Urban income mobility patterns in the United States: 1980-2010

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Abstract

Spatial income inequality between neighborhoods within and across cities has been attracting substantive attention. As a static view cannot provide a complete picture for understanding the driving processes of urbanization and spatial polarization, this paper turns its lens to spatial income mobility, which ties together spatial inequality at different moments in time and provides insights into the underlying inequality dynamics. Specifically, this paper provides an empirical study of the urban spatial income mobility in the United States with the decennial census and American Community Survey (ACS) datasets for 294 metropolitan statistical areas (MSAs) over periods 1980, 1990, 2000, and 2010. We use decomposition methods to unpack the overall spatial mobility into contributing components, which are Exchange, Growth, and Dispersion mobility, to get new insights into the multidimensional urban processes. One focal point is to investigate the dominant force, as well as whether, how, and why it changed across space and over time. We find a very clear decline trend in the dominant position of Growth mobility, along with a trend of Exchange mobility gradually dominating the overall process over 1980-2010, indicating a high level of temporal heterogeneity in the spatial income inequality dynamics which remains underexplored in the current literature. The temporal heterogeneity is also reflected in how the spatial income mobility within each MSA evolved, and how this has been driven by different socioeconomic factors over time.

Keywords

Spatial income mobility, Neighborhood change, Multidimensional, Decomposition, Economic development

Introduction

In 2018, the United Nations reported that 55% of the world's population lived in urban areas. Moreover, this number is expected to grow to 68% by 2050 (United Nations 2018b). This rapid urbanization process has been taking place in mega, medium, and small cities within developing as well as developed countries in recent decades (United Nations 2018a). With more and more people residing in cities, it is essential to study not only cities themselves, but also their economic development processes whose effects cascade onto city residents. Although there is evidence that the income level and the urban population share for 180 countries in 2000 are positively correlated (Bloom et al. 2008), questions remain unanswered surrounding the relationship between urbanization and spatial inequality within cities.

Increasing urbanization is occurring alongside a return to historic levels of interpersonal income inequality (Piketty and Saez 2003). Not all members of society have benefited equally from the extensive economic growth experienced over the recent decade. Instead, the wealthiest parts of the income distribution have claimed the lion share of the growth. While these patterns have been well-documented, what is unclear is if this form of distributional polarization is being played out within expanding cities fueling the urbanization process. More specifically, we do not know if the growth of cities exacerbates the level of spatial inequality within cities, or if the aggregate growth of a city triggers new types of intraurban income mobility. Mobility in the broader income distribution literature is the process that ties together inequality at different moments in time. Reframing mobility to the case of intraurban spatial income distributions provides us with the opportunity to examine the questions surrounding urbanization and spatial polarization.

In this paper, we turn a spatially explicit lens on the patterns of intraurban income mobility across the US metropolitan areas over the period 1980-2010. In doing so, we pose the following questions. First, we focus on the direction of intraurban income mobility - have there been secular increases, decreases, or have these patterns been episodic? Second, what have been the roles of different components of intraurban mobility? As we discuss more fully below, a global indicator may mask different types of mobility. Therefore, unpacking the contributions of these different types of mobility is an important undertaking. Third, are these patterns spatially uniform, or is there spatial heterogeneity in mobility dynamics across the US? If it is the latter case, what are the underlying mechanisms?

The majority of attention on the question of income mobility has focused on national systems. More recently, a number of scholars have begun to examine the questions of *spatial income mobility*. Modai-Snir and van Ham (2018a,b) were the first to apply the income mobility decomposition technique to differentiate the multiple processes underlying neighborhood socioeconomic change in urban areas of Israel and US. While Modai-Snir and van Ham (2018a) focuses on the Tel-Aviv metropolitan area - the largest in Israel, Modai-Snir and van Ham (2018b) extends the analysis to 22 largest metropolitan statistical areas (MSAs) in U.S. Specifically, they focus on *median household income* and evaluate how the contributions from exchange, growth and dispersion mobility processes varied across those large MSAs over a single period 1980-2010. The latter two processes combine into the so-called structural component and account for half or more of the overall income mobility in half of the MSAs examined.

This paper contributes to the literature on urban inequality dynamics in four ways. First, we consider a larger number of US metropolitan areas, including not only the largest cities, but also those in the middle and lower tail of the city size distribution; this sample yields over 54,000 census tracts from 294 US MSAs over the period 1980-2010. Second, we place a particular emphasis on the evolution of mobility patterns within this period, considering whether different components of income mobility follow different paths over time. Third, we develop an inferential framework for the income mobility decomposition that moves the literature beyond its current descriptive orientation. Finally, we examine the spatial distribution of overall income mobility and its contributing components through both global and local spatial autocorrelation indices, and provide a preliminary study towards identifying the determinants of spatial income mobility.

In the remainder of the paper, we first review the literature on spatial income inequality and mobility. Next, we provide an overview of the construction of our dataset and introduce the framework of the income mobility measurement that we employ. We then present our results, focusing first on the overall trends in long-term urban income mobility, followed by an unpacking of the global trends to examine spatial and temporal heterogeneity, then a spatial regression analysis exploring explanatory factors for the observed pattern. In the end, we discuss the results and conclude by summarizing our key findings and their implications for policy, and identifying future research directions.

Literature review

Interpersonal inequality and mobility

The relationship between interpersonal income inequality and income mobility can be considered from a number of perspectives. Interpersonal income inequality is concerned with the level of disparity between the incomes of individuals in a society and a vast literature has examined the question of interpersonal income inequality at the urban (Glaeser et al. 2009), regional (Tselios et al. 2012), national (Smeeding 2005), and global scales (Darvas 2019; Sala-i Martin 2006). The dynamics of interpersonal inequality have also commanded substantial attention, again at different spatial scales and international contexts (Lukiyanova and Oshchepkov 2012; Aristei and Perugini 2015; Khor and Pencavel 2006).

Income mobility can also take on different meanings in different contexts. Considering personal income distributions, Fields (2006) identified six facets of income mobility: (1) *time-dependence* considers the extent to which individuals' positions in the current income distribution are dependent on their positions in the past; (2) *positional-movement* reflects changes in the rank or percentile individuals experiences; (3) *share movement* is due to changes in the shares of total income individuals holds over time; (4) *income flux* reflects the size of changes in individuals' incomes over time; (5) *directional income movement* is about the directions and magnitudes of individuals' income changes; (6) *mobility as an equalizer of long term incomes* compares snap-shot inequality at one point in time with inequality over a longer horizon.

In addition to the question of different spatial scales, investigations of interpersonal income can also consider different time horizons. From a short-run perspective, the question becomes one of intragenerational income mobility, or how one individual's income changes from one year to the next. One thread of such studies is concerned about the relationship between individual income inequality and intragenerational income mobility. A positive relationship is considered as evidence for supporting the "prospect of upward mobility" (POUM) hypothesis which is a key component of redistribution theory (Benabou and Ok 2001). In Europe, household income inequality has been found to be positively related to income mobility at the national (Rodríguez et al. 2008) and regional (Prieto-Rodríguez et al. 2010) scales, provide evidence for the opposition to income redistribution policies.

Focusing on the longer term process of intergenerational mobility, Chetty et al. (2014a,b) find that U.S. commuting zones with high levels of upward mobility have lower residential segregation, lower income inequality, better schools, greater social capital, and higher family stability. The distinction between intergenerational and intragenerational frames is important as income mobility ties two (or more) distributions with associated inequality measures. The time frames are fundamentally distinct between studies of intragenerational and intergenerational mobility.

Spatial income inequality and mobility

Thus far, the focus on space as been limited to questions of how the geographical context may influence personal income mobility and personal income inequality. A related set of questions surround the notions of *intraurban spatial income inequality and mobility*. Here the focus is the income distribution defined on spatial units within a city (e.g. neighborhoods), and how this distribution evolves over time. Put differently, spatial income mobility is concerned with the degree to which different neighborhoods ascend or decline, whether these dynamics differ by region, and how processes like globalization and *urbanization* affect them.* Another way to view this issue is through the lens of neighborhood stability and change. As Modai-Snir and van Ham (2018a, p. 2) describe,

> Increasing inequality affects urban areas by changing their income distributions. This follows from the change in incomes of those living in the urban area but also from the change in characteristics of those leaving and entering the urban area.

Framed this way, it is clear that a wide variety of factors could influence spatial income mobility; If existing residents experience wage growth (either from occupational change or sectoral growth), then growth is the result of an *economic* process. If the income distribution shifts due to aggregate population gain or loss, then a *demographic* function is at play. Another possibility is that *cultural* processes like segregation and stigma are decreasing over time, leading to intra-regional migration that reshapes the composition of neighborhoods (without necessarily changing the income of any resident). Finally, shifts in urban development and infrastructure provision would indicate a *policy* process that could affect the allocation of people into neighborhoods. Together, these processes suggest a variety of ways in which the economic characteristics of neighborhoods inside a given metro region can evolve over time, some of which include residential mobility, others of which do not.

