Annals of the American Association of Geographers

ISSN: 2469-4452 (Print) 2469-4460 (Online) Journal homepage: https://www.tandfonline.com/loi/raag21

How Entrenched Is the Spatial Structure of Inequality in Cities? Evidence from the Integration of Census and Housing Data for Denver from 1940 to 2016

Dylan Shane Connor, Myron P. Gutmann, Angela R. Cunningham, Kerri Keller Clement & Stefan Leyk

To cite this article: Dylan Shane Connor, Myron P. Gutmann, Angela R. Cunningham, Kerri Keller Clement & Stefan Leyk (2020) How Entrenched Is the Spatial Structure of Inequality in Cities? Evidence from the Integration of Census and Housing Data for Denver from 1940 to 2016, Annals of the American Association of Geographers, 110:4, 1022-1039, DOI: 10.1080/24694452.2019.1667218

To link to this article: https://doi.org/10.1080/24694452.2019.1667218

How Entrenched Is the Spatial Structure of Inequality in Cities? Evidence from the Integration of Census and Housing Data for Denver from 1940 to 2016

Dylan Shane Connor,* Myron P. Gutmann,† Angela R. Cunningham,‡ Kerri Keller Clement,§ and Stefan Leyk‡

*School of Geographical Sciences and Urban Planning, Arizona State University
†Institute of Behavioral Science and Department of History, University of Colorado Boulder
‡Department of Geography, University of Colorado Boulder
§Department of History, University of Colorado Boulder

How entrenched is the spatial structure of inequality in cities? Although recent discussions provide conflicting answers to this question, the absence of long-term, longitudinal neighborhood data curtails direct examination of the issue. Focusing on the city of Denver, we develop a new strategy for analyzing neighborhood dynamics from 1940 to the present day. Our analysis of these data reveals surprising persistence in the income rank of neighborhoods between 1940 and 2016, which appears to be driven by the enduring position of white, upper-income places at the top of the neighborhood hierarchy. When low-income neighborhoods do rise in income rank, we find that change tends to be spatially concentrated in specific areas of the city and accelerates during broader historical episodes of urban change. We conclude that neighborhood inequality in Denver has endured over long periods of time and through substantial shifts in the wider urban landscape. *Key Words: gentrification, GIS, inequality, neighborhoods, spatial demography.*

城市的不平等空间结构有多么根深蒂固？近期对这个问题的讨论似乎得出相互矛盾的结论。此外，由于缺乏长期的纵向社区数据，也限制了以直接方法验证这个问题。我们以丹佛为例开发出一种新方法，用用户分析 1940 年至今的社区动态数据。对这些数据的分析显示出：从 1940 年至 2016 年间，社区收入排名保持了惊人的持续性，基本上都是由社区中上层的高收入白人群体所驱动。我们还发现，尽管也有低收入社区排名上升的情况，但变化在空间上集中在城市中的某些具体区域，在更广义的城市变化历史阶段中，会出现加速的现象。我们得出的结论是，丹佛的社区不平等现象一直长期持续存在，但在更广义的城市范围内经历了实质性的变化。*关键词：中产阶层化、地理信息系统、不平等、领域、空间人口统计学。*

¿Qué tan arraigada es la estructura espacial de la desigualdad en las ciudades? Si bien las discusiones recientes dan respuestas conflictivas a esta pregunta, la ausencia de datos longitudinales y a largo plazo a nivel de barrio limita el examen directo de este asunto. Enfocándonos en la ciudad de Denver, nosotros desarrollamos una nueva estrategia para analizar la dinámica del barrio desde 1940 hasta el día de hoy. Nuestro análisis de estos datos revela una sorprendente persistencia en el rango de ingresos de los barrios entre 1940 y 2016, que parece orientada por la posición duradera de los lugares de blancos con ingresos altos en el tope de la jerarquía vecinal. Cuando las barriadas de ingreso bajo logran ascender en el rango de ingresos, hallamos que el cambio tiende a estar concentrado espacialmente en áreas específicas de la ciudad y se acelera durante episodios históricos más amplios de cambio urbano. Concluimos que la desigualdad vecinal de Denver ha perdurado durante largos períodos de tiempo y a través de cambios sustanciales en el paisaje urbano más amplio. *Palabras clave: barrios, demografía espacial, desigualdad, gentrificación, SIG.*

In the United States, neighborhoods are the spatial foundations of inequality (Sampson 2019). The hierarchy of neighborhoods within cities not only parallels societal patterns of income inequality but also reinforces racial and class disparities in income, opportunity, and health (Sampson 2012).

Annals of the American Association of Geographers, 110(4) 2020, pp. 1022–1039 © 2019 by American Association of Geographers
Initial submission, December 2018; revised submissions, July and August 2019; final acceptance, August 2019
Color versions of one or more figures in the article can be found online at www.tandfonline.com/raag
Published by Taylor & Francis, LLC.

In a recent study of intergenerational mobility, for example, Chetty and Hendren (2018) estimated that up to 80 percent of the income differences observed among adults are attributable to the neighborhoods in which they had spent their childhoods. Given the current context of escalating inequality, the entrenchment of neighborhood differences is of profound importance to social equity issues.

Efforts to understand the endurance of inequality across the urban landscape, however, are severely constrained by the absence of consistent neighborhood observations through time. This is largely a result of how changes in the enumeration of the decennial censuses inhibit longitudinal neighborhood analysis (see Kirk and Laub 2010; Sheehan et al. 2017). In this article, we develop a new approach for integrating household-level data from the 1940 complete-count decennial census of the United States within contemporary enumeration units. We use these data to study the persistence of neighborhood inequality in the city of Denver across a seventy-six-year period. In future work, this approach could be extended beyond Denver to cities throughout the United States.

Our analysis contributes to research concerned with neighborhood inequality and demographic change. Recent studies have focused on the persistence of segregation (Ellis et al. 2017; Ellis et al. 2018), gentrification (Hwang and Lin 2016; Atuesta and Hewings 2018; Bardaka, Delgado, and Florax 2018), and socioeconomic stability (Owens 2012; Solari 2012; Landis 2016; Malone and Redfearn 2018). Relatedly, Delmelle (2016, 2017) and Wei and Knox (2014) recently developed clustering-based approaches to characterize multivariate spatial changes across neighborhoods. These cited studies, however, have focused on the post-1970 period. In extending our analysis back to 1940, we contribute to this work by taking a long-term view of neighborhood inequality through periods of substantial change in the spatial structure of cities.

Our first insight from these new data is that the income rank of neighborhoods has remained surprisingly stable since 1940. By income rank, we refer to the percentile ranking or position of neighborhoods in Denver according to average income.[1] We find a strong positive correlation in the income rank of tracts in Denver from 1940 to 2016 (+0.56), and the interdecadal rank correlation is often higher than +0.90. Further, high rates of stability among upper-income tracts appear to be driving much of this persistence in income position. That is, most upper-income neighborhoods in 1940 still have relatively high incomes today. Perhaps unsurprising, we find that black and Hispanic neighborhoods continue to be overrepresented at lower-income ranks. That is, we consistently observe racialized patterns in the income stratification of neighborhoods over time. These findings are consistent with theory that emphasizes the enduring racialized structure of cities in the United States (e.g., Hwang and Sampson 2014; Sampson 2019).

When neighborhoods rise in income rank, upwardly shifting neighborhoods appear to be spatially concentrated in particular areas of the city and tend to have smaller populations. During the mid-twentieth-century era of suburbanization, for example, neighborhoods along Denver's sparsely populated periphery were more likely to increase in income rank. Since 2000, in contrast, the neighborhoods improving in income position have been concentrated around Denver's central business district (CBD), an area that experienced substantial depopulation between 1940 and 1980. The coincidence of these patterns with the historical economic dynamics described by urban economic geographers (e.g., Scott 1982, 2018) suggests that periodic economic shocks might be a key mechanism driving the spatial reconfiguration of neighborhood inequality.

Neighborhood Inequality Dynamics

Neighborhoods are highly differentiated by income, and these disparities partly reflect spatial differences in the provision of public goods, amenities, and access to jobs across places (Tiebout 1956; Roback 1982). Because these attributes differentially affect whether households can satisfy their lifestyle and economic goals (Clark and Dieleman 1996), housing markets sort people into neighborhoods by their ability to pay. This sorting process contributes to persistent differences in the relative income position of neighborhoods.

Race relations also play a key role in shaping differences in neighborhood socioeconomic status (SES). Hwang and Sampson (2014) noted that U.S. cities exhibit an "imposed neighborhood racial hierarchy where white neighborhoods are the most favored, black neighborhoods the least, and Asian and Latino neighborhoods (are) in the middle, paralleling the racial ordering of inequality generally found in contemporary U.S. society" (728). On the one hand, the correlation of neighborhood racial composition and SES partly reflects income differences between white and non-white households. Housing markets are themselves arenas of racial subordination, however, where actors in dominant racial positions seek to minimize the presence of non-white neighbors (Logan and Molotch 1987; Massey and Denton 1993; Crowell and Fossett 2018). Thus, race relations have been an active ingredient in shaping the landscape of U.S. cities.

