Persistence in Environmental Exposure: Evidence from Anchoring

Ruohao Zhang[a,*], Huan Li[b], Kaiyi Wen[c], Neha Khanna[d]

[a] *Department of Agricultural Economics, Sociology, and Education, Pennsylvania State University, State College, PA*

[b] *Department of Economics, North Carolina A&T State University, Greensboro, NC*

[c] *Department of Economics and Finance, The University of Texas at El Paso, El Paso, TX*

[d] *Department of Economics, Binghamton University, Binghamton, NY*

January 24, 2026

Abstract

Why do individuals raised in environmentally disadvantaged areas often remain in similar conditions as adults? We propose a behavioral mechanism of environmental anchoring, where past lived experiences serve as a reference point for future residential choices. We develop a discrete choice model of residential sorting that incorporates reference-dependent preferences, positing that individuals discount the utility of amenities, such as air quality or climate, when they diverge substantially from their formative baseline. This framework offers a micro-foundation for the intergenerational persistence of environmental exposure: individuals from low-amenity origins may undervalue improvements in environmental quality, leading them to self-sort into similarly disadvantaged locations. We test this theory empirically using an augmented gravity model of U.S. county-to-county migration flows from 2013 to 2017. By constructing a measure of environmental distance between origin and destination, we isolate the role of environmental anchoring in migration decisions. We find robust evidence that migration flows are significantly larger between counties with similar environmental and socioeconomic profiles, even after controlling for physical distance and economic opportunities. These findings suggest that spatial inequality is reinforced not only by structural constraints but by internalized preferences, implying that policies aiming to promote intergenerational mobility must account for the behavioral stickiness of past environmental exposure.

Keywords: Anchoring, air pollution, $PM_{2.5}$, gravity model, migration, environmental justice

JEL codes: Q53 Q56

* Corresponding author: Ruohao Zhang, Email: rjz5261@psu.edu. Huan Li, Email: hli1@ncat.edu. Kaiyi Wen, Email: kwen@utep.edu. Neha Khanna, Email: nkhanna@binghamton.edu.

1 Introduction

Where we choose to live is often dictated by where we came from - not just geographically, but environmentally. Consider the striking pattern presented in Figure 1. It plots the rank of particulate matter (PM) exposure during childhood against the rank of exposure in adulthood. The strong positive correlation reveals a stylized fact of environmental persistence: individuals raised in polluted environments tend to reside in similarly polluted locations as adults, while those from cleaner backgrounds remain in cleaner areas. While economic constraints and structural barriers undoubtedly play a role in this stickiness, the linearity and strength of this relationship suggest a deeper behavioral mechanism at play. We argue that this persistence is driven in part by an "anchoring effect". Much like a traveler who judges the temperature of a new city based on the climate of their home, individuals implicitly use their past-life environmental conditions as a reference point. A level of air quality that might seem intolerable to someone from a pristine environment may be perceived as normal or even acceptable to someone anchored in a more industrial setting. This paper formalizes that story, proposing that our history shapes our preferences, and consequently, our migration decisions.

To capture this mechanism, we propose a new residential discrete choice model that incorporates anchoring effects from past lived experiences into individuals' location decisions. In standard random utility frameworks of residential sorting (e.g., Tiebout (1956)), people choose where to live based on current local amenities and constraints. Our innovation is to extend the utility function with a reference-dependent component: individuals evaluate amenities in a potential location relative to the conditions they used to live in. We introduce a utility discount factor that penalizes locations whose environmental quality diverges from one's previous environment. This anchoring mechanism offers a novel explanation for why residential conditions and locational choices may persist across a long time span or generations, as people tend to seek (or remain in) environments familiar to their formative years (or, in general, lived experience).

Environmental conditions often exhibit intergenerational persistence; families can remain in similar environmental settings across generations. For example, children raised in heavily polluted or disaster-prone areas frequently end up living in comparably challenging environments as adults. Conversely, those who grow up amid clean air or mild climates often settle in places with similar amenities (Banzhaf and Walsh, 2008; Manduca and Sampson, 2019; Vitale et al., 2022). Such patterns suggest that beyond economic constraints, preferences shaped by previous experiences play a role in residential choice. Behavioral theory provides a useful lens: individuals carry an implicit "anchor" from lived experiences that influences their later decisions (Albouy et al., 2021; Kellstedt et al., 2024). In the context of residential choice, anchoring means people tend to view a new location's amenties through the prism of what they have long known. A region with objectively high pollution or climate extremes might still attract individuals who are accustomed to those conditions, while even moderate pollution or a harsh winter could deter individuals from pristine or mild origins. These intuitive observations align with evidence of preference persistence in environmental tastes. Recent studies show that early exposure to natural amenities can have lifelong effects (Kellstedt et al., 2024). Who we are environmentally

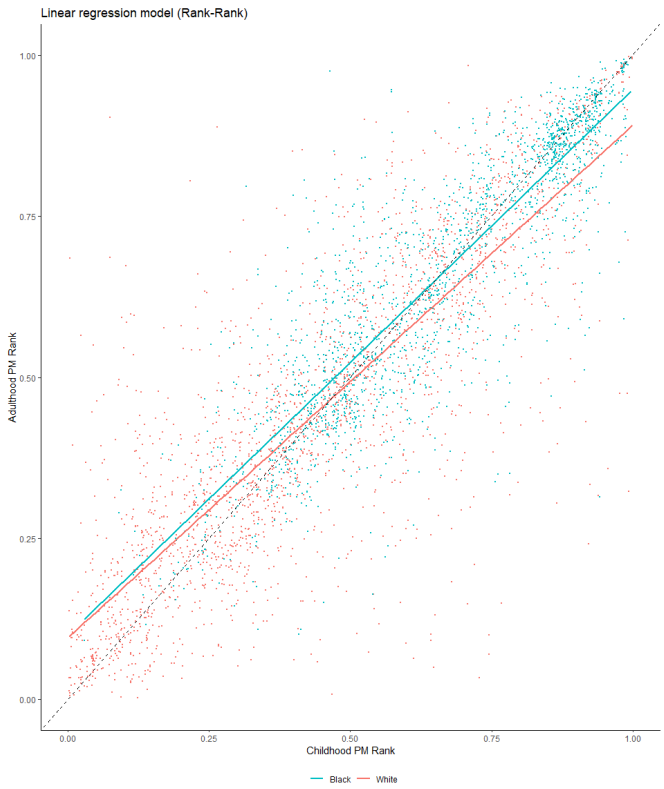


Figure 1: MWTP with Anchoring Effects

is partly forged by previous life experience, and this anchor may steer our later choices.

Understanding this anchoring effect is important because it offers a micro-foundation for persistent inequalities. If individuals from environmentally disadvantaged areas (e.g. high pollution, frequent floods) discount amenities that exceed their familiar baseline, they may be less inclined, ceteris paribus, to move to cleaner or safer areas. Likewise, those from clean environments might avoid moving to places with lower environmental quality. Such tendencies can reinforce intergenerational cycles of (dis)advantage. Children of families long exposed to environmental disamenities could remain trapped in low-amenity locations, perpetuating disparities in health and quality of life. This motivation resonates with the classic "neighborhood effects" idea in sociology, which holds that growing up in a poor or polluted neighborhood can imprint lasting effects on preferences and opportunities (Chetty et al., 2014). Our paper builds on this intuition by formally modeling how previous environmental context (or non-environmental context like access to healthcare, public transportation, large airport, etc.) anchors later choices, specifically residential location, thereby contributing to the broader question of why location-based advantages or disadvantages persist over time.

Our work bridges three strands of literature: residential sorting and local amenities, intergenerational mobility and persistence, and migration models. We draw on insights from each while highlighting the gap our theory fills.

Residential Sorting and Environmental Amenities: Individuals sort themselves spatially according to their preferences for local public goods and amenities, subject to their budget

constraint. This idea dates back to Tiebout (1956)'s hypothesis that households "vote with their feet" by moving to communities that best match their preferences for amenities and budgets. A rich literature has since examined how amenities, including environmental quality, shape migration and location choices. For example, air quality significantly influences where people choose to live, indicating that environmental amenities carry substantial weight in residential decisions (Bayer et al., 2009). Such findings imply that improving local environmental quality can attract households and potentially improve long-run outcomes. However, a notable feature of the sorting process is that it tends to reflect and reinforce inequality. Standard models attribute this reinforcement primarily to wealth disparities: families with greater resources cluster in high-amenity areas, while poorer households are priced out and concentrated in lower-amenity areas (Banzhaf et al., 2019). Our framework suggests an additional, behavioral explanation for this persistence: the anchoring effect. If preferences are endogenous to past exposure, individuals raised in disadvantaged environments may internalize these conditions as a baseline, effectively "discounting" the utility of superior amenities. This behavioral inertia suggests that inequality is reinforced not only by external budget constraints but also by internalized preferences, as children raised in high-amenity communities inherit not only better immediate environments but also higher reference points that drive them to seek similar communities in adulthood. Conversely, children from disadvantaged environments may have neither the means nor the inclination to seek out dramatically better environments later on. These patterns underscore the need to understand preference formation: why do some individuals not pursue the highest possible environmental quality, subject to their resource constraint? Our approach, introducing anchoring in lived experiences, provides one answer - that people's valuation of amenities is relative to what they have historically experienced, rather than absolute.

Intergenerational Persistence and Anchoring: Research on intergenerational mobility typically focuses on outcomes like income, education, and occupation, but there is growing recognition that place-based attributes (neighborhood quality, environmental conditions) also transmit across generations (Corak, 2013). For example, neighborhood economic declines during childhood have been shown to depress long-run labor market outcomes and social mobility, helping to explain persistent urban poverty (Wilson, 2012). Behavioral theory also provides a useful lens: individuals carry an implicit "anchor" from past-life conditions that influences their later decisions. In the spirit of reference-dependent preferences (Kőszegi and Rabin, 2006, 2007), people's previous experiences serve as baseline reference points, shaping how people evaluate their later choices. Empirical work also provides evidence that childhood exposure to natural environments strongly predicts adult environmental engagement and well-being (Vitale et al., 2022; Kellstedt et al., 2024).

Gravity Models and Environmental Migration: Our study connects to the extensive empirical literature on human migration. We focus, in particular, on gravity models which analogize migration flows to Newton's law of gravity, predicting that bilateral flows increase with origin and destination "mass" (typically measured by population or economic size) and decrease with distance (a proxy for migration costs). This framework has proven remarkably

successful in explaining migration patterns and remains widely used due to its intuitive appeal and empirical fit (Borjas, 1987; Anderson and Van Wincoop, 2003). Traditional gravity analyses emphasize economic drivers, such as income differentials and labor demand, and frictions like distance or language barriers (Adserà, 2015; Ramos, 2016). In recent years, researchers have extended the gravity framework to incorporate environmental variables, examining climate and pollution as push and pull factors. There is within- and cross-country evidence to show that environmental stressors, ranging from natural disasters to gradual climate deterioration can significantly influence migration rates. For example, countries or regions experiencing frequent floods or droughts tend to exhibit higher rates of emigration (Entwisle, 2021). In China, worsening air quality decreases migration inflows and increases outflows, consistent with individuals "voting with their feet" toward cleaner environments so that a 10 $\mu g/m^3$ increase in $PM_{2.5}$ reduces a city's probability of being chosen by migrants by 21% (Shen et al., 2023).

While these gravity frameworks account for idiosyncratic heterogeneity in preferences, they generally estimate an average effect of destination amenities (e.g., pollution levels) on migration inflows. This implicitly assumes that the marginal disutility of pollution is the same regardless of whether a migrant arrives from a pristine environment or a heavily polluted one. Our contribution is to relax this assumption by embedding anchoring effects into the gravity framework, allowing the valuation of environmental differences to explicitly depend on migrants' origin baselines. Emerging evidence suggests this nuance matters: migrants' responses to environmental attributes are mediated by their socioeconomic backgrounds, exposure histories, and constraints. For example, environmental conditions strongly influence both migration and settlement choices within China, but that poorer households are less able or willing to relocate, remaining "stuck" in degraded areas (Liu et al., 2022). Similarly, persistent disparities in pollution exposure among U.S. populations suggest structural and behavioral factors that limit environmental mobility (Bakhtsiyarava and Nawrotzki, 2017). That U.S. counties with high pollution did not experience markedly higher out-migration than cleaner counties, but attracted significantly fewer new migrants (Hunter, 1998), suggests inertia among long-term residents and avoidance among outsiders. Together, this evidence highlights the need to formally model the role of lived experiences, as it can enrich our understanding of migration flows and environmental sorting beyond what traditional gravity models capture.

