

Changes in the economic status of neighbourhoods in US metropolitan areas from 1980 to 2010: Stability, growth and polarisation

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Abstract

In this paper we move away from a static view of neighbourhood inequality and investigate the dynamics of neighbourhood economic status, which ties together spatial income inequality at different moments in time. Using census data from three decades (1980–2010) in 294 metropolitan statistical areas, we use a statistical decomposition method to unpack the aggregate spatiotemporal income dynamic into its contributing components: stability, growth and polarisation, providing a new look at the economic fortunes of diverse neighbourhoods. We examine the relative strength of each component in driving the overall pattern, in addition to whether, how, and why these forces wax and wane across space and over time. Our results show that over the long run, growth is a dominant form of change across all metros, but there is a very clear decline in its prominence over time. Further, we find a growing positive relationship between the components of dispersion and growth, in a reversal of prior trends. Looking across metro areas, we find temporal heterogeneity has been driven by different socioeconomic factors over time (such as sectoral growth in certain decades), and that these relationships vary enormously with geography and time. Together these findings suggest a high level of temporal heterogeneity in neighbourhood income dynamics, a phenomenon which remains largely unexplored in the current literature. There is no universal law governing the changing economic status of neighbourhoods in the US over the last 40 years, and our work demonstrates the importance of considering shifting dynamics over multiple spatial and temporal scales.

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Keywords

decomposition, multidimensional, neighbourhood change, spatial income inequality, spatial polarisation

摘要

在本文中，我们突破关于街区不平等的静态观点，研究街区经济地位的动态变化，将不同时空点的空间收入不平等联系在一起。我们利用 294 个大都市区统计区的四十年（1980 年至 2010 年）人口普查数据，使用统计分解方法将总的时空收入动态分解为各个组成部分：稳定性、增长和两极分化，从而提供了对不同街区经济命运的新视角。我们研究每个组成部分在驱动整体模式方面的相对强度，以及这些力量是否、如何以及为什么随着空间和时间的变换而消退。我们的研究结果表明，从长远来看，增长是所有大都市区的主要变化形式，但随着时间的推移，其重要性明显下降。此外，我们发现离差和增长这两个组成部分之间的正相关关系日趋明显，这与先前的趋势相反。纵观各大都市区，我们发现在长期中时间异质性是由不同的社会经济因素（例如在某几十年中的部门增长）驱动的，并且这些关系随着地区和时间不同而有很大差异。这些研究结果共同表明，街区收入动态存在高度的时间异质性，这一现象在当前的文献中基本上未被研究。在过去 40 年里，美国街区的经济地位变化没有普遍规律，我们的研究证明在多个空间和时间尺度上考虑动态变化的重要性。

关键词

分解、多维、街区变化、空间收入不平等、空间两极分化

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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, 2018). This rapid urbanisation process has been taking place in mega, medium and small cities within developing as well as developed countries in recent decades. With more and more people residing in urban areas, it is essential to study not only cities or larger metropolitan regions, but also neighbourhoods within those regions since the spatial arrangement of neighbourhoods and the sorting of people among them help shape the coordination and interaction within a region (Ellen and O'Regan, 2010).

Increasing urbanisation 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 recent decades. Instead, the wealthiest parts of the income distribution have claimed the lion's share of the growth. While these patterns have been well documented, what is unclear is if this form of distributional polarisation is being played out within expanding cities fuelling the urbanisation 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 neighbourhood dynamics. The measure of such dynamics is similar to the income mobility

measure in the individual income distribution literature that ties together income inequality at different moments in time. Reframing income mobility to the case of neighbourhood dynamics within a metropolitan context provides us with the opportunity to examine questions surrounding urbanisation and spatial polarisation.

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

This paper contributes to the literature on neighbourhood dynamics in the urban US in four ways. Firstly, we consider a large 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 metropolitan statistical areas (MSAs) over the period 1980–2010. Secondly, we place a particular emphasis on the dynamics of mobility patterns within this period, considering whether different components of income mobility follow different paths over time. Thirdly, 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 neighbourhood income dynamics

and its contributing components through both global and local spatial autocorrelation indices, and provide a preliminary study towards identifying the determinants.

In the remainder of the paper, we first review the literature on neighbourhood dynamics. 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 average trend in long-term neighbourhood income dynamics, followed by an unpacking of the global trends to examine spatial and temporal heterogeneity, and a spatial regression analysis exploring explanatory factors for the observed patterns. We then provide a discussion of these results. The paper concludes with a summary of our key findings and their implications for policy, and the identification of future research directions.

Theories and empirics of neighbourhood dynamics

The relationship between neighbourhood conditions and social inequality has been a focus of urban studies since the field's genesis. For several decades, the primary mode of analysis has been attempting to distil the ways that neighbourhoods facilitate the inequality among individuals residing in different neighbourhoods, via pathways of contextual advantages and externalities. The manifestation of these pressures is often called neighbourhood effects (Chetty and Hendren, 2018; Sampson, 2012), and work in this area examines, for example, how neighbourhood conditions like concentrated poverty and poor access to resources stunt individual income mobility. Thus far, the focus on spatial relationships in this research has been limited to questions of how geographical context may influence personal income mobility and personal income inequality – that is, spatial context is

external, and the focus remains on the individuals who live in a given place (or set thereof).

A related set of questions focus on notions of *intraurban spatial income inequality and mobility*. Unlike the work just described, this literature focuses not on individuals but rather aggregates of individuals in space, examining the distribution of geographic zones as first-class units of analysis. Work in this body examines, for example, the income distribution among neighbourhoods in a city, and how this distribution evolves over time. Research questions in this vein share parallels with the economics literature on income convergence, which hypothesises that economies of lower per capita incomes tend to have higher growth rates, and will catch up with economies of higher per capita incomes in the long run (Barro and Sala-i-Martin, 2003). The difference here is that the spatial aggregate in the literature of income convergence is larger, such as a country or region. In contrast, the investigation of *intraurban spatial income inequality and mobility* in this paper looks at smaller spatial aggregates which do not usually qualify as functional economies.

To interrogate these processes, scholars have begun to examine questions of *spatial income mobility*. Modai-Snir and van Ham (2018, 2019) were among the first to apply the income mobility decomposition technique to differentiate the multiple processes underlying neighbourhood socioeconomic change in urban areas of Israel and the US. While Modai-Snir and van Ham (2018) focus on the Tel Aviv metropolitan area – the largest in Israel, Modai-Snir and van Ham (2019) extend the analysis to 22 of the largest MSAs in the US. Specifically, they focus on median household income and evaluate contributions from three distinct processes – exchange, growth and dispersion mobility – 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.