Consider the economic restructuring that took place in the United States over the last several decades as it has moved from the manufacturing economy to a knowledge and service-based economy. During this transition, the larger structural process (economic restructuring at the national level) led to an overall decline in manufacturing jobs, triggering an exchange in the neighborhood hierarchy in some metropolitan regions because wage, occupation, and educational segregation imply that manufacturing workers are more likely to cluster in similar neighborhoods, and the loss of a critical employment base means some neighborhoods will experience greater levels of joblessness and wage decline as a result. In this example, both structural and urban-level processes interact, causing changes in both total inequality and the spatial distribution thereof as the city gets more polarized and experiences a neighborhood re-shuffling simultaneously. Similarly, these processes can work in the other direction, with urban-level processes triggering structural exchange. Consider, for example, if a city such as Los Angeles makes a major infrastructure investment in fixed-rail transit. The new modality will shift accessibility to amenities triggering a change in the neighborhood hierarchy, and leading to considerable exchange mobility—but may also trigger in-migration of lower-income transit-dependent residents for whom the city is now available, again affecting both exchange and dispersion.

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*A key distinction between spatial income mobility and personal income mobility is that the former involves panels of locations, while the latter uses panels of individuals. Panels of locations will be a mixture of different individuals over time, some being residents remaining in a location over the interval, as well as individuals who enter during the panel, or exit through migration, births, and deaths.

Finally, consider a major demographic event such as the great migration, during which black Americans emigrated in great numbers from the South into other regions of the country (Sharkey 2015). Here again, the demographic process results in shifts to both structural and urban dynamic components of economic inequality, since both intra-urban segregation and the structural position of African-Americans in the larger economy mean that both exchange and dispersion components will be affected as such a large population group moves dramatically in space. Perhaps more importantly, this scenario also presents an opportunity to examine critically overlooked aspects of socio-spatial economic mobility that include spatial dependence and geographic scale. Both the demographic and economic examples described above have distinctly regional manifestations, as certain demographic groups and employment categories are overly concentrated in certain regions of the country. As such, it can be difficult to disentangle structural processes from urban dynamic processes because of their interrelationship at the meso-geographic (regional) scale.

Thus, in the following paper, we conduct a decomposition of economic mobility following a similar framework as Modai-Snir and van Ham (2018a). We expand upon their empirical work, however, by applying our framework to every MSA in the U.S. in three cross-sectional time periods, a strategy that permits us to examine how spatial and temporal heterogeneity in the underlying processes of income mobility may lead to different outcomes in different regions of the U.S. This allows us to examine whether, for example economic restructuring tends to be a larger driving factor in the industrial midwest, whereas cultural processes and slowly-eroding historical racism in the antebellum South may be a more important process in that region. This strategy also allows us to parse different distinct time periods, each of which was shaped by vastly different political, economic, and cultural atmospheres, and describe how each different context led to different forms of spatial economic mobility.

Data and Methodology

Study Area and Data

We adopt neighborhoods as our units of analysis to reveal the spatial income mobility patterns of urban areas in the United States. Census tracts, which contain about 4,000 residents and can be considered homogeneous internally, are used as a proxy for neighborhoods. Urban researchers have adopted the same strategy in various studies of neighborhood effects (Leventhal and Brooks-Gunn 2003), neighborhood change (Delmelle 2017; Zwiers et al. 2017), and residential segregation (Reardon and Bischoff 2011; Bischoff and Reardon 2014). Although census tracts are designed to be relatively permanent statistical subdivisions over time, they could undergo changes such as merge, split, and corrections due to population change. As such, boundaries are re-drawn during each decennial census, creating difficulties for longitudinal analyses because enumeration units are inconsistent. In this study, we account for this issue by leveraging the Longitudinal Tract Data Base (LTDB) which provides a set of consistent tract boundaries with earlier decades "cross-walked" to 2010 representations (Logan et al. 2014). We focus on average per capita incomes within tracts in census years 1980, 1990, 2000 and 2010. After removing bad records and missing values, and further abandoning MSAs which have less than 25 tracts of meaningful average per capita income values, our sample results in 54,275 census tracts distributed within 294 MSAs[†]. We adjust all income values for inflation and express them in 2010 dollars.

Income mobility measures and processes

We investigate the spatial income mobility patterns in the urban U.S. with income mobility measures. Income mobility analysis is concerned with measuring the changes of individuals' economic status/well-being over time (Fields and Ok 1999). There are several approaches for assessing the extent of changes, with many different mobility indices developed to study a variety of conceptually-specific dynamics (Fields 2006).

Apart from measurements that constitute mobility, another important topic in the literature focuses on the underlying processes that *drive* income changes. Prior work in the field differentiates two general processes in income dynamics: exchange and structural processes (Ruiz-Castillo 2004). While the former captures reranking processes in the income distribution, the latter captures changes in the shape of the distribution. We use the income changes of three individuals (or neighborhoods in this paper) to illustrate these two processes. As shown in Table 1, the initial income values of the three individuals constitute vector $y0$ while the income values in the next time period constitute vector $y1$. The income changes are denoted as $y0 \rightarrow y1$. Processes I, III, IV do not give rise to changes in rank, in the sense that three individuals (tracts in our case) keep their initial ranks, and thus, we observe no exchange process in the income distribution. On the other hand, processes II, V, VI, and VIII lead to rank exchanges between the first and third individuals.

Analyses of structural change consider two properties of the income distribution: mean and dispersion. The former describes growth or decline in the economy as a whole, while the latter relates to the changes in the shares each individual receives and is central to inequality dynamics. In Table 1 ($y0 \rightarrow y1$), process III only experiences an increase in the size of the economy (mean/total income doubles), and is a pure growth process, while process IV is pure dispersion process, as the only change comes from the changes in the income shares of individuals 1 and 2. Processes V, VI, VII, and VIII are a mixture of two or three mobility processes.

[†] Out of the 294 MSAs, three are not within the lower 48 states: Anchorage MSA in Alaska, as well as Urban Honolulu and Kahului-Wailuku-Lahaina MSAs in Hawaii. We include these three MSAs in the mobility analysis, but exclude them for further exploratory and confirmatory spatial analysis on estimated mobility statistics.

[Table 1 about here.]

In the sections above, we outline six mobility concepts (Fields 2006) that capture one or more underlying processes (exchange/growth/dispersion). Despite lively inquiry into each of the six dimensions, different income indices are not comparable and the question of finding the dominant process or force driving overall income mobility remains unresolved. To address this gap, we leverage a decomposition technique commonly used in economics and econometrics to separate an income mobility measure into its underlying exchange and structural (and further, growth and dispersion) processes as components of the combined measure (Fortin et al. 2011). Using this framework, the components are comparable and we can evaluate which process dominates changes in the income distribution over a given time period.

Measure of income flux We select a measure of income flux as our measure to decompose and analyze since it is sensitive to all three processes. Income flux is concerned with the degree to which individuals' incomes remain stable over time. Since it does not differentiate gain from loss, it is also referred to as "non-directional income movement". The measure of income flux we consider in this article is based on the absolute difference in log incomes (Fields and Ok 1999). This measure has several useful properties - an important one is subgroup decomposition. Suppose we have n observations for an initial time period 0 and a subsequent period 1, and $y0$ and $y1$ are n-vectors of incomes. The income flux measure M for this two-period framework is defined in Equation (1):

$$M(y0, y1) = \frac{1}{n}\sum_{i=1}^{n} |\log(y1_i) - \log(y0_i)|. \tag{1}$$

The usage of log difference is to take the initial incomes into account. In other words, a dollar change would be smaller for a higher initial income compared with a lower initial income. We do not weight this measure by populations within the spatial boundaries (census tracts here) as the discussion from the regional inequality literature suggests that the "weighted" approach is conceptually inconsistent and does not yield an estimate of regional inequality (Gluschenko 2018).

A hierarchical decomposition We decompose the income flux measure M into two explanatory factors–exchange and structural–while the structural factor is further subdivided into growth and dispersion factors:

$$\begin{aligned} M &= M_E + M_S \\ &= M_E + M_G + M_D \end{aligned} \tag{2}$$

where M_E, M_S, M_G and M_D are mobility components contributed by the "Exchange", "Structural", "Growth", and "Dispersion" processes respectively. One intuitive approach to decomposition is to assess the marginal impact of each process, that is, to remove the process and assess the income mobility difference between pre- and post-removal (van Kerm 2004). The idea is to construct a counterfactual income vector with the process removed, and this vector would replace the second income vector $y1$. We will use process VIII ($(1, 2, 3) \rightarrow (5, 4, 3)$) in Table 1 to explain the construction of counterfactual vectors.

