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ORIGINAL PAPER

Estimating excess migration associated with tropical storms in the USA 1990–2010

Eugenio Paglino[1]

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Abstract
Tropical storms are among the most devastating natural disasters in the USA. Climate change is projected to make them even more destructive, and the number of people and properties at risk has steadily increased over the past several decades. Migration is often seen by scholars as an adaptation strategy to reduce exposure to future natural disasters. However, studies of migration after tropical storms have led to inconsistent results and have not analyzed post-storm migration from the viewpoint of exposure to future events. This paper adopts an innovative approach to estimate "excess migration" associated with tropical storms using Bayesian hierarchical models, and decomposes migration by risk of exposure to natural disasters of the origin and destination to understand whether migrants move to safer areas or rather riskier ones. Findings indicate that excess migration after tropical storms is rare and generally fails to reduce the number of people at risk of experiencing future natural disasters. Only the most destructive tropical storms are associated with significant excess migration. Finally, findings further suggest that neither the amount of post-disaster assistance nor the socio-demographic characteristics of the affected counties are strongly associated with excess migration.

Keywords Environmental migration · Climate change · Bayesian statistics

Introduction

Given the increasing threat posed by tropical storms in the USA (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 of this impact is how populations respond to these environmental shocks, particularly through migration.

✉ Eugenio Paglino
paglino@sas.upenn.edu

1 Population Studies Center and Department of Sociology, University of Pennsylvania, Philadelphia, USA

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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 et al., 2011a, b; 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 et al., 2011a).

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 to these disasters. 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 work 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, which would provide valuable insights into the processes underlying population change. Second, few prior studies have examined where the "lost" population is moving to and where the "gained" population is coming from (see Curtis et al., 2015; DeWaard et al., 2016; Fussell et al., 2014 for some 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, leveraging novel data sources and methods to build on the existing literature in three key ways. First, 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 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. Second, I decompose inflows by risk level of the origin and outflows by risk level of the destination, allowing me to investigate whether individuals moving out from areas recently affected by a tropical storm resettle in areas with lower or higher risk of experiencing natural disasters 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 county characteristics as moderators. In doing so, this study expands understandings of the magnitude, characteristics, and determinants of tropical storm-related migration.

Population recovery from environmental disasters

The body of literature on migration after tropical storms has rapidly grown over the last two decades. However, many studies have focused on understanding the impact of specific events on population change and migration rather than on building an overarching theory of recovery, resulting in a fragmented literature of case studies focusing on specific tropical storms. In particular, the tropical storms that have received extensive attention include 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), Hurricane Sandy (Binder & Greer, 2016; Binder et al., 2015, 2019; Bukvic & Owen, 2017; Bukvic et al., 2015; Koslov, 2016), and more recently Hurricane Maria (Alexander et al., 2019; DeWaard et al., 2020; Santos-Lozada et al., 2020; West, 2023).

Although these case studies improved understandings of recovery following environmental disasters, they have also focused on the most extreme events in terms of damage, limiting their 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), often resulting in mixed findings, generally unique to each specific hurricane. Studies focusing on Hurricane Katrina found dramatic post-disaster population loss in New Orleans (Fussell, 2015) but a relative fast recovery in other areas (Curtis et al., 2015). Results are similarly mixed for Hurricane Andrew (Elliott & Pais, 2010; Zhang & Peacock, 2009) and Hurricane Maria (DeWaard et al., 2020; Santos-Lozada et al., 2020; West, 2023), while no complete assessment of post-disaster migration for Hurricane Sandy has yet been published. This fragmentation of the literature highlights the need for a more systematic approach built on general theories of post-disaster migration. In the following sections, I briefly summarize four foundational theories, and the supporting empirical evidence, that have been formulated to explain patterns of post-disaster migration, as well as the hypothesized role of insurance and disaster-related aid as key determinants of tropical storm-related migration.

Functional recovery

The functional recovery hypothesis, traced back to the work of Haas et al. (1977), posits that communities struck by an environmental disaster can recover in a short amount of time, and are unlikely to experience long-term population or economic loss because of the disaster. The first rigorous empirical test of this hypothesis was conducted by Wright and colleagues (1979) who investigated the impact of all major tornadoes, floods, and hurricanes that occurred in the US from 1960 to 1970. 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 (Wright et al., 1979). More recently, Fussell et al. (2017) replicated Wright et al.'s design to investigate the impact of damage from hurricanes on population growth between 1980 and 2012. They find that damage affects population growth only in high-density counties whose population was growing before the event (Fussell et al., 2017). While current year damage suppresses population growth, 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.

The implication of homogeneous recovery for post-disaster migration is that one 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 functional recovery approach and the desire to formulate a more nuanced understanding of recovery after environmental disasters. Despite the heterogeneity observed for some subpopulations, taken together, the foundational work on post-disaster population dynamics paints recovery as a remarkably regular and uniform process (Bates et al., 1963; Dacy & Kunreuther, 1969; Friesema et al., 1979; Haas et al., 1977; Wright et al., 1979). 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). Similarly, 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. Comerio (1998) reaches similar conclusions investigating four destructive disasters that occurred between 1989 and 1994 (Comerio, 1998).

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

Recovery machines and the stimulus hypothesis

Aiming to update functional recovery theory with data from more recent natural disasters, Pais and Elliot (2008) formulated the concept of "recovery machines," or 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. The key idea introduced by Pais and Elliot is that "the recovery machine rarely stops at functional recovery." In this framework then, natural disasters can end up promoting population growth even beyond a return to the pre-disaster population size.

In a more systematic study building methodologically on Wright et al. (1979), and theoretically on Pais and Elliott (2008), 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). If the recovery machine hypothesis is correct, areas hit by a tropical storm should experience positive net migration for some years following the storm, likely as a result of increased in-migration and stable or reduced out-migration.