These racialized neighborhood differences are important drivers of racial economic inequality. Experimental research continues to show that the disproportionate exposure of low-income, non-white households to disadvantaged neighborhood contexts has self-reinforcing effects on long-term income differences by race (Sampson 2012; Sharkey 2013; Chetty et al. 2014). Thus, addressing racialized neighborhood differentiation might be the key to tackling racial inequality.

In this respect, the historical development of Denver provides a compelling case from which to investigate neighborhood inequality. Over the second half of the twentieth century, the racial composition of Denver changed substantially. The black share of Denver's population was around 2.5 percent in 1940 and had increased fivefold to 12.0 percent by 1980.[2] Likewise, the Hispanic share of Denver's population grew from 5.5 percent to 12.0 percent between 1940 and 1980. Thus, within the time frame of our analysis, Denver has experienced growth in at least two sizable racialized populations. Despite starting with a smaller black population than many major cities, the black population share of Denver grew at rates similar to that of cities such as Chicago (8 percent in 1940, 40 percent in 1980), New York (6 percent in 1940, 25 percent in 1980), and Los Angeles (4 percent in 1940, 17 percent in 1980).

Further, Denver's spatial structure has experienced shocks to its urban landscape that resemble those of many other U.S. cities. As suburban neighborhoods continued to grow between 1940 and 1980, the countervailing fall in population in central-city neighborhoods in Denver and elsewhere is linked to middle-income concentration in the suburbs and the emergence of an increasingly depressed and disproportionately non-white central city (see Boustan 2016). Although suburbanization was partly precipitated by "White Flight," urban decentralization in this period was also heavily influenced by technological and infrastructural changes such as new highways, automotive transport, and other forces affecting the locations of workers and jobs (Anas, Arnott, and Small 1998).

Denver now has a resurgent central city. While the population of tracts outside Denver's CBD fell slightly between 1980 and 2016, the average population of central-city tracts grew by up to 20 percent. Rising populations and incomes in central-city neighborhoods are not uncommon in the United States today (Glaeser, Kolko, and Saiz 2001; Hwang and Lin 2016), and this trend appears to be linked to the role of knowledge-intensive economic activity in reshaping land-use dynamics and white-collar residential patterns (Scott 2018).[3] Like suburbanization, these shifts in spatial structure resemble a period-specific shock to the organizational structure of cities.

Long-term neighborhood analysis is crucial for assessing how neighborhood inequality relates to both changing racial dynamics and historical shifts in urban spatial structure. The appropriate examination of how race relations relate to neighborhood inequality requires that we examine segregation patterns as they initially unfolded before 1960. This necessary expansion of our research focus calls into question recent findings that the spatial structures of cities have solidified since 1970 (e.g., Malone and Redfearn 2018). This is because it is unclear whether the post-1970 decades are an unusually dormant period of urban spatial and technological change. A long window of observation is therefore necessary to understand the interplay of race and spatial structure with neighborhood income rank.

The remainder of this article focuses on our data integration strategy and examining the persistence of neighborhood income rank since 1940. We begin by detailing our procedure for constructing the longitudinal neighborhood database spanning the 1940 to 2016 period and our strategy for analyzing these data. We then describe spatial changes in the characteristics of Denver neighborhoods since 1940 and analyze three key issues of interest: the long-term persistence of neighborhood inequality, how neighborhood income stratification relates to racial composition, and neighborhood income position changes within the context of Denver's evolving spatial structure.

Constructing Longitudinal Neighborhood Data

Our primary methodological challenge is to construct spatially consistent neighborhood data back to 1940. We follow other geographers in using census tracts as our main neighborhood unit of analysis (e.g., Delmelle 2016, 2017; Ellis et al. 2017).[4] Although census tracts are key enumeration units for the decennial census of the United States, their boundaries are split, consolidated, and changed from decade to decade in ways that can severely obstruct place-level analysis over time (Schroeder 2007; Buttenfield, Ruther, and Leyk 2015). Thus, we devise a strategy to enumerate historical census data (particularly from the 1940 census) within the boundaries of contemporary census tracts.

Key Data Sources

We rely on the nonanonymized 1940 complete count census to construct our first observations of neighborhoods. The 1940 data have been made accessible to researchers through a collaboration between the Minnesota Population Center and Ancestry.com. These data contain the individual characteristics required to describe neighborhoods in 1940 with respect to income, race, ethnicity, and demographic structure, as well as notations about the geographic location of individuals' households in the form of enumeration districts (EDs) and street addresses. We compute neighborhood characteristics in 1940 by assigning 1940 households to 2010 census tracts based on these geographical markers. We describe this allocation procedure in the next section.

We compare these allocated neighborhood characteristics to tract-level attributes for later decades from two other data sources. The Longitudinal Tract Database (LTDB), constructed by Logan, Xu, and Stults (2014), uses areal interpolation techniques to reallocate data from different censuses within 2010 tract boundaries back to 1970.[5] We use these harmonized data to measure the characteristics of tracts in 1970, 1980, 1990, 2000, and 2010. We also link the 2010 data to the five-year estimates from the 2016 American Community Survey (ACS) so that we can also characterize recent changes within the city.[6] Our integration of these data with 1940 census records within consistent analytical units allows us to examine neighborhood transitions between 1940 and 2016.

Allocating 1940 Census Records to 2010 Tract Boundaries

We demarcate our study area using the 1940 administrative boundaries of the city of Denver. Although much of the new growth occurring in the Denver metropolitan area between 1940 and 2016 was in surrounding counties and suburbs, those places did not have substantial populations in 1940. We take the more reserved approach of studying change within Denver's 1940 boundaries, leaving alternative approaches to future research efforts. We then devised a multistage procedure to link the 1940 census geography to 2010 tract boundaries and the data sources discussed earlier. Our method permits us to link almost all 1940 households to 2010 tracts.

We describe our allocation approach in Table 1. We began by georeferencing and digitizing the ED boundaries from historical maps for Denver County in 1940.[7] Although this digitization was labor intensive, it was necessary for completing the following steps. First, the georeferenced boundaries revealed which EDs were completely nested within single 2010 tracts and which EDs overlapped. When the georeferenced boundaries showed that an ED was completely contained by a single 2010 tract, we could directly assign all households reported by the census as being within that ED to a contemporary tract (direct assignment). When the ED was shown to overlap tract boundaries, we used the street address listed by the census to geocode the households recorded in that ED to derive a more precise dwelling location.[8] We then spatially joined these household points with the digitized, historic ED boundaries to assign each household a location-based 1940 ED number and a likely 2010 tract identifier.

We tested the quality of our address matches by comparing the consistency between the census-reported and location-based ED (verified geolocation). If we found no discrepancy between the two EDs, we assumed that the dwelling address was correctly located. If we found discrepancies, however, we exploited the contiguity of neighboring records in the census. Because dwellings enumerated next to one another also tended to be proximately located in space, the ordering of the census provides valuable information. Thus, if a dwelling had a location-based

Table 1. Description of steps to allocate 1940 census records to 2010 census tracts

Name	Share assigned (%)	Description
Step 1. Direct assignment	61	If a 1940 enumeration district is fully contained within the boundaries of a 2010 tract, we allocate all households within that 1940 enumeration district to the 2010 tract.
Step 2. Verified geolocation	86	For households in enumeration districts that overlap with multiple census tracts, we use a modern geolocation algorithm to approximate their spatial location. We verify the accuracy of the geolocation by examining whether the census-recorded enumeration district of the household matches the enumeration district in which the household was geolocated. If the two enumeration districts match, we assume that the dwelling was correctly geolocated and assign this household to the corresponding 2010 census tract.
Step 3. Backward assignment	99	If a household is geolocated outside of its census-based enumeration district, we then assign the household the coordinates of the previous 1940 census household that was geolocated within its correct enumeration district (as verified in Step 2). We again verify whether the census-reported enumeration district matches the enumeration district of the (previous) neighboring record. If the enumeration districts match, we assign the household to the location of the correctly located neighboring record.
Step 4. Forward assignment	100	If the enumeration districts still do not match, we assign the household the coordinates of the next correctly located household in the census and follow the verification and assignment procedure from Step 3. Because only 1% of households still had an incorrectly matching enumeration district after forward assignment, we omit this very small number of cases from the analysis.

Notes: In Table S.5 (supplemental materials), we show how the characteristics of the 1940 sample change at each stage of the allocation procedure.

ED that did not match the census-reported ED (evidence of misplacement by the geocoder), we assigned it the location of the last nondiscrepant household in the census (backward assignment). If the location-based ED still did not match the census-reported ED, we assigned the household the location of the next correctly matched address (forward assignment).