Exchange process The counterfactual income vector y^E with the exchange component removed is constructed by sorting $y1$ based on the order of $y0$ without changing anything else. For the case of process VIII, $y^E = (3, 4, 5)$ (equivalent to$y1$ in VII). Thus, the marginal effect for the Exchange process is

$$M_E = M(y0, y1) - M(y0, y^E). \tag{3}$$

Structural process The counterfactual income vector y^S is constructed by removing the structural process from the original process $y0 \rightarrow y1$. That is, we need to remove changes to the shape of the income distribution, including the mean and the dispersion. Thus, y^S is constructed by sorting $y0$ based on the order of $y1$ - only keeping the reranking. For the case of process VIII, $y^S = (3, 2, 1)$ (equivalent to $y1$ in II). The marginal effect for the Structural process is

$$M_S = M(y0, y1) - M(y0, y^S). \tag{4}$$

Shapley procedure Both Equations (3) and (4) are first-round marginal effects and they do not necessarily add up to the income flux measure $M(y0, y1)$ and, thus, do not fulfill our purpose. To ensure the decomposition is exact and additive, we adopt a sequential marginalist procedure. We can either start with Equation (3) to obtain the Exchange component, and then obtain the Structural component by further removing the Structural component from the remaining effect ($M(y0, y^E) - M(y0, y0) = M(y0, y^E)$ as the counterfactual vector with the structural process removed for y^E is $y0$), which is identical to deducting M_E from the total income flux value. Alternatively, we could start with Equation (4) to obtain the Structural component, and then obtain the Exchange component by deducting M_S from the total income flux value. To ensure the decomposition is symmetric, in the sense that the contribution from each factor is independent of the order in which the factor is evaluated, we adopt the Shapley decomposition procedure which averages all potential sequences and has proven to be an effective and general solution to assess the relative importance of contributory factors (Shorrocks 2013):

$$
\begin{aligned}
M_E &= \frac{1}{2}\{\{M(y0, y1) - M(y0, y^E)\} + M(y0, y^S)\}, \\
M_S &= \frac{1}{2}\{M(y0, y^E) + \{M(y0, y1) - M(y0, y^S)\}\}.
\end{aligned}
\tag{5}
$$

Growth and dispersion processes To further decompose the Structural component M_S into Growth and Dispersion components, we construct correspondent counterfactual income vectors for the process $y0 \to y^E$ (that is, process VII - $(1, 2, 3) \to (3, 4, 5)$ since the exchange factor has been removed from the original process) in a similar fashion. Starting with the marginal impact of the Growth process, the counterfactual income vector with the growth factor removed is constructed by rescaling y^E such that its mean is identical to the mean of $y0$: $y^{E,G} = \frac{\mu_{y0}}{\mu_{y^E}} y^E$, where μ_{y0} and μ_{y^E} are means of $y0$ and y^E. Thus, the first-round marginal impact of the Growth process is

$$
M_G = M(y0, y^E) - M(y0, y^{E,G}), \tag{6}
$$

and the second-round marginal impact of the Dispersion process is equal to $M(y0, y^{E,G})$.

To obtain the first-round marginal impact of the Dispersion process, we construct the counterfactual income vector $y^{E,D}$ with the growth component removed from the Structural process y^E by forcing the income shares in y^E to be identical to those in the initial vector $y0$. Thus, the first-round marginal impact of the Dispersion process is

$$
M_D = M(y0, y^E) - M(y0, y^{E,D}), \tag{7}
$$

and the second-round marginal impact of the Growth process is equal to $M(y0, y^{E,D})$.

We apply the hierarchical Shapley procedure, which evaluates the primary factors E and S first, followed by the secondary factors G and D, resulting in averaging the marginal effects from 4 different sequencings.

Jackknife resampling inference We adopt the Jackknife resampling technique for estimating the standard errors of the income flux measure as well as the three contributory factors. We consider each pair of incomes in $(y0_i, y1_i), i \in \{1, \ldots, n\}$ as an observation and the Jackknife resampling works by omitting an observation from the original dataset and calculating the estimates for M, M_E, M_G, and M_D. After $n-1$ resampling and calculations, we can obtain the Jackknife estimate of the standard error for each estimator (Miller 1974; Efron and Tibshirani 1993; van Kerm 2004).

Global and local spatial analytics

After estimating the income flux measure and its three contributory components for each MSA, we proceed with exploratory spatial analytics to examine their spatial distributions. Here, we are interested in whether more/less mobile MSAs are proximate to the more/less mobile, which provides a sense of regional and local economic development modes, and could have important implications for the regional/local policy. Put differently, spatial analytics can provide insight into whether MSAs near one another tend to display similar dynamics (suggesting benefits for cooperative spatial economic policies) or whether they follow different patterns (suggesting a spatially competitive environment and policies that favor specialization). We adopt the widely used Moran's I, a global indicator of spatial association, to evaluate global spatial autocorrelation of the MSA income influx estimates as well as the proportions of the Exchange, Growth, and Dispersion mobility components. For N MSAs ($N = 291$ in this article) with attribute x, Moran's I statistic is defined as:

$$I = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} z_i w_{i,j} z_j}{\sum_{i=1}^{N} z_i z_i}, \tag{8}$$

where $z_i = x_i - \bar{x}$ is the deviation from the mean, and $w_{i,j}$ is the ijth entry of the row-normalized spatial weight matrix which represents a prior notion of the neighboring structure of MSAs (k nearest neighbor weight is adopted). Inference is made based on random spatial permutations where values of x are randomly assigned to N locations to simulate the null - spatial randomness.

Next, we decompose the global Moran's I statistic into its local variety (Local Moran's I (Anselin 1995)), to further investigate whether hot or cold spots exist, with geographic clusters of of highly economically mobile/immobile MSAs. The Local Moran's I statistic for the variable x at location i is defined as:

$$I_i = \frac{(N-1) z_i \sum_{j=1}^{N} w_{i,j} z_j}{\sum_{j=1}^{N} z_j^2}. \tag{9}$$

Inference is made based on the pseudo-p value obtained from the conditional randomization where for a focal MSA i, its value x_i is hold fixed, while all the others are randomly permuted across remaining MSAs in order to simulate the null hypothesis of local spatial randomness. The multiple testing issue is addressed by controlling the False Discovery Rate (FDR) (Benjamini and Yekutieli 2001)[‡].

To summarize, we apply the mobility decomposition and the subsequent spatial analytics to all tracts across the full time period, 1980-2010, to examine the long-term change; we also investigate pairs of

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[‡]We conduct all calculations in python with the open source python packages - pysal/libpysal (Rey et al. 2019a), pysal/esda (Rey et al. 2019b), and pysal/spreg (Rey and Anselin 2007).

consecutive decades (1980-1990, 1990-2000 and 2000-2010) to explore short-term mobility patterns and whether they display temporal heterogeneity. We then apply subgroup decomposition of the income flux measure (Fields and Ok 1999) to identify contributions from each MSA. Finally, we examine local hot and cold spots based on the Local Moran's I statistics for the overall and contributing mobility components.

Determinants of Spatial Income Mobility

We further carry out a spatial econometric analysis as a first step to identify the explanatory factors of spatial income mobility in urban U.S.. Compared with spatial income inequality (Rodríguez-Pose and Ezcurra 2009; Wei 2015), scholarship on income mobility at the spatial aggregate level is lacking considerably. We address that gap by formally model the relationship between the metro-level income mobility (and its contributory components) and 9 metro-level variables at the beginning year of each decade. These 9 variables cover urban development, spatial income disparity, industrial composition, education attainment, and residential racial composition and segregation as shown in Table 2[§]. We have also tested against the decadal changes in these variables, leading to another set of models with 18 predictor variables. An Ordinary Lease Square (OLS) model as shown in Equation (10) is constructed and estimated for each mobility measure (M, M_E, M_G, and M_D) over each decadal period (1980-1990, 1990-2000, and 2000-2010). We also run spatial diagnostics and formally model the spatial dependence effect with the spatial lag specification as shown in Equation (11) where W is the k nearest neighbor weight matrix, consistent with the exploratory spatial analytics, ρ is the spatial autoregressive parameter indicating the direction and strength of spatial spillover effects, and $\epsilon \sim N(0, \sigma^2 I)$ is the error term.

$$y_i = \beta_i X_i + \epsilon_i \tag{10}$$

$$y_i = \rho W y_i + \beta_i X_i + \epsilon_i \tag{11}$$

[Table 2 about here.]

Results

Among the $54,275$ census tracts in 294 MSAs under study, we find both the mean and the standard deviation (as well as the interquartile range) of cross-sectional per capita incomes have been increasing

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[§] We have also attempted to include variables such as metro average per capita/total income, foreign born population, unemployment rate, poverty rate, age distribution, etc. These variables are rarely significant and cause multicollinearity.

consistently from 1980 to 2010 as shown in Table 3. This indicates shifts of tract-level income distribution to the right (i.e. tracts getting richer over time) accompanied by a widening tendency (larger tract-level inequality) over time. While this consistent rise also applies to the 50th and 75th percentiles, the 25th percentile experienced a decline from 2000 to 2010, indicating uneven development between core and periphery tracts. More specifically, poor tracts in 2000 were actually hosting higher-earning urban residents compared to poor tracts in 2010. Since we cannot know whether the tracts at the 25th percentile are the same ones across 2000 and 2010, we turn to the income mobility measures to trace the dynamics in more details.

[Table 3 about here.]

Long-term Urban Income Mobility

The estimate of the overall income mobility (income flux) in the long term (1980-2010) for $54,275$ urban tracts under study is 0.401 and the estimates of three contributory factors, exchange, growth and dispersion components, are 0.126, 0.272 and 0.003 as listed in Table 4. Since the decomposition is additive, meaning that the three mobility factors combine to equal the income flux, we can evaluate the proportions of relative contribution from each of them. The proportions are displayed as a percentage within square brackets in Table 4; standard errors are displayed within brackets. It is obvious that the dominant form of urban income mobility is Growth, with a proportion of 67.9%, indicating a substantial increase in aggregate per capita incomes in the metropolitan U.S. from 1980 to 2010. The second driving force is Exchange mobility, with a proportion of 31.4%, pointing to a mild extent of leapfrogging or catching up of tracts in terms of per capita incomes. In contrast, the small contributing proportion (0.7%) of the dispersion factor indicates that the income shares of tracts did not experience substantial changes.

[Table 4 about here.]

