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From Evacuation to Relocation: Hurricane Mobility Sequences and Climate Migration Destination Choice

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Abstract

Post-disaster evacuation and residential relocation are typically studied as separate phenomena, yet the destinations people move to may be shaped by the same underlying social geography. This study examines post-hurricane mobility across these two distinct phases following Hurricanes Helene and Milton (2024). Combining GPS-based point-of-interest visit data to measure evacuation flows with address history data to identify residential relocation, we construct inter-county origin-destination matrices for both phases and estimate a quasi-Poisson gravity model pooling relocation flows across a pre-hurricane baseline year (2019), the hurricane year (2024), and the subsequent year (2025). Descriptive analysis reveals that evacuation and relocation destinations are largely distinct. Only 11.7% of active origin-destination pairs qualify as both evacuation and relocation hotspots, and the clearest feature distinguishing these dual-use hotspots is family tie strength. Gravity model estimates show that racial similarity loses significance once distance, population size, and housing market conditions are controlled, while income and industry similarity retain modest independent effects. Critically, the association between family ties and relocation flows is significantly stronger in the hurricane year relative to the baseline year, suggesting that social networks become a more decisive guide to destination choice when displacement is sudden and information is incomplete. These findings suggest that family ties measured from pre-disaster mobility data can help planners anticipate where post-disaster migrants will settle.

Keywords

Climate Displacement, Climate Migration, Receiving Communities, Family Ties, Social Homophily

1. Introduction

Disaster-induced displacement hit a global record in 2024, with the United States alone accounting for 11 million displaced individuals (IDMC, 2025). Climate-related hazards are increasingly forcing people from their homes, and the trend is expected to accelerate as climate change amplifies the severity of such events while populations continue to concentrate in high-risk urban and coastal areas (Hauer et al., 2020; IOM, IDMC, 2023). Affected individuals often relocate to other cities to sustain their urban lives, placing sudden and uneven demand on receiving communities (Groen & Polivka, 2010). Yet cities remain unprepared for incoming climate migrants, which should begin with understanding where affected people will move and what receiving communities should expect. This paper focuses on hurricanes as a case study of disaster-induced displacement, using Hurricanes Helene and Milton as events through which to examine the full sequence of post-disaster mobility.

Current literature treats routine human mobility, evacuation, and relocation as separate phenomena, missing the critical reality that these processes are sequentially linked (Fussell, Curtis, et al., 2014; Raipat & Yabe, 2025). Under normal circumstances, people move for commutes, holiday family reunions, and recurring leisure travel, and build familiarity with certain places, reinforcing family ties. Post-disaster mobility, however, unfolds in at least two distinct phases: an evacuation phase, in which households depart rapidly under compressed timeframes and incomplete information, and a longer-term residential relocation phase, in which some households make address changes in the weeks and months that follow.

The three phases (pre-shock, evacuation, relocation) are not independent. Yet the literature treats them as separate phenomena, leaving unanswered not only how the short-term emergency phase shapes the longer-term residential outcome, but also whether the factors and mechanisms that govern migration destination choice in ordinary times (e.g., family ties, socioeconomic sorting, distance decay) hold, intensify, or weaken in post-disaster contexts (Fussell, Curtis, et al., 2014; Raipat & Yabe, 2025).

This study closes that gap by examining evacuation and permanent relocation destination choices following Hurricanes Helene and Milton, which struck 26 Florida counties in late September and early October 2024. We combine two high-resolution data sources, Advan Research mobile GPS-based point-of-interest visit data, which capture the evacuation patterns during the hurricane period, and the InfutorData consumer address history data, which tracks individual address changes, to produce inter-county migration flows in the month that followed. These datasets allow us to map all phases of post-hurricane mobility across the hurricanes and examine destination choice mechanisms in each phase.

We focus on family ties as the central explanatory factor for relocation destination choice patterns. Social networks are among the most consistently documented determinants of destination choice in ordinary migration (Massey et al., 1993), and in hurricane evacuation, where a large share of evacuees stay with relatives or friends (Lindell et al., 2011). Also, prior work using Thanksgiving-period travel as a behavioral proxy for family ties has shown that this measure predicts both relocation destinations from Puerto Rico after Hurricane Maria (Han et al.,

2024) and evacuation destinations during Hurricane Milton (Han & Guhathakurta, 2026). However, whether the same ties also structure long-term relocation, and whether their influence changes after a disaster, has not been tested. If they shape both evacuation and relocation, they offer receiving communities an indicator of where displaced households are likely to arrive.

We address four research questions using two analytic approaches. Descriptively, we examine whether evacuation destinations become relocation destinations (**R1**), identifying which locations serve as hotspots for both functions, which serve only one, and how these destination types differ in family ties. Inferentially, we estimate a Quasi-Poisson gravity model pooling migration flows across a non-hurricane baseline year, the hurricane year, and a subsequent non-hurricane year to test: (**R2**) whether post-hurricane migrants sort into socioeconomically similar destinations, as residential sorting theory and social homophily theory predict (McPherson et al., 2001); (**R3**) whether stronger pre-existing family ties predict higher migration volumes, as social network theory of migration suggests (Massey et al., 1993); and (**R4**) whether these associations differ between hurricane and non-hurricane years, revealing whether the disaster context disrupts normal migration patterns.

In the following sections, Section 2 reviews the literature on migration destination choice, climate migration, and data and modeling frameworks. Section 3 describes the data and methods. Section 4 reports results. Section 5 discusses findings in relation to theory and planning. Section 6 concludes the paper.

2. Literature Review

2.1. Migration and Residential Location Choice Theories

Ravenstein's laws of migration (Ravenstein, 1885) and Lee's foundational push-pull framework (1966) explain that migration is determined by forces that *repel* individuals from their origin (e.g., economic stagnation, environmental hazard, housing unaffordability) and forces that *attract* them to particular destinations (e.g., job opportunity, lower costs of living, and social connections). Geographic distance from original residence is an *intervening* obstacle that reduces destination attractiveness, as formalized in the gravity model of migration, which predicts that migration flows between two places scale with their populations and decay with the distance between them (T. Liu & Li, 2025; Stillwell et al., 2016; Zipf, 1946).

The determinants of residential location choice span economic, social, and environmental dimensions. On the origin side, economic stagnation, housing unaffordability, unemployment, and environmental degradation reduce the utility of staying and motivate mobility (Lee, 1966; Sjaastad, 1962). For households moving due to climate-induced disasters, the key distinction from other migrants is that the disaster simultaneously triggers most push factors at once, destroying housing, disrupting job availability, and perceiving environment as temporarily or permanently uninhabitable, compressing what is normally gradual into a compressed timeframe (T. Liu & Li, 2025).

Economic geography theories suggest that migrants are attracted to destinations that offer higher wage differentials and greater employment opportunities (Fan, 1996; Harris & Todaro, 1970). Amenity-based theories argue that public services including education, healthcare, and transportation access, as well as natural environmental quality such as better climate and air quality attract migrants (Glaeser & Gottlieb, 2006; Mastrorillo et al., 2016; Rodríguez-Pose & Ketterer, 2012). The relative weight of economic versus amenity-based attraction remains debated, with evidence suggesting it varies by skill level and life stage (Buch et al., 2014; Chen & Rosenthal, 2008; Scott, 2010).

