Internal Migration and Relocation Aversion

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Abstract

Urban economics has long relied on the assumption of perfect mobility, where workers relocate in direct response to differences in local economic conditions. In contrast, recent evidence on internal migration reveals persistent frictions and a strong distance gradient. This paper develops a static general equilibrium model of migration in which workers differ in their aversion to relocation. We distinguish geographic and non-geographic factors behind relocation decisions, modeling the former as a continuous variable that workers perceive logarithmically. The framework shows how large cities disproportionately attract workers with low relocation aversion and high tolerance for long-distance migration. A counterfactual exercise further demonstrates that the removal of distance-related frictions would flatten the city-size distribution, with smaller cities experiencing a proportionally larger reduction in agglomeration intensity than larger ones.

Keywords: geographic mobility, internal migration, agglomeration
JEL classification: J61, R23

1 Introduction

1.1 Domestic Migratory Patterns

Internal migration in the U.S. exhibits a pronounced geographic gradient: the number of movers sharply declines with distance. Most in-migrants to cities originate from nearby areas, and long-distance relocation remains rare. Figure 1(a) illustrates this pattern for the St. Louis metropolitan area, where most new residents are from Missouri and Illinois despite mobility being unrestricted at the national level.[1]

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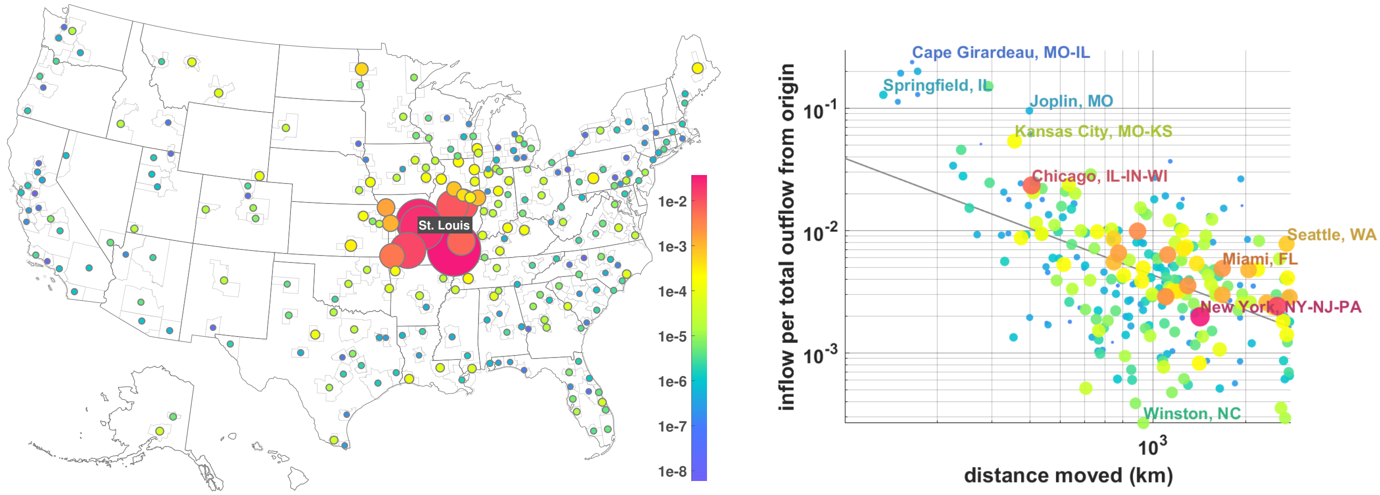
[1]All uses of data in this paper, including descriptive plots, summary statistics, and regression analyses, are based on the U.S. Census Bureau's American Community Survey (ACS), 2009–2013, unless otherwise



(a) Origins of incoming residents. Dot sizes represent the inflow from each location, normalized by the total outflow from it.

(b) Incoming residents by distance moved. Dots are proportionate to the log of origin size.

Figure 1. In-migrants to St. Louis Metropolitan Statistical Area (MSA).

Figure 1(b) confirms this exponential decay in inflows with distance. The sharp distance decay in migration flows suggests that geographic proximity plays a central role in relocation decisions.[2]

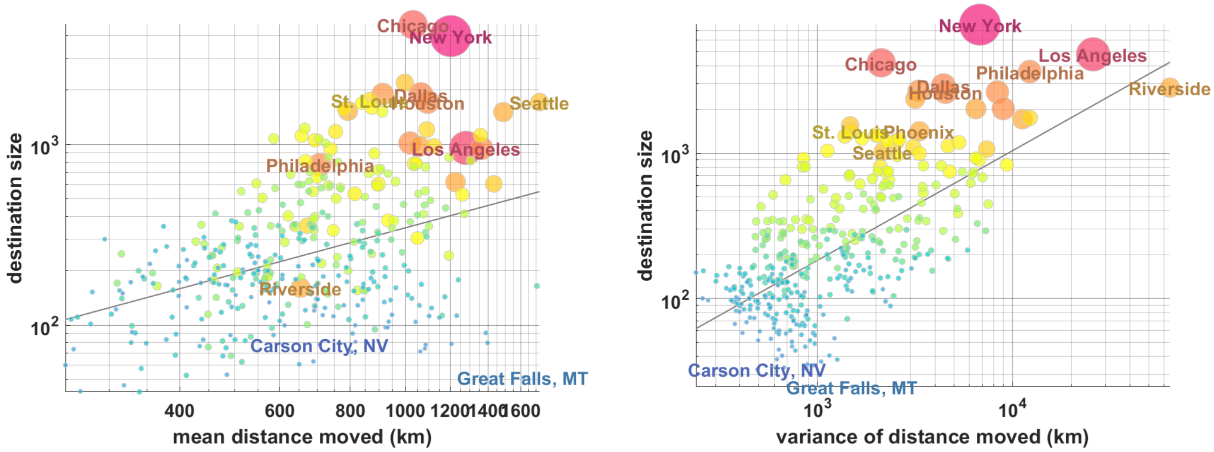
Moreover, the nature of migration varies with city size. Larger cities draw migrants from a broader set of origins and over greater average distances, as shown in Figure 2. In addition to the variation in the origins of migrants and the distances they travel, cities also differ in the overall volume of domestic migration. Figure 3 shows the annual inflows and outflows by city. Some cities experience churn rates as high as 12% annually, while others see much lower levels of turnover.

These differences matter. Migration is not merely a demographic backdrop—it plays an active role in shaping the urban economy. Since agglomeration economies scale with population, variation in migration intensity alters the strength of those economies. Inflows expand the labor market, introduce new skills, and reinforce scale effects; outflows can diminish them. Understanding migration behavior—and the frictions that modulate it—is thus central to explaining the formation, persistence, and divergence of cities.

These patterns highlight the importance of understanding how variation in geographic mobility influences population distribution and urban agglomeration. We develop a parsimonious model in which individuals differ in their relocation aversion—a latent trait that governs the cost they associate with moving. We focus especially on the role of distance as a constraint, modeling its influence on migration decisions and, in turn, on equilibrium city sizes.

specified. See Appendix A.7 for data description.

[2]This observation echoes Tobler's First Law of Geography: "everything is related to everything else, but near things are more related than distant things." (Tobler, [Tob70]).



(a) Mean distance moved, controlled for variance.

(b) Variance of distance moved, controlled for mean.

Figure 2. Mean and standard deviation of distance moved among in-migrants to each destination. Dot sizes are proportionate to destination sizes. The distance moved exhibits high variance. Among those who made intercity migrations, the average distance moved was 981 km—roughly the distance between New York and Indianapolis—with a standard deviation of 1,186 km. The geometric mean was 478 km, with a standard deviation of 427 km.

1.2 Related Literature

The idea that workers relocate in response to spatial differences in economic conditions has a long tradition. Seminal work by Sjaastad [Sja62] and Harris and Todaro [HT70] modeled migration as an investment in future earnings, focusing on expected wage differentials. McFadden [McF74] further formalized location decisions in terms of observable and unobservable characteristics of places and individuals.

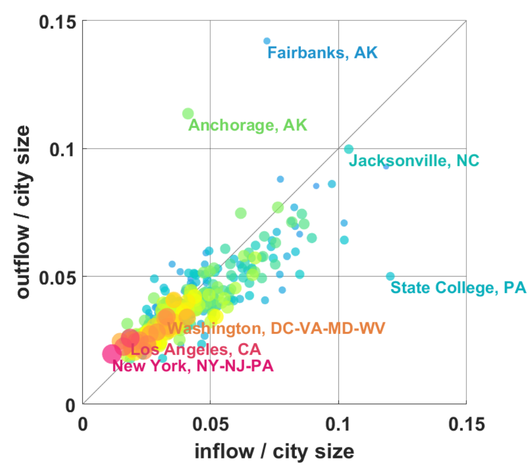


Figure 3. Annual inflows and outflows by city as a share of population. Dot sizes are proportional to the log of city population. Migration intensity varies substantially across metropolitan areas, with significant implications for urban growth and agglomeration dynamics.

Subsequent research extended these models to incorporate heterogeneous preferences and market imperfections. Borjas et al. [BBT92] and Kennan and Walker [KW11] modeled skill-dependent sorting, while Diamond [Dia16] shows how cities endogenously generate amenities that attract high-skilled workers, reinforcing spatial inequality. In parallel, much of urban economics has traditionally assumed perfect mobility, that is, workers face no barriers in relocating to utility-maximizing locations (Starrett [Sta78]; Boyd and Conley [BC97]). This simplifying assumption enabled important theoretical advances in general equilibrium modeling.

