

Beyond Net Migration: Disaster-Related Population Turnover and Socio-economic Selectivity in the United States

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Abstract: Disaster-related migration is often evaluated through total population or net migration changes, which may obscure simultaneous inflows and outflows as well as heterogeneity in migrant composition. By integrating analyses of migration flows and socio-economic compositions in the flows, this study examines disaster-related migration across the contiguous United States (CONUS) from 2012 to 2021. Using origin-destination migration flows, this study focuses on four major disaster types: floods, hurricanes, wildfires, and tornadoes. Poisson pseudo-maximum likelihood gravity models (PPML) are used to estimate associations between disasters and aggregate migration flows. Binomial generalized linear models (GLMs) are then used to assess whether disasters are associated with increases or decreases in the proportions of income, age, education, and employment groups within migration flows. The results indicate that floods and tornadoes are associated with increases in both outflows and inflows, suggesting population turnover rather than one-directional population loss. Hurricanes show limited associations with aggregate migration flows, but extreme hurricanes are linked to clearer selective migration patterns: the proportion of high-income migrants increases in inflows to hurricane-affected areas, the proportion of older migrants increases in both inflows and outflows of the affected areas, and the proportion of younger migrants decreases in both directions. These findings suggest that disasters may reshape migration not only by changing the volume and direction of flows, but also by changing the socio-economic composition of migrants. Disaster recovery and adaptation policies should therefore look beyond aggregate migration volumes and consider whether post-disaster mobility is reinforcing inequality in affected communities.

Keywords: Origin-destination flows; selective migration; socio-economic inequality; gravity model; Binomial generalized linear models; Spatial Analysis

1 Introduction

In recent decades, the United States has experienced a series of catastrophic weather- and climate-related disasters that have threatened human lives and generated substantial property damage and economic losses (Smith, 2020), and the frequency of such disasters is projected to increase in coming decades (Cunningham et al., 2024; Knutson et al., 2010). In addition to their immediate impacts, disasters have also generated profound socio-economic consequences by damaging local housing stock (Stoler et al., 2025), disrupting labor market conditions (Roth Tran & Wilson, 2025), weakening infrastructures and amenities (Winkler & Rouleau, 2020), and heightening perceptions of future hazard risk (Hermans & Kizilkaya, 2025). These effects may force residents to leave the affected areas, deter potential migrants from moving into high-risk places, or attract new and returning migrants through reconstruction activities, family or cultural ties, and persistent local amenities (Aldrich & Meyer, 2015; K. McConnell et al., 2024; Paul et al., 2024). Thus, beyond short-term displacement and evacuation, disasters may also reshape population landscapes through long-term migration.

Existing studies show that disasters can change migration volume, but directions and persistence of these effects vary across hazard types and population groups (DeWaard et al., 2023; Li et al., 2026). Hurricanes often generate immediate displacement followed by uneven return and recovery migration. For example, after Hurricane Katrina, return and in-migration to New Orleans varies in different neighborhoods, which were affected by damage severity, social ties, and established regional migration networks with nearby communities (Elizabeth Fussell et al., 2014;

Jeffrey A Groen & Anne E Polivka, 2010). Floods may affect migration through property loss, perceived future risk, and housing-market adjustment (Mutlu & Filatova, 2026). Recurrent floods can increase both outflows and inflows, indicating population turnover rather than simple depopulation (Fan et al., 2025). Wildfire effects appear more threshold-dependent: moderate wildfire exposure may not substantially alter migration, whereas highly destructive wildfires that damage housing and infrastructure are more likely to trigger relocation (Kathryn McConnell et al., 2024). Tornadoes are more spatially concentrated and short-duration, and severe tornadoes may produce limited net population change even when they disrupt local communities (Ethan J. Raker, 2020). Overall, these studies suggest that disaster-related migration is not a uniform process of population loss, but a hazard-specific and complex form of population changes that may occur at various spatial and temporal scales.

Published evidence also shows that disaster-related migration is socio-economically selective. Lee (1966) argues that migration is inherently selective because individuals differ in how they evaluate origin conditions, destination opportunities, intervening obstacles, and personal circumstances. *Selective migration* therefore refers to the process by which migrants and non-migrants differ in socio-economic and demographic characteristics (Norman et al., 2005). In disaster contexts, this selectivity may be amplified because households differ in their capacity to absorb losses and recover after disasters (De Haas, 2021). Financial resources and housing constraints determine whether households can relocate or remain trapped (Clark & Lisowski, 2025), while housing damage, social ties, and regional migration networks influence post-disaster return (E. Fussell et al., 2014; J. A. Groen & A. E. Polivka, 2010). In some regions, post-disaster rebuilding and climate adaptation may also contribute to *climate gentrification*, whereby safer neighborhoods are more occupied wealthier households while vulnerable residents are displaced

in high risk areas (Keenan et al., 2018; Kim & Park, 2023). Disaster-related migration can therefore reshape local demographic composition, labor markets, and patterns of neighborhood inequality (E. J. Raker, 2020). Recent studies support this perspective: post-flood migration can involve the selective departure of younger, better-educated, and employed residents and the in-migration of older, less-educated, and unemployed groups, causing socio-economic and labor-market changes (Fan et al., 2025). Lower-income households may face housing pressure that leads to relocation even without prior moving intentions (Clark & Lisowski, 2025). Recent studies further show that disaster mobility is not a simple or uniform push response. For example, highly destructive wildfires affect migration mainly after severe built-environment loss, suggesting threshold-dependent and mechanism-specific effects (McConnell et al., 2024). Thus, similar migration volumes may conceal different demographic and socio-economic outcomes depending on which groups leave, move in, return, or remain after disasters.

Various modeling frameworks have been used to analyze the spatial patterns of migration flows. As a classical approach, gravity models explain origin-destination flows as a function of population size, destination attractiveness, and distance-related frictions (Zipf, 1946). Related approaches, such as the intervening-opportunities model (Schneider, 1959) and the radiation model (Simini et al., 2012), treat migration flows as structured spatial interaction rather than isolated population change. More recent work has extended these classical models in several ways. Silva and Tenreyro (2006) showed that Poisson pseudo-maximum likelihood (PPML) estimation is better suited to highly skewed and heteroskedastic flow data. Panel gravity models extend the gravity framework to repeated origin-destination flows observed over time, making them well suited to annual migration panels that aim to estimate time-varying shocks while controlling for persistent origin, destination, and dyadic heterogeneity (Baltagi et al., 2015; Cameron & Poot,

2019). Deep Gravity models integrate deep neural networks into gravity-based logic to account for richer geographic context, nonlinear learning, and network-based spatial dependence (Luca et al., 2021; Simini et al., 2021; Zhu & Ma, 2026). These AI and machine learning approaches are particularly important for modeling disaster-related migration because slow-onset climate conditions and extreme events can alter migration patterns in nonlinear and spatially uneven ways (Hoffmann et al., 2024; Ton et al., 2025).

Taken together, prior research indicates that disaster-related migration is not simply a process of population loss, but may involve displacement, return migration, and population turnover. However, how these processes are reflected in origin-destination migration flows remains less clear, particularly when outflows from affected places occur alongside return migration or new in-migration. Evidence based on population or net migration changes provides important insight but may obscure whether apparent population stability reflects limited mobility or the offsetting effects of simultaneous inflows and outflows. It may also miss cases in which aggregate migration volumes change modestly while the socio-economic composition of migrants shifts substantially. Therefore, a key unresolved question is how different hazards are associated with both the direction of migration flows and the selectivity of the migrants who move.