In the supplemental materials, we show the strength of our procedure in allocating almost the entire 1940 population of Denver to 2010 census tracts. Across our different allocation steps, the racial share of the assigned sample resembles the total share for the city (Table S.5 in the supplemental materials). Confirming previous historical evidence (e.g., Connor 2017), we find that high-income households are geolocated with greater precision than low-income households. Nonetheless, our verification procedure and our allocation of almost all 1940 households to a 2010 tract provide a high degree of confidence in the suitability of these data to studying long-term neighborhood dynamics.

Analytical Strategy and Variables of Interest

We used this new longitudinal tract data to examine the dimensions of neighborhood inequality outlined previously. To assess which neighborhoods are increasing in income position, we follow recent neighborhood studies in examining the income ranking of neighborhoods (tracts) over time (Malone and Redfearn 2018). We use the median household income of tracts to compute percentile ranks for every tract in each decade:

$$\text{Income rank}_{it} = \frac{(\text{rank of income} - 1)_{it}}{(n-1)}, \qquad (1)$$

where the numerator is the income rank of each tract i in time t in terms of their median household income and the denominator standardizes for the total number of tracts in Denver. This allows us to generate a hierarchical ranking of neighborhoods in each period, where the highest income neighborhood is assigned a value of 1, the lowest income neighborhood a 0, and the median neighborhood an approximate rank of 0.5.

We then examine how changes in rank correlate with time-variant and -invariant neighborhood attributes related to race and ethnicity, population and indoor floor area, and spatial location (see Table 2). We test the persistence of income rank over time and hypothesize that tracts with larger Hispanic and black population shares will be less likely to increase in rank. We used data from the

Table 2. Average characteristics of tracts by distance from Denver's CBD

Variable	Description	Year	Mean values by distance from Denver's CBD			
			All tracts	Less than 3 km	3–5 km	More than 5 km
Population (independent variable)	The total population residing in tracts as measured in the decennial census or the American Community Survey	1940	3,443	4,978	3,724	2,037
		1980	3,827	3,156	4,099	4,118
		2010	4,008	3,448	4,041	4,409
Indoor floor area (independent variable)	The total indoor floor area of tracts as measured in millions of square feet from the ZTRAX database	1940	1.24	1.85	1.21	0.79
		1980	3.29	4.13	2.65	3.17
		2010	4.55	6.18	3.26	4.35
Black share (independent variable)	The black share of the population of each tract as measured from the decennial census or the American Community Survey	1940	0.02	0.03	0.02	0.01
		1980	0.17	0.22	0.16	0.15
		2010	0.15	0.15	0.14	0.16
Hispanic share (independent variable)	The Hispanic share of the population of each tract as measured from the decennial census or the American Community Survey	1940	0.03	0.07	0.02	0.01
		1980	0.14	0.16	0.19	0.08
		2010	0.30	0.22	0.38	0.30
Income rank (dependent variable)	The rank of each tract from zero (lowest) to one (highest) according to median income. See Equation 1 and text for calculation	1940	0.49	0.33	0.53	0.59
		1980	0.50	0.24	0.50	0.71
		2010	0.50	0.43	0.47	0.57
Observations (tracts)			88	26	28	34

Notes: Denver's CBD is measured as the Denver Civic Center. Distance from the CBD is measured from the centroid of each tract to the Denver Civic Center. All variables are measured from the decennial census of the United States or the American Community Survey except for the indoor floor area variable, which comes from Zillow's ZTRAX data. Further information on accessing the ZTRAX data can be found at http://www.zillow.com/ztrax. CBD = central business district.

LTDB on the total Hispanic and non-Hispanic black population to calculate the black and Hispanic share of tracts.[9]

We derive two measures relating to the economic potential of neighborhoods. Across many metropolitan areas, the balance between urban residential patterns since the mid-twentieth century has shifted from central-city neighborhoods to suburban areas. Thus, we measure the distance of each tract from the CBD.[10] We anticipated that distance from the CBD would be associated with improvements in income rank during postwar suburbanization and that this pattern would have reversed over recent decades.

We also measure investment in building using Zillow's newly available Transaction and Assessment Dataset (ZTRAX). The ZTRAX database is an impressive compilation of geospatial housing data based on assessor records from more than 200 million parcels across the United States (Leyk and Uhl 2018a, 2018b; Zillow 2018). These data are valuable for historical research because they contain the year of construction or remodeling for (relatively precisely geolocated) structures in urban areas back to the nineteenth century. At present, there are no comparable sources of spatially consistent and finely geolocated historical building data for the United States. From prior studies (e.g., Smith 1987), we hypothesize that investment in new building will be associated with increases in the income position of neighborhoods. As such, we use the ZTRAX data to measure changes in the indoor floor area of buildings over time as a proxy for new building investment.[11]

Results

Describing Changes in Neighborhood Attributes Since 1940

We begin by using our variables of interest to describe general changes in the spatial population structure of Denver neighborhoods since the mid-twentieth century (harmonized tracts). Table 2 presents the average characteristics of tracts for 1940, 1980, and 2010. We present the average values for our variables of interest across all tracts, tracts within 3 km of the CBD, tracts from 3 to 5 km from the CBD, and tracts more than 5 km from the CBD.

The total population counts across decades illustrate that Denver's residential geography has changed substantially through time. Although Table 2 shows that the average population of census tracts in Denver grew modestly from 3,443 to 4,008 (or 16 percent) between 1940 and 2010, change was highly uneven throughout the city. The population of tracts in immediate proximity to the CBD fell by 30 percent, whereas the populations of tracts more than 5 km from the CBD more than doubled. Although much of this population decentralization occurred between 1940 and 1980, the data indicate that central-city tracts started to increase in population again from 1980 on. Worded differently, whereas Denver was characterized by population decentralization throughout much of the late twentieth century, this trend has started to reverse over recent decades.

Perhaps surprising, the changes we observe in indoor floor area do not mirror growth in the residential population. Between 1940 and 2010, average indoor floor area increased almost fourfold across the city, rising from just over 1.2 million square feet to more than 4.5 million square feet. With more than 2 million extra square feet of indoor floor area, however, the depopulating tracts of the CBD experienced the largest gains in building. Although outlying tracts also experienced substantial growth in new building, these gains were more modest than in the CBD. The inverse correlation between building patterns and the residential population counts reflects the fact that indoor floor area measures commercial and industrial building in addition to housing.

These shifts in total population and building are also associated with changes in the racial composition of tracts. Citywide, the average black and Hispanic shares of tracts grew from 2 to 3 percent in 1940 to 15 percent and 30 percent, respectively, by 2010. From 1940 to 1980, the black and Hispanic shares grew most quickly in tracts within 5 km of the CBD. These patterns likely reflect the in-migration of black and Hispanic households and the disproportionate out-migration of white households to more peripheral neighborhoods. These statistics therefore reveal an image of intensifying racial segregation between central-city and more outlying tracts between 1940 and 1980. In the sections to come, we return to the correlation between growth in the black and Hispanic population shares and the changing income position of tracts.

The changes evident in the spatial patterning of neighborhood income stratification over time are also worth noting. In 1940, tracts within 3 km of the CBD were ranked lower than more outlying tracts, and by 1980 the difference between tracts nearest and farthest from the CBD had widened to almost 50 percentile points. By 2010, however, this difference had narrowed again to only 14 percentile points. This convergence is so substantial that by 2010, income rank was almost evenly balanced between central-city and outlying tracts. Taken together with the other changes occurring across neighborhoods, we observe growth in the total population, white share, and income rank of tracts farther from the CBD prior to 1980 and either a halting or a reversal of each of these trends after 1980.

Long-Term Persistence in Neighborhood Inequality

Given these substantial shifts in the residential structure of the city, do our data indicate that the income ranking of neighborhoods tends to be generally fluid over time? We begin to answer this question in Figure 1 by plotting the income rank of tracts in 1940 against their corresponding 2016 levels. To gain insight into the possible sources of rank persistence, we symbolize the points in this scatterplot so that tracts with larger black and Hispanic population shares across the 1940 to 2016 period have larger symbols.

The most notable feature of Figure 1 is that the income rank of tracts is highly correlated between 1940 and 2016. The correlation coefficient for tract rank in 1940 and 2016 is +0.56 (significant at $p < 0.05$). Given the major shifts that occurred in the wider income distribution and in the demographic characteristics of Denver neighborhoods over this period, a correlation of +0.56 is surprisingly strong.[12] Further, in most cases, the interdecadal correlation of tract rank is greater than +0.90.[13] These simple correlations provide credence for the supposition that the income structure of neighborhoods is persistent over long time periods.