More recent work has relaxed this assumption to better reflect a growing body of empirical evidence on persistent frictions in relocation. Piyapromdee [Piy21] develops a spatial equilibrium model with migration costs that shape internal mobility and wage responses to immigration, providing an empirically grounded treatment of frictions across locations. Similarly, Ahlfeldt et al. [ABRS24] examine how spatial frictions interact with quality-of-life differences across cities, using a structural framework that highlights the welfare consequences of mobility barriers.

Beyond economic frictions, cultural, familial, and institutional factors play a critical role in shaping mobility patterns as underscored by Moretti [Mor12], who emphasizes both monetary and psychological relocation costs. Falck et al. [FHLS12] document that Germans are reluctant to leave regions sharing their dialect. Helliwell [Hel97] and Woodard [Woo11] find similar effects in Canada and the U.S., where social or linguistic boundaries constrain movement. Zabek [Zab24] highlights the role of local ties in constraining migration, showing that attachment to place generates heterogeneity in mobility responses and affects the spatial allocation of workers. Green [Gre24] shows that U.S. Navy veterans randomly assigned to WWII ships were more likely to co-locate later in life, demonstrating the persistence of peer networks in shaping mobility decisions.

Relocation rates remain persistently below standard model predictions. Jia et al. [JMSW23] note that the relocation costs required to rationalize observed migration flows often exceed plausible financial or logistical barriers. This has motivated research into deeper, often unobservable sources of mobility frictions, including psychological, cultural, and network-based mechanisms discussed above.

Against this backdrop, the present article offers a narrow but complementary perspective. Instead of introducing new migration frictions, it uses a simple framework to show how heterogeneity in relocation behavior interacts with agglomeration forces to shape the city-size distribution. Whereas prior work has emphasized welfare or labor market implications, this paper highlights relocation heterogeneity as one of several centrifugal forces influencing urban structure. Empirically, the framework leverages observable geographic frictions (distance moved) while treating non-geographic frictions (relocation aversion) as unobserved heterogeneity.

In this article, **perfect mobility** refers to a situation in which individuals face identical relocation costs, so that migration decisions do not vary across people. We distinguish between two dimensions of perfect mobility. Perfect **geographic** mobility means that migration decisions are independent of distance—relocation costs may exist but are uniform across space. Perfect **non-geographic** mobility means that, moving distance aside, individuals have identical tolerance for moving, so there is no heterogeneity in their willingness to relocate. In contrast, this paper focuses on **imperfect mobility**, where individuals differ in their relocation tolerance, and where distance interacts with that heterogeneity to shape migration flows. This heterogeneity, in turn, influences the strength and spatial pattern of agglomeration forces.

The rest of the paper is organized as follows: In the upcoming section we lay out the model and describe the relationship among relocation, distance moved, inflow and agglomeration. We will empirically validate our theoretical predictions in Section 3. Section 4 concludes our analysis.

2 Model

2.1 Landscape

Consider a closed production economy situated on a circle with unit circumference. There are $I \in \mathbb{N}$ cities along the circumference, indexed by i.

Each city is endowed with a unit mass of potential consumers who may choose to relocate there. This framework assumes that each city hosts a unique set of potential in-migrants, referred to as type-i households. To simplify notation, we focus on a representative city and suppress the index i unless necessary.

Each potential migrant draws a pair of attributes $(x, y) \in \left[0, \frac{1}{2}\right] \times \mathbb{R}$ that jointly determine her migration behavior. As discussed in Section 1, many factors shape a worker's willingness to relocate. In this model, we isolate the role of distance by decomposing relocation aversion into two parts:

geographic frictions distance x between birthplace and destination

non-geographic frictions all other idiosyncratic factors, summarized by relocation tolerance y.[3]

We refer to $f_X(x)$ and $f_Y(y)$ as the marginal probability density functions (PDFs) for distance and relocation tolerance, respectively, with $F_X(x)$ and $F_Y(y)$ denoting the corresponding cumulative distribution functions (CDFs).

If a worker is born in the destination city, $x = 0$; if she is born at the farthest point on the circle, $x = \frac{1}{2}$. To distinguish the two locations conceptually, we refer to the destination city as "urban" and the birthplace x as "rural", regardless of the local density $f_X(x)$.

We assume the model is static: each worker simultaneously and independently decides whether to relocate. A type-i individual chooses between remaining at her birthplace x or moving to city i. We assume that y is independently drawn from $f_Y(y)$ and

[3]The tolerance variable y absorbs all non-distance determinants of relocation behavior—such as income, education, family structure, and social ties—without modeling them separately. This reduced-form approach isolates the role of geographic distance while accommodating realistic heterogeneity in individual mobility. This follows the spirit of Borjas et al. [BBT92], who treat unobserved mobility determinants via a reduced-form index.

uncorrelated with x. This assumption reflects the view that relocation tolerance is not inherently tied to birthplace.[4]

Furthermore, we assume y is drawn from a common distribution $f_Y(y)$ across all types. This assumption is motivated by the idea that relocation tolerance is not determined by acquired traits such as education or earnings potential. Instead, heterogeneity in migration outcomes emerges through individual migration decisions taken conditional on the draw of y from this identical distribution, not from type-specific assumptions about mobility.

Each worker's migration choice depends on three variables: distance x, relocation tolerance y, and city size s. City size s affects urban productivity and, consequently, wage levels. It also influences the cost of urban living through rent and congestion. A lower x, higher y, or larger s increases the likelihood of relocation.

All types are ex ante identical in distribution: a type-i worker draws (x, y) from the same joint distribution as a type-j worker. Equilibrium variation in city sizes arises ex post from differences in the realized draws of (x, y).

2.2 Moving Workers

Each worker consumes a single homogeneous good produced using labor and incurs costs when relocating. In line with the spatial equilibrium tradition, her utility depends on both the consumption level at the destination and the cost of moving from her origin.[5]

Each consumer is endowed with a unit of time and an equal amount of capital. She divides her time into leisure $1-l$ and labor l, from which she produces numéraire composite consumption good c. Along with labor and leisure, she also chooses her residence, either her birthplace x or city i. Her preferences are represented by $c + (1-l)^\beta$, where $\beta \in (0,\ 1)$.

She also requires one unit of land at her destination for accommodation. For simplicity, consuming more than one unit of land provides no additional utility, and housing rent rises with city size, such that housing costs are given by ps^δ, where p is a constant, $s \in [0,\ 1]$ is the (endogenous) destination size, and $\delta > 0$, in line with the treatment in Behrens et al. [BDRN14].

With l units of labor, she produces output and earns labor income at the rate of w per unit of **effective labor** L, defined as $s^{-\gamma} l$ with $\gamma > 0$ (following Eeckhout [Eec04], with structural underpinning in Rossi-Hansberg and Wright [RHW07]). Effective labor reflects working time net of commuting time and declines with city size, capturing congestion

[4] While y and x may be correlated in practice—for example, if certain regions foster greater openness to migration—we treat them as independent to focus on distance itself as a friction.

[5] This setup parallels the structure in Allen and Arkolakis [AA14], whose indirect utility is a function of wages and bilateral migration costs. Our framework simplifies their treatment by focusing on behavioral aversion to distance rather than trade frictions.

externalities.

In addition, each consumer receives dividend π. From her income $wL+\pi$, **the cost of relocation** $r = r(x, y)$ (≥ 0) is deducted. Her budget constraint is then $wL+\pi-r(x, y)-ps^{\delta} \geq c$. We will describe the cost of relocation next.

Relocation from birthplace x to city i entails both benefits and costs. On the benefit side, the worker gains access to urban productivity, which is reflected in the higher wage rate w relative to her rural birthplace. In this formulation, agglomerative advantages of the city are transmitted entirely through wages. On the cost side, relocation requires paying both the moving cost $r(x, y)$ and the housing cost ps^{δ}. These expenses are defined separately from wages, capturing the burdens of relocation and urban housing without overlapping with the productivity effect embedded in w. The opportunity cost of staying in the birthplace is therefore given by $wL - r(x, y) - ps^{\delta}$. We characterize the relocation cost as below:

Assumption 2.1 Moving Distance, Relocation Tolerance and Costs

Relocation cost $r(x, y)$ *is continuously differentiable and satisfies the following:*

$$\frac{\partial r(x, y)}{\partial x} > 0, \tag{1}$$

$$\frac{\partial^2 r(x, y)}{\partial x^2} < 0, \quad \textit{and} \tag{2}$$

$$\frac{\partial r(x, y)}{\partial y} < 0, \tag{3}$$

for $(x, y) \in \left(0, \frac{1}{2}\right) \times \mathbb{R}$.

These properties imply: 1) Relocation cost increases with distance; 2) individuals perceive distance non-linearly (concave in x); and 3) greater tolerance y reduces relocation cost.