This study examines whether disasters are associated with both the volume and socio-economic composition of origin-destination migration flows across the contiguous United States (CONUS). The analysis links migration flows derived from the Public Use Microdata Sample (PUMS) with four major disaster types, including floods, hurricanes, wildfires, and tornadoes, during the decade from 2012 to 2021. The analyses utilize migration flow data, disaster data, and socio-economic data to evaluate how disasters are associated with migration flows and whether they contribute to selective migration across socio-economic groups. Specifically, this study aims

to answer three research questions: (1) How well do gravity-based models quantify population flows between MIGPUMAs in the CONUS? (2) How are disasters associated with changes in O-D migration flows? (3) Are disasters associated with the socio-economic composition of migration flows? To address these questions, we first employ various forms of gravity models and Automated Machine Learning (AutoML) benchmark to evaluate predictive performance for total migration flows. We then use constrained PPML gravity models to examine origin-side and destination-side disaster associations and apply generalized linear models (GLMs) to evaluate whether disasters are associated with the representation of specific socio-economic groups within migration flows. By jointly examining migration volume and migrant selectivity, this study provides new evidence on how disasters may reshape regional demographic change and spatial inequality in the United States.

2 Data

2.1 Migration Flows

Migration flows were derived from the Census Bureau's American Community Survey (ACS) Public Use Microdata Sample (PUMS) files (Bureau, 2021b; Ruggles et al., 2022). The dataset records respondents' current place of residence at the Public Use Microdata Area (PUMA) level and their place of residence one year earlier at the Migration Public Use Microdata Area (MIGPUMA) level, which can be used as destinations and origins, respectively, to construct annual migration flows (Figure 1). To ensure spatial consistency, we used areal interpolation to convert migration-flow destinations from PUMAs to MIGPUMAs. The data also includes individual migrants' attributes, such as age, educational attainment, poverty status, and employment status, which allow us to estimate the socio-economic composition of migration flows.

This study focuses on the 2012-2021 period because the PUMA boundary delineation is consistent within this period.

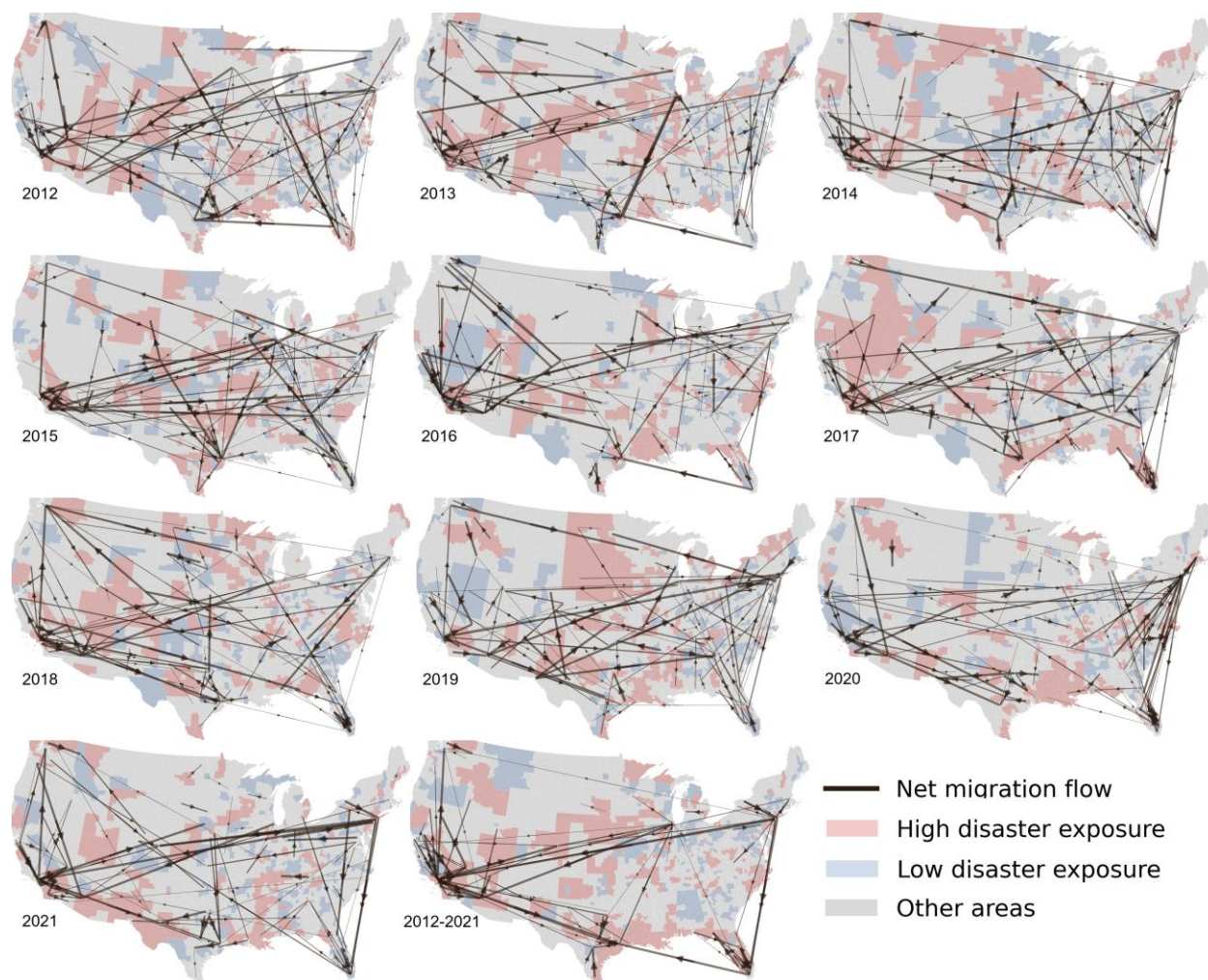


Figure 1. Annual and cumulative net migration flows and disaster exposure across MIGPUMAs, 2012-2021. Arrows show the 100 largest net migration flows among MIGPUMA pairs more than 200 km apart, with width proportional to net-flow magnitude. Background colors indicate high and low disaster exposure, defined as the upper and lower quartiles of total per-capita property damage from floods, hurricanes, wildfires, and tornadoes.

2.2 Disaster Data

Disaster data were derived from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), a county-level hazard database widely used in disaster research (Arizona State University & Homeland, 2025). SHELDUS provides historical records of natural

hazard events from 1960 to the present and includes detailed information on the timing, location, disaster type, and induced property damage, fatalities, injuries of each event. This study focuses on four major disaster types: hurricanes, floods, wildfires, and tornadoes, because they are among the most economically and socially consequential disasters in the United States and are closely related to disaster-related displacement and migration responses (NOAA, 2023). This study extracts SHELDUS data from 2009 to 2021, including the study period from 2012-2021 as well as disaster data in 2009-2011 to represent disaster exposure during the preceding three years. Disaster-induced property damage is used as the primary disaster indicator because it provides a comparable measure of disruption across disaster types, regions, and years (Figure 2). Property-damage estimates were adjusted for inflation to constant 2024 U.S. dollars. Disasters whose property damage ranked within the top 5% of all disaster records in the same year were defined as extreme disasters. This measure was coded as a binary indicator to distinguish severe events.