Concentration, displacement, and segmented withdrawal

The final theoretical contribution is offered by Elliott and Pais (2010) who, comparing the impact of Hurricane Andrew in Miami and in rural Louisiana, observe two directionally opposite processes of segmentation (Elliott & Pais, 2010). In rural areas, disadvantaged residents became more concentrated as more advantaged residents left after the hurricane. The authors label this process the "concentration hypothesis." Conversely, in urban areas, disadvantaged residents were 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." 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. 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” (Logan et al., 2016).

As for the segmented recovery hypothesis, which tries to add more nuance to functional recovery theory, the concentration and displacement hypothesis complicate the stimulus hypothesis story arguing that population loss might be observed in some areas. If the concentration hypothesis provides a good description of reality, we would expect tropical storms to cause population loss, especially in areas with a high proportion of high-income White residents. In contrast, if the displacement hypothesis has more explanatory power, and in agreement with the segmented recovery hypothesis, one would expect population loss to be concentrated in more disadvantaged communities.

Key determinants: the role of insurance and disaster aid

Crucial to our understanding of the theoretical hypotheses surrounding tropical storm-related migration are the practical policy implications of such migration. In particular, disaster aid in the USA 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–\$1150, implying that post-disaster funds might occasionally 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. Examining 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 a., 2023). A positive connection between the influx of resources in the post-disaster phase and in-migration is indeed part of the recovery machine framework (Pais &

Elliott, 2008) and is also consistent with 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

I test four hypotheses corresponding to the four theories summarized above:

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

Regarding the risk dimension of migration, the literature on environmental migration suggests that out-migration 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. Finally, based on the review of the existing literature, financial assistance in the aftermath of a tropical 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). Previous studies have used IRS data to investigate migration after hurricane Katrina (Curtis et al., 2015; DeWaard et al., 2016; Fussell et al., 2014), but this is the first study to leverage these data source to simultaneously study multiple events. 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. The exclusion of more recent years for the analysis means that changes in the relationship between natural disasters and migration that occurred after 2010 would not be captured. A more careful discussion of this limitation is included in the discussion section. While counties are not the ideal unit of analysis, this is the lowest geographical level for which detailed origin–destination flows are tracked over time. I discuss why this might be a problem in the discussion section.

Population counts by county, race, Hispanic origin, and age for the period 1987–2010 come from the SEER database. Other than to construct migration rates, population counts are used to compute the proportion of the population identifying as White, and the proportion of the population 65 or older. 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, d), 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). 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. County-level median house prices in 1990, which I use to adjust damage, insurance, and assistance amounts, come from the 1990 Census. Table 1 summarizes sample characteristics.

Methods

The main goal of the paper is to estimated excess migration from and to storm-affected counties associated with the occurrence of a tropical storm. In this paper, I define as storm-affected all counties for which FEMA issues at least one disaster declaration related to a tropical storm over the period 1986–2010 and for which SHELDUS registers a positive amount of damage associated with tropical storms. To build excess migration estimates, this paper extends the excess framework, universally employed to detect and measure excess mortality related to seasonal influenza, pandemics, heat waves, and other public health threats (Fouillet et al., 2006; Gergonne et al. 2010; Kosatsky, 2005; Toulemon & Barbieri, 2008). In particular, this paper leverages recent developments in the application of Bayesian statistics to the estimation of small area excess mortality in the context of the COVID-19 epidemic (Davies et al., 2021; Konstantinoudis et al., 2022; Msemburi et al., 2022; Paglino et al., 2023), extending these approaches to the migration domain. Within a Bayesian framework, spatial models are more easily integrated with temporal models, making Bayesian models an ideal candidate for small area estimation over time. Additionally, by directly providing full posterior distributions of all model parameters, Bayesian models allow for efficient construction of uncertainty intervals on any quantity of interest (such as the number of excess out-migrants in a given state and year) which would be difficult to obtain in a frequentist framework.

As in the general excess framework, a model of appropriate complexity, able to capture both geographical and temporal variation in migration rates, is fit to

Table 1 Descriptive statistics

	$N = 10{,}668$	Percentiles				
Characteristic	**Mean (SD)**	25th	50th	75th	90th	95th
In-migration rate (per 100,000)	4219.95 (2024.35)	2785	3766	5304	6855	7950
Out-migration rate (per 100,000)	4010.60 (1939.85)	2912	3602	4594	6039	7137
Net migration rate (per 100,000)	209.36 (1556.80)	−484	44.9	744	1742	2432
N.D. damage P.C	361.43 (6537.29)	0.218	2.48	19.3	141	531
N.D. damage P.C. (last 3 years)	1085.24 (11,265.97)	7.19	37.1	199	1182	3297
N.D. damage P.C. as a % of median house price	0.35 (6.31)	0.000	0.002	0.019	0.148	0.528
N.D. damage P.C. as a % of median house price (last 3 years)	1.05 (10.78)	0.006	0.035	0.208	1.21	3.40
T.S. damage P.C	222.94 (4754.28)	0.000	0.000	0.000	7.21	149
T.S. damage P.C. (last 3 years)	685.50 (8233.08)	0.000	0.000	14.6	504	1858
T.S. damage P.C. as a % of median house price	0.21 (4.88)	0.000	0.000	0.000	0.006	0.146
T.S. damage P.C. as a % of median house price (last 3 years)	0.65 (8.44)	0.000	0.000	0.014	0.456	1.86
NFIP payments P.C	30.21 (728.66)	0.000	0.017	1.23	9.80	30.0
NFIP payments P.C. (last 3 years)	89.58 (1257.16)	0.000	1.30	10.2	53.4	152
NFIP payments P.C. as a % of median house price	0.03 (0.60)	0.000	0.000	0.001	0.009	0.027
NFIP payments P.C. as a % of median house price (last 3 years)	0.07 (1.04)	0.000	0.001	0.009	0.051	0.128
FEMA assistance P.C	87.64 (1373.29)	0.000	0.000	2.81	40.8	168
(Missing)	6096					
FEMA assistance P.C. (last 3 years)	370.39 (2887.26)	0.000	10.9	101	408	900
(Missing)	7614					
FEMA assistance P.C. as a % of median house price	0.08 (1.19)	0.000	0.000	0.002	0.041	0.174
(Missing)	6096					
FEMA assistance P.C. as a % of median house price (last 3 years)	0.35 (2.49)	0.000	0.009	0.101	0.452	0.960
(Missing)	7614					