Turning to production, a worker who moved to city i produces non-tradable composite goods in a perfectly competitive environment according to $c = s^{\alpha} k^{1-\beta} L^{\beta}$. Exponent $\alpha (> 0)$ reflects agglomeration-driven productivity. Each firm employs effective labor L along with fixed capital k. Exponent $\beta \in (0, 1)$ is the labor share. The citywide total productivity s^{α} itself is increasing in size as documented in Rosenthal and Strange [RS04]. Furthermore, the equilibrium real wage $w = \beta s^{\alpha-(\beta-1)\gamma}\left(s^{\frac{\alpha-\beta\gamma}{\beta-1}}+k\right)^{-\beta+1}$ increases with s for sufficiently large s and/or k.[6]

Putting this together, the indirect utility function of a relocating worker is $V(x, y, s) = v(s) - r(x, y)$, where $v(s) := s^{\alpha-\beta\gamma}\left(s^{\frac{\alpha-\beta\gamma}{\beta-1}}+k\right)^{-\beta+1} - ps^{\delta}$. This parallels McFadden's framework [McF74], where the utility of a location depends on observable characteristics (here,

[6]This is consistent with empirical findings on agglomeration economies; see Combes et al. [CDGR12]. A common reduced-form approach specifies wages as $w(s) = As^{\kappa}$ (see Moretti [Mor12] and Allen and Arkolakis [AA14] for examples of reduced-form log-linear wage functions). Our specification is aligned with this tradition with agglomeration economies captured by α and congestion-related diseconomies by γ.

distance x and city size s) and unobserved individual traits (relocation tolerance y), summarized through $r(x, y)$.

2.3 Non-Moving Workers

Outside the city, the economy is autarkic. Non-moving workers incur no relocation costs or urban rents, but they forgo the productivity advantages generated by urban agglomeration. Let $\bar{V}$ denote the utility level that a non-moving worker achieves. We assume $\bar{V}$ is constant across all birth locations. This simplifying assumption enables closed-form solutions in the analysis to follow.

In reality, local economic conditions may vary across birthplaces. We assume such variation is partly captured by the distribution $f_X(x)$, that is, by the likelihood of being born at a given distance x from the city. As we will discuss later, the migration decision implied by this structure resembles a gravity model.

2.4 Migration Decision

Let $\varphi(x,\ y,\ s;\ \bar{V})$ denote the utility difference between migrating to the city and staying in one's birthplace:

$$\varphi\left(x,\ y,\ s;\ \bar{V}\right) := V(x, y, s) - \bar{V} = v(s) - r(x, y) - \bar{V}.$$

Assumption 2.2 Urban-Rural Utility Differential

Given destination size s, the marginal worker at the threshold of relocating satisfies:

$$\varphi\left(x,\ y,\ s;\ \bar{V}\right) = 0. \tag{4}$$

Remark. For simplicity, we suppress $\bar{V}$ and write $\varphi\,(x, y, s)$ in what follows.

Along the locus $\varphi(x, y, s) = 0$, we analyze how the marginal indifference condition responds to changes in distance, relocation tolerance, and city size. The marginal utility gain from increasing s is $\partial v/\partial s$,[7] which must be offset by a corresponding increase in relocation cost $\partial r/\partial s$. That is, workers who are indifferent at higher values of s must face higher effective relocation costs—either because they are farther from the city or less tolerant of relocation.

We specify the impact of moving distance and relocation tolerance on agglomeration as follows:

[7] We assume that parameters α, γ, and δ satisfy $(\alpha - \beta\gamma)s^{\alpha-\beta\gamma+1}k\left(s^{\frac{\alpha-\gamma}{\beta-1}} + k\right)^{-\beta} - p\delta s^{\delta-1} > 0$, ensuring that $\partial v/\partial s > 0$. In economic terms, the agglomeration economies represented by α outweigh the diseconomies associated with γ and δ. This parameterization rules out counterintuitive cases where smaller cities would attract more workers than larger ones.

Proposition 2.1 Distance Moved, Relocation Tolerance and Agglomeration

Along $\varphi(x, y, s) = 0$,

$$\frac{\partial x}{\partial s} = \frac{-\varphi_s}{\varphi_x} = \frac{v_s}{r_x} > 0, \tag{5}$$

$$\frac{\partial y}{\partial s} = \frac{-\varphi_s}{\varphi_y} = \frac{v_s}{r_y} < 0, \quad \textit{and} \tag{6}$$

$$\frac{\partial y}{\partial x} = \frac{-\varphi_x}{\varphi_y} = \frac{-r_x}{r_y} > 0. \tag{7}$$

Proof. These follow from the implicit function theorem applied to (4), using the monotonicity conditions in Assumption 2.1. □

Remark. Equation (5) implies that, for a fixed y, larger cities draw migrants from farther away: higher urban productivity offsets greater distance. Equation (6) shows that, for a fixed distance, higher relocation tolerance is needed to move to smaller cities. Equation (7) reveals that among marginal workers born at different distances, those farther away must exhibit higher tolerance to be indifferent.

The responsiveness of these trade-offs depends on the curvature of the relocation cost function. If $r(x, y)$ is highly sensitive to x or y, then even small changes in distance or tolerance are associated with large changes in s. Thus, the shape of $r(x, y)$ plays a central role in determining the degree of agglomeration.

Finally, note that in the absence of any centrifugal forces, all workers would move to a single city, yielding $s_i = 1$ for any i. Standard urban models address this by incorporating forces such as land scarcity or commuting costs. Here, relocation costs provide an additional mechanism to sustain a non-degenerate city-size distribution.

2.5 Competitive Equilibrium

We define equilibrium as follows:

Definition 2.3 Competitive Equilibrium

An equilibrium is a set of feasible allocations $\big(c(x, y),\ l(x, y)\big)$, *a city size* s, *and a wage* w *such that:*

1. *For each consumer with* (x, y), *the allocation* $\big(c(x, y),\ l(x, y)\big)$ *maximizes utility given* w *and* s, *and*
2. *The population size* s *satisfies the fixed-point condition:*

$$s - \iint_{M(s)} f_X(x) f_Y(y)\, dx\, dy = 0, \tag{8}$$

where $M(s) = \{(x,\ y) :\ \varphi(x, y, s) \geq 0\}$ *is a set of attributes such that individuals with* (x, y) *in this set earn a higher utility level by migrating to the city.*

Remark. The equilibrium defined above corresponds to a static spatial equilibrium in which relocation decisions occur simultaneously and birthplace locations are taken as fixed rather than endogenously shaped by historical agglomeration forces. A more detailed discussion of this modeling choice and its relationship to dynamic frameworks is provided in Appendix A.1. In addition, Appendix A.2 provides a sufficient condition for uniqueness of the equilibrium city size.

Equation (8) ensures that the realized city size equals the measure of individuals who choose to migrate there. While it defines equilibrium size implicitly, it does not generally admit a closed-form solution. We adopt a heuristic approach instead to study how imperfect mobility shapes agglomeration.

Suppose a representative consumer drew (x, y). If $\varphi(x, y, s) > 0$, she chooses to migrate, implying upward pressure on s; if $\varphi(x, y, s) < 0$, she opts not to, putting downward pressure on s. In equilibrium, these forces balance, and $\varphi(x, y, s) = 0$. Here, $\varphi(x, y, s) = 0$ characterizes the marginal agent at the cutoff; almost all agents are infra-marginal in equilibrium.

Under this logic, the probability that city size takes a particular value s corresponds to the probability that a drawn (x,y) satisfies the indifference condition $\varphi(x, y, s) = 0$. For instance, the probability that $s \geq \bar{s}$ equals the probability that $\varphi(x, y, \bar{s}) \geq 0$.

We formalize this mapping by treating s as a function of two random variables x and y distributed as $f_X(x)$ and $f_Y(y)$. Let (x, y) satisfy the condition $\varphi\big(x, y, s(x, y)\big) = 0$, and define the change of variable:

$$t = x, \quad s = s(x, y), \tag{9}$$

with inverse

$$x = x(t, s), \quad y = y(t, s). \tag{10}$$

Since $\varphi(\cdot)$ is strictly monotonic in x, y and s, the mapping is bijective.

<u>PROPOSITION 2.2 CITY-SIZE DISTRIBUTION</u>

Under transformation (9) and (10), the distribution of equilibrium city sizes $f_S(s)$ is given by:

$$f_S(s) = \int_0^{\frac{1}{2}} f_X(t) f_Y\big(y(t, s)\big) \frac{v_s(s)}{-r_y\big(t,\ y(t, s)\big)} dt \tag{11}$$

in equilibrium.

Proof. Joint pdf of s and t is

$$f_{TS}(t, s) = f_{XY}(x, y) |\det J| = f_X\big(x(t, s)\big)\, f_Y\big(y(t, s)\big) \left| \frac{-\partial y(t, s)}{\partial s} \right| \tag{12}$$

by a change of variables, where J denotes Jacobian $\frac{\partial(x,y)}{\partial(t,s)}$ of (9). Apply the implicit function theorem to (4) to replace $|-\partial y(t, s)/\partial s|$ in (12) with $|-v_s(s)/r_y(x, y)|$. It is equal to $-v_s(s)/r_y(x, y)$ for (6). Finally, marginalize t out to obtain (11). $\square$

Remark. Appendix A.3 derives an alternative form of (11).

Equation (11) relates agglomeration to mobility:

PROPOSITION 2.3 PASS-THROUGH

The variance of city size increases as the relocation cost function $r(x, y)$ becomes more responsive to x or y. This amplification is especially pronounced for low values of x (nearby individuals), where migration responses are more elastic.