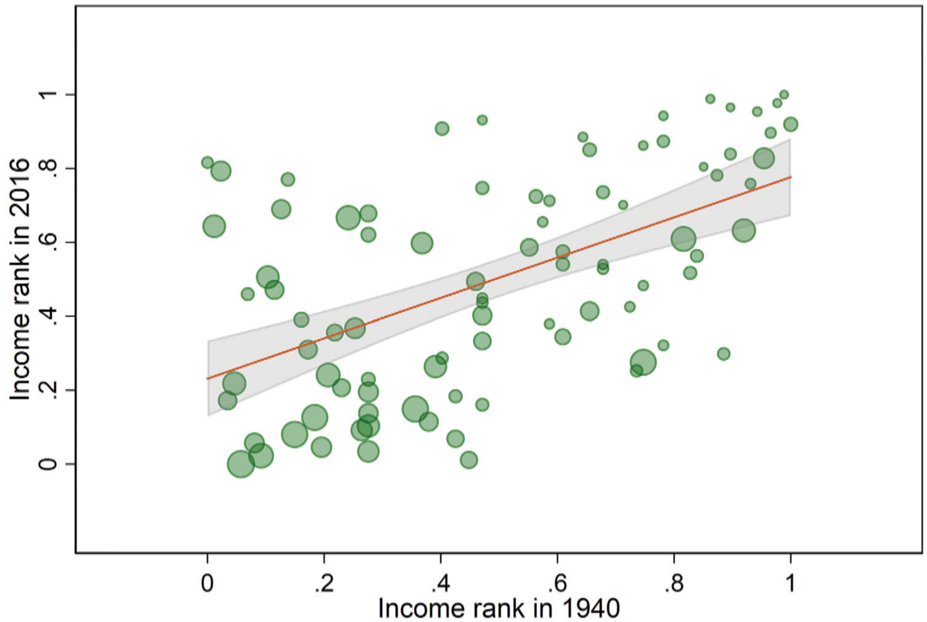

Figure 1. Persistence in income rank from 1940 to 2016. Symbol sizes are proportional to the average black and Hispanic share of tracts from 1940 to 2016, with larger points reflecting larger average Hispanic and black population shares across the 1940 to 2016 period.

Table 3. Neighborhood transitions across income quartiles from 1940 to 2016

		Income quartile in 2016				
		Upper (highest income)	Upper–middle	Lower–middle	Lower (lowest income)	Total
Income quartile in 1940	Upper (highest incomes)	14 (70%)	4 (20%)	2 (10%)	0 (0%)	20 (100%)
	Upper–middle	3 (15%)	10 (50%)	7 (35%)	0 (0%)	20 (100%)
	Lower–middle	2 (8%)	4 (15%)	8 (31%)	12 (46%)	26 (100%)
	Lower (lowest incomes)	3 (14%)	4 (18%)	5 (23%)	10 (45%)	22 (100%)
	Total	22 (25%)	22 (25%)	22 (25%)	22 (25%)	88 (100%)

Notes: The income quartiles are based on similarly sized bins based on the average incomes of tracts in 1940 and 2016. The row percentages are rounded to the nearest whole number and presented in parentheses.

To determine whether certain neighborhoods are particularly likely to change in income position, we examine which tracts, according to their initial 1940 income rank, moved up or down the income hierarchy over time. Table 3 shows transitions between income quartiles from 1940 to 2016 and allows us to examine whether, for example, high-income neighborhoods have been more likely to hold their income position since 1940 than medium- or low-income neighborhoods. We can also assess whether neighborhoods that change income position tend to make larger or smaller moves within the income hierarchy.

The first insight we glean from Table 3 is that the stability of upper-income neighborhoods is one of the key drivers of persistence in the neighborhood income structure. This is evident from comparison of the top-left cell (upper income persistence) and the bottom-right cell (lower income persistence) of Table 3. Whereas 70 percent of top quartile neighborhoods in 1940 were still in the top quartile in 2016, only 45 percent of the lowest quartile neighborhoods were still in the lowest quartile seventy-six years later. One might be concerned that the sparse settlement of many low-income places in 1940 might have predisposed these places to substantial change. Even when we average across the entire bottom half of neighborhoods in 1940, though, only 38 percent of tracts in the lower 50 percent (according to income) are still in their initial income quartile by 2016. Differences in income rank persistence between initially high- and low-income tracts is also evident from the dispersion of points in Figure 1.

When upper-income neighborhoods move down income quartiles, are the falls modest or dramatic? We can answer this question in Table 3 by examining whether initially upper- and lower-income neighborhoods that change quartile make similarly sized transitions over time. The bottom left quadrant of the transition matrix shows the share of lower- and lower–middle-ranked tracts in 1940 that moved into upper-income positions in 2016. Roughly 32 percent of lower ranked neighborhoods in 1940 had moved into the top half of the neighborhood income hierarchy by 2016. This number is distinctly different when we look to the commensurate downward moves in the top right of the matrix: By 2016, 7 percent of upper–middle-income tracts in 1940 and only 2 percent of the highest income tracts experienced downward mobility into the bottom half. Thus, it appears that when upper-income tracts change position, change tends to be relatively modest.

In summary, these descriptive analyses imply that while the general structure of neighborhood inequality might be slow to change, there are some notable caveats. First, the rigidness of the upper tier of neighborhoods appears to be a key driver of persistence in the neighborhood income hierarchy. Second, when upper-income neighborhoods do descend the hierarchy, they generally do not fall far (relative to the moves made by lower-income neighborhoods). This implies that the upper tier of neighborhoods is particularly stable over time. The remainder of our analysis focuses on examining which types of places manage to climb the neighborhood income hierarchy over time.

Neighborhood Income Stratification and Racial Composition

Cross-Sectional Estimates. Figure 1 (discussed earlier) provides preliminary support for the hypothesis that tracts with larger non-white populations will tend to be confined to lower income positions. In Figure 1, persistently high-ranking tracts (upper right) are depicted using small symbols, which indicates very low black and Hispanic population shares. Conversely, persistently low-income tracts (bottom left) have larger minority shares across the study period. By comparing these two quadrants, it is evident that persistently low-ranking tracts tend to have larger minority population shares than persistently high-ranking tracts. Moreover, the tracts shown in the top left—low ranked in 1940 but higher ranked by 2016—also have visibly smaller minority shares than consistently low-ranked tracts. This suggests that non-white neighborhoods are particularly confined to lower-income positions.

We formally examine whether this racialized ranking of tracts was already in place by 1940 and, if not, when this neighborhood structure emerged. We examine this question using a model of the following form:

$$\begin{aligned}\text{Income rank}_{it} = {} & \text{Income rank}_{1940} + \text{Income rank}_{1970} \\ & + \text{Black and Hispanic share}_{1940} \\ & + \Delta\text{Black and Hispanic share}_{1940-70},\end{aligned} \tag{2}$$

where our estimates are derived from six separate regression equations where the dependent variable is the income rank of a tract in 1970, 1980, 1990, 2000, 2010, or 2016 (see estimates in supplemental materials, Table S.7). To better identify the association between racial composition and tract rank, we include control variables for the income rank of tracts in 1940 and 1970.[14] Our independent variables of interest are a composite measure of the black and Hispanic shares of tracts in 1940 and the change in those shares over the 1940 to 1970 period. We use these variables to assess whether, after controlling for the initial income position of tracts, there is a long-term association between the black and Hispanic population shares and the income rank of tracts.[15]

Figure 2 presents the decade-on-decade estimates from these cross-sectional regression models. The y-axis refers to standardized regression coefficients predicting income rank with means of zero and standard deviations of one. Each point refers to the

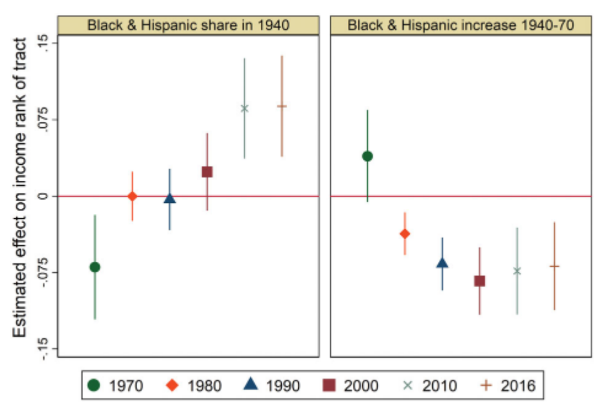

Figure 2. Income rank of tracts and historical racial composition.

estimated effect of the variable named in the panel header on income rank in each decade.

In the first panel of Figure 2, we find weak and counterintuitive associations between the 1940 black and Hispanic shares of tracts and their income ranks over time. Although we do find a negative association between black and Hispanic shares in 1940 and the rank of tracts in 1970, we do not observe this relationship in any later decade. We observe no significant association between 1980 and 2000, and we find a positive association between the 1940 minority share and the income rank of tracts in 2010 and 2016. These results hold when we drop the correlated measure of growth in the black and Hispanic share from 1940 to 1970 (see supplemental materials, Figures S.4 and S.5).