Henceforth, we adopt a lens of neighbourhood stability and change. In this sense, neighbourhood income dynamics is concerned with the degree to which different neighbourhoods ascend or decline, whether these dynamics differ by region, and how processes like globalisation and urbanisation affect them.¹ As Modai-Snir and van Ham (2018: 109) 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 neighbourhood income dynamics. 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* shock 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 neighbourhoods (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 neighbourhoods. Together, these processes suggest a variety of ways in which the economic characteristics of neighbourhoods inside a given metro region can evolve over time, some of which include residential mobility, and others which do not. In the sections below, we identify how modern social theories of neighbourhood dynamics map onto the components of growth, exchange and dispersion.

Changes and persistence in the economic status of neighbourhoods

One important mechanism behind neighbourhood dynamics is selective mobility in and out of neighbourhoods, which is essential for a better understanding of neighbourhood effects (Van Ham et al., 2013). Theories of neighbourhood selection and selective mobility are often tied to locational attainment, and differential ability of demographic groups (e.g. racial groups or income classes) to translate personal income or education growth into higher status neighbourhoods (Logan et al., 1996a, 1996b; South and Crowder, 1997). Foundational work in locational attainment has shown that racial and ethnic segregation persists in American cities, in part due to the ways that income growth translates to neighbourhood inequality. Locational attainments map most directly onto a neighbourhood dynamic of exchange mobility, in which different neighbourhoods trade ranks in the income distribution. Exchange processes describe uneven development or flows of households across neighbourhoods driven by processes such as gentrification, displacement and segregation. Theories of locational attainment suggest that as residents of disadvantaged neighbourhoods climb the income ladder, they can translate income mobility into spatial capital by relocating to higher income neighbourhoods. Recent work, however, confirms longstanding patterns that racial and ethnic minorities do so less often than their white counterparts (Bruch and Mare, 2006; Malone, 2020; Quillian, 2012; Sampson and Sharkey, 2008).

From the perspective of intraregional spatial income mobility dynamics, these patterns suggest that regions characterised by high levels of racial and ethnic segregation that also experience minority income growth may reveal patterns of exchange mobility

where neighbourhoods change rank in the income distribution. If minority residents are less spatially mobile when they climb the (individual) income ladder, then income mobility among minority groups may lead to exchange mobility among neighbourhoods. In such a situation, minority incomes rise in place, rather than incomes rising in concert with spatial mobility of individuals. However, if high levels of segregation are coupled with low minority income growth and limited movement out of poor minority neighbourhoods, we would expect low levels of neighbourhood exchange mobility. While existing work has shown that there is remarkable stability in the income ranks of neighbourhoods within a majority of US MSAs (Malone and Redfearn, 2018; Wheeler and La Jeunesse, 2008), we know little about the reasons *why* such stability persists, suggesting segregation and racial dynamics as a useful avenue for exploration.

Growing inequality through the power of place

In addition to exchange mobility, an important element to consider in spatial income dynamics is dispersion mobility, in which the regional distribution of incomes among spatial units changes shape (i.e. by widening). Such a process implies growing inequality between rich and poor neighbourhoods and could be associated with the sociological concept of spatial stigma (Logan, 1978; Malone, 2020; Sharkey, 2013; Wyly, 1999), which implies a recurrent feedback loop in which disadvantaged neighbourhoods become more so through compounded resource deprivation, or with the economic concept of spatially uneven decay of durable goods such as housing and transportation systems (Rosenthal and Ross, 2015). Urban policy measures can also play a prominent

role in dispersion income dynamics. Responding to issues such as growing concentrated poverty, federal policy initiatives have used research on neighbourhood effects to advocate mixed-income housing (Sampson et al., 2015) with the explicit purpose of affecting dispersion mobility. By helping to integrate mixed-income neighbourhoods, policies such as HOPE VI (Sampson et al., 2015), the Chicago Gautreaux programme (Rosenbaum, 1995) and Baltimore's regional housing policy initiative (Darrah and DeLuca, 2014; DeLuca and Rosenblatt, 2017) explicitly seek to narrow the neighbourhood income distribution.

Neighbourhood dynamics: Structural process

Neighbourhood dynamics are a complex blend of short- and long-term forces (Sampson et al., 2017). The latter include the secular trend towards higher levels of income inequality as well as large-scale immigration. Short-term shocks, such as the recent Great Recession and global COVID-19 pandemic, can also impact neighbourhood dynamics. In addition, generational shifts in residential preferences (e.g. the revaluation of urban amenities proposed by Ehrenhalt, 2012) can alter the attractiveness of a region, leading to a 'rising of all boats'. This can be due to either an influx of new residents with greater purchasing power or the in situ rise of the incomes of existing residents as they move into higher earning age cohorts.

Thus, while there are a variety of theoretical traditions through which to couch neighbourhood income dynamics, in the following, we conduct a decomposition of economic mobility following a similar quantitative framework to that of Modai-Snir and van Ham (2018). We expand upon their empirical work by applying our framework to an extended sample of MSAs in the US in three cross-sectional periods. This strategy

allows us to examine how spatial and temporal heterogeneity in the underlying processes of income mobility may lead to different outcomes across the regions of the US. For example, we can ask if economic restructuring tends to be a more prominent driving factor in the industrial Midwest. In contrast, cultural processes and slowly-eroding historical racism may be more prominent in the antebellum South. This design allows us to parse distinct periods, each shaped by potentially different political, economic and cultural atmospheres, and describe how each distinct context led to various forms of spatial economic mobility.

Measuring neighbourhood income mobility

Study area and data

We adopt neighbourhoods as our units of analysis to reveal the neighbourhood income dynamics patterns of urban areas in the United States. Census tracts, which are defined by the US Census to contain an average of 4000 residents, are often used as proxies for neighbourhoods. Urban researchers have adopted the same strategy in various studies of neighbourhood effects (Leventhal and Brooks-Gunn, 2003), neighbourhood change (Delmelle, 2017; Zwiers et al., 2017) and residential segregation (Bischoff and Reardon, 2014; Reardon and Bischoff, 2011). Although census tracts are designed to be relatively permanent statistical subdivisions over time, they can undergo changes such as merges, splits and corrections due to population change. As such, boundaries are often 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

Table 1. Example cases of income mobility ($y_0 \rightarrow y_1$ for three neighbourhoods $n = 3$).

	y_0	y_1	Process
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

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 records with 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.² We adjust all income values for inflation and express them in 2015 dollars using the Consumer Price Index from the Bureau of Labour Statistics.³

Income mobility measures and processes

We investigate the dynamics of neighbourhood incomes in the urban US by adapting mobility measures that have been applied to personal income distribution dynamics. Mobility analysis is concerned with measuring the changes in economic status or 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 neighbourhoods to illustrate these two processes. As shown in Table 1, the initial income values of the three neighbourhoods constitute vector y_0 while the income values in the next time period constitute vector y_1 . The income changes are denoted as $y_0 \rightarrow y_1$. Cases I, III, IV, VII do not give rise to changes in rank, in the sense that three neighbourhoods keep their initial ranks, and thus, we observe no exchange mobility in the income distribution. On the other hand, cases II, V, VI and VIII lead to rank exchanges between the first and third neighbourhoods.