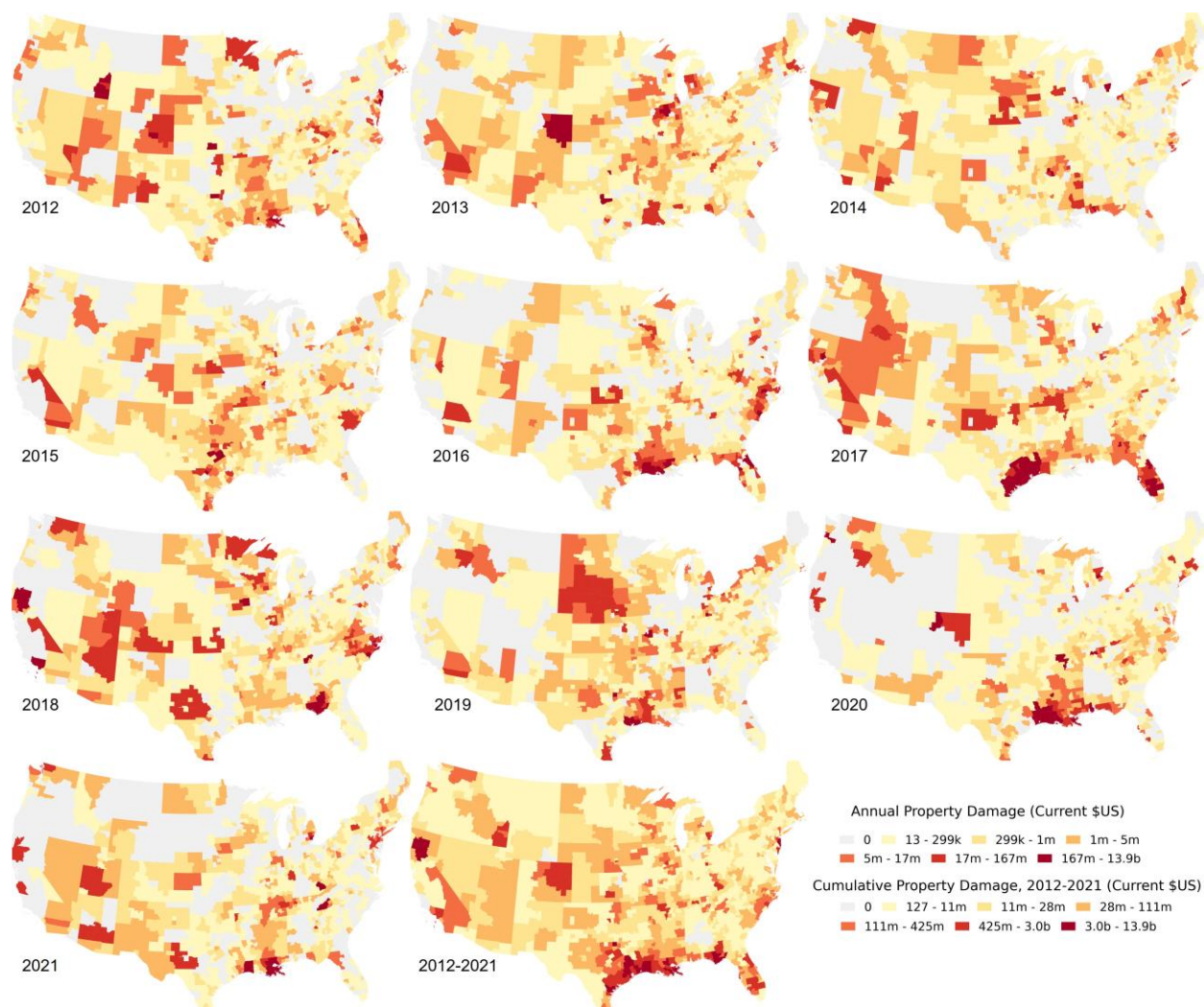


Figure 2. Spatial distribution of disaster-related property damage across MIGPUMAs, 2012-2021. Annual panels show year-specific property damage, and the final panel shows cumulative property damage over the study period. Light gray denotes no recorded property damage; warmer colors indicate higher property-damage categories. In the legend, m denotes million and b denotes billion U.S. dollars.

2.3 Socio-Economic Variables

Socio-economic variables in origin and destination MIGPUMAs were derived from ACS 5-year summary estimates (Bureau, 2016, 2021a). Compared with ACS 1-year estimates, the 5-year files offer more complete coverage and greater reliability for smaller areas. To align with the study period of migration data, the 2012-2016 and 2017-2021 ACS 5-year estimates were used to represent the socio-economic conditions (e.g., population size, density, income, age structure,

education, employment, amenity, and resilience) in origin and destination MIGPUMAs. These variables characterize the socio-economic contexts of both origins and destinations and capture place-based factors that may influence migration patterns.

Additional socio-economic variables in MIGPUMAs were derived from the Baseline Resilience Indicators for Communities (BRIC) (Derakhshan et al., 2025) and the USDA Natural Amenity Scale (NAS) (McGranahan, 1999). These variables were originally reported at the county level, which were aggregated in MIGPUMAs using population-weighted areal interpolation. BRIC was included to capture local community resilience related to disaster preparedness, response, and recovery. The 2015 and 2020 BRIC datasets were used to represent resilience conditions during the study period. The NAS was included to measure long-run environmental attractiveness, such as climate, topography, and access to water bodies. Although the NAS benchmark dataset was released in 1999, its use is appropriate for this analysis because these environmental conditions are generally stable over time. Together, these measures supplement ACS socio-economic indicators by reflecting broader structural characteristics of places that may influence migration patterns. Table 1 summarizes all variables used in the study.

Table 1: variables used in this study

Category	Variables	Datasets	Spatial Scale	Time Range
Migration Flows and their Socio-Economic Compositions	Total Flows % Poverty in Flows % High-Income in Flows % Age Elder in Flows % Age Younger in Flows % Employed in Flows % Unemployed in Flows % Bachelor+ in Flows % Low-Educated in Flows	PUMS	MIGPUMA-PUMA	2012-2021
Disasters	Total Property Damage	SHELDUS	County	2012-2021
Socio-Economic & Environmental Conditions	Population Size Population Density % Poverty Per Capita Income % Unemployment	ACS 5-Years	PUMA	2012-2016; 2017-2021

	% Limited English Proficiency			
	% Vehicle			
	% Age 65+			
	% Age 18-			
	Resilience Index	BRIC	County	2015; 2020
	Amenity Scale	USDA	County	1999

3 Methods

This study examines the disaster-migration association using an annual origin-destination panel across the CONUS from 2012 to 2021. Specifically, the following modeling approaches are used. First, four PPML gravity models and an AutoML model to predict total migration flows using socio-economic, environmental and disaster variables in the origin and destination MIGPUMAs. Second, binomial generalized linear models (GLMs) are used to evaluate whether disasters are associated with changes in the proportions of specific socio-economic groups within migration flows.

3.1 Data Preprocessing

Before the modeling work, all variables were converted into a consistent MIGPUMA-MIGPUMA origin-destination framework. In the PUMS data, origins are reported at the MIGPUMA level, whereas destinations are reported at the PUMA level. ACS variables are also reported at the PUMA level. To ensure the consistency of the spatial units, both migration flow data and ACS-based socio-economic variables in the origin PUMAs were aggregated to the MIGPUMA level using areal interpolation.

County-level datasets were aggregated in MIGPUMA areas using crosswalk-based weighted allocation. Because county boundaries do not map directly onto PUMA or MIGPUMA boundaries, the Geographic Correspondence Engine (Geocorr) was used to aggregate county-level data to the PUMA level through different weighted allocation (Center, 2016). Specifically, population-weighted conversion was applied to disaster variables and resilience index because

these variables are related to human dimensions. In contrast, area-weighted conversion was applied to the amenity scale because it represents place-based environmental characteristics. After aggregation to the PUMA level, these variables were further aggregated to the MIGPUMA level using the area-weighting method.

Several continuous variables exhibited strong right-skewed distributions and were log-transformed before model estimation. Disaster-related property damage, total population, and population density were transformed using the natural logarithm of one plus the original value, $\log(1 + x)$. This transformation retains observations with zero reported damage or zero-valued measures while reducing the influence of extreme values and improving scale comparability across variables. For disaster-related damage variables, the $\log(1 + x)$ transformation was applied to current-year exposure, one-year lagged exposure, and three-year cumulative exposure measures before they were included in the migration flow and selective migration models.

Before model estimation, descriptive analyses were conducted to examine changes in migration flows and migrant composition associated with origin-side disaster exposure. As disasters mainly have push effects (Cazabat & Yasukawa, 2020; Li et al., 2026), we selected the flows based on origin's disaster exposure. For each disaster type, an origin-destination flow from origin i to destination j was selected when origin i had no recorded exposure to that disaster type in year $t-1$ but had recorded exposure in year t . For these selected flows, percent changes in total migration volume from year $t-1$ compared to year t were calculated. To examine compositional change, percent changes in the proportions of each socio-economic group within the same flow from year $t-1$ to year t were calculated and reported in each OD flow. These descriptive analyses provide baseline evidence on how migration volume and migrant composition changed when a disaster occurs.