Spatial patterns of income mobility across MSAs We now turn to metropolitan-scale urban income mobility, which is the result of a subgroup decomposition (tracts grouped by MSAs). The estimates of overall urban income mobility (income influx measure) for 294 MSAs display considerable variation, ranging from 0.2 to 0.68, and they are not distributed geographically randomly. As shown in Figure 1a, MSAs with similar mobility levels tend to cluster together in space: high values are concentrated in the Northeast and West coast, while low values are clustered in the Great Lakes area. We formally examine the global spatial pattern of the MSA income flux by adopting the global Moran's I statistic. The statistic is always positive and the null hypothesis of spatial randomness is always rejected at the 5% significance level based on spatial permutations regardless of the number of nearest neighbors ($k \in [3, 20]$) used for constructing the k-nearest neighbor spatial weight matrix ¶.

The property of positive spatial autocorrelation also applies to the proportions contributed from the Exchange, Growth, and Dispersion factors, the spatial distributions of which are visualized in Figures 1b, 1c and 1d. The Growth factor has the widest range - [0.08, 0.91], indicating that the neighborhood income mobility of some MSAs are dominated (as large as 91%) by the absolute change in the average income level. The Exchange and Dispersion factors have smaller ranges - [0.6, 0.57] and [0.3, 0.58] respectively. Interestingly, the Growth factor seems to be negatively correlated with the Exchange and Dispersion factors, while the overall mobility level seems to be positively correlated with the Growth factor. We adopt the Pearson's correlation coefficient to formally examine the potential linear relationship between each pair and results are shown in Figure 2. The positive correlation coefficient 0.68 between the overall mobility level and the Growth mobility indicates that more mobile MSAs are typically dominated by change in the absolute average income level, and these MSAs tend to host tracts with fewer rank exchanges or changes in the income shares, indicated by the negative correlation coefficients -0.6 and -0.51. The opposite is true for MSAs hosting economically "stable" tracts.

[Figure 1 about here.]

[Figure 2 about here.]

Based on the Local Moran's I statistic while using spatial weight based on 8 nearest neighbors ‖, we identify hot and cold spots of MSAs in terms of the overall mobility level as well as the contributing proportions of the Exchange, Growth, and Dispersion factors. Having controlled the FDR to deal with the multiple testing issue, we obtain hot and cold spots for each term at the 5% significance level as shown in Figure 3. Some interesting patterns emerge from four maps. Several MSAs in the Northeast are identified as hot spots in maps 3a and 3c and cold spots in map 3b, while some MSAs in the Great Lake region are almost the opposite - cold spots in maps 3a and 3c and hot spots in map 3d. The divergent spatial income mobility patterns of these two regions over 1980-2010 represent two different economic development trajectories, and are worthy of further investigation to guide place-based policy making.

[Figure 3 about here.]

¶ We construct the spatial weight matrix based on k-nearest neighbor for 294 US MSAs. Global Moran's I is always positive and significant for $k \in [3, 20]$ under random spatial permutations.

‖ The spatial weight based on 8 nearest neighbors gives the largest global Moran's I value and is thus adopted for the subsequent spatial statistical analysis.

Temporal heterogeneity

There are substantial differences in the decennial income movement patterns (across every two consecutive census years) as displayed by the black line in the left plot of Figure 4. In fact, the overall income mobility has been decreasing over time, indicating that urban neighborhoods have become more resistant to change. This decreasing trend also holds for the decennial growth rate (red curve). Contributions from the Exchange, Growth and Dispersion mobility processes have also been shifting over time. During the 1980-1990 period, the dominant process was Growth, as indicated by the yellow area in the right plot. Its dominant position was eventually replaced by the Exchange process (green area) during the 2000-2010 period. Over the three decades, the contribution from the Dispersion process (blue area) gradually increased, indicating that the income shares owned by urban neighborhoods were transformed more drastically in the recent decade.

[Figure 4 about here.]

The drastic temporal heterogeneity in the contributing proportions of three mobility components also manifests at the the MSA level. Since the three proportions $[Prop_E, Prop_G, Prop_D]$ are constrained to always add up to 1, they comprise a vector of compositional data (Aitchison and Egozcue 2005). We plot the ternary diagrams which are a powerful visualization tool for exploring compositional data in Figure 5 to investigate the distribution of the MSA-level mobility compositions in the long term and over decennial intervals. For each diagram, the horizontal, right and left axes represent Exchange, Growth, and Dispersion mobility proportions respectively. If an MSA is located very close to the top corner, its intra-MSA neighborhood mobility is dominated by the Growth component (about 100%); the same holds for the right corner for the Exchange component and left corner for the Dispersion component. The fact that most points cluster near the top corner in Figure 5a indicates that the dominant force of neighborhood income mobility within most MSAs is Growth over the long term. Comparatively, as shown in Figure 5b, the center of mass has been shifting over time from the top corner to the right corner, indicating a trend in which Exchange mobility comes to dominate Growth. We also note that points rarely cluster near the left corner, indicating negligible shifting among income shares - by either increasing or decreasing the dispersion of neighborhood per capita incomes within individual MSAs.

[Figure 5 about here.]

Spatial distribution of decennial MSA income mobility and the decomposition Similar to the case with the long-term analysis, we also decompose national-scale urban income mobility into the MSA-scale, followed by a further decomposition into three contributing mobility processes. The local hot and cold spots of MSA neighborhood-level income flux and the proportions of Exchange, Growth and Dispersion processes for each of three decades are visualized in Figures A1, A2 and A3[**]. The spatial patterns are most distinct for the first decade 1980-1990 in terms of the number of hot and cold spots detected. Similar to the long-term spatial pattern, the northeast coast stands out as a hot spot for the overall mobility level and Growth, and a cold spot for Exchange and Dispersion. By contrast, the Great Lake region fails to stand out at this scale; instead Texas, New Mexico and Louisiana host cold spots of Growth, and hot spots of Exchange and Dispersion. In the next decade (1990-2000), we observe cold spots for overall mobility and Growth, as well as hot spots for Exchange in the West coast. For the most recent decade 2000-2010, the Great Lake region stands out as the host of MSAs with high contributions from Growth mobility and low contributions from Exchange mobility.

The relationships between the overall mobility level for each MSA, and the proportions contributed from Exchange, Growth, and Dispersion mobility processes across each decade have also undergone drastic changes as shown in Figure 6. Though the relationship between the income flux level and the Growth contribution has been always positive, it has weakened over time. Another noticeable change comes from the relationship between the Dispersion and the other two components. Over the three decades we study, the initial negative relationship between Dispersion and Growth has been gradually replaced by a weak positive relationship, while on the contrary, the initial positive relation between Dispersion and Exchange has been replaced by a negative relationship.

[Figure 6 about here.]

Determinants of spatial income mobility

We turn our focus to the correlation between spatial income mobility and several metropolitan properties which could be potential factors explaining the spatially heterogeneous income mobility patterns we observed for each decade. The spatial diagnostic tests led us to a spatial lag specification as shown in Equation (11). Therefore, we only present the results for this spatially explicit specification, the estimation of which relies on using the Maximum Likelihood technique.

It turns out that most factors were not significantly correlated with intraurban spatial income mobility in the U.S.. What's more, for those which were significant in some periods, they could be insignificant in other periods, indicating potentially divergent urban processes and dynamics over time. For instance, percent of manufacturing employees has only been significant for the period 1980-1990 as shown in Table A1. After incorporating its decadal increase in the model, it was positively related to the spatial income influx level and Growth mobility. Racial composition including the percentages of the Hispanic

[**]The estimates of all four measures for 294 MSAs and the visualization of the spatial distributions are available upon request

and Asian, the racial segregation level, and higher education attainment were only significant in the latest time period 2000-2010 (Table A3). While the initial percentage of Hispanic population was negatively related to the spatial income influx level and Growth mobility, the story was the opposite for the initial percentage of Asian population. Residential segregation was (weakly) negatively related to the spatial income influx level and Dispersion mobility, a potential evidence for a stagnating effect of segregation on neighborhood income mobility.

Urban development level proxied by population and population density was only significant for the periods 1980-1990 and 2000-2010. It was positively correlated with the overall spatial income mobility and Growth mobility, and negatively correlated with Exchange and Dispersion mobility for 1980-1990. While for 2000-2010, the increment in population density was negatively correlated with the overall spatial income mobility, though the initial population was positively correlated with Exchange mobility.

Comparatively, the level of spatial income inequality was the only factor significant across all three decades. Initially across 1980-1990, it was positively correlated with Exchange mobility and negatively correlated with Growth mobility, while its decadal increment was positively correlated with Dispersion mobility. The pattern was similar in the subsequent periods 1990-2000 (Table A2) and 2000-2010. One prominent observation is that the level of spatial income inequality and its decadal increase was also positively correlated with the overall spatial income mobility. We will discuss the interpretation and potential policy implications in the next section.

Discussion

Our results provide intriguing insight into the dynamics of spatial inequality in American cities over the last three decades that have not been explored in the literature, particularly when examining different spatial and temporal scales. More specifically, our results highlight the considerable ways that the American economy has evolved through space and time, and elucidate the ways in which different regions of the country have borne witness to unique changes as they move through certain time periods.

Before diving into the results in detail, it is useful to recount briefly the ways that the global industrial structure has shifted the last thirty years, and the spatial heterogeneity through which such changes affect American cities. Through the early part of the 20th century, America's economy rose to prominence thanks to a dominant manufacturing sector that flourished throughout the midwest, particularly in prominent cities like Chicago, Detroit, Cleveland, Pittsburgh and Milwaukee. The primary demographic trend during this period was "white flight", or the suburbanization of white, well-educated and affluent families (Baum-Snow and Hartley 2019). Through the new millennium, however, as the country shifted away from manufacturing and embraced a high-tech digital and information economy, midwestern dominance waned and eventually developed the "rustbelt" moniker for its legacy and aesthetic of factories, foundries and warehouses beginning to fall into disrepair.