The growth of the black and Hispanic shares over the 1940 to 1970 period, in contrast, exhibits a more intuitive relationship with later outcomes. For our first estimate, we find a positive but nonsignificant association between the increase in the black and Hispanic shares from 1940 to 1970 and the income rank of tracts in 1970. This weak association, however, departs from every decade after 1970, where we observe strong and persistent negative relationships between growth in the black and Hispanic shares over the 1940 to 1970 period and the income position of tracts. Worded differently, tracts experiencing higher rates of growth in their black and Hispanic shares between 1940 and 1970 tend to be have significantly lower incomes up to 2016. This implies that the racial segregation patterns that emerged between 1940 and 1970 are still highly visible in the income stratification of neighborhoods today.

Panel Estimates. The relationships we observe between racial segregation patterns and the subsequent income rank of tracts could reflect other unobserved neighborhood characteristics such as locational amenities. We use a series of panel models to deal with omitted variables and to better delineate the true relationship between racial composition and neighborhood income stratification. We do this by examining how changes in the black and Hispanic population shares relate to tract income rank. Our panel regression models take the following form:

$$\text{Upward income transition}_{i,t-t+1} = \beta_k X_{kit} + \text{Decade}_t + \text{Tract}_i + \text{Top quartile}_{it}, \quad (3)$$

where the model is a linear probability panel model predicting whether tract i moved up a full income quartile between time t and $t+1$ by our k neighborhood characteristics of interest, which we measure in time t. In this specification, we use the characteristics of tracts at the beginning of each period to predict whether a tract experienced a substantial increase in income rank. We estimate these models with robust standard errors to account for heteroskedasticity and we ensure the robustness of our estimates to invariant and trending omitted variables by including a fixed effect for each tract and decade (Allison 2009).

We present estimates from the four related panel models in Table 4. In these models, the dependent variable is whether a tract moved up income quartiles; each column sequentially adds new independent variables. Because tracts in the top rank cannot increase in income position, we include a time-varying dummy variable for whether tract i was in the top income quartile at time t. For comparability, we transform all independent variables into standard units with a mean of zero and a standard deviation of one.[16] Thus, a positive and significant coefficient on a specific independent variable suggests that an increase in that variable is associated with increases in neighborhood income rank and a negative coefficient is indicative of lower rates of upward neighborhood mobility.

We first discuss the panel estimates with no time or tract fixed effects from the first two columns. In the first column, a standard deviation increase in the Hispanic share is associated with around a 6 percent reduction in the probability of a neighborhood moving up income quartiles and the same increase in the black share yields a 3 percent reduction in the probability of upward mobility. Adding a control for the distance of tracts from the CBD (second column) strengthens the negative relationships between minority share and the probability of neighborhoods to move up in income position. This implies that the link between racial composition and tract income rank is not solely driven by the disproportionate residence of racial minority households in central-city areas.

To confirm that these estimates reflect race relations rather than other omitted neighborhood characteristics, we introduce several key controls in the third column. We rule out decade-specific trends and account for general compositional shifts in the population over time by using a time fixed effect. We also include tract fixed effects to help rule out

Table 4. Panel regression of upward income transitions for tracts

	1 Upward income transition	2 Upward income transition	3 Upward income transition	4 Upward income transition
Income rank	−0.376***	−0.512***	−0.686***	−0.508***
	(0.096)	(0.107)	(0.164)	(0.108)
Hispanic share	−0.0618***	−0.0632***	−0.142***	−0.0636***
	(0.017)	(0.015)	(0.041)	(0.015)
Black share	−0.0268**	−0.0347***	−0.0975***	−0.0763***
	(0.011)	(0.013)	(0.025)	(0.016)
Population	−0.0335**	−0.0390***	−0.0321	−0.0394***
	(0.014)	(0.013)	(0.032)	(0.014)
Indoor floor area	−0.0271	−0.0147	−0.0236	−0.0147
	(0.017)	(0.015)	(0.037)	(0.015)
Distance from CBD		0.0597***		0.0573***
		(0.018)		(0.018)
Period (reference = 1990–2000)				
1940–1970			0.108***	0.108***
			(0.038)	(0.038)
1970–1980			0.0228	0.0229
			(0.031)	(0.031)
1980–1990			−0.000348	−0.000259
			(0.028)	(0.028)
2000–2016			0.0918**	0.0916**
			(0.039)	(0.038)
Interactions				
Black share × 1940–1970				0.0400**
				(0.019)
Black share × 1970–1980				0.0467**
				(0.018)
Black share × 1980–1990				0.0301*
				(0.016)
Black share × 2000–2016				0.0928*
				(0.048)
Constant	0.262***	0.323***	0.380***	0.276***
	(0.050)	(0.053)	(0.069)	(0.048)
Observations	436	436	436	436
R^2	0.13	0.16	0.14	0.20
Robust standard errors	Yes	Yes	Yes	Yes
Tract fixed effects	No	No	Yes	No
Top quartile control	Yes	Yes	Yes	Yes

Notes: Standard errors are shown in parentheses. These estimates are derived from a linear probability panel model with robust standard errors. All independent variables are converted into standard units with a mean of zero and a standard deviation of one. As Column 3 includes tract fixed effects, all time-invariant independent variables are omitted (e.g., distance from CBD). Because tracts in the top income quartile are unable to move up, we include a time-varying dummy variable for whether a tract is in the top quartiles. The measure of indoor floor area is derived from data provided by Zillow through ZTRAX. More information on accessing the data can be found at http://www.zillow.com/ztrax. The source code for the analysis can be accessed on request from the corresponding author. CBD = central business district.
*$p < 0.10$.
**$p < 0.05$.
***$p < 0.01$.

other confounding characteristics. The tract fixed effects leverage variation from changes occurring within tracts over time to rule out time-invariant differences between tracts. The addition of these controls in the third column strengthens the negative black and Hispanic share coefficients, further increasing the estimated penalty on upward income transitions for these neighborhoods by 6 to 7 percentage points. These more stringent controls reinforce our finding that black and Hispanic neighborhoods tend to be disproportionately confined to lower income ranks.[17]

In our final investigation related to racial composition, we examine whether the association between the black share and tract income stratification has changed over time. Because evidence from other cities suggests that non-white neighborhoods might have made higher income gains in recent decades (Owens 2012), we test this hypothesis for Denver by interacting the black share with our time fixed effects in the fourth column. We choose the 1990s as the reference category, because this period exhibits the strongest negative association between minority population share and the probability of tracts moving up in income position.

Despite some change in magnitude over time, we find relatively consistent relationships between the black share and the probability of neighborhoods increasing in income rank. The coefficients on the interaction terms for each decadal snapshot up to 1990 are positive and significantly different from the 1990 to 2000 average. This implies that tracts with higher black shares faced the greatest penalties on upward income transitions in the 1990s. Despite this difference between the 1990s and earlier decades, the coefficients nonetheless suggest that across the second half of the twentieth century, black neighborhoods were less likely to increase in income rank.

In this respect, the period from 2000 to 2016 appears to deviate from this longer running trend. The fourth column shows the interaction between the black share and the 2000 to 2016 coefficient to be large, positive, and statistically significant. In fact, from adding the respective coefficients in this interaction together, the black share is even slightly positively correlated with increases in tract income rank after 2000. Thus, we provide evidence that the inhibited rate of upward income transitions for black neighborhoods has strongly attenuated since 2000. Our tests for Hispanic share interaction effects over time resemble what we find for the black share in direction but were not significantly different from zero (supplemental materials, Table S.1).

Our findings, therefore, strongly indicate that low-income positions are disproportionately occupied by tracts with larger racial minority population shares. This is evident from both the panel estimates and the long-term cross-sectional analysis of postwar change in racial composition and segregation. Our main qualification to this finding is that the short-term association between race and upward neighborhood income transitions in Denver weakened after 2000, suggesting a potential decline in the salience of racial composition for neighborhood income changes. It is not clear, however, whether the rising income position of relatively black tracts is also leading to the displacement of black residents.

Multivariate Analysis of Neighborhood Income Stratification and Spatial Structure

Panel Estimates. The models presented in Table 4 also allow us to evaluate the role of residential population change and new building investment (indoor floor area) in generating changes in neighborhood income position. First, our data confirm that population size and upward tract mobility are strongly inversely correlated. We find that a standard deviation increase in total tract population is associated with a 3.4 to 3.9 percentage point reduction in the probability of a tract moving up a full income quartile. Even if it is not statistically significant, the point estimate remains similar in the more stringent tract fixed effect model. Because the outcome variable is defined by tracts moving up a full income quartile (a large change in rank position), the negative effect of total population is not likely driven by statistical noise generated by slight changes among tracts with smaller populations. Our claim that these estimates reflect true neighborhood dynamics rather than statistical noise is supported throughout our primary and supplementary analyses, which conclusively suggest that less-populated places tend to make larger gains in income rank.