Analyses of structural mobility consider two properties of the income distribution: mean and dispersion. The former describes growth or decline in the city economy as a whole, while the latter relates to the changes in the shares each neighbourhood receives and is central to inequality dynamics. In Table 1 ($y_0 \rightarrow y_1$), case III represents an increase in the size of the economy (mean/total income doubles), and is a pure growth process, while case IV is a pure dispersion process, as the only change is in the income shares of neighbourhoods 1 and 2. Cases V,

VI, VII and VIII are a mixture of two or three mobility processes (growth, exchange and dispersion).

Fields (2006) identified six mobility concepts, which are time dependence, positional movement, share movement, income flux, directional income movement, and mobility as an equaliser of long-term incomes. Each captures 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 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 an income flux measure to decompose and analyse if it is sensitive to all three processes. Income flux is concerned with the degree to which neighbourhood 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 y_0 and y_1 are n -vectors of incomes. The income flux measure M for this two-period framework is defined in equation (1):

$$M(y_0, y_1) = \frac{1}{n} \sum_{i=1}^n |\log(y_{1i}) - \log(y_{0i})|. \quad (1)$$

The difference in logs takes the initial incomes into account, as a dollar change would be relatively smaller for a higher initial income compared with a lower initial income.

A hierarchical decomposition. Our approach is to decompose the income flux measure M into two components, exchange and structural. The structural component is further divided into growth and dispersion components:

$$\begin{aligned} M &= M_E + M_S \\ &= M_E + M_G + M_D, \end{aligned} \quad (2)$$

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 particular component and assess the income mobility difference between pre- and post-removal (Van Kerm, 2004). The idea is to construct a counterfactual income vector with a mobility component removed, and this vector would replace the second income vector y_1 . 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 y_1 based on the order of y_0 without changing anything else. For the case of process VIII, $y^E = (3, 4, 5)$ (equivalent to y_1 in VII). Thus, the marginal effect for the Exchange process is

$$M_E = M(y_0, y_1) - M(y_0, y^E). \quad (3)$$

Structural process. The counterfactual income vector y^S is constructed by removing the

structural process from the original process $y^0 \rightarrow y^1$. 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 y^0 based on the order of y^1 . For the case of process VIII, $y^S = (3, 2, 1)$ (equivalent to y^1 in II). The marginal effect for the Structural process is

$$M_S = M(y^0, y^1) - M(y^0, y^S). \quad (4)$$

Shapley procedure. Both equations (3) and (4) are first-round marginal effects and they do not necessarily add up to the income flux measure $M(y^0, y^1)$ and, thus, do not fulfil 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 ($M(y^0, y^E) - M(y^0, y^0) = M(y^0, y^E)$ as the counterfactual vector with the structural process removed for y^E is y^0). This 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):

$$\begin{aligned} M_E &= \frac{1}{2} \{ \{M(y^0, y^1) - M(y^0, y^E)\} + M(y^0, y^S) \}, \\ M_S &= \frac{1}{2} \{ M(y^0, y^E) + \{M(y^0, y^1) - M(y^0, y^S)\} \}. \end{aligned} \quad (5)$$

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 $y^0 \rightarrow y^E$ (i.e. case VII $-(1, 2, 3) \rightarrow (3, 4, 5)$ since the exchange factor has been removed from the original process). 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 y^0 : $y^{E,G} = \frac{\mu_{y^0}}{\mu_{y^E}} y^E$, where μ_{y^0} and μ_{y^E} are means of y^0 and y^E . Thus, the first-round marginal impact of the Growth process is

$$M_G = M(y^0, y^E) - M(y^0, y^{E,G}), \quad (6)$$

and the second-round marginal impact of the Dispersion process is equal to $M(y^0, y^{E,G})$.

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 y^0 . Thus, the first-round marginal impact of the Dispersion process is

$$M_D = M(y^0, y^E) - M(y^0, y^{E,D}), \quad (7)$$

and the second-round marginal impact of the Growth process is equal to $M(y^0, y^{E,D})$.

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 four different sequences.

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

Table 2. 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 3. Neighbourhood income mobility decomposition in the long term (1980–2010).

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

Note: Numbers in parentheses are standard errors for estimates. Numbers in square brackets are estimates of proportions.

$(y0_i, y1_i), i \in \{1, \dots, n\}$ 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 (Efron and Tibshirani, 1993; Van Kerm, 2004).

Results: Neighbourhood income mobility

Among the 54,275 neighbourhoods in 294 MSAs under study, we find that, both the mean and the standard deviation (as well as the interquartile range) of cross-sectional per capita incomes have been increasing consistently from 1980 to 2010 (Table 2). This indicates shifts of tract-level income distributions 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 rich and poor neighbourhoods. More specifically, poor tracts in 2000 were actually hosting higher-earning urban residents compared with 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.

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 3. Since the decomposition is additive, we can evaluate the proportions of relative contribution due to each component. The proportions are displayed as a percentage within square brackets in Table 3; standard errors are displayed within brackets. 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 US 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.

These results are averages taken over all neighbourhoods from the 54,275 tracts. We now turn to a more granular examination of the spatial and temporal patterns of neighbourhood income mobility.

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 MSAs which have experienced more drastic changes in neighbourhood economic status are spatially proximate to those having a similar experience. This provides a sense of regional and local economic development modes, and could have important implications for the regional/local policy. 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 ($N = 291$ after excluding 3 MSAs outside the continental US) with attribute x , Moran's I statistic is defined as:

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

where $z_i = x_i - \bar{x}$ is the deviation from the mean, and $w_{i,j}$ is the ij th entry of the row-normalised spatial weight matrix which

represents a prior notion of the neighbouring structure of MSAs (a k -nearest neighbour 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 MSAs with high or low neighbourhood income mobility. The local Moran's I statistic for the variable x at location i is defined as:

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

Inference is based on the pseudo- p value obtained from the conditional randomisation where for a focal MSA i , its value x_i is held fixed, while all the others are randomly permuted across remaining MSAs in order to simulate the null hypothesis of local spatial randomness.⁴

The estimates of overall urban income mobility (income influx measure) for 291 MSAs display considerable variation, ranging from 0.2 to 0.68, and they are not distributed randomly in space.⁵ 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 neighbours ($k \in [3, 20]$) used for constructing the k -nearest neighbour spatial weight matrix.⁶