In our current era, this demographic trend has thus largely reversed, thanks to the "back to the city" movement and the dominance of new high-tech job hubs like San Francisco and Seattle that have overtaken midwestern cities in cultural and economic dominance. These trends are particularly useful context for interpreting our results on the spatial and temporal patterns of economic mobility because they highlight (1) the important regional nature of American economics and demography, (2) the important temporal phases that define the country's economic history, and (3) the relationship between space and time in laying the foundation for the economic mobility of American neighborhoods.

Long Term Trends

Over the long term (1980-2010) our results are consistent with these economic and demographic narratives. The northeastern megaregion showed little evidence of internal restructuring in that it hosted coldspots for exchange mobility. At the same time however, it hosted hotspots for growth mobility. At a local scale, this means that neighborhoods in New York and Washington DC dod not trade ranks often; prominent neighborhoods in NYC and DC stayed as such. On a national scale, however, these same cities continue dto outpace smaller, and more centrally located ones, like Detroit, that were once dominant on the national scale. Indeed, the midwest displayed largely the opposite patterns, representing a statistical coldspot for overall mobility over the full 1980-2010 time period and similarly a coldspot for growth. Economists and geographers have long recognized the importance of agglomeration economies in helping to foster economic growth, but our results are the first of which we are aware that demonstrate the statistical significance of these meso-scale economic regions whose metropolitan statistical areas tended to follow similar mobility trends. Indeed, these results have strong implications for (mega)regional economic development policy and national economic inequality more broadly, but we also find considerable nuance within each decade, which we explore below.

1980s

In the 1980s, deregulation and the transitioning economy led to reshaping of urban inequality across the U.S.. Metropolitan regions with larger shares in manufacturing employment saw an overall decrease in economic mobility, whereas economic deregulation led to considerable growth in financial centers along the Northeast corridor.

In general, the 1980s were good years for large American cities. Metropolitan regions with larger populations and denser development were positively associated with growth and negatively associated with exchange and dispersion. Put differently, large, dense cities on average, did quite well in the 1980s, with most neighborhoods moving up the economic ladder together, albeit with few changes in position. The northeast megaregion stood out as a statistically significant hotspot in this respect, as nearly all of the major metropolitan regions along the seaboard experienced these trends together.

For smaller and more rural parts of the country, however, a different story emerged. In metros with large shares of the economy dedicated to manufacturing, neighborhoods generally saw an economic decline. Portions of the South and Midwest stood out as spatially significant hotspots for dispersion and widening inequality, whereas the rustbelt in Western Pennsylvania stood out as a significant coldspot for economic growth.

1990s

The 1990s seemed to be a period of polarization and widening inequality, with the gap growing fastest in places already characterized by a high spatial Gini index. Further, metropolitan regions with large college-educated populations saw a larger change in economic dispersion. In spatial terms, these trends were apparent most obviously in the northeast and the sunbelt who appeared as statistically significant coldspots for growth mobility. Instead, these places were in states of internal dynamics, as they also appeared as hotspots for exchange mobility. In retrospect, these patterns may be explained by the start of the technology boom, with residents in high-tech metros like Boston, New York, and San Francisco beginning to benefit from the embrace of the information economy.

As a result, many of the largest metros in the 90s seemed to be characterized by widening inequality, as low-tech high-paying jobs in the manufacturing sector began disappearing from high-cost cities. Together, those trends were consistent with a narrative describing the reshuffling of affordable neighborhoods on the national scale along the nascent origins of the "back to the city" movement, two trends that together had sweeping implications for gentrification and urban displacement in the following decade (STURTEVANT and JUNG 2011; Hyra 2015).

2000s

Indeed, through the new millennium spatial trends in economic mobility continued apace, albeit with a newly emerging racial patterning in which areas with large Hispanic and Latino populations were insulated from economic growth whereas areas with large Asian populations accelerated. As with the 1990s, cities in the 2000s that had large shares of college-educated citizens were more likely to experience dispersion and a lack of economic growth. This also applied to growing inequality, as cities that already had large spatial Gini were more likely to continue a trend toward exchange and dispersal. In other words, through the 2000s, many of Americas most unequal cities grew even more so. From a spatial perspective, there was considerably less statistical patterning, although a significant pattern of exchange mobility emerged through Silicon Valley and the Detroit metro region.

Concluding remarks

This paper provides an empirical study of the U.S. spatial income mobility with the decennial census and ACS datasets covering a variety of mega, medium, and small cities over long term 1980-2010, as well as short terms 1980-1990, 1990-2000, 2000-2010. A decomposition technique is adopted for unpacking the overall spatial mobility index into contributing components, which are Exchange, Growth, and Dispersion mobility, to obtain insights into the multidimensional urban and neighborhood processes. This paper represents one of the first comprehensive studies of spatial income mobility in the urban U.S. covering a broad set of cities and a variety of temporal scales with spatially explicit exploratory and confirmatory analytics.

We found a dominant position of Growth mobility at the national scale followed by Exchange mobility in the long term. However, this dominating-dominated relationship was reversed over time in the short terms, indicating temporal heterogeneous urban and neighborhood processes. This temporal heterogeneity is also confirmed by looking at the MSA-level spatial mobility. In the long term, a strong negative relationship between Growth and Exchange/Dispersion mobility was found while Growth mobility was positively related to the overall spatial mobility, indicating that more mobile MSAs were typically dominated by changes in the absolute average income level, and these MSAs tended to host tracts with fewer rank exchanges or changes in the income shares. However, these relationships have been changing when looking at short terms. A set of regression analyses demonstrating the temporally varied statistically significant determinants also confirmed such heterogeneity, and thus the importance of studying urban processes through an evolutionary lens. Aside from temporal heterogeneity, another significant finding is the spatial agglomeration effect of intraurban spatial income mobility, e.g., the Northeastern and the Great Lakes regions have been hosting either hotspots or coldspots of spatial income mobility and its contributing components.

As has been demonstrated in the paper, different temporal scales could manifest diverging spatial income mobility patterns and thus varying urban and neighborhood dynamics. While we look at a 30-year long term, as well as the three decadal short terms, we are missing the smaller temporal scales, such as the five-year mobility, or even the yearly mobility, which could be the defining force or turning point in the more extended period. An interesting endeavor would be to utilize the ACS 5-year estimates (2009-2018) to investigate smaller temporal scales though this comes with the downside of dealing with larger margins-of-errors. Another limitation of the current paper is the limited set of explanatory variables adopted for the spatial regression analysis. It could be very interesting and promising to interrogate the household movement across neighborhoods and MSAs as this could give us a better sense of how the observed spatial income mobility, as well as the Growth, Dispersion, Exchange components, was related to demographic processes such as the gentrification or general displacement.

Despite these limitations, the paper contributes to bringing the multidimensional processes of urban spatial income mobility and its spatial and temporal dynamics to the fore with the results which have important implications. It provides a new perspective to the literature of spatial income inequality and raises interesting questions that deserve further research.

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Appendix A

Table A1. Correlates of urban income mobility 1980-1990 (Spatial lag specification with Maximum Likelihood estimation)

	Mobility I	Mobility II	Exchange I	Exchange II	Growth I	Growth II	Dispersion I	Dispersion II
CONSTANT	0.0629***	0.0263	-0.0071	-0.0074	0.0722***	0.0448	0.0103	0.0059
	(0.0237)	(0.0278)	(0.0071)	(0.0087)	(0.0252)	(0.0304)	(0.0070)	(0.0068)
popstd	-0.0000	-0.0059	0.0024*	0.0026	-0.0010	-0.0075	-0.0006	0.0001
	(0.0044)	(0.0051)	(0.0014)	(0.0016)	(0.0048)	(0.0056)	(0.0013)	(0.0013)
densitystd	0.0110***	0.0131***	-0.0040***	-0.0041***	0.0134***	0.0177***	-0.0008	-0.0034***
	(0.0043)	(0.0045)	(0.0014)	(0.0014)	(0.0047)	(0.0050)	(0.0013)	(0.0011)
gini	0.0500	0.0253	0.2573***	0.2571***	-0.1782**	-0.1864**	0.0420*	0.0261
	(0.0709)	(0.0705)	(0.0246)	(0.0247)	(0.0792)	(0.0790)	(0.0220)	(0.0181)
pmanuf	-0.1165***	-0.0187	-0.0206	-0.0169	-0.0892**	-0.0005	-0.0040	0.0010
	(0.0407)	(0.0650)	(0.0128)	(0.0208)	(0.0447)	(0.0717)	(0.0125)	(0.0164)
pcol	-0.0235	-0.0003	0.0113	0.0201	-0.0157	0.0175	-0.0164	-0.0328*
	(0.0540)	(0.0680)	(0.0170)	(0.0218)	(0.0593)	(0.0749)	(0.0167)	(0.0172)
pnhblk	0.0044	0.0187	-0.0111	-0.0212*	0.0173	0.0312	0.0017	0.0138
	(0.0225)	(0.0355)	(0.0071)	(0.0114)	(0.0247)	(0.0392)	(0.0069)	(0.0090)
phisp	-0.0124	0.0004	0.0005	0.0080	-0.0028	0.0039	-0.0115	-0.0117
	(0.0340)	(0.0451)	(0.0107)	(0.0144)	(0.0373)	(0.0497)	(0.0105)	(0.0114)
pasian	-0.1941	-0.2193	-0.1206*	-0.1695**	-0.1571	-0.1332	0.0163	0.0092
	(0.1968)	(0.2165)	(0.0623)	(0.0695)	(0.2163)	(0.2387)	(0.0607)	(0.0546)
multiInfor	0.0131	0.0381	0.0122*	0.0115	-0.0009	0.0411	0.0000	-0.0161*
	(0.0228)	(0.0329)	(0.0072)	(0.0105)	(0.0250)	(0.0362)	(0.0070)	(0.0083)
popstd_change		0.0073		-0.0001		0.0075		-0.0007
		(0.0046)		(0.0015)		(0.0050)		(0.0012)
densitystd_change		-0.0059		0.0000		-0.0055		-0.0003
		(0.0043)		(0.0014)		(0.0047)		(0.0011)
gini_change		0.2130		-0.0025		-0.1480		0.4881***
		(0.1484)		(0.0476)		(0.1635)		(0.0389)
pmanuf_change		0.1269**		0.0058		0.1195*		-0.0009
		(0.0599)		(0.0192)		(0.0660)		(0.0151)
pcol_change		0.0307		0.0118		0.0342		-0.0135
		(0.0534)		(0.0171)		(0.0589)		(0.0135)
pnhblk_change		0.0107		-0.0094		0.0098		0.0097
		(0.0274)		(0.0088)		(0.0302)		(0.0069)
phisp_change		0.0032		0.0085		-0.0014		-0.0049
		(0.0340)		(0.0109)		(0.0374)		(0.0086)
pasian_change		0.1726		-0.0725		0.2231		0.0115
		(0.1498)		(0.0480)		(0.1651)		(0.0378)

