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So close yet so unequal: Spatial inequality in American cities

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Abstract

Rich income data and a new methodology are employed to investigate patterns and consequences of spatial inequality in American cities over the last 35 years. New Gini-type indices, which assess spatial inequality using individual neighborhoods of variable size as primitives, uncover from the data robust evidence of growing income inequality within the neighborhood. The welfare implications of this trend are investigated through reduced-form models, addressing potential bias due to sorting across and within cities. An exogenous increase of the income mix in the neighborhood is found to yield a significant drop in intergenerational mobility gains for young people.

Keywords: Neighborhood inequality, Gini, individual neighborhood, geostatistics, census, ACS, causal neighborhood effects, life expectancy, divided city, mixed city.

JEL codes: D31, D63, C21, R23, J62, I14.

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1 Introduction

The growing debate about the spatial dimensions of the income distribution in the U.S. has bought evidence that American cities are not all alike in terms of income inequality (Chetty, Hendren, Kline and Saez 2014). In some cities, income inequality has skyrocketed in the last decades, while in others it has stagnated and even decreased in others. For instance, the Gini index of disposable equivalent household income in New York City in 2014 is over 0.5, while it is below 0.4 in other major cities such as Washington, DC. Differences in income inequality across major U.S. cities can be explained by the distribution of skills and human capital across these cities (Glaeser, Resseger and Tobio 2009, Moretti 2013), as well as by the composition of local amenities (Albouy 2016). Growing disparities across cities have important consequences for local policies, for targeting program participation based on the location of the treated, and for designing the federal redistribution schemes that reduce inequalities also locally (Sampson 2008, Reardon and Bischoff 2011b).

What this picture fails to show is that not all places within the same city are made equally unequal. Contributions at the frontier of economics, sociology and urban geography have recognized that inequality at the local level, i.e. measured among close neighbors, is generally not representative of citywide inequality in U.S. cities. Inequality within cities is a consequence of the underlying behavior of households, who sort across the urban space on the basis of their income (de Bartolome and Ross 2003, Brueckner, Thisse and Zenou 1999), thus fostering non-trivial spatial patterns of income inequality.

The features of spatial inequality at the urban level are accounted for in the literature by focusing on differences in incomes within and between neighborhoods identified by the administrative partition of the urban space (Shorrocks and Wan 2005, Dawkins 2007, Wheeler and La Jeunesse 2008, Kim and Jargowsky 2009). Evaluations based on this approach, however, put the administrative neighborhood and not the individual, who is responsible for sorting decisions, at the center. The geography of incomes can be better taken into account by adopting the notion of the "individual neighborhood", corresponding to the set of neighbors living within a certain distance range from any given individual in the city, thereby placed at the center of his own neighborhood.[1]

The aim of this paper is to model and to measure spatial inequality using individual neighborhoods as primitive information, and to assess how incomes are distributed within and across individual neighborhoods.

The first contribution is on the measurement side. In Section 2, we introduce two new spatial inequality measures, the *Gini Individual Neighborhood Inequality* (GINI) indices. These inequality measures explicitly account for the urban geography of incomes. The first GINI-type index measures the average level of income inequality *within* individual neighborhoods. According to this view, spatial inequality arises when the incomes of close neighbors differ one from the other. The second GINI-type index measures instead the inequality in average incomes *between* individual neighborhoods. According to this view, spatial inequality arises from differences in average neighborhood incomes among residents in the city. The two dimensions of spatial inequality account for separate consequences of income sorting across the urban space and, differently from existing approaches, they do not stem from a decomposition of citywide inequality. Hence, the GINI within and between indices may vary independently and citywide inequality becomes an asymptotic case of spatial inequality where the role of individual neighborhood is weakened to the extreme, i.e., to the extent that every individual neighborhood includes the whole population of the city in the within case, or only one individual in the between case.

The statistical foundations of the GINI indices are established building on connections with geostatistics literature. A methodological appendix develops innovative asymptotic results based on stationarity assumptions common in this literature (Cressie 1991). The advantages of the GINI indices are discussed, and differences with alternative measurement frameworks, such as those involving within-between decomposition techniques and income segregation indices, are highlighted.

[1]Galster (2001) and Clark, Anderson, Östh and Malmberg (2015) develop this notion in geographic analysis. On the one hand, individual neighborhoods capture the relevant space where factors such as the housing market, amenities, preferences and social interactions (Schelling 1969) combine to shape the sorting of high income and low income people across the city. On the other hand, the notion of individual neighborhood is used to identify the extent of external effects exerted by neighbors on the individual's behavior and income (Durlauf 2004, Sampson 2008, Ludwig, Duncan, Gennetian, Katz, Kessler, Kling and Sanbonmatsu 2013, Chetty, Hendren and Katz 2016).

The second contribution of this paper takes advantage of the GINI indices methodology to document the pattern of spatial inequality across the 50 most populated American cities (Section 3). Making use of a rich income database constructed from U.S. census data spanning almost four decades, we identify and estimate values of GINI indices at any meaningful distance threshold (from zero to the size of the city). We document strong resemblances in patterns of spatial inequality among the 50 cities, with high levels of within neighborhood inequality steadily increasing over time. Patterns of spatial inequality between individual neighborhoods are consistent across cities and always display a peak in the 90s and a subsequent decline over the following 25 years.[2] The GINI indices capture different aspects of spatial inequality that turn out to be orthogonal in cross-metros comparisons. This allows to highlight four models of cities along the dimensions of spatial inequality (as discussed in Sections 2.4 and 3.3).

Changes in spatial inequality are difficult to evaluate on purely normative grounds. For instance, when negative externalities arise from deprivation and envy (Luttmer 2005), within neighborhood inequality probably is the relevant dimension to look at to capture these externalities. A policy aiming at mitigating the incidence of these externalities should focus on reducing inequalities within the neighborhood, for instance by implementing local redistribution or by increasing the distance between rich and poor people. However, the proximity among people of different social status might raise ambitions and generate opportunities for the poor and also benefit the rich person (Ellen, Mertens Horn and O' Regan 2013).

In Section 4, we use an extended sample including all American Metropolitan Statistical Areas for which spatial inequality within the neighborhood can be computed, and we associate cross-metro variability in spatial inequality to two outcomes that are tightly related to urban social welfare. The first outcome we look at measures intergenerational mobility gains that are causally related to the place people were exposed to in young age (from Chetty and Hendren 2016). The second outcome consists of life expectancy estimates of poor, long-term residents in American cities (from Chetty, Stepner, Abraham,

[2] These findings match with evidence presented in the literature (Hardman and Ioannides 2004, Wheeler and La Jeunesse 2008), despite being obtained from a substantially different methodological perspective.

Lin, Scuderi, Turner, Bergeron and Cutler 2016). Mechanisms discussed in the literature hint on the possibility that both these outcomes correlated with spatial inequality within the individual neighborhood, which is measured by the GINI within index. We identify the desired effects in a reduced form setting based on cross sections of American cities. We enrich the model with substantive information about covariates that explicitly deal with cross- and within-metro sorting of households (based on demographics, local finance, schooling and school quality distribution, crime, amenities and information on citywide income distribution). We also explore historical changes in the minimum wage coverage at the industry level across regions in the U.S. as an exogenous shift for spatial inequality within the neighborhood. This strategy allows to identify the effect of an exogenous change in spatial inequality on the outcome of interest, overcoming the simultaneity bias due to sorting of household across neighborhoods on the basis of the reference outcome.

Conditional on sorting, we bring evidence that an exogenous shift in spatial inequality within the neighborhood yields a negative and significant effect on intergenerational mobility gains. The result provides a fairly robust account of existence of a Great Gatsby Curve (Corak 2013) at the neighborhood level, suggesting that the local income mix (a trademark of the "just city", see Fainstein 2010) produces negative spillovers on the lifelong opportunities of children exposed to it.

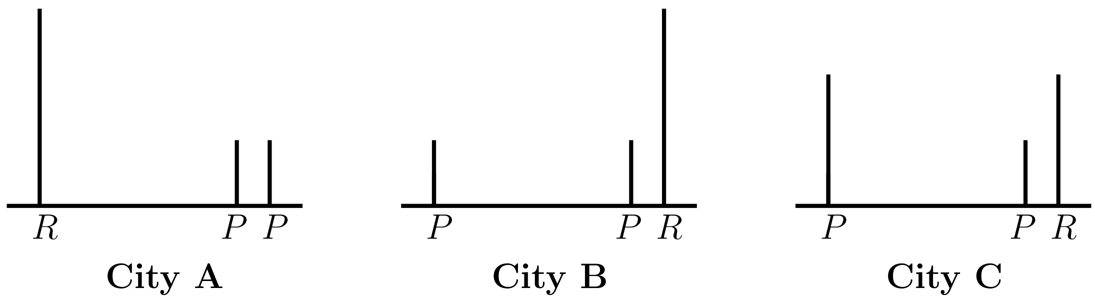
Section 5, which concludes the paper, offers additional interpretations of the results.

2 Spatial inequality measurement

2.1 Dimensions of spatial inequality

We model spatial inequality measures to capture the degree of inequality in the distribution of income both within and across individual neighborhoods, constructed for each individual living in the city and gathering the individual's close neighbors. Inequality *within* an individual neighborhood occurs if the income of the individual is different from the income of her close neighbors. Inequality *between* individual neighborhoods occurs, instead, when average neighborhood incomes differ across individuals. An intuitive ex-

Figure 1: Spatial distribution of incomes (vertical spikes) among the poor P, and the rich R in three linear cities.



ample, based on the spatial distributions of incomes in three hypothetical cities shown in Figure 1, highlights the main feature of spatial inequality.

Consider first the two stylized cities *City A* and *City B*. There are three people living in each city, two poor (P) and one rich person (R). The two cities display the same overall income inequality, but differ in the way people are located in the urban space: in City A the poor persons are close neighbors and the rich person is isolated, while in City B a poor person lives near the rich one, and the other poor person is isolated. To evaluate spatial inequality, we first identify individual neighborhoods by drawing circles of given diameter around each individual, and then we study the income distribution within and among individual neighborhoods. The size (or equivalently, the degree of inclusiveness) of the individual neighborhood can vary. When the size is not too large,[3] the average degree of inequality (captured by the extent of income differences) within the individual neighborhoods is smaller in City A than in City B. This occurs because the rich person in City A lives isolated and the other two persons are equally poor. Conversely, the inequality between average incomes observed in each individual neighborhood of City B is smaller than the inequality observed in City A. This occurs because some income inequality between the rich and the poor person in City B is averaged out when computing

[3]In Figure 1, individual neighborhoods are delimited by intervals centered on each individual. When each interval includes just one individual, there is no inequality within the neighborhood and inequality between neighborhoods coincides with citywide inequality. When each individual neighborhood is large enough to comprise the remaining two individuals, spatial inequality within the neighborhood coincides with citywide inequality, while inequality between neighborhoods is zero (since average incomes coincide across individual neighborhoods). All in-between cases, individual neighborhoods are not "too large", that is at least one individual neighborhood comprises two individuals.

the mean incomes at the individual neighborhood level.

In this framework, a *movement of people* across locations of a city may give rise to changes in spatial inequality that are not trivial, although citywide income distribution would not be affected by this displacement. For instance, if individuals R and P living at the extremes of City A exchange their location, the resulting spatial distribution of incomes would be that of City B, implying an raise (a drop) in within (between) inequality.[4] Differently from standard inequality analysis, also *rich-to-poor transfers* have ambiguous effects on spatial inequality. Consider now *City C* in Figure 1. This hypothetical city represents the spatial distribution of R and P people after a rich-to-poor transfer of income has eliminated income differences between the two individuals located at the outskirts of the city. Arguably, this transfer reduces citywide inequality irrespective of whether the initial distribution is that of City A or of City B. Spatial inequality between individual neighborhoods is also reduced by the transfer. The implications for spatial inequality within individual neighborhoods, however, are ambiguous. Spatial inequality within the neighborhood would have been reduced by the transfer if the starting configuration were as in City B, whereas it would have been increased if the starting configuration were as in City A. This highlights that even rich-to-poor income transfer might give rise to divergent patterns of spatial inequality when the location of the population is taken into account.

The features of spatial inequality highlighted in the example are now incorporated into the Gini Individual Neighborhood Inequality indices presented in the next section.

2.2 The GINI indices

Consider a population of $n \geq 3$ individuals, indexed by $i = 1, ..., n$, and let $y_i \in \mathbb{R}_+$ be the income of individual i and $\mathbf{y} = (y_1, y_2, ..., y_n)$ the income vector with average $\mu > 0$. A popular measure of income inequality is the Gini coefficient, defined as

$$G(\mathbf{y}) = \frac{1}{2n(n-1)\mu} \sum_i \sum_j |y_j - y_i|.$$

[4] This movement reflects the implications of gentrification occurred in the last decades across all major American cities, where rich people previously isolated in wealthy suburbs moved towards a more densely populated area of the city, pricing out the poor people who are then marginalized.

In what follows, information on the income distribution is assumed to come with information about the location of each income recipient on the city map. For any individual, neighbors are identified as the group of people located at most as far as d distance units from this individual. The Euclidian distance is used to determine the extent of the neighborhood.[5] The set of neighbors located within a distance range d from individual i is designated as d_i, such that $j \in d_i$ if the distance between individuals i and j is less than or equal to d. The cardinality of d_i is denoted n_{id}, that is the number of people living within a range d from i (including i). The average income of individual i's neighborhood of length d, capturing the neighborhood's affluence, is $\mu_{id} = \frac{\sum_{j \in d_i} y_j}{n_{id}}$.

The first spatial inequality index that we consider is the Gini Individual Neighborhood Inequality within index, indicated by $GINI_W$. It measures the average degree of relative income inequality within individual neighborhoods. The $GINI_W$ index is inspired by Pyatt (1976), who provides a probabilistic interpretation of the Gini inequality index. According to Pyatt, the Gini index can be seen as the expected gain accruing to a randomly chosen individual from the income distribution if her income is replaced with the income of another individual randomly drawn from the same distribution. The $GINI_W$ index assumes that income comparisons are carried over exclusively within individual neighborhoods of a given size. For each individual i, the average distance between i's income and the income of her neighbors is computed and then this quantity is scaled by the neighborhood average income so that it ranges over the unit interval. This gives:

$$\Delta_i(\mathbf{y}, d) = \frac{1}{\mu_{id}} \sum_{j \in d_i} \frac{|y_i - y_j|}{n_{id}}.$$

Given the relevant notion of individual neighborhood parametrized by d, there are $1/n_{id}$ chances of drawing a neighbor of i with whom she can compare her income with. This probability changes across individuals, reflecting the population density of individual neighborhoods. The $GINI_W$ index averages the normalized mean income gaps Δ_i across

[5] For a discussion of the use of multidimensional notions of distance, see Conley and Topa (2002).

the whole population:

$$GINI_W(\mathbf{y}, d) = \frac{1}{2} \sum_{i=1}^{n} \frac{1}{n} \Delta_i(\mathbf{y}, d).$$

The $GINI_W$ index captures the overall degree of inequality that would be observed if income comparisons were limited only to neighbors located at a distance smaller than d. The index is bounded, with $GINI_W(\mathbf{y}, d) \in [0, 1]$ for any $\mathbf{y}$ and d. Moreover, $GINI_W(\mathbf{y}, d) = 0$ if and only if all incomes within individual neighborhoods of size d are equal. Notice that this cannot exclude inequalities among people located at a distance larger than d. Additionally, $GINI_W(\mathbf{y}, d)$ can take values that are either larger or smaller than $G(\mathbf{y})$.[6] When d reaches the size of the city, spatial inequality coincides with citywide inequality, that is $GINI_W(\mathbf{y}, \infty) = G(\mathbf{y})$.