Table 1 (continued)

	$N=10,668$	Percentiles				
Characteristic	**Mean (SD)**	25th	50th	75th	90th	95th
Population (thousands)	45.30 (94.91)	7.07	14.7	41.1	111	191
Population density (per square kilometer)	52.52 (141.40)	5.05	10.9	29.9	121	247
Proportion aged 65 +	0.19 (0.05)	0.158	0.183	0.209	0.244	0.285
Proportion White	0.71 (0.18)	0.602	0.747	0.855	0.930	0.961

The sample size *N* refers to the number of county-years (508 storm-affected counties each observed for 21 years). Median house prices are county-specific and measured in 1990

TS tropical storms, *ND* natural disasters, *PC* per capita observations which are thought to be unaffected by the event one wants to study. The predictions from this model are then compared with observed rates or counts to compute excess migration. Typically, when the framework is applied to study excess deaths from recurrent events such as influenza or heat waves, observations for winter and summer months respectively are removed from the training set. In the case of tropical storms and migration, because the effects are likely felt for a longer period, I experimented with removing three, four, and five years after each storm, with substantially similar results. Because removing additional years increases the model uncertainty, the results presented in the paper are obtained with a three-year window. Examples of the results using the additional windows are reported in Supplementary Tables 2a, b and 3a, b.

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. To measure risk of experiencing an environmental disaster, I compute the total per capita damage from environmental disasters over the period 1969–2019 using data from SHELDUS and expressing it as a fraction of the median house price in the same county in 1990 to adjust for differences in home values. I use a longer time period compared to the one for which migration is investigated so that the estimates are more stable and that rare but destructive events (such as earthquakes) are also captured. Using shorter windows of time did not alter the ranking. I then divide US counties into 5 quintiles (or levels of risk). Counties in the top quintile (high-risk counties) experienced cumulative per-capita damage equal to more than 7.8% of the median house price, while those in the bottom quintile (low-risk counties) experienced damage for less than 0.8%. Figure 1 shows how all counties in the US score on the risk scale and clarifies which counties are classified as storm-affected.[1] For the analyses in this paper, I define a migration flow as adaptive if the origin of the flow has a higher risk level than the destination. I fit a total of ten models, represented by the equation below, including two for each of the five risk categories, one for in-migration and one for out-migration.

Let y_{tsr} be the flow of migrants between spatial unit s and other counties[2] with risk level r at time t. 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:

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

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

[1] I tested different inclusion criteria as well as different measures of exposure to natural hazards and found that the results were not sensitive to these choices. Supplementary Fig. 1 shows how different inclusion criteria would change the sample.

[2] I keep the direction of the flow unspecified to use a common notation for the models for in- and out-migration.

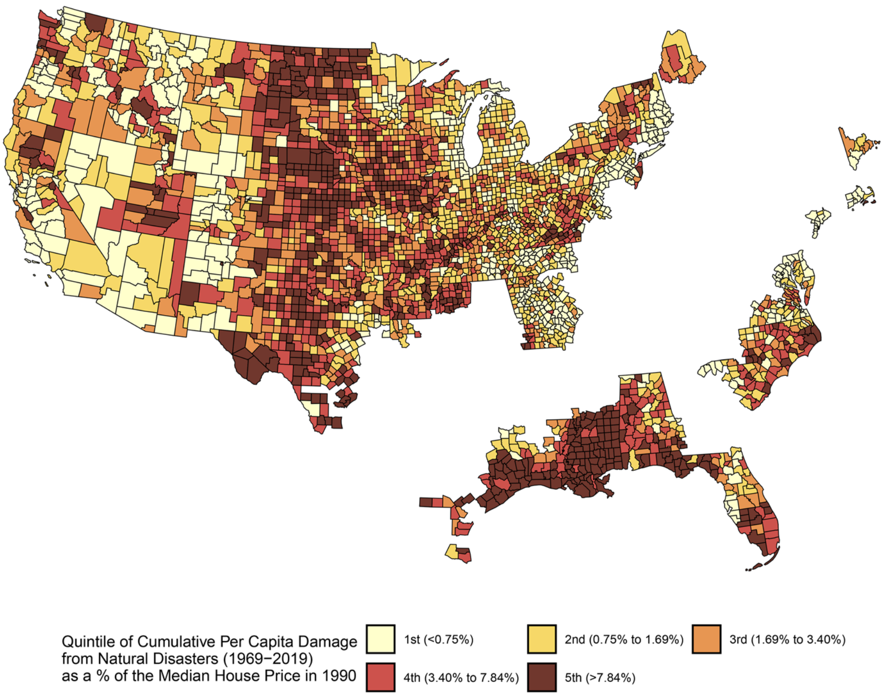


Fig. 1 Ranking of counties in the contiguous USA in the distribution of total per capita damage from natural disasters (1969–2019) as a fraction of the county-specific median household price in 1990. The counties separated from the rest on the right are those classified as storm-affected and for which outflows and inflows were modeled. All counties are colored according to their position in the distribution of per capita damage from all natural disasters (risk level)

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 $\beta_{t,s}^{time:county}$ are modeled as random walks of first order (RW1) with a common standard deviation for the RW1 process. County-specific intercepts β_s^{county} are modeled using the modified Besag-York-Mollie spatial model proposed by Riebler et al. (2016); this is a common choice for modeling county-level demographic rates (Davies et al., 2021; Graetz & Elo, 2022; Konstantinoudis et al., 2022; Paglino et al., 2023) and allows for spatial correlation between nearby counties. I fit the models using the Integrated Nested Laplace Approximation (INLA) method, through the R-INLA software package (Rue et al., 2009). Examples of the model fit and more methodological details on the Bayesian approach used in this study are presented in the Supplementary Methodology.