The property of positive spatial autocorrelation also applies to the proportions

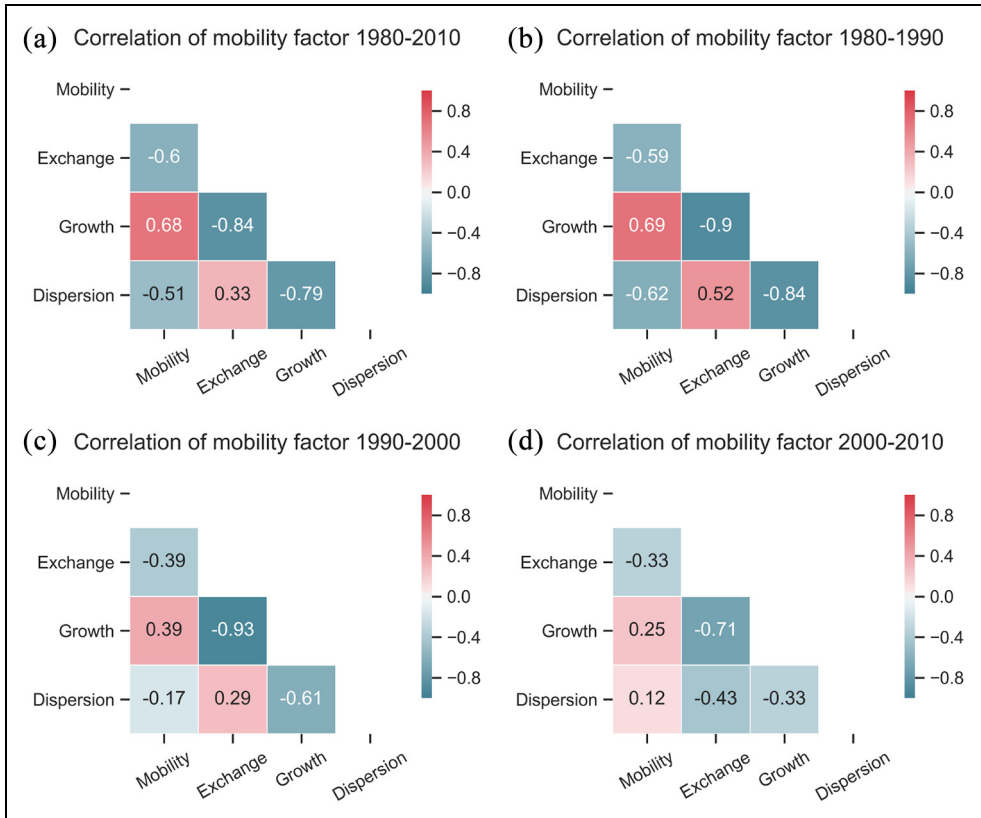


Figure 1. Correlation coefficients between mobility and its contributing factors. (a) 1980–2010. (b) 1980–1990. (c) 1990–2000. (d) 2000–2010.

contributed from the Exchange, Growth and Dispersion factors. The Growth factor has the widest range – [0.08, 0.91], indicating that the neighbourhood income mobility of some MSAs is dominated (as large as 91%) by the absolute change in the average income level. The Exchange and Dispersion factors have smaller ranges – [0.06, 0.57] and [0.3, 0.58], respectively. Interestingly, the Growth factor is 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 1(a). The positive correlation (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.

Based on the local Moran's I statistic while using spatial weights based on the eight nearest neighbours,⁷ we identify hot and cold spots of MSAs in terms of the overall mobility level as well as the contributing

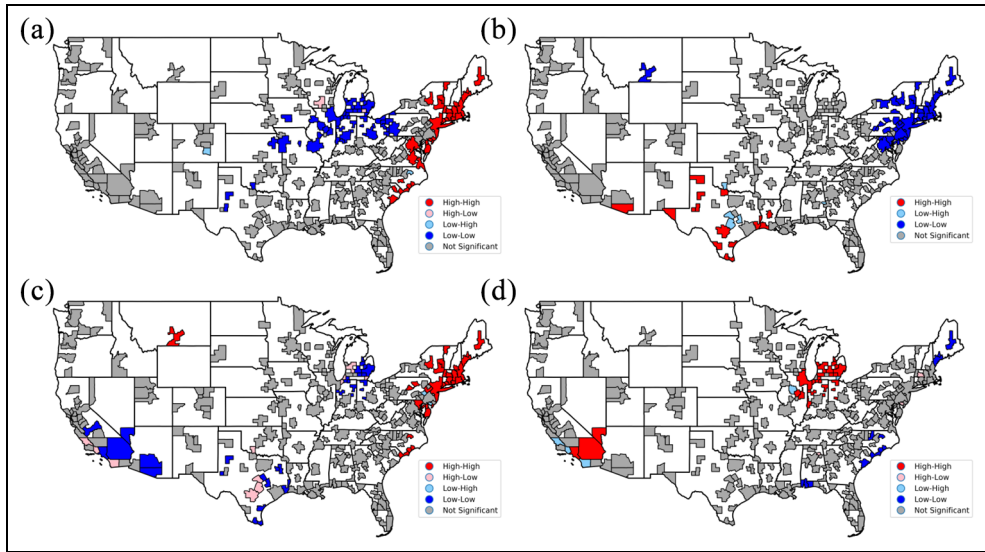


Figure 2. Local hot and cold spots of US MSA income mobility and the proportions of exchange, growth and dispersion mobility components across 1980–2010. (a) Income flux mobility levels. (b) Exchange mobility proportions. (c) Growth mobility proportions. (d) Dispersion mobility proportions.

proportions of the Exchange, Growth and Dispersion factors. Having controlled the false discovery rate (FDR) to deal with the multiple testing issue, we identify hot and cold spots for each term at the 5% significance level as shown in Figure 2. Some interesting patterns emerge from these four maps. Several MSAs in the Northeast are identified as hot spots in maps 2a and 2c and cold spots in map 2b, while some MSAs in the Great Lakes region are almost the opposite – cold spots in maps 2a and 2c and hot spots in map 2d.

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 3. In fact, the overall income mobility has been decreasing over time, indicating that urban neighbourhood income distributions 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 neighbourhoods were transformed more drastically in recent decades.

The pronounced temporal heterogeneity in the contributing proportions of three mobility components also manifests at 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