3.2 Migration Flow Models

Gravity models were used to examine how disaster and socio-economic variables are associated with migration flows between origins and destinations. In this framework, migration flows are modeled as a function of attributes of origins, attributes of destinations, and associated independent variables between them. The models were estimated using Poisson pseudo-maximum likelihood (PPML). PPML is appropriate for migration flow data because bilateral flows are non-negative, highly skewed, and often characterized by substantial heteroskedasticity. Compared with traditional gravity models, PPML preserves the multiplicative structure of the gravity model while avoiding bias associated with log transformation under heteroskedasticity (Silva & Tenreyro, 2006).

Four specifications of PPML gravity models were assessed: an unconstrained model, an origin-constrained model, a destination-constrained model, and a doubly-constrained model (Equation 1-4). The unconstrained model estimates bilateral migration flows using both origin- and destination-side covariates. The origin-constrained model includes origin fixed effects and estimates how migrants from the same origin are distributed across destinations. This specification is used to identify destination-side pull effects. The destination-constrained model includes destination fixed effects and estimates how migrants arriving at the same destination are distributed across origins. This specification is used to identify origin-side push effects. The doubly-constrained PPML model includes origin, destination, and year fixed effects. This specification controls for persistent origin- and destination-specific heterogeneity and common year shocks. Accordingly, the doubly constrained model is used only as a benchmark for comparison with the other PPML specifications. It is estimated with dyadic baseline factors and without origin- or

destination-side disaster variables and is not interpreted as estimating disaster-related push or pull effects.

The unconstrained model is specified as:

$$E(F_{ij,t}) = \exp(\beta_0 + \beta_1 X_{i,t} + \beta_2 X_{j,t} + \beta_3 Dis_{i,t} + \beta_4 Dis_{j,t} + \delta_t) \quad \text{Equation (1)}$$

The origin-constrained model is specified as:

$$E(F_{ij,t}) = \exp(\beta_0 + \beta_1 X_{j,t} + \beta_2 Dis_{j,t} + \delta_t + \alpha_i) \quad \text{Equation(2)}$$

The destination-constrained model is specified as:

$$E(F_{ij,t}) = \exp(\beta_0 + \beta_1 X_{i,t} + \beta_2 Dis_{i,t} + \delta_t + \gamma_j) \quad \text{Equation(3)}$$

The doubly-constrained model is specified as:

$$E(F_{ij,t}) = \exp(\beta_0 + \beta_1 X_{ij,t} + \alpha_i + \gamma_j + \delta_t) \quad \text{Equation(4)}$$

Where $F_{ij,t}$ is the observed migration flow from i to j in year t , and $E(F_{ij,t})$ denotes the expected migration flow estimated by the PPML model. $X_{i,t}$ and $X_{j,t}$ represent socio-economic covariates for the origin and destination, respectively, while $Dis_{i,t}$ and $Dis_{j,t}$ represent disaster exposure measures for the origin and destination. The vector β contains the coefficients associated with the observed covariates. Year fixed effects are denoted by δ_t , origin fixed effects by α_i , and destination fixed effects by γ_j . Depending on the model specification, the origin-constrained model includes origin fixed effects, the destination-constrained model includes destination fixed effects, and the doubly constrained model includes both origin and destination fixed effects.

In addition, Automated Machine Learning (AutoML) was implemented as a predictive benchmark for total origin-destination migration flows. The dependent variable was the total migration flow, and the predictor set was kept consistent with the PPML flow models. The AutoML framework trained a set of tree-based and boosting models, including CatBoost, LightGBM, histogram-based gradient boosting, Random Forest, Extra Trees, XGBoost, and depth-

limited XGBoost. Candidate models were tuned and compared using the same training and validation structure, and the final benchmark performance was evaluated using the Common Part of Commuters (CPC). Because the purpose of this study is to interpret origin- and destination-side disaster associations rather than to maximize prediction alone, AutoML was used only for predictive comparison and was not used for coefficient-based interpretation.

To capture different temporal relationships between disaster exposure and migration flows, we constructed models of disaster measures in three temporal windows: (1) the model with current-year disaster exposure, (2) the model with one-year lagged disaster exposure, and (3) the model with three-year cumulative disaster exposure. The current-year model captures contemporaneous associations between disasters and migration flows. The one-year lagged model captures delayed migration responses after the disaster, consistent with studies showing that migration effects may intensify in the year after severe hazards and that return migration depends on housing damage, social ties, and recovery conditions (K. McConnell et al., 2024). The three-year cumulative specification captures accumulated exposure over the previous three years, capturing that migration may respond to repeated hazard exposure, cumulative economic damage, and prolonged recovery constraints rather than a single-year shock (Best et al., 2025). For each PPML model, disaster outcomes were measured in two ways: (1) logged property damage, which captures variation in disaster intensity, and (2) a binary indicator denoting whether a disaster was classified as an extreme event.

3.3 Selective Migration Models

Binomial generalized linear models (GLMs) were used to examine selective migration across socio-economic groups. Specifically, GLM models quantify the relations between disasters and changes in the proportions of specific population groups within migration flows. In the GLM

models, the dependent variable is the proportion of migrants in a specific subgroup within the total migration flow. The independent variables include disaster exposure and socio-economic characteristics for both origin and destination areas, as well as bilateral distance and year fixed effects. The model is specified as:

$$Y_{ij,t}^{(k)} \sim \text{Binomial}(F_{ij,t}, p_{ij,t}^{(k)}) \quad \text{Equation (5)}$$

The corresponding logit link function is specified as:

$$p_{ij,t}^{(k)} = g(\alpha + \beta_1 X_{i,t} + \beta_2 X_{j,t} + \beta_3 \text{Dis}_{i,t} + \beta_4 \text{Dis}_{j,t} + \delta_t) \quad \text{Equation (6)}$$

Where $Y_{ij,t}^{(k)}$ denotes the number of migrants in subgroup k moving from origin i to destination j in year t . $F_{ij,t}$ is the total migration flow for that corridor, and $p_{ij,t}^{(k)}$ is the probability that a migrant belongs to subgroup k . g is logistic link function, $X_{i,t}$ and $X_{j,t}$ include bilateral distance, origin and destination socio-economic conditions, $\text{Dis}_{i,t}$ and $\text{Dis}_{j,t}$ are disaster exposure, as well as δ_t represents year fixed effects.

Separate GLM models were estimated for the proportions of multiple socio-economic groups, including % of poverty migrants, % of high-income migrants, % of elder migrants, % of younger migrants, % of employed migrants, % of unemployed migrants, % of high educational attainment migrants, and % of low educational attainment migrants. The GLM framework therefore evaluates whether disasters are associated with changes in the representation of specific population groups within migration flows. The same current-year, one-year lagged, and three-year cumulative disaster specifications were used to evaluate selective migration responses in different time windows. And the GLM models used the same two disaster measurements, logged property damage and extreme-disaster indicators, to compare compositional responses under regular disaster damage and severe disaster events.

3.4 Model Evaluation

Model performance was evaluated using the Common Part of Commuters (CPC), Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). CPC measures the degree of overlap between observed and predicted origin-destination migration flows and is defined as:

$$CPC = \frac{2 \sum_{ij} \min(F_{ij}, \hat{F}_{ij})}{\sum_{ij} F_{ij} + \sum_{ij} \hat{F}_{ij}} \quad \text{Equation (7)}$$

Where F_{ij} and $\hat{F}_{ij}$ denote observed and predicted flows, respectively. *CPC* ranges from 0 to 1, with higher values indicating a closer match between the observed and predicted migration structure. *RMSE* captures the magnitude of prediction errors with greater penalty on large deviations, while *MAE* represents the average absolute prediction error.

These performance metrics were compared in two model specifications: a baseline model excluding disaster variables and an extended model including disaster indicators. Comparing these versions makes it possible to assess whether disaster-related variables improve model performance beyond socio-economic and spatial control variables.