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 the number of excess migrants as e_{tsr} and the corresponding rate as m_{tsr}^e. 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 use the excess in-, out-, and net migration rates (per 1000 residents) as the dependent variables and restrict the sample to county-years affected by a tropical storm. I explore the role of NFIP insurance payments, FEMA IHP and PA payments, total damage, and selected county characteristics: percentage of the population 65 or older, percentage of the population identifying as White, the Social Vulnerability Index (SVI), and the metro category of each county (non-metro, medium or small metro, large fringe metro, and large central metro). All county characteristics are time-invariant and measured in 1990 to avoid issues of endogeneity (the SVI is the only exception being measured in 2000). I first fit a set of univariate models, and then a multivariate model. For damage, I compute the total amount per capita received in the last three years by a given county expressed as a fraction of the median house price in 1990. For FEMA assistance and NFIP payments, I compute the total amount per-capita received in the three years preceding the current one (from t-3 to t-1) by a given county expressed as a fraction of the median house price. For damage, NFIP payments, and FEMA assistance, I use a cumulative measure to allow for lagged effects and account for damage from successive tropical storms. For NFIP payments and FEMA assistance, the measure is additionally lagged to avoid endogeneity. 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 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. For the univariate analysis, I fit the following linear models:

$$m^e_{tsr} = \sum_q \delta_{j,q} X_{j,qst} + \pi_t + \varepsilon_{tsr}$$

where X_{qst} is a dummy variable indicating whether the value for the covariate j for county s at time t falls in the q^{th} quantile, and π_t are year fixed effects. For the multivariate analysis, all variables are included simultaneously, and the model becomes:

$$m^e_{tsr} = \sum_j \sum_q \delta_{j,q} X_{j,qst} + \pi_y + \varepsilon_{tsr}$$

I used quintiles for the percentage of the population aged 65 or older and the percentage of the population self-identifying as White. I instead grouped FEMA assistance and NFIP payments into the percentiles < 25th, 25th to 49th, 50th to 74th, 75th to 89th, 90th to 94th, and 95th and above. Finally, I grouped damage into the percentiles < 50th, 50th to 74th, 75th to 89th, 90th to 94th, and 95th and above. The decision to use a more granular partition for these three variables was motivated by their highly non-linear effect in the right tails of the distribution. For all variables, I use the first group as the reference category. Because FEMA assistance is only available from 2002 onwards, and since it is included in the model as percentiles of the cumulative sum for the last three years, models including this variable only use observations from 2004 onwards. For this reason, they are presented separately

Table 2 Summary results for county-years

	Percentage of county-years with posterior probability of non-zero excess > 80%		
	Negative excess	Positive excess	Percentage of county-years with posterior probability of non-zero excess ≤ 80%
Net migration	3.56	4.25	92.19
In-migration	3.87	5.00	91.12
Out-migration	2.42	3.49	94.08

Rows should sum to 100% but may not do so exactly due to rounding

in Supplementary Fig. 7 and in Supplementary Table 6a and b 5. I also tested two-way fixed effects models with county and state fixed effects. These models can't be used to estimate the effect of time-invariant characteristics (percentage of the population aged 65 +, percentage of the population identifying as White, metro category, and SVI measured in 2000), which are captured by the county fixed effects; nevertheless, they account for all unobserved time-invariant county characteristics and should thus be more robust to confounders. The results for these models for the effect of damage, NFIP payments, and FEMA payments are essentially identical to those of the main models and are reported in Supplementary Fig. 9a and b.

Results

Spatial and temporal patterns of excess migration

Table 2 summarizes the results at the county-year level. Of the 3177 county-years affected by a tropical storm (~30% of all county-years in the sample), only 3.56% had net migration exceeding the lower bound of expected migration (negative and significant excess net migration), and only 4.25% had net migration exceeding the upper bound (positive and significant excess net migration). The corresponding figures for in-migration are 3.87% and 5.00%. Those for out-migration are 2.42% and 3.49%. 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. These findings do not reflect the size of excess migration flows but only their presence and are robust to exclusion of certain events or time periods (Supplementary Table 2c and d show how the results change if county-year affected by Hurricane Katrina are removed and all county-years after 2004 are removed).

Figure 2 shows which counties experienced positive or negative excess migration (expressed in rates per 100,000 residents) in each of four five-year periods from 1990 to 2010 (the last period has six years). The maps show that in each of the periods, a sizeable share of counties did not experience substantial excess in- or out-migration (Supplementary Fig. 2 shows that the rates translate into excess in- and out-migration generally within ± 1%, with a majority within ± 10%). However, large excess migration