Against this background, we develop a discrete choice model of residential sorting that, for the first time, incorporates an anchoring effect of past life experience into the utility function. In our model, the utility derived from a local amenity is discounted when that amenity deviates (in either direction) from the individual's previous experience. This theoretical formulation extends the classic random utility framework by introducing a reference-dependent preference (Kőszegi and Rabin, 2006, 2007). We formally define a continuous utility discount function $f(\Delta_{ij})$ where Δ_{ij} is the absolute difference between the amenity level at the prospective location j and the amenity level historically experienced by individual i. By solving the individual's utility maximization with this anchoring effect, we show that the marginal willingness-to-pay for environmental quality is diminished when the current environment deviates from one's baseline

experience. The model yields intuitive predictions: all else equal, an individual is more likely to choose a location with environmental amenities that are similar to their previous experience than one that is very different.

Our framework offers a novel explanation couched in microeconomic theory for the intergenerational persistence in exposure to (and preference for) local amenities. Whereas most studies of intergenerational mobility emphasize income and human capital channels, we highlight an environmental preference channel. We are able to show that anchoring behavior can generate intergenerational cycles in which environmental advantages or disadvantages are passed down not just through neighborhood sorting by parents, but through the preferences of the children themselves. Our framework thus connects the residential sorting literature with the mobility literature by identifying a preference-based mechanism for the intergenerational persistence of environmental exposure. It complements existing arguments about structural constraints (e.g., credit constraints or segregation) by showing that even in the absence of external barriers, lived experience and internalized preferences can lead to sustained stratification of environmental quality. While previous studies have described anchoring as a form of social or emotional attachment to a home region (Grzymala-Kazlowska and Ryan, 2022), we formally model it as a behavioral bias where past environmental exposure serves as a baseline for valuing future amenities. By formally modeling this process, we contribute to the literature on environmental justice and mobility, offering a new lens to interpret why, for example, polluted neighborhoods often remain populated by successive generations of disadvantaged groups.

We bring the theory to data by empirically testing the existence and strength of anchoring effects in migration flows in the United States. Using a panel of county-to-county migration flows from 2013 to 2017, we estimate an augmented gravity model where the key independent variable is the environmental dissimilarity between origin and destination. Following the gravity tradition, we include standard controls for origin and destination population, economic conditions, and distance between counties, and we introduce measures of local amenities, including three environmental amenities (air quality, flood risk, climate) for both origin and destination. Crucially, we construct an "anchoring difference" variable Δ_{ij} for each local amenity, defined as the absolute gap in that attribute between the origin and destination. This variable reflects the "psychological distance" between and origin and destination. Our empirical specification then examines whether migration flows M_{ij} are lower when Δ_{ij} is larger, conditional on origin and destination amenities. This approach allows us to isolate the preference for environmental similarity as predicted by our theory. To ensure robust inference, we incorporate high-dimensional fixed effects (for origin, destination, and year) and account for multilateral migration resistance factors in line with best practices in gravity modeling. In doing so, our study is among the first to quantitatively estimate reference-dependent anchoring effects in a migration context. The empirical findings provide robust evidence of anchoring, particularly regarding climatic conditions, suggesting that past environmental experiences significantly shape migration behavior.

By elucidating anchoring effects in location choice, our paper carries implications for policies aiming to improve mobility and reduce environmental inequities. If preferences are anchored

in lived experience, simply providing information or opportunities may not be sufficient to induce relocation to better environments. Instead, policies that improve local environmental conditions can have long-lasting benefits not just directly (better health, etc.) but indirectly by recalibrating what future generations consider acceptable or desirable in a living environment. Conversely, ignoring anchoring effects could lead to underestimating the stickiness of residential patterns. People may not move away from environmental risks as readily as classical models predict, due to habituation or attachment. By formally accounting for anchoring, policymakers and researchers can better predict migration responses to environmental changes and design interventions that enhance intergenerational mobility in terms of environmental quality.

2 A Theoretical Discrete Choice Model

We construct a residential discrete choice model, assuming that individuals choose neighborhoods based on their preferences for local characteristics and subject to budget constraints (Tiebout, 1956; Bayer et al., 2009). We extend the standard model by incorporating the influence of lived experiences on preferences and decision-making. Specifically, we construct a random utility model that considers not only the local characteristics of an individual's potential residential location but also those in the individual's lived experience.

We assume that, conditional on choosing a residential location j, individual i selects her consumption of a composite commodity $C_{i,j}$ and housing $H_{i,j}$ to maximize her utility $U_{i,j}$:

$$\begin{aligned} \max_{C_{i,j},H_{i,j}} \; & U(C_{i,j}, H_{ij}; A_j, \Delta_{ij}) = C_{i,j}^{\beta_C} H_{i,j}^{\beta_H} f(\Delta_{ij}) A_j^{\beta_A} e^{MC_{ij}+\zeta_j+\eta_{i,j}} \\ s.t. \quad & C_{i,j} + \rho_j H_{i,j} = I_{i,j}, \end{aligned} \tag{1}$$

where A_j is the non-market local amenity that generates utility. The anchoring effect implies that the utility derived from local amenities is discounted when the amenity level deviates from the individual's lived experience. Let $\tilde{A}_i$ be the individual i's lived experience of the relevant non-market amenity; then $\Delta_{ij} = |A_j - \tilde{A}_i|$ is the absolute difference between lived experience and current residential choice. A higher value of Δ_{ij} indicates that the local amenity in an individual's current residential location is more different from her lived neighborhood. We model the utility discount function $0 \leq f(\Delta_{ij}) \leq 1$, a continuous function of Δ_{ij}. Therefore, A_j affects total utility through $g(A_j, \Delta_{ij}) = f(\Delta_{ij}) A_j^{\beta_A}$, which is a function of itself as the good and Δ_{ij} as the discount factor, simultaneously. We refer to the utility discount function $f(\Delta_{ij})$ as the anchoring effect, and make several assumptions on its functional form.

Assumption 1: Holding A_j constant, as A_j becomes more different from lived experiences, individuals marginal utility of A_j declines at an increasing rate. For any $\Delta_{ij} > 0$, $\frac{\partial g(A_j,\Delta_{ij})}{\partial \Delta_{ij}} < 0$, $\frac{\partial^2 g(A_j,\Delta_{ij})}{\partial \Delta_{ij}^2} < 0$, which is equivalent to $f'(\Delta_{ij}) < 0$, $f''(\Delta_{ij}) < 0$.

Assumption 2: If A_j is the same as an individual's lived experiences, her utility is not affected by the anchoring effect, $g(A_j, \Delta_{ij} = 0)$ represents individuals' preferences on A_j without the

anchoring effect, $g(A_j, \Delta_{ij} = 0) = A_j^{\beta_A}$, $f(0) = 1$.

Assumption 3: Even with the existence of the anchoring effect, individuals' marginal utility of A_j is always positive, $\frac{dg(A_j,\Delta_{ij})}{dA_j} = \beta_A A_j^{\beta_A - 1} + A_j^{\beta_A} f'(\Delta_{ij}) \frac{d\Delta_{ij}}{dA_j} > 0$. This is always true for $A_j \leq \tilde{A}_i$ because $f'(\Delta_{ij}) < 0$ and $\frac{d\Delta_{ij}}{dA_j} = -1$. For $A_j > \tilde{A}_i$, $\frac{d\Delta_{ij}}{dA_j} = 1$, the assumption implies the utility discount from Δ_{ij} does not outweigh the utility gain from A_j, $\beta_A A_j^{\beta_A - 1} + A_j^{\beta_A} f'(\Delta_{ij}) > 0$, $f'(\Delta_{ij}) > -\frac{\beta_A}{A_j}$.

For the remaining components of the utility function, MC_{ij} is a nonparametric mobility cost, measuring the long-run disutility to individual i of migrating to location j. ζ_j is the location fixed effect, capturing the remaining unobserved local attributes; $\eta_{i,j}$ is a random individual idiosyncratic component of utility. ρ_j is the unit price of housing service H in location j, $I_{i,j}$ is individual i's income in the job market of location j.

2.1 Preferences under Anchoring

Solving the optimization problem represented by equation 1 for the individual's optimal choices of $H_{i,j}^*$ and $C_{i,j}^*$, we derive the conditional indirect utility function as:

$$V_{i,j} = \frac{\beta_C^{\beta_C} \beta_H^{\beta_H}}{(\beta_C + \beta_H)^{(\beta_C + \beta_H)}} I_{i,j}^{(\beta_C + \beta_H)} \rho_j^{-\beta_H} A_j^{\beta_A} f(\Delta_{ij}) e^{MC_{ij} + \zeta_j + \eta_{i,j}}. \tag{2}$$

The utility indifference curve between income and A can be derived by holding V_{ij} constant. Conditional on location j, the additional income that compensates for a marginal change in the non-market local amenity, or MWTP for A_j, can be illustrated as the slope of the utility indifference curve.

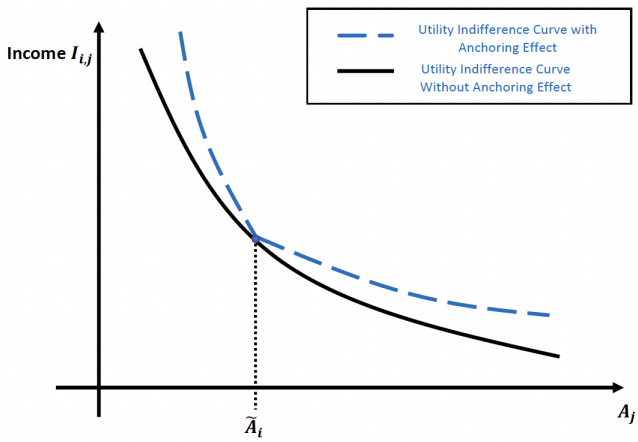


Figure 2: MWTP with Anchoring Effects

Figure 2 visualizes how anchoring affects the individual's preference structure. The solid line represents the indifference curve derived from a standard utility function, i.e., without the

anchoring effect, whereas the dashed line shows the indifference curve derived from the indirect utility function in equation 2. As shown in the Figure, anchoring creates a kink at the point $\tilde{A}_i$ and distorts the indifference curve in opposite directions:

$$\begin{aligned} MWTP_{A_j} = \frac{MU_{A_j}}{MU_{I_{i,j}}} &= \frac{\beta_A I_{i,j}}{(\beta_C+\beta_H)A_j} + \frac{I_{i,j}}{(\beta_C+\beta_H)}\frac{f'(\Delta_{ij})}{f(\Delta_{ij})} \quad if\ A_j > \tilde{A}_i; \\ &= \frac{\beta_A I_{i,j}}{(\beta_C+\beta_H)A_j} \qquad\qquad\qquad\qquad if\ A_j = \tilde{A}_i; \\ &= \frac{\beta_A I_{i,j}}{(\beta_C+\beta_H)A_j} - \frac{I_{i,j}}{(\beta_C+\beta_H)}\frac{f'(\Delta_{ij})}{f(\Delta_{ij})} \quad if\ A_j < \tilde{A}_i, \end{aligned} \tag{3}$$

where $\frac{\beta_A I_{i,j}}{(\beta_C+\beta_H)A_j}$ is the MWTP for the local amenity A if there are no anchoring effects. Since $\frac{f'(\Delta_{ij})}{f(\Delta_{ij})} < 0$, the anchoring effect decreases MWTP if $A_j > \tilde{A}_i$ and increases MWTP if $A_j < \tilde{A}_i$. Intuitively, compared with preference structure without the anchoring effect, an individual is willing to pay less for a marginal improvement in local amenities when that amenity exceeds their lived experience, since the improvement widens the difference between the past and present amenity and generates disutility. Conversely, an individual whose current local amenity less than their lived experience is willing to pay more for additional improvements in those amenities, because it narrows the difference and mitigates the utility discount associated with the anchoring effect. These results imply the following proposition:

Proposition 1: If an individual has Cobb-Douglas preferences as described in equation 1 and given the Assumptions 1–3 on the discount function as described above, an anchoring effect that discounts utility will decrease the MWTP for the local amenity A_j when it is greater than the anchoring point created by lived experience, and increase the MWTP if the local amenity A_j is lower than the anchoring point.