4 Results

4.1 Descriptive Analyses

Figures 3 and 4 summarize year-over-year migration changes among MIGPUMAs that experienced disasters in the current year but not in the previous year. Figure 3a shows that disaster-exposed MIGPUMAs generally experienced increases in both inflows and outflows compared to the previous year. The magnitude of change differed by hazard type. Floods and tornadoes showed the largest increases in both directions, while wildfires showed smaller changes. A different pattern emerges for extreme disaster occurrences (Figure 3b). Extreme hurricanes and floods were associated with larger increases in outflows than inflows, whereas extreme tornadoes showed

larger increases in inflows than outflows. Extreme wildfires showed comparatively smaller changes in both directions.

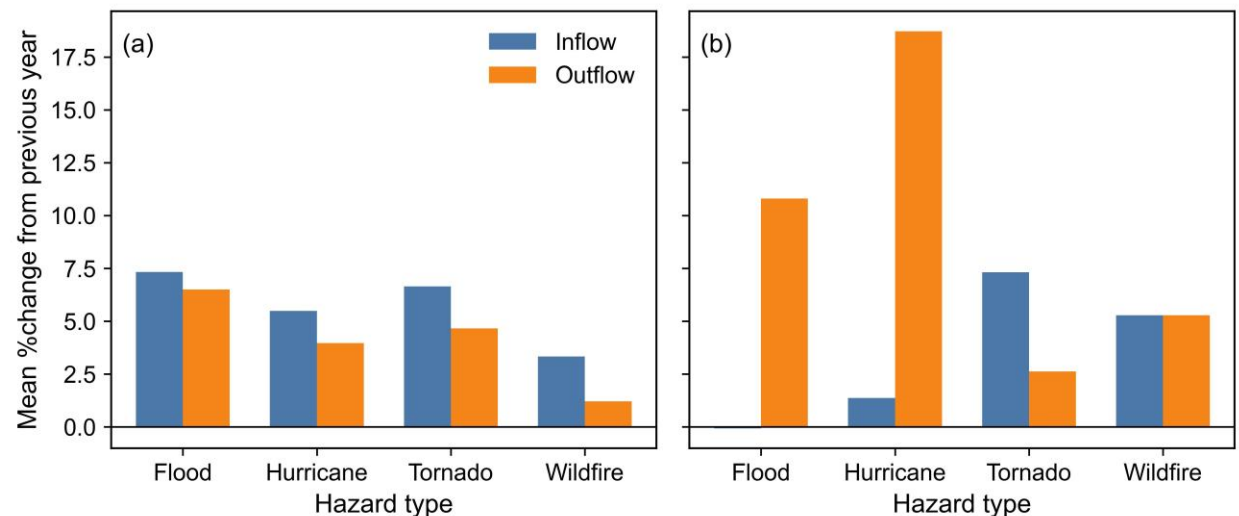


Figure 3. Mean year-over-year percentage changes in migration inflows and outflows among MIGPUMAs at disaster onset. Disaster onset is defined as disaster exposure in year t following no disaster exposure in year $t-1$. Panel (a) reports disasters' property damage, and Panel (b) reports extreme disasters.

As shown in Figure 4, substantial heterogeneity in how disasters are associated with outflows and inflows across socio-economic and demographic groups. For the poverty group, both outflows and inflows generally decline across the four disaster types and under extreme-disaster conditions. This pattern suggests that disasters are associated with fewer migrants from and to poverty populations, consistent with potential mobility constraints among economically disadvantaged groups.

Older adults and highly educated populations show a different pattern. Across most disaster types, both outflows and inflows increase for these two groups. These positive changes suggest that older and highly educated populations may have greater access to resources, information, social support, or relocation capacity that enables movement after disasters.

The unemployed group shows a more mixed and hazard-specific pattern. Floods and tornadoes are consistently associated with declines in both outflows and inflows. In contrast, hurricanes and wildfires are generally associated with increases in both out-migrant and in-migrant counts among unemployed populations. This suggests more active population exchange in these hazard types, with some unemployed migrants leaving affected areas and others moving into them. Rather than reflecting a one-directional outflow pattern, these changes may indicate a dynamic redistribution of unemployed migrants across places. This pattern may also reflect the fact that hurricane- and wildfire-affected areas often overlap with regions connected to larger labor markets, seasonal employment, or post-disaster recovery-related job opportunities.

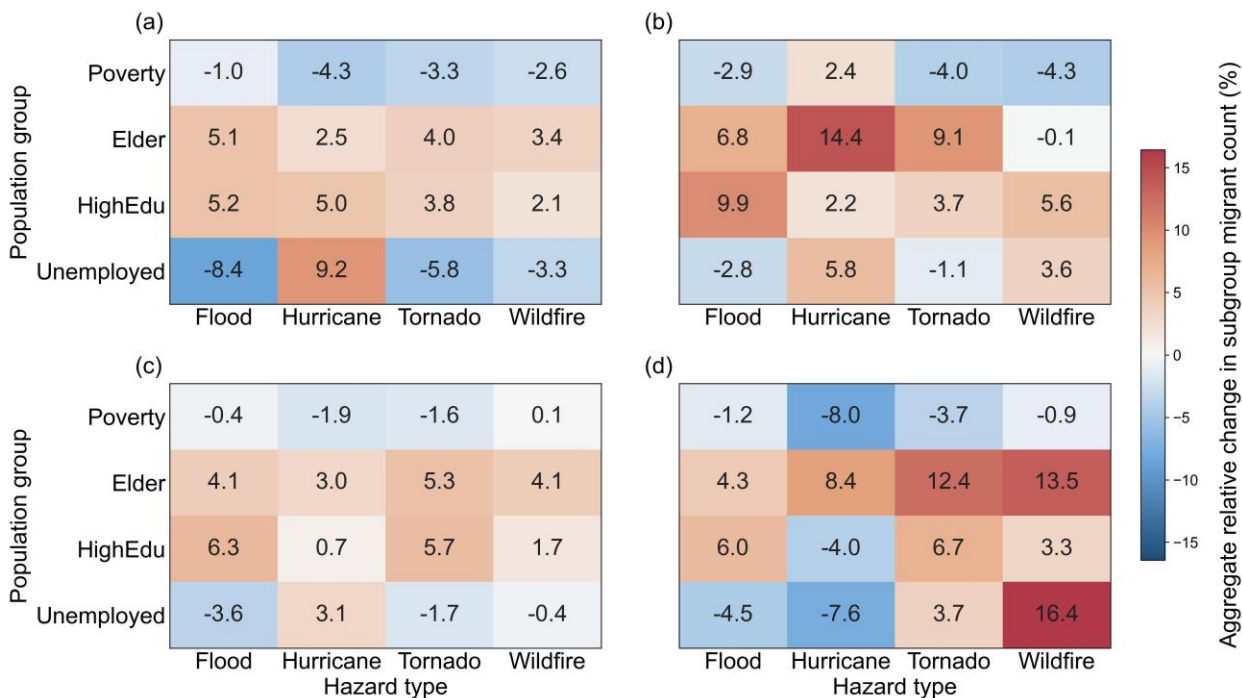


Figure 4. Average changes in subgroup migrant count by hazard type and population group. Panels (a) and (b) report average changes in outflows from origin MIGPUMAs experiencing disasters and extreme disasters, respectively. Panels (c) and (d) report average changes in inflows to origin MIGPUMAs experiencing disasters and extreme disasters, respectively.

4.2 Model Performance Evaluation

Table 2 compares model performance with and without disaster variables. AutoML achieved the strongest predictive performance overall, with the highest CPC and the lowest RMSE and MAE in both specifications. After disaster variables were added, AutoML performance improved from 0.635 to 0.643 in CPC, from 639.190 to 618.250 in RMSE, and from 261.573 to 247.052 in MAE. However, compared to gravity-based models, AutoML is hard to provide the coefficient-based interpretation which is then regarded as a benchmark.