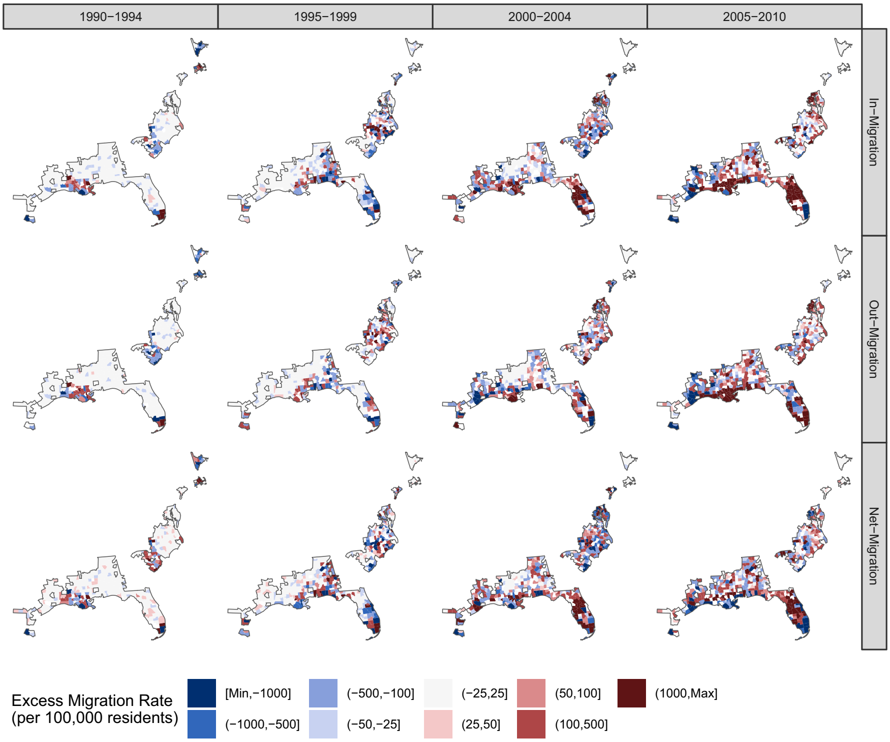


Fig. 2 Excess in-migration, out-migration, and net migration rates by county and five-year period. Counties are colored according to the estimated number of excess migrant (per 100,000 residents) associated with tropical storms occurred in each five-year period. The figure is divided into rows, representing excess in-migration (first row), excess out-migration (second row), and excess net migration (third row), and columns, each representing a five-year period (except the last one which includes six years). Estimates of excess migration are obtained by comparing observed migration to expected migration. In turn, expected migration derived under the counterfactual of no tropical storms is estimated with a set of spatio-temporal models described in more detail in the Methods section and in the Supplementary Material

rates are observed for some counties and periods, notably for counties in the Mississippi Delta and in Florida in 2004–2009 and in 2005–2010. In some cases, high excess out-migration coexists with high excess in-migration of the same sign, implying increased mobility but relatively stable net migration (e.g., St. Tammany Parish in 2005–2010). However, in other cases, declines in in-migration and increases in out-migration lead to negative excess net migration (e.g., Miami-Dade County in 2005–2010), or vice versa (e.g., Miami-Dade County in 2000–2004). As expected, we observe negative excess net migration along Louisiana's coast in 2005–2010 but also positive excess net migration in counties farther from the coast. Supplementary Fig. 3 reports the probabilities of non-zero excess for each county-period, revealing that few of the observed deviations in in-, out-, or net migration fall outside of the uncertainty intervals. Supplementary Fig. 2 replicates the maps (for in- and out-migration) expressing excess migration as a proportion of expected migration.

Table 3 presents estimate of excess net-, in-, and out-migration by year.[3] Table 3 reveals that large rates of excess in- or out-migration are rare and confined to few years. There are no years in which net migration is higher or lower than expected with a probability greater than 80%. This finding hides significant excess in both in- and out-migration that compensate each other. In-migration is significantly lower than expected in 1990, 1991, 1995, 2000, and 2010 and significantly higher than expected in 2004, 2005, and 2006. Out-migration is significantly lower than expected in 1990, 1991, 1995, and 2010 and significantly higher in 1992, 2005, and 2006. 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[4] damage. If we remove all county-years affected by Hurricanes Katrina and Rita, which only imperfectly corresponds to "removing" these two shocks from the data, the estimated rate of excess in- and out-migration decreases by about half for the affected years (Supplementary Table 3c).

Figure 3 goes one step further and decomposes flows by risk level of the origin (in-migration) and of the destination (out-migration). Figure 3 reveals that, at the national level, a large share of excess migrants from counties affected by a tropical storm move between high-risk counties in the top two quantiles of the risk distribution. Results by state in Supplementary Fig. 4 show that this pattern holds also at the state level except for Florida and Virginia. Overall, we can conclude that excess migration does not have an adaptive character as defined in this paper.

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, which effectively controls for the imbalance of the pre-storm migration network towards geographically close counties. To simplify the exposition, Fig. 4 presents the estimates of relative excess by year and risk level for Louisiana only and focusing on the period 2005–2010 (results for all states are presented in Supplementary Fig. 5). Figure 4 and Supplementary Fig. 5 reveal that while most excess out-migrants move to 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. The same pattern holds for in-migration except for 2005. Overall, these findings signify that excess out-migration associated with tropical storms is unusually adaptive when compared

[3] This change of metric does not affect which county-years display significant excess migration but makes comparisons between years with varying shares of the total population affected by tropical storms easier.

[4] Adjusted to 2022 values.

Table 3 Estimates of excess in-migration, out-migration, and net migration rates per 100,000 residents by year

	Excess in-migration			Excess out-migration			Excess migration (net)		
Year	Median	10th percentile	90th percentile	Median	10th percentile	90th percentile	Median	10th percentile	90th percentile
1990	−23.38	−43.37	−5.68	−28.05	−48.42	−9.09	2.31	−11.27	16.56
1991	−23.31	−40.95	−5.18	−22.25	−42.70	−4.07	−0.24	−12.73	12.71
1992	17.55	−14.64	46.89	40.65	9.40	70.73	−11.78	−34.24	10.04
1993	14.99	−23.67	50.07	−6.10	−40.15	28.33	10.10	−15.64	35.44
1994	15.85	−14.85	43.80	8.86	−19.25	36.12	2.90	−16.82	22.67
1995	−27.65	−42.39	−13.71	−14.78	−28.43	−2.08	−6.16	−16.54	4.09
1996	−3.02	−30.69	21.08	4.92	−19.30	28.63	−4.34	−21.91	12.27
1997	−25.57	−55.19	2.71	−5.06	−35.24	22.14	−9.92	−29.83	9.65
1998	−22.80	−58.96	12.07	5.97	−31.94	40.43	−13.38	−39.66	10.12
1999	−47.44	−114.93	14.57	−31.06	−106.72	28.09	−6.24	−55.52	42.37
2000	−95.86	−164.74	−23.57	−54.89	−137.71	15.54	−18.52	−71.78	31.83
2001	−3.10	−85.60	71.57	−50.32	−137.56	33.15	23.14	−32.81	82.20
2002	−29.05	−98.78	23.64	−41.97	−113.01	14.45	5.83	−41.14	50.57
2003	−23.70	−100.47	50.28	−39.03	−129.51	36.67	9.70	−47.23	66.41
2004	109.23	16.72	194.48	6.72	−92.29	88.47	50.99	−16.68	118.03
2005	468.96	361.39	570.60	581.45	469.23	680.17	−53.34	−130.22	18.03
2006	155.86	37.10	244.74	144.75	29.65	239.38	4.24	−70.71	83.87
2007	67.54	−67.22	162.73	45.88	−84.19	142.86	8.85	−77.04	92.83
2008	−12.67	−172.58	89.21	−76.75	−227.32	30.41	32.03	−67.88	128.20
2009	−98.15	−283.98	24.19	−129.95	−303.48	−9.31	15.31	−100.85	126.23
2010	−145.60	−356.71	−12.08	−149.06	−340.96	−25.65	−1.17	−130.91	119.35