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Table A1 continued

	Mobility I	Mobility II	Exchange I	Exchange II	Growth I	Growth II	Dispersion I	Dispersion II
multiInfor_change		0.0287		0.0008		0.0428		-0.0118*
		(0.0280)		(0.0090)		(0.0309)		(0.0071)
Wy	0.7941***	0.8051***	0.4016***	0.4041***	0.8068***	0.7946***	0.5545***	0.3443***
	(0.0390)	(0.0366)	(0.0688)	(0.0689)	(0.0362)	(0.0372)	(0.0722)	(0.0712)
R-squared	0.6220	0.6401	0.4811	0.4889	0.6552	0.6673	0.2416	0.5102
Spatial R-squared	0.2909	0.1934	0.4278	0.4379	0.2713	0.3670	0.0851	0.4969

***, **, and * indicate significance at the 1%, 5%, and 10% level respectively.

Table A2. Correlates of urban income mobility 1990-2000 (Spatial lag specification with Maximum Likelihood estimation)

	Mobility I	Mobility II	Exchange I	Exchange II	Growth I	Growth II	Dispersion I	Dispersion II
CONSTANT	0.0607***	0.0675***	-0.0123	-0.0161*	0.0618***	0.0705***	0.0058	0.0070
	(0.0189)	(0.0203)	(0.0080)	(0.0087)	(0.0164)	(0.0178)	(0.0054)	(0.0059)
popstd	0.0015	-0.0010	0.0034**	0.0016	-0.0005	-0.0039	-0.0018	0.0009
	(0.0032)	(0.0073)	(0.0016)	(0.0037)	(0.0031)	(0.0071)	(0.0011)	(0.0025)
densitystd	-0.0049	-0.0014	-0.0016	-0.0027	-0.0014	0.0037	-0.0014	-0.0033*
	(0.0031)	(0.0053)	(0.0016)	(0.0027)	(0.0030)	(0.0051)	(0.0011)	(0.0018)
gini	0.0507	0.0544	0.1953***	0.2178***	-0.1672***	-0.1750***	0.0772***	0.0818***
	(0.0453)	(0.0472)	(0.0244)	(0.0253)	(0.0444)	(0.0463)	(0.0160)	(0.0165)
pmanuf	0.0128	-0.0115	-0.0048	-0.0017	0.0181	0.0022	0.0020	0.0018
	(0.0438)	(0.0532)	(0.0221)	(0.0266)	(0.0425)	(0.0515)	(0.0152)	(0.0183)
pcol	0.0278	0.0224	0.0429**	0.0300	-0.0101	0.0051	-0.0077	-0.0045
	(0.0383)	(0.0450)	(0.0193)	(0.0226)	(0.0371)	(0.0437)	(0.0133)	(0.0155)
pnhblk	0.0041	-0.0012	-0.0170*	-0.0116	0.0232	0.0089	-0.0013	0.0043
	(0.0204)	(0.0231)	(0.0103)	(0.0115)	(0.0198)	(0.0224)	(0.0071)	(0.0079)
phisp	-0.0304	-0.0120	-0.0069	-0.0052	-0.0182	-0.0037	-0.0083	-0.0041
	(0.0254)	(0.0299)	(0.0128)	(0.0149)	(0.0246)	(0.0290)	(0.0088)	(0.0103)
pasian	-0.0596	-0.1661	-0.0551	-0.0660	-0.0023	-0.0244	0.0083	-0.0597
	(0.1034)	(0.1592)	(0.0522)	(0.0796)	(0.1002)	(0.1543)	(0.0358)	(0.0547)
multiInfor	-0.0064	-0.0132	0.0195*	0.0156	-0.0099	-0.0037	-0.0118*	-0.0226**
	(0.0206)	(0.0259)	(0.0104)	(0.0129)	(0.0200)	(0.0251)	(0.0071)	(0.0089)
popstd_change		0.0034		0.0019		0.0044		-0.0031
		(0.0079)		(0.0039)		(0.0076)		(0.0027)
densitystd_change		-0.0056		0.0001		-0.0071		0.0025
		(0.0060)		(0.0030)		(0.0059)		(0.0021)

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Table A2 continued

	Mobility I	Mobility II	Exchange I	Exchange II	Growth I	Growth II	Dispersion I	Dispersion II
gini_change		0.0335		0.1861***		-0.1020		0.0510
		(0.1215)		(0.0613)		(0.1179)		(0.0418)
pmanuf_change		-0.0899		-0.0148		-0.0383		-0.0101
		(0.1487)		(0.0744)		(0.1442)		(0.0511)
pcol_change		-0.0887		0.0656		-0.1474		-0.0572
		(0.1535)		(0.0770)		(0.1488)		(0.0527)
pnhblk_change		0.0551		0.0224		0.0186		-0.0176
		(0.0908)		(0.0455)		(0.0881)		(0.0312)
phisp_change		-0.0688		-0.0062		-0.0843		0.0034
		(0.0860)		(0.0431)		(0.0834)		(0.0296)
pasian_change		0.3021		0.0504		0.0455		0.1798*
		(0.2748)		(0.1374)		(0.2664)		(0.0944)
multiInfor_change		-0.0295		0.0045		0.0142		-0.0399*
		(0.0662)		(0.0331)		(0.0642)		(0.0228)
Wy	0.6299***	0.6264***	0.4464***	0.4133***	0.7367***	0.7284***	0.2711***	0.2616***
	(0.0630)	(0.0632)	(0.0709)	(0.0716)	(0.0477)	(0.0487)	(0.0965)	(0.0970)
R-squared	0.3273	0.3360	0.4509	0.4694	0.4937	0.5003	0.1643	0.1901
Spatial R-squared	0.1306	0.1454	0.4128	0.4489	0.1203	0.1633	0.1410	0.1739

***, **, and * indicate significance at the 1%, 5%, and 10% level respectively.

Table A3. Correlates of urban income mobility 2000-2010 (Spatial lag specification with Maximum Likelihood estimation)

	Mobility I	Mobility II	Exchange I	Exchange II	Growth I	Growth II	Dispersion I	Dispersion II
CONSTANT	0.1019***	0.0640***	-0.0012	-0.0126	0.0519***	0.0610***	0.0504***	0.0148
	(0.0183)	(0.0184)	(0.0095)	(0.0115)	(0.0116)	(0.0145)	(0.0111)	(0.0100)
popstd	0.0021	-0.0006	0.0053***	0.0045**	0.0003	-0.0017	-0.0029	-0.0026
	(0.0027)	(0.0032)	(0.0017)	(0.0023)	(0.0022)	(0.0029)	(0.0020)	(0.0020)
densitystd	-0.0045*	0.0001	-0.0036**	-0.0019	0.0015	0.0038	-0.0023	-0.0015
	(0.0027)	(0.0028)	(0.0017)	(0.0020)	(0.0022)	(0.0026)	(0.0020)	(0.0017)
gini	0.2072***	0.2629***	0.2030***	0.2084***	-0.0128	-0.0162	-0.0045	0.0472**
	(0.0403)	(0.0354)	(0.0261)	(0.0261)	(0.0315)	(0.0317)	(0.0286)	(0.0211)
pmanuf	-0.0484	-0.0474	0.0168	0.0120	-0.0484	-0.0683	-0.0150	0.0129
	(0.0431)	(0.0531)	(0.0267)	(0.0376)	(0.0346)	(0.0488)	(0.0314)	(0.0325)
pcol	-0.0975***	-0.0797**	0.0291	0.0499**	-0.0858***	-0.1041***	-0.0356*	-0.0115
	(0.0291)	(0.0335)	(0.0180)	(0.0237)	(0.0233)	(0.0308)	(0.0212)	(0.0205)
pnhblk	0.0040	0.0112	-0.0076	-0.0062	0.0047	0.0083	0.0069	0.0115