Relevant to the migration push-pull factors, residential sorting theory holds that households select destinations that match their socioeconomic position. Schelling demonstrated that even mild individual preferences for same-group neighbors generate strong aggregate segregation (Schelling, 1971), a mechanism found empirically across racial and income dimensions in U.S. metropolitan areas (Bischoff & Reardon, 2014; Massey & Denton, 1993). At the inter-metropolitan scale, income sorting produces persistent spatial inequality in which higher-earning households concentrate in expensive, high-amenity cities (Diamond, 2016), while racial minorities face constrained destination choice sets due to housing market discrimination and the spatial concentration of affordable housing stock (Rothstein, 2017).

Additionally, social homophily, defined as the tendency to move and interact among socially similar individuals, provides a complementary mechanism for residential sorting (McPherson et al., 2001). Migrants prefer destinations where racial and socioeconomic composition resembles their community of origin, a preference theorized to stem from anticipated social comfort, access to co-ethnic job market networks, and familiar institutions (Greenwood, 1997; Massey & Denton, 1993). In addition, social network theory holds that once migration between places is established, networks of kin and community lower the cost and uncertainty of subsequent moves to the same destination, producing self-reinforcing migration systems (Massey et al., 1993). Cumulatively, each migrant along an established origin-destination (OD) pair reduces the social and informational costs for those who come after, making network-dense destinations more attractive over time.

These theories, however, treat destination choice as a single decision made under stable informational conditions. Carling's aspiration-capability framework extends these theories by recognizing that destination choice is constrained not only by objective resources but by the imaginative geography of potential movers, meaning that people only move to destinations they can concretely envision as possibilities (Carling, 2002). Familiarity, prior visitation, and the presence of known contacts expand aspirations. A place encountered directly can become imaginable in ways that abstractly known places are not. This insight is particularly relevant in disaster contexts, where emergency displacement brings households into direct contact with destinations they may never have considered under normal conditions.

2.2. Climate Migration and Disaster Displacement

Climate migration, defined as displacement or relocation driven in whole or in part by environmental hazard or climatic change, has emerged as a distinct subfield within migration studies, though definitional debates persist (Black et al., 2011; IOM, 2018). Disaster displacement is a type of climate migration, which also encompasses slow-onset processes such as sea level rise and agricultural decline.

Three features distinguish disaster-induced displacement initiated by an acute hazard from economically motivated migration. First, the displacement trigger is exogenous and abrupt. Economic migration typically unfolds gradually in response to shifting opportunity gradients, allowing for deliberate information-gathering and social comparison of alternatives (Sjaastad, 1962). Disaster displacement of this kind compresses decision time and simultaneously affects large numbers of households in the same origin, removing the usual counterfactual of staying (Fussell, 2015). Second, such disaster displacement is often involuntary at initiation even when it becomes voluntary over time. For instance, households that evacuate may intend to return but find that housing destruction, local economic collapse, or institutional failure forecloses that option (Fussell et al., 2010; Pais & Elliott, 2008). Third, disaster displacement is spatially concentrated in ways that create sudden demand shocks at destination, stressing receiving communities' housing markets, social services, and labor markets in ways that ordinary migration typically does not (Groen & Polivka, 2010; Myers et al., 2008).

Prior empirical studies have examined hurricane-induced displacement in the United States, largely generated by Hurricanes Katrina, Harvey, and Maria. Studies of post-Katrina population dynamics documented substantial displacement from New Orleans, particularly among lower-income African American households (J. R. Elliott & Pais, 2006; Fussell et al., 2010), establishing that climate displacement is not socioeconomically neutral. Post-Maria studies documented large-scale outflows from Puerto Rico to Florida and New York – flows shaped by pre-existing social networks (Han et al., 2024; Hinojosa et al., 2018), consistent with social network theory. Across these cases, social vulnerability indices, including low income, non-white race, and rental tenure predicted non-return, suggesting that who can relocate and where they go reflects pre-existing inequality as much as the disaster itself (Adger et al., 2018; Black et al., 2011).

Notably, studies treat post-disaster evacuation and migration as effectively separate phenomena, studied with different conceptual frameworks (Fussell, Hunter, et al., 2014; Raipat & Yabe, 2025). The evacuation literature, drawing on emergency management and transportation science, produces rich accounts of departure timing, route choice, and shelter use, but typically terminates its analysis within days or weeks of the event (Lindell et al., 2011). The migration literature analyzes population flows months or years later but treats destination choice as emerging from the household's pre-disaster socioeconomic position and social networks without modeling how emergency displacement may have altered those parameters. Neither literature examines whether the destinations people flee to in the short run are the destinations they settle in over the long run, and what explains any overlap or divergence. This sequential structure,

from pre-disaster routine mobility to emergency evacuation and permanent relocation, implies that each phase of mobility may be shaped by the preceding one.

From the aspiration-capability framework perspective, households tend to move to places they already know. From a social network perspective, evacuation may activate or strengthen latent social ties at a destination, reducing the informational cost of subsequent permanent moves to the same destination (Massey et al., 1993). Whether and when these mechanisms operate and what distinguishes the destinations that attract migrants from those that serve only evacuees is the first research question this study addresses.

2.3. Data and Modeling Frameworks in Large-Scale Migration Studies

Empirical research on migration destination choice historically utilizes data sources with several temporal, spatial, or observational limitations. For instance, Internal Revenue Service (IRS) county-to-county migration flows, derived from year-over-year address changes on tax returns, offer national coverage but are limited to tax-filing households and exhibit filing lags that obscure the timing of disaster-induced moves (Molloy et al., 2011). The American Community Survey (ACS) provides individual-level socioeconomic detail but at low geographic resolution and with a five-year rolling sample that conflates decisions made in very different contexts. These aggregated data cannot observe short-term displacement that usually occurs without address changes or allow researchers to distinguish evacuation from relocation.

Consumer address history data, constructed from credit applications, utility activations, property transactions, and mail-forwarding records, have emerged as a high-frequency alternative. Commercially maintained panels such as the InfutorData Consumer Identity Database track individual-level address changes at monthly frequency without the income constraints of IRS data (Gallagher & Hartley, 2017). Gallagher and Hartley (2017) used a similar commercial address dataset to document post-disaster displacement after Katrina, finding that disaster severity predicted address changes at substantially elevated rates relative to pre-disaster baseline mobility.

The primary limitation of such datasets is potential underrepresentation of renters and lower-income households who generate fewer formal records. Thus, it must be noted that such selection may lead to conservative estimates of displacement among vulnerable residents. In addition, timestamps in such datasets may reflect the first observed consumer activity at a given address rather than the true move-in date, which may introduce temporal imprecision when individuals delay address-related transactions, although these data remain much more precise compared to annual aggregated migration data. Acknowledging these limitations, this study leverages consumer address history data to identify relative spatial trends rather than to produce precise population counts or exact relocation timings.

For short-term evacuation, mobile device location data have been increasingly adopted as a real-time observational window. Point-of-interest (POI) visit data, which record stops at categorized locations with timestamps and geographic coordinates, allow researchers to construct OD flows during disaster events without relying on self-reported recall (Raipat & Yabe, 2025;

Yabe et al., 2020). Studies employing GPS mobility data have documented that residents of mandatory evacuation zones evacuate at substantially higher rates than those in voluntary or no-order areas, and that socioeconomic vulnerability predicts both the probability and distance of evacuation (Darzi et al., 2021; Yabe et al., 2022). Combining GPS-based evacuation measures with address-history-based relocation measures across the same set of events, as this study does, offers a previously unavailable empirical window onto the full temporal arc of post-disaster mobility.