Estimates of excess migration are obtained by comparing observed migration to expected migration. In turn, expected migration derived under the counterfactual of no tropical storms is estimated with a set of spatio-temporal models described in more detail in the Methods section and in the Supplementary Material

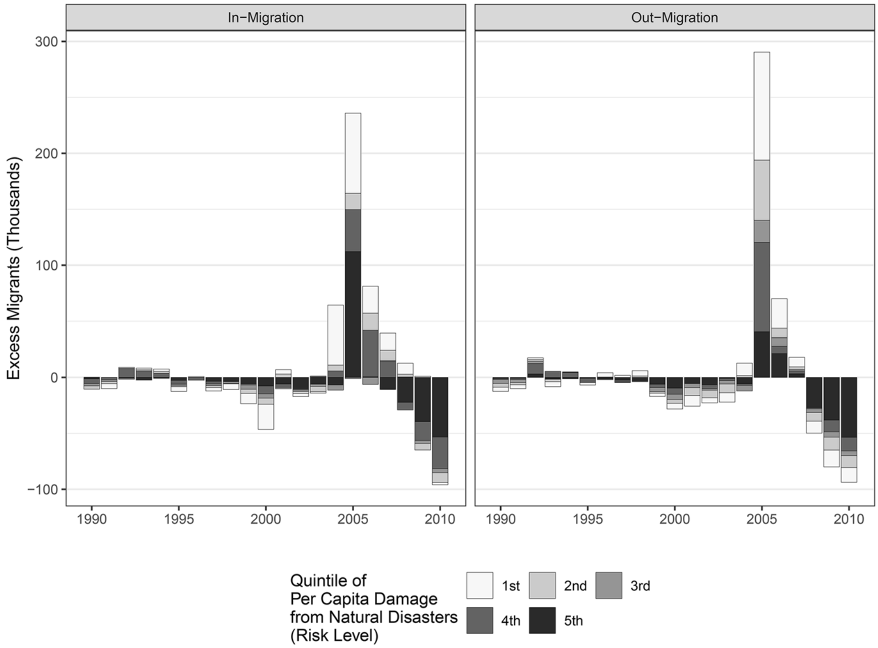


Fig. 3 Number of excess migrants (in thousands) by year and risk level. Excess migration by year decomposed by risk level of the origin (for in-migration) or the destination (out-migration). Excess in-migration is presented in the left panel and excess out-migration in the right panel. Estimates of excess migration are obtained by comparing observed migration to expected migration. In turn, expected migration derived under the counterfactual of no tropical storms is estimated with a set of spatio-temporal models described in more detail in the Methods section and in the Supplementary Material

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, and county characteristics in explaining variability of excess migration. The results are presented in Fig. 5 (with corresponding regression tables in Supplementary Table 4a, for the multivariate models, and Supplementary Table 4b, for the univariate models). In both the univariate and multivariate analyses, none of the proportion of population identifying as White, the proportion of the