Among the PPML gravity models, the constrained specifications generally outperformed the unconstrained model. The doubly constrained PPML model had the highest CPC among the gravity models, but the origin- and destination-constrained models are more relevant for the subsequent interpretation of destination-side pull and origin-side push associations. Adding disaster variables modestly improved both one-way constrained models. For the origin-constrained model, CPC increased from 0.602 to 0.604, RMSE declined from 707.115 to 698.885, and MAE declined from 295.511 to 294.000. For the destination-constrained model, CPC increased from 0.606 to 0.607, RMSE declined from 682.178 to 679.096, and MAE declined from 289.150 to 288.654. These limited changes indicate that disaster variables add little to aggregate predictive accuracy, but their coefficients remain important for assessing how specific disaster exposures are associated with directional migration flows.

Table 2 Predictive performance of PPML gravity models and AutoML models with and without disaster variables.

Model	Without Disaster Variables			With Disaster Variables		
	CPC	RMSE	MAE	CPC	RMSE	MAE
Unconstrained PPML	0.593	715.729	301.089	0.595	710.456	299.582
Origin-Constrained PPML	0.602	707.115	295.511	0.604	698.885	294.000
Destination-Constrained PPML	0.606	682.178	289.150	0.607	679.096	288.654
Doubly-Constrained PPML	0.610	681.388	286.463	0.610	681.379	286.444
AutoML	0.635	639.190	261.573	0.643	618.250	247.052

4.3 Results of Flow Model

Table 3 presents the PPML gravity model coefficients for migration flows. A positive coefficient indicates that the corresponding variable is associated with higher expected migration flows, while a negative coefficient indicates lower expected migration flows. The origin-constrained model controls for origin fixed effects and is used to evaluate destination-side pull effects, whereas the destination-constrained model controls for destination fixed effects and is used to assess origin-side push effects.

The classical control variables in the gravity model show consistent and statistically significant associations with migration flows across all model specifications. Distance is consistently negatively associated with migration flows, the same-state indicator is positively associated with migration flows, and population size is positively associated with flows on both the origin and destination sides. These patterns are aligned with the distance-decay effect in migration and highlight higher mobility intensity of more populous urban areas.

Several socio-economic variables show clear origin-destination differences. Per capita income shows significant positive relation with migration flows only on the origin side, whereas the percentage of aged residents is negatively associated with migration on both origin and destination sides. Resilience is positively associated with migration in most specifications. Amenity is significant only on the destination side, indicating that amenity is more relevant to a pull effect attracting people to move in.

Disaster variables show distinct patterns across hazard types. Flood damage is positively related to migration in both origin- and destination-constrained models, but extreme flood indicators are significant mainly on the origin side. It suggests that extreme flood occurrence is significantly associated with increased out-migration from affected origins. Hurricanes show little

evidence of association, as both hurricane damage and extreme hurricane occurrence are insignificant. Wildfire damage shows positive and significant associations in most origin- and destination-constrained models, but the extreme wildfire occurrence is not significant. Tornadoes show the opposite pattern: tornado damage is insignificant, whereas extreme tornado occurrence is positive and significant in both constrained models. This implies that extreme tornadoes are associated with increased outflows from affected origins and also increased inflows to affected destinations.

Table 3 Coefficients and significance level in PPML gravity models

Category	Variables	Coefficients in Destination-Constrained Model (Push Effect)			Coefficients in Origin-Constrained Model (Pull Effect)		
		Current Year	1-Year Lagged	3-Year Cumulative	Current Year	1-Year Lagged	3-Year Cumulative
Control Variables	Distance	-0.63***	-0.64***	-0.64***	-0.62***	-0.62***	-0.65***
	Same State	0.34***	0.34***	0.34***	0.33***	0.34***	0.35***
	Population (per 100,000)	0.02***	0.02***	0.02***	0.01***	0.02***	0.02***
Socio-Economic Variables	Pop Density	0.12***	0.12***	0.11***	0.14***	0.14***	-0.058*
	% Poverty	0.17	0.17	0.10	-0.27	-0.24	0.49
	% Unemployment	0.94	0.84	1.05	0.96	0.91	-4.61**
	% No Vehicle	-0.13	-0.11	0.04	-0.90	-0.88	-0.03
	Per Capita Income (per \$10,000)	0.04**	0.05**	0.05***	0.02	0.02	0.02
	% Age 65+	-2.43***	-2.42***	-2.46***	-3.09**	-3.08**	-2.67**
	% Poor English	0.57	0.59	0.60	-1.14	-1.15	-2.39***
	Resilience	0.01***	0.01***	0.01***	0.01***	0.01***	-0.01***
Disaster-Related Variables	Amenity	0.02	0.02	0.02	0.04*	0.04*	0.03
	Flood Damage	0.01***	0.01***	0.01***	0.01**	0.01**	0.01
	Extreme Flood	0.12*	0.13*	0.134*	0.17*	0.14	0.15
	Hurricane Damage	0.01	0.01	0.01	0.01	0.01	0.01
	Extreme Hurricane	-0.07	-0.01	-0.03	-0.02	0.03	0.09
	Wildfire Damage	0.01*	0.01**	0.01**	0.01**	0.01**	0.01**
	Extreme Wildfire	-0.13	-0.04	-0.12	-0.04	-0.03	-0.08
	Tornado Damage	0.01	0.01	0.01	0.01	0.01	-0.01
	Extreme Tornado	0.09***	0.11**	0.12**	0.12*	0.09**	0.09***

*** means $p < 0.001$, ** means $p < 0.01$, and * means $p < 0.05$

4.4 Results of Selective Migration Model

Tables 4 and 5 report the GLM model results based on logged disaster damage and extreme disaster indicators, respectively. These models examine whether disasters are associated with

434 higher or lower proportions of specific socio-economic groups within migration flows. A positive
435 coefficient indicates that the disaster variable is associated with a higher proportion of that group
436 in the flow, while a negative coefficient indicates a lower proportion. Therefore, these models
437 should be interpreted as changes in migrant composition rather than changes in migration volume.

438 In Table 4, flood and hurricane damage show limited and inconsistent associations with
439 migrant composition. Wildfire damage is mainly associated with economic composition. It is
440 associated with lower proportions of migrants in poverty in both origin and destination sides,
441 meaning smaller proportions of people in poverty leave or enter wildfire-affected areas. Wildfire
442 damage is associated with higher proportions of high-income migrants in the origin-side models,
443 suggesting that outflows from wildfire-affected origins contain a larger proportion of high-income
444 migrants. Tornado damage shows the clearest pattern. It is associated with lower proportions of
445 migrants in poverty and higher proportions of high-income migrants in both origin and destination
446 sides. This means that migration flows related from tornado-affected areas contain a smaller
447 proportion of people in poverty and a larger proportion of high-income migrants, both among
448 people leaving affected origins and among people entering affected destinations. Tornado damage
449 is also associated with lower proportions of younger migrants mainly in lagged outflows and
450 inflows, lower proportions of highly educated migrants in both directions, and higher proportions
451 of low-educated migrants in both outflows from affected origins and inflows to affected
452 destinations.

453 In Table 5, extreme hurricane occurrence shows the most consistent associations with
454 migrant composition. It is associated with lower proportions of migrants in poverty and higher
455 proportions of high-income migrants mainly in the destination side. This indicates that inflows to
456 hurricane-affected destinations tend to contain a smaller proportion of people in poverty and a

larger proportion of high-income migrants. Extreme hurricane occurrence is also associated with higher proportions of older migrants and lower proportions of younger migrants in both outflows from hurricane-affected origins and inflows to hurricane-affected destinations. In contrast, younger migrants account for a smaller proportion of these flows. In addition, employed migrants account for lower proportions of both outflows from hurricane-affected origins and inflows to hurricane-affected destinations, especially in the one-year lagged and three-year cumulative specifications.

In contrast, extreme flood occurrences show few consistent associations across socioeconomic groups, with significant coefficients appearing only sporadically. For example, unemployed migrants account for lower proportions of inflows to flood-affected destinations in the one-year lagged and three-year cumulative specifications. Extreme wildfire occurrences show mixed compositional patterns, including lower poverty proportions and higher high-education proportions in outflows from wildfire-affected origins in the three-year cumulative specification, as well as lower older proportions and higher unemployed proportions in some inflows to wildfire-affected destinations.