The $GINI_W$ index implements a relative concept of inequality, since income distances within each neighborhood are divided by the neighborhood average income. As a consequence, the distribution of incomes within the individual neighborhood does not necessarily resemble that of the city as a whole, even if measured inequality in relatively small neighborhoods approaches citywide inequality. In fact, average incomes might substantially differ across individual neighborhoods. Inequality between individual neighborhoods can be valued by the Gini index for the vector $(\mu_{1d}, \ldots, \mu_{nd})$. The elements of this vector depend upon spatial proximity of individuals. For instance, if a high-income person lives near to many low-income people, her income contributes to rising the mean income not only in the high-income person neighborhood, but also in the individual neighborhoods of all her low-income neighbors. However, if the high-income person is located at an isolated point on the urban map, her income does not generate any positive effect on other people's average neighborhood income, provided that the notion of individual neighborhood is sufficiently exclusive. As a consequence, the average value of the vector $(\mu_{1d}, .., \mu_{nd})$, designated μ_d, generally differs from μ. The between dimension of spatial inequality is captured by the GINI between index, which is denoted $GINI_B$ and defined defined as:

[6] Consider, for instance, the following distribution of incomes among four individuals: $(\$0, \$0, \$1000, \$2000)$. The Gini inequality index of this income distribution is 0.77. Suppose these individuals are distributed in space such that each of the two poor individuals lives close to a non-poor person, while the two pairs are far apart one from the other. Then, spatial inequality within the neighborhoods is maximal (i.e., $GINI_W(., d) = 1$ for d small) and larger than citywide inequality.

$$GINI_B(\mathbf{y},d) = \frac{1}{2n(n-1)\mu_d} \sum_i \sum_j |\mu_{id} - \mu_{jd}|.$$

As expected, $GINI_B(\mathbf{y}, d) \in [0, 1]$ for any $\mathbf{y}$ and d. The index is equal to $G(\mathbf{y})$ at a zero-distance and whenever all incomes within each individual neighborhood of length d are equal. $GINI_B$ converges to zero when d approaches the size of the city.

A simple and insightful picture of within and between spatial inequality patterns can be drawn by computing GINI indices for different values of d and plotting their values on a graph against d (on the horizontal axis). The curve interpolating these points is called the spatial inequality curve, generated by either the $GINI_W$ or the $GINI_B$ index. The $GINI_B$ curve takes the value of the overall Gini index when each individual is considered as isolated (that is, when $d = 0$) and approaches 0 when each individual neighborhood spans the whole city. The curve originated by $GINI_W$ can exhibit a less predictable shape. First, it can locally decrease or increase in d according to the spatial distribution of incomes. Second, when each individual neighborhood is large enough to include the whole population of the city, then $GINI_W(\mathbf{y}, d)$ approaches $G(\mathbf{y})$. Third, the graph of $GINI_W(\mathbf{y}, d)$ can be flat, meaning that incomes are randomized across locations and the spatial component of inequality is irrelevant. Fourth, the curve can increase with d, indicating that individuals with similar incomes tend to sort themselves in the city. The shape of the spatial inequality curves also suggests the degree to which citywide income inequality can be correctly inferred from randomly sampling individuals from the city.[7]

For a given size of the individual neighborhood, spatial inequality comparisons can be carried over by looking at the level of the GINI within or between index at the corresponding distance threshold. Each of these evaluations generates a complete ranking of the income distributions, although these rankings may contradict each others. Comparisons of spatial inequality curves can be used to draw evaluations of spatial inequality that are robust *vis-à-vis* the size of the neighborhood. We propose to use these curves to

[7] When the role played by space is negligible, i.e. the spatial inequality curves are rather flat, any random sample of individuals taken from a given point in the space is representative of overall inequality. When space is relevant and people locations are stratified according to income, then a sample of neighbors randomly drawn could underestimate the level of citywide inequality.

carry over robust spatial inequality assessments.

The GINI indices are measures of inequality that account for the spatial association of unequal incomes. In the following section we formalize the connections with the way in which spatial association is treated in *geostatistics* literature.

2.3 Spatial inequality and geostatistics

A spatial income distribution can be represented through its data generating process $\{Y_s : s \in \mathcal{S}\}$. This process is a collection of random variables Y_s located over the random field $\mathcal{S}$, which serves as a model of the relevant urban space. The process is distributed as $F_{\mathcal{S}}$, the joint distribution function combining information on the marginal income distributions in each location and the degree of spatial dependence of incomes on $\mathcal{S}$. Through geolocalization, it is possible to compute the distance "$||.||$" between locations $s, v \in \mathcal{S}$. Let $||s - v|| \leq d$ indicate that the distance between the two locations is smaller than d, or equivalently $v \in d_s$. The cardinality of the set of locations d_s is n_{d_s}, while n is the total number of locations. The observed income distribution $\mathbf{y}$ is a particular realization of the process, where only one income realization y_i is observed in location s.

Consider first the $GINI_W$ index of the spatial process $F_{\mathcal{S}}$. It can be written in terms of first order moments of the random variables Y_s as follows:[8]

$$GINI_W(F_{\mathcal{S}}, d) = \sum_s \sum_{v \in d_s} \frac{1}{2n\, n_{d_s}} \frac{\mathbb{E}[|Y_s - Y_v|]}{\mathbb{E}[Y_v]}.$$

The degree of spatial dependence represented by $F_{\mathcal{S}}$ enters in the $GINI_W$ formula through the expectation terms conditional on $\mathcal{S}$. Consider first the case displaying no spatial dependence in incomes, that is, the random variables Y_s and Y_v are i.i.d. for any $s, v \in \mathcal{S}$. One direct implication is that $GINI_W(F_{\mathcal{S}}, d) = \frac{\mathbb{E}[|Y_s - Y_v|]}{\mathbb{E}[Y_v]}$, which coincides with the definition of the standard Gini inequality coefficient (see for instance Muliere and Scarsini 1989).

If, instead, spatial dependence is at stake, then the expectation $\mathbb{E}[|Y_s - Y_v|]$ varies

[8] Biondi and Qeadan (2008) use a related estimator to assess dependency across time in paleorecords observed in a given location.

across locations and cannot be identified and estimated from the observation of just one data point in each location. It is standard in geostatistics to rely on assumptions about the stationarity of $F_{\mathcal{S}}$ (Cressie and Hawkins 1980, Cressie 1991). The first assumption is that the random variables Y_s have stationary expectations over the random field, i.e., $\mathbb{E}[Y_v] = \mu$ for any v. The second assumption is that the spatial dependence in incomes between two locations s and v only depends on the distance between the two locations, $||s - v||$, and not on their position in the random field. Here, we consider radial distance measures for simplicity, so that $||s - v|| = d$. This gives $\mathbb{E}[(Y_s - Y_v)^2] = 2\gamma(||s - v||) = 2\gamma(d)$, where the function 2γ is the *variogram* of the distribution $F_{\mathcal{S}}$ (Matheron 1963).

The function $2\gamma(d)$ is informative of the correlation between two random variables that are exactly d distance units away one from one other. The slope of the graph of the variogram function displays the extent to which spatial association affects the joint variability of the elements of the process. Generally, $2\gamma(d) \to 0$ as d approaches 0, indicating that random variables that are very close in space tend to be strongly spatially correlated and variability in incomes at the very local scale is small. Conversely, $2\gamma(d) \to 2\sigma^2$ when d is sufficiently large, indicating spatial independence between two random variables Y_s and Y_v far apart on the random field.

Together, the two assumptions listed above depict a form of *intrinsic stationarity* of the data generating process (see Chilès and Delfiner 2012). If, additionally, Y_s is assumed to be Gaussian with mean μ and variance σ^2, $\forall s \in \mathcal{S}$, it is possible to show that the $GINI_W$ index is a function of the variogram, which gives:

$$GINI_W(F_{\mathcal{S}}, d) = \sum_s \sum_{v \in d_s} \frac{1}{\sqrt{\pi}} \frac{1}{n\, n_{d_s}} \frac{\sqrt{\gamma(||s - v||)}}{\mu}.$$

With some additional algebra, it is also possible to show that the $GINI_B$ index is a function of the variogram under stationarity and the Gaussian assumptions. Both indices can hence be described as averages, taken over the space of distances between locations, of distance-sensitive coefficients of variation. All results are formally derived in the Appendix.

The possibility of expressing the GINI indices as transformations of the variogram leads to two considerations. The first is that the GINI indices measure spatial inequality as a direct expression of the spatial dependence in the data generating process (represented under stationarity assumptions by the variogram) without imposing external normative hypotheses about the interactions between incomes, income inequality and space.

The second consideration is that the empirical counterpart of the variogram sets the basis for estimating asymptotic standard errors of the GINI indices.[9] Furthermore, under the intrinsic stationarity and the Gaussian assumption about the data generating process, we can show that the GINI estimators sampling distribution is asymptotically normal. As discussed in the Appendix, these results are used to test hypotheses on (i) the extent and (ii) the speed of convergence of spatial inequality towards citywide inequality, as well as (iii) the changes in spatial inequality across time and geographies.[10]

2.4 Connections with the literature

The inequality literature largely agrees that relative inequality indices should satisfy at least four normatively relevant properties (Atkinson 1970): (i) invariance with respect to population replication; (ii) invariance to the measurement scale; (iii) anonymity, that is, invariance to any permutation of the incomes across the income recipients; (iv) the Pigou-Dalton principle, implying that every rich-to-poor income transfer should not increase inequality. While properties (i) and (ii) have desirable implications for the measurement of spatial inequality and are satisfied by the GINI indices,[11] anonymity strongly conflicts

[9] Distribution free, non-parametric estimators for the GINI indices are estimated in a general setting where sample information about the process $F_{\mathcal{S}}$ is available. The $GINI_B$ index estimator is the plug-in estimator as in Binder and Kovacevic (1995) and Bhattacharya (2007). The $GINI_W$ estimator involves comparisons of individual income realizations. Standard errors for GINI indices are derived using results for ratio-measures estimators (see Hoeffding 1948, Goodman and Hartley 1958, Tin 1965, Xu 2007, Davidson 2009) under intrinsic stationarity and normality (Cressie and Hawkins 1980, Cressie 1985). The latter assumption does not immediately translate into normality. However, it is sufficient to show that the GINI estimators are linear in the variogram, implying asymptotic normality.

[10] A Stata routine implementing the $GINI_W$ and the $GINI_B$ indices and spatial inequality curves curves, along with their standard error estimators, is made available by the authors.

[11] Direct implications of these properties are that populations of different size and different average incomes can be made comparable. Replication invariance, in particular, guarantees that replacing single individuals by equally-sized groups in given locations does not affect spatial inequality. Both properties are satisfied by the GINI indices by standardizing income gaps by individual neighborhood-specific

with the idea that location matters in spatial inequality evaluations. Anonymity would not be a concern if incomes *and* locations were both permuted across individuals. An example illustrates the drawbacks of a weaker notion of anonymity which retains permutations of incomes alone.

Consider, for instance, the income distribution in Figure 1 in Section 2.1. The spatial configuration of incomes in City B can be obtained from that in City A by permuting the incomes of the individuals living at the margins of the city. Anonymity, which judges City A and City B as equal from a citywide inequality perspective, does not extend to spatial inequality, which instead rises in the within dimension and decreases in the between dimension after the permutation.

Different solutions have been proposed in order to weaken the notion of anonymity to analyze the spatial features of the income distribution. One possibility is to rely on assessments of inequality within and between neighborhoods originating from a well-defined partition of the city into administrative areas, such as urban blocks, census tracts, etc (Shorrocks and Wan 2005, Dawkins 2007, Wheeler and La Jeunesse 2008). Some authors have focused on a particular aspect of spatial inequality, called income segregation (by analogy with racial segregation), which is insensitive to the overall income distribution in the city and rather captures how rich and poor people sort unevenly across the cells of an administrative partition of the city. In this spirit, Kim and Jargowsky (2009) suggested breaking down overall inequality in the components associated with within and between neighborhoods variability in incomes, and to assess spatial segregation as the share of citywide inequality due to the between component. Reardon and Bischoff (2011b) focus instead on the degree of disproportionality of rich and poor individuals across neighborhoods.

The approaches mentioned above retain anonymity at two levels: first, among individuals living in the same neighborhood; second, in terms of average incomes across neighborhoods. These measures of spatial inequality, which put the emphasis on the neighborhood as the unit of analysis, are subject to the Modifiable Areal Units Problem

population counts and average incomes.

(MAUP, see Openshaw 1983, Wong 2009), arising from "scaling" and "zonation" issues, which respectively refer to the size and the shape of administrative neighborhoods.[12]

The analysis based on the GINI indices differs from the previous literature in using individual neighborhoods as primitives. In fact, individual neighborhoods do not originate from a partition of the urban space, but rather can display some degree of overlapping: the fact that individual k is in the neighborhood of individual i *and* of individual j does not imply that i and j are also neighbors. This logic leads to discard anonymity within individual neighborhoods regardless of their size (permuting the incomes of any two neighbors might have substantial implications for other individual neighborhoods) and is also robust in relation to the issue of zonation. Furthermore, the degree of inclusiveness of individual neighborhoods can increase without strengthening anonymity within the neighborhoods. Anonymity (also called symmetry) is a necessary condition for Schur-convexity, a mathematical property satisfied by all inequality indices consistent with the Pigou-Dalton transfer principle (see Marshall and Olkin 1979, p.54). By weakening anonymity, both rich-to-poor income transfers and relocation policies switching the position of poor and rich people across the city (without affecting citywide inequality) may give rise to unpredictable implications for spatial inequality, who are likely amplified by the behavioral responses of people who can sort across space along the income dimension (Durlauf 2004).

As a consequence of this representation of spatial inequality, the GINI indices of inequality within and across individual neighborhoods are not necessarily intertwined, as it would have been the case if they were obtained from a within/between decomposition of the citywide Gini index. Thus, the two indices offer one additional degree of freedom compared to the traditional between-within decomposition techniques (where, for given citywide inequality, a high degree of within inequality mechanically involves low between inequality and vice-versa).

[12]To overcome the scaling issue, some authors have proposed assessing inequality between neighborhoods at different scales of aggregation of the initial partition (Hardman and Ioannides 2004, Shorrocks and Wan 2005, Wheeler and La Jeunesse 2008). To avoid the zonation issues, Dawkins (2007) has proposed to account for the dependence of income segregation on the spatial arrangement of administrative neighborhoods.

In the following section, we use the GINI indices to draw out stylized facts about spatial inequality trends of the 50 largest U.S. cities, and we highlight joint patterns is spatial inequality within and between individual neighborhoods therein.

3 Spatial inequality in American cities: 1980-2014

3.1 Data

We assess spatial inequality based on information on incomes distributions within U.S. cities over four decades, drawing on the census files of the U.S. Census Bureau for 1980, 1990 and 2000. Information about population counts, income levels and family composition at a very fine spatial grid is taken from the decennial census Summary Tape File 3A.[13] Due to anonymization issues, the STF 3A data are given in the form of statistical tables representative at the block group level, the finest available statistical partition of the American territory. After 2000, the STF 3A files have been replaced with survey-based estimates of the income tables from the American Community Survey (ACS), which runs annually since 2001 on representative samples of the U.S. resident population. We focus on the 2010-2014 5-years Estimates ACS module. Sampling rates in ACS vary independently at the census block level according to 2010 census population counts, covering on average 2% of the U.S. population over the 2010/14 period. To our knowledge, ACS 2010/14 wave has not yet been used for empirical analysis of urban inequality.

The units of analysis are households with one or more income recipients. The focus is on the gross household income distribution. There are two available sources of information that can be used to model the income distribution at the block group level. The first set of tables display aggregate income at the block group level. The second set of tables show instead counts of households per income interval at the block group level.[14] There are 17

[13]The Census STF 3A provides cross-sectional data for all U.S. States and their subareas in hierarchical sequence down to the block group level (the finest urban space partition available in the census). The geography of the block group partition changes over the decades to keep track with demographic changes within the Counties of each State.

[14]The ACS estimates of population counts should be interpreted as average measures across the 2010-2014 time frame. The survey runs over a five years period to guarantee the representativeness of income and demographic estimates at the block group level.

income intervals in the census 1980, 25 in the census 1990 and 16 in the census 2000 and in the ACS. In all cases, the highest income bracket is not top-coded. We use a methodology based on Pareto distribution fitting as in Nielsen and Alderson (1997), to convert tables of household counts across income intervals into a vector of representative incomes for each income interval, along with the associated vector of households frequencies corresponding to these incomes.[15] Estimates of incomes and household frequencies vary across block groups, implying strong heterogeneity within the city in block-group specific household gross income distributions.