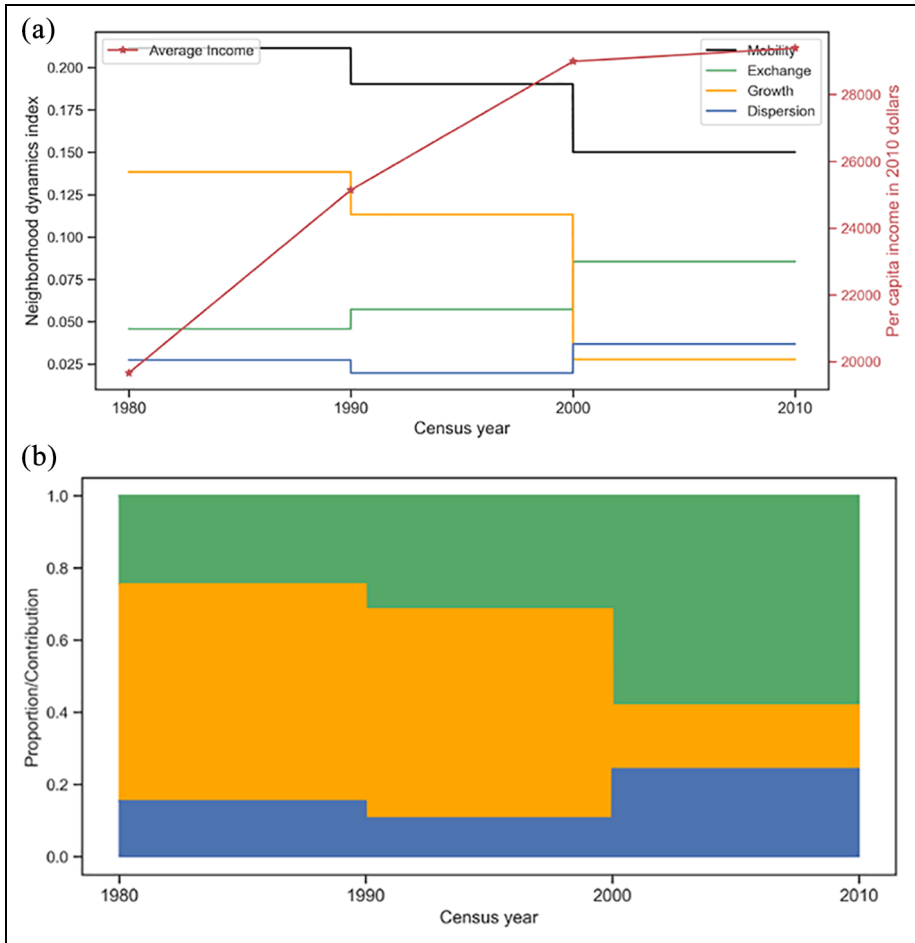


Figure 3. Average multidimensional neighbourhood dynamics across all MSAs under study. (a) Average multidimensional neighbourhood income dynamics across all MSAs. (b) Averages of contributions of exchange, growth and dispersion processes across all MSAs.

diagrams, which are a powerful visualisation tool for exploring compositional data in Figure 4, 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 neighbourhood 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 4(a) indicates that the dominant force of neighbourhood income mobility within most MSAs is Growth over the long term. Comparatively, as shown in Figure 4(b), the centre of mass has been shifting over time from the top corner to the right corner,

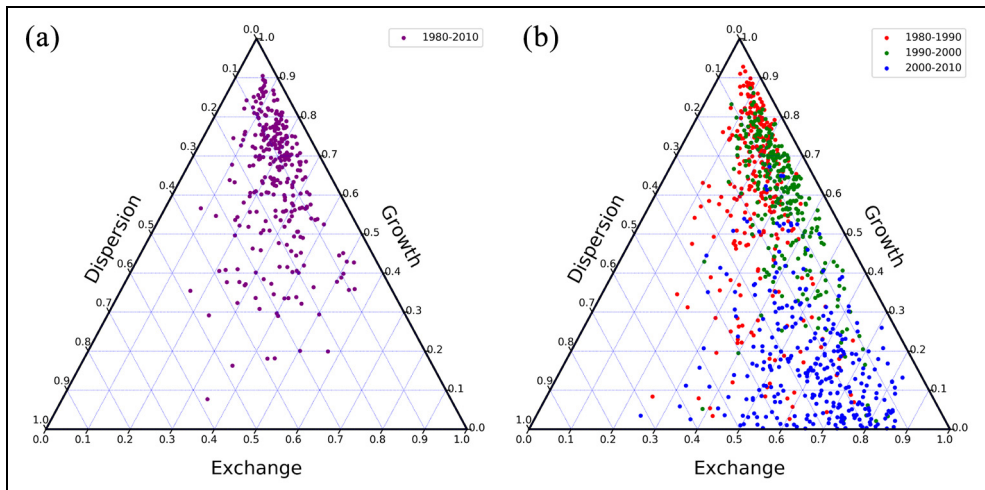


Figure 4. Ternary diagrams for proportions of exchange, growth and dispersion mobility components (a) in the long term 1980–2010, and (b) in the short terms 1980–1990, 1990–2000 and 2000–2010. (a) Long-term ternary diagram. (b) Decennial ternary diagram.

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 neighbourhood per capita incomes within individual MSAs.

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.⁸ 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 stood out as a hot spot for the overall mobility level and Growth mobility, and a cold spot for Exchange and Dispersion mobility. By contrast, the Great Lakes region failed to stand out; instead Texas, New Mexico and

Louisiana hosted 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 mobility, as well as hot spots for Exchange mobility in the West coast. For the most recent decade 2000–2010, the Great Lakes region stood 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 1. 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

Table 4. 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 urbanisation	Yes
gini	Gini index measuring spatial inequality between neighbourhoods within each MSA	Yes
pmanuf	Percentage of manufacturing employees. Proxy for industrial structure	Yes
pcol	Percentage of persons with at least a four-year college degree	Yes
pnhblk	Percentage of Non-Hispanic Black population	Yes
phisp	Percentage of Hispanic population	Yes
pasian	Percentage of Non-Hispanic Asian population	Yes
multinfor	Multigroup Information Theory index for residential segregation (Reardon and Firebaugh, 2002)	Yes

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.

Generalising neighbourhood income mobility

Given the widespread temporal and spatial heterogeneity in the neighbourhood mobility results that we have identified, we carry out a spatial econometric analysis as a first step to identify the possible factors that may be driving neighbourhood income dynamics in urban US regions. Compared with spatial income inequality (Rodríguez-Pose and Ezcurra, 2010; Wei, 2015), scholarship on income mobility at the spatial aggregate level is considerably limited. We address this gap by formally modelling the relationship between the metro-level income mobility (and its contributory components) and the metro-level variables at the beginning year of each decade listed in Table 4. These nine variables cover urban development, spatial income disparity, industrial composition,

education attainment and residential racial composition and segregation. We have also tested against the decadal changes in these variables, leading to another set of models with 18 predictor variables.⁹

Our point of departure is the classic linear model in equation (10) specified 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 neighbour 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.

$$y = X\beta + \epsilon \quad (10)$$

$$y = \rho Wy + X\beta + \epsilon \quad (11)$$

y is the vector of MSA mobility measures, and X the matrix of explanatory variables for a given 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.

The estimation results for these specifications for the three decades are reported in Tables 5 to 7. The results mirror the temporal heterogeneity seen in our exploratory results in that factors that are associated with neighbourhood income mobility vary over the decades. For example, the percentage of manufacturing employment has only been significant for the period 1980–1990 as shown in Table 5. After incorporating its decadal increase in the model (model II), manufacturing employment was positively related to the spatial income influx level and Growth mobility. Racial composition including the percentages of Hispanic and Asian, the racial segregation level, and higher education attainment were only significant in the latest time period 2000–2010 (Table 7). 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, potential evidence for a stagnating effect of segregation on neighbourhood income mobility.