Pre-disaster social tie measurement has relied on retrospective self-reports, administrative proxies, or aggregate social network indices. The Social Connectedness Index, derived from Facebook friendship links, provides a scalable proxy but samples a small fraction of population and reflects the full range of social relationships from old friends to relatives (Bailey et al., 2018). The present study uses travel patterns derived from GPS mobility data during Thanksgiving holiday as a proxy for family tie density between county pairs (Han et al., 2024; Han & Guhathakurta, 2026). This approach isolates family-oriented travel from routine commuting or business travel to produce a destination-specific family-tie index, operationalizing the social network cost-reduction mechanism identified by Massey et al. (1993).

Gravity model has been a dominant empirical framework for estimating migration flows at the OD pair level since Zipf (1946). Its log-linear form maps naturally onto Poisson regression specifications when migration flows are measured as counts of movers, as in this study; flows reported as rates or shared instead call for log-linear or fractional-response specifications (Flowerdew & Aitkin, 1982; Silva & Tenreyro, 2006). The incorporation of social and demographic similarity covariates extends the classic framework to accommodate sorting and network mechanisms. For instance, Xu et al. (2023) estimated a multilevel gravity model of California inter-county flows (2014-2021) using Department of Motor Vehicles address-change records, combining origin- and destination-specific predictors, such as population, median household income, unemployment rate, and wildfire exposure frequency, with a shared industry composition similarity measure constructed from Census County Business Patterns data (Xu, 2023). Liu et al. (2019) applied a log-scaled gravity model to IRS-derived national county-to-county flows aggregated over 2002-2015, incorporating industry composition similarity alongside standard economic and demographic covariates, and documented that net migration flows toward politically co-partisan counties are statistically detectable and most pronounced among the most politically extreme counties (X. Liu et al., 2019).

A recurring concern in this class of models is overdispersion, as migration counts are typically fat-tailed, violating the equi-dispersion assumption (i.e., variance equals the mean) of standard Poisson regression. Quasi-Poisson regression, which inflates standard errors by the estimated dispersion parameter while preserving coefficient estimates, provides a remedy with appropriately conservative inference (Cameron & Trivedi, 2013). Pooling flows across multiple years with year-fixed effects and year-by-predictor interaction terms allows identification of hurricane-specific shifts in the determinants of destination choice, which is the approach adopted in this study.

3. Data and Methods

This study examines the relationships between pre-hurricane routine mobility, post-hurricane evacuation, and post-hurricane relocation patterns in the context of Hurricanes Helene and Milton, both of which struck Florida in 2024. The following data sections describe the event characteristics (Section 3.1), the methods used to quantify each phase of mobility (Sections 3.2, 3.3., 3.4), the control variables (Section 3.5), and the modeling approach (Section 3.6). Data sources and distributions are summarized in Table 3.

3.1. Study Events: Hurricanes Helene and Milton

Forming as a tropical storm on September 24, 2024, Hurricane Helene rapidly intensified over the Gulf of Mexico before reaching Category 4 strength on the evening of September 26. The storm made landfall on Florida's Big Bend coast with peak sustained winds of 140 mph (Hagen et al., 2026). Helene reached deep inland across the southern Appalachian region, where flooding claimed hundreds of lives and caused billions of dollars in property losses (NOAA National Weather Service, 2024). Several Florida coastal communities endured record-breaking storm surge, with local emergency management officials estimating that more than 70% of structures in affected areas were entirely destroyed (Hagen et al., 2026; US Department of Commerce, n.d.). Hurricane-force winds threatened an estimated 1.9 million residents across Florida, Alabama, and Georgia (Meyers, 2024), though no authoritative figures exist for the total number of people displaced by the storm. Helene had a path of roughly 500 miles from the Florida Panhandle through North Carolina and Tennessee, leaving more than 250 dead and an estimated $78.7 billion in total damages (NOAA NCEI, 2025).

Just thirteen days later, Hurricane Milton approached Florida as a Category 5 storm with maximum sustained winds of 180 mph before weakening to Category 3 at landfall near Siesta Key on the evening of October 9, 2024 (Beven II et al., 2025). Florida issued a state of emergency and initiated one of the largest evacuation operations in the state's history, placing approximately 5.9 million residents across 14 counties under mandatory or voluntary evacuation orders (Al Jazeera Staff, 2024). Milton was directly responsible for 15 deaths, with an additional 27 fatalities attributed indirectly to post-storm hazards including power outages, cleanup accidents, and health complications arising during storm preparations. The storm inflicted an estimated $34.3 billion in damages (NOAA NCEI, 2025).

3.2.Migration Patterns

To construct a county-to-county migration matrix, we utilized consumer address history data sourced from InfutorData. The dataset compiles monthly address change history for U.S. individuals by integrating a wide range of public and proprietary sources, including the Census, USPS records, county assessor files, published directories, retail and digital marketing data, warranty registrations, and event sign-ups (InfutorData, 2025).

Individual-level residential address history is reconstructed to show addresses before and after each hurricane event. For each individual, residential records were first temporally ordered to form a sequential history of observed addresses. Addresses with missing effective dates were removed. If consecutive records shared the same address ID (i.e., repeated records of the same residence), they were collapsed into a single residential record dated by the earliest effective date, which marks when the individual first appeared at that address. Individuals marked as deceased prior to the hurricane were excluded. Individuals whose most recent activity date (ODATE) was before 2021 were removed, based on the assumption that individuals would generate at least one recorded consumer transaction (e.g., credit, utility, or delivery activity) in the roughly three years before the hurricanes, especially since many activities moved online during the COVID-19 pandemic. Sensitivity analyses to this year cut-off are presented in the Supplementary Materials Figure S1. Addresses of "PO box" and "General Delivery" were dropped (5.11% of total records), as were addresses with missing values (0.22%). After geocoding, 90.2% of addresses were matched.

A pre-hurricane residence was identified as the most recent address observed prior to the month Hurricanes Helene and Milton occurred (Sep. 2024). The 26 counties that issued evacuation orders during hurricanes were selected as the "affected" counties. Then individuals who changed their address within one month after the hurricane (Oct. 2024) were identified as "migrants." We captured the number of address changes and the number of unique destinations observed after the hurricanes (Figure 1). In Oct. 2024, 31,549 individuals left the affected counties, of whom 28,153 had identifiable OD county pairs. The number of destination counties is summarized in Table 2 and the distribution of county-to-county number of migrants is summarized in Table 3.