2.2 Location Choices and Residential Persistence

Consider an individual i facing two otherwise identical locations but with different levels of the local amenity of interest and income. Location 1 is denoted by $(A_1, I_{i,1})$, and location 2 is denoted by $(A_2, I_{i,2})$. Suppose location 1 is more similar to the individual's previous location, $\Delta_{i1} < \Delta_{i2}$. The individual chooses location 1 if $V_{i,1} \geq V_{i,2}$. Consider two scenarios with and without the anchoring effects, the individual chooses location 1 if

$$\begin{aligned} &I_{i,1}^{(\beta_C+\beta_H)} A_1^{\beta_A} e^{\eta_{i,1}} \geq I_{i,2}^{(\beta_C+\beta_H)} A_2^{\beta_A} e^{\eta_{i,2}} && \textit{no anchoring effects,} \\ &I_{i,1}^{(\beta_C+\beta_H)} A_1^{\beta_A} f(\Delta_{i1}) e^{\eta_{i,1}} \geq I_{i,2}^{(\beta_C+\beta_H)} A_2^{\beta_A} f(\Delta_{i2}) e^{\eta_{i,2}} && \textit{with anchoring effects.} \end{aligned} \tag{4}$$

Let $\tilde{\eta}_i = \eta_{i,2} - \eta_{i,1}$, where $\eta_{i,j}$ is the idiosyncratic component in individual i's utility. Then, the probability that individual i prefers location 1 over location 2 is

$$\begin{aligned} Pr_i(1|\textit{No Anchoring Effects}) &= Pr\Big(\tilde{\eta}_i \leq \big[(\beta_C + \beta_H) ln\frac{I_{i,1}}{I_{i,2}} + \beta_A ln\frac{A_1}{A_2}\big]\Big), \\ Pr_i(1|\textit{With Anchoring Effects}) &= Pr\Big(\tilde{\eta}_i \leq \big[(\beta_C + \beta_H) ln\frac{I_{i,1}}{I_{i,2}} + \beta_A ln\frac{A_1}{A_2} + ln\frac{f(\Delta_{i1})}{f(\Delta_{i2})}\big]\Big). \end{aligned} \tag{5}$$

Because $f'(\Delta_{ij}) < 0$ and $\Delta_{i1} < \Delta_{i2}$, we have $f(\Delta_{i1}) > f(\Delta_{i2})$, $ln\frac{f(\Delta_{i1})}{f(\Delta_{i2})} > 0$, and

$$Pr_i(1|\textit{With Anchoring Effects}) > Pr_i(1|\textit{No Anchoring Effects}), \tag{6}$$

which implies the following proposition.

Proposition 2: Given the Cobb-Douglas preference described in equation 1 and the decreasing utility discount function $f(\Delta_{ij})$, the anchoring effects increase the probabilities that individuals prefer locations more similar to their lived experiences.

2.3 Comparative Statics

To further analyze how individuals' lived experience, $\tilde{A}_i$, affect their later residential location choices. Consider two individuals, a and b, choosing between two locations. Assume that the two individuals have identical characteristics but differ in lived amenities, $\tilde{A}_a > \tilde{A}_b$, and receive the same income at each location 1 and 2. Let (A_1, I_1) and (A_2, I_2) denote the combinations of local amenities and income at locations 1 and 2, respectively. Assume $A_1 > A_2$. The probability that each individual chooses location 1 over location 2 is

$$\begin{aligned} Pr_a(1|\textit{With Anchoring Effects}) &= Pr\Big(\tilde{\eta}_a \leq \big[(\beta_C + \beta_H) ln\frac{I_1}{I_2} + \beta_A ln\frac{A_1}{A_2} + ln\frac{f(\Delta_{a1})}{f(\Delta_{a2})}\big]\Big). \\ Pr_b(1|\textit{With Anchoring Effects}) &= Pr\Big(\tilde{\eta}_b \leq \big[(\beta_C + \beta_H) ln\frac{I_1}{I_2} + \beta_A ln\frac{A_1}{A_2} + ln\frac{f(\Delta_{b1})}{f(\Delta_{b2})}\big]\Big). \end{aligned} \tag{7}$$

The critical term distinguishing these probabilities is the ratio of anchoring discounts, $f(\Delta_{i1})/f(\Delta_{i2})$. The magnitude of this term depends on where an individual's reference point $\tilde{A}_i$ lies relative to the options A_1 and A_2. For instance, the trade-off differs if both locations are superior to the individual's past experience (upward mobility) versus if they are inferior (downward mobility). In the Appendix, we exhaustively analyze the six possible permutations of the amenity ordering (i.e., the relative rankings of $\tilde{A}_a$, $\tilde{A}_b$, A_1, and A_2 on the amenity spectrum). We demonstrate that across all such scenarios, the individual with the higher reference point is consistently more likely to choose the higher-amenity location, concluding that $Pr_a(1|\textit{With Anchoring Effects}) > Pr_b(1|\textit{With Anchoring Effects})$. This implies the following proposition:

Proposition 3: Given the Cobb-Douglas preferences and Assumptions 1–3 on the discount function as described above, with anchoring effects, individuals with higher levels of past lived amenities are more likely to choose locations with higher amenity levels, *ceteris paribus*.

Next, we examine how the MWTP changes in response to a marginal change in lived amenity $\tilde{A}_i$. According to **Assumption 1**, individuals become less sensitive to adulthood amenity levels as the adulthood amenity A_j deviates from the anchoring point $\tilde{A}_i$. Specifically, this implies that the marginal utility derived from the amenity is discounted at an increasing rate as the gap between current conditions and past experience widens. That is, the anchoring effect $f(\Delta_{ij})$ decreases in a increasing rate, $f''(\Delta_{ij}) < 0$. Therefore, given A_j, the change in the MWTP in response to a marginal change in lived amenity $\tilde{A}_i$ is

$$\begin{aligned} \frac{\partial MWTP_{A_j}}{\partial \tilde{A}_i} &= -\frac{I_{i,j}}{(\beta_C + \beta_H)} \times \left(\frac{f''(\Delta_{ij})}{f(\Delta_{ij})} - \frac{f'(\Delta_{ij})^2}{f(\Delta_{ij})^2} \right) > 0 \quad \text{for all } \tilde{A}_i \neq A_j, \\ &= 0 \quad \text{if } \tilde{A}_i = A_j, \end{aligned} \tag{8}$$

since $\frac{f''(\Delta_{ij})}{f(\Delta_{ij})} - \frac{f'(\Delta_{ij})^2}{f(\Delta_{ij})^2} < 0$. Intuitively, individuals who have experienced higher levels of local amenities in the past exhibit a higher MWTP for marginal improvements in contemporaneous local amenities. This implies the following proposition.

Proposition 4: Given the Cobb-Douglas preferences and Assumptions 1–3 on the discount function as described above, MWTP increases in the anchoring point $\tilde{A}_i$.

These theoretical results generate a clear, testable implication for aggregate migration patterns: the flow of migrants between two locations should depend not only on the absolute quality of the destination's amenities but also on the *environmental distance* between the origin and destination. If preferences are indeed anchored, individuals effectively face a utility penalty when moving to locations that diverge sharply from their experienced baseline (Δ_{ij}). This implies that environmental dissimilarity should act as a barrier to mobility, functioning similar to physical distance or informational frictions. To empirically validate this prediction, we move from the individual discrete choice framework to an aggregate analysis using the gravity model of migration. By augmenting the traditional gravity equation with our measure of anchoring, we can formally test whether the divergence in amenities between origin and destination significantly dampens migration flows, as our theory suggests.

3 Application to the Gravity Model of Migration

3.1 Econometric Specification

Since (Tinbergen, 1962)'s original exposition, the gravity model has been widely used to study spatial interactions such as international trade (e.g., Anderson, 2011) and human migration (e.g., Beine et al., 2016). The starting point for these models is Newton's law of universal

gravitation:

$$F = g\frac{m_1 m_2}{r^2} \tag{9}$$

where F is the gravitational force between two objects, m_1 and m_2 are the masses of the objects, r is the distance between the centers of their masses, and g is the gravitational constant. In the classic gravity model of migration (Lowry, 1966), the volume of migration from location i to location j in year t, denoted by M_{ijt} is positively correlated to the populations of both locations and negatively correlated to the geographic distance between them, and is modeled using a Cobb-Douglas functional form: $M_{ijt} = gP_{it}^{\beta_1}P_{jt}^{\beta_2}D_{ij}^{\beta_3}$, where P_{it} and P_{jt} are the populations of the origin and destination locations in year t, respectively, and D_{ij} is the great-circle distance between location centroids.[1] We introduce the anchoring effect (Δ_{ijt}), which measures the psychological distance, into the formula as follows:

$$M_{ijt} = gP_{it}^{\beta_1}P_{jt}^{\beta_2}D_{ij}^{\beta_3}\Delta_{ijt}^{\rho} \tag{10}$$

This psychological distance is based on the characteristics of the origin and destination counties and captures how "far" the origin and destination counties are in terms of selected socioeconomic, public goods, or environmental amenities. Operationally, we quantify this distance $\Delta_{i,j}$ using a multidimensional measure of Euclidean distance.

We estimate Equation 10 using the Poisson Pseudo-Maximum Likelihood (PPML) estimator, which is robust to a high proportion of zeros and consistently estimates the parameters of a log-linear model:

$$M_{ijt} = exp\left[\beta_1 ln(P_{it}) + \beta_2 ln(P_{jt}) + \beta_3 \ln(D_{ij}) + \rho ln(\Delta_{ij}) + \lambda_i + \eta_j + \mu_{ijt}\right] \tag{11}$$

where λ_i and η_j are origin and county fixed effects, which are used to absorb unobserved characteristics. μ_{ijt} contains other idiosyncratic factors affecting migration. Standard errors are clusterd at the origin county level.

3.2 Data

The number of households migrating from an origin county to a destination county is obtained from the Internal Revenue Service Statistics of Income (SOI) Migration Data.[2] This dataset provides annual information on migration flows across US states and counties, based on year-to-year address changes reported on individual income tax returns. Although the data excludes

[1] The great-circle distance is the shortest distance between two points on the surface of a sphere, measured along the surface of the Earth (as opposed to a straight line through the Earth's interior).

[2] SOI Tax Stats - Migration Data, https://www.irs.gov/statistics/soi-tax-stats-migration-data, accessed on May 12, 2025. The data are available beginning in 2010; however, our sample starts in 2013 due to major revisions in the IRS migration data methodology implemented in the 2013–2014 period, which resulted in significant discontinuities relative to earlier years. Although the most recent available data are from 2021, we restrict our analysis to 2017 because of computational constraints in the regression. In the robustness check, we also conduct the same analysis for data in years 2014–2018; 2015–2019; 2016–2020; 2017–2021.

non-filers, it covers the vast majority of the population and are considered as a reliable source for understanding internal migration patterns in the US.

We construct a panel of bilateral county pairs for all counties in the contiguous U.S. from 2013 to 2017. Each observation corresponds to an origin – destination county pair in a given year and reports the number of households that migrate between the two counties.

For each origin–destination county pair, we match a comprehensive set of environmental and socioeconomic variables to characterize both local conditions and potential drivers of migration. We obtain county-level fine particulate matter ($PM_{2.5}$) concentrations from the Atmospheric Composition Analysis Group at Washington University in St. Louis (V6.GL.02.02). We measure climate conditions using (1) annual average temperature data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) Weather Data[3], (2) annual counts of extreme heat/cold event days or degree-day measures (heating and cooling degree days) from .Fard et al. (2023)[4]; and (3) the annual count of flood events reported in NOAA's Storm Events Database which we use to proxy flood risk. To account for demographic and economic characteristics, we use county-level measures from the American Community Survey (ACS-5), including total population, median household income, unemployment rate, and the percentage of adults without a high school diploma. In addition, we include the number of hospitals and hospital employees as measures of public goods, which were collected from the Census County Business Patterns.

The full dataset contains 52,246,297 origin-destination pair observations during 2013 – 2017. Table 1 reports yearly summary statistics of county-to-county migration flows, calculated using observations with non-zero migration counts, as the majority of migration between counties are zero in a given year. On average, origin counties are linked to approximately 2,800 destination counties each year. Conditional on non-zero migration flows, the mean number of migrating households ranges from about 116 to 123 across years. Migration flows are highly skewed, with minimum flows of around 20 households and maximum flows exceeding 20,000 households in some years. In relative terms, the average share of migration households is small—around 0.2 percent—but varies considerably across county pairs. Similar patterns are observed for individual migration flows: the mean number of migrating individuals ranges from roughly 215 to 240 per county pair, while the maximum exceeds 40,000 in later years, indicating substantial heterogeneity in migration intensity across county pairs.

[3]PRISM Group, Oregon State University, https://prism.oregonstate.edu, data created 4 Feb 2014, accessed on 23 Sep 2025.

[4]A day is classified as an extreme heat event if the excess heat factor reaches or exceeds the 85th percentile of historical values for that specific location over a 16-year period (2008–2023). A day is classified as an extreme cold event if the excess cold factor reaches or falls below the 15th percentile of historical values for that location.