The coefficients for indoor floor area are less conclusive. In the first column, a standard deviation increase in the indoor floor area of tracts is associated with a 2.7 percentage point reduction in the probability of moving up income quartiles (not significant at $p < 0.10$). This coefficient indicates that there is a negative correlation between new building in tracts and upward income transitions. This finding is counter to our initial hypothesis that new development would signal or spur increases in the average incomes of residents. Further, introducing the variable for the distance of tracts from the CBD attenuates the negative coefficient on indoor floor area by around half, suggesting that the negative association between building and income position reflects the fact that CBD tracts tend to be both more built up and less upwardly mobile over time. In short, we find a weak relationship between our proxy for new building and increases in income rank over time.

Our finding of a strong association between total population and changes in income rank raises the question of whether this is a general relationship or whether this association is period specific and related either to new suburban neighborhoods on previously undeveloped land or recent reinvestment into previously disinvested city center properties. We take two approaches to this issue. First, because new suburban development largely unfolded in the postwar decades, we examined the correlation of total population and rank change before and after 1990. We found an almost identical correlation coefficient of around −0.50 for the two periods, suggesting that this relationship is not confined to a specific moment in our data but is present across our study period.

Second, to gain insight on whether this relationship is driven by new suburban or previously developed central-city areas, we tested for interactions between total population and both indoor floor area and distance from the CBD (supplemental materials, Table S.4). Again, we found no notable interactions between these variables. Our findings therefore strongly suggest that the inverse association between population and income rank change appears to be a general relationship that is not simply confined to new developments on greenfield sites through suburbanization or reinvestment into central-city areas.

Mapping. Because we are limited in our ability to measure the forces driving changes in the spatial structure of the city, we instead simply examine the spatial patterning of increases in tract income rank across time (Figure 3). After mapping the tracts that moved up income quartiles across each decade, we identified three distinct periods of change and stability. These historical periods are characterized by distinct rates and spatial patterns of change and roughly span the decades from 1940 to 1980, 1980 to 2000, and 2000 to 2016.

The first period of change spans the decades from 1940 to 1980. In this period, upward neighborhood mobility was heavily concentrated at the edge of the city. Because these peripheral areas were more sparsely populated and had land that was less intensively built on, we label this era as one of peripheral development. From our data, we calculate that 9 percent of lower income neighborhoods moved up at least one income quartile per decade over this period. Because we do not observe more outlying suburbs and lack strict decadal snapshots within the 1940 to 1970 period, we believe that the rate of 9 percent is a lower bound estimate.

The second period we observe spans the years from 1980 to 2000 and reflects what we describe as neighborhood immobility. In contrast to the 1940 to 1980 period, increases in tract income position are mixed between central-city and peripheral areas. Further, the rate of upward neighborhood mobility appears to have been low: The decadal rate drops from 9.0 percent over the 1940 to 1980 period to 4.5 percent in the 1980s and 1990s. These periods were therefore characterized by a diffuse pattern

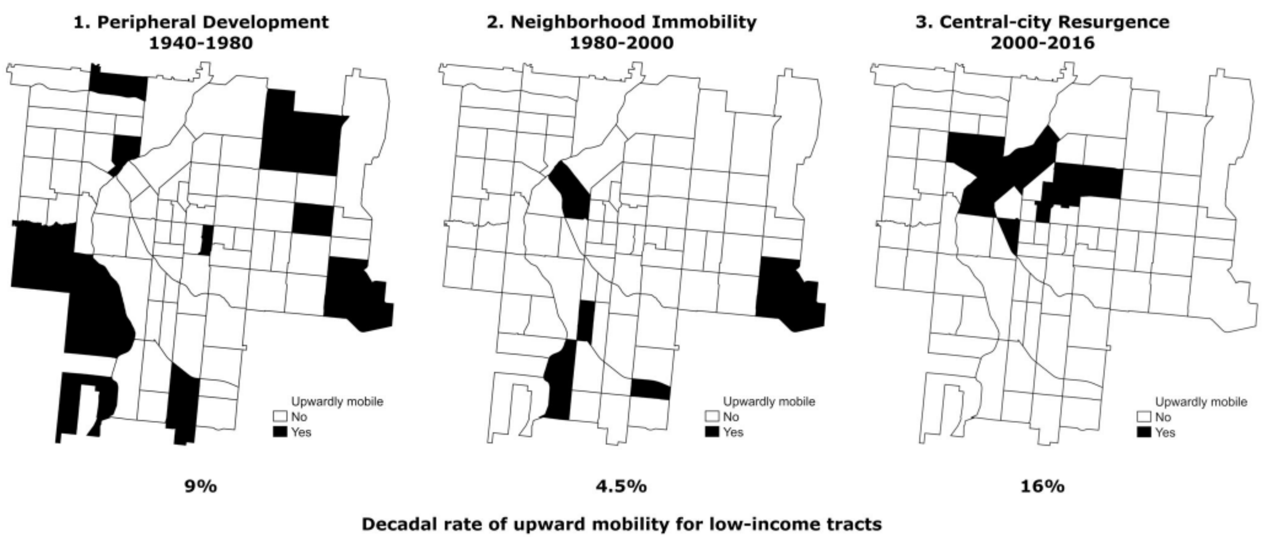

Figure 3. Spatial patterns of upward neighborhood income transitions from 1940 to 2016. We define an upward income transition as tracts moving up at least one income quartile from the previous period of observation.

of change that was confined to a small number of neighborhoods.

The final period of change we identify spans the post-2000 period, which overlaps with the period of focus for much recent gentrification scholarship.[18] This period is striking in that upward income transitions increased substantially compared to earlier decades: The decadal rate of upward neighborhood mobility roughly tripled from 4.5 percent over the 1980 to 2000 period to 16.0 percent between 2000 and 2016. From our estimates, this rate of upward income transition is unprecedented in the history of the city. The second key feature of this period is the patterning of income ascent around Denver's CBD and the visible absence of such moves outside of the urban core. This central-city pattern can partly account for the accelerated upward income movements of black tracts in this period (see Table 4). Because these patterns are effectively the reverse of those observed from 1940 to 1980, we label the post-2000 period as one of central-city resurgence.

Although the visualization of these patterns does not account for the underlying forces driving the (re)stratification of neighborhoods, they are highly suggestive of the link between shifts in urban spatial structure and changes in the hierarchical ranking of neighborhoods. Our finding of a robust inverse association between total population and upward neighborhood mobility suggests that population loss (or low population levels) might set the stage for changes in income position down the line. Our proxy for building investment (indoor floor area) does not, however, provide support for the hypothesis that broad patterns of new investment in building are a primary mechanism of change. We note that this weak effect for new building could reflect further unobserved heterogeneity in the types of new building occurring across the city over time. Therefore, our analysis reveals that changes in urban spatial structure might partially disrupt existing spatial patterns of neighborhood inequality, but further work is required to isolate the causal chain underlying these shifts.

Discussion and Conclusion

How deeply entrenched is the spatial structure of inequality within cities? After analyzing a new database covering Denver residential patterns over seventy-six years, we find surprising persistence in the long-term income rank of neighborhoods between 1940 and 2016. We show that much of this persistence is generated by the entrenched position of a set of largely white, upper-income neighborhoods whose income ranks have not shifted much over time. What change does occur has been concentrated among lower- and middle-income neighborhoods, with whiter places more likely to move up the residential income hierarchy than black and Hispanic neighborhoods.

These findings are important given the increasing recognition that neighborhood inequality reinforces racial and class disparities across a range of personal outcomes. Our findings highlight that through both suburbanization and the more recent resurgence of Denver's central city, change has remained concentrated among neighborhoods outside of this upper-income tier of neighborhoods. The evidence from Denver therefore suggests that without considerable shifts in policy (see Sharkey 2013), we are not likely to see serious short-term alterations to general structure of neighborhood inequality.

With respect to the changes that have occurred among neighborhoods over time, we provide new evidence of reshuffling in the income stratification of neighborhoods during historical periods of urban spatial change. Specifically, we found that the income position of low-income areas in Denver improved with the rise of new suburbs between 1940 and 1980 (peripheral development), stagnated from 1980 to 2000 (neighborhood stagnation), and has started to rise again in central-city areas since 2000 (central-city resurgence). These periods of reordering in neighborhood income positions appear to coincide with wider shifts in the urban economy and landscape. Further, although we know that the growth of suburban neighborhoods helped cement a specific spatial form of racial division in U.S. cities, it remains an open question as to how the recent ascent of many central city areas will affect racial inequality in the future.

As such, the root and impact of historical shifts in urban spatial structure is a key area for continued research. Given that widespread urban spatial changes like suburbanization or the current trajectories of central-city ascent and growing suburban poverty are linked to structural changes in the urban economy, we need further investigation into how these transitions unfold in space (e.g., changes in the geography of employment, new transportation networks, urban amenities). The role of policy is important here: In Denver, for example, many of the neighborhoods that have recently risen in income position were previously the target of urban renewal and transportation projects (Page and Ross 2017; Bardaka, Delgado, and Florax 2018). Assessing the explicit impact and temporality of such policies requires detailed long-term comparative examination.