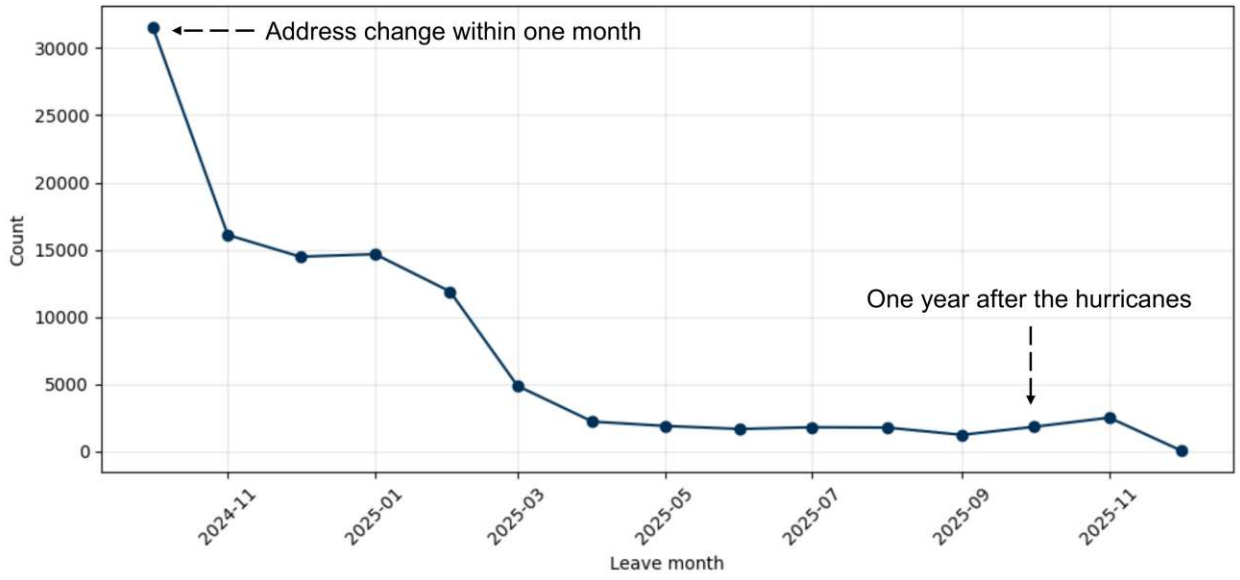


Figure 1. Trend of Post-Hurricane Migrants from Affected Origin Counties

3.3. Evacuation Patterns

Short-term evacuation mobility patterns are drawn from POI visit records provided by Advan Research Weekly Patterns (Advan Research, 2026). The dataset includes POI classifications by NAICS code, geographic coordinates, raw daily visitor counts, and aggregated information on visitors' home census block groups. As illustrated in Table 1, visitor home block groups are reported at the weekly level, and daily visitor totals are structured as a seven-element list corresponding to each day of the week beginning on Monday. The data have been employed in several disaster mobility studies (Han & Guhathakurta, 2026; X. Li et al., 2024), and their correspondence with U.S. Census data at the census tract level has been established in earlier validation work (Z. Li et al., 2024).

Table 1 Example of Weekly Patterns Data for One Week

ID	POI Name	Lat	Lon	NAICS	Number of Visitors	Visitors Home CBG
1	Starbucks	x.xx	x.xx	xxxx	[23, 46, 48, 70, ..,]	{‘12001xxxxxx’:12, ..}
2	McDonalds	x.xx	x.xx	xxxx	[50, 34, 25, 68, ..,]	{‘12001xxxxxx’:8, ..}

For each hurricane event, the analysis distinguishes between two temporal windows: a hurricane period and a normal period. The hurricane period covers the week of landfall, when evacuation-driven mobility peaks. Following previous post-hurricane mobility research (Anyidoho et al., 2023; Hong & Frias-Martinez, 2020), the normal period comprises the three weeks immediately before the hurricane period for each event, as summarized in Table 2. Both events share the same baseline period because the weeks immediately preceding Milton's landfall coincided with the aftermath of Helene, during which travel behavior was already disrupted and would have been an unreliable baseline. POI visit flows recorded during the normal period serve as a pre-storm behavioral baseline against which hurricane-period flows are evaluated. A three-week average is used rather than a single reference week to minimize the influence of week-to-week variability in travel behavior. Evacuation inflow at each evacuation destination county is defined as the net change in the number of POI visits from all origin areas to a given county during the hurricane period compared to the normal period (Example time plots in Supplementary Material Figure S2, National Map in Figure S3). The number of destinations for each event and week is reported in Table 2.

Table 2. Study Event Details

	Helene	Milton
Hurricane Landfall	2024-09-27	2024-10-10
Baseline/Normal Period	2024-09-02 - 09-22	2024-09-02 - 09-22
Hurricane Period	2024-09-23 - 09-29	2024-10-07 - 10-13
Evacuation Destinations	1,152 counties	1,206 counties
Relocation Destinations		
Baseline year: 2019/10	559 counties	

Hurricane year: 2024/10	804 counties
Subsequent year: 2025/10	100 counties

3.4. Capturing Family Ties from Routine Mobility

To quantify the strength of inter-county family ties, we use the same Advan Weekly Patterns data and draw mobility flows during the Thanksgiving holiday window. The underlying logic is that travel around Thanksgiving, which consistently represents the peak family reunion period in the United States, reflects destination choices driven by personal relationships rather than economic or recreational motivations. To avoid capturing recreational travel, POIs with tourism or recreational features are excluded from the index. As such, the geographic distribution of Thanksgiving travel serves as a meaningful footprint of where social networks are concentrated.

Such a method is utilized and validated in previous research (Han et al., 2024), which uses normalized flows by a pre-holiday baseline. However, that ratio-based measure discards information about absolute visitor volume, which itself carries an important signal. A destination drawing 1,000 holiday visitors represents a meaningfully different social relationship than one drawing 100, even when both reflect the same proportional lift over baseline. Therefore, this study applies a log-transformed, origin-standardized measure of tie strength:

$$Z_Social\ Ties_{ij} = \frac{\log\left(1 + Thanksgiving\ Visitors_{ij}\right) - \mu_i}{\sigma_i}$$

The log transformation compresses the skewed visitor-count distribution while preserving differences in absolute volume. Subtracting the origin-specific mean and dividing by the origin-specific standard deviation then re-expresses each destination's log visitor count in terms of how far it deviates from that origin's typical travel distribution. The resulting z-score thus reflects not just where people go for Thanksgiving, but where they go in disproportionate numbers relative to their own travel tendencies. Therefore, the index is interpretable as revealed family tie strength, net of population scale effects.

Under this metric, a negative z-score denotes a below-average social connection between an origin and a given destination; a positive z-score signals an above-average connection; and a z-score of exactly 0 corresponds to the average tie strength that origin maintains across all destinations. To avoid year-specific patterns inflating or deflating the measure, z-scores were computed separately for 2019, 2022, 2023, and 2024, then averaged. We deliberately excluded 2020 and 2021, as pandemic-related travel restrictions would have altered holiday travel behavior and introduced noise.

3.5. Other Variables

We computed the distance between each origin and destination county as the great-circle distance in kilometers between county centroids using coordinates from the Census Bureau's TIGER/Line shapefiles and entered it in log form to capture nonlinear decay in migration probability with geographic separation.

Origin housing value was derived from Zillow's Home Value Index (ZHVI) and entered as the log of median estimated home value at the origin county before the hurricane, serving as a proxy for residents' asset base and financial capacity to relocate. The change in housing value (Δ Housing Value) captures the difference in log ZHVI between the destination and origin county, reflecting whether movers are moving toward appreciating or depreciating markets relative to where they left.