Urban development level proxied by population and population density was significant for 1980–1990 and 2000–2010. It was positively correlated with the overall neighbourhood income dynamics 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 neighbourhood income dynamics, 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 6) and 2000–2010 (Table 7). One prominent observation is that in the last decade (i.e. 2000–2010), the level of spatial income inequality and its decadal increase was also positively correlated with the overall neighbourhood income dynamics.

There is strong evidence of spatial dependence across all three decades. The spatial lag is significant for all types of MSA-level neighbourhood mobility measures, with the only exception being the dispersion component in the final decade. This form of dependence reflects the regional patterning we found earlier in the hot (cold)-spot analysis. The temporal constancy of the spatial dependence stands in stark contrast to the temporal heterogeneity reflected in the other correlates of neighbourhood income mobility.

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. Our results highlight the considerable ways that the American urban economy has differed over space and changed through 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.

We can view these results in a broader historical context. 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

Table 5. 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*** (0.0237)	0.0263 (0.0278)	-0.0071 (0.0071)	-0.0074 (0.0087)	0.0722*** (0.0252)	0.0448 (0.0304)	0.0103 (0.0070)	0.0059 (0.0068)
popstd	-0.0000 (0.0044)	-0.0059 (0.0051)	0.0024* (0.0014)	0.0026 (0.0016)	-0.0010 (0.0048)	-0.0075 (0.0056)	-0.0006 (0.0013)	0.0001 (0.0013)
densiystd	0.0110*** (0.0043)	0.0131*** (0.0045)	-0.0040*** (0.0014)	-0.0041*** (0.0014)	0.0134*** (0.0047)	0.0177*** (0.0050)	-0.0008 (0.0013)	-0.0034*** (0.0011)
gini	0.0500 (0.0709)	0.0253 (0.0705)	0.2573*** (0.0246)	0.2571*** (0.0247)	-0.1782*** (0.0792)	-0.1864*** (0.0790)	0.0420* (0.0220)	0.0261 (0.0181)
pmanuf	-0.1165*** (0.0407)	-0.0187 (0.0650)	-0.0206 (0.0128)	-0.0169 (0.0208)	-0.0892*** (0.0447)	-0.0005 (0.0717)	-0.0040 (0.0125)	0.0010 (0.0164)
pcol	-0.0235 (0.0540)	-0.0003 (0.0680)	0.0113 (0.0170)	0.0201 (0.0218)	-0.0157 (0.0593)	0.0175 (0.0749)	-0.0164 (0.0167)	-0.0328* (0.0172)
pnhlk	0.0044 (0.0225)	0.0187 (0.0355)	-0.0111 (0.0071)	-0.0212* (0.0114)	0.0173 (0.0247)	0.0312 (0.0392)	0.0017 (0.0069)	0.0138 (0.0090)
phisp	-0.0124 (0.0340)	0.0004 (0.0451)	0.0005 (0.0107)	0.0080 (0.0144)	-0.0028 (0.0373)	0.0039 (0.0497)	-0.0115 (0.0105)	-0.0117 (0.0114)
pasian	-0.1941 (0.1968)	-0.2193 (0.2165)	-0.1206* (0.0623)	-0.1695** (0.0695)	-0.1571 (0.2163)	-0.1332 (0.2387)	0.0163 (0.0607)	0.0092 (0.0546)
multinfor	0.0131 (0.0228)	0.0381 (0.0329)	0.0122* (0.0072)	0.0115 (0.0105)	-0.0009 (0.0250)	0.0411 (0.0362)	0.0000 (0.0070)	-0.0161* (0.0083)
popstd_change		0.0073 (0.0046)		-0.0001 (0.0015)		0.0075 (0.0050)		-0.0007 (0.0012)
densiystd_change		-0.0059 (0.0043)		0.0000 (0.0014)		-0.0055 (0.0047)		-0.0003 (0.0011)
gini_change		0.2130 (0.1484)		-0.0025 (0.0476)		-0.1480 (0.1635)		0.4881*** (0.0389)
pmanuf_change		0.1269** (0.0599)		0.0058 (0.0192)		0.1195* (0.0660)		-0.0009 (0.0151)
pcol_change		0.0307 (0.0534)		0.0118 (0.0171)		0.0342 (0.0589)		-0.0135 (0.0135)
pnhlk_change		0.0107 (0.0274)		-0.0094 (0.0088)		0.0098 (0.0302)		0.0097 (0.0069)
phisp_change		0.0032 (0.0340)		0.0085 (0.0109)		-0.0014 (0.0374)		-0.0049 (0.0086)
pasian_change		0.1726 (0.1498)		-0.0725 (0.0480)		0.2231 (0.1651)		0.0115 (0.0378)
multinfor_change		0.0287 (0.0280)		0.0008 (0.0090)		0.0428 (0.0309)		-0.0118* (0.0071)
W	0.7941*** (0.0390)	0.8051*** (0.0366)	0.4016*** (0.0688)	0.4041*** (0.0689)	0.8068*** (0.0362)	0.7946*** (0.0372)	0.5545*** (0.0722)	0.3443*** (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 6. 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*** (0.0189)	0.0675*** (0.0203)	-0.0123 (0.0080)	-0.0161* (0.0087)	0.0618*** (0.0164)	0.0705*** (0.0178)	0.0058 (0.0054)	0.0070 (0.0059)
popstd	0.0015 (0.0032)	-0.0010 (0.0073)	0.0034** (0.0016)	0.0016 (0.0037)	-0.0005 (0.0031)	-0.0039 (0.0071)	-0.0018 (0.0011)	0.0009 (0.0025)
densistd	-0.0049 (0.0031)	-0.0014 (0.0053)	-0.0016 (0.0016)	-0.0027 (0.0027)	-0.0014 (0.0030)	0.0037 (0.0051)	-0.0014 (0.0011)	-0.0033* (0.0018)
gini	0.0507 (0.0453)	0.0544 (0.0472)	0.1953*** (0.0244)	0.2178*** (0.0253)	-0.1672*** (0.0444)	-0.1750*** (0.0463)	0.0772*** (0.0160)	0.0818*** (0.0165)
pmanuf	0.0128 (0.0438)	-0.0115 (0.0532)	-0.0048 (0.0221)	-0.0017 (0.0266)	0.0181 (0.0425)	0.0022 (0.0515)	0.0020 (0.0152)	0.0018 (0.0183)
