958	11,098
1993	6,569	−8,311	22,096	−1,158	−15,760	12,063	7,530	−13,058	29,758
1994	8,320	−5,808	20,316	5,818	−7,760	18,138	2,908	−16,919	20,366
1995	−8,622	−13,962	−2,968	−5,244	−9,945	−425	−3,413	−10,576	3,871
1996	−1,602	−8,754	5,426	−2,243	−8,949	4,139	402	−8,935	10,994
1997	−7,067	−15,250	360	−2,219	−9,255	4,499	−5,088	−15,153	5,608
1998	−10,138	−20,125	−3	−2,358	−13,194	8,220	−7,586	−22,360	7,576
1999	−21,647	−48,795	4,325	−11,072	−40,418	14,308	−8,656	−46,934	26,674
2000	−44,644	−76,271	−16,613	−22,032	−52,337	7,501	−22,940	−65,231	18,707
2001	−3,945	−36,222	28,083	−21,220	−55,349	10,396	18,029	−27,831	60,706
2002	−12,562	−39,078	10,201	−13,560	−42,538	8,473	1,324	−33,809	37,988
2003	−8,166	−40,494	21,654	−13,670	−45,161	16,926	4,607	−38,309	48,620
2004	62,184	26,520	100,354	15,078	−25,638	54,116	48,999	−3,907	103,215
2005	200,799	156,493	244,346	289,105	241,418	332,395	−89,622	−146,584	−26,768
2006	66,378	19,527	105,007	75,133	27,552	120,787	−9,066	−74,610	51,288
2007	33,040	−22,277	75,773	25,076	−31,954	71,216	9,596	−62,707	79,446
2008	408	−66,631	47,834	−31,306	−99,716	17,283	31,085	−53,332	117,340
2009	−37,258	−114,034	18,959	−53,992	−134,056	946	17,172	−82,923	115,200
2010	−58,919	−154,073	741	−61,504	−158,614	−1,238	8,472	−105,502	114,693

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



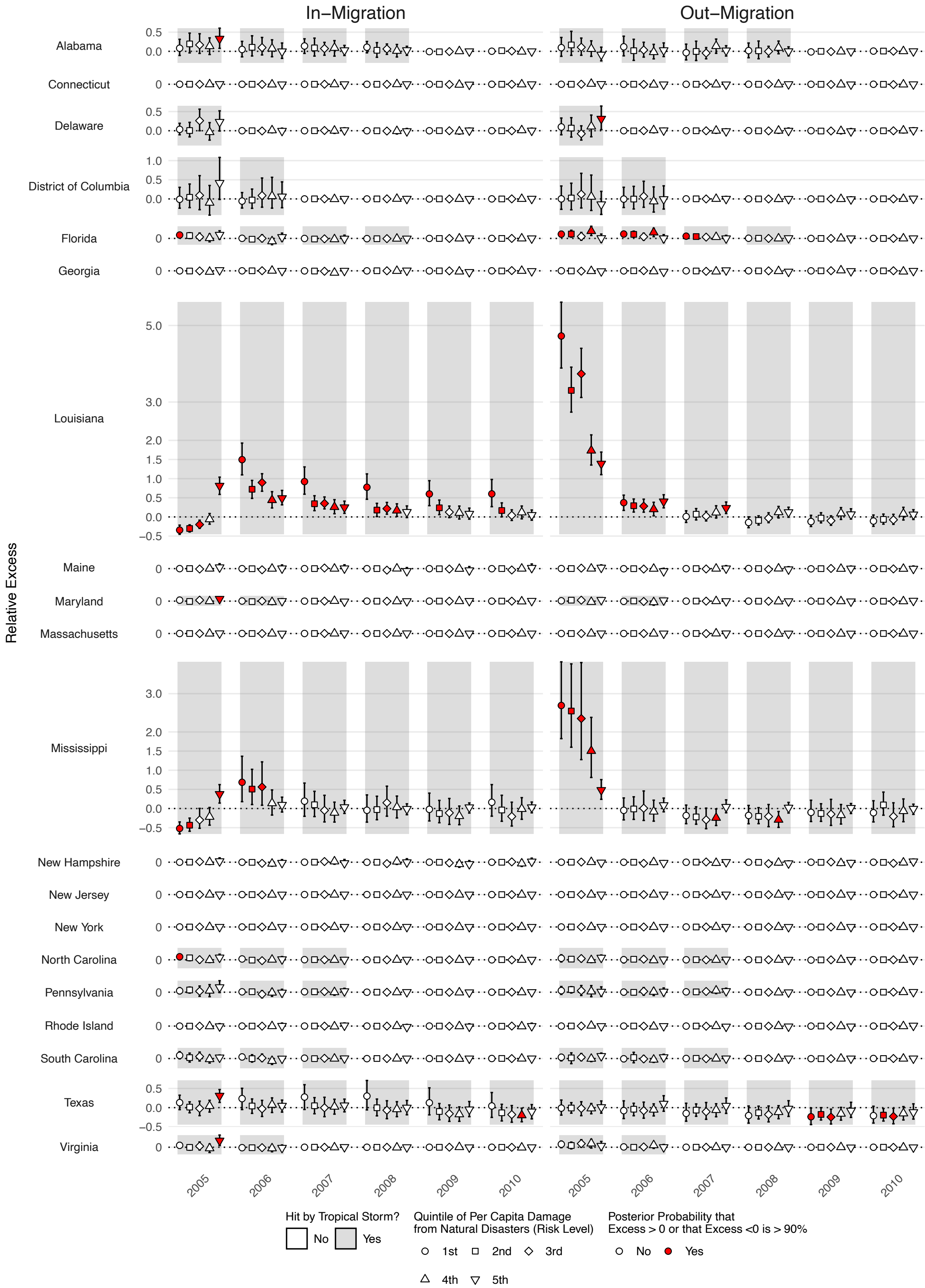
Notes: The counties separated from the rest on the right are those classified as coastal and for which outflows and inflows were computed. All counties are colored according to their position in the distribution of per-capita damage from all natural disasters (risk level).