The STF 3A files and the ACS also provide tables of household counts by size (scoring from 1 to 7 or more household members) for each block group. To draw conclusions about the distribution of income across block groups that differ in households demographics, we construct equivalence scales that are representative at the block group level (the square root of average household composition in the block group level, obtained from households counts information). We can hence convert the representative incomes at the block group level into the corresponding equivalized incomes by scaling the estimated reference income values by the block group-specific equivalence scale.

Income reference levels, population frequencies associated with these levels and equivalence scales are estimated separately for each block group of a city in each census and ACS years. All block groups are georeferenced, and measures of distance between the block groups centroids can therefore be constructed. All income observations within the same block group are assumed to occur on its centroid. To identify the relevant urban space, defining the extension of a city, we resort to the Census definition of a Metropolitan

[15]The procedure consists in fitting a Pareto distribution to the grouped data (population shares and income thresholds) and then estimating references incomes within each interval. For income intervals below the median, the estimated reference income is the midpoint of the interval. For other intervals, estimates are obtained under the constraint that estimated average income at the block-group level should coincide with the observed average income in the data. Estimated medians for top income intervals are used as reference incomes, and empirical population counts as weights. Fitting methods consist in GMM (preferred) and quantile estimation as in Quandt (1966). Alternative estimation methods draw instead from the log-normality assumption, as in Wheeler and La Jeunesse (2008). Incomes estimates based on the preferred method display an MSA-year level average correlation of 95.2% with quantile fitting income estimates (MSA-years population weighted correlations range between $min = 76\%$ and $max = 98.9\%$, with 95% of the correlations larger than 89.3%), and 90.4% average correlation with log-normal fitting income estimates at the block group level (MSA-years population weighted correlations range between $min = 45.6\%$ and $max = 97.1\%$, with 95% of the correlations larger than 85.1%).

City	Year	# Blocks	Hh/block	Eq. scale	Equivalent household income				
					Mean	*20%*	*80%*	*Gini*	*90%/10%*
Chicago (IL)	1980	3756	1122	1.630	13794	5798	20602	0.434	11.351
	1990	4444	1217	2.029	21859	9132	32316	0.461	11.903
	2000	4691	1173	1.625	41193	16076	61667	0.473	11.533
	2010/14	4763	1060	1.575	55710	20022	89856	0.486	13.452

Table 1: The household equivalent gross income distribution in Chicago, IL

Statistical Area (MSA) based on the 1980 Census definition.[16] For each city-year pair we therefore obtain an income database consisting of strings of incomes and frequency weights at each geocoded location on the map. Thus, weighted variants of the GINI index estimators can be used to evaluate facts about spatial inequality at various distance scales.

The case of Chicago, IL serves to illustrate the functioning of the GINI methodology. The analysis will also allow to illustrate the general trends for the largest American cities, discussed afterwards.

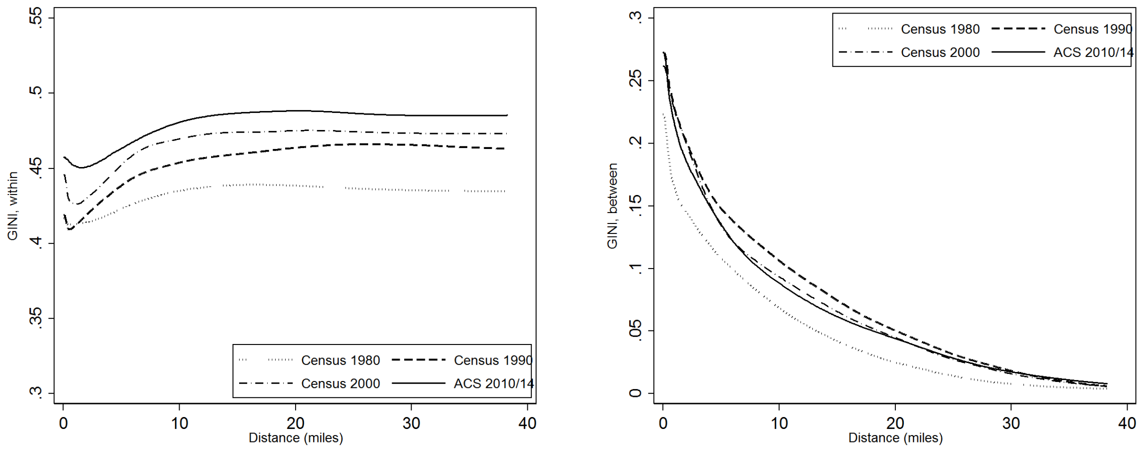
3.2 Spatial inequality in Chicago, IL

Table 1 provides summary information of the household population and the respective income distribution in Chicago.[17] Average equivalent household income increased fourfold over 1980-2014 in nominal terms, corresponding to a 73% increase in real terms. Table 1 shows that the top 10% to bottom 10% income ratio sharply increased from 11.53 in 2000 to almost 13.5 in the 2010/2014 period, indicating increased dispersion at the tails of the

[16] The U.S. counties defining the MSAa in 1980 can be found at this link: *http://www.census.gov/population/metro/files/lists/historical/80mfips.txt.* The 1980 Census definition of MSA guarantees comparability of estimates across urban areas that are expanding or shrinking over the 35 years considered in this study.

[17] The extent of the Chicago metro area, based on 1980 definition of Chicago primary MSA, comprises Cook County, Du Page County and McHenry County surface.For some of the block groups of 1980 Census it is not possible to establish geocoded references. Hence, these units cannot be included in the index computation and might have an impact on the estimation of the GINI patterns. Reardon and Bischoff (2011b) and other contributions have demonstrated, however, that the impact of this kind of missing information is negligible on overall trends of inequality within the 100 largest U.S. Commuting Zones. Throughout the four decades considered in this study, the block group partition of Chicago has become finer, with the number of block groups increasing 1000 units. This change keeps track of the demographic boom in Chicago, implying a roughly stable demographic composition in each block group (around 1100 households on average).

Figure 2: Spatial GINI indices for Chicago (IL), 1980, 1990, 2000 and 2010/14



(a) $GINI_W$ (b) $GINI_B$

Note: Authors analysis of U.S. Census and ACS data.

distribution. The relative gap between the low income (bottom 20%) and high income households (top 20%) has increased at a constant yet lower pace. The citywide Gini index increased from 0.43 to 0.48 over the same period.

Values of the $GINI_W$ and the $GINI_B$ indices are computed for 1980, 1990, 2000 and 2010/2014 waves to assess the evolution of equivalent household income across individual neighborhoods. Figure 2 represents the full distribution of GINI indices (on the vertical axis) as a function of the size of the individual neighborhood (in miles, reported on the horizontal axis). At distance zero up to approximately 0.2 miles, the $GINI_W$ index captures the average inequality in estimated income levels within block groups. Data confirm substantial income inequality within block groups in 2000,[18] with the Gini index fluctuating between 0.2 to above 0.6, and standing at 0.4 when averaging across Chicago's block groups. This explains the relatively high intercept of the $GINI_W$ curves shown in Figure 2.(a). Inequality slightly decreases as the neighborhood size reaches two miles and then quickly rises to reach its city-wide level when the size of the neighborhood is larger than 20 miles. Comparing the $GINI_W$ curves of the different decades, within neighborhood inequality appears to increase over time, for any size of the neighborhood.

[18]For this year block group level estimates of inequality are collected in the census tables.

The between individual neighborhood inequality curves from 1980 to 2010/14 are plotted in Figure 2.(b). For individual neighborhoods of narrow size, the $GINI_B$ index values are generally smaller than 0.3. As expected, between neighborhood inequality decreases with the size of the neighborhood, but in a very smooth manner. For neighborhoods smaller than two miles, the $GINI_B$ index is generally larger than 0.25. It decreases to 0.1 only for neighborhoods of at least 16 miles range. Overall, this pattern is robust across Census years. Contrasting the $GINI_B$ curves over the last three decades, it can be noted that between inequality is on the rise up to 1990, decreases in 2000 and stabilizes thereafter.

Are these patterns statistically significant? Estimates for small size individual neighborhoods might in fact be biased by the approximations used to estimate block-group level income distributions. To assess significance, we first compute empirical estimators of the variograms based on geolocalized income data (see Appendix A), and then derive standard errors and confidence intervals of the GINI within and between indices at pre-selected distance thresholds. Confidence bounds are drawn for each spatial inequality curve, and dominance relations across spatial inequality curves are tested making use of t-statistics at selected distance ranges.[19] Overall, we find evidence of the following patterns of spatial inequality in Chicago: i) for neighborhoods of small size (below 2 miles), the $GINI_W$ index ranges from 0.41 in 1980 to 0.45 in 2010/2014, and increases slightly with the size of the neighborhood; ii) the $GINI_B$ index decreases smoothly with neighborhood size and reaches 0.1 only for relatively large (more than 10 miles) neighborhoods, hence indicating persistence of inequality across the urban space; iii) the $GINI_W$ index is constantly on the rise over the period considered at any distance threshold, although there is little statistical evidence supporting these changes; iv) the $GINI_B$ index is on the rise during 1980-1990, it slightly (yet significatively) declined in 2000 and has re-

[19] To do so, we compute all pairwise differences in spatial inequality curves across all the decades under analysis. These differences, measured at pre-determined distance abscissae (along with the associated confidence bounds), are then plotted on a graph. If the horizontal line passing from the origin of the graph (indicating the null hypothesis of no differences in spatial inequality at every distance threshold) falls within these bounds, we conclude that the gap in the spatial inequality curves under scrutiny are not significant at standard confidence levels. For a detailed description of results, we refer to the supplemental Appendix.

maind stable thereafter. The changes we describe are robust over the entire domain of the neighborhood size parameter.

3.3 Trends of spatial inequality in largest American cities

Figures 3 and 4 show spatial inequality curves for the years 1980, 1990, 2000 and 2010/2014. There are 50 curves in each panel, one for each city. The bold dark curve in each panel represents a fifth degree polynomial fit of the 50 curves plotted in each figure. These curves are then collected and plotted altogether in Figure 5.[20]

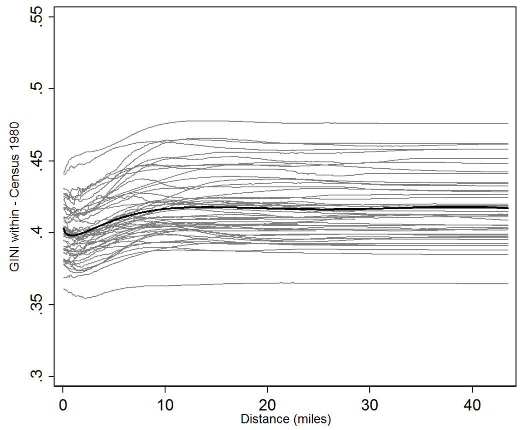
We identify three stylized facts about spatial inequality across American cities. First, spatial inequality within individual neighborhoods has been on the rise over the last 35 years at every distance abscissa. Second, the trends and patterns displayed by the between and within spatial inequality curves of the 50 largest U.S. cities are similar to those recorded for Chicago: The $GINI_W$ index estimates are high even for small distances and rapidly converge to the citywide level of inequality; the $GINI_B$ index estimates fluctuate around 0.3 and smoothly converge to zero for substantially large (more than 15 miles) individual neighborhoods. On average, inequality between individual neighborhoods increased in the 80's and stagnated afterwards.[21]

The third stylized fact concerns the substantial heterogeneity in levels of spatial inequality across the 50 cities. When the neighborhood size is smaller than 10 miles, this heterogeneity does not reflect heterogeneity in citywide inequality observed across the 50 cities. For individual neighborhoods of larger size, heterogeneity in within individual neighborhood inequality collapses to an "intercept" dimension, which approximates citywide inequality and captures differences in fundamentals across cities, such as the distribution of skills across local labor markets (Baum-Snow and Pavan 2013, Moretti 2013).

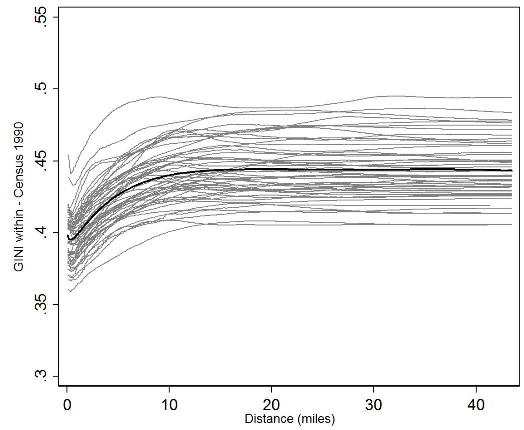
[20] Census Bureau Data on demographic size of the 50 largest U.S. cities can be downloaded from: *http://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?src=bkmk*. The list of cities, ordered by size, can be found in Table 12 in the supplemental Appendix, Section C. We stick to the 1980 Census definition of metropolitan statistical areas for each of these cities to define the relevant urban space. In this way, within-city patterns of spatial inequality can be meaningfully compared across decades.

[21] This evidence is in line with the previous findings of Wheeler and La Jeunesse (2008), who considered two different exogenous spatial partitions of US metropolitan areas and found high and persistent levels of spatial inequality within block groups. They also pointed out that the major changes over 1980-2000 were driven by the between component of inequality.

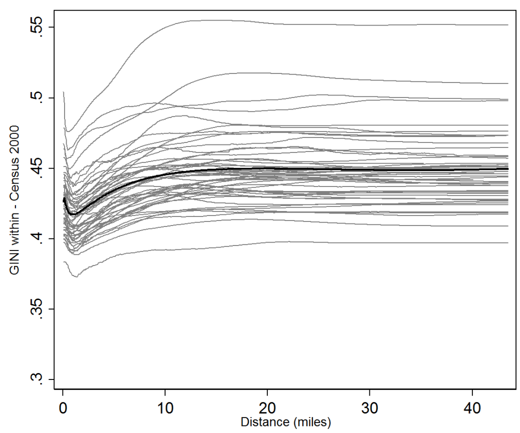
Figure 3: Inequality within individual neighborhood for 50 largest U.S. metro areas



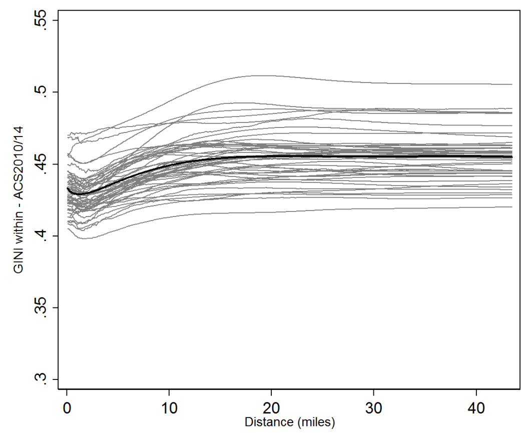
(a) Census 1980



(b) Census 1990



(c) Census 2000



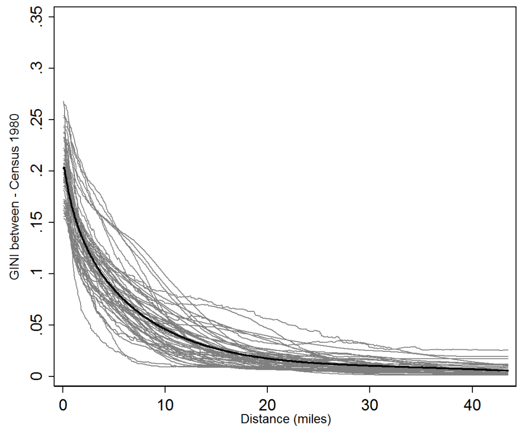
(d) ACS 2010/2014

Note: Authors analysis of U.S. Census and ACS data.