pcol	0.0278 (0.0383)	0.0224 (0.0450)	0.0429** (0.0193)	0.0300 (0.0226)	-0.0101 (0.0371)	0.0051 (0.0437)	-0.0077 (0.0133)	-0.0045 (0.0155)
pnhblk	0.0041 (0.0204)	-0.0012 (0.0231)	-0.0170* (0.0103)	-0.0116 (0.0115)	0.0232 (0.0198)	0.0089 (0.0224)	-0.0013 (0.0071)	0.0043 (0.0079)
phisp	-0.0304 (0.0254)	-0.0120 (0.0299)	-0.0069 (0.0128)	-0.0052 (0.0149)	-0.0182 (0.0246)	-0.0037 (0.0290)	-0.0083 (0.0088)	-0.0041 (0.0103)
pasian	-0.0596 (0.1034)	-0.1661 (0.1592)	-0.0551 (0.0522)	-0.0660 (0.0796)	-0.0023 (0.1002)	-0.0244 (0.1543)	0.0083 (0.0358)	-0.0597 (0.0547)
multinfor	-0.0064 (0.0206)	-0.0132 (0.0259)	0.0195* (0.0104)	0.0156 (0.0129)	-0.0099 (0.0200)	-0.0037 (0.0251)	-0.0118* (0.0071)	-0.0226** (0.0089)
popstd_change		0.0034 (0.0079)		0.0019 (0.0039)		0.0044 (0.0076)		-0.0031 (0.0027)
densistd_change		-0.0056 (0.0060)		0.0001 (0.0030)		-0.0071 (0.0059)		0.0025 (0.0021)
gini_change		0.0335 (0.1215)		0.1861*** (0.0613)		-0.1020 (0.1179)		0.0510 (0.0418)
pmanuf_change		-0.0899 (0.1487)		-0.0148 (0.0744)		-0.0383 (0.1442)		-0.0101 (0.0511)
pcol_change		-0.0887 (0.1535)		0.0656 (0.0770)		-0.1474 (0.1488)		-0.0572 (0.0527)
pnhblk_change		0.0551 (0.0908)		0.0224 (0.0455)		0.0186 (0.0881)		-0.0176 (0.0312)
phisp_change		-0.0688 (0.0860)		-0.0062 (0.0431)		-0.0843 (0.0834)		0.0034 (0.0296)
pasian_change		0.3021 (0.2748)		0.0504 (0.1374)		0.0455 (0.2664)		0.1798* (0.0944)
multinfor_change		-0.0295 (0.0662)		0.0045 (0.0331)		0.0142 (0.0642)		-0.0399* (0.0228)
Wy	0.6299*** (0.0630)	0.6264*** (0.0632)	0.4464*** (0.0709)	0.4133*** (0.0716)	0.7367*** (0.0477)	0.7284*** (0.0487)	0.2711*** (0.0965)	0.2616*** (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 7. 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*** (0.0183)	0.0640*** (0.0184)	-0.0012 (0.0095)	-0.0126 (0.0115)	0.0519*** (0.0116)	0.0610*** (0.0145)	0.0504*** (0.0111)	0.0148 (0.0100)
popstd	0.0021 (0.0027)	-0.0006 (0.0032)	0.0053*** (0.0017)	0.0045** (0.0023)	0.0003 (0.0022)	-0.0017 (0.0029)	-0.0029 (0.0020)	-0.0026 (0.0020)
densiystd	-0.0045* (0.0027)	0.0001 (0.0028)	-0.0036** (0.0017)	-0.0019 (0.0020)	0.0015 (0.0022)	0.0038 (0.0026)	-0.0023 (0.0020)	-0.0015 (0.0017)
gini	0.2072*** (0.0403)	0.2629*** (0.0354)	0.2030*** (0.0261)	0.2084*** (0.0261)	-0.0128 (0.0315)	-0.0162 (0.0317)	-0.0045 (0.0286)	0.0472** (0.0211)
pmanuf	-0.0484 (0.0431)	-0.0474 (0.0531)	0.0168 (0.0267)	0.0120 (0.0376)	-0.0484 (0.0346)	-0.0683 (0.0488)	-0.0150 (0.0314)	0.0129 (0.0325)
pcol	-0.0975*** (0.0291)	-0.0797** (0.0335)	0.0291 (0.0180)	0.0499** (0.0237)	-0.0858*** (0.0233)	-0.1041*** (0.0308)	-0.0356* (0.0212)	-0.0115 (0.0205)
pnhlbk	0.0040 (0.0180)	0.0112 (0.0221)	-0.0076 (0.0112)	-0.0062 (0.0156)	0.0047 (0.0145)	0.0083 (0.0203)	0.0069 (0.0131)	0.0115 (0.0135)
phisp	-0.0637*** (0.0193)	-0.0452** (0.0203)	-0.0045 (0.0119)	-0.0040 (0.0144)	-0.0415*** (0.0154)	-0.0399** (0.0187)	-0.0159 (0.0140)	0.0023 (0.0125)
pasian	0.1615*** (0.0601)	0.1376** (0.0569)	-0.0256 (0.0373)	-0.0349 (0.0403)	0.1112** (0.0482)	0.1303*** (0.0523)	0.0661 (0.0438)	0.0230 (0.0348)
multinfor	-0.0391** (0.0199)	-0.0455* (0.0239)	0.0158 (0.0123)	0.0184 (0.0169)	-0.0306* (0.0159)	-0.0335 (0.0220)	-0.0257* (0.0145)	-0.0284* (0.0147)
popstd_change		0.0042 (0.0032)		0.0010 (0.0023)		0.0021 (0.0029)		0.0008 (0.0020)
densiystd_change		-0.0071** (0.0029)		-0.0023 (0.0020)		-0.0042 (0.0026)		-0.0005 (0.0018)
gini_change		0.8601*** (0.0906)		0.1387** (0.0639)		-0.1491* (0.0828)		0.8912*** (0.0555)
pmanuf_change		0.0276 (0.0530)		0.0083 (0.0375)		-0.0268 (0.0486)		0.0517 (0.0324)
pcol_change		0.0156 (0.0242)		0.0244 (0.0171)		-0.0150 (0.0222)		0.0154 (0.0148)
pnhlbk_change		0.0087 (0.0194)		0.0004 (0.0137)		0.0054 (0.0178)		0.0055 (0.0119)
phisp_change		0.0232 (0.0169)		-0.0007 (0.0120)		0.0139 (0.0155)		0.0099 (0.0104)
pasian_change		0.0255 (0.0430)		0.0196 (0.0304)		0.0268 (0.0395)		-0.0316 (0.0263)
multinfor_change		-0.0180 (0.0219)		0.0044 (0.0155)		-0.0036 (0.0201)		-0.0137 (0.0134)
W	0.3474*** (0.0881)	0.3551*** (0.0769)	0.4608*** (0.0686)	0.4768*** (0.0671)	0.4890*** (0.0785)	0.5003*** (0.0765)	0.0897 (0.1141)	-0.0158 (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.

Chicago, Detroit, Cleveland, Pittsburgh and Milwaukee. The primary demographic trend during this period was ‘white flight’, or the suburbanisation of white, well-educated and affluent families (Baum-Snow and Hartley, 2020). 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 the Midwest 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 (Ehrenhalt, 2012). These trends are a 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 neighbourhoods.