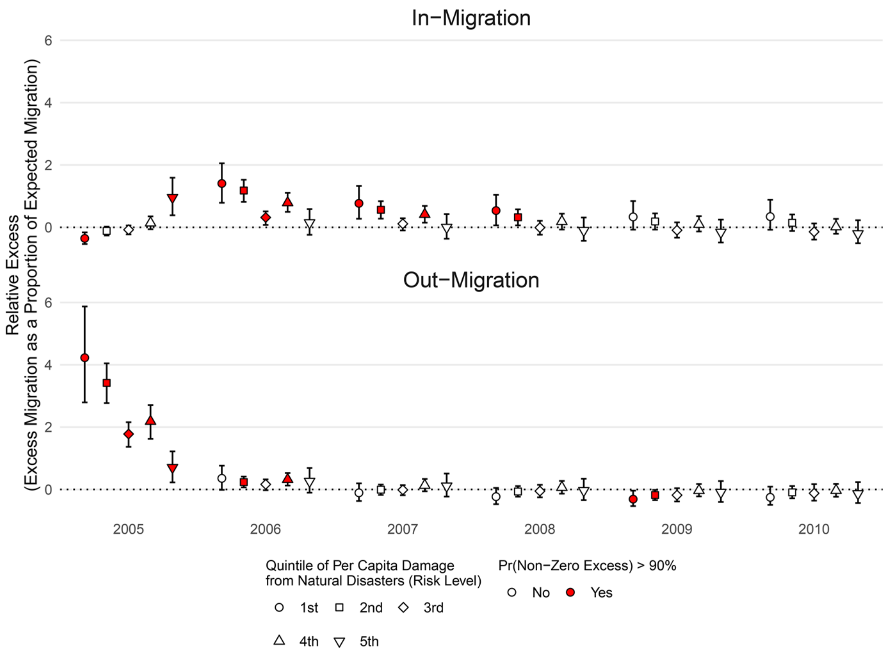
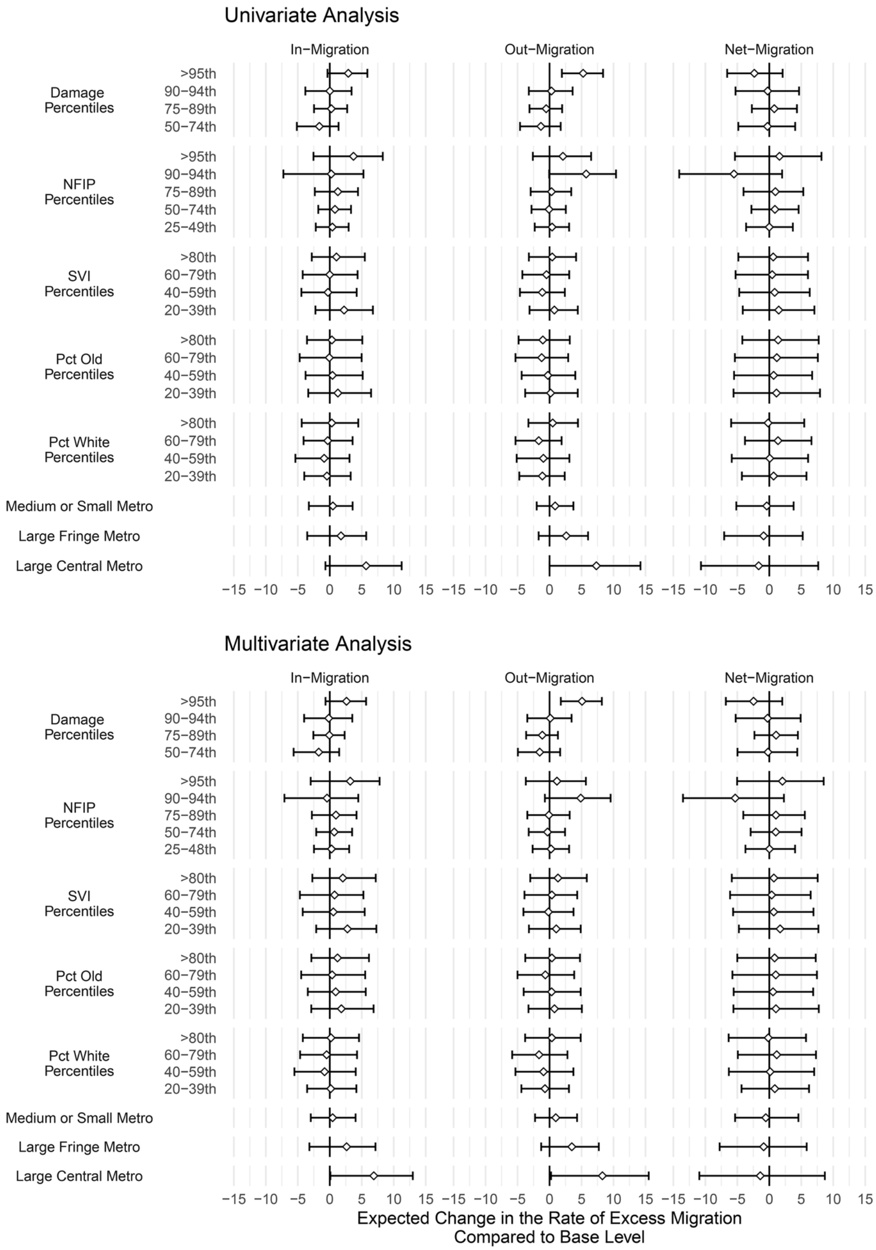


Fig. 4 Relative excess in-migration and out-migration associated with tropical storms by year and risk level (Louisiana, 2005–2010). This figure only includes estimates for the period 2005–2010 and for Louisiana to simplify the exposition. Each dot represents relative excess (in-migration on the top and out-migration on the bottom), with shapes identifying the level of risk of the origin (in-migration) and the destination (out-migration). Relative excess migration refers to the proportional increase in migration over the expected migration counts. For example, a value of 2 on the vertical axis indicates that excess migration was twice the expected migration, or equivalently that there was a 200% increase in 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. Estimates of excess migration are obtained by comparing observed migration to expected migration. In turn, expected migration derived under the counterfactual of no tropical storms is estimated with a set of spatio-temporal models described in more detail in the Methods section and in the Supplementary Material

population aged 65 +, the SVI, and NFIP payments are associated with excess in-, out-, or net migration. Large central metro counties have higher excess out-migration and in-migration, while metro category does not appear to predict excess net migration. Damage from tropical storms is positively associated with excess out-migration but not with excess in- or net migration. However, only county-years with very high levels of damage have significantly higher excess out-migration. FEMA assistance, whose association is investigated in Supplementary Fig. 7, Supplementary Table 6a, b, does not appear to be a significant predictor of excess migration. Overall, this analysis suggests that only devastating tropical storms have a strong effect on migration and only on out-migration. Additionally, large metro counties appear to be particularly susceptible to experiencing both excess in- and out-migration, with no effect on net migration.