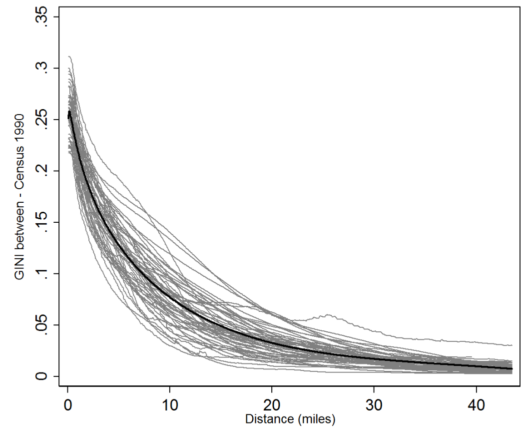
Shrinking spatial inequality patterns around the common trend provides evidence of convergence in fundamentals across the cities, while differences in gradients account for city specific sorting patterns of low and high income households. The rise of citywide inequality observed in the period 1980-1990 was accompanied by increasing values of the within and between GINI indices. This trend is consistent with rich and poor people moving far apart and high income households getting richer in those neighborhoods where they are over-represented, while middle class households' income grew at a slower pace.

In the following years (1990-2014) despite the persistent growth of citywide and GINI

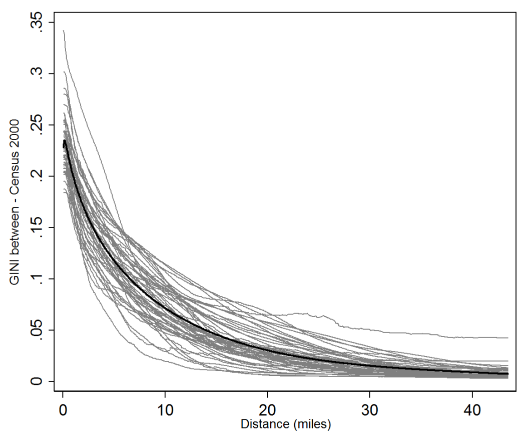
Figure 4: Inequality between individual neighborhoods for 50 largest U.S. metro areas



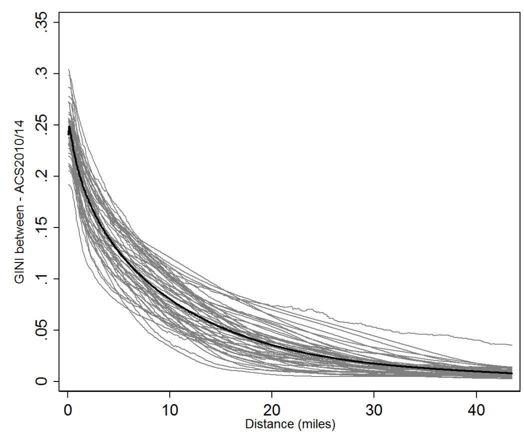
(a) Census 1980



(b) Census 1990



(c) Census 2000

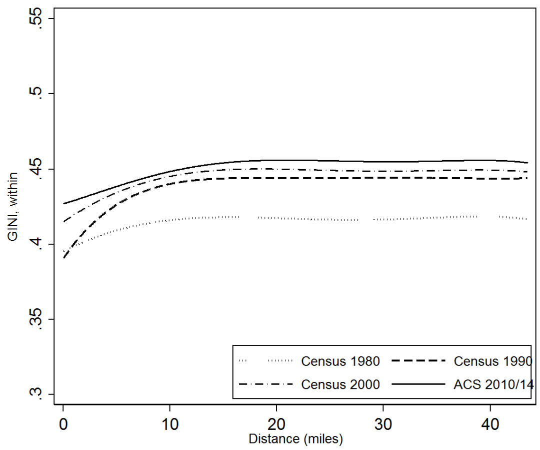


(d) ACS 2010/2014

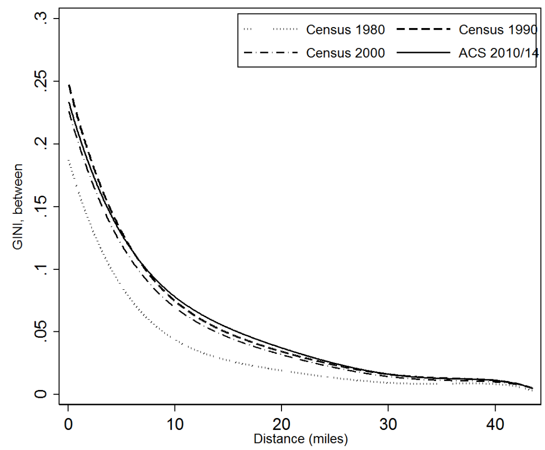
Note: Authors analysis of U.S. census and ACS data.

within inequality, income inequality between individual neighborhoods first decreased and then stabilized. These trends might mirror the effects of a recent wave of gentrification of wealthy and skilled people from suburbia to inner city (the "Great Inversion" hypothesis proposed by Ehrenhalt 2012), accompanied by the concentration of income poverty in suburbs (Kneebone 2016). Rich households move closer to the middle class households, pricing out poor households from neighborhoods where urban poverty has been historically concentrated. This change could explain the substantial inequality within individual neighborhoods, leveraging on the increasing disparity in incomes between rich households

Figure 5: Spatial inequality in major U.S. metro areas (average), 1980, 1990, 2000 and 2010/14



(a) $GINI_W$



(b) $GINI_B$

Note: Authors analysis of U.S. census and ACS data. Year-specific polynomial fittings of $GINI_W$ and $GINI_B$ across 50 largest U.S. metro areas.

and the rest, and the simultaneous reduction/stability of inequality between individual neighborhoods.[22]

To sum up, our analysis accommodates the increasing trends of citywide and within neighborhoods inequality over the last 35 years with two distinct and opposite phases of between neighborhoods inequality, which appears first increasing and then balanced by the "Great Inversion". As expected, spatial inequality (either within or between individual neighborhoods) displays small positive association with citywide inequality, although evidence is less conclusive in 2000 and in more recent ACS waves. Furthermore, it is not associated with the average household income in the city.[23] This confirms that the spatial aspects of inequality captured by the GINI indices, albeit stable across the main metropolitan areas in the U.S., cannot be anticipated from the sole knowledge of citywide income distribution features. The next paragraph shows that similar levels of city wide inequality can lead to very different patterns of spatial inequality.

[22]These results help to disentangle the effects of changes in inequality from those in segregation. Reardon and Bischoff (2011a) document increasing income segregation over the whole period under exam. However the trends of segregation for the groups of rich and poor families they find are consistent with our findings (see Figure 3, p.16).

[23]See the supplemental Appendix for an in-depth discussion of these correlations.

3.4 A tale of four cities

There is slight evidence of correlation in the patterns of spatial inequality captured by the $GINI_W$ and the $GINI_B$ indices across the 50 largest U.S. cities. This confirms that the two indices capture different features of cross sectional spatial inequality. The 50 metro areas can hence be classified according to the levels of within and between spatial inequality. Figure 6 displays a taxonomy of these cities based on four categories generated by low/high levels of GINI indices in year 2000 (which serves as benchmark). Moving along the vertical dimension, high levels of the $GINI_B$ index indicate a "divided city", with citywide inequality and spatial sorting patterns that separate poor from rich people across the urban space.[24] Along the horizontal dimension, high levels of the $GINI_W$ index instead occur in presence of "mixed neighborhoods", where both relatively poor and rich people live side by side. Combining these two dimensions, we define four models for the American cities. The first model, illustrated by the example of Detroit, MI, is that of a "polarized city" where high values of the $GINI_B$ index are paired with low levels of the $GINI_W$ index and rich and poor people are divided both in income and spatial dimensions.[25]

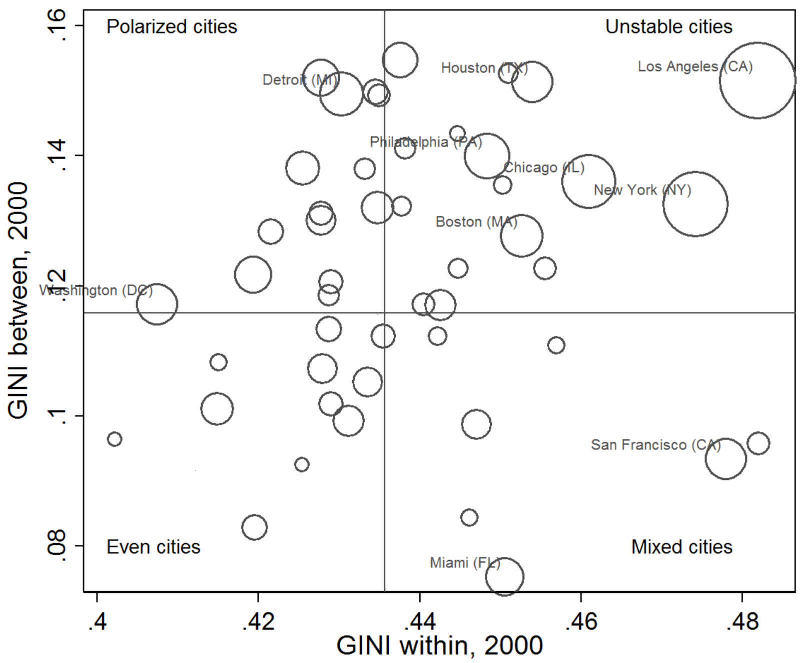
Los Angeles, CA, New York City, NY and Chicago, IL can instead be classified as "unstable cities", displaying high values of both GINI indices. In this case, a high variability of average incomes across individual neighborhoods is accompanied by high income heterogeneity also within neighborhoods, suggesting that dimensions other than income (such as ethnicity) might play a significant role in the sorting process (Boal 2010, Scholar 2006, Deaton and Lubotsky 2003) amplifying the effects of income inequality.

Among the largest cities, San Francisco, CA and Miami, FL fall into the third category of "mixed cities", where high values of the $GINI_W$ index are paired with low levels of the

[24] The image of a "divided city" provided in the recent Habitat (2016) report (chapter 4) and discussed in van Kempen (2007), evokes the implicit social tensions in the urban fabric arising because of strong differences in incomes across neighborhoods.

[25] Duclos, Esteban and Ray (2004) describe polarization through the concept of alienation between groups, here captured by the size of the individual neighborhood in relation to a relevant attribute, such as income. Alienation is stronger when groups are more homogeneous and cohesive (i.e., the lowest is inequality within the individual neighborhood) and more diverse (i.e., there is a high degree of inequality between neighborhoods).

Figure 6: Taxonomy of major U.S. metro areas, census 2000



Note: Authors analysis of 2000 U.S. census data. Spatial inequality at the city level is obtained by averaging the GINI indices values over the distance spectrum with uniform weighting across distance levels. The maximum distance is set to 20 miles. Metro areas are grouped according to the GINI indices levels. High/low GINI values are computed with respect to the a polynomial fitting of $GINI_W$ and $GINI_B$ values across 50 largest U.S. metro areas.

$GINI_B$ index and give the image of cities with mixed neighborhoods mirroring citywide inequality evenly spread across the urban space.

The mixed city model is a recurrent typology in the urban planning literature (Sarkissian 1976), often associated with gentrification processes (Lees 2008) and seen as a potential stimulus for socio-economic opportunities for the residents (Musterd and Andersson 2005, Manley, van Ham and Doherty 2012). Eventually, none of the 10 largest U.S. cities fits in the last category of "even city", where low levels of the $GINI_W$ and $GINI_B$ indices mean that inequality within individual neighborhoods is low and neighborhoods resemble each other in terms of income composition (for a broader discussion of the *Just City*, see Fainstein 2010).

4 The welfare effects of neighborhood inequality

Spatial inequality affects urban social welfare in non-trivial ways: While income inequality per se might be seen as welfare-reducing, spatial equilibrium arguments suggest that income sorting is driven by individual preferences and resources. It is then difficult to claim the desirability of a larger income mix within the neighborhood in American cities without disentangling the implications of sorting from those that can be solely attributed to an exogenous change in spatial inequality.

In this section, we investigate the effects of spatial inequality on two dimensions of individual well-being that can be considered good proxies for urban social welfare.

4.1 Implications of spatial inequality within the neighborhood

The first welfare indicator we focus on is informative of the intergenerational mobility associated with the place of residence. Chetty et al. (2014) have documented substantial heterogeneity in economic intergenerational mobility (i.e., the probability that a children born in a family from the bottom income quartile make it to the top income quartile) across American Commuting Zones. Chetty and Hendren (2016) exploit quasi-experimental approximations to identify and estimate the causal effect of the neighborhood of residence experienced during youth on the percent rank occupied in the national income distribution at age 26,[26] a measure we refer to as the *intergenerational mobility gain*. They estimate these effects for children raised in poor families (at the bottom quartile of the parental national income distribution), providing evidence of the causal effect of the neighborhood of residence on future economic opportunities. Identification relies on children that moved across metro areas during youth, implying that intergenerational mobility gains vary substantially across American cities.

[26] Their identification strategy aims at disentangling the causal effect of neighborhood of residence during childhood from implications related to sorting of people with different income prospects across Commuting Zones. To do so, they focus on people whose parents moved across Commuting Zones during their childhood, the timing of the move being an exogenous treatment to the children. They use administrative data to measure mobility prospects by the fraction of the difference in earnings of children living in the Commuting Zone of destination (relative to the earning of children who did not move from the Commuting Zone of departure) that a child would attain by moving in early age during childhood.

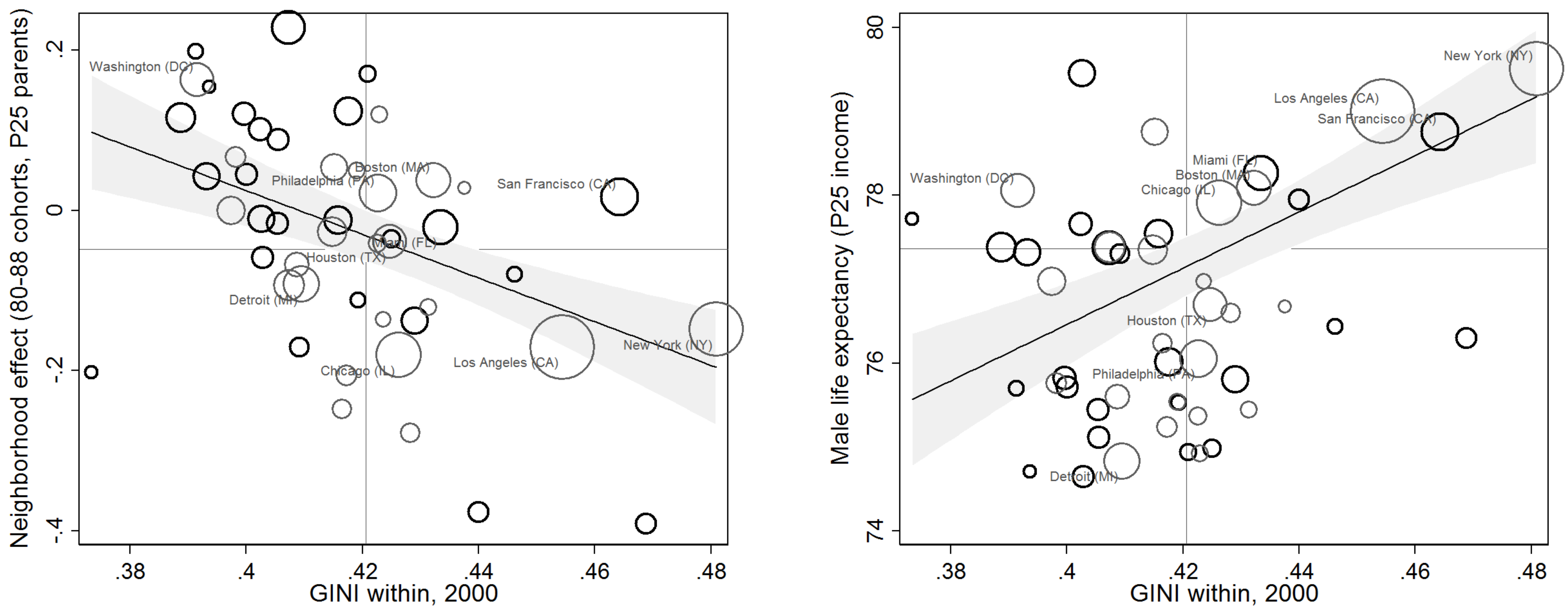
Different mechanisms can explain the correlation between the characteristics of the neighborhood experienced during childhood and the long-term intergenerational mobility gain in adulthood that can be assigned to that neighborhood. One mechanism has to do with social interactions among neighbors. Other mechanisms leverage on environmental and institutional factors (see for instance Leventhal and Brooks-Gunn (2000) and Ch. 12 in Shonkoff and Phillips (2000)). The extent of the effects of these mechanisms depends on the social composition at the neighborhood level, rather than on the characteristics of the city, such as overall inequality. We investigate the extent at which inequality within the neighborhood experienced during youth (approximated by the $GINI_W$ index for the *parental* income distribution) is associated with intergenerational mobility gains of the *children*. The identification strategy suggested by Chetty and Hendren (2016) develops on evidence that potential for neighborhood effects vanishes after children reach their late teens. It is then reasonable to associate intergenerational mobility gains estimates at the city level for children aged 26 in 2006-2014 to the within-neighborhood spatial inequality of parental income measured during their teens. This is well approximated by the $GINI_W$ index of gross household equivalent income in 2000.[27]

Figure 7 gives a graphical account of the association between income inequality within individual neighborhoods of small size (less than 2 miles) and the long-term implications of the neighborhood of residence across the 50 largest MSA in the U.S. Panel (a) displays empirical correlations between neighborhood effects expressed by intergenerational mobility gains estimated in Chetty and Hendren (2016) and the $GINI_W$ index in 2000, based on the sample of cities included in this study. We find significant evidence that causal neighborhood effects on children mobility prospects are negatively associated with the $GINI_W$ index in 2000 when the background notion of individual neighborhood is restrictive enough.[28] The negative association inferred from the figure is suggestive about

[27]Causal neighborhood effects in Chetty and Hendren (2016) are estimated by the percentage gain (or loss) in ranks (on the national income distribution) at age 26 attributed to spending one more additional year during childhood in a given Commuting Zone. These estimates refer to children born 1980-88 whose parents moved to another Commuting Zone in 1996-2012, i.e., when the children was nine or older. Spatial income inequality in 2000 is used to represent the average composition of a neighborhood at the moment of the move, in line with the underlying identification strategy.