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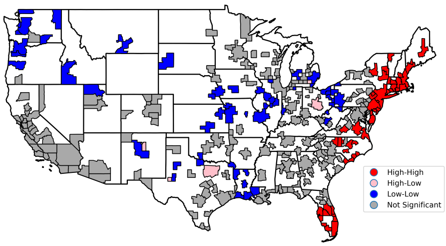
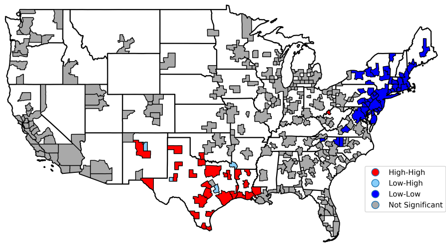
Table A3 continued

	Mobility I	Mobility II	Exchange I	Exchange II	Growth I	Growth II	Dispersion I	Dispersion II
	(0.0180)	(0.0221)	(0.0112)	(0.0156)	(0.0145)	(0.0203)	(0.0131)	(0.0135)
phisp	-0.0637***	-0.0452**	-0.0045	-0.0040	-0.0415***	-0.0399**	-0.0159	0.0023
	(0.0193)	(0.0203)	(0.0119)	(0.0144)	(0.0154)	(0.0187)	(0.0140)	(0.0125)
pasian	0.1615***	0.1376**	-0.0256	-0.0349	0.1112**	0.1303**	0.0661	0.0230
	(0.0601)	(0.0569)	(0.0373)	(0.0403)	(0.0482)	(0.0523)	(0.0438)	(0.0348)
multiInfor	-0.0391**	-0.0455*	0.0158	0.0184	-0.0306*	-0.0335	-0.0257*	-0.0284*
	(0.0199)	(0.0239)	(0.0123)	(0.0169)	(0.0159)	(0.0220)	(0.0145)	(0.0147)
popstd_change		0.0042		0.0010		0.0021		0.0008
		(0.0032)		(0.0023)		(0.0029)		(0.0020)
densitystd_change		-0.0071**		-0.0023		-0.0042		-0.0005
		(0.0029)		(0.0020)		(0.0026)		(0.0018)
gini_change		0.8601***		0.1387**		-0.1491*		0.8912***
		(0.0906)		(0.0639)		(0.0828)		(0.0555)
pmanuf_change		0.0276		0.0083		-0.0268		0.0517
		(0.0530)		(0.0375)		(0.0486)		(0.0324)
pcol_change		0.0156		0.0244		-0.0150		0.0154
		(0.0242)		(0.0171)		(0.0222)		(0.0148)
pnhblk_change		0.0087		0.0004		0.0054		0.0055
		(0.0194)		(0.0137)		(0.0178)		(0.0119)
phisp_change		0.0232		-0.0007		0.0139		0.0099
		(0.0169)		(0.0120)		(0.0155)		(0.0104)
pasian_change		0.0255		0.0196		0.0268		-0.0316
		(0.0430)		(0.0304)		(0.0395)		(0.0263)
multiInfor_change		-0.0180		0.0044		-0.0036		-0.0137
		(0.0219)		(0.0155)		(0.0201)		(0.0134)
Wy	0.3474***	0.3551***	0.4608***	0.4768***	0.4890***	0.5003***	0.0897	-0.0158
	(0.0881)	(0.0769)	(0.0686)	(0.0671)	(0.0785)	(0.0765)	(0.1141)	(0.0932)
R-squared	0.2340	0.4336	0.4654	0.4848	0.2116	0.2349	0.0852	0.5219
Spatial R-squared	0.1948	0.3863	0.4087	0.4191	0.0812	0.0884	0.0812	0.5220

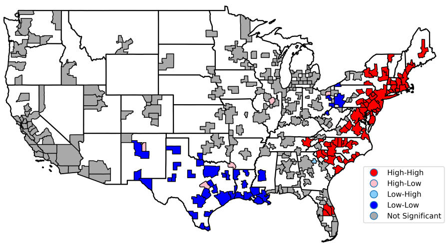
***, **, and * indicate significance at the 1%, 5%, and 10% level respectively.



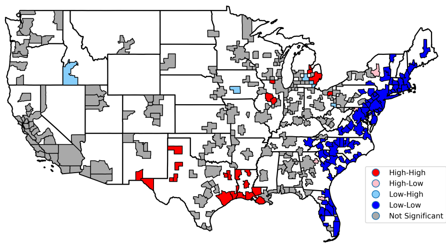
(a) Income flux mobility levels



(b) Exchange mobility proportions

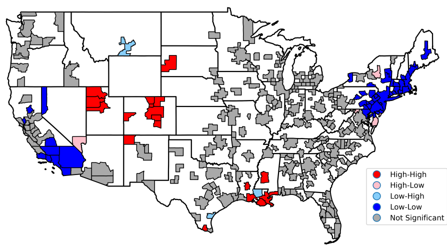


(c) Growth mobility proportions

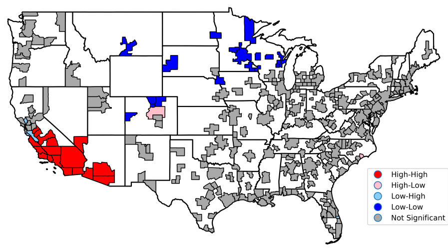


(d) Dispersion mobility proportions

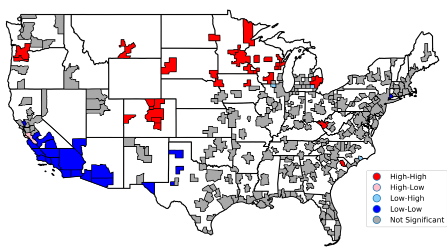
Figure A1. Local hot and cold spots of US MSA income mobility and the proportions of exchange, growth and dispersion mobility components across 1980-1990.



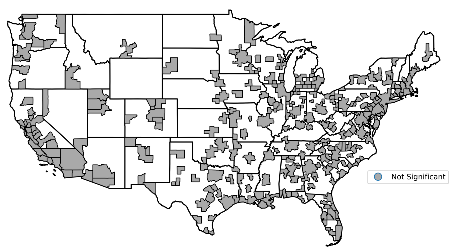
(a) Income flux mobility levels



(b) Exchange mobility proportions

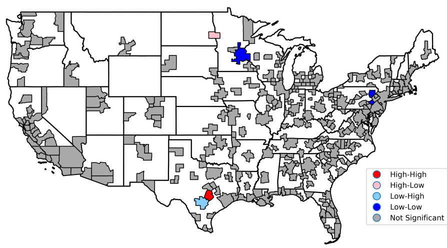


(c) Growth mobility proportions

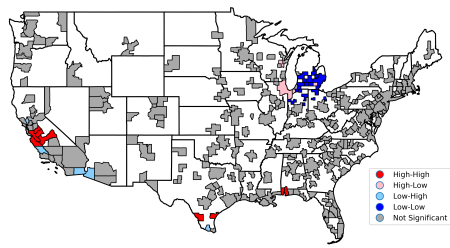


(d) Dispersion mobility proportions

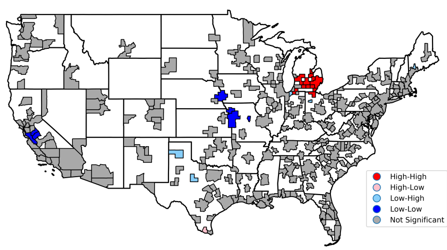
Figure A2. Local hot and cold spots of US MSA income mobility and the proportions of exchange, growth and dispersion mobility components across 1990-2000.



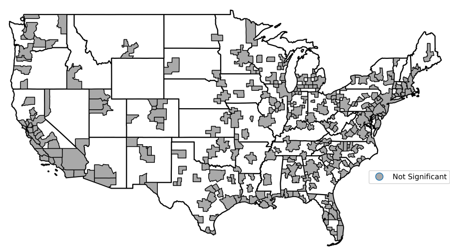
(a) Income flux mobility levels



(b) Exchange mobility proportions



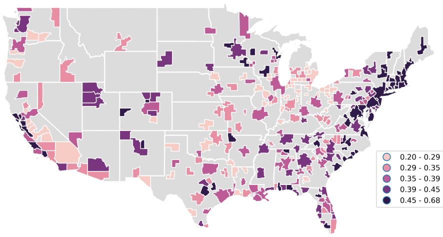
(c) Growth mobility proportions



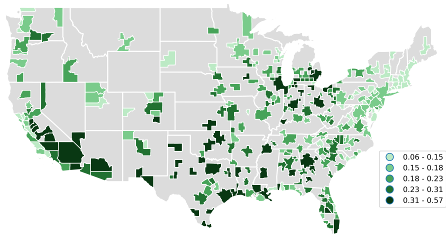
(d) Dispersion mobility proportions

Figure A3. Local hot and cold spots of US MSA income mobility and the proportions of exchange, growth and dispersion mobility components across 2000-2010.

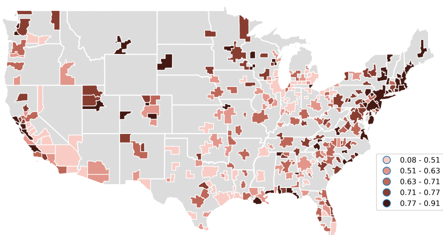
List of Figures



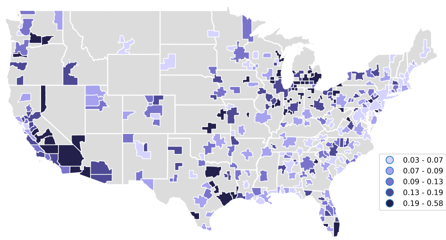
(a) Income flux mobility levels



(b) Exchange mobility proportions



(c) Growth mobility proportions



(d) Dispersion mobility proportions

Figure 1. Spatial distributions of MSA income mobility and the proportions of exchange, growth and dispersion mobility components across 1980-2010. Quantile classification is used for each of the choropleth maps.