Table 1: Summary Statistic – Migration Data

			Number of Migrating Households				Share of Migrating Households			
Year	Orig.	Dest.	Mean	SD	Min	Max	Mean	SD	Min	Max
2013	2846	2802	116.18	431.28	18	19238	0.0020	0.0044	0	0.0918
2014	2761	2702	113.28	391.76	19	15621	0.0020	0.0040	0	0.0807
2015	2838	2794	120.20	451.92	20	20065	0.0020	0.0044	0	0.0800
2016	2890	2867	128.39	524.77	20	25334	0.0021	0.0049	0	0.1069
2017	2852	2786	122.88	470.73	20	21031	0.0020	0.0044	0	0.0966
			Number of Migration Individuals				Share of Migration Individuals			
Year	Orig.	Dest.	Mean	SD	Min	Max	Mean	SD	Min	Max
2013	2846	2802	218.19	813.74	20	35602	15.16	33.00	0.03	547.62
2014	2761	2702	206.37	727.55	20	30386	14.10	29.06	0.03	542.96
2015	2838	2794	221.59	835.40	20	37393	14.63	31.88	0.03	637.41
2016	2890	2867	239.52	978.21	20	49355	15.53	36.03	0.03	708.30
2017	2852	2786	223.06	858.49	21	41482	14.43	31.97	0.02	665.59

Among all county-to-county flows, 69% occur within the same state and 31% across states. Among the top 500 county-to-county flows, 94% are within-state while only 6% cross state boundaries. As shown in Figure 3, the majority of migration flows occur over a relatively short distance. Figure 4, which maps the top 200, 400, and 600 flows from 2010 to 2017, shows that most migration involves short- or medium-distance moves, often between neighboring counties within large metropolitan areas such as Southern California, South Florida, the New York–New Jersey, and the Washington, D.C. region. The long-distance flows are almost exclusively between major metropolitan areas. These patterns highlight that the domestic migration is overwhelmingly localized, and when households do move across longer distances, they are primarily relocating between large population centers.

To visualize the migration patterns in relation to differences in environmental amenities, we randomly pick three counties – Cook County IL, Kings County NY, and Guilford County NC – as examples, and focus on the level of $PM_{2.5}$ between origin and destination counties. As shown in Figures ?? and 5, Cook County is highlighted in green, while destination counties are outlined in red and shaded by the absolute difference in mean $PM_{2.5}$levels relative to Cook County. The upper map depicts all migration destinations, showing that migrants from Cook County relocate to a wide range of counties nationwide, spanning both nearby Midwestern counties and distant destinations in the South, West, and East Coast. The lower map focuses on the top 50 migration destinations, showing a much more concentrated spatial pattern: these high-volume destinations are primarily located in regions with relatively smaller $PM_{2.5}$ differences, particularly within the Midwest and parts of the Southeast. Together, the two maps suggest that while Cook County migrants disperse broadly across the country, the most common migration flows tend to be directed toward destinations that are more environmentally similar to the origin, consistent with the idea that environmental conditions—alongside economic and social factors—may play a role in shaping migration choices. The similar stories are also shown in Kings County NY (Figures ?? and 6) and Guilford County NC (Figures ??; 7)

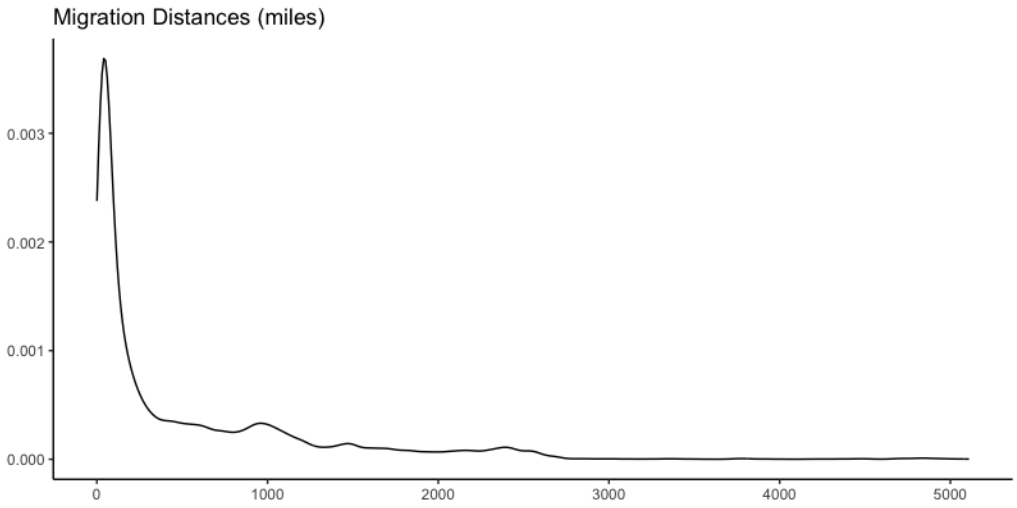


Figure 3: Distribution of the Migration Distance

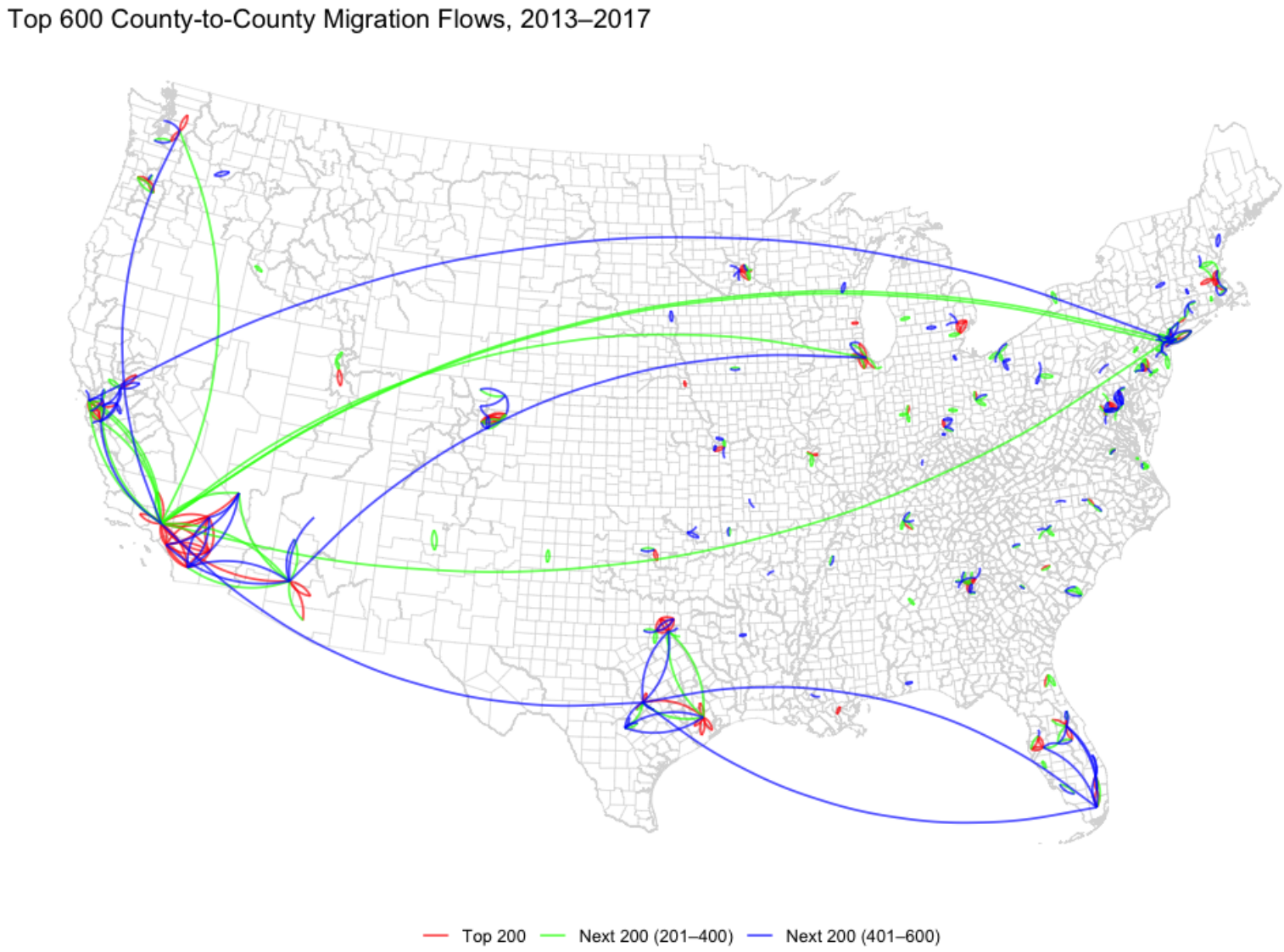


Figure 4: Top 600 County-to-County Migration Flows, 2013–2017

Note: green shaded county is the origin county; counties with red boundaries are the destinations:

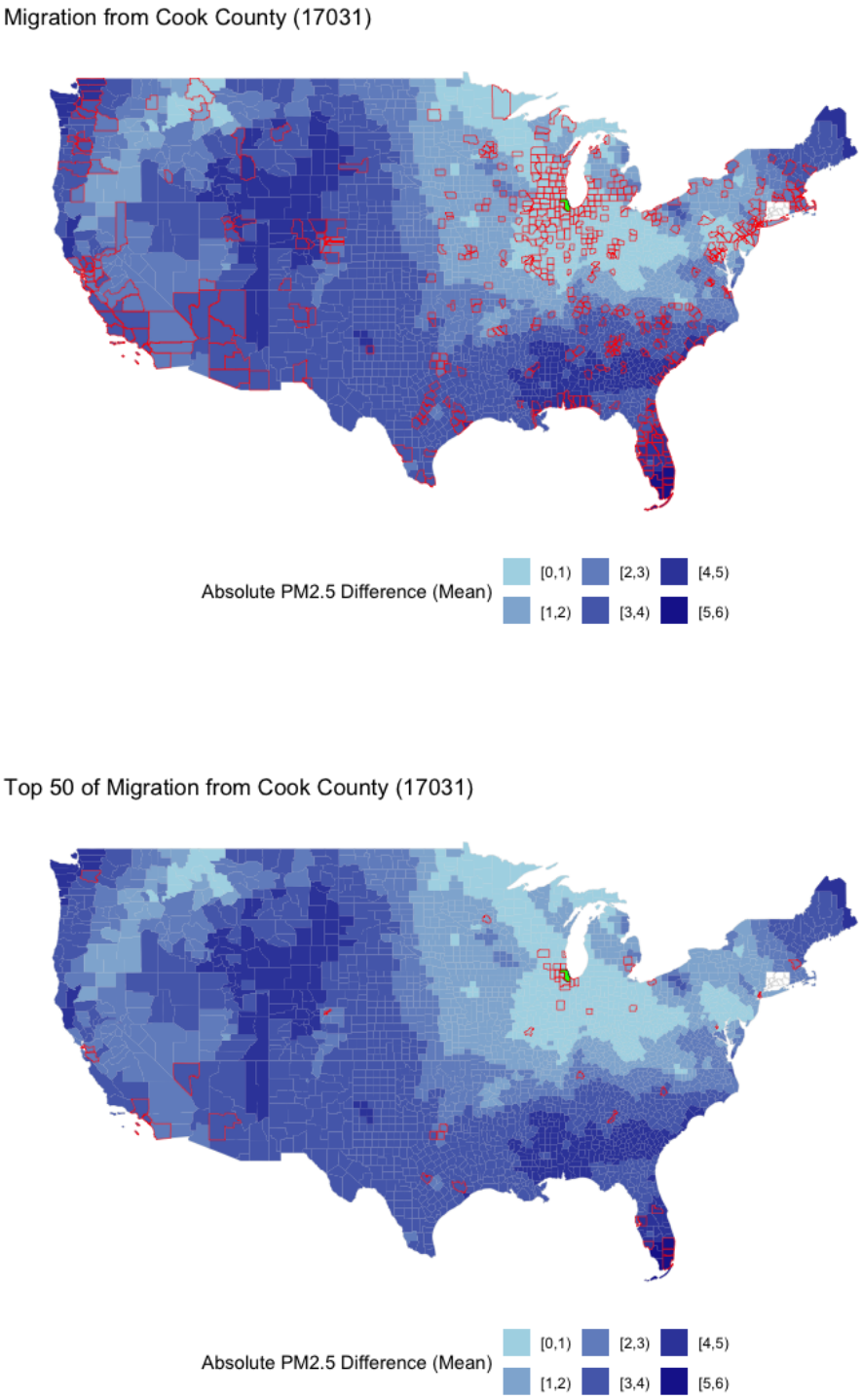
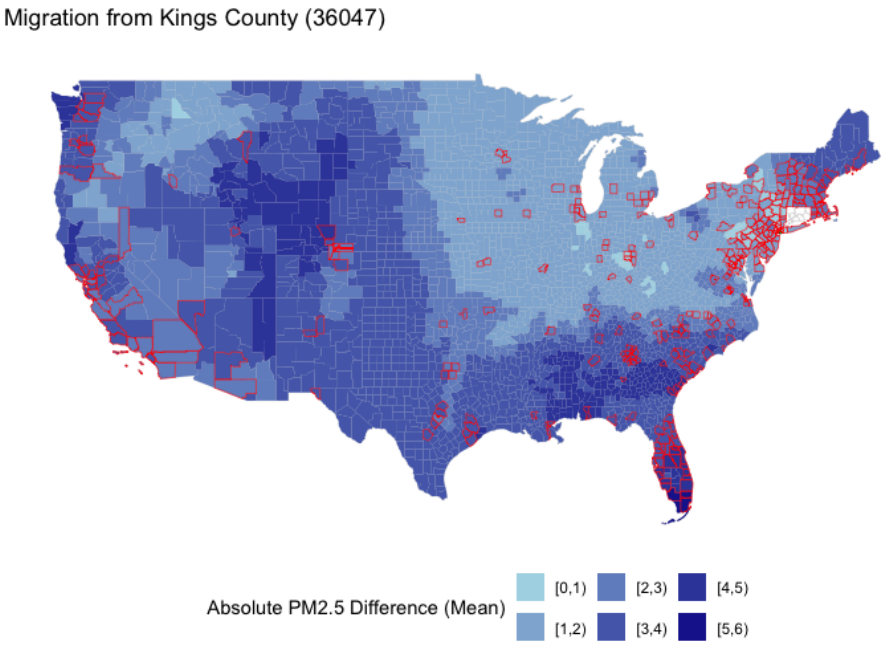