[28]Neighborhood effects on children of poor families are also negatively associated with the degree of inequality between parental individual neighborhoods. This correlation might capture the implications of

Figure 7: Spatial inequality within the neighborhood and lifelong individual outcomes across U.S. cities.



(a) Neighborhood effects

(b) Life expectancy of the poor

Note: Authors processing of 2000 U.S. Census for 50 largest U.S. Metropolitan Statistical Areas in 2014. Spatial inequality computed at distance range of two miles. Causal neighborhood effects measure the gain or loss in income at age 26 from spending one more year of childhood in a given Commuting Zone for people whose parents were in the bottom quartile of the national income distribution. Data are as in Chetty and Hendren (2016), variable *causal_p25_czkr26*. Life expectancy is the point estimate of life expectancy in years calculated at age 40 for men at the bottom quartile of household income distribution. Data are as in Chetty, Stepner, Abraham, Lin, Scuderi, Turner, Bergeron and Cutler (2016), variable *le_raceadj_q1_M*. All data are freely accessible on the web from the authors webpages (extracted from *http://www.equality-of-opportunity.org/data/* on October 21, 2016). Causal neighborhood effects and life expectancy estimates are on the Commuting Zone scale (generally larger than MSA concepts of cities used here). Commuting Zone estimates for Norfolk, VA, are not available. The horizontal gray lines correspond to weighted averages of causal neighborhood effects and life expectancy estimates. The vertical gray lines correspond to average levels of $GINI_W$ in 2000, while black (resp., gray) circles refer to cities with $GINI_B$ below (resp., above) the sample average for 2000 (see reading note Figure 5). The shaded area indicated the 95% confidence bounds of regression predictions.

the existence of a Great Gatsby curve (Corak 2013) at the individual neighborhood level: cities where low-income parents experience on average less income mix among their close neighbors are also the cities where their children experienced larger upward income mobility gains from the place they were exposed to in young age.

This view can be contrasted with estimate of health achievements of long-term poor residents. Using administrative data on incomes and mortality rates representative for the U.S. population for the period 2001-2014, Chetty, Stepner, Abraham, Lin, Scuderi, Turner, Bergeron and Cutler (2016) have recovered patterns of life expectancy of high and low income people across U.S. Commuting Zones. They show that while life expectancy does not significantly vary across American Commuting Zones for high income individuals, geography is a strong predictor of longevity for the poor residents. We retain *life expectancy (for the population of poor males aged 40)* as the second welfare indicator of interest.

Chetty, Stepner, Abraham, Lin, Scuderi, Turner, Bergeron and Cutler (2016) find that life expectancy estimates are positively associated with differences in healthy lifestyle, education and affluence across U.S. Commuting Zones. Based on this evidence, it can be conjectured that low income people benefit from the presence of more educated and affluent neighbors, who might serve as role models for a healthy lifestyle and consumption (Manley et al. 2012). Panel (b) of Figure 7 displays the correlation between life expectancy estimates and the $GINI_W$ index values in the selected sample of cities. The values of $GINI_W$ in year 2000 are used to measure inequality in the neighborhood experienced by the population for which more reliable longevity estimates are available. Based on the restricted sample of the 50 largest metro areas in the U.S., we find evidence of a positive association of spatial inequality within the neighborhood and longevity of poor, long-term residents.

Altogether, Figure 7 draws contrasting pictures: On the one hand, the income mix within the neighborhood seems desirable from the perspective of long-term residents,

negative externalities of neighbors' income on child performance. Poor parents that move to cities with a high values of the $GINI_B$ index are more likely to be located in poor areas of the city, with negative external effects due to the economic status of the local community.

for whom life expectancy represents an important dimension of well-being. On the other hand, however, the income mix threats economic opportunities of children exposed to it in young age, by substituting to alternative transmission mechanisms that are neighborhood-specific. This evidence rests, however, on spurious correlations between spatial inequality and the outcomes of interest. In fact, spatial inequality within the neighborhood might reflect the location patterns of rich and poor households across and within American metro areas, who might also sort on the basis of expectations on life expectancy and of income mobility perspectives of their children, thereby inducing a simultaneity bias in our results. In the rest of the section, we implement different strategies to tackle these issues.

4.2 Testing the effect of spatial inequality on intergenerational mobility gains

To quantify the effect of spatial inequality on intergenerational mobility gains we resort to the full sample of 450 Commuting Zones in Chetty and Hendren (2016). We have assigned to each Commuting Zone the corresponding level of spatial inequality at the MSA level based on 2000 U.S. Census data.[29] The $GINI_W$ index has been normalized to have standard deviation equal to one across Commuting Zone in the full sample. The regression coefficients in Table 2 can hence be interpreted as the effects of one standard deviation increase in the $GINI_W$ (approximatively 0.025 points) on the intergenerational mobility gain estimates by Chetty and Hendren (2016). These regressions are based on the full cross-section of American Commuting Zones weighted by population size in year 2000, and can be interpreted under the (somehow stringent) hypothesis of homogeneity of the effect across American metro areas.

As expected, the raw effect (model (1) in the table) is negative and significant in the general model. It reflects in size and sign the slope of the regression line in Figure 7. We estimate that across American cities, a unitary standard deviation increase in the $GINI_W$ index is associated with a significant decrease of 0.039 percent points of intergenerational

[29] We have used local labor market geography crosswalk files accessible from D. Dorn webpage (see Autor and Dorn 2013). We first match MSA-level estimates of spatial inequality to underlying counties and then we have matched counties to Commuting Zones based on the cross walk files.

	OLS					IV		
						SI1990	FMW	RMW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$GINI_W$ 2000	-0.039**	-0.036**	-0.029**	-0.045**	-0.032	-0.004	-0.194$^+$	-0.240$^+$
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.13)	(0.16)
Controls:								
A) Demographics	-	x	x	x	x	x	x	x
B) Local finance	-	-	x	x	x	x	x	x
C) Education	-	-	-	x	x	x	x	x
D) Sorting	-	-	-	-	x	x	x	x
E) Regional fe	-	-	-	-	-	-	x	x
R-squared	0.033	0.128	0.146	0.224	0.342	0.347	0.235	0.150
MSA	450	450	450	319	263	262	245	245
First stage	-	-	-	-	-	32.903**	3.416**	-1.522**
						(1.74)	(1.42)	(0.68)

Table 2: Spatial inequality within the neighborhood and intergenerational mobility gains. *Note:* Based on authors' analysis of data from 1990 and 2000 U.S. Census, CCD, PSS, CPS March Supplement and Chetty and Hendren (2016). The dependent variable is defined as in Figure 7. $GINI_W$ in 2000 normalized by the full-sample standard deviation. Individual neighborhoods based on less than two miles range. Significance levels: $^+ = 15\%$, $^* = 10\%$ and $^{**} = 5\%$.

mobility gains.

The estimated effect in model (1) is potentially biased, because differences in income inequalities across U.S. cities can mask implications of agglomeration, racial composition and segregation in the city.[30] We address this issue in model (2), where we control for demographic factors such as population density, racial composition and racial segregation (measured by the dissimilarity index) at the Commuting Zone level. We find no effect on the sign, size and significance of the spatial inequality effect. The estimates are stable even after controlling additionally for differences across cities in terms of public finance (including information on average tax rate and EITC exposure in the city, as well as per capital fiscal revenue and expenditure) and local spending (model (3)), as well as for the quality of public education services provided in the city (such as the average student/teacher ratio and per capita budget of public schools in 2000), as highlighted by model (4).[31]

[30]Deaton and Lubotsky (2003), for instance, highlight that the positive association between citywide income inequality and mortality found in the literature is indeed confounded by the effect of racial segregation.

[31]In Section B.3 of the supplemental appendix we provide an in-depth description of data sources and matching methods. Demographic (A) and schooling (C) estimates at the Commuting Zone level are from the 2000 Census, the Common Core of Data (CCD) 2000/2001 waves and from the Private School Survey

Demographics, local finance and education controls rule out mechanisms that reflect differences in educational resources available to children and contribute explaining sorting of these children's families across Commuting Zones. Sorting within the same Commuting Zone is also an important driver of spatial inequality which may affect mobility prospect of children. For instance, two cities with similar average quality of public educational services (captured for instance by the school-specific student/teacher ratio or school finance) can substantially differ in terms of distribution of schools quality across catchment areas within the same city. Sorting incentives are stronger in places with public schools of heterogeneous quality, and effects on intergenerational mobility hampered. We use the Common Core of Data and the Private School Survey to assess the dispersion of quality of private and public schools in each metro area, and we use this information as a further control in the regression. Other aspects of sorting within the metro area are instead captured by the feature of the income distribution within the city that are not captured by spatial inequality measures, but that are tightly correlated to the $GINI_W$ index and with the outcome variable. We control for average income, poverty rate, citywide inequality (Gini index) and for income segregation. The distribution of local amenities is another potential source of sorting in the city. We control for their joint implications by using median rent values.[32] We also include controls for the presence and intensity of crime events in the city, an important measure of quality of life conditions in the most distressed areas of the city.

Model (5) is enriched by the list of controls listed above. The estimated sign and size of the effect of spatial inequality on intergenerational mobility gains are consistent with the previous results. Nevertheless, the effect turns out to be statistically non-significant at conventional levels. The drop in significance may be the result of attenuation bias resulting from simultaneity in the sorting behavior of parents on the basis of the expected mobility gains of the children. Identification of the correct effect can be achieved through a shock on spatial inequality that is orthogonal to the unobserved components of sorting affecting

(PSS) 2003/2004 waves. Local public finance (C) estimates are instead from the online data appendix of Chetty and Hendren (2016).

[32] Hedonic pricing models claim that, after controlling for differences in income and purchasing power across cities, rents can be used to value amenities offered locally.

intergenerational mobility gains, but that cannot be accounted for by the controls A to D in model (5). We exploit an instrumental variables strategy to reproduce the effects of such exogenous shock.

4.3 IV estimates

The first instrument we consider is a measure of the $GINI_W$ taken from the 1990 Census. The rationale behind this choice is that historical patterns of inequality within the neighborhood are strong predictors of actual inequality patterns, but might be orthogonal to idiosyncratic unobserved factors (such as parental preferences) that are correlated with sources of intergenerational mobility gains for the generation of the children. The first stage coefficient of model (6) in Table 2 highlights the relevance of the instrument (SI1990) for the $GINI_W$ in 2000. Nevertheless, the second stage estimate is modest and strongly non-significant.[33]

The second instrument we consider is intended to introduce a shock on spatial inequality that is exogenous to sorting patterns both across and within cities. Following Bartik (1991) and Blanchard and Katz (1992), we adopt a shift-share instrument for spatial inequality that isolates shifts in local labor share coverage of minimum wage policies that come from national shocks on growth rates of industry-specific employment.[34] Minimum wage regulation affects the bottom of income distribution and the intensity varies with coverage across industries (which correlates with earnings inequality). Changes in minimum wage regulations and industry coverage hence produce strong implications for citywide and local income inequality. The focus here is on federal and regional decennial changes in industry growth rates, and identification leverage on the fact that these changes are exogenous to unobservable confounders correlated with spatial inequality in 2000 and with the mobility gains accruing to children facing these local inequalities during childhood. Federal and regional changes are interacted with historic minimum wage coverage

[33]The result may be driven by the fact that both the endogenous regressor and the instrument suffer from measurement bias (mostly due to the way income data are reported in the 1990 and 2000 Census), implying that the instrumentation strategy simply magnifies the attenuation bias.

[34]See Baum-Snow and Ferreira (2015) for a review of the literature on shift-share instruments applied to local labor supply models.

by industry (as of 1980) in the city, under the assumption that coverage is pre-determined to sorting motives for the people observed in 2000 (conditional on the observables in model (5)).

The incidence of minimum wage regulation across industries within the same Commuting Zone is captured by the percent share of workers in each Commuting Zone i that are employed in industry j (defined at the two-digits industry level) and that receive an hourly wage below the federal minimum wage in 1980.[35] Let denote this share MW_{ij}. The regional[36] changes in industry-specific labor demand from 1980 to 2000, denoted $1+g_{j80/00}$, is used as an exogenous regional shifter of industry-level minimum wage coverage. The coefficient $g_{j80/00}$ is negative for industries where relative employment is expanding over 1980, and positive otherwise, this capturing the joint effect of changes labor supply skills and equilibrium wage adjustments.[37] Minimum wage coverage at the Commuting Zone level in year 2000 is obtained by averaging across industries prior information on minimum wage coverage (likely exogenous to mechanisms explaining children mobility gains from their place of residence) interacted with decennial regional shocks in employment, thus giving $MW_i^{2000} = 1 - \sum_j MW_{ij} \cdot (1 + g_{j80/00})$.

We use the March Supplement of the Current Population Survey (1980 and 2000) to estimate minimum wage coverage at the industry level. CPS guarantees representativeness up to the State level geography. State-level information is then used to predict Commuting Zone-level instruments. Following Kerr (2014), we also consider interacting this instrument with the growth rate of minimum wages, to reflect changes in regulation. We adopt two alternative specifications of the instrument. In the first specification, changes

[35] We use federal minimum wage to exclude correlations in minimum wage State regulation with unobservable characteristics of the Commuting Zone which may endogenously affect sorting behavior, hence invalidate the instrument.

[36] We consider U.S. regions as defined in the CPS: Northeast, Midwest, West and South Regions.

[37] The interpretation of the coefficient is grounded on labor market equilibrium arguments. An industry paying low skilled workers less than the minimum wage in 1980 which expands labor demand over year 2000, is forced to increase wages to attract labor supply. Altogether with technological progress (implying larger demand for skilled workers) and skills shifts in the American labor force (implying higher reservation wages), the expansion in industry-level employment should lead to increasing wages and minimum wage coverage. Under these conditions, labor demand shifters that increase industry-specific employment are expected to have a negative effect (which is captured by $g_{j80/00} < 0$) on the predicted number of employees whit hourly pays below minimum wage.

in federal minimum wage over 1980 to 2000 (which increased from \$3.10 to \$5.15) are interacted with the predicted minimum wage coverage, giving: $FMW_i = ln(3.10/5.15) \cdot MW_i^{2000}$. The second specification further exploits changes in minimum wage regulations across states and time, as captured by variables smw_{i1980} and smw_{i2000}. A regional minimum wage instrument is produced that combines geographical and time variation in minimum wage regulation with the predicted minimum wage coverage: $RMW_i = ln(smw_{i1980}/smw_{i2000}) \cdot MW_i^{2000}$.[38]

Columns (7) and (8) of Table 2 report the effect of $GINI_W$ in 2000 on mobility gains outcome after instrumenting spatial inequality with the FMW and the RMW instruments (in the regressions, we also control for four regional dummies to account for regional specificities in industry structure). In both cases, estimated effects are negative, and marginally significant (with p-values smaller than 0.12), but fivefold larger in magnitude than previous estimates in models (1)-(5). The first stage coefficient of the FMW instrument in model (7) is positive, implying that a larger predicted minimum wage coverage increases local spatial inequality.[39] These estimates are preferred to model (8), where changes in minimum wage regulation at State level might be seen themselves related to decennial changes in inequality in major cities where production activities are located (hence explaining the negative first stage coefficient of RMW).