Origin and destination population were obtained from the U.S. Census Bureau's American Community Survey (ACS) 5-year estimates and entered as logged counts. Both are included to account for the mechanical mass effect in gravity models, ensuring that estimates for the key predictors reflect compositional patterns beyond differences in county size.

We operationalized racial, income, and industry similarity between each origin–destination county pair as cosine similarity scores computed from the respective compositional vectors of the two counties, then computed z-scores to standardize across the full three-year analytic sample.

We constructed racial similarity from ACS 5-year estimates of racial and ethnic composition at the county level. Each county's composition vector contains the non-white population ratio and Hispanic population ratio, and cosine similarity between the origin and destination vectors captures how closely the two counties resemble each other in racial and ethnic composition, independent of their absolute population sizes.

Income similarity was constructed from ACS-derived median household income and the ratio of the population living below the poverty line. Because the raw variables have very different scales, we first converted each variable to percentile ranks before computing cosine similarity. This normalization prevents scale-dominant variables from driving the similarity score and ensures the measure reflects true resemblance across counties.

Industry similarity was constructed using county-level industry employment shares from the Census Bureau's County Business Patterns (CBP) data, aggregated to two-digit NAICS sectors. Cosine similarity between origin and destination industry share vectors captures how alike the two labor markets are, which may shape whether destinations offer compatible job opportunities for migrating residents.

Table 3. Quasi-Poisson Model Data Summary

	Mean	**Min**	**Median**	**Max**	**Source**
Number of Migrants	3.79	1	1	434	InfutorData
Gravity Factors					
Distance	6.62	3.36	6.98	9.00	TIGER/Line Shapefiles
Origin Population	736,910	12,276	772,902	1,468,560	2023 ACS 5-yr
Destination Population	618,093	1,746	279,729	9,936,690	
Social Network, Social Homophily, Economic Factors					
Family Tie	-0.04	-3.00	0.44	4.84	Advan Research

Racial Similarity	0.00	-9.60	0.39	0.86	2023 ACS 5-yr
Income Similarity	0.00	-3.73	0.32	0.89	
Industry Similarity	0.00	-6.85	0.27	1.14	Census Business Patterns
Other Controls					
$\boldsymbol{log}\Delta$ House Value Index (ZHVI)	-0.11	-2.18	-0.12	1.78	Zillow
$\boldsymbol{log}$ Origin House Value Index (ZHVI)	12.70	11.82	12.77	13.32	

3.6. Quasi-Poisson Gravity Model

Migration flows between county pairs are non-negative integer counts that are heavily right-skewed, as most county pairs record zero or few observed movers. A Poisson regression model is the natural baseline for count outcomes, as it models the expected count as a log-linear function of predictors, constrains predictions to non-negative values, and yields coefficient estimates interpretable as log-rate ratios.

The sample is restricted to inter-county migration flows, as within-county moves have zero geodesic distance and all pairwise similarity measures equal 1, producing degenerate covariates that cannot identify the sorting mechanisms of interest. The sample only includes OD pairs with at least one observed mover, as pairs with no recorded flows carry no information about the direction or magnitude of destination sorting. The pooled sample consists of 3,243 active OD pairs across three years (1,080 pairs in 2019 (559 destination counties), 1,901 pairs in 2024 (804 destination counties), and 262 pairs in 2025 (100 destination counties).

In the model specification below, Y_{ijt} denote the number of movers observed from origin county i to destination county j in year t, where $t \in \{2019, 2024, 2025\}$. The core gravity specification models the conditional expectation as:

$$\log \mathbb{E}\left[Y_{ijt}\right] = \log(\text{Pi} \cdot \text{Pj}) + \alpha + \beta_1 \log d_{ij} + \beta_2 \,\text{FamilyTie}_{ij} + \beta_3 \,\text{RacialSim}_{ij} + \beta_4 \,\text{IncomeSim}_{ij} + \beta_5 \,\text{IndustrySim}_{ij} + \delta_t \cdot \text{FamilyTie}_{ij} + \boldsymbol{X'_{ij}\theta} + \gamma_t$$

where $d_{ij}$is the geodesic distance between county centroids, $P_i$and $P_j$are origin and destination population introduced as a combined offset with coefficient constrained to one, so that the model explains variation in the per-capita migration rate rather than raw flow counts. $\text{FamilyTie}_{ij}$is the Thanksgiving-travel-based family tie index between county pairs.

RacialSim_{ij}, IncomeSim_{ij}, $\text{IndustrySim}_{ij}$are pairwise similarity measures that are z-score standardized before estimation so coefficients are interpretable as the expected log-rate change associated with a one-standard-deviation increase. δ_t are year-by-predictor interaction coefficients, $\boldsymbol{X_{ij}}$is a vector of other controls, $\boldsymbol{\theta}$ is a vector of their coefficients, and $\gamma_t$are year fixed effects (with 2019 as the omitted baseline). To examine whether family ties are associated with different destination-sorting patterns in hurricane years relative to an ordinary year, we pool

OD flows across three years and include year-by-family-tie interaction terms. Distance, population, and flow counts enter in log form, consistent with the gravity model's theoretical foundations and standard practice in the literature (Silva & Tenreyro, 2006).

With the number of migrants between county pairs as the outcome variable, we detected overdispersion in the regular Poisson model (Pearson's dispersion statistic φ=5.33). This excess variability persists even after accounting for the fact that flows leaving the same origin county tend to move together. We therefore report quasi-Poisson standard errors as our primary specification, as widely used in gravity-model migration research (Cameron & Trivedi, 2013; Flowerdew & Aitkin, 1982; Silva & Tenreyro, 2006). Models are estimated in Python using the 'statsmodels' GLM library with Poisson family and post-hoc quasi-Poisson dispersion scaling, and reported standard errors incorporate the $\varphi = 4.10$ correction. Within-origin variance shares averaged 87-89% across all three years, confirming that the fixed effects model leaves sufficient within-origin variation to identify destination-level predictors.

4. Results

4.1. Comparing Evacuation and Migration Hotspots

The evacuation dataset covers 18,115 OD county pairs originating from 26 Florida counties affected by Hurricanes Milton and Helene, with 2,669 unique destination counties. Of these pairs, 2,462 pairs show an increase in visitor inflow during the hurricane period compared to the baseline weeks, while the remainder show no measurable increase. The relocation dataset contains 19,346 OD pairs, of which 1,375 pairs recorded at least one migrant. After merging the two datasets, 30,951 OD pairs appear in at least one dataset. Among them, 676 pairs (2.2%) record both a positive evacuation inflow and at least one migrant, suggesting that while overlap exists, evacuation and relocation destinations are largely distinct. This finding addresses our first research question.

Restricting to the 3,161 OD pairs with at least one positive signal in either evacuation or relocation, we classify pairs into four types using median splits on absolute evacuation inflow and number of migrants. Dual-use hotspots (i.e., OD pairs with above-median visitor influx and number of migrants) account for 371 pairs (11.7%). Evacuation-only hotspots constitute 860 pairs (27.2%), relocation-only hotspots 431 pairs (13.6%), and non-hotspot corridors with weak signals in both dimensions make up the remaining 1,499 pairs (47.4%) (Figure 2a). Among dual-use hotspot destinations, the Pearson correlation between visitor influx during evacuation and number of migrants is substantial and positive (0.71). Notably, the clearest distinguishing feature across corridor types is family tie strength (Figure 2b). Dual-use hotspots show a median family tie z-score of 1.92, far above evacuation-only hotspots (0.79), relocation-only hotspots (0.56), and non-hotspots (0.34). Because the family tie index is a within-origin z-score, a value of 0 corresponds to an origin's average tie strength. The median values for both evacuation-only and relocation-only hotspots are therefore still above average, but they are less than half the median for dual-use hotspots.