480 Table 4 Coefficients and significance of GLM models between disaster damage and migrant
481 composition

Group	Effects	Model	Flood Dmg	Hurricane Dmg	Wildfire Dmg	Tornado Dmg
Poverty	Push	Current Year	-0.001	-0.003	-0.001	-0.003*
		1-Year Lag	-0.001	-0.001	-0.004**	-0.002
		3-Year Cum	-0.002	-0.001	-0.005***	-0.003*
Poverty	Pull	Current Year	0.001	-0.001	-0.003	-0.006***
		1-Year Lag	0.001	-0.002	-0.006**	-0.005**
		3-Year Cum	0.001	-0.003	-0.007***	-0.006**
High Income	Push	Current Year	-0.001	0.003	-0.001	0.003**
		1-Year Lag	-0.001	0.002	0.002*	0.003**
		3-Year Cum	-0.001	0.002	0.002**	0.003**
High Income	Pull	Current Year	0.001	0.001	0.001	0.004***
		1-Year Lag	-0.001	0.001	0.001	0.005***
		3-Year Cum	-0.001	0.001	0.001	0.004**
Elder	Push	Current Year	-0.001	-0.006	0.002	0.001
		1-Year Lag	0.001	-0.001	0.003	-0.001
		3-Year Cum	0.001	-0.002	0.005***	-0.002
Elder	Pull	Current Year	0.003	0.003	0.005	0.003*
		1-Year Lag	0.002	0.003	0.003*	0.003
		3-Year Cum	0.003	0.003	0.004	0.003
Younger	Push	Current Year	-0.001	0.001	0.001	-0.002
		1-Year Lag	-0.001	0.001	0.001	-0.002**
		3-Year Cum	-0.001	-0.001	-0.002*	-0.002
Younger	Pull	Current Year	-0.001	-0.005*	-0.002	-0.004**
		1-Year Lag	-0.001	-0.003	-0.002	-0.003*
		3-Year Cum	-0.001	-0.003	-0.003*	-0.003
High-Edu	Push	Current Year	0.002	-0.003*	-0.002	-0.003*
		1-Year Lag	0.002	-0.002	-0.003	-0.003**
		3-Year Cum	0.002	-0.001	-0.001	-0.002
High-Edu	Pull	Current Year	0.001	-0.003	0.001	-0.001
		1-Year Lag	0.002*	-0.001	-0.001	-0.003*
		3-Year Cum	0.003**	-0.001	-0.001	-0.002*
Low-Edu	Push	Current Year	-0.001	0.005**	-0.002	0.003**
		1-Year Lag	-0.001	0.001	0.001	0.003**
		3-Year Cum	-0.002	0.002	0.001	0.003**
Low-Edu	Pull	Current Year	0.001	0.001	0.001	0.004***
		1-Year Lag	-0.001	0.001	0.001	0.004***
		3-Year Cum	-0.001	0.001	0.001	0.003**
Unemployed	Push	Current Year	0.001	0.001	-0.001	0.001
		1-Year Lag	0.000	-0.002	-0.005***	-0.001
		3-Year Cum	-0.001	-0.001	-0.002*	0.001
Unemployed	Pull	Current Year	-0.001	-0.001	-0.001	0.002
		1-Year Lag	-0.002	-0.001	-0.001	0.002
		3-Year Cum	-0.002	-0.003*	-0.001	0.001
Employed	Push	Current Year	0.001	-0.001	0.001	-0.001
		1-Year Lag	0.001	-0.001	-0.001	-0.001
		3-Year Cum	0.001	-0.001	-0.001	-0.001
Employed	Pull	Current Year	-0.001	-0.002	-0.001	-0.001
		1-Year Lag	-0.001	-0.002	0.001	-0.001
		3-Year Cum	0.001	-0.001	0.001	-0.001

*** means $p < 0.001$, ** means $p < 0.01$, and * means $p < 0.05$

483 Table 5 Coefficients and significance of GLM models between extreme disasters and migrant
484 composition in GLM models

Group	Effects	Model	Extreme Flood	Extreme Hurricane	Extreme Wildfire	Extreme Tornado
Poverty	Push	Current Year	-0.031	-0.026	-0.037	-0.043
		1-Year Lag	0.033	-0.023	-0.088	-0.085***
		3-Year Cum	0.001	-0.035	-0.132*	-0.084**
Poverty	Pull	Current Year	-0.093	-0.154*	0.036	-0.097
		1-Year Lag	-0.037	-0.158*	-0.022	-0.099
		3-Year Cum	-0.031	-0.193***	0.032	-0.044
High Income	Push	Current Year	0.017	0.062	-0.038	0.016
		1-Year Lag	0.019	0.003	-0.038	0.025
		3-Year Cum	0.001	0.027	0.007	0.051
High Income	Pull	Current Year	0.053	0.017	-0.012	0.050
		1-Year Lag	-0.001	0.179**	0.026	0.036
		3-Year Cum	-0.005	0.148**	0.001	-0.015
Elder	Push	Current Year	0.054	0.001	-0.035	0.043
		1-Year Lag	0.029	0.238**	0.069	0.036
		3-Year Cum	0.035	0.167***	0.093	-0.034
Elder	Pull	Current Year	0.072	0.245***	-0.059	0.036
		1-Year Lag	0.087	0.102	-0.126*	0.019
		3-Year Cum	0.043	0.095*	-0.097	0.017
Younger	Push	Current Year	-0.026	-0.037	0.002	-0.087***
		1-Year Lag	-0.008	-0.102***	-0.024	-0.072**
		3-Year Cum	-0.005	-0.113***	-0.039	-0.035
Younger	Pull	Current Year	-0.052	-0.251***	0.031	-0.018
		1-Year Lag	-0.050	-0.152**	0.049	-0.041
		3-Year Cum	-0.039	-0.169***	0.053	-0.040
High-Edu	Push	Current Year	-0.012	-0.072	0.101	-0.058
		1-Year Lag	-0.041	-0.099	-0.001	-0.036
		3-Year Cum	0.008	-0.053	0.102***	-0.014
High-Edu	Pull	Current Year	-0.001	-0.052	-0.048	-0.010
		1-Year Lag	0.033	-0.024	-0.014	-0.001
		3-Year Cum	0.057*	-0.030	-0.047	0.014
Low-Edu	Push	Current Year	-0.005	-0.001	-0.068	0.034
		1-Year Lag	0.027	-0.079	-0.071*	0.045
		3-Year Cum	-0.014	-0.045	-0.047	0.043
Low-Edu	Pull	Current Year	0.038	0.055	0.023	0.020
		1-Year Lag	-0.015	0.159**	0.022	0.008
		3-Year Cum	-0.001	0.107**	0.026	-0.027
Unemployed	Push	Current Year	0.033	-0.042	0.075	0.043
		1-Year Lag	-0.012	-0.084	-0.159***	-0.043
		3-Year Cum	0.003	0.007	-0.021	-0.001
Unemployed	Pull	Current Year	-0.009	0.032	0.019	0.050
		1-Year Lag	-0.067*	-0.163	0.047	-0.001
		3-Year Cum	-0.072**	-0.145***	0.071**	0.034
Employed	Push	Current Year	0.001	-0.038	0.049	0.001
		1-Year Lag	-0.016	-0.074***	0.036	0.024
		3-Year Cum	0.031	-0.065***	0.042	0.018
Employed	Pull	Current Year	-0.001	-0.072*	-0.020	0.032
		1-Year Lag	0.021	-0.111***	0.007	0.021
		3-Year Cum	-0.018	-0.105***	-0.010	0.017

*** means $p < 0.001$, ** means $p < 0.01$, and * means $p < 0.05$

5 Discussion

5.1 Hazard-Specific Flow Responses and Population Turnover

The flow results suggest that disaster-related migration should not be understood only as population loss from affected areas. Instead, disasters may also generate population turnover. This pattern is most evident for floods. Flood damage is positively associated with both outflows from flood-affected origins and inflows to flood-affected destinations, suggesting that flooding may simultaneously create pressure for some residents to leave while also being followed by return, replacement, or new in-migration. This interpretation is consistent with recent evidence that flood exposure can reshape both departures and arrivals rather than producing a simple decline in local population (Fan et al., 2025). At the same time, extreme flood indicators were more clearly associated with origin-side push effects, indicating that severe flooding may cross a threshold at which housing disruption, infrastructure damage, or perceived future risk generates stronger departure pressure. This pattern is consistent with recent evidence that disaster damage and recovery resources can operate through competing pathways, with direct damage reducing population stability while public assistance, insurance, and recovery investment may support continued or renewed movement into affected areas (Han et al., 2024).