Proof. In (12), $|\det J|$ becomes smaller when $r_y(x, y)$ becomes larger in magnitude, i.e., when $r(x, y)$ becomes more sensitive to y. Then a region in $X \times Y$ maps to a larger region in $S \times T$ in (9), rendering the distribution of s more spread out. See Appendix A.3 for the proof in terms of x. □

Remark. Analogously, stronger agglomerative forces also spread the distribution of city sizes. An increase in urban productivity (higher α), weaker congestion effects (lower γ), or lower housing costs (lower δ) all reduce $|\det J|$, thereby increasing the variance of city sizes as above.

Imperfect mobility introduces dispersion in the city size distribution via two channels:

1. Heterogeneity in (x, y): If relocation tolerance and distance are homogeneous, $f_S(s)$ collapses to a point mass.
2. Relocation friction function $r(x, y)$: A more responsive cost function amplifies the impact of heterogeneity in (x, y).

Thus, $r(x, y)$ governs how much of the joint distribution $f_{XY}(x, y)$ passes through to the equilibrium distribution of city sizes.

2.6 Tolerance Cutoff

To assess the impact of imperfect mobility on agglomeration, we would ideally observe x, y, and s, estimate the function $r(x, y)$, and compute $|\det J|$ to measure the extent to which heterogeneity in mobility shapes locational variation in agglomeration. In practice, while x and s are observable, y is not, making direct empirical validation infeasible. Against this backdrop, we focus on the threshold value of y derived in Assumption 2.2. Specifically, we express $y(x, s)$ using the inverse function of $r(x, y)$ as follows:

DEFINITION 2.4 CUTOFF LEVEL OF TOLERANCE

*Define the **cutoff level of tolerance** by*

$$y(x, s) := r^{-1}\left(x,\, s^{\alpha-\beta\gamma}\left(s^{\frac{\alpha-\beta\gamma}{\beta-1}} + k\right)^{-\beta+1} - ps^{\delta} - \bar{V}\right). \tag{13}$$

If $y \lesseqgtr y(x, s)$, then $\varphi(x, y, s) \lesseqgtr 0$. This threshold characterizes the minimum tolerance level required for a worker born at x to choose the city over her birthplace. Thus, from observed (x, s) pairs, we can infer the implied threshold $y(x, s)$ that separates movers from non-movers.

We restate Proposition 2.3 in terms of the cutoff tolerance:

Proposition 2.4 Cutoff Level and Agglomeration

If $|\partial y(x, s)/\partial s|$ declines, the variance of s increases.

Proof. Immediate from (12). □

Intuitively, a low value of $|\partial y(x, s)/\partial s|$ implies that a small change in tolerance is associated with a large change in city size. As shown in Proposition 2.3, this flattens the distribution of s, increasing its variance.

While $r_y(x, y)$ is unobservable, $\partial y(x, s)/\partial s$ can be computed from data. A low empirical value of $|\partial y(x, s)/\partial s|$ suggests a high sensitivity of relocation costs to y, amplifying the influence of heterogeneous mobility on agglomeration outcomes.[8]

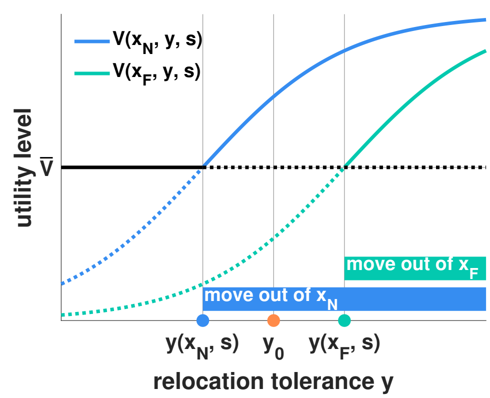


Figure 4. Urban and rural utility levels at x_N near the city and $x_F(> x_N)$ farther out. The solid line traces utility profiles across y. Workers with $y \geq y(x, s)$ relocate to the city. Note that $V(\cdot, s)$ shifts upwards as s increases.

Figure 4 illustrates the relationship between the cutoff tolerance and migration behavior. The blue curve represents urban utility at x_N, while the black line represents rural utility $\bar{V}$. The cutoff tolerance $y(x,s)$ is located where these two lines intersect. Workers drawing y above this threshold relocate to the city, while those below remain.

Lower cutoff levels increase the likelihood of migration. As Figure 4 indicates, the fraction of movers increases as the cutoff $y(x, s)$ falls.

Notably, spatial sorting occurs along both x and y. An individual with a given y_0 would relocate if born at x_N but not if born at $x_F > x_N$, reflecting the joint dependence of migration decisions on birthplace and relocation tolerance.

Perfect geographic mobility then emerges as a special case where $\partial y(x, s)/\partial x = 0$ for any x. In this case, the relocation decision of an individual with tolerance level y is identical regardless of the distance x she draws. Intuitively, distance ceases to play any role in migration decisions, so birthplace geography no longer shapes inflows. Consequently,

[8] Analogously, one could define a cutoff moving distance $x(y, s)$ and relate $\partial x(y, s)/\partial s$ to the influence of distance on agglomeration (see Appendix A.3). However, empirical implementation is difficult because y is not directly observed. Consequently, we proceed by estimating $y(x, s)$ rather than $x(y, s)$ in the empirical analysis to follow.

variation in $f_S(s)$ originates exclusively from $f_Y(y)$ rather than from the joint distribution $f_{XY}(x, y)$. Section 3.3 explores this scenario.

Turning to estimation, we model the migration flow from x to a city of size s as

$$m(x, s) = f_X(x) \int_{y(x,s)}^{\infty} dF_Y(y) = f_X(x) G_Y\big(y(x, s)\big), \tag{14}$$

where $G_Y(y)$ denotes the survival function of $F_Y(y)$. Since $G_Y\big(y(x, s)\big)$ declines with x for (7), the normalized migration flow $m(x, s)/f_X(x)$ also declines with x.

In equilibrium, city size satisfies $s - \int_0^{\frac{1}{2}} m(x, s)dx = 0$ as defined in Definition 2.3. Although no closed-form solution exists, the cutoff tolerance level $y(x, s)$ can be extrapolated from observed migration flows by rearranging (14):

$$y(x, s) = G_Y^{-1}\left(\frac{m(x, s)}{f_X(x)}\right). \tag{15}$$

To implement (15), the form of $G_Y(y)$ must be specified. For expositional clarity, we assume that y follows a standard normal distribution. Nonetheless, (15) holds under any strictly increasing $F_Y(y)$.

The present framework attributes variation in agglomeration not to external differences across cities, but to internal frictions arising from heterogeneous mobility among workers. In the next section, we compute empirical cutoff values and quantify their impact on agglomerative patterns, leveraging the theoretical foundation developed here.

3 Empirical Validation

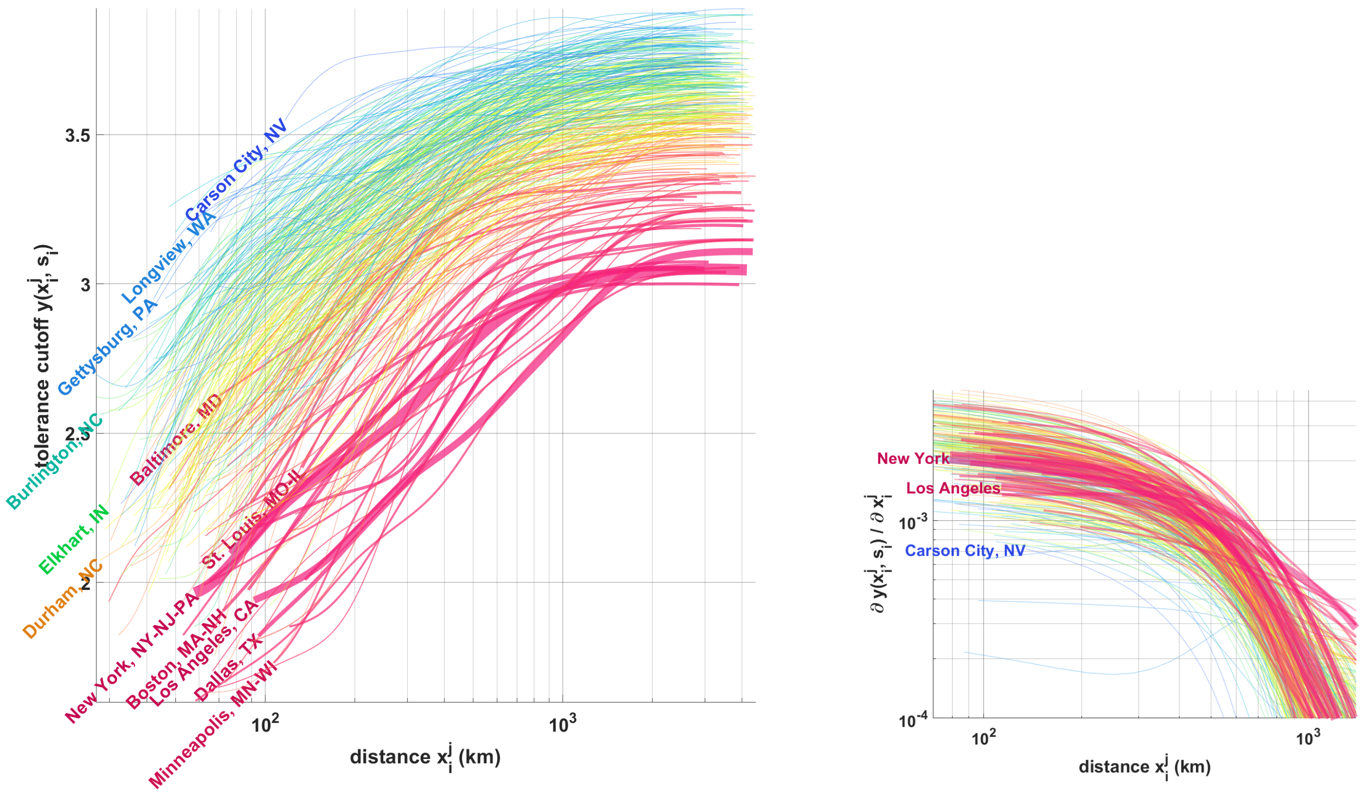
3.1 Data Employed

To test our model predictions, we use the U.S. Census Bureau's American Community Survey (ACS) 2009–2013. See Appendix A.7 for the details of this dataset.