Figure 5: Destination Counties for Migrants from Cook County, IL



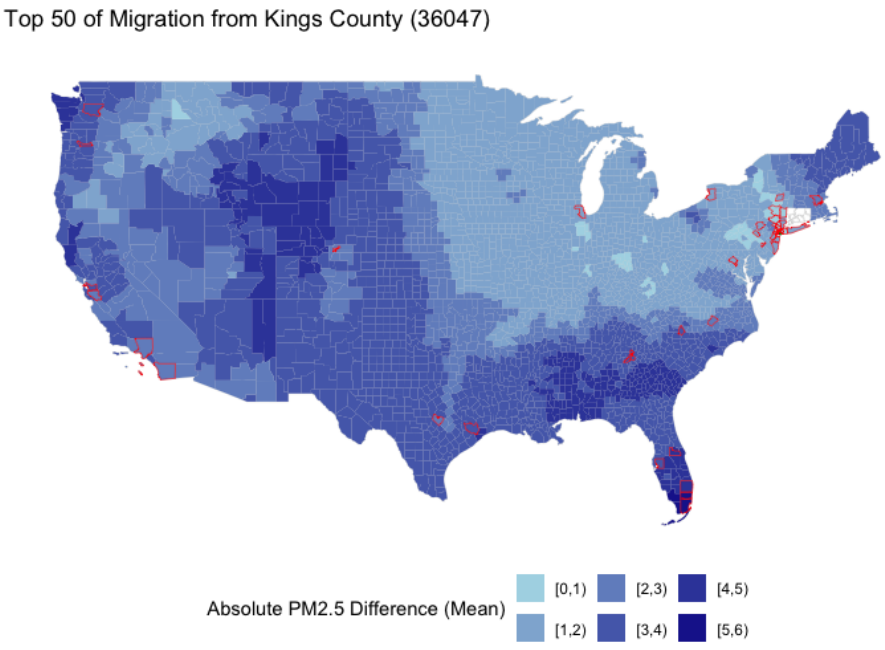
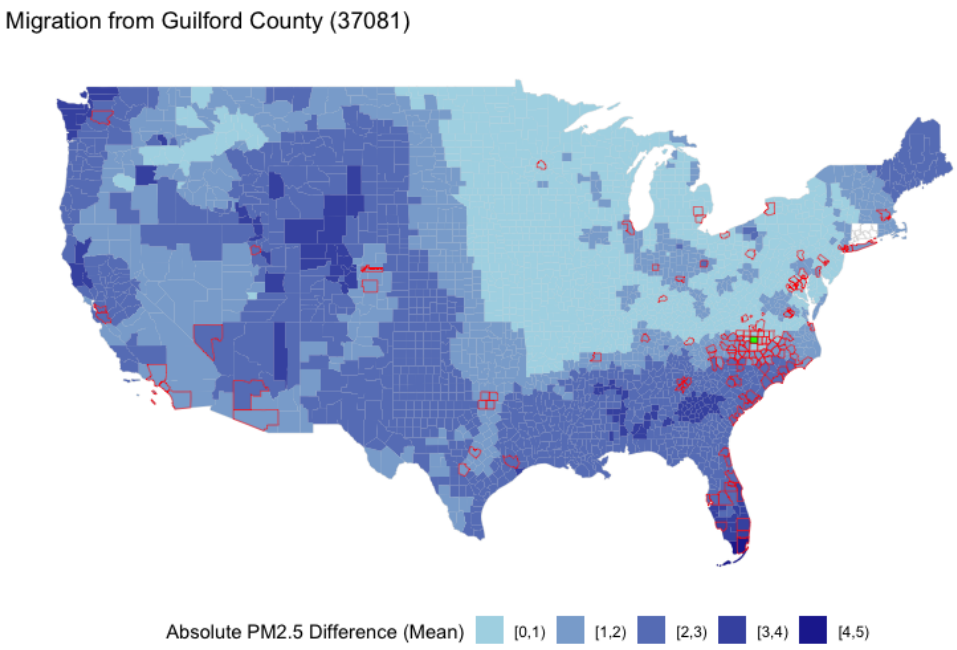


Figure 6: Destination Counties for Migrants from Kings County, NY



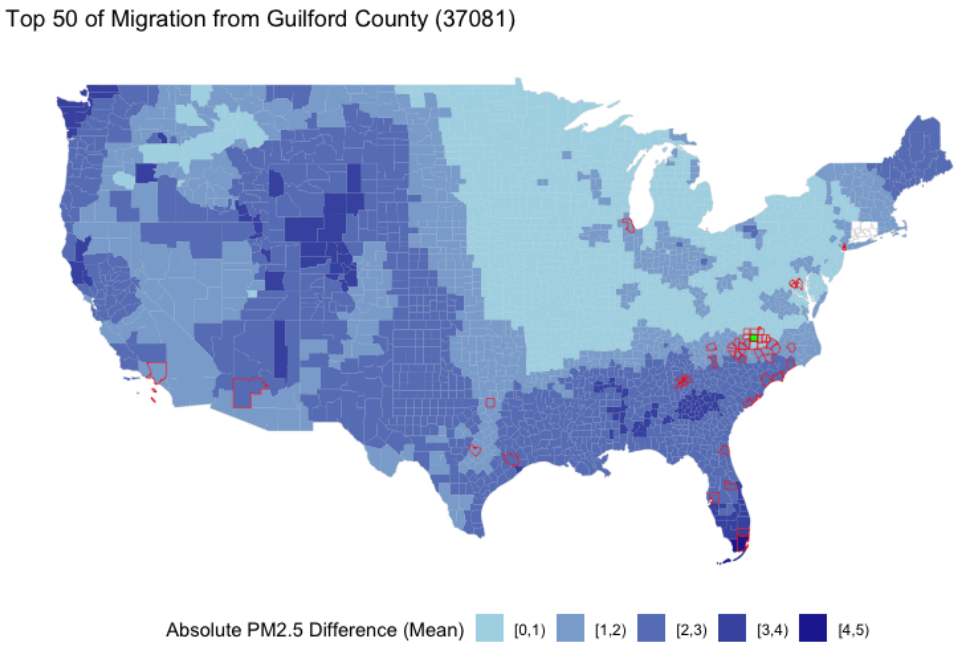


Figure 7: Destination Counties for Migrants from Guilford County, NC

Table 2 reports summary statistics for key demographic, economic, environmental, and health-care characteristics of origin and destination counties. Overall, the distributions of these variables are remarkably similar across origin and destination locations. Mean and median values for population size, median income, housing values, unemployment rates, educational attainment, and hospital capacity are closely aligned, suggesting that origin and destination

counties share broadly comparable socioeconomic profiles. Environmental and climate-related variables, including PM2.5 concentrations, extreme temperature days, flood incidence, and average temperatures, also exhibit nearly identical central tendencies and dispersion across origins and destinations. The similarity in both levels and variability across county characteristics indicates that migration flows predominantly occur between counties with comparable observable attributes, rather than between systematically different origin–destination pairs

Table 2: Summary Statistics – Origin and Destination Variables

	Origin County			Destination County		
	Mean	Median	SD	Mean	Median	SD
Total Population	786154.86	362151.00	1300807.07	756608.78	343729.00	1248753.30
Median Income ($)	61743.99	57685.00	18314.69	61016.92	57207.00	17516.93
Median Housing Value ($)	238652.10	190900.00	154404.51	231911.40	188500.00	146576.35
Unemployment Rate (%)	6.76	6.26	2.55	6.73	6.22	2.53
Less than Highschool Degree (%)	0.12	0.11	0.05	0.12	0.11	0.05
$PM_{2.5}$ ($\mu g/m^3$)	5.97	5.82	1.73	5.82	5.63	1.72
Extreme Cold Days (annual average)	4.06	3.00	3.86	3.98	3.00	3.83
Extreme Hot Days (annual average)	6.08	5.00	4.94	3.98	3.00	3.83
Number of Floods	5.63	2.00	10.00	5.42	2.00	9.81
Avg. Temperature	14.33	13.82	4.72	14.70	14.36	4.88
Max Daily Temperature	21.16	20.19	5.10	21.56	21.14	5.14
Min Daily Temperature	6.82	6.78	5.35	7.13	7.23	5.59
Number of Hospitals	12.11	6.00	18.48	11.87	6.00	18.11
Number of Hospital Employees	14467.26	5212.00	24895.57	13819.03	4518.00	24094.07

Notes: In Fard et al. (2023), a day is classified as an extreme heat event if the excess heat factor reaches or exceeds the 85th percentile of historical values for that specific location over a 16-year period (2008–2023). A day is classified as an extreme cold event if the excess cold factor reaches or falls below the 15th percentile of historical values for that location.

Table 3 reports summary statistics for geographic distance and Euclidean distance measures constructed using both original variable values and standardized values using z-score. Distances calculated using original values are likely to have substantial variation, reflecting the wide variation in magnitudes across underlying variables such as population, income, and housing values. For example, Euclidean distances based on original socioeconomic characteristics are dominated by variables with large scales, resulting in extremely large means and standard deviations. In contrast, Euclidean distances computed using z-scores are more tightly distributed and comparable across dimensions, with means generally close to one and substantially reduced variation. This z-score based Euclidean distance ensures that no single variable disproportionately influences the composite distance measure and provides a more scale-invariant measure of county-to-county similarity.

3.3 Results

Table 4 presents estimated PPML coefficients for US county-to-county migration. To quantify the anchoring effect, we consider a list of socioeconomic variables including median household income; median house values; unemployment rate; percentage of population with less than high school degree; two public goods via., the number of hospitals and the number of hospital

Table 3: Summary Statistics – Absolute Distances and Euclidean Distances

	Mean	Median	SD
Distance (Miles)	991.12	812.90	798.48
PM2.5	1.15	0.63	1.32
Extreme cold days	2.07	1.00	3.16
Extreme heat days	3.80	2.00	4.22
Mean Temperature	3.28	1.55	3.85
Number of hospital employees	19255.25	8685.00	28848.09
Number of hospitals	14.42	7.00	21.55
Number of floods	7.15	3.00	11.43
Total population	935669.75	389752.50	1556144.73
Median income	14981.59	10816.50	13858.42
Median housing value	109995.53	60200.00	136956.96
Unemployment rate	1.83	1.42	1.60
Less than high school degree	0.05	0.04	0.04
Euclidean distance 1	4.11	3.66	2.49
Euclidean distance 2	2.85	2.32	2.41
Euclidean distance 3	2.69	2.47	1.44

Notes: Euclidean distance 1 is computed using all variables; Euclidean distance 2 is based on all socioeconomic variables and health resource related variables; Euclidean distance 3 is based on environmental variables.

employees; as well as a vector of natural and environmental and infrastructural factors ($PM_{2.5}$, the number of floods, number of extreme heat days, number of extreme cold days, and average temperature), all of which are measured at the county level in both the origin and the destination county. Using these variables, we consider five alternative specifications of anchoring measures: Anchor 1 is defined as a high-dimensional Euclidean distance constructed from the z-scored values of all variables. Anchor 2 decomposes this measure into two separate Euclidean distances: one based on socioeconomic and public goods variables, and the other based on environmental variables. Anchor 3 keeps the Euclidean distance constructed from socioeconomic and public goods variables, and includes the absolute differences of each individual environmental variable. Similarly, Anchor 4 keeps the Euclidean distance constructed from environmental variables and replaces the socioeconomic and public goods component with the absolute differences of each individual socioeconomic and public goods variable. Anchor 5 fully disaggregates the measure and consists of the absolute differences of all individual variables.