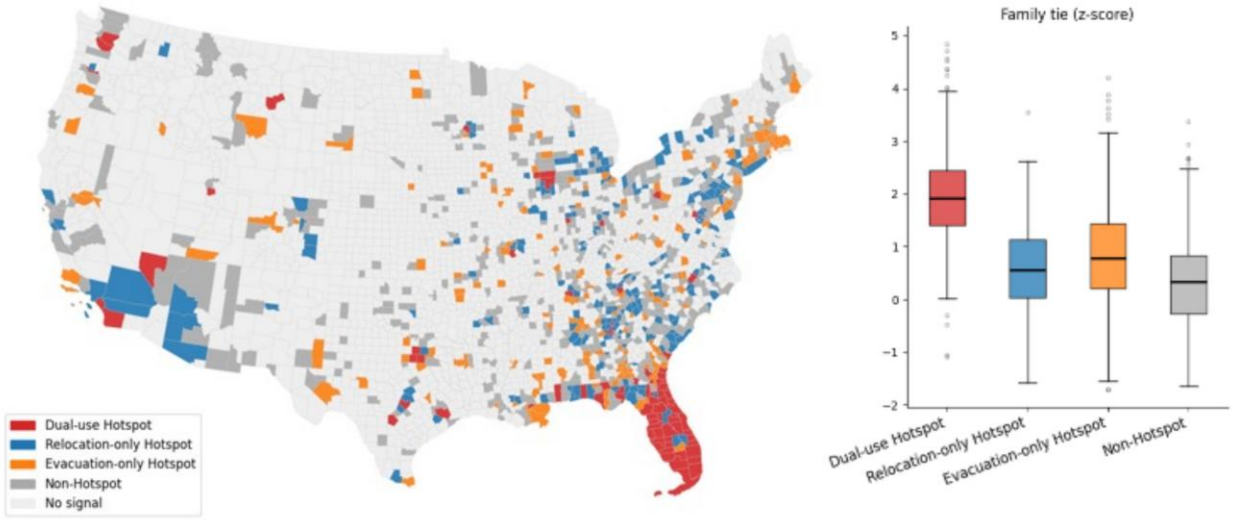


Figure 2. a. Map of Destinations by Hotspot Type (left), b. Distribution of Family Tie by Destination Type (right)

4.2.Within-County vs. County-to-County Migration Patterns

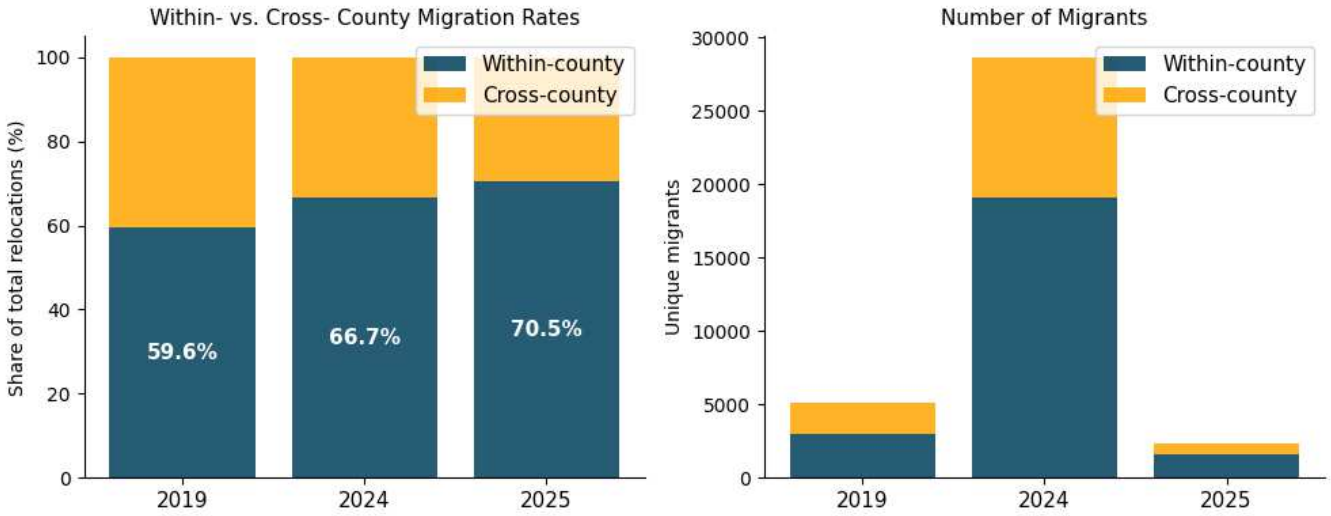


Figure 3. Within- vs. Cross- County Migration Rates

Figure 3 shows the volume of within-county and cross-county moves before and after the 2024 hurricanes. In Oct. 2019, within-county and cross-county moves were roughly comparable in scale. In Oct. 2024, both increased sharply: within-county moves grew to 19,112, about 6.3 times the 2019 level, while cross-county moves grew to approximately 4.7 times the 2019 level. This asymmetry suggests that moves that occurred right after the hurricanes were much more

concentrated within county, aligning with prior studies that found climate displacement occuring mostly within proximate areas (J. Elliott, 2025).

As modeling within-county moves require individual-level data unavailable here, the remainder of this analysis focuses on cross-county migration. The subsequent sections examine what drives the selection of destination counties, specifically the roles of family ties, sociodemographic similarity, and gravity factors in shaping county-pair-level migration flows.

4.3. Post-Hurricane Migration Patterns

Census-tract-level descriptive patterns suggest racial sorting in migration destinations (Figure 4). More than 95% of individuals from majority-White origins moved to majority-White destinations, while individuals from majority-Black origins split roughly evenly between majority-White and majority-Black destinations. The same tendency for movers to go to destinations resembling their origins appears for Hispanic composition, poverty levels, education, homeownership, and elderly population shares, consistent with prior work showing that sociodemographic similarity predicts destination choice. Majority-White origins appear to exhibit particularly strong homophily effects.

These patterns, however, do not necessarily reflect active sorting by racial similarity. Much of the apparent homophily may be explained by other factors, such as distance, population size, and housing market conditions. For example, residents of majority-White counties could live farther from majority-nonwhite counties, have stronger family ties to similarly composed areas, and face different housing cost constraints. To disentangle these mechanisms, we estimate a county-pair-level Quasi-Poisson gravity model that simultaneously accounts for distance, population size, family ties, housing market conditions, and sociodemographic similarity (Table 4, Figure 5).