We find conclusive evidence that an exogenous standard deviation increase in spatial inequality within a narrow individual neighborhood yields, on average, a drop of 0.194 percentage points in the intergenerational mobility gains (measured in percentage ranks) of American children raised in poor families, which can be assigned to their place of residence during youth. We provide robustness checks in the Appendix. There we show that the effect is stable even when the notion of individual neighborhood is relaxed to include all neighbors within a range of six miles. Furthermore, we provide evidence that spatial inequality does not have a significant effect on intergenerational mobility itself,

[38] An historical account of basic minimum wages in non-farm employment under 1980 and 2000 State Law are available on the United States Department of Labor website: *https://www.dol.gov/whd/state/stateMinWageHis.htm.*

[39] The positive coefficient likely follows from greater dispersion in the wage distribution in the presence of income growth at the bottom of the distribution.

as measured by percentage rank mobility of long-term residents in a given metro area. Our conjecture is that intergenerational mobility gains estimates isolate components of intergenerational transmission of income that are tightly related to characteristics of the neighborhood experienced during youth and are not confounded by the implications of innate ability transmission and parental investment strategies, which are more family-specific. The regressions in Table 2 pick up local mechanisms better than other features of the citywide income distribution (including income segregation).

Social interaction mechanisms, such as social contagion or collective socialization among peers, substantiate the causality claim stated above. Contagion has positive implications for the future economic prospects of children exposed to an advantageous context, the effect being stronger if the local social structure is more cohesive. Income inequality within the neighborhood, measured in the place of destination at the moment when treated children move from one metro area to another, might also capture aspects of neighborhood cohesiveness that are relevant for children born in poor families. In Census Zones characterized by low $GINI_W$ values, children of poor parents who move may end up in neighborhoods that are on average more cohesive, hence expect stronger positive neighborhood effects. The effect, instead, attenuates as the expected degree of inequality within the neighborhood rises.

Evidence from Table 2 allows to conclude that the income mix in the neighborhood of the average American metro area has potentially negative effects on the mobility gains that the metro area might grant to its young resident. One can consider the negative effects of local spatial inequality as detrimental for welfare if parents have motives for sorting across and within metro areas based on future mobility gains of the children, which turn out to be significantly reduced by increasing the income mix at the neighborhood level.

4.4 Testing the effect of spatial inequality on life expectancy

Table 3 reports the effects of a standard deviation increase in $GINI_W$ in 2000 on the life expectancy estimates for poor long-term male residents at age 40 (the extended table is reported in the Appendix). Differently from the previous case, we do not find significant

	OLS							IV FMW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$GINI_W$ 2000	0.211*	0.092*	0.124**	0.192**	0.098**	-0.035	-0.022	-0.139
	(0.11)	(0.05)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(1.01)
Controls:								
F) Health	-	x	x	x	x	x	x	x
A) Demographics	-	-	x	x	x	x	x	x
B) Local finance	-	-	x	x	x	x	x	x
C) Education	-	-	-	x	-	-	x	x
D) Sorting								
- Schooling	-	-	-	-	x	-	x	x
- Other	-	-	-	-	-	x	x	x
E) Regional fe	-	-	-	-	-	-	-	x
R-squared	0.008	0.815	0.942	0.913	0.945	0.964	0.956	0.956
MSA	449	447	447	319	406	417	264	264
First stage	-	-	-	-	-	-	-	1.231
								(1.54)

Table 3: Spatial inequality within the neighborhood and life expectancy of long-term residents

Note: Based on authors' analysis of data from U.S. Census, CCD, PSS, CPS March Supplement and Chetty, Stepner, Abraham, Lin, Scuderi, Turner, Bergeron and Cutler (2016). The dependent variable is defined as in Figure 7. $GINI_W$ in 2000 normalized by the full-sample standard deviation. Individual neighborhoods based on less than six miles range. Significance levels: $^{+}$ = 15%, * = 10% and ** = 5%.

effects of spatial inequality on the health outcome of interest when adopting a restrictive notion of individual neighborhood (less than two miles). For this reason, we exclusively focus on the case of individual neighborhoods smaller than six miles in size. The estimated effect based on the full sample of American metro areas is positive and strongly significant (model (1)), substantiating the positive correlation visualized in Figure 7.

The size of the effect may mask the implications of exposure to diversity of healthy behaviors of residents in the neighborhoods, that is found to be positively associated with local income inequality (see Chetty, Stepner, Abraham, Lin, Scuderi, Turner, Bergeron and Cutler 2016). In model (2) we estimate the same effect while controlling for indicators of attitude of the residents towards healthy lifestyles (controls F) such as the percentage of smokers, of obese and of people practicing exercise in the metro area. We consider estimates of healthy lifestyles for people in the bottom and top quartile of the income distribution altogether. In model (2), we find that the sign and significance of the $GINI_W$ effect on life expectancy are unaltered. We draw a similar conclusion even after controlling for explanatory variables related to sorting across Commuting Zones, such as demographics, the local finance and the public education system coverage and quality offered at the Commuting Zone level (model (4)).

The effect of interest turns out to be non-robust to sorting. Models (6) and (7) highlight that the effect of $GINI_W$ on life expectancy becomes statistically insignificant after controlling for observable covariates that are related to sorting within the city, but not necessarily connected to the distribution of public and private educational quality across neighborhoods of the city (accordingly to the way we break down the list of controls D in the table). Evidence on lack of an effect of spatial inequality on life expectancy is robust even after controlling for simultaneity or measurement error biases through the FMW instrument (model (8)). We conclude that the features of the income distribution (especially poverty and inequality) as well as differences across neighborhoods in the distribution of income (as captured by income segregation measures) are more tightly associated with mechanisms explaining life expectancy than with spatial inequality itself.

5 Concluding remarks

Information about the income distribution in the neighborhood surrounding each individual is exploited to derive new spatial inequality measures connected to the Gini index. We establish new stylized facts about spatial inequality in the 50 largest U.S. cities from 1980 to 2014: i) inequality within individual neighborhoods is high also for individual neighborhoods of small size; ii) inequality between individual neighborhoods is also high and decreases smoothly with the size of the individual neighborhood; iii) inequality between individual neighborhoods has risen over the last four decades reflecting the trends of the "Great Inversion" (Ehrenhalt 2012); iv) spatial inequality is poorly associated with citywide average income and inequality; vi) American cities can be classified into four distinct groups, on the basis of the values of the within and between GINI indices; v) spatial inequality within individual neighborhoods matters for upward mobility prospects of young people raised in poor families and for life expectancy of low-income residents in America's cities.

Results i)-iii) highlight the increasing importance of income sorting. Despite increasing citywide inequality registered throughout the US largest metro area in recent decades, income sorting seems not to have mitigated inequality at the local scale. Decomposing the changes in inequality by skill and labor attachment type might shed light on the implications for the neighborhood income distribution of households sorting along those dimensions that are more relevant for explaining differences in inequality across cities (Baum-Snow and Pavan 2013). Result iv) suggests that the income mix among neighbors is stronger in cities of larger size, which are all clustered in the "Divided City" typology. Result v) suggests that the desirability of more spatial inequality within the neighborhood is conditional on the timing when this inequality is experienced. The income mix in the neighborhood is beneficial to low-income, long-term adult residents, although this effect masks consequences of sorting behavior. However, more income mix in the neighborhood is significantly associated with smaller and even negative upward mobility gains experienced by children raised in disadvantaged families. Along these lines, policies that aim at improving the chances of success of poor American children should prove more effective by exploiting income targeting to move poor households with young children into cohesive and wealthy neighborhoods, rather than promoting income-mixed local communities. This message, based on cross-metro areas evidence, aligns with findings from randomization studies such as MTO and provides a basis for their generalization.

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Supplemental Appendix

A Standard errors and confidence bounds for spatial inequality measures

A.1 Setting

Let $\mathcal{S}$ denote a random field. The spatial process $\{Y_s : s = 1, \ldots, n\}$ with $s \in \mathcal{S}$ is defined on the random field and is jointly distributed as $F_{\mathcal{S}}$. Suppose data come equally spaced on a grid, so that for any two points $s, v \in \mathcal{S}$ such that $||v - s|| = h$ we write $v = s + h$. The process distributed as $F_{\mathcal{S}}$ is said to display *intrinsic (second-order) stationarity* if $E[Y_s] = \mu$, $Var[Y_s] = \sigma^2$ and $Cov[Y_s, Y_v] = c(h)$ when the covariance function is isotropic and $v = s + h$. Under these circumstances, let $Var[Y_{s+h} - Y_s] = E[(Y_{s+h} - Y_s)^2] = 2\sigma^2 - 2c(h) = 2\gamma(h)$ denote the variogram of the process at distance lag h.

Noticing that $E[Y_{s+h} \cdot Y_s] = \sigma^2 - \gamma(h) + \mu^2$, the covariance between differences in random variables can be written as $Cov[(Y_{s+h_1} - Y_s), (Y_{v+h_2} - Y_v)] = \gamma(s - v + h_1) + \gamma(s - v - h_2) - \gamma(s - v) - \gamma(s - v + h_1 - h_2)$ as in Cressie and Hawkins (1980). Let first assume that the spatial data occur on a transect. Denote $s - v = h$ where h indicates that the random variables are located within a distance cutoff of h units. It follows that $Cov[(Y_{s+h_1} - Y_s), (Y_{v+h_2} - Y_v)] = \gamma(|h + \min\{h_1, h_2\}|) + \gamma(|h - \max\{h_1, h_2\}|) - \gamma(|h|) - \gamma(|h - |h_1 - h_2||)$, which yields the formula above when $h_1 > h_2$. We adopt the convention that $\gamma(-h) = \gamma(h)$ in what follows.

We now introduce one additional distributional assumption: Y_s is gaussian with mean μ and variance σ^2. The random variable $(Y_{s+h} - Y_s)$ is also gaussian with variance $2\gamma(h)$, which implies $|Y_{s+h} - Y_s|$ is *folded-normal* distributed (Leone, Nelson and Nottingham 1961) and its first and second moment depend exclusively on the variogram, having expectation $E[|Y_{s+h} - Y_s|] = \sqrt{2/\pi Var[Y_{s+h} - Y_s]} = 2\sqrt{\gamma(h)/\pi}$ and variance $Var[|Y_{s+h} - Y_s|] = (1 - 2/\pi)2\gamma(h)$.

A.2 GINI indices and the variogram

Under the assumptions above, the GINI indices of spatial inequality in the population can be written as explicit functions of the variogram. We maintain the assumption that the spatial random process is defined on a transect, and occurs at equally spaced lags. For given d, we can thus partition the distance spectrum $[0, d]$ into B_d intervals of fixed size d/B_d. Each interval is denoted by the index b with $b = 1, \ldots, B_d$. We also denote with d_{bi} the set of locations at interval b (and thus distant $b \cdot d/B_d$) within the range d from location s_i. The cardinality of this set is $n_{d_{bi}} \leq n_{d_i} \leq n$. Under all the prevous assumptions, the $GINI_W$ index rewrites

$$\begin{aligned}
GINI_W(F_{\mathcal{S}}, d) &= \sum_i \sum_{j \in d_i} \frac{1}{2n\, n_{d_i}} \frac{E[|Y_{s_j} - Y_{s_i}|]}{\mu} \\
&= \sum_i \sum_{j \in d_i} \frac{1}{2n\, n_{d_i}} \frac{\sqrt{4\gamma(||s_j - s_i||)/\pi}}{\mu} \\
&= \sum_i \frac{1}{n} \sum_{b=1}^{B_d} \frac{n_{d_{bi}}}{n_{d_i}} \sum_{j \in d_{bi}} \frac{1}{2\, n_{d_{bi}}} \frac{\sqrt{4\gamma(s_i + b - s_i)/\pi}}{\mu} \\
&= \frac{1}{2} \sum_{b=1}^{B_d} \left(\sum_i \frac{n_{d_{bi}}}{n\, n_{d_i}} \right) \frac{\sqrt{4\gamma(b)/\pi}}{\mu}. \qquad (1)
\end{aligned}$$

The $GINI_W$ index is an average of a concave transformation of the (semi)variogram function, weighted by the average density of observed incomes at given distance cutoff b on the transect. This average is then normalized by the average income, to produce a scale-invariant measure of inequality. The index can be also conceptualized as an average of coefficients of variation, where the standard deviation is replaced by a measure of dispersion that accounts for the spatial dependence of the underlying process.

Similarly, also the spatial $GINI_B$ index can be written as a function of the variogram. This can be shown under the assumption that the process Y_s is gaussian, as above, which implies that $\mu_{s_i d} = \frac{1}{n_{di}} \left(Y_{s_i} + \sum_{j \in d_i} Y_{s_j} \right)$ is also gaussian under the intrinsic stationarity assumption, with expectation $E[\mu_{s_i d}] = \mu$ for any i. From this, it follows that the difference in random variables $|\mu_{s_i d} - \mu_{s_\ell d}|$ occurring in two locations s_i and s_ℓ is a folded-normal distributed random variable with expectation $E[|\mu_{s_id} - \mu_{s_\ell d}|] = \sqrt{2/\pi \, Var[\mu_{s_id} - \mu_{s_\ell d}]}$. The variance term can be decomposed as follows:

$$Var[\mu_{s_id} - \mu_{s_\ell d}] \;=\; Var[\mu_{s_id}] + Var[\mu_{s_\ell d}] - 2Cov[\mu_{s_id};\ \mu_{s_\ell d}]. \tag{2}$$

Developing the variance and covariance terms we obtain:

$$\begin{aligned}
Var[\mu_{s_id}] &= Var\left[\frac{1}{n_{di}}\left(Y_{s_i} + \sum_{j\in d_i} Y_{s_j}\right)\right] = \frac{1}{n_{di}^2}\sum_{j\in d_i\cup\{i\}}\ \sum_{k\in d_i\cup\{i\}} E[Y_{s_j}Y_{s_k}] - \mu^2 \\
&= \frac{1}{n_{di}^2}\sum_{j\in d_i\cup\{i\}}\ \sum_{k\in d_i\cup\{i\}} c(||s_j - s_k||) \qquad (3)\\
&= \sum_{b=1}^{B_d}\sum_{j\in d_{bi}}\frac{1}{n_{di}}\sum_{b'=1}^{B_d}\sum_{k\in d_{b'i}}\frac{1}{n_{di}}c(|s_i + b - (s_i + b')|) \qquad (4)\\
&= \sigma^2 - \sum_{b=1}^{B_d}\sum_{b'=1}^{B_d}\frac{n_{d_{bi}}n_{d_{b'i}}}{n_{di}^2}\gamma(b - b'), \qquad (5)
\end{aligned}$$

where (3) follows from the definition of the covariogram, (4) is a consequence of the assumption that the process can be represented on a transect and, for simplicity, it is assumed that the set of location at $b = 1$ is $d_{1i} \cup \{i\}$ with cardinality $n_{d_{bi}}$, while (5) follows from the definition of the variogram. Similarly, the covariance term in (2) can be manipulated to obtain the following:

$$\begin{aligned}
Cov[\mu_{s_id};\ \mu_{s_\ell d}] &= \sum_{j\in d_i}\sum_{k\in d_\ell}\frac{1}{n_{d_i}n_{d_\ell}}E[Y_jY_k] - \mu^2 \\
&= \sigma^2 - \sum_{b=1}^{B_d}\sum_{b'=1}^{B_d}\frac{n_{d_{bi}}n_{d_{b'\ell}}}{n_{d_i}n_{d_\ell}}\gamma(s_i - s_\ell + |b - b'|), \qquad (6)
\end{aligned}$$

where the assumption that the process can be represented on a transect allows to write the variogram as a function of $s_i - s_\ell$. Plugging (5) and (6) into (2), and denoting $i - \ell = m$ to recall that the gap between locations s_i and s_ℓ is m, with m positive integer such that $m \leq B$ with B being the maximal distance between any two locations on the transect, we obtain

$$\begin{aligned}
Var[\mu_{s_i d} - \mu_{s_\ell d}] &= \sum_{b=1}^{B_d}\sum_{b'=1}^{B_d} 2\frac{n_{d_{bi}} n_{d_{b'\ell}}}{n_{d_i} n_{d_\ell}} \gamma(s_i - s_\ell + |b - b'|) - \\
&\quad - \sum_{b=1}^{B_d}\sum_{b'=1}^{B_d} \left(\frac{n_{d_{bi}} n_{d_{b'i}}}{n_{d_i}^2} + \frac{n_{d_{b\ell}} n_{d_{b'\ell}}}{n_{d_\ell}^2} \right) \gamma(b - b') \\
&= \sum_{b=1}^{B_d}\sum_{b'=1}^{B_d} 2\frac{n_{d_{bi}} n_{d_{b'\ i+m}}}{n_{d_i} n_{d_{i+m}}} \gamma(m + |b - b'|) - \\
&\quad - \sum_{b=1}^{B_d}\sum_{b'=1}^{B_d} \left(\frac{n_{d_{bi}} n_{d_{b'i}}}{n_{d_i}^2} + \frac{n_{d_{b\ i+m}} n_{d_{b'\ i+m}}}{n_{d_{i+m}}^2} \right) \gamma(b - b') \\
&= V(\gamma, i, m). \qquad (7)
\end{aligned}$$