Table 4 reports the main results. Across all models, the distance to destination is negative and statistically significant, confirming the strong negative effect of geographic distance on migration flows. In column (1), the aggregate anchoring measure (Anchor 1) is negative and statistically significant, indicating that households are generally more likely to move to locations that are similar to their origin. Decomposing the Euclidean distance into two dimensions in column (2) yields similar results, suggesting that greater dissimilarity across both socioeconomic and environmental dimensions discourages migration. Under the more disaggregated anchoring structures in Anchors 3–5, we further find that people are likely to move to places with similar population sizes, median income, unemployment rate, and hospital employment, as Euclidean distances related to those factors are negative and statistically significant. Yet, differences in

median housing values were not statistically significant drivers of migration flows.

We also find evidence of climate anchoring: the coefficient for the difference in extreme heat days is negative and statistically significant, indicating households tend to remain in climates with similar heat profiles. However, we find only weak evidence that migrants seek dissimilar environments regarding disaster risk: the coefficient for differences in flood exposure is positive and marginally significant in Model 4, but becomes insignificant in Model 5. Differences in mean temperature and extreme cold days were not statistically significant drivers of migration flows. As a sensitivity analysis, we run the same regressions excluding Southern California, Florida, and Texas, three most popular destination states, to test if the positive coefficient of floods are driven by people moving to warmer places or coastal areas where floods are more frequent. As shown in Table 5, when the three destination areas were excluded from the sample, the coefficient of the absolute differences in floods frequency is no longer significant while the other coefficients remain consistent, suggesting that .... (Neha, can you add the reasoning here? I am lost about why the absolute difference in flood frequency can be confounded by people moving to these areas?)

4 Policy Implications

Our empirical findings highlight a pervasive behavioral friction in residential mobility: households exhibit a strong tendency to "anchor" not only on socioeconomic characteristics but also on climatic conditions. We find that migrants predominantly move between locations with similar population sizes, income levels, unemployment rates, and crucially, similar profiles of extreme heat. Contrary to the expectation that environmental risks universally push households toward safer climates, our results suggest that familiarity often trumps adaptation. This comprehensive anchoring effect poses significant challenges for policymakers aiming to facilitate climate adaptation and economic mobility.

First, the robust evidence of socioeconomic anchoring (driven by similarities in income, unemployment, and population size) suggests that economic opportunity alone is insufficient to induce migration from disadvantaged to prosperous regions. If households from lower-income or high-unemployment areas prefer moving to locations with similar economic struggles due to social fit or familiarity, simply creating jobs in high-growth metropolitan areas will not automatically attract residents from lagging communities. To break these "socioeconomic silos", policies must address the non-monetary costs of moving. This could involve mobility vouchers paired with social integration services, or housing policies in high-opportunity neighborhoods designed to lower cultural barriers (Chetty et al., 2026). Without such "de-anchoring" interventions, migration flows may simply churn populations within existing tiers of advantage and disadvantage rather than fostering upward mobility.

Second, the negative relationship between migration and differences in extreme heat days reveals a potential "climate trap." Rather than moving to cooler, lower-risk climates, households appear to select destinations that replicate the thermal environment of their origin. This suggests that as regions become increasingly uninhabitable due to heat stress, residents may

Table 4: The Anchor Effects on Migration - PPML

2013 - 2017

Dependent Variable:	Number of Migrated Households				
	Anchor 1	Anchor 2	Anchor 3	Anchor 4	Anchor 5
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
log(distance_miles)	-1.88***	-1.88***	-1.89***	-1.96***	-1.96***
	(0.13)	(0.13)	(0.13)	(0.15)	(0.15)
log(e_dist_all)	-0.49***				
	(0.07)				
log(e_dist_z)		-0.09***	-0.09***		
		(0.03)	(0.03)		
log(e_dist_x)		-0.34***		-0.37***	
		(0.06)		(0.06)	
log(tot_pop_in_min_out+1)			-0.07***		-0.08***
			(0.02)		(0.02)
log(median_income_in_min_out+1)			-0.06***		-0.06***
			(0.01)		(0.01)
log(median_hs_value_in_min_out+1)			-0.01		0.00
			(0.02)		(0.01)
log(unemployment_rate_in_min_out+1)			-0.09*		-0.09**
			(0.05)		(0.04)
log(pct_hs_less_in_min_out+1)			-0.89		-1.06
			(0.72)		(0.81)
log(emp_in_min_out+1)			-0.03***		-0.03***
			(0.01)		(0.01)
log(hosp_in_min_out+1)			0.00		-0.01
			(0.03)		(0.03)
log(pm_in_min_out+1)				0.03	0.03
				(0.11)	(0.11)
log(cold_total_event_days_in_min_out+1)				-0.01	-0.02
				(0.02)	(0.02)
log(heat_total_event_days_in_min_out+1)				-0.09***	-0.09***
				(0.02)	(0.02)
log(tmean_in_min_out+1)				0.17	0.17
				(0.12)	(0.12)
log(flood_t_in_min_out+1)				0.03*	0.02
				(0.02)	(0.02)
Fixed-effects					
out_cntyfips	Yes	Yes	Yes	Yes	Yes
in_cntyfips	Yes	Yes	Yes	Yes	Yes
out_year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	41,720,619	41,720,619	41,720,619	41,720,619	41,720,619
Squared Correlation	0.77	0.77	0.78	0.78	0.79
Pseudo R^2	0.88	0.87	0.87	0.88	0.87
BIC	45,844,275.6	46,091,016.4	46,183,463.1	45,971,858.6	46,074,227.8

Clustered (out_state) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: The Anchor Effects on Migration - PPML

2013 - 2017; Southern California, Florida, and Texas Excluded

Dependent Variable:	Number of Migrated Households				
	Anchor 1	Anchor 2	Anchor 3	Anchor 4	Anchor 5
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
log(distance_miles)	-2.12***	-2.13***	-2.13***	-2.13***	-2.14***
	(0.11)	(0.11)	(0.11)	(0.13)	(0.13)
log(e_dist_all)	-0.60***				
	(0.06)				
log(e_dist_z)		-0.09***	-0.10***		
		(0.02)	(0.02)		
log(e_dist_x)		-0.43***		-0.45***	
		(0.05)		(0.05)	
log(tot_pop_in_min_out+1)			-0.07***		-0.07***
			(0.02)		(0.02)
log(median_income_in_min_out+1)			-0.06***		-0.06***
			(0.01)		(0.01)
log(median_hs_value_in_min_out+1)			-0.03		-0.03
			(0.02)		(0.02)
log(unemployment_rate_in_min_out+1)			-0.13***		-0.13***
			(0.03)		(0.03)
log(pct_hs_less_in_min_out+1)			-0.14		-0.20
			(0.90)		(0.91)
log(emp_in_min_out+1)			-0.01**		-0.01**
			(0.00)		(0.00)
log(hosp_in_min_out+1)			-0.11***		-0.11***
			(0.03)		(0.03)
log(pm_in_min_out+1)				0.04	0.04
				(0.09)	(0.09)
log(cold_total_event_days_in_min_out+1)				-0.05***	-0.05***
				(0.02)	(0.02)
log(heat_total_event_days_in_min_out+1)				-0.12***	-0.12***
				(0.02)	(0.02)
log(tmean_in_min_out+1)				0.01	0.01
				(0.06)	(0.06)
log(flood_t_in_min_out+1)				0.02	0.02
				(0.01)	(0.01)
Fixed-effects					
out_cntyfips	Yes	Yes	Yes	Yes	Yes
in_cntyfips	Yes	Yes	Yes	Yes	Yes
out_year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	35,029,815	35,029,815	35,029,815	35,029,815	35,029,815
Squared Correlation	0.77	0.77	0.77	0.78	0.78
Pseudo R^2	0.88	0.88	0.88	0.88	0.88
BIC	33,284,804.4	33,495,599.5	33,672,772.6	33,447,853.7	33,635,527.2

Clustered (out_state) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6: The Anchor Effects on Migration - PPML

2013 - 2017; Southern CA Excluded

Dependent Variable:	Number of Migrated Households				
	Anchor 1	Anchor 2	Anchor 3	Anchor 4	Anchor 5
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
log(distance_miles)	-1.95***	-1.96***	-1.96***	-2.06***	-2.06***
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
log(e_dist_all)	-0.51***				
	(0.06)				
log(e_dist_z)		-0.08***	-0.09***		
		(0.03)	(0.03)		
log(e_dist_x)		-0.37***		-0.40***	
		(0.04)		(0.04)	
log(tot_pop_in_min_out+1)			-0.09***		-0.10***
			(0.01)		(0.01)
log(median_income_in_min_out+1)			-0.05***		-0.06***
			(0.01)		(0.01)
log(median_hs_value_in_min_out+1)			-0.02		-0.02
			(0.02)		(0.02)
log(unemployment_rate_in_min_out+1)			-0.05		-0.06
			(0.04)		(0.04)
log(pct_hs_less_in_min_out+1)			-1.07		-1.42
			(0.83)		(0.90)
log(emp_in_min_out+1)			-0.02***		-0.02***
			(0.01)		(0.01)
log(hosp_in_min_out+1)			-0.02		-0.02
			(0.03)		(0.03)
log(pm_in_min_out+1)				0.11	0.10
				(0.09)	(0.09)
log(cold_total_event_days_in_min_out+1)				-0.04**	-0.04***
				(0.01)	(0.01)
log(heat_total_event_days_in_min_out+1)				-0.11***	-0.11***
				(0.01)	(0.01)
log(tmean_in_min_out+1)				0.22**	0.22*
				(0.11)	(0.11)
log(flood_t_in_min_out+1)				0.01	0.01
				(0.01)	(0.01)
Fixed-effects					
out_cntyfips	Yes	Yes	Yes	Yes	Yes
in_cntyfips	Yes	Yes	Yes	Yes	Yes
out_year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	41,604,629	41,604,629	41,604,629	41,604,629	41,604,629
Squared Correlation	0.78	0.78	0.79	0.79	0.79
Pseudo R^2	0.88	0.88	0.88	0.88	0.88
BIC	42,625,708.1	42,821,470.8	42,954,227.6	42,582,066.2	42,716,090.6

Clustered (out_state) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7: The Anchor Effects on Migration - PPML

2013 - 2017; Florida Excluded

Dependent Variable:	Number of Migrated Households				
	Anchor 1	Anchor 2	Anchor 3	Anchor 4	Anchor 5
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
log(distance_miles)	-1.95***	-1.95***	-1.96***	-1.96***	-1.97***
	(0.14)	(0.14)	(0.14)	(0.16)	(0.16)
log(e_dist_all)	-0.54***				
	(0.07)				
log(e_dist_z)		-0.11***	-0.12***		
		(0.02)	(0.02)		
log(e_dist_x)		-0.37***		-0.39***	
		(0.06)		(0.06)	
log(tot_pop_in_min_out+1)			-0.06***		-0.07***
			(0.02)		(0.02)
log(median_income_in_min_out+1)			-0.07***		-0.07***
			(0.01)		(0.01)
log(median_hs_value_in_min_out+1)			-0.01		-0.01
			(0.02)		(0.02)
log(unemployment_rate_in_min_out+1)			-0.14***		-0.14***
			(0.03)		(0.03)
log(pct_hs_less_in_min_out+1)			-0.15		-0.17
			(0.59)		(0.61)
log(emp_in_min_out+1)			-0.02***		-0.02***
			(0.01)		(0.01)
log(hosp_in_min_out+1)			-0.04		-0.04
			(0.04)		(0.04)
log(pm_in_min_out+1)				-0.07	-0.07
				(0.10)	(0.10)
log(cold_total_event_days_in_min_out+1)				-0.02	-0.02
				(0.02)	(0.02)
log(heat_total_event_days_in_min_out+1)				-0.10***	-0.10***
				(0.02)	(0.02)
log(tmean_in_min_out+1)				0.04	0.03
				(0.07)	(0.08)
log(flood_t_in_min_out+1)				0.03*	0.03
				(0.02)	(0.02)
Fixed-effects					
out_cntyfips	Yes	Yes	Yes	Yes	Yes
in_cntyfips	Yes	Yes	Yes	Yes	Yes
out_year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	40,496,351	40,496,351	40,496,351	40,496,351	40,496,351
Squared Correlation	0.77	0.77	0.77	0.78	0.78
Pseudo R^2	0.88	0.88	0.88	0.88	0.88
BIC	41,325,310.1	41,589,347.8	41,684,896.5	41,587,326.1	41,699,695.0