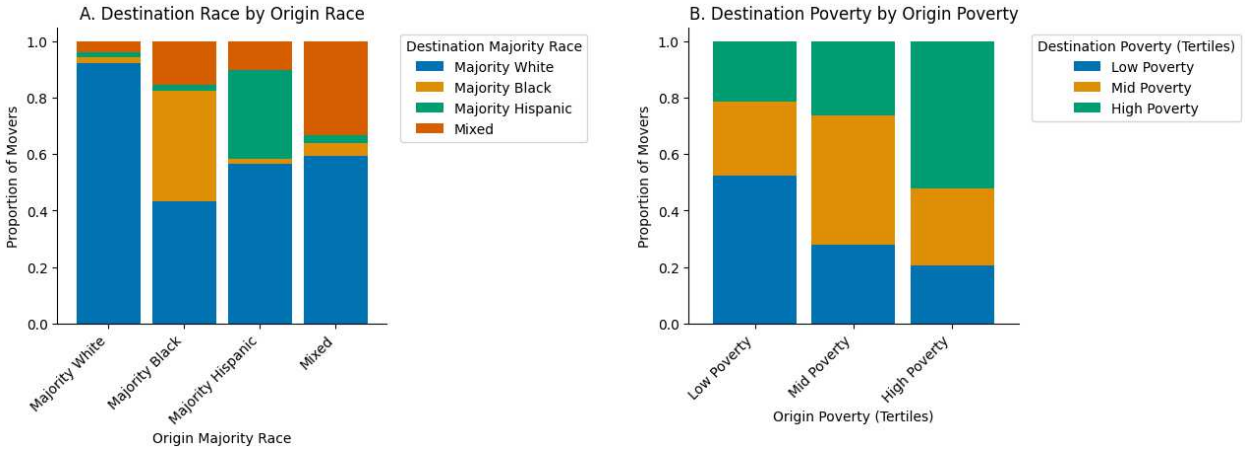


Figure 4. a. Origin and Destination race composition, b. Origin and Destination Poverty Ratio

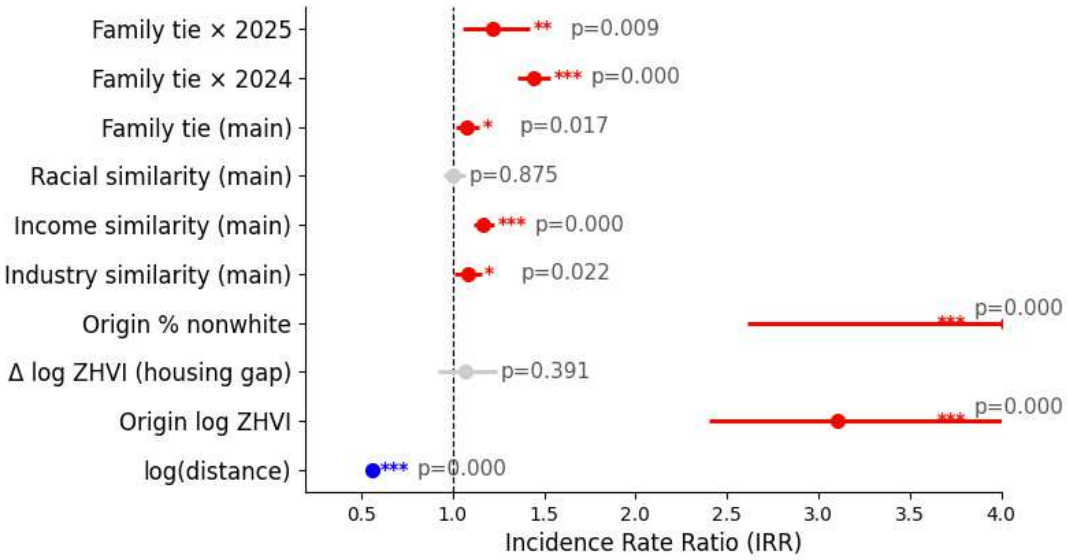


Figure 5. Quasi-Poisson Gravity Model Incident Rate Ratio Plot (point=IRR, bars=95% CI)
Note: Main variables are the family tie index (z-score) and its interactions with 2024 and 2025; racial, income, and industry similarity between origin and destination counties (standardized cosine similarity); log distance; origin nonwhite ratio; log origin housing value; and the destination-origin difference in log housing value. Year effects are relative to 2019, and origin and destination populations enter as an offset.
** $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.*

The Quasi-Poisson gravity model fits the data well (McFadden pseudo-R^2 = 0.54). Distance shows the strongest negative association with migration flows (IRR = 0.56): each log-unit increase in distance is associated with a 44% lower expected mover count. Origin housing value is positively and significantly associated with out-migration (IRR = 3.11), suggesting that residents from higher-value housing markets have greater mobility resources, while the destination-origin housing price gap shows no significant association. Counties with higher nonwhite population shares at origin also exhibit markedly higher out-migration (IRR = 4.03), pointing to differential displacement exposure across racial groups.

Crucially, once these factors are held constant, racial similarity is not significantly associated with migration flows. The apparent homophily observed in descriptive patterns is largely accounted for by distance and other covariates, rather than an independent preference for racially similar destinations. Income similarity, however, shows a significant positive association (IRR = 1.17), indicating that people are more likely to move to counties with similar income composition. Industry similarity also shows a modest but significant positive association (IRR = 1.08), independent of family ties.

4.4. Family Ties in Post-Hurricane Migration Patterns

The main effect of family tie strength is positive and significant (IRR = 1.08), confirming that established social networks are associated with greater migration flows even in non-hurricane years. This association is stronger during the hurricane period, as seen in the family tie × 2024 interaction term yielding IRR of 1.44. The family tie × 2025 interaction also remains elevated at IRR of 1.22.

Table 4. Quasi-Poisson Gravity Model Results (Reference year: 2019, N=3,243 county-pairs)

Variable	IRR	SE	p
Year fixed effects (ref: 2019)			
2024 (Milton/Helene)	0.95	0.095	0.586
2025 (No hurricane)	0.24***	0.225	<0.001
Family ties			
Family tie (main)	1.08*	0.031	0.017
Family tie × 2024	1.44***	0.031	<0.001
Family tie × 2025	1.22**	0.077	0.009
Demographic similarity			
Racial similarity (main)	1.00	0.031	0.875
Income similarity (main)	1.17***	0.025	<0.001
Industry similarity (main)	1.08*	0.034	0.022
Controls			
Distance	0.56***	0.026	<0.001
Origin nonwhite ratio	4.03***	0.222	<0.001
Origin housing value (log)	3.11***	0.132	<0.001
Δ Housing value (log)	1.07	0.076	0.391

Note: IRR = incidence rate ratio (exp(coef)). McFadden pseudo-R^2 = 0.54. Population (origin, destination) entered as offset.
** $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.*

4.5. Post-Hurricane vs. Ordinary Migration Patterns

After controlling for distance, family ties, racial/economic similarity, and housing prices, the baseline migration rate in 2024 does not significantly differ from 2019 (the 2024 year fixed effect is not significant; IRR = 0.95, p = 0.586). This null main effect reflects the selective nature of the post-hurricane migration. Rather than a uniform increase across all OD pairs, the additional migration was concentrated in high-family-tie OD pairs. By contrast, the 2025 year fixed effect is significantly below one (IRR = 0.24), indicating that baseline migration along these OD pairs was lower in Oct. 2025 than in Oct. 2019, even though the family tie × 2025 interaction remained positive.