We provide a methodology for undertaking such long-term investigations. Our integration of the 1940 complete-count census, building characteristics from ZTRAX, and contemporary census data provides a replicable method for studying long-term neighborhood income dynamics. With the ongoing efforts to digitize the historical enumeration boundaries of U.S. cities (see Logan and Zhang 2018), this approach could be extended to cities throughout the United States.[19] These data would allow a more complete assessment of the long-term impact of urban policy and its relation to social inequality (see Aaronson, Hartley, and Mazumder 2017).

Finally, enhancing the ZTRAX data to allow identification of the function of new buildings and land use over time could provide vast new opportunities to study urban spatial structure. Our inability to distinguish between commercial, residential, and industrial building investment here could account for the weakness of our indoor floor area measure in predicting changes in neighborhood income position. It will soon be possible, however, to filter along these functional and land-use dimensions, which will allow clearer distinction between shifts in residential or commercial activity through time. We expect that through these innovations and others, the opportunity to study long-term neighborhood dynamics will expand for years to come.

Acknowledgments

We sincerely thank Ling Bian (editor) and two anonymous reviewers for their feedback and assistance with this research. For their insightful and constructive comments, we also recognize Elizabeth Roberta, Johannes Uhl, Seth Speilman, Peter Catron, Katrin Anacker, and participants at the annual meetings of the Population Association of America (Denver, 2018) and the Social Science History Association (Phoenix, 2018). We also thank the participants of the Geographical Perspectives on Inequality series at the Annual Meeting of the American Association of Geographers.

Funding

This research has benefited from research, administrative, and computing support provided by the University of Colorado Population Center (Project 2P2CHD066613-06), funded by the Eunice Kennedy Shriver National Institute of Child Health and Human Development. This content is the sole responsibility of the authors and does not necessarily represent the official views of the University of Colorado, CUPC, or NIH. We have also received support from the University of Colorado Boulder. The authors were provided access to the Zillow Transaction and Assessment Dataset (ZTRAX) through a data use agreement between the University of Colorado Boulder and Zillow, Inc. We gratefully acknowledge support by Zillow, Inc. More information on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the author(s) and do not reflect the position of Zillow Group.

Supplemental Materials

Supplemental data for this article can be accessed on the publisher's site.

ORCID

Dylan Shane Connor http://orcid.org/0000-0002-8988-170X
Myron P. Gutmann http://orcid.org/0000-0002-6808-3573
Stefan Leyk http://orcid.org/0000-0001-9180-4853

Notes

1. In any given year, for example, the ranking of the highest income tract will be 1, the lowest income tract will be 0, and the median tract will be ranked at approximately 0.5.
2. These numbers are calculated from IPUMS (Ruggles et al. 2017).
3. In some cities, this return to the city has co-occurred with growing suburban poverty (Kneebone and Garr 2010; Cooke and Denton 2015).
4. Although it is challenging (perhaps impossible) to precisely demarcate a neighborhood (see Spielman and Logan 2013), census tracts are designed to be coherent spatial units and are thus suitable for our purposes.

5. Other tract databases are available, but the quality of the LTDB appears to be at least as good as these other products (Logan, Stults, and Xu 2016).
6. Because the data from ACS are based on estimates from sample data, the Census Bureau provides margins of error. In this analysis, we use the primary estimate from the ACS. To allay concerns that error in the ACS might distort our conclusion, however, we reran all analyses with no ACS data with the end year as the 2010 decennial census of the United States. These alternate results are almost identical to those that we obtained with the ACS (see supplemental materials).
7. These maps can be accessed in the National Archives Catalog.
8. We undertook our address matching within the statistical software R using the "ggmap" package and the Data Science Toolkit spatial data source, itself based on OpenStreetMap data (Kahle and Wickham 2015).
9. Because the 1970 census data do not contain detailed information on the Hispanic population, we undertake a simple linear interpolation for 1970 based on the 1940 and 1980 margins. This issue also highlights the fact that racial categories such as non-Hispanic white have only appeared in the census since 1980 (Omi and Winant 2014). We found no difference, though, when we used the individual records of the 1940 census to test the sensitivity of our results to using an all-black or non-Hispanic black classification.
10. We use the Denver Civic Center as the Denver CBD.
11. We derived these measures by sequentially subsetting the original ZTRAX data and generating raster layers of the building characteristics at different time points (Leyk and Uhl 2018b). The retrospective ZTRAX data underestimate the presence of historical buildings, and we continue to work on developing products to adjust for data missingness due to rebuilding.
12. This correlation is even stronger for absolute income levels and is roughly +0.61 from 1940 to 2016.
13. The correlation between the rank of tracts in 1940 and 1980 is +0.70 and is +0.50 for 1980 and 2016.
14. We include the 1940 income rank control so that our 1970 regression is comparable to other years. When the dependent variable is the 1940 or 1970 income rank, we do not include a control for the income rank of the tract in that same year. Our estimates from 1980 are not seriously affected by the inclusion of the 1940 income rank control.
15. In Figure S.6 (supplemental materials), we present the black and Hispanic estimates separately. The results are very similar whether we use a composite or separate measure of the black and Hispanic population shares.
16. In the supplemental materials, we show the conclusion to be generally similar whether or not we standardize the variables in this way (Table S.6).
17. Because the actual income levels of the Hispanic and black populations also vary over time, one might be concerned that racialized differences in income could be the sole driver of the trends we observe over specific place-based racial status effects. In the supplemental materials, we estimate a model with time-varying, group-specific income controls and find little change in our results (Table S.2).
18. See Lawton (2019) for a recent perspective and review of gentrification and uneven development.
19. These efforts could be further aided by using the ZTRAX data as a basis from which to undertake dasymetric refined interpolation to improve the accuracy of historical neighborhood estimates (Ruther, Leyk, and Buttenfield 2015; Zoraghein and Leyk 2019).

References

Aaronson, D., D. Hartley, and B. Mazumder. 2017. The effects of the 1930s HOLC "redlining" maps. Social Science Research Network Working Paper. Accessed October 2, 2019. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3038733

Allison, P. D. 2009. *Fixed effects regression models*, vol. 160. Thousand Oaks, CA: Sage.

Anas, A., R. Arnott, and K. A. Small. 1998. Urban spatial structure. *Journal of Economic Literature* 36 (3): 1426–64.

Atuesta, L. H., and G. J. Hewings. 2018. Housing appreciation patterns in low-income neighborhoods: Exploring gentrification in Chicago. *Journal of Housing Economics* 44:35–47. doi: 10.1016/j.jhe.2018.08.005.

Bardaka, E., M. S. Delgado, and R. J. Florax. 2018. Causal identification of transit-induced gentrification and spatial spillover effects: The case of the Denver light rail. *Journal of Transport Geography* 71:15–31. doi: 10.1016/j.jtrangeo.2018.06.025.

Boustan, L. 2016. *Competition in the promised land: Black migrants in northern cities and labor markets*. Princeton, NJ: Princeton University Press.

Buttenfield, B. P., M. Ruther, and S. Leyk. 2015. Exploring the impact of dasymetric refinement on spatiotemporal small area estimates. *Cartography and Geographic Information Science* 42 (5):449–59. doi: 10.1080/15230406.2015.1065206.

Chetty, R., and N. Hendren. 2018. The impacts of neighborhoods on intergenerational mobility I: Childhood exposure effects. *The Quarterly Journal of Economics* 133 (3):1107–62. doi: 10.1093/qje/qjy007.

Chetty, R., N. Hendren, P. Kline, and E. Saez. 2014. Where is the land of opportunity? The geography of intergenerational mobility in the United States. *The Quarterly Journal of Economics* 129 (4):1553–1623. doi: 10.1093/qje/qju022.

Clark, W. A., and F. M. Dieleman. 1996. *Households and housing: Choice and outcomes in the housing market*. New Brunswick, NJ: Transaction.

Connor, D. S. 2017. Poverty, religious differences and child mortality in the early 20th century: The case of Dublin. *Annals of the American Association of Geographers* 107 (3):625–46. doi: 10.1080/24694452.2016.1261682.

Cooke, T. J., and C. Denton. 2015. The suburbanization of poverty? An alternative perspective. *Urban Geography* 36 (2):300–313. doi: 10.1080/02723638.2014.973224.

Crowell, A. R., and M. Fossett. 2018. White and Latino locational attainments: Assessing the role of race and resources in U.S. metropolitan residential segregation. *Sociology of Race and Ethnicity* 4 (4):491–507. doi: 10.1177/2332649217748426.

Delmelle, E. C. 2016. Mapping the DNA of urban neighborhoods: Clustering longitudinal sequences of neighborhood socioeconomic change. *Annals of the American Association of Geographers* 106 (1):36–56. doi: 10.1080/00045608.2015.1096188.

Delmelle, E. C. 2017. Differentiating pathways of neighborhood change in 50 U.S. metropolitan areas. *Environment and Planning A* 49 (10):2402–2424. doi: 10.1177/0308518X17722564.