3.2 Correlation between Tolerance Cutoff and Agglomeration

We locate the cutoff tolerance value using specification (15). We discretize distances by origin-destination pairs and scale inflows by the originating population. To match the model's unit mass assumption, we normalize standardized inflows so that the destination with the highest total inflow attains a value of one. This normalization allows us to estimate cutoff tolerances consistently across cities.

Figure 5(a) plots the cutoff values across the 377 MSAs in the sample. The cutoff values differ systematically with destination size, consistent with Proposition 2.4. The correlation coefficient between the cutoff and the log of destination size is −0.3968 with t-statistic −95.22. It is unlikely that heterogeneity in mobility and variations in agglomeration are independent.



(a) Tolerance cutoff (kernel smoothed).

(b) The slope of tolerance cutoff.

Figure 5. Tolerance cutoff. Line widths are proportional to city sizes.

That said, tolerance cutoff is a function of s **and** x. To isolate the role of distance, we approximate

$$y(x, s) \approx y_x(x_0, s_0)\,x + y_s(x_0, s_0)\,s + \frac{1}{2} y_{xx}(x_0, s_0)\,x^2 + \bar{y} \tag{16}$$

about some $(x_0, s_0) \in \left[0, \ \frac{1}{2}\right] \times \mathbb{R}_+$, where $\bar{y}$ is a constant.

Table 1 summarizes regressions of the cutoff value on distance and size. We emphasize that these regressions serve only to gauge the marginal effect of moving distance.

Under perfect geographic mobility, the coefficient on moving distance would be zero. The data reject this: moving distance significantly affects relocation decisions.

Moreover, the signs predicted in Proposition 2.1 align with our estimates: $y_x > 0$ and $y_s < 0$. Distance raises the cutoff, while destination size lowers it. In addition, $y_{xs} \approx 0$ (see Figure 5(b)), namely, the cutoff values run parallel to each other in Figure 5(a).[9] If this value was positive, smaller cities would have a wider catchment area than larger cities. The data reject this as well.

[9] The coefficient of correlation between $\partial y(x, s)/\partial x$ and s comes to -0.01067 and it is not significant at the 5% level.

	1	2	3
constant	4.225	0.2122	5.662
	(205.08)	(3.36)	(318.08)
$\log x$	0.2119	1.448	
	(116.72)	(78.01)	
$(\log x)^2$		-0.09267	
		(66.89)	
$\log s$	-0.1693	-0.1707	-0.1611
	(-123.38)	(-130.02)	(-120.31)
in-state			-0.6949
			(-125.97)
R^2	0.3421	0.3977	0.3651
adjusted R^2	0.3421	0.3976	0.3651

Table 1. The numbers in brackets denote t-statistics. All coefficients are significant at 1%. The log specifications help distribute data points more evenly.

The coefficient on $(\log x)^2$ is negative, consistent with the assumption in Assumption 2.1 that relocation costs grow at a decreasing rate with distance. Thus, cutoff sensitivity to distance diminishes at longer distances. This result provides theoretical justification for the common empirical practice of grouping moves by broad distance categories, such as local, intrastate, or interstate moves—as reflected in the strong predictive power of the in-state indicator in column 3 of Table 1.

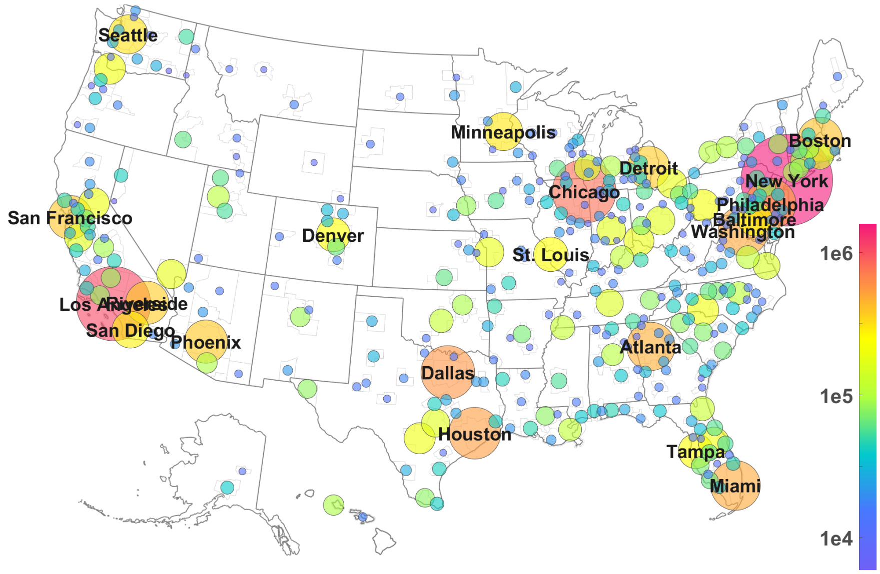
As a robustness check, we replicate the analysis using a different empirical strategy: estimating the gradient of inflow decay by city and linking it to city size. The results, presented in Appendix A.6, confirm that cities drawing migrants from a broader range of distances tend to be larger, reinforcing the role of heterogeneous distance tolerance in shaping agglomeration patterns.

Overall, the empirical results validate the key comparative statics of the model: relocation frictions matter, and their effects vary systematically with both distance and agglomeration size.

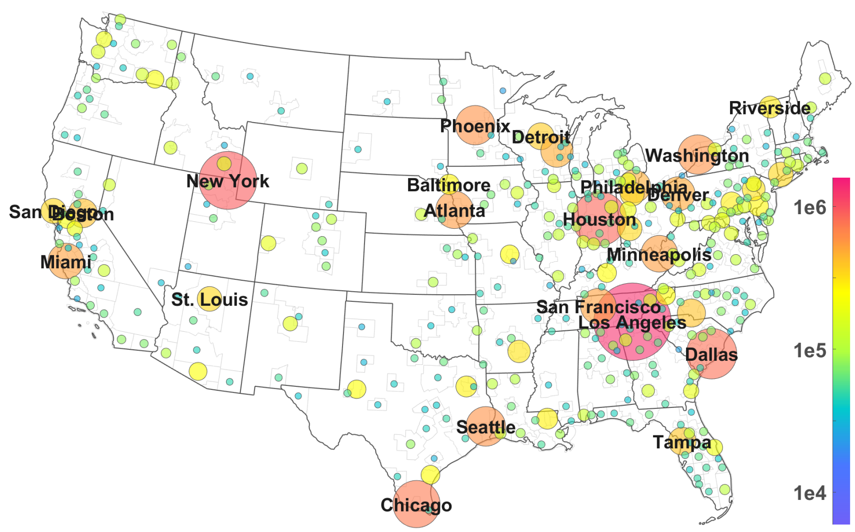
3.3 Agglomeration under Perfect Geographic Mobility

We conduct a counterfactual exercise to isolate the role of imperfect geographic mobility in shaping agglomeration patterns. Consider an alternative scenario where migration decisions are independent of distance, namely, $\frac{\partial y(x,s)}{\partial x} = 0$ in (13), emulating perfect geographic mobility.[10]

[10]Since cutoff tolerance is a function of both x and s, we could also consider the opposite scenario in which $y(x,s)$ is independent of s, i.e., perfect non-geographic mobility, where only distance matters. In our dataset,



(a) Actual destination sizes.



(b) An example of a permutation.