Clustered (out_state) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 8: The Anchor Effects on Migration - PPML

2013 - 2017; Texas Excluded

Dependent Variable:	Number of Migrated Households				
	Anchor 1	Anchor 2	Anchor 3	Anchor 4	Anchor 5
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
log(distance_miles)	-1.92***	-1.93***	-1.94***	-2.02***	-2.03***
	(0.15)	(0.15)	(0.15)	(0.18)	(0.18)
log(e_dist_all)	-0.51***				
	(0.07)				
log(e_dist_z)		-0.08***	-0.08***		
		(0.03)	(0.03)		
log(e_dist_x)		-0.35***		-0.38***	
		(0.06)		(0.07)	
log(tot_pop_in_min_out+1)			-0.06***		-0.07***
			(0.02)		(0.02)
log(median_income_in_min_out+1)			-0.06***		-0.06***
			(0.01)		(0.01)
log(median_hs_value_in_min_out+1)			0.00		0.00
			(0.02)		(0.02)
log(unemployment_rate_in_min_out+1)			-0.12**		-0.13***
			(0.05)		(0.04)
log(pct_hs_less_in_min_out+1)			-0.63		-0.76
			(0.93)		(1.01)
log(emp_in_min_out+1)			-0.02***		-0.02***
			(0.01)		(0.01)
log(hosp_in_min_out+1)			-0.03		-0.04
			(0.04)		(0.04)
log(pm_in_min_out+1)				0.08	0.08
				(0.13)	(0.13)
log(cold_total_event_days_in_min_out+1)				-0.02	-0.02
				(0.02)	(0.02)
log(heat_total_event_days_in_min_out+1)				-0.08***	-0.08***
				(0.02)	(0.02)
log(tmean_in_min_out+1)				0.19	0.19
				(0.13)	(0.14)
log(flood_t_in_min_out+1)				0.03	0.02
				(0.02)	(0.02)
Fixed-effects					
out_cntyfips	Yes	Yes	Yes	Yes	Yes
in_cntyfips	Yes	Yes	Yes	Yes	Yes
out_year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	36,339,085	36,339,085	36,339,085	36,339,085	36,339,085
Squared Correlation	0.77	0.77	0.77	0.77	0.78
Pseudo R^2	0.87	0.87	0.87	0.87	0.87
BIC	41,469,094.6	41,718,861.3	41,840,079.4	41,564,830.2	41,696,113.2

Clustered (out_state) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

be psychologically or physiologically conditioned to seek out similarly hot environments, even if those locations face similar long-term risks. Consequently, "managed retreat" policies that rely on voluntary migration to cooler latitudes may face resistance not just from economic constraints, but from a preference for climatic familiarity. Adaptation planning may therefore need to focus heavily on in situ resilience for hot regions, or alternatively, invest in information campaigns that explicitly counter the bias toward familiar but increasingly dangerous climates.

Finally, the lack of significant movement away from flood risks (as indicated by the weak and inconsistent results for flood exposure differences) further underscores the stickiness of residential sorting. The fact that large differences in flood risk do not consistently drive migration suggests that disaster risks may be underestimated or normalized by residents, or that the pull of familiar social and institutional structures (such as the observed anchoring on hospital availability) outweighs the push of environmental hazards. Regional development policies should therefore aim to harmonize service quality across regions. By raising the baseline of public goods in safer, high-opportunity areas, policymakers can reduce the "institutional amenity shock" that currently deters vulnerable populations from relocating to safer ground.

5 Conclusion

We introduce and test the concept of "anchoring effects" in residential sorting, proposing that individuals' migration decisions are shaped not just by the absolute amenities of a destination, but by how those amenities compare to their lived experiences. We formalize this mechanism in a discrete choice model and test it using a gravity model of migration across U.S. counties from 2013 to 2017.

Our theoretical framework predicts that migration costs are partly psychological: deviations from a familiar baseline, whether in air quality, income, or community structure, impose a utility penalty. Our empirical results provide robust support for this hypothesis, revealing a pattern of residential sorting that is far stickier than traditional models suggest. We find strong evidence of similarity seeking in the aggregate: migration flows are significantly larger between counties that share similar socioeconomic profiles. Households appear to anchor heavily on economic status and institutional capacity, moving predominantly between locations with comparable median incomes, unemployment rates, and healthcare resources. This confirms that spatial sorting is path-dependent; people do not merely chase the highest wage, but the most familiar context.

Crucially, our results challenge the assumption that environmental risks inevitably trigger adaptation or retreat. Contrary to the expectation that households would migrate away from disparate climate risks, we find evidence of climatic anchoring. Migration flows are higher between counties with similar frequencies of extreme heat days, suggesting that individuals prioritize thermal familiarity over climate optimization. Furthermore, we find no consistent evidence that large differences in flood risk drive migration flows. This paints a picture of pervasive inertia: rather than fleeing environmental stressors, households appear to sort into locations that replicate both the socioeconomic and environmental conditions of their origin.

Ultimately, our work connects the literature on residential sorting with intergenerational mobility by identifying a preference-based mechanism for spatial persistence. If preferences are endogenous to past experience, then spatial inequality may be self-reinforcing not only through external constraints but through internalized valuation. The fact that migrants anchor on both economic class and climate suggests that disadvantaged populations may be doubly "trapped", not only by a lack of resources but by a preference for the familiar conditions of their home regions, even when those conditions carry long-term risks. Future research should further disentangle these effects using individual-level longitudinal data to observe how preferences evolve over time after a move. For now, our findings serve as a reminder that to change where people live, we must first understand and perhaps re-frame their relationship with where they came from.

A Online Appendix

A.1 Proof of Proposition 3

(Still working on Scenario 5,6) The probabilities of each individuals to choose different locations are

$$\begin{aligned}
Pr_a(1|\,With\ Anchoring\ Effects) &= Pr\Big(\tilde{\eta}_a \leq \big[(\beta_C+\beta_H)ln\frac{I_1}{I_2}+\beta_A ln\frac{A_1}{A_2}+ln\frac{f(\Delta_{a1})}{f(\Delta_{a2})}\big]\Big).\\
Pr_a(2|\,With\ Anchoring\ Effects) &= Pr\Big(\tilde{\eta}_a \leq \big[(\beta_C+\beta_H)ln\frac{I_2}{I_1}+\beta_A ln\frac{A_2}{A_1}+ln\frac{f(\Delta_{a2})}{f(\Delta_{a1})}\big]\Big).\\
Pr_b(1|\,With\ Anchoring\ Effects) &= Pr\Big(\tilde{\eta}_b \leq \big[(\beta_C+\beta_H)ln\frac{I_1}{I_2}+\beta_A ln\frac{A_1}{A_2}+ln\frac{f(\Delta_{b1})}{f(\Delta_{b2})}\big]\Big).\\
Pr_b(2|\,With\ Anchoring\ Effects) &= Pr\Big(\tilde{\eta}_b \leq \big[(\beta_C+\beta_H)ln\frac{I_2}{I_1}+\beta_A ln\frac{A_2}{A_1}+ln\frac{f(\Delta_{b2})}{f(\Delta_{b1})}\big]\Big).
\end{aligned} \tag{A1}$$

We consider six different scenarios:

Scenario 1: if the geographical disparities in A become greater, $A_1 > \tilde{A}_a > \tilde{A}_b > A_2$, we have $\Delta_{a,1} < \Delta_{b,1}$ and $\Delta_{a,2} > \Delta_{b,2}$, $ln\frac{f(\Delta_{a,1})}{f(\Delta_{a,2})} > ln\frac{f(\Delta_{b,1})}{f(\Delta_{b,2})}$,

$$Pr_a(1|\,With\ Anchoring\ Effects) > Pr_b(1|\,With\ Anchoring\ Effects). \tag{A2}$$

Individual a is more likely to choose location 1 than individual b. Similarly, individual b is more likely to choose location 2 than individual a. Social disparities increase in this scenario.

Scenario 2: if there is an improvement in A for all locations, $A_1 > A_2 > \tilde{A}_a > \tilde{A}_b$, we have $\Delta_{a,1} < \Delta_{b,1}$ and $\Delta_{a,2} < \Delta_{b,2}$. In addition, let $\tilde{\Delta}_{a,b} = \tilde{A}_a - \tilde{A}_b$, then $\Delta_{b,1} = \Delta_{a,1} + \tilde{\Delta}_{a,b}$, $\Delta_{b,2} = \Delta_{a,2} + \tilde{\Delta}_{a,b}$, we have

$$\frac{f(\Delta_{b,1})}{f(\Delta_{b,2})} = \frac{f(\Delta_{a,1}+\tilde{\Delta}_{a,b})}{f(\Delta_{a,2}+\tilde{\Delta}_{a,b})} = \frac{f(\Delta_{a,1})+\int_{\Delta_{a,1}}^{\Delta_{a,1}+\tilde{\Delta}_{a,b}} f'(\Delta)d\Delta}{f(\Delta_{a,2})+\int_{\Delta_{a,2}}^{\Delta_{a,2}+\tilde{\Delta}_{a,b}} f'(\Delta)d\Delta}. \tag{A3}$$

Since $\Delta_{a,1} > \Delta_{a,2}$ and $f''(\Delta) < 0$, then

$$\int_{\Delta_{a,1}}^{\Delta_{a,1}+\tilde{\Delta}_{a,b}} f'(\Delta)d\Delta < \int_{\Delta_{a,2}}^{\Delta_{a,2}+\tilde{\Delta}_{a,b}} f'(\Delta)d\Delta. \tag{A4}$$

Let $C = \int_{\Delta_{a,2}}^{\Delta_{a,2}+\tilde{\Delta}_{a,b}} f'(\Delta)d\Delta < 0$, we have

$$\frac{f(\Delta_{b,1})}{f(\Delta_{b,2})} < \frac{f(\Delta_{a,1})+C}{f(\Delta_{a,2})+C}. \tag{A5}$$

Because $\Delta_{a,1} > \Delta_{a,2}$, $f(\Delta_{a,1}) < f(\Delta_{a,2})$,

$$\begin{aligned}\frac{f(\Delta_{a,1})+C}{f(\Delta_{a,2})+C} - \frac{f(\Delta_{a,1})}{f(\Delta_{a,2})} &= \frac{f(\Delta_{a,1})f(\Delta_{a,2}) + Cf(\Delta_{a,2}) - f(\Delta_{a,1})f(\Delta_{a,2}) - Cf(\Delta_{a,1})}{f(\Delta_{a,2})\big[f(\Delta_{a,2})+C\big]} \\ &= \frac{C\big[f(\Delta_{a,2}) - f(\Delta_{a,1})\big]}{f(\Delta_{a,2})f(\Delta_{b,2})} < 0.\end{aligned} \tag{A6}$$

Therefore, we can conclude that

$$\frac{f(\Delta_{b,1})}{f(\Delta_{b,2})} < \frac{f(\Delta_{a,1})+C}{f(\Delta_{a,2})+C} < \frac{f(\Delta_{a,1})}{f(\Delta_{a,2})}, \tag{A7}$$

which is equivalent to

$$Pr_a(1|\textit{With Anchoring Effects}) > Pr_b(1|\textit{With Anchoring Effects}). \tag{A8}$$

This results also imply that individual a is more likely to choose location 1 than individual b. Similarly, individual b is more likely to choose location 2 than individual a. Social disparities persist in this scenario.