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



Notes: Migration in excess of prediction by state and year decomposed by risk level of the origin (for in-migration) or the destination (out-migration). Excess in-migration is presented in the left panel of each pair of plots, with excess out-migration in the right panel. States are ordered by the maximum observed number of excess migrants. National-level counts are presented at the bottom of the figure.

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



Notes: This figure only includes estimates for the period 2005-2010 to simplify the exposition. Each dot represents relative excess (in-migration on the left and out-migration on the right). Shaded gray areas indicate state-years hit by at least one tropical storm in the last three years. The dot's shape reflects the risk level of the origin (in-migration) or the destination (out-migration). Dots colored in red identify observations for which the probability of either positive or negative excess exceeds 90%. The vertical lines indicate 80% posterior intervals around the point estimate.

Figure 4: Factors Associated with Excess Migration

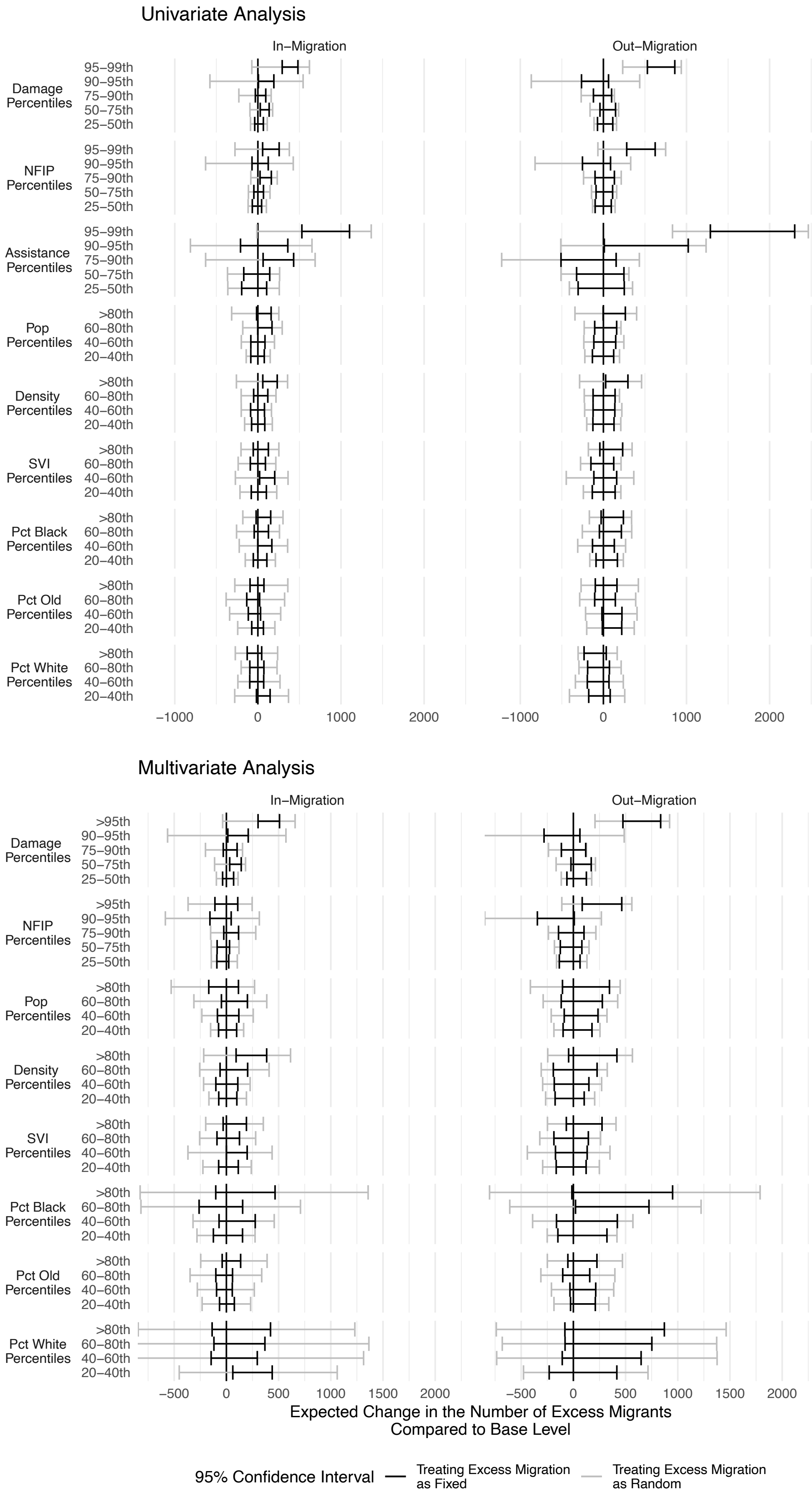
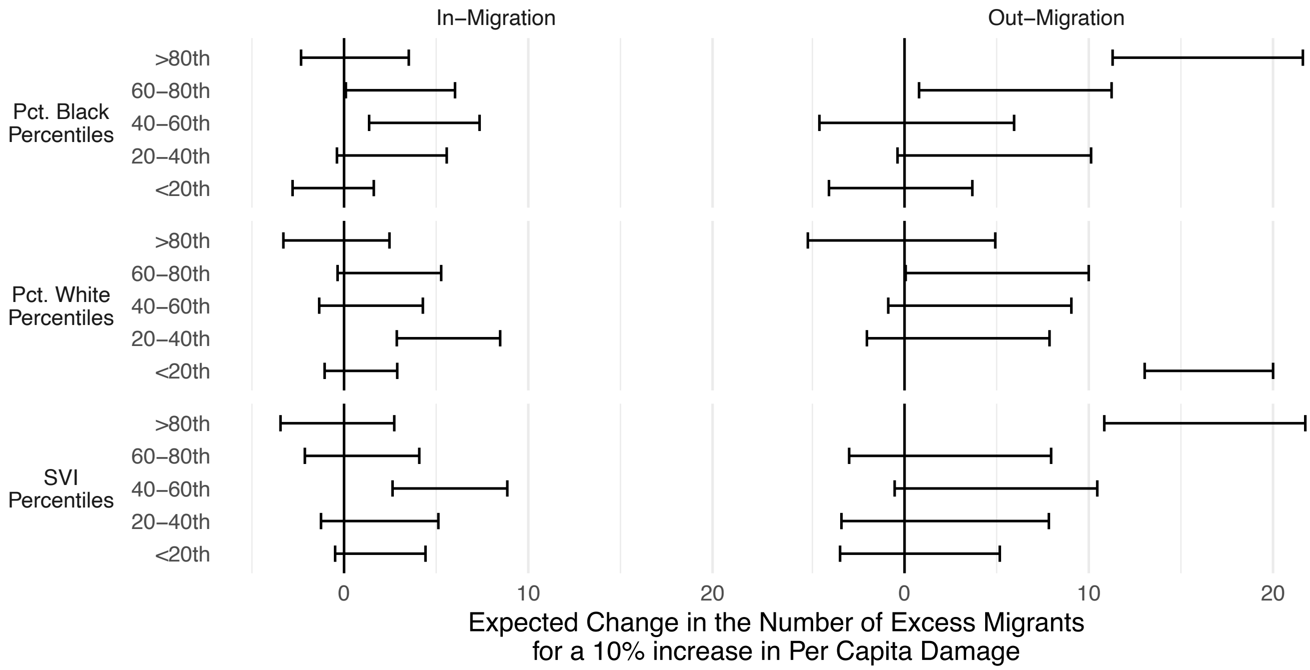


Figure 5: Moderators of the Impact of Damage on Excess Migration



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