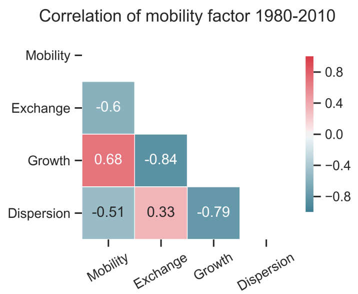
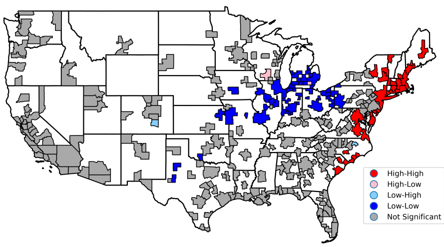
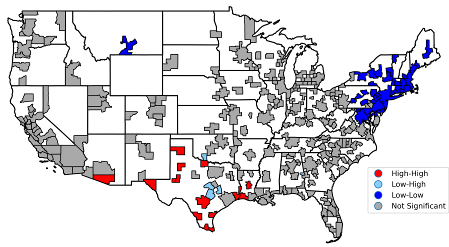


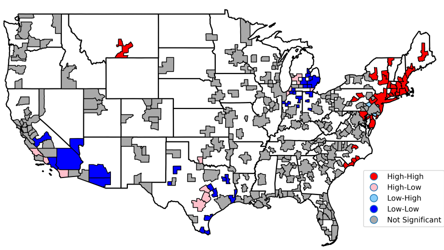
Figure 2. Correlation coefficients between mobility and contributory proportions in US MSAs 1980-2010



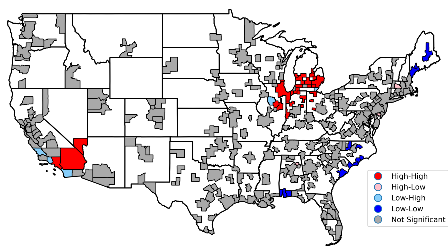
(a) Income flux mobility levels



(b) Exchange mobility proportions



(c) Growth mobility proportions



(d) Dispersion mobility proportions

Figure 3. Local hot and cold spots of US MSA income mobility and the proportions of exchange, growth and dispersion mobility components across 1980-2010.

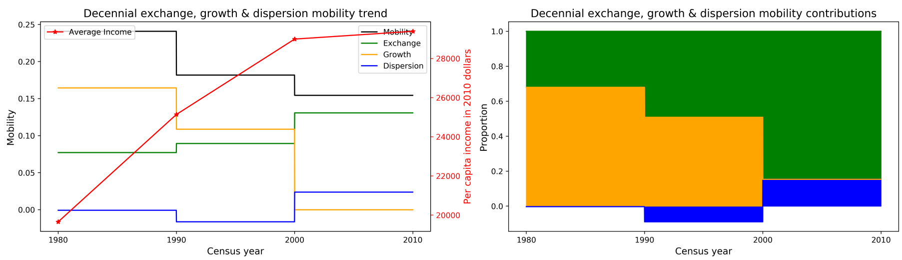
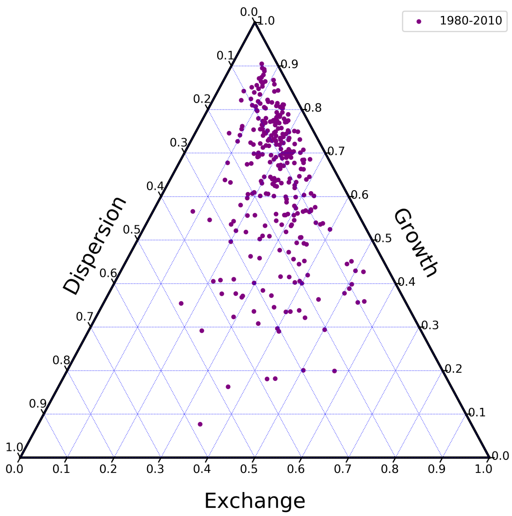
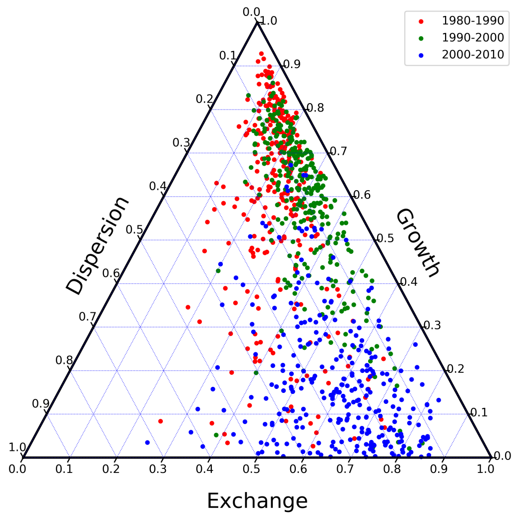


Figure 4. Decennial urban neighborhood income mobility and its decomposition 1980-2010. The left figure shows the overall mobility and its decomposition into exchange, growth and dispersion components as well as the trend of real per capital incomes at the tract level. The right figure shows the proportions of contributions from exchange, growth and dispersion processes to the overall mobility.

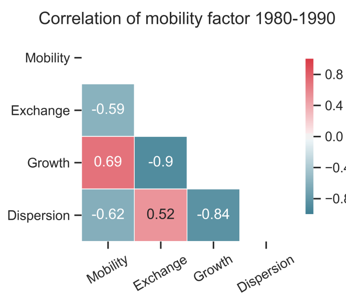


(a) Long-term ternary diagram.

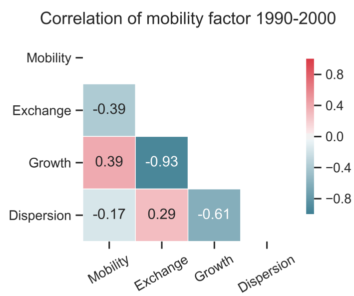


(b) Decennial ternary diagram.

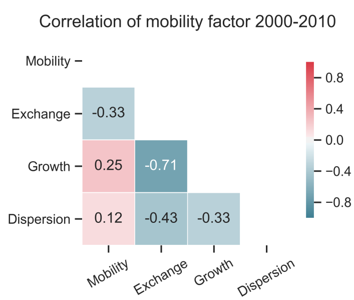
Figure 5. Ternary diagrams for proportions of Exchange, Growth and Dispersion mobility components (a) in the long term 1980-2010, and (b) in the short terms 1980-1990, 1990-2000, and 2000-2010.



(a) 1980-1990



(b) 1990-2000



(c) 2000-2010

Figure 6. Correlation coefficients between decennial mobility and its contributing factors.

List of Tables

Table 1. Example processes of income changes ($y0 \rightarrow y1$ for three individuals/neighborhoods $n = 3$).

	$y0$	$y1$	Processes
I	(1, 2, 3)	(1, 2, 3)	None
II	(1, 2, 3)	(3, 2, 1)	Exchange
III	(1, 2, 3)	(2, 4, 6)	Growth
IV	(1, 2, 3)	(1.5, 2, 2.5)	Dispersion
V	(1, 2, 3)	(2.5, 2, 1.5)	Exchange + Dispersion
VI	(1, 2, 3)	(6, 2, 4)	Exchange + Growth
VII	(1, 2, 3)	(3, 4, 5)	(Structural) Growth + Dispersion
VIII	(1, 2, 3)	(5, 4, 3)	Exchange + Growth + Dispersion

Table 2. Predictor Variables in the Regression Models.

Variable	Description	Change
popstd	z-score of population. Proxy for urban development	Yes
densitystd	z-score of population density. Proxy for urbanization	Yes
gini	Gini index measuring intraurban spatial inequality	Yes
pmanuf	Percent of manufacturing employees. Proxy for industrial structure	Yes
pcol	Percentage of persons with at least a four-year college degree	Yes
pnhblk	Percentage of Black population	Yes
phisp	Percentage of Hispanic population	Yes
pasian	Percentage of Asian population	Yes
multiInfor	Multigroup Information Theory index for residential segregation (Reardon and Firebaugh 2002)	Yes

Table 3. Descriptive statistics of real per capita incomes of urban census tracts in the US.

	1980	1990	2000	2010
Mean	19,656	25,142	28,992	29,389
25%	15,306	17,713	19,924	19,166
50%	18,707	22,951	26,193	26,277
75%	22,549	29,437	34,136	35,506
Standard Deviation	7,381	12,489	14,819	15,768
Interquartile Range	7,243	11,724	14,212	16,340

Table 4. Urban income mobility decomposition in the long term (1980-2010).

	Value	Proportion
Exchange Factor	0.126	[31.4%]
	(0.001)	(0.2%)
Growth Factor	0.272	[67.9%]
	(0.001)	(0.29%)
Dispersion Factor	0.003	[0.7%]
	(0.001)	(0.16%)

Numbers in brackets are standard errors for estimates above them. Numbers in square brackets are estimates of proportions.