The contrast between flood and hurricane results further suggests that disaster-related migration depends on how different disasters influence migration and how well those movements are captured by annual origin-destination flow data. Unlike floods, hurricane damage and extreme hurricane indicators were not consistently associated with aggregate migration volumes after accounting for spatial interaction, socio-economic conditions, and origin- or destination-side heterogeneity. This pattern should not be interpreted as evidence that hurricanes have little demographic importance. Rather, hurricane-related mobility often involves evacuation, temporary

relocation, staged return, processes that may occur within shorter time windows or be offset by return migration in annual residence-based data (Anand et al., 2024; Deng et al., 2021). The hurricane results therefore highlight an important boundary of this study: annual migration flows are better suited to capturing longer-term changes in residence than short-term displacement and return dynamics.

More broadly, the variation across hazards indicates that disaster-related migration is shaped by the interaction between damage severity, spatial footprint, temporal duration, and recovery capacity. Hazards with broad and recurrent impacts may produce clearer turnover patterns, whereas hazards with more localized or threshold-dependent damage may reshape mobility in more selective and place-specific ways. This interpretation is consistent with evidence that highly destructive wildfire events can generate migration responses through built-environment loss (K. McConnell et al., 2024), and that severe tornadoes may produce demographic change without necessarily producing large net population decline (E. J. Raker, 2020). Taken together, these findings suggest that aggregate flow models capture only one dimension of post-disaster demographic change. When total flows change modestly or inconsistently, the socio-economic composition of those flows may reveal whether disasters are reshaping who leaves, who enters, and who remains connected to affected places.

5.2 Selective Migration as a Hidden Dimension of Disaster Mobility

The selective migration results show that disaster-related mobility may be more visible in the composition of migrants than in aggregate flow volume. This is most evident for hurricanes. Although hurricane exposure was not significantly associated with total migration flows in the PPML models, extreme hurricane occurrence showed the most consistent associations with migrant composition in GLM models. In particular, inflows to hurricane-affected destinations

532 contained lower proportions of migrants in poverty and higher proportions of high-income
533 migrants, while older migrants became more represented and younger migrants less represented in
534 both origin- and destination-side flows. These patterns suggest that hurricane-related mobility may
535 be socially filtered: the total number of movers may not change consistently, but the socio-
536 economic profile of those who move can shift substantially.

537 This pattern is consistent with post-Katrina research showing that hurricane recovery is
538 socioeconomically selective. Return to New Orleans was more likely among residents with
539 stronger local ties, less severe housing damage, and access to recovering neighborhoods (E. Fussell
540 et al., 2014; J. A. Groen & A. E. Polivka, 2010). As a result, population recovery did not simply
541 restore the pre-disaster population. Instead, recovery migration changed who lived in the city, as
542 some displaced residents did not return and new or returning migrants became part of the rebuilt
543 population (Deryugina et al., 2018). Our results extend this argument beyond a single hurricane
544 case by showing that, in a national origin-destination framework, extreme hurricanes are more
545 clearly associated with compositional sorting than with aggregate flow volume. In other words,
546 the absence of a strong aggregate hurricane coefficient does not necessarily imply the absence of
547 demographic change, but it may indicate that hurricane effects operate through selective return,
548 selective in-migration, and differential mobility capacity.

549 Selective patterns for the other hazards were more uneven, suggesting that socio-economic
550 sorting does not operate through the same mechanism across all disaster types. Flood-related
551 compositional effects were less consistent in our GLM results, although recent flood research
552 shows that floods can produce selective out-migration and in-migration across socio-economic
553 groups (Fan et al., 2025). Wildfire and tornado damage were more closely associated with
554 economic composition in some specifications, particularly lower proportions of migrants in

poverty and higher proportions of high-income migrants. These patterns are consistent with broader migration research showing that income, employment, housing resources, and social networks shape mobility capacity after environmental disruption (Best et al., 2025; Jia et al., 2023). Together, the results suggest that selective disaster migration is hazard-specific: different events may filter mobility through different combinations of housing loss, recovery resources, labor-market conditions, age-specific constraints, social networks, and perceived future risk.

5.3 Implications for Inequality and Recovery

The combination of bi-directional flows and selective migration has important implications for how post-disaster recovery is evaluated. Population recovery is often assessed through total population counts, net migration, or aggregate inflows and outflows. However, our results suggest that these aggregate measures may conceal substantial social reorganization. If outflows from affected origins are offset by inflows into the same areas, total population change may appear limited even when the composition of migrants has changed. Similarly, if high-income, older, or otherwise more mobile groups become more represented in disaster-related flows, apparent population recovery may coexist with unequal mobility outcomes.

This perspective shifts the interpretation of disaster migration from movement volume to mobility capacity. Disasters may create opportunities for some groups to relocate, return, or enter recovering areas, while leaving others facing housing constraints, financial barriers, or involuntary immobility. This is consistent with recent research emphasizing that environmental migration is strongly conditioned by inequality, household resources, housing access, employment, and social networks (Jia et al., 2023). In this sense, limited migration among disadvantaged groups should not automatically be interpreted as resilience or place attachment; it may also reflect constrained mobility.

These dynamics also connect disaster-related migration to broader debates on climate gentrification. Recovery investment, rebuilding, risk perception, and adaptation can change the desirability and affordability of affected or lower-risk places, potentially reshaping who is able to remain in, return to, or move into recovering communities (Connolly, 2025; Kim & Park, 2023). The policy implication is that recovery monitoring should not focus only on whether population levels rebound. It should also track who leaves, who returns, who moves in, and which groups remain unable to exercise meaningful mobility choices after disasters.

5.4 Limitations and Future Work

Several limitations should be acknowledged. First, variables, such as disaster, resilience and amenity indicators, originally reported at the county level, were aggregated to MIGPUMA level, with unavoidable spatial aggregation errors. Second, the annual ACS migration measure can only capture residence at survey date and one year earlier, making it less suitable for identifying short-term displacement, multiple moves within a year, or moves within the same area.

Future research could apply stronger quasi-experimental designs, longer time horizons, and linked individual- or household-level data to examine how repeated disaster exposure shapes selective migration over time. Additional work could also connect origin-destination migration flows with post-disaster housing markets, recovery investments, and local demographic change to assess how selective mobility contributes to longer-term regional inequality and recovery capacity.

6 Conclusion

This study examined disaster-related migration across the contiguous United States by integrating analyses of both aggregate migration flows and migrant composition. Using origin-destination migration data from 2012 to 2021, the analysis showed that disaster-related migration varied substantially across hazard types, severity, temporal window, and migration directions.

Disasters may intensify both outflows and inflows rather than produce one-directional population loss. Hurricanes showed limited associations with aggregate migration volume, but extreme hurricane conditions were linked to clearer selective migration patterns, including changes in the age, income, employment, and poverty composition of migrants. These findings demonstrate that disasters influence not only how many people move, but also which groups are represented in migration flows. By distinguishing aggregate migration volume from migrant composition, this study shows that limited net or total migration change may still conceal important forms of selective redistribution. As climate risks intensify, understanding both the volume and composition of disaster-related migration is important for anticipating regional inequality, recovery capacity, and long-term demographic change.

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