5. Discussion

5.1. Summary of findings

This study examined whether evacuation hotspots become long-term relocation hotspots, and whether the mechanisms governing ordinary migration destination choice hold, intensify, or weaken in the post-hurricane context.

Regarding R1, the descriptive analysis found that only 11.7 % of OD pairs with an evacuation or relocation signal served as both evacuation and relocation hotspots. In other words, the places visited during short-term evacuations were generally not the places people chose for long-term resettlement. This finding challenges the intuitive assumption that evacuation data can be a leading indicator of long-term population redistribution. Instead, it suggests that each phase of post-disaster mobility operates under different constraints and should not be conflated. Evacuation destinations are shaped by urgency, accessibility, and short-term objectives, while permanent relocation is more constrained by where labor and housing markets align with the household's long-term needs.

The small set of destinations that serve as both evacuation and relocation hotspots is characterized by strong pre-existing family ties. County pairs with strong family ties are substantially overrepresented among destinations that attract both evacuees and permanent movers, while single-use and non-hotspot pairs show much weaker family ties. This is consistent with the aspiration-capability framework (Carling, 2002), which holds that people tend to move to places where they can image going to and where they have the practical support to.

Regarding R3 and R4, the association between family ties and destination choice intensifies in the post-hurricane context. The family tie main effect is positive and significant in the baseline year, and the family tie × 2024 interaction shows a larger positive coefficient. This supports our hypothesis that family ties become more influential when displacement is sudden, and information about destinations is incomplete (Massey et al., 1993). Importantly, the 2025 interaction also remains larger than the main effect, suggesting the amplification of association may have persisted the next year.

Regarding R2, what looked like racial sorting from the descriptive analysis disappears after controlling for distance, family ties, and housing costs. The tract-level data analysis reveals that over 95% of movers from majority-White origins went to majority-White destinations. But once distance, population, family ties, and housing conditions are held constant, racial similarity is no longer significantly associated with migration flows. Income similarity and industry similarity both remain significant after controls, suggesting that economic compatibility independently shapes where people go, and whereas racial similarity is not independently associated with migration flows. This finding, however, should be interpreted with caution as it may be specific to the demographic character of the affected population. Hurricane-affected counties skew older and wealthier compared to the national average (Supplementary Materials

Table S1), and such populations may be influenced more by distance and social connections than by whether the destination resembles their community of origin in racial composition.

Post-hurricane relocation did not raise migration evenly across all county pairs. The 2024-year fixed effect, which represents migration along pairs with average family ties ($z = 0$), is not significantly different from 2019. The surge in migration observed that year was concentrated along county pairs with strong pre-existing family ties, not spread uniformly across all OD pairs observed in the baseline period. This has an important implication for receiving-community preparedness, as the burden of incoming climate migrants is not evenly distributed across all proximate destinations but concentrated in a predictable set of locations identifiable from family ties.

Several limitations deserve acknowledgment. First, InfutorData records may be subject to reporting lag, as address changes register only when individuals interact with credit, utility, or property systems following a move or change of address in digital platforms. We re-collected the 2025 data several months after the initial extraction and found the counts essentially unchanged, suggesting that reporting lag does not drive the lower 2025 migration rate; nonetheless, the 2025 estimates should be interpreted with caution. Second, the findings may not generalize to other disaster types or regions with different population compositions and mobility resources, as the study focuses on a single set of hurricanes. Third, the quasi-Poisson model does not support causal identification of hurricane effects. The affected counties differ from unaffected counties in geography, housing stock, and demographic composition in ways that may independently predict destination choice. Future work using causal models, such as difference-in-differences designs with broader spatial coverage or variation in hurricane track intensity across counties, would be better positioned to isolate the causal effect of hurricanes on destination choice.

5.2. Implications

The findings suggest that evacuation flow data, while useful for immediate emergency response planning, may be a poor guide for estimating long-term relocation. Family ties and economic similarity with affected areas predict relocation better. The strong associations between the origin nonwhite ratio and migrants also point to possible disparities in relocation rates by race. Counties with higher nonwhite populations show substantially greater outmigration pressure. Receiving-community planning that focuses only on aggregate flow volumes risks missing the populations facing the greatest displacement burden.

The findings confirm and refine several migration theories. Most importantly, the social network theory of migration (Massey et al., 1993) is confirmed and extended. The theory holds that established OD flows self-reinforce because each mover lowers the cost and uncertainty of the next move along the same county pair. This study shows that the same logic applies under disaster conditions, and that the association between family ties and migration is significantly larger in the hurricane year than in the baseline. Family tie geographies constructed from routine pre-disaster mobility data, such as the Thanksgiving travel-based index used here, can help predict post-disaster destination choice without post-event observation.

The null finding on racial similarity, once distance, population size, and housing market conditions are controlled, contributes to ongoing debates in residential sorting theory. Schelling's segregation model and subsequent empirical work (Massey & Denton, 1993) have established racial homophily as a robust driver of residential location choice at the intra-metropolitan scale. This study suggests the mechanism may be weaker or absent in this study's context. As mentioned earlier, the affected population in this study skews older, wealthier, and predominantly White, a demographic for whom economic and network considerations may dominate racial preference in destination choice. Whether racial homophily would emerge as an independent predictor in a more racially and economically diverse affected population is an open question that future disaster migration studies should examine.

Finally, the income and industry similarity findings suggest that economic similarity remains a critical factor of destination choice, consistent with social homophily theory along the dimensions of income (Diamond, 2016) and labor market fit (Sjaastad, 1962). Economic opportunity continues to shape destination selection even in the post-hurricane context.

6. Conclusion

This study asked whether evacuation hotspots become long-term relocation hotspots, and whether ordinary migration mechanisms hold, intensify, or weaken in the post-hurricane context. After analyzing mobility patterns following Hurricanes Helene and Milton, evacuation and relocation destinations prove largely distinct. Only 11.7% of evacuation and relocation OD pairs served as hotspots for both phases, and this overlap is concentrated in pairs with strong pre-existing family ties. Ordinary migration mechanisms, meanwhile, persist, and when family ties exist, they measurably intensify. Family ties predict destination choice in the baseline year and are significantly more associated with migration in the hurricane year, consistent with the cost-reduction logic of network migration theory (Massey et al., 1993). Racial similarity loses significance once distance, population size, and housing market conditions are controlled, while income and industry similarity remain independently predictive.

These findings carry both theoretical and practical implications. Theoretically, they suggest that pre-disaster routine mobility, evacuation, and residential relocation are not independent decisions, but sequential phases tied together by the underlying social geography. Households go where they already have connections, and that pull strengthens when the movement occurs in a compressed timeframe. This sequential structure, in which pre-shock family ties shape both where people evacuate and where they settle, is not captured by single-phase migration models. Practically, the findings suggest that family tie geographies constructed from routine mobility data, such as the Thanksgiving travel index used here, can serve as ex ante indicators of where climate-displaced households will concentrate, providing planners with foresight before hurricanes make landfall once the likely affected areas are known.

As hurricane intensity and geographic reach expand under climate change, anticipating population redistribution before displacement becomes increasingly consequential. Linking pre-disaster family ties to evacuation and relocation offers an empirically grounded starting point for

that forecasting challenge, and future work should extend it to more racially and economically diverse disaster populations and event types.

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