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 cold spots for exchange mobility. At the same time, however, it hosted hotspots for growth mobility. At a local scale, this means that neighbourhoods in New York and Washington DC did not trade ranks often; prominent neighbourhoods in New York and DC stayed as such. On a national scale, however, these same cities continue to 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 cold spot for overall mobility over the full 1980–2010 time period and, similarly, a cold spot for growth.

Economists and geographers have long recognised 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.

In the 1980s, deregulation and the transitioning economy led to reshaping of urban inequality across the US, metropolitan regions with larger shares in manufacturing employment saw an overall decrease in economic mobility, whereas economic deregulation led to considerable growth in financial centres along the Northeast corridor. 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 neighbourhoods 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 emerges. In metros with large shares of the economy dedicated to manufacturing, neighbourhoods 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 cold spot for economic growth.

The 1990s seemed to be a period of polarisation and widening inequality, with the gap growing fastest in places already characterised by a high spatial Gini index. Further, metropolitan regions with large college-educated populations saw a larger change in economic dispersion. Many of the largest metros in the 90s seemed to be characterised 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 neighbourhoods on the national scale along with 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 (Hyra, 2015; Sturtevant and Jung, 2011).

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 indices were more likely to continue a trend towards exchange and dispersal. In other words, through the 2000s, many of America’s 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.

Although our results show nuance in each decade, some long-term trends are

nonetheless important to discuss. In particular, while the spatial and economic consequences of deindustrialisation have been explored at length in the urban economic literature (Dawkins, 2003), a critically under-examined component of economic restructuring has been its impact on prevailing political ideology and the spatial patterning thereof: a phenomenon Rodríguez-Pose (2018: 189) has called ‘a wave of political populism with strong territorial, rather than social foundations’. The result, as Rodríguez-Pose describes, is that political persuasions have polarised in the US and elsewhere, revealing a pattern in which ‘populism took hold not among the poorest of the poor, but in a combination of poor regions and areas that had suffered long periods of decline. It has been thus the places that don’t matter, not the “people that don’t matter”, that have reacted’ (2018: 201). Our findings underscore this perspective. While the American rustbelt was once an engine of economic opportunity, providing high paying jobs in manufacturing and mining, our results demonstrate a sustained period of slow growth, whose explicitly regional manifestation carries political implications for the electoral map, as well as for national unity and inequality.

Conclusions

This paper provides an empirical study of US neighbourhood income dynamics using decennial census and American Community Survey (ACS) datasets covering a variety of mega, medium and small cities over both long-term time spans (1980–2010), as well as short terms 1980–1990, 1990–2000, 2000–2010. We adopt a decomposition technique for unpacking an overall spatial income mobility index into its contributing components (namely Exchange, Growth and Dispersion mobility) to obtain insights into processes of multidimensional urban and

neighbourhood change. The paper represents one of the first comprehensive studies of neighbourhood income dynamics in the metropolitan United States, covering a broad set of cities and a variety of temporal scales and using spatially explicit exploratory and confirmatory analytics.

We find that, at the national scale, Growth mobility dominates followed by Exchange mobility in the long term. However, this dominating–dominated relationship is reversed over time in the short term, indicating temporally heterogeneous urban and neighbourhood processes. We confirm this temporal heterogeneity by examining MSA-level spatial mobility. In the long term, we uncover a strong negative relationship between Growth and Exchange/Dispersion mobility, while Growth mobility appears positively related to overall spatial mobility. Together these findings indicate that more mobile MSAs were typically dominated by changes in absolute average income level, and these MSAs tend to host tracts with fewer rank exchanges or changes in income shares. These relationships, however, have been changing in shorter time frames, a finding we confirm through a set of regression analyses demonstrating temporal variation in statistically significant determinants. This finding, we argue, stresses the importance of studying urban processes through a dynamic lens. Aside from temporal heterogeneity, another significant finding is the spatial agglomeration effect of intraurban neighbourhood income dynamics; for example, the Northeastern and the Great Lakes regions have been hosting either hot spots or cold spots of neighbourhood income dynamics and its contributing components.

As we demonstrate in the paper, different temporal scales can manifest diverging neighbourhood income patterns and thus varying urban and neighbourhood dynamics. While we look at a 30-year long term, as well as the

three decadal short terms, we lack information on 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 endeavour would be to utilise the ACS five-year estimates (2009–2018) to investigate smaller temporal scales though this comes with the downside of dealing with larger margins of error. Another limitation of the current paper is the limited set of explanatory variables adopted for the spatial regression analysis. A promising avenue for further research is, thus, to interrogate household migration across neighbourhoods and MSAs, which may provide a better sense of how the observed neighbourhood income dynamics, as well as the Growth, Dispersion, Exchange components, relate to demographic processes such as gentrification or displacement. Another interesting dimension is to explore whether and how institutions as well as technology and innovation have been shaping smaller-scale inequality dynamics, as they have been demonstrated to impact dynamics at the larger scales (Lee and Rodríguez-Pose, 2016; Rodríguez-Pose, 2013; Storper et al., 2015).

Future work should also consider a spatially explicit view of neighbourhood inequality dynamics within MSAs. Although the decomposition method we present here allows for a comprehensive analysis of multiple neighbourhood processes within each MSA, it falls short of shedding light on potential spatial spillovers. In other words, it does not provide insights into whether nearby neighbourhoods tend to move together in ranks, absolute income growth, or income shares. Future research could be directed to a further decomposition of the current measure, which will enable a spatially explicit view or an application of extant spatially explicit income mobility measures (Kang and Rey, 2020; Rey, 2016).

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Notes

1. A key distinction between neighbourhood income dynamics 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 or exit the panel through migration, births, and deaths.
2. 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.
3. The CPI adjustment table can be accessed at the following URL: <https://www.bls.gov/cpi/research-series/allitems.xlsx> (accessed 15 January 2020).
4. The multiple testing issue is addressed by controlling the False Discovery Rate (FDR) (Benjamini and Yekutieli, 2001).
5. Maps visualising spatial distributions of MSA income mobility and the proportions of exchange, growth and dispersion mobility components across 1980–2010 are available upon request.

6. We construct the spatial weight matrix based on k -nearest neighbour for 294 US MSAs. Global Moran's I is always positive and significant for $k \in [3, 20]$ under random spatial permutations.
7. The spatial weight based on eight nearest neighbours generated the largest global Moran's I value and is thus adopted for the subsequent spatial statistical analysis.
8. Maps of the local hot and cold spots of MSA neighbourhood-level income flux and the decomposed Exchange, Growth and Dispersion components for each of three decades are available upon request.
9. We have also attempted to include variables such as metro average per capita/total income, foreign born population, unemployment rate, poverty rate, age distribution (Rodden, 2019), etc. These variables are removed from the final model specification as they are rarely significant and cause multicollinearity.

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