Ellis, M., R. Wright, L. Fiorio, and S. Holloway. 2018. Predicting neighborhood racial change in large U.S. metropolitan areas, 1990–2010. *Environment and Planning B: Urban Analytics and City Science* 45 (6): 1022–37. doi: 10.1177/2399808317744558.

Ellis, M., R. Wright, S. Holloway, and L. Fiorio. 2017. Remaking white residential segregation: Metropolitan diversity and neighborhood change in the United States. *Urban Geography* 39:519–45. doi: 10.1080/02723638.2017.1360039.

Glaeser, E. L., J. Kolko, and A. Saiz. 2001. Consumer city. *Journal of Economic Geography* 1 (1):27–50. doi: 10.1093/jeg/1.1.27.

Hwang, J., and J. Lin. 2016. What have we learned about the causes of recent gentrification? *Cityscape* 18 (3):9–26.

Hwang, J., and R. J. Sampson. 2014. Divergent pathways of gentrification: Racial inequality and the social order of renewal in Chicago neighborhoods. *American Sociological Review* 79 (4):726–51. doi: 10.1177/0003122414535774.

Kahle, D., and H. Wickham. 2015. *ggmap: A package for spatial visualization with Google Maps and OpenStreet Map, 2013 (R Package Version 2)*.

Kirk, D. S., and J. H. Laub. 2010. Neighborhood change and crime in the modern metropolis. *Crime and Justice* 39 (1):441–502. doi: 10.1086/652788.

Kneebone, E., and E. Garr. 2010. *The suburbanization of poverty*. Washington, DC: Brookings Institute.

Landis, J. D. 2016. Tracking and explaining neighborhood socioeconomic change in U.S. metropolitan areas between 1990 and 2010. *Housing Policy Debate* 26 (1):2–52. doi: 10.1080/10511482.2014.993677.

Lawton, P. 2019. Unbounding gentrification theory: Multidimensional space, networks and relational approaches. *Regional Studies* 1–12. Advance online publication. doi: 10.1080/00343404.2019.1646902.

Leyk, S., and J. Uhl. 2018a. HISDAC-US, historical settlement data compilation for the conterminous United States over 200 years. *Scientific Data* 5 (1): 180175. doi: 10.1038/sdata.2018.175.

Leyk, S., and J. Uhl. 2018b. Historical built-up intensity layer series for the U.S. 1810–2015. Harvard Dataverse. Accessed October 2, 2019. https://doi.org/10.7910/DVN/1WB9E4.

Logan, J., and H. Molotch. 1987. *Urban fortunes: The political economy of place*. Berkeley, CA: University of California Press.

Logan, J., B. J. Stults, and Z. Xu. 2016. Validating population estimates for harmonized census tract data, 2000–2010. *Annals of the American Association of Geographers* 106 (5):1013–29. doi: 10.1080/24694452.2016.1187060.

Logan, J., Z. Xu, and B. J. Stults. 2014. Interpolating U.S. decennial census tract data from as early as 1970 to 2010: A longitudinal tract database. *The Professional Geographer* 66 (3):412–20. doi: 10.1080/00330124.2014.905156.

Logan, J., and W. Zhang. 2018. Developing GIS maps for U.S. cities in 1930 and 1940. In *The Routledge companion to spatial history*, ed. D. Lafreniere, I. Gregory, and D. Debats, 229–49. London and New York: Routledge.

Malone, T., and C. L. Redfearn. 2018. Shocks & ossification: The durable hierarchy of neighborhoods in U.S. metropolitan areas from 1970 to 2010. *Regional Science and Urban Economics* 69:94–121. doi: 10.1016/j.regsciurbeco.2018.01.002.

Massey, D. S., and N. A. Denton. 1993. *American apartheid: Segregation and the making of the underclass*. Cambridge, MA: Harvard University Press.

Omi, M., and H. Winant. 2014. *Racial formation in the United States*. London and New York: Routledge.

Owens, A. 2012. Neighborhoods on the rise: A typology of neighborhoods experiencing socioeconomic ascent. *City & Community* 11 (4):345–69. doi: 10.1111/j.1540-6040.2012.01412.x.

Page, B., and E. Ross. 2017. Legacies of a contested campus: Urban renewal, community resistance, and the origins of gentrification in Denver. *Urban Geography* 38 (9): 1293–1328. doi: 10.1080/02723638.2016.1228420.

Roback, J. 1982. Wages, rents, and the quality of life. *Journal of Political Economy* 90 (6):1257–78. doi: 10.1086/261120.

Ruggles, S., S. Flood, R. Goeken, J. Grover, E. Meyer, J. Pacas, and M. Sobek. 2019. IPUMS USA: Version 9.0 [dataset]. Minneapolis, MN: IPUMS. https://doi.org/10.18128/D010.V9.0.

Ruther, M., S. Leyk, and B. P. Buttenfield. 2015. Comparing the effects of an NLCD-derived dasymetric refinement on estimation accuracies for multiple areal interpolation methods. *GIScience & Remote Sensing* 52 (2):158–78. doi: 10.1080/15481603.2015.1018856.

Sampson, R. J. 2012. *Great American city: Chicago and the enduring neighborhood effect*. Chicago: University of Chicago Press.

Sampson, R. J. 2019. Neighbourhood effects and beyond: Explaining the paradoxes of inequality in the changing American metropolis. *Urban Studies* 56 (1):3–32. doi: 10.1177/0042098018795363.

Schroeder, J. P. 2007. Target-density weighting interpolation and uncertainty evaluation for temporal analysis of census data. *Geographical Analysis* 39 (3):311–35. doi: 10.1111/j.1538-4632.2007.00706.x.

Scott, A. 1982. Locational patterns and dynamics of industrial activity in the modern metropolis. *Urban Studies* 19 (2):111–41. doi: 10.1080/00420988220080261.

Scott, A. 2018. Residential adjustment and gentrification in Los Angeles, 2000–2015: Theoretical arguments and empirical evidence. *Urban Geography* 40 (4): 506–28. doi: 10.1080/02723638.2018.1500253.

Sharkey, P. 2013. *Stuck in place: Urban neighborhoods and the end of progress toward racial equality*. Chicago: University of Chicago Press.

Sheehan, C. M., P. A. Cantu, D. A. Powers, C. E. Margerison-Zilko, and C. Cubbin. 2017. Long-term neighborhood poverty trajectories and obesity in a sample of California mothers. *Health & Place* 46:49–57. doi: 10.1016/j.healthplace.2017.04.010.

Smith, N. 1987. Gentrification and the rent gap. *Annals of the Association of American Geographers* 77 (3): 462–65. doi: 10.1111/j.1467-8306.1987.tb00171.x.

Solari, C. D. 2012. Affluent neighborhood persistence and change in U.S. cities. *City & Community* 11 (4): 370–88. doi: 10.1111/j.1540-6040.2012.01422.x.

Spielman, S. E., and J. Logan. 2013. Using high-resolution population data to identify neighborhoods and establish their boundaries. *Annals of the Association of American Geographers* 103 (1):67–84. doi: 10.1080/00045608.2012.685049.

Tiebout, C. M. 1956. A pure theory of local expenditures. *Journal of Political Economy* 64 (5):416–24. doi: 10.1086/257839.

Wei, F., and P. L. Knox. 2014. Neighborhood change in metropolitan America, 1990 to 2010. *Urban Affairs Review* 50 (4):459–89. doi: 10.1177/1078087413501640.

Zillow. 2018. Zillow data. https://www.zillow.com/research/data/.Zillow 2018

Zoraghein, H., and S. Leyk. 2019. Data-enriched interpolation for temporally consistent population compositions. *GIScience & Remote Sensing* 56 (3): 430–61. doi: 10.1080/15481603.2018.1509463.

DYLAN SHANE CONNOR is an Assistant Professor at the School of Geographical Sciences and Urban Planning at Arizona State University, Tempe, AZ 85287. E-mail: dsconnor@asu.edu. His research focuses on geographical inequality, spatial demography, and immigration.

MYRON P. GUTMANN is Professor of History and Director of the Institute of Behavioral Science at the University of Colorado Boulder, Boulder, CO 80309. E-mail: myron.gutmann@colorado.edu. His research interests include historical populations and their relationship with the environment, health, and the economy.

ANGELA R. CUNNINGHAM is a PhD alumna of the Geography Department at the University of Colorado Boulder, Boulder, CO 80309. E-mail: angela.cunningham@colorado.edu. Her research interests include population geography, spatial history, and the coconstitutive relationships of place and individual life courses.

KERRI KELLER CLEMENT is a PhD Candidate in History at the University of Colorado Boulder, Boulder, CO 80309. E-mail: kerri.clement@colorado.edu. Her research interests include Indigenous people's historic relationships with borders, disease, environments, and animals.

STEFAN LEYK is Associate Professor of Geography at the University of Colorado Boulder, Boulder, CO 80309. E-mail: stefan.leyk@colorado.edu. His research interests include uncertainty in the geospatial sciences and spatiotemporal analysis for the study of socioenvironmental systems.