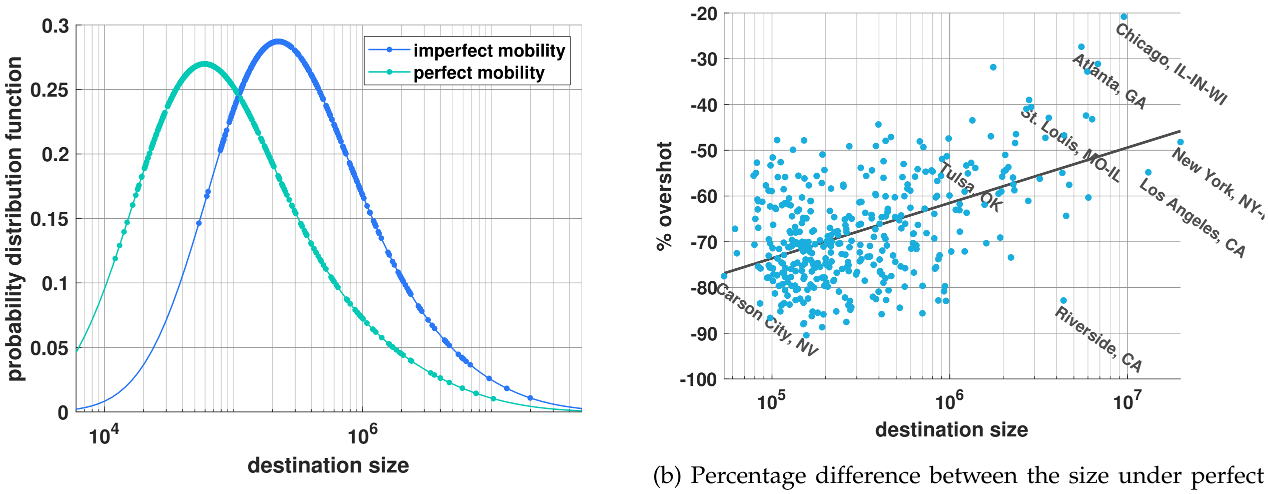
Figure 6. Actual and counterfactual destination sizes. In Figure 6(b), New York is reassigned to Logan, UT-ID and Los Angeles is reassigned to Cleveland, TN. New York is predicted to be smaller than Los Angeles under this mapping, as it is placed in a region containing smaller and more sparsely distributed cities, resulting in a lower predicted inflow than in the actual configuration. Four MSAs in Alaska and Hawaii are excluded in this exercise (See Appendix A.8).

In this counterfactual, origins are randomly reassigned across locations. If distance plays no role, the inflow from any origin to a destination would be invariant to the ori-

Columbus, IN has the smallest average distance to other birthplaces, while Bellingham, WA has the largest. Destinations near the former would be expected to gain inflows, whereas those near the latter would be expected to lose them.

gin's actual location. Figure 6(b) represents one such reassignment, along with the actual destination size in Figure 6(a) for comparison. Permuting origins across the dataset effectively filters out the distance-driven component of migration, allowing us to reconstruct hypothetical destination sizes under perfect mobility.

Figure 7 compares the actual and expected city-size distributions obtained from permutations. Figure 7(a) plots the distributions under perfect and imperfect geographic mobility. Under perfect geographic mobility, the variance of destination sizes is lower: the standard deviation falls by 59.1%, from 1.62 million to 0.896 million. Thus, imperfect geographic mobility magnifies disparities in city sizes, in line with Proposition 2.3.



(a) Size distribution under perfect and imperfect mobility.

(b) Percentage difference between the size under perfect mobility (counterfactual) and the size under imperfect mobility (actual).

Figure 7.

The evening-out of city sizes in the counterfactual stems from the interplay between birthplace concentration and geographic frictions. In the observed data, most workers relocate over short distances (see Figure 11(b)), effectively anchoring population close to their birthplaces. Since birthplaces themselves are spatially concentrated in a limited number of locations, this reinforces large agglomerations and limits the scale of many smaller cities. When distance ceases to matter, this anchoring effect disappears: the link between birthplace geography and city size is severed, and workers are redistributed across destinations in proportion to non-geographic characteristics. This flattening of the distribution is therefore not driven by changes in agglomerative forces in destinations but by the removal of the spatial frictions that make birthplace geography matter in the first place.[11]

Figure 7(b) further shows that the relative size reductions are concentrated among

[11] Because tolerance cutoffs increase exponentially with distance, removing spatial frictions not only compresses the size distribution but also reduces overall city sizes. In particular, the loss of nearby inflows is not fully offset by gains from distant sources.

smaller destinations. Larger cities experience smaller proportional declines because they already draw workers from a wide range of birthplaces, including distant ones, making their inflows less sensitive to geographic rearrangements. Smaller destinations, in contrast, rely heavily on nearby birthplaces and lose most of their inflows when those are reassigned elsewhere.[12]

While our counterfactual focuses on physical distance, we speculate that similar patterns would emerge with respect to non-geographic mobility such as social or economic relocation frictions, which are not directly observable in the data. Investigating such frictions remains an avenue for future research.

4 Conclusion

This paper develops a framework linking workers' relocation tolerance to the equilibrium distribution of city sizes. Each worker draws a geographic and non-geographic mobility factor from a common distribution and chooses whether to relocate to a city to access urban productivity. In equilibrium, migration outcomes reflect both birthplace geography and individual aversion to relocation, allowing urban size patterns to be traced back to micro-level heterogeneity in mobility.

The model generates two core predictions: first, that variation in distance tolerance underpins variation in agglomeration intensity across cities; second, that individuals perceive distance on a nonlinear, approximately logarithmic scale, a feature that helps rationalize the common empirical practice of classifying moves as local, intrastate, or interstate. Both predictions are supported by U.S. migration data: a small subset of highly mobile workers disproportionately drives the formation of large cities, while most remain anchored near their birthplaces.

While non-geographic relocation tolerance is unobservable, it can be inferred from observed migration patterns. The cutoff value, the minimum tolerance level required to justify relocation, can be recovered from equilibrium inflow data and the distribution of distances. The employed data indicate that this value rises with moving distance but at a diminishing rate, and tends to be lower in larger destinations.

Counterfactual analysis suggests that eliminating variation in birthplace would significantly compress the city-size distribution, leading to smaller and more uniform cities. Imperfect geographic mobility therefore appears to act as an amplifying force behind urban concentration and the heavy-tailed city-size distribution.

The analysis is subject to several important limitations. The model abstracts from heterogeneity in worker characteristics, treating each city as hosting a single type. Urban productivity is not linked to migrant characteristics, and the framework captures a static

[12] If the reduction in spatial frictions is targeted at a single location rather than nationwide, it may instead boost inflows into that destination. Appendix A.4 examines such a localized policy scenario.

snapshot rather than dynamic migration and growth processes. Moreover, it assumes independence between birthplace and non-geographic relocation tolerance, whereas real-world patterns, such as cultural norms, labor market institutions, or corporate transfers, may generate correlations. Extending the framework to allow for type co-location, endogenous productivity accumulation, and dynamic feedback would offer fruitful directions for future research.

A Appendix

A.1 Static Framework and Endogeneity of Birthplaces

A key limitation of the present analysis is that the distribution of birthplaces is treated as exogenous rather than determined endogenously by historical agglomeration forces. In reality, long-run economic and demographic dynamics shape both migration patterns and the spatial distribution of birthplaces. Beyond first-nature advantages, understood as exogenous geographic fundamentals, these patterns are strongly reinforced by second-nature advantages including agglomeration and historical path dependence, where locations with persistent advantages attract and retain larger populations (see Rosenthal and Strange [RS04], and Ellison and Glaeser [EG99]).

Modeling this coevolution would require a dynamic framework in which migration and agglomeration interact over multiple periods. For tractability and given data limitations, the present article adopts a static spatial equilibrium framework, in which relocation decisions occur simultaneously and birthplace locations are fixed. This treatment aligns with models including Glaeser and Mare [GM01] and Eeckhout [Eec04], where migration is treated as a one-time decision, abstracting from intertemporal optimization. A static framework makes analytical characterization and estimation feasible.

The equilibrium in Definition 2.3 should be interpreted as describing a short- to medium-run allocation of population, over a horizon in which the distribution of birthplaces can be considered approximately fixed. While every migration event technically alters the birthplace distribution for future cohorts, these adjustments occur gradually as new cohorts are born and migration accumulates. Empirically, major shifts in birthplace concentration tend to unfold over decades, whereas migration decisions are typically made within a single cohort's working life. The static model therefore captures a snapshot of spatial sorting over a period during which fundamentals are relatively stable, but does not aim to represent the long-run coevolution of migration and population concentration.

By contrast, there is a growing body of work that takes dynamic approaches to endogenize birthplace distributions. For example, Behrens et al. [BDRN14] extend their framework to an infinite-horizon setting. Giannone et al. [GLPP23] identify dynamic trade-offs involving consumption, migration, and savings, while Davis et al. [DFV21] analyze the response of population dynamics to productivity shocks. Implementing such approaches typically requires longitudinal migration data that go beyond what is available in the ACS dataset used here. Extending the framework to incorporate moving distance, migration frictions and endogenous birthplace dynamics is therefore left as an avenue for future research.

A.2 Uniqueness

This appendix provides a sufficient condition for uniqueness of equilibrium city size. Using (14), define the mass of incoming residents (for $s \in (0, 1]$) as

$$H(s) := \int_0^{\frac{1}{2}} f_X(x)\, G_Y(y(x, s))\, dx, \tag{17}$$

where $y(x, s)$ is the cutoff relocation tolerance (13) defined implicitly by the indifference condition $\varphi(x, y, s) = 0$. Since $v(s)$ is analytically defined and continuously differentiable on $(0, \infty)$ under the maintained parameter restrictions, and $r(x, y)$ is differentiable in y by Assumption 2.1, the cutoff function $y(x, s)$ and the inflow mapping $H(s)$ are continuously differentiable in s.