Variogram models suggested in the literatures (for a review, see Cressie 1991) guarantee that $V(\gamma, i, m) > 0$. Using (7), we derive an alternative formulation of the $GINI_B$ index:

$$\begin{aligned}
GINI_B(F_{\mathcal{S}}, d) &= \frac{1}{2}\sum_i \sum_{\ell \neq i} \frac{1}{n(n-1)} \frac{E[|\mu_{s_i d} - \mu_{s_\ell d}|]}{\mu} \\
&= \frac{1}{2}\sum_i \frac{1}{n} \sum_{m=1}^{B} \sum_{\ell \in n_{mi}} \frac{1}{(n-1)} \frac{E[|\mu_{s_i d} - \mu_{s_\ell d}|]}{\mu} \\
&= \frac{1}{2}\sum_{m=1}^{B} \frac{\left(\sum_i \frac{1}{n}\frac{n_{mi}}{(n-1)} \sqrt{2V(\gamma, i, m)/\pi}\right)}{\mu}. \qquad (8)
\end{aligned}$$

Under stationarity assumptions we can show that the $GINI_B$ index of spatial inequality can be written as an average of coefficients of variations, each discounted by a weight controlling for the spatial density of income observations.

Formulations of the GINI within and between indices in (1) and (8) clarify the role of spatial dependence (as modeled by the variogram function) on the measurement of spatial inequality. Standard errors and confidence intervals of the GINI indices can be calculated exploiting the variogram properties.

A.3 Standard errors for the $GINI_W$ index

Confidence interval bounds for the $GINI_W$ index are derived under three key assumptions: 1) the underling spatial process is supposed to be stationary; 2) the spatial process occurs on a transect at equally spaced points; 3) the Gaussian law. This allows to build confidence intervals for the empirical $GINI_W$ index estimator of the form $\hat{GINI}_W(\mathbf{y}, d) \pm z_\alpha SE_{W\,d}$, where z_α is the standard normal critical value for confidence level $1-\alpha$ (for instance, 95%) and $SE_{W\,d}$ is the standard error of the $GINI_W$ estimator. For a given empirical income distribution, the confidence interval changes as a function of the distance parameter selected. Hence, the confidence interval estimator can be used to derive confidence bounds for the spatial inequality curve originated from the $GINI_W$ index. Null hypothesis of dominance or equality for the spatial inequality curves can be tested by using confidence bounds, which define the rejection region (alike to statistical tests for strong forms of stochastic dominance relations, as in Bishop, Chakraborti and Thistle 1989, Dardanoni and Forcina 1999).

Asymptotic standard errors (SE in brief) are derived for the weighted $GINI_W$ index. We assume that the random field $\mathcal{S}$ is limited to n locations. We denote these locations for simplicity by i such that $i = 1, \ldots, n$. The spatial process is then a collection of n random variables $\{Y_i : i = 1, \ldots, n\}$ that are spatially correlated. The joint distribution of the process is F. Each location is associated with a weight $w_i \geq 0$ with $w = \sum_i w_i$, which might reflect the underling population density at a given location. These weights are assumed to be non-stochastic. We also assume intrinsic stationarity as before. The first implication is that, asymptotically, the random variable $\mu_{id} = \sum_{j \in d_i} \frac{w_j}{\sum_{j \in d_i} w_j} Y_j$ is equivalent in expectation to $\tilde{\mu} = \sum_i \frac{w_i}{\sum_i w_i} Y_i$, i.e., $E[\tilde{\mu}] = \mu$. The second implication is that the spatial correlation exhibited by F is stationary in d and can be represented through the variogram of F, denoted $2\gamma(d)$.

An asymptotically equivalent version of the weighted $GINI_W$ index of the process distributed as F where individual neighborhood have size d is

$$GINI_W(F, d) = \frac{1}{2\mu} \sum_{i=1}^{n} \sum_{j \in d_i} \frac{w_i w_j}{2\,w\, \sum_{j \in d_i} w_j} |Y_i - Y_j| = \frac{1}{2\mu} \Delta_{W\,d}. \tag{9}$$

The $GINI_W$ index can thus be expressed as a ratio of two random variables. Asymptotic SE for ratios of random variables have been developed in Goodman and Hartley (1958) and Tin (1965). These SE can be equivalently retrieved from the U-statistics estimators pioneered in Hoeffding (1948) and adopted to derive asymptotic SE for the Gini coefficient of inequality under simple and complex random sampling by Xu (2007) and Davidson (2009). We exploit these results to write the asymptotic variance of the $GINI_W$ index in (9) as:

$$\begin{aligned} Var\left[GINI_W(F,d)\right] &= \frac{1}{4n\mu^2}Var[\Delta_{W\,d}] + \frac{(GINI_W(F,d))^2}{n\mu^2}Var[\tilde{\mu}] - \\ &\quad \frac{GINI_W(F,d)}{n\mu^2}Cov[\Delta_{W\,d},\tilde{\mu}] + O(n^{-2}), \end{aligned} \tag{10}$$

where the asymptotic SE is $SE_{W\,d} = \sqrt{Var\left[GINI_W(F,d)\right]}$ at any d.

To link the variance and covariance terms in (10) and the variogram, the additional assumptions reported above are introduced. The first assumption is that the process distributed as F occurs on a transect, as explained before. We use scalars m, b, b' and so on to identify equally spaced points on the transect. Second, we assume that Y_i is Gaussian with expectation μ and variance σ^2, $\forall i$. These assumptions are taken from Cressie and Hawkins (1980). Under these assumptions, the variance of $\tilde{\mu}$ writes

$$\begin{aligned} Var[\tilde{\mu}] &= \sum_i \frac{w_i}{w}\sum_j \frac{w_j}{w}E[Y_iY_j] - \mu^2 \\ &= \sum_i \frac{w_i}{w}\sum_{m=1}^{B}\frac{\sum_{j\in d_{mi}} w_j}{w}\sum_{j\in d_{mi}}\frac{w_j}{\sum_{j\in d_{mi}} w_j}c(||s_i - s_j||) \qquad (11) \\ &= \sum_{m=1}^{B}\left(\sum_i \frac{w_i}{w}\frac{\sum_{j\in d_{mi}} w_j}{w}c(|m|)\right) \qquad (12) \\ &= \sigma^2 - \sum_{m=1}^{B}\omega(m)\gamma(m), \qquad (13) \end{aligned}$$

where (13) is obtained from (12) by renaming the weight scores so that $\sum_{m=1}^{B}\omega(m) = 1$, and by using the definition of the variogram.

The second variance component of (10) can be written as follows:

$$
\begin{aligned}
Var[\Delta_{W\,d}] &= \sum_{i=1}^{n}\sum_{j\in d_i}\frac{w_i w_j}{w\sum_{j\in d_i} w_j}\sum_{\ell=1}^{n}\sum_{k\in d_\ell}\frac{w_\ell w_k}{w\sum_{k\in d_\ell} w_k}E[|Y_i-Y_j||Y_\ell-Y_k|] \\
&\quad -\left(\sum_i \frac{w_i}{w}\sum_{j\in d_i}\frac{w_j}{\sum_{j\in d_i} w_j}E[|Y_j-Y_i|]\right)^2 .
\end{aligned}
$$

The first component of $Var[\Delta_{W\,d}]$ cannot be further simplified, as the absolute value operator enters the expectation term in multiplicative way. Under the Gaussian assumption, the expectation can be nevertheless simulated, since the random vector (Y_j, Y_i, Y_k, Y_ℓ) is normally distributed with expectations (μ,μ,μ,μ) and its variance-covariance matrix $Cov[(Y_j, Y_i, Y_k, Y_\ell)]$ is:

$$
Cov[(Y_j, Y_i, Y_k, Y_\ell)] = \begin{pmatrix}
\sigma^2 & c(||s_j-s_i||) & c(||s_j-s_k||) & c(||s_j-s_\ell||) \\
 & \sigma^2 & c(||s_i-s_k||) & c(||s_i-s_\ell||) \\
 & & \sigma^2 & c(||s_k-s_\ell||) \\
 & & & \sigma^2
\end{pmatrix}.
$$

Data occur on a transect at equally spaced points, where $s_j = s_i + b$ and $s_k = s_\ell + b'$ for the positive integers $b \le B_d$ and $b' \le B_d$. We take the convention that $b' > b$ and we further assume that there is a positive gap m, with $m \le B$ between points s_i and s_ℓ. Using this notation, we can express the variance-covariance matrix as a function of the variogram

$$
Cov[(Y_j, Y_i, Y_k, Y_\ell)] = \begin{pmatrix}
\sigma^2 & \sigma^2-\gamma(b) & \sigma^2-\gamma(m-|b'-b|) & \sigma^2-\gamma(m+\min\{b',b\}) \\
 & \sigma^2 & \sigma^2-\gamma(m-\max\{b',b\}) & \sigma^2-\gamma(m) \\
 & & \sigma^2 & \sigma^2-\gamma(b') \\
 & & & \sigma^2
\end{pmatrix}.
$$

The expectation $E[|Y_i - Y_j||Y_\ell - Y_k|]$ can be simulated from a large number S (say, $S = 10,000$) of independent draws $(y_{1s}, y_{2s}, y_{3s}, y_{4s})$, with $s = 1,\ldots,S$, from the random vector (Y_j, Y_i, Y_k, Y_ℓ). The simulated expectation is a function of the variogram parameters

m, b, b' and d and of σ^2. It is denoted $\theta_W(m, b, b', d, \sigma^2)$ and estimated as follows:

$$\theta_W(m, b, b', d, \sigma^2) = \frac{1}{S} \sum_{s=1}^{S} |y_{2s} - y_{1s}| \cdot |y_{4s} - y_{3s}|.$$

With some algebra, and using the fact that $E[|Y_\ell - Y_i|] = 2\sqrt{\gamma(m)/\pi}$ for locations ℓ and i at distance $m \leq B$ one from each other, it is then possible to write the term $Var[\Delta_{W\,d}]$ as follows:

$$\begin{aligned} Var[\Delta_{W\,d}] &= \sum_{m=1}^{B} \sum_{b=1}^{B_d} \sum_{b'=1}^{B_d} \omega(m, b, b', d) \theta_W(m, b, b', d, \sigma^2) \\ &\quad -4 \left(\sum_{m}^{B_d} \omega(m, d) \sqrt{\gamma(m)/\pi} \right)^2. \end{aligned} \tag{14}$$

In the formula, $\omega(m, b, b', d) = \sum_i \frac{w_i}{w} \sum_{j \in d_{bi}} \frac{w_j}{\sum_{j \in d_i} w_j} \sum_{\ell \in d_{mi}} \frac{w_\ell}{w} \sum_{k \in d_{b'\ell}} \frac{w_k}{\sum_{k \in d_\ell} w_k}$ while $\omega(m, d) = \sum_i \frac{w_i}{w} \sum_{j \in d_{mi}} \frac{w_j}{\sum_{j \in d_i} w_j}$ are calculated as before.

The third component of (10) is the covariance term. It can be written as a function of the variogram. To show this, we take as given that the process is defined on the transect and i and j are separated by b units of spacing while i and ℓ are separated by m unit of spacing, as we rely on the following equivalence:

$$\begin{aligned} E[|Y_j - Y_i| Y_\ell] &= E[|Y_j Y_\ell - Y_i Y_\ell|] = E[Y_j Y_\ell] - E[Y_i Y_\ell] - 2E[\min\{Y_j Y_\ell - Y_i Y_\ell, 0\}] \\ &= c(||s_j - s_\ell||) + \mu^2 - c(||s_i - s_\ell||) - \mu^2 - 2E[\min\{Y_j Y_\ell - Y_i Y_\ell, 0\}] \\ &= \gamma(m) - \gamma(m - b) - 2E[\min\{Y_j Y_\ell - Y_i Y_\ell, 0\}]. \end{aligned} \tag{15}$$

The expectation $E[\min\{Y_j Y_\ell - Y_i Y_\ell, 0\}]$ is non-liner in the underlying random variables. Under the Gaussian hypothesis it can be nevertheless simulated from a large number S (say, $S = 10,000$) of independent draws (y_{1s}, y_{2s}, y_{3s}), with $s = 1, \ldots, S$, from the random vector (Y_j, Y_i, Y_ℓ) which is normally distributed with expectations (μ, μ, μ) and variance-covariance matrix $Cov[(Y_j, Y_i, Y_\ell)]$. As the process occurs on the transect, the variance-covariance matrix writes

$$Cov[(Y_j, Y_i, Y_\ell)] = \begin{pmatrix} \sigma^2 & \sigma^2 - \gamma(b) & \sigma^2 - \gamma(m) \\ & \sigma^2 & \sigma^2 - \gamma(m-b) \\ & & \sigma^2 \end{pmatrix}$$

for given m, b and d. The resulting simulated expectation is denoted $\phi_W(m, b, d, \sigma^2)$ and computed as follows:

$$\phi_W(m, b, d, \sigma^2) = \frac{1}{S}\sum_{s=1}^{S} \min\{y_{2s}y_{3s} - y_{1s}y_{3s}, 0\}.$$

Based on this result, the covariance term in (10) is:

$$\begin{aligned} Cov[\Delta_{W\,d}, \tilde{\mu}] &= \sum_i \frac{w_i}{w} \sum_{j\in d_i} \frac{w_j}{\sum_{j\in d_i} w_j} \sum_\ell \frac{w_\ell}{w} E[|Y_j - Y_i|Y_\ell] \\ &\quad -\mu \sum_i \frac{w_i}{w} \sum_{j\in d_i} \frac{w_j}{\sum_{j\in d_i} w_j} E[|Y_j - Y_i|] \\ &= \sum_{m=1}^{B}\sum_{b=1}^{B_d} \omega(m, b, d)\left[\gamma(m) - \gamma(m-b) - 2\phi_W(m, b, d, \sigma^2)\right] \\ &\quad -2\mu \sum_{m=1}^{B_d} \omega(m, d)\sqrt{\gamma(m)/\pi}. \end{aligned} \tag{16}$$

The weights in (16) coincide respectively with $\omega(m, b, d) = \sum_i \frac{w_i}{w} \sum_{\ell\in d_{mi}} \frac{w_\ell}{w} \sum_{j\in d_{bi}} \frac{w_j}{\sum_{j\in d_i} w_j}$ and $\omega(m, d) = \sum_i \frac{w_i}{w} \sum_{j\in d_{mi}} \frac{w_j}{\sum_{j\in d_i} w_j}$.