Univariate Analysis
In−Migration
Out−Migration
Net−Migration
Damage Percentiles
>95th
90−94th
75−89th
50−74th
NFIP Percentiles
>95th
90−94th
75−89th
50−74th
25−49th
SVI Percentiles
>80th
60−79th
40−59th
20−39th
Pct Old Percentiles
>80th
60−79th
40−59th
20−39th
Pct White Percentiles
>80th
60−79th
40−59th
20−39th
Medium or Small Metro
Large Fringe Metro
Large Central Metro
−15 −10 −5 0 5 10 15
Multivariate Analysis
In−Migration
Out−Migration
Net−Migration
Damage Percentiles
>95th
90−94th
75−89th
50−74th
NFIP Percentiles
>95th
90−94th
75−89th
50−74th
25−48th
SVI Percentiles
>80th
60−79th
40−59th
20−39th
Pct Old Percentiles
>80th
60−79th
40−59th
20−39th
Pct White Percentiles
>80th
60−79th
40−59th
20−39th
Medium or Small Metro
Large Fringe Metro
Large Central Metro
−15 −10 −5 0 5 10 15
Expected Change in the Rate of Excess Migration Compared to Base Level

◀ **Fig. 5** County-level factors associated with excess in-, out-, and net migration rates in a univariate and multivariate regression frameworks. The estimates presented in this figure were obtained from a linear regression analysis where excess migration rates (the dependent variable) are related to several predictors. The univariate panel presents results from univariate models, in which each predictors is included separately. The multivariate panel presents results from multivariate models, in which all predictors are included simultaneously. Point estimates are represented with diamonds, 95% confidence intervals, presented with error bars, account for the fact that the dependent variable (excess migration rates) is also estimated. Damage from tropical storms and NFIP payments are time-variant. The percentage of the population 65 or older and identifying as White are time-invariant and measured in 1990; the SVI is also time-invariant and measured in 2000. All other variables vary by county and year. Estimates of excess migration are obtained by comparing observed migration to expected migration. In turn, expected migration derived under the counterfactual of no tropical storms is estimated with a set of spatio-temporal models described in more detail in the Methods section and in the Supplementary Material

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, which would predict positive net migration, or the concentration and displacement hypotheses that would predict population decline at least in some counties.

Second, this study uniquely explores the redistributive effect of post-disaster migration from the viewpoint of vulnerability to all environmental disasters. I argue 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, and (2) when they move, they do not travel long distances. Furthermore, I argue 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 exposure to natural disasters 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, the analysis in this paper 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.

Finally, this study examines the thus-far understudied role of NFIP insurance payments, FEMA assistance, damage, social vulnerability, and county characteristics as determinants of excess migration associated with tropical storms. Only tropical storm damage is associated with excess out-migration (positively) but shows no association with excess in-migration and net migration. Moreover, only county-years in the top five percentile of the damage and insurance payments distribution exhibit higher excess out-migration rates, suggesting that only devastating tropical storms are associated with increases in excess out-migration, with insurance payments potentially acting as an additional push factor. Large metro counties appear more likely to experience both excess in- and out-migration in the aftermath of tropical storms but metro type does not appear to predict excess net migration.

This study is not without limitations. First, due to issues with migration data from the IRS after 2010, I was unable to capture the most recent tropical storms in my analysis. There are several major storms that occurred after 2010 that are not included in the analysis, from Hurricane Sandy to the record hurricane season of 2017. Recent work on Hurricane Maria, which struck Puerto Rico in 2017, led to contrasting findings. Santos-Lozada et al. (2020) conclude that disaster-induced migration after Hurricane Maria was mostly temporary and that long-term migration dynamics are driven by economic factors (Santos-Lozada et al., 2020). An opposite conclusion was reached by DeWaard et al. (2020) and by West (2023) with both works finding long-term population loss in the aftermath of the hurricane (DeWaard et al., 2020; West, 2023). Unfortunately, I am not aware of alternative data sources that would allow me to construct the county-to-county yearly migration series needed for this study for a more recent period. The American Community Survey (ACS) can be used to produce county-to-county migration flows but only by pooling five years of data, thus lacking the temporal granularity needed by the analysis in this paper (US Census Bureau, 2021). Additionally, while it would permit an extension of the period under study to more recent years, the first five-year file is the one for 2005–2009, limiting the events that could be studied with these data to those occurred after 2004. Another data source for internal migration in the US, the Current Population Survey (CPS) Annual Social and Economic Supplement (ASEC), in addition to having a sample one third the size of the ACS one, contains information on state of previous residence but not county, thus lacking the geographic granularity needed for the analysis conducted in this study (Molloy et al., 2011). Another limitation of the IRS data is that it only captures year-long movements and not temporary migration. However, because temporary migration cannot lead to population change, the absence of short-term movements from the analysis does not alter the main conclusions regarding changes in the population distribution in the aftermath of tropical storms.

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).

A third and related limitation concerns the definition of adaptive migration used in the paper. The definition is partially unsatisfactory for two reasons: (1) it ignores within-county heterogeneity in risk, and (2) it relies on a static definition of risk, ignoring the possibility that movers might adopt mitigation strategies after they moved. Despite these limitations, defining adaptive migration in terms of risk levels of the origin relative to the destination allows me to test hypotheses regarding the adaptive character of migration in a consistent way over time and at the county level.

A fourth limitation concerns the assumptions used to estimate excess migration associated with tropical storms. The methodology used in this paper makes two main assumptions: (1) that past trends in migration are predictive of future trends in the absence of tropical storms, and (2) that the effect of tropical storms on migration will disappear after three years. While the second assumption is partially testable by comparing the results using longer windows, which I have done in the Supplementary Material, the validity of the first assumption cannot be demonstrated. However, for a shock unrelated to the occurrence of a tropical storm to severely bias the excess migration estimates presented in this paper, the shock would have to (1) cause deviations from migration trends large enough to be incompatible with historical variability, (2) occur in the same year and the same county as a tropical storm, and (3) have an effect that lasts less than three years. While possible, I think that the presence of many such shocks is unlikely. Additionally, one of the main results of this paper that large changes in migration occurring after tropical storms are relatively rare would only be made stronger if some of the observed deviations are explained by shocks unrelated to tropical storms.

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. My findings indicate that migration in the aftermath of tropical storms does not in itself reduce the exposure of the individuals involved to future natural disasters, suggesting a 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. In the face of an increasing threat of climate disasters, it is crucial that we better understand the implications of these disasters for the affected populations.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11111-024-00452-9.

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Data availability Data (or instruction on how to obtain them) and codes to replicate the analysis in this study are available on GitHub https://github.com/eugeniopaglino/storms-and-migrations.

Declarations

Competing interests The authors declare no competing interests.

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