Scenario 3: if there is an decline in A for all locations, $\tilde{A}_a > \tilde{A}_b > A_1 > A_2$, we have $\Delta_{a,1} < \Delta_{b,1}$ and $\Delta_{a,2} < \Delta_{b,2}$. In addition, $\Delta_{b,1} = \Delta_{a,1} + \tilde{\Delta}_{a,b}$, $\Delta_{b,2} = \Delta_{a,2} + \tilde{\Delta}_{a,b}$, we have

$$\frac{f(\Delta_{a,1})}{f(\Delta_{a,2})} = \frac{f(\Delta_{b,1}) + \int_{\Delta_{b,1}}^{\Delta_{b,1}+\tilde{\Delta}_{a,b}} f'(\Delta)d\Delta}{f(\Delta_{b,2}) + \int_{\Delta_{b,2}}^{\Delta_{b,2}+\tilde{\Delta}_{a,b}} f'(\Delta)d\Delta} \tag{A9}$$

Since $\Delta_{b,1} < \Delta_{b,2}$ and $f''(\Delta) < 0$, then

$$\int_{\Delta_{b,1}}^{\Delta_{b,1}+\tilde{\Delta}_{a,b}} f'(\Delta)d\Delta > \int_{\Delta_{b,2}}^{\Delta_{b,2}+\tilde{\Delta}_{a,b}} f'(\Delta)d\Delta. \tag{A10}$$

Let $C = \int_{\Delta_{b,2}}^{\Delta_{b,2}+\tilde{\Delta}_{a,b}} f'(\Delta)d\Delta < 0$, we have

$$\frac{f(\Delta_{a,1})}{f(\Delta_{a,2})} > \frac{f(\Delta_{b,1})+C}{f(\Delta_{b,2})+C}. \tag{A11}$$

Because $\Delta_{b,1} < \Delta_{b,2}$, $f(\Delta_{b,1}) > f(\Delta_{b,2})$

$$\begin{aligned}\frac{f(\Delta_{b,1})+C}{f(\Delta_{b,2})+C} - \frac{f(\Delta_{b,1})}{f(\Delta_{b,2})} &= \frac{f(\Delta_{b,1})f(\Delta_{b,2}) + Cf(\Delta_{b,2}) - f(\Delta_{b,1})f(\Delta_{b,2}) - Cf(\Delta_{b,1})}{f(\Delta_{b,2})\big[f(\Delta_{b,2})+C\big]} \\ &= \frac{C\big[f(\Delta_{b,2}) - f(\Delta_{b,1})\big]}{f(\Delta_{b,2})f(\Delta_{a,2})} > 0.\end{aligned} \tag{A12}$$

Therefore, we can conclude that

$$\frac{f(\Delta_{a,1})}{f(\Delta_{a,2})} > \frac{f(\Delta_{b,1})+C}{f(\Delta_{b,2})+C} > \frac{f(\Delta_{b,1})}{f(\Delta_{b,2})}, \tag{A13}$$

which is again equivalent to

$$Pr_a(1|\,\textit{With Anchoring Effects}) > Pr_b(1|\,\textit{With Anchoring Effects}). \tag{A14}$$

Scenario 4: if $\tilde{A}_a > A_1 > \tilde{A}_b > A_2$, then $\Delta_{a,2} = \Delta_{a,1} + \Delta_{b,1} + \Delta_{b,2}$, we have

$$\begin{aligned}\frac{f(\Delta_{b,2})}{f(\Delta_{b,1})} &= \frac{f(\Delta_{a,2}-\Delta_{b,1}-\Delta_{a,1})}{f(\Delta_{b,1})} > \frac{f(\Delta_{a,2}-\Delta_{a,1})}{f(0)} > \frac{f(\Delta_{a,2}-\Delta_{a,1})+D}{f(0)+D} \\ &= \frac{f(\Delta_{a,2}-\Delta_{a,1})+D}{f(\Delta_{a,1})},\end{aligned} \tag{A15}$$

where $D = \int_0^{\Delta_{a,1}} f'(\Delta)d\Delta$. Since $f''(\Delta) < 0$,

$$\int_0^{\Delta_{a,1}} f'(\Delta)d\Delta > \int_{\Delta_{a,2}-\Delta_{a,1}}^{\Delta_{a,2}} f'(\Delta)d\Delta, \tag{A16}$$

we may conclude

$$\frac{f(\Delta_{b,2})}{f(\Delta_{b,1})} > \frac{f(\Delta_{a,2}-\Delta_{a,1})+D}{f(\Delta_{a,1})} > \frac{f(\Delta_{a,2}-\Delta_{a,1})+\int_{\Delta_{a,2}-\Delta_{a,1}}^{\Delta_{a,2}} f'(\Delta)d\Delta}{f(\Delta_{a,1})} = \frac{f(\Delta_{a,2})}{f(\Delta_{a,1})}, \tag{A17}$$

which is equivalent to

$$\frac{f(\Delta_{b,1})}{f(\Delta_{b,2})} < \frac{f(\Delta_{a,1})}{f(\Delta_{a,2})}, \tag{A18}$$

and

$$Pr_a(1|\,\textit{With Anchoring Effects}) > Pr_b(1|\,\textit{With Anchoring Effects}). \tag{A19}$$

Scenario 5: If individual a's lived experience is between the two locations, while individual b's is lower than both: $A_1 > \tilde{A}_a > A_2 > \tilde{A}_b$. We have distances defined as:

$$\Delta_{a,1} = A_1 - \tilde{A}_a, \quad \Delta_{a,2} = \tilde{A}_a - A_2$$

$$\Delta_{b,1} = A_1 - \tilde{A}_b, \quad \Delta_{b,2} = A_2 - \tilde{A}_b$$

Note that the distance between locations is $d = A_1 - A_2$. For individual a, $\Delta_{a,1} + \Delta_{a,2} = d$. For individual b, $\Delta_{b,1} = d + \Delta_{b,2}$. Since $f''(\Delta) < 0$ (Assumption 1), $\ln f(\Delta)$ is a concave function. The decay in utility accelerates as distance from the anchor increases. Consequently, the utility loss for individual b (who faces the largest total distance $\Delta_{b,1}$) outweighs the utility loss for individual a:

$$\frac{f(\Delta_{a,1})}{f(\Delta_{a,2})} > \frac{f(\Delta_{b,1})}{f(\Delta_{b,2})} \tag{A20}$$

This inequality holds because the ratio on the right-hand side represents a jump in distance of size d starting from an already positive distance $\Delta_{b,2}$, whereas the left-hand side represents an internal division of the distance d. Given the increasing rate of decay, the penalty on the RHS is strictly larger. Taking the logarithm and substituting back into the probability function yields:

$$Pr_a(1|\text{With Anchoring Effects}) > Pr_b(1|\text{With Anchoring Effects}). \tag{A21}$$

Scenario 6: If individual a's lived experience is higher than both locations, while individual b's is lower than both: $\tilde{A}_a > A_1 > A_2 > \tilde{A}_b$. This scenario represents the widest divergence in anchoring points.

- For individual a, the anchor $\tilde{A}_a$ is closer to A_1 than A_2 because $A_1 > A_2$. Thus, $\Delta_{a,1} < \Delta_{a,2}$. Since $f'(\Delta) < 0$, this implies $f(\Delta_{a,1}) > f(\Delta_{a,2})$, and therefore:

$$\frac{f(\Delta_{a,1})}{f(\Delta_{a,2})} > 1$$

- For individual b, the anchor $\tilde{A}_b$ is closer to A_2 than A_1. Thus, $\Delta_{b,2} < \Delta_{b,1}$. This implies $f(\Delta_{b,2}) > f(\Delta_{b,1})$, and therefore:

$$\frac{f(\Delta_{b,1})}{f(\Delta_{b,2})} < 1$$

Combining these two inequalities, we obtain the strongest preference divergence:

$$\frac{f(\Delta_{a,1})}{f(\Delta_{a,2})} > 1 > \frac{f(\Delta_{b,1})}{f(\Delta_{b,2})} \tag{A22}$$

Which leads to the conclusion:

$$Pr_a(1|\text{With Anchoring Effects}) > Pr_b(1|\text{With Anchoring Effects}). \tag{A23}$$

This confirms that in all scenarios where $\tilde{A}_a > \tilde{A}_b$ and $A_1 > A_2$, individual a is more likely to choose Location 1 than individual b, completing the proof for Proposition 3.

References

Adserà, A. (2015). Language and culture as drivers of migration. *IZA World of Labor*.

Albouy, D., H. Cho, and M. Shappo (2021). Immigration and the pursuit of amenities. *Journal of Regional Science 61*(1), 5–29.

Anderson, J. E. (2011). The gravity model. *Annu. Rev. Econ. 3*(1), 133–160.

Anderson, J. E. and E. Van Wincoop (2003). Gravity with gravitas: A solution to the border puzzle. *American economic review 93*(1), 170–192.

Bakhtsiyarava, M. and R. J. Nawrotzki (2017). Environmental inequality and pollution advantage among immigrants in the united states. *Applied Geography 81*, 60–69.

Banzhaf, H. S. and R. P. Walsh (2008). Do people vote with their feet? an empirical test of tiebout's mechanism. *American economic review 98*(3), 843–863.

Banzhaf, S., L. Ma, and C. Timmins (2019). Environmental justice: The economics of race, place, and pollution. *Journal of Economic Perspectives 33*(1), 185–208.

Bayer, P., N. Keohane, and C. Timmins (2009). Migration and hedonic valuation: The case of air quality. *Journal of Environmental Economics and Management 58*(1), 1–14.

Beine, M., S. Bertoli, and J. Fernández-Huertas Moraga (2016). A practitioners' guide to gravity models of international migration. *The World Economy 39*(4), 496–512.

Borjas, G. J. (1987). Self-selection and the earnings of immigrants. *The American Economic Review*, 531–553.

Chetty, R., J. N. Friedman, N. Hendren, M. R. Jones, and S. R. Porter (2026). The opportunity atlas: Mapping the childhood roots of social mobility. *American Economic Review 116*(1), 1–51.

Chetty, R., N. Hendren, P. Kline, and E. Saez (2014). Where is the land of opportunity? the geography of intergenerational mobility in the united states. *The quarterly journal of economics 129*(4), 1553–1623.

Corak, M. (2013). Income inequality, equality of opportunity, and intergenerational mobility. *Journal of Economic Perspectives 27*(3), 79–102.

Entwisle, B. (2021). Population responses to environmental change: looking back, looking forward. *Population and environment 42*(4), 431–444.

Fard, P., C. J. Patel, and H. Estiri (2023). Spatial Catalog of the Extreme Heat and Cold Events in the U.S.

Grzymala-Kazlowska, A. and L. Ryan (2022). Bringing anchoring and embedding together: Theorising migrants' lives over-time. *Comparative Migration Studies 10*(1), 46.

Hunter, L. M. (1998). The association between environmental risk and internal migration flows. *Population and Environment 19*(3), 247–277.

Kellstedt, D. K., C. S. Suess, and J. E. Maddock (2024). Influences of outdoor experiences during childhood on time spent in nature as an adult. *AJPM focus 3*(4), 100235.

Kőszegi, B. and M. Rabin (2006). A model of reference-dependent preferences. *The Quarterly Journal of Economics 121*(4), 1133–1165.

Kőszegi, B. and M. Rabin (2007). Reference-dependent risk attitudes. *American Economic Review 97*(4), 1047–1073.

Liu, R., R. Greene, Y. Yu, and H. Lv (2022). Are migration and settlement environment-driven? environment-related residential preferences of migrants in china. *Journal of Cleaner Production 377*, 134263.

Lowry, I. S. (1966). Migration and metropolitan growth: two analytical models. *(No Title)*.

Manduca, R. and R. J. Sampson (2019). Punishing and toxic neighborhood environments independently predict the intergenerational social mobility of black and white children. *Proceedings of the national academy of sciences 116*(16), 7772–7777.

Ramos, R. (2016). Gravity models: A tool for migration analysis. *IZA World of Labor*.

Shen, F., Q. Wang, J. Zou, H. Yan, and B. Wang (2023). Air pollution and migration decision of migrants in low-carbon society. *International Journal of Environmental Research and Public Health 20*(1), 870.

Tiebout, C. M. (1956). A pure theory of local expenditures. *Journal of political economy 64*(5), 416–424.

Tinbergen, J. (1962). Shaping the world economy; suggestions for an international economic policy.

Vitale, V., L. Martin, M. P. White, L. R. Elliott, K. J. Wyles, M. H. Browning, S. Pahl, P. Stehl, S. Bell, G. N. Bratman, et al. (2022). Mechanisms underlying childhood exposure to blue spaces and adult subjective well-being: An 18-country analysis. *Journal of Environmental Psychology 84*, 101876.

Wilson, W. J. (2012). *The truly disadvantaged: The inner city, the underclass, and public policy*. University of Chicago Press.