A consistent estimator for the SE, denoted $\hat{SE}_{W\,d}$, is obtained by plugging into (10) the empirical counterparts of the variogram and the lag-dependent weights, using the formulas in (13), (14) and (16). These estimators are discussed in Section A.5.

A.4 Standard errors for the $GINI_B$ index

Confidence interval bounds $\hat{GINI}_B(\mathbf{y}, d) \pm z_\alpha SE_{B\,d}$ for the $GINI_B$ index are obtained under the same assumptions outlined in the previous section. We assume that the spatial process $\{Y_s : s \in \mathcal{S}\}$ is limited to n locations. We index these locations for simplicity by

i such that $i = 1, \dots, n$. The spatial process is then a collection of n random variables $\{Y_i : i = 1, \dots, n\}$ which are spatially correlated. The joint distribution of the process is F. Each location is associated with a weight $w_i \geq 0$ with $w = \sum_i w_i$. These weights are assumed to be non-stochastic.

Under stationary assumptions, the neighborhood averages $\mu_{id} = \sum_{j \in d_i} \frac{w_j}{\sum_{j \in d_i} w_j} Y_j$ and $\mu_d = \sum_i \frac{w_i}{w} \mu_{id}$ are equivalent in distribution to $\tilde{\mu}$, and hence $\tilde{\mu}$ can be used to assess $Var[\mu_d]$, as $Var[\mu_d] = Var[\tilde{\mu}]$. These equivalences apply as well to μ_d.

An asymptotically equivalent version of the weighted GINI index for inequality between individual neighborhoods of the process distributed as F where individual neighborhood have size d is:

$$GINI_W(F, d) = \frac{1}{2\mu} \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{w_i w_j}{w^2} |\mu_{id} - \mu_{jd}| = \frac{1}{2\mu} \Delta_{B\,d}. \tag{17}$$

We use results on variance estimators for ratios to derive the SE of (17) as follows:

$$\begin{aligned} Var\left[GINI_B(F, d)\right] \quad = \quad & \frac{1}{4n\mu^2} Var[\Delta_{B\,d}] + \frac{(GINI_B(F, d))^2}{n\mu^2} Var[\tilde{\mu}] - \\ & - \frac{GINI_B(F, d)}{n\mu^2} Cov[\Delta_{B\,d}, \mu_d] + O(n^{-2}), \end{aligned} \tag{18}$$

where the asymptotic SE is $SE_{B\,d} = \sqrt{Var\left[GINI_B(F, d)\right]}$ at any d. The variance and covariance terms in (18) are shown to be related to the variogram. We show that this holds for each of the three elements adding up to (18), under two assumptions. Assume first that the process distributed as F occurs on a transect, as explained before. We use scalars m, b, b' and so on to identify equally spaced points on the transect. Second, assume that Y_i is Gaussian with expectation μ and variance σ^2, $\forall i$.

The variance term $Var[\tilde{\mu}]$ in (18) is given as in (12).

The second variance component in (18) can be written as follows:

$$
\begin{aligned}
Var[\Delta_{B\,d}] \quad = \quad & \sum_i \sum_j \frac{w_i w_j}{w^2} \sum_\ell \sum_k \frac{w_\ell w_k}{w^2} E[|\mu_{id} - \mu_{jd}||\mu_{\ell d} - \mu_{kd}|] \\
& - \left(\sum_i \frac{w_i}{w} \sum_j \frac{w_j}{w} E[|\mu_{jd} - \mu_{id}|] \right)^2 . \qquad (19)
\end{aligned}
$$

The first component of $Var[\Delta_{B\,d}]$ cannot be further simplified as the absolute value operator enters the expectation term in multiplicative way. Under the Gaussian assumption, the expectation can be nevertheless simulated. This can be done since the random vector $(\mu_{jd}, \mu_{id}, \mu_{kd}, \mu_{\ell d})$ is normally distributed with expectations (μ, μ, μ, μ) and variance-covariance matrix $\mathbf{C}$ of size 4×4. The cells in the matrix $\mathbf{C}$ are indexed accordingly to vector $(\mu_{jd}, \mu_{id}, \mu_{kd}, \mu_{\ell d})$, so that element C_{12}, for instance, is used to indicate the covariance between the random variables μ_{jd} and μ_{id}. The sample occurs on a transect. We use scalars b and b' to denote a well defined distance gap between any location indexed by $\{j, i, k, \ell\}$ and any other location that is b or b' units away from it, within a distance range d. We use scalars m to indicate the gap between i and ℓ, so that $\ell = i + m$; we use m' to indicate the gap between i and j, so that $j = i + m'$ and we use m'' to indicate the gap between k and ℓ, so that $\ell = k + m''$. Based on this notation, we can construct a weighted analog of (6) to explicitly write the elements of $\mathbf{C}$ as transformations of the variogram. This gives:

$$\begin{aligned}
C_{11} &= \sigma^2 - \sum_{b=1}^{B_d}\sum_{b'=1}^{B_d} \omega_1(b,d)\omega_1(b',d)\gamma(b-b'),\\
C_{22} &= \sigma^2 - \sum_{b=1}^{B_d}\sum_{b'=1}^{B_d} \omega_2(b,d)\omega_2(b',d)\gamma(b-b'),\\
C_{33} &= \sigma^2 - \sum_{b=1}^{B_d}\sum_{b'=1}^{B_d} \omega_3(b,d)\omega_3(b',d)\gamma(b-b'),\\
C_{44} &= \sigma^2 - \sum_{b=1}^{B_d}\sum_{b'=1}^{B_d} \omega_4(b,d)\omega_4(b',d)\gamma(b-b'),\\
C_{12} &= \sigma^2 - \sum_{b=1}^{B_d}\sum_{b'=1}^{B_d} \omega_1(b,d)\omega_2(b',d)\gamma(m'+|b-b'|),\\
C_{13} &= \sigma^2 - \sum_{b=1}^{B_d}\sum_{b'=1}^{B_d} \omega_1(b,d)\omega_3(b',d)\gamma(m+|b-b'|),\\
C_{14} &= \sigma^2 - \sum_{b=1}^{B_d}\sum_{b'=1}^{B_d} \omega_1(b,d)\omega_4(b',d)\gamma(m+|b-b'|),\\
C_{23} &= \sigma^2 - \sum_{b=1}^{B_d}\sum_{b'=1}^{B_d} \omega_2(b,d)\omega_3(b',d)\gamma(m+|b-b'|),\\
C_{24} &= \sigma^2 - \sum_{b=1}^{B_d}\sum_{b'=1}^{B_d} \omega_2(b,d)\omega_4(b',d)\gamma(m+|b-b'|),\\
C_{34} &= \sigma^2 - \sum_{b=1}^{B_d}\sum_{b'=1}^{B_d} \omega_3(b,d)\omega_4(b',d)\gamma(m''+|b-b'|),
\end{aligned}$$

where we denote, for instance, $\omega_1(b,d) = \sum_j \frac{w_j}{w} \sum_{j' \in d_{b\,j}} \frac{w_{j'}}{\sum_{j' \in d_j} w_{j'}}$ and similarly for the other elements.

The expectation $E[|\mu_{jd} - \mu_{id}||\mu_{kd} - \mu_{\ell d}|]$ can be simulated from a large number S (say, $S = 10,000$) of independent draws $(\bar{y}_{1s}, \bar{y}_{2s}, \bar{y}_{3s}, \bar{y}_{4s})$, with $s = 1, \ldots, S$, of the random vector $(\mu_{jd}, \mu_{id}, \mu_{kd}, \mu_{\ell d})$. The simulated expectation will be a function of the variogram parameters m, m', m'' and d and of σ^2. It is denoted $\theta_B(m, m', m'', d, \sigma^2)$ and estimated as follows:

$$\theta_B(m, m', m'', d, \sigma^2) = \frac{1}{S}\sum_{s=1}^{S} |\bar{y}_{2s} - \bar{y}_{1s}| \cdot |\bar{y}_{4s} - \bar{y}_{3s}|.$$

The summations in $Var[\Delta_{B\,d}]$ run over four indices i, j, k, ℓ. These can be equivalently represented through summations at given distance lags m, m', m''. For instance, we write $\sum_i \frac{w_i}{w} \sum_j \frac{w_j}{w} = \sum_{m'=1}^{B} \sum_i \frac{w_i}{w} \sum_{j \in d_{m'i}} \frac{w_j}{w}$ to indicate that i and j are separated by a lag of m' units on the transect. Repeating this for each of the three pairs of indices i, j and ℓ, k and i, ℓ we end up with three summations over m', m'' and m respectively, where the aggregate weight is denoted

$$\omega(m, m', m'', d) = \sum_i \frac{w_i}{w} \sum_{j \in d_{m'i}} \frac{w_j}{w} \cdot \sum_\ell \frac{w_\ell}{w} \sum_{k \in d_{m''\ell}} \frac{w_k}{w} \cdot \sum_i \frac{w_i}{w} \sum_{\ell \in d_{mi}} \frac{w_\ell}{w}.$$

The first term of $Var[\Delta_{B\,d}]$, $\sum_i \sum_j \frac{w_i w_j}{w^2} \sum_\ell \sum_k \frac{w_\ell w_k}{w^2} E[|\mu_{id} - \mu_{jd}||\mu_{\ell d} - \mu_{kd}|]$, can be written as follows:

$$\sum_{m=1}^{B} \sum_{m'=1}^{B} \sum_{m''=1}^{B} \omega(m, m', m'', d)\theta_B(m, m', m'', d, \sigma^2). \tag{20}$$

The second term of $Var[\Delta_{B\,d}]$, we make use of the gaussian assumption and the variogram properties to express the square of the expectation as a weighted analog of (8), that is

$$\begin{aligned}
Var[\Delta_{B\,d}] &= E\left[\sum_i \sum_j \frac{w_i w_j}{w^2} |\mu_{id} - \mu_{jd}|\right]^2 \\
&= \left(\sum_i \sum_j \frac{w_i w_j}{w^2} E[|\mu_{id} - \mu_{jd}|]\right)^2 \\
&= \left(\sum_i \sum_j \frac{w_i w_j}{w^2} \sqrt{Var[|\mu_{id} - \mu_{jd}|]} \sqrt{\frac{2}{\pi}}\right)^2 \\
&= \frac{2}{\pi}\left(\sum_i \frac{w_i}{w} \sum_{m'=1}^{B} \frac{\sum_{j \in d_{mi}} w_j}{w} \sum_{j \in d_{mi}} \frac{w_j}{\sum_{j \in d_{mi}} w_j} \sqrt{Var[|\mu_{id} - \mu_{jd}|]}\right)^2 \\
&= \frac{2}{\pi}\left(\sum_{m'=1}^{B} \sum_i \sum_{j \in d_{mi}} \omega_{ij}(m, d) \sqrt{Var[|\mu_{id} - \mu_{jd}|]}\right)^2
\end{aligned} \tag{21}$$

where

$$Var[|\mu_{id} - \mu_{jd}|] = \sum_{b=1}^{B_d} \sum_{b'=1}^{B_d} 2\omega_{ij}(b, b', d)\gamma(m - |b - b'|) - (\omega_i(b, b', d) + \omega_j(b, b', d))\gamma(b - b').$$

Both weighting schemes in (20) and in (21) cannot be easily estimated in reasonable computation time: they involve multiple loops across the observed locations, so that the length of estimation increases exponentially with the density of the spatial structure. In Section A.5 we discuss estimators of the weights $\omega_{ij}(m, m', m'', d)$, $\omega_{ij}(m, d)$, $\omega_{ij}(b, b', d)$, $\omega_i(b, b', d)$ and $\omega_j(b, b', d)$ that are feasible, and provide the empirical estimator of the variance $Var[\Delta_{B\,d}]$.

The third component of (18) is the covariance term $Cov[\Delta_{B\,d}, \mu_d]$. The indices i, j, ℓ identify three locations and the average income in a neighborhood of size d in each of the three location is represented by the vector $(\mu_{id}, \mu_{jd}, \mu_{\ell d})$. Under normality and stationarity assumptions, we can write the covariance term as follows

$$\begin{aligned}
Cov[\Delta_{B\,d}, \mu_d] &= Cov[\sum_i \sum_j \frac{w_i w_j}{w^2} |\mu_{id} - \mu_{jd}|, \sum_\ell \frac{w_\ell}{w} \mu_{\ell d}] \\
&= \sum_\ell \frac{w_\ell}{w} Cov[\sum_i \sum_j \frac{w_i w_j}{w^2} |\mu_{id} - \mu_{jd}|, \mu_{\ell d}] \\
&= \sum_\ell \frac{w_\ell}{w} \sum_i \sum_j \frac{w_i w_j}{w^2} E[|\mu_{id} - \mu_{jd}| \mu_{\ell d}] - \\
&\quad - \sum_\ell \frac{w_\ell}{w} E[\mu_{\ell d}] \sum_i \sum_j \frac{w_i w_j}{w^2} E[|\mu_{id} - \mu_{jd}|] \\
&= \sum_\ell \frac{w_\ell}{w} \sum_i \sum_j \frac{w_i w_j}{w^2} E[|\mu_{id} - \mu_{jd}| \mu_{\ell d}] - \\
&\quad - \sqrt{\frac{2}{\pi}} \mu \sum_i \sum_j \frac{w_i w_j}{w^2} \sqrt{Var[\mu_{id} - \mu_{jd}]}. \qquad (22)
\end{aligned}$$

The first term of (22) is the expectation of a non-linear function of convex combinations of normally distributed random variables. Under the Gaussian hypothesis, the expectation $E[|\mu_{id} - \mu_{jd}| \mu_{\ell d}]$ can be nevertheless simulated from a large number S (say, $S = 10,000$) of independent draws $(\bar{y}_{1s}, \bar{y}_{2s}, \bar{y}_{3s})$ with $s = 1, \ldots, S$ from the random vector $(\mu_{id}, \mu_{jd}, \mu_{\ell d})$ which is normally distributed with expectations (μ, μ, μ) and variance-covariance matrix

C of size 3×3. Let use scalars b and b' to denote a well defined distance gap between any observation indexed by $\{i, j, \ell\}$ and any other observation that is b or b' units away from it, within a distance boundary d. We use scalars m' to indicate the gap between i and j, so that $j = i + m'$; we use m'' to indicate the gap between i and ℓ, so that $\ell = i + m''$. Based on this notation, we obtain a convenient formulation for the covariances of mean neighborhood incomes that are weighted analog of (6), thus giving:

$$
\begin{aligned}
C_{11} &= \sigma^2 - \sum_{b=1}^{B_d} \sum_{b'=1}^{B_d} \omega_1(b,d)\omega_1(b',d)\gamma(b-b'), \\
C_{22} &= \sigma^2 - \sum_{b=1}^{B_d} \sum_{b'=1}^{B_d} \omega_2(b,d)\omega_2(b',d)\gamma(b-b'), \\
C_{33} &= \sigma^2 - \sum_{b=1}^{B_d} \sum_{b'=1}^{B_d} \omega_3(b,d)\omega_3(b',d)\gamma(b-b'), \\
C_{12} &= \sigma^2 - \sum_{b=1}^{B_d} \sum_{b'=1}^{B_d} \omega_1(m'+b,d)\omega_2(b',d)\gamma(m'+|b-b'|), \\
C_{13} &= \sigma^2 - \sum_{b=1}^{B_d} \sum_{b'=1}^{B_d} \omega_1(b,d)\omega_3(m''+b',d)\gamma(m''+|b-b'|), \\
C_{23} &= \sigma^2 - \sum_{b=1}^{B_d} \sum_{b'=1}^{B_d} \omega_2(m'+b,d)\omega_3(m''+b',d)\gamma(|m'-m''|+|b-b'|),
\end{aligned}
$$

where we denote, for instance, $\omega_1(b,d) = \sum_i \frac{w_i}{w} \sum_{i' \in d_{b\,i}} \frac{w_{i'}}{\sum_{i' \in d_i} w_{i'}}$ and similarly for the other elements. See previous notation for further details. The expectation $E[|\mu_{jd} - \mu_{id}|\mu_{\ell d}]$ is simulated from a number S of independent draws $(\bar{y}_{1s}, \bar{y}_{2s}, \bar{y}_{3s})$ with $s = 1, \