The equilibrium condition (8) can be written as the fixed-point problem $s = H(s)$. A sufficient condition for uniqueness is the contraction condition

$$\sup_{s\in\mathbb{S}} |H'(s)| < 1, \tag{18}$$

on a relevant interval $\mathbb{S} \subseteq (0, 1]$. Indeed, by the mean value theorem, for any $s_1, s_2 \in \mathbb{S}$, $|H(s_1) - H(s_2)| \leq \left(\sup_{s\in\mathbb{S}} |H'(s)|\right) |s_1 - s_2|$. Thus, if s_1 and s_2 are both fixed points, then

$$|s_1 - s_2| = |H(s_1) - H(s_2)| \leq \left(\sup_{s\in\mathbb{S}} |H'(s)|\right) |s_1 - s_2|,$$

which implies $s_1 = s_2$ whenever (18) holds.

Differentiating (17) yields

$$H'(s) = \int_0^{\frac{1}{2}} f_X(x)\, g_Y(y(x, s))\, \frac{-\partial y(x, s)}{\partial s} dx. \tag{19}$$

From the implicit function theorem on $\varphi(x, y, s) = 0$, $\dfrac{\partial y(x, s)}{\partial s} = \dfrac{v'(s)}{r_y(x, y(x, s))}$. Substituting this expression into (19) gives

$$H'(s) = v'(s) \int_0^{\frac{1}{2}} f_X(x) \frac{g_Y(y(x, s))}{-r_y(x, y(x, s))} dx. \tag{20}$$

Condition (18) therefore requires that the marginal urban advantage $v'(s)$ is not too large relative to (i) how strongly relocation costs respond to tolerance (controlled by $-r_y$)

and (ii) how much probability mass lies near the cutoff (controlled by g_Y). Intuitively, (18) ensures that a small increase in s induces less than a one-for-one increase in the mass of incoming residents, ruling out self-reinforcing amplification that could otherwise generate multiple fixed points.

A.3 City-Size Distribution in an Alternative Form

By substituting the transformation (9) with $z = y$ and $s = s(x, y)$; (10) with $x = x(z, s)$ and $y = y(z, s)$, we obtain an alternative representation of the city-size distribution in (11):

$$f_S(s) = \int_{\mathbb{R}} f_X\big(x(z, s)\big) f_Y(z) \frac{v_s(s)}{r_x\big(x(z, s), z\big)} dz. \tag{21}$$

This form is analogous to that in Proposition 2.2, except that the roles of x and y are re-parameterized to facilitate analysis of how the geographic distribution of population shapes $f_S(s)$. Just as y governs heterogeneity in individual relocation tolerance, x governs spatial frictions through the relocation cost $r(x, y)$.

In addition, Assumption 2.1 implies that the cost increase tapers off with distance x. Thus, larger differences in x are required to produce the same impact on $f_S(s)$ at longer ranges.

This representation is useful for analyzing how sensitive agglomeration patterns are to the initial spatial distribution of the population $f_X(x)$. For example, if a large inland city such as Denver or Phoenix were hypothetically relocated to a denser coastal region, the mass of $f_X(x)$ would shift toward shorter distances to other population centers, potentially increasing the city's inflows and amplifying its size. Equation (21) allows these geographic counterfactuals to be evaluated explicitly.

A.4 Local Policies to Reduce Relocation Frictions

Whereas a countrywide reduction in spatial frictions lowers city sizes across the board (see footnote 11), a localized reduction in relocation costs increases the size of the targeted city while holding frictions to other destinations constant.

Some recent policy efforts aim to promote domestic migration toward smaller or mid-sized cities. A prominent example is the Tulsa Remote Program, which offers financial incentives to remote workers who relocate to Tulsa, OK. Similar initiatives have emerged in other U.S. cities and states, targeting mobile, high-skill individuals to enhance local development. In this section, we assess such policies in light of our model.

This type of targeted relocation subsidy echoes the environment analyzed by Zabek [Zab24], who examines place-based transfers in a dynamic general equilibrium setting. More broadly, Austin et al. [AGS18] highlight the role of place-based interventions in addressing persistent spatial inequality and regional economic divergence. By contrast, the present analysis focuses on short-run, localized relocation responses within a static, partial equilibrium framework. This scope should be interpreted as complementary to studies that incorporate nationwide general equilibrium feedbacks. It also reflects the structure of the ACS data, which capture annual migration flows rather than long-run population dynamics.

Our framework accommodates these initiatives by allowing the cost of relocation $r(x, y)$ to decline in cities offering such subsidies. Since $r_x(x, y) > 0$ and $r_y(x, y) < 0$, a relocation grant effectively shortens the perceived distance to the city or raises the tolerance for relocation. While we lack data to directly convert monetary incentives into equivalent distances, we approximate their effect by reducing the effective moving distance.

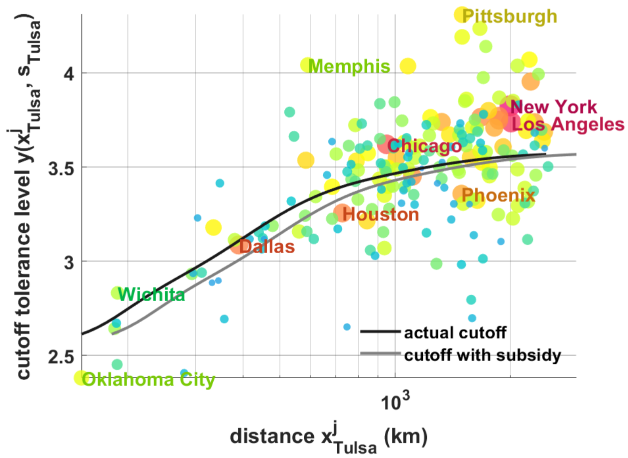


Figure 8. Cutoff tolerance among movers to Tulsa, OK. The horizontal axis measures the log distance from birthplaces to Tulsa. Dots represent the empirical cutoff tolerance levels at each birthplace, with their sizes proportional to the log of birthplace populations, accompanied by the black line representing the kernel smoothed cutoff tolerance. The gray line represents a hypothetical cutoff tolerance assuming a relocation subsidy equivalent to a 20% reduction in distance.

Table 1 indicates that a 1% reduction in moving distance reduces the cutoff tolerance by approximately 0.21%. This translates into a 1.56% increase in in-migration to Tulsa.[13]

Importantly, flat-rate subsidies may disproportionately attract migrants from nearby states rather than distant ones, as the impact of distance reduction diminishes with actual distance. Figure 8 compares the empirical cutoff tolerance profile with a hypothetical one under a 20% distance reduction. The cutoff tolerance level declines sharply for birthplaces near Tulsa, while the change is marginal for distant locations such as Los Angeles. As examined in Proposition 2.3, cutoff tolerance becomes less sensitive to distance at longer ranges. Consequently, most applicants to such programs are expected to originate from neighboring states.

Similarly, the incoming migrant pool is likely to be disproportionately composed of individuals who were just below the original cutoff tolerance. By contrast, the subsidy is unlikely to affect those with low y, such as individuals with strong local ties, whose relocation decisions are less responsive to moderate changes in moving costs.

A.5 Adjustments for the Shape of Country

The theoretical model assumes a circular country where all cities are equally reachable, with a maximum distance of $1/2$. In contrast, the actual U.S. landmass is irregularly

[13] See Figure 9 for other destinations.

shaped, and the maximum distance to each MSA varies. For example, Omaha-Council Bluffs, NE-IA has the shortest maximum range at 2,309 km (to Santa Rosa, CA), while Bangor, ME and Santa Cruz-Watsonville, CA have the longest maximum range at 4,474 km (to each other).

This geographic asymmetry could bias estimates of distance tolerance: cities located near the edges of the country may appear smaller than predicted because their average distance to birthplaces is greater than that of more centrally located cities.

In practice, however, we find little evidence that such geographic bounds systematically affect city size.[14] This suggests that geographic bounds do not meaningfully distort city sizes, particularly since distance is perceived logarithmically as discussed in (2), compressing the perceived difference between long and very long distances.

A.6 Gradient of Cutoff Tolerance

To validate the cutoff estimation, we examine whether cities that draw migrants from greater distances tend to be larger. For each MSA, we regress inflow on $\log x$ to estimate two parameters: α_i (intercept) and β_i (distance elasticity). See Figure 1(b). We then estimate the following relationship: $\log s_i = \gamma_0 + \gamma_1 \alpha_i + \gamma_2 \beta_i$. The estimated γ_2 is significantly positive, indicating that cities with flatter inflow decay curves, i.e., those that retain inflows over longer distances, are systematically larger. This aligns with the model's prediction that variation in relocation tolerance contributes to differences in city size.

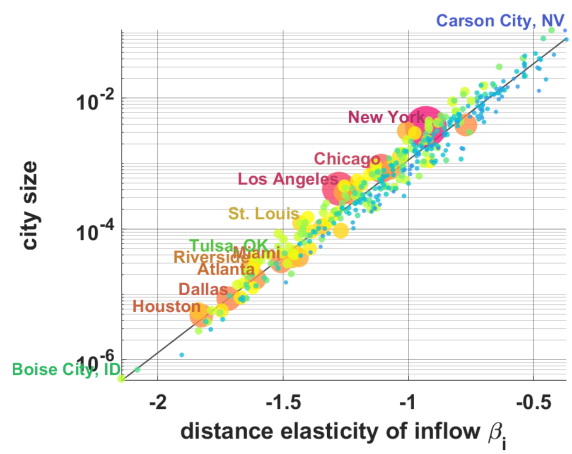


Figure 9. City sizes (controlled for α_i) over distance elasticity of inflow β_i. Dot sizes are proportional to city size.

To reinforce this point, we also regress city size on the mean and standard deviation of inflow distances. Both are positively associated with population size: large cities not only draw from farther away but also from a more varied range of locations.

These results are visualized in Figures 2 and 9 and are inconsistent with perfect geographic mobility, which would imply invariant inflow patterns across cities.

[14] To test whether geographic bounds bias city size estimates, we regressed log city size on the log of the maximum distance from each city to any origin. The result,

$$\text{size} = \underset{(1.91)}{5.229} + \underset{(2.71)}{0.9109} \text{ max range}, \quad (R^2 = .01926)$$

(t-statistics in the parentheses) indicates no statistically meaningful relationship. The small positive coefficient reflects the geographic placement of large cities rather than a causal effect of maximum range itself: major metropolitan areas are concentrated along the East and West Coasts, where maximum distances are naturally longer.

A.7 Data Appendix

This appendix documents the data sources, sample construction, and variable definitions used throughout the paper. All empirical analyses use data from the U.S. Census Bureau, American Community Survey (ACS), 2009–2013, 5-year estimates. Specifically, we use Metro Area-to-Metro Area Migration Flows. In the span of five years, ACS surveyed a sample of 10.6 million households nationwide. The questionnaire asked respondents where they lived a year prior to the survey, along with their residence at the time of survey. Migration records are tabulated by Metropolitan Statistical Area (MSA). There are 381 MSAs. Figure 10 visualizes the 381×381 origin-destination matrix. For empirical analyses in the main text, two MSAs in Alaska and two in Hawaii are excluded from regression analyses due to their geographic isolation (see Appendix A.8 for details).

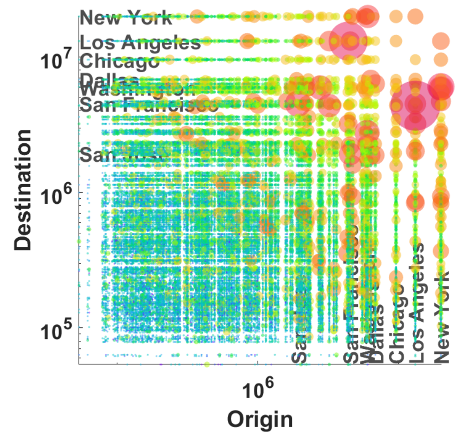


Figure 10. Origin-destination migration matrix. Each dot represents a migration flow, with its size proportional to the number of movers. Both origin and destination MSAs are sorted by population size, and both axes are displayed on a logarithmic scale.

Table 2 reports descriptive statistics for the main variables used in the analysis, accompanied by the density plot represented in Figure 11(a).

variable	mean	std. dev.	geometric mean	min	max
population	7.12E+05	1.63E+06	3.16E+05	53,736	1.99E+07
migration flow	173	812	42	1	90,494
distance (km)	1,662	1,035	1,307	27	4,474

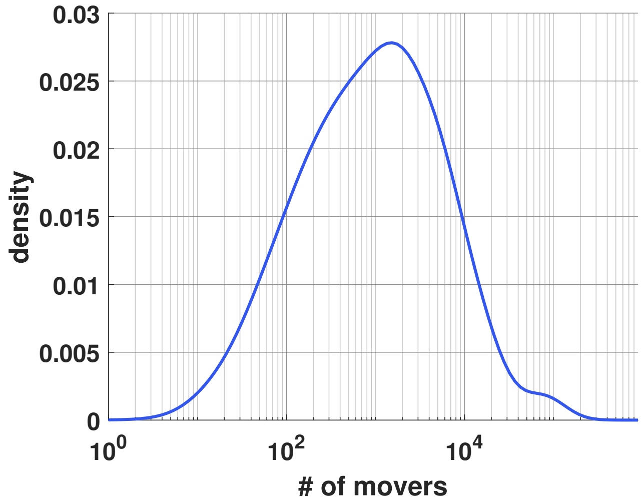
Table 2. Summary statistics for main variables.

Table 3 lists five city pairs with the largest migration flows. Figure 11(b) presents the frequency of moving distance.

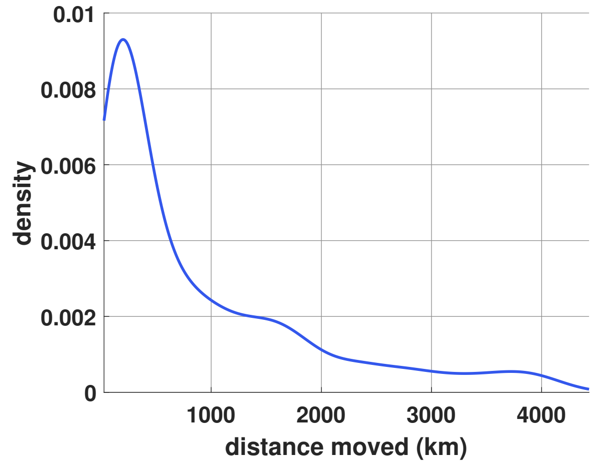
	from	population	to	population	movers	distance (km)
1	Los Angeles	13,106,114	Riverside	4,371,914	90,494	194
2	Riverside	4,371,914	Los Angeles	13,106,114	54,711	194
3	New York	19,901,696	Philadelphia	6,030,541	26,957	163
4	San Jose	1,924,569	San Francisco	4,521,312	24,536	125
5	Washington DC	5,950,951	Baltimore	2,768,374	22,944	95

Table 3. City pairs with largest annual migration flows.

Distance x is the great-circle distance between birthplace and destination MSA centroids, computed from U.S. Census TIGER/Line Shapefiles.



(a) Distribution of movers. The heavy right tail reflects the skewness in the destination size distribution, with a small number of large metropolitan areas accounting for a disproportionate share of total inflows.



(b) Distribution of movers by distance moved. The right tail declines gradually, reflecting the geographic concentration of major metropolitan areas along the East and West Coasts. For instance, the distance between New York and Los Angeles spans 3,935 km.

Figure 11.

	MSA	population	inflow	inflow/population (%)
1	Los Angeles, CA	13,106,114	244,099	1.86
2	New York, NY-NJ-PA	19,901,696	228,599	1.15
3	Washington, DC-VA-MD-WV	5,950,951	196,434	3.30
4	Riverside, CA	4,371,914	178,510	4.08
5	Dallas, TX	6,817,518	172,896	2.54

	MSA	population	outflow	outflow/population (%)
1	New York, NY-NJ-PA	19,901,696	391,089	1.97
2	Los Angeles, CA	13,106,114	339,083	2.59
3	Chicago, IL-IN-WI	9,553,268	215,029	2.25
4	Washington, DC-VA-MD-WV	5,950,951	203,730	3.42
5	Dallas, TX	6,817,518	160,285	2.35

Table 4. Cities with largest inflows and outflows.

Replication code and data extraction scripts are available upon request.

A.8 Exclusion of MSAs in Alaska and Hawaii

As is customary in the field, we exclude MSAs in Alaska and Hawaii from all empirical analyses. While their long distance to MSAs in the contiguous U.S. does not pose a major issue in itself for movers' logarithmic perception of distance (see (2)), the absence of nearby birthplaces generates a systematic incongruity in the estimation of relocation tolerance.

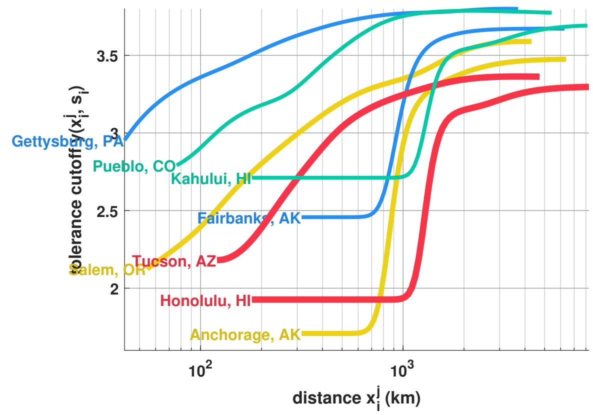


Figure 12. Cutoff tolerance for four MSAs outside the contiguous U.S., compared with four MSAs in the contiguous U.S. of similar size. This plot corresponds to Figure 5(a).

To illustrate, consider the cutoff tolerance values. Figure 12 plots the cutoff tolerance for the four MSAs in Alaska and Hawaii, along with four MSAs in the contiguous U.S. of comparable size: Honolulu and Tuscon; Anchorage and Salem; Kahului and Pueblo; Fairbanks and Gettysburg. The Alaskan and Hawaiian MSAs maintain relatively low cutoff tolerance values for the first hundreds of kilometers, whereas their mainland counterparts show higher cutoff levels at similar distances. This is not because these MSAs attract individuals with intrinsically low relocation tolerance y, but rather because the closest birthplace on the contiguous U.S. is located 2,267 to 3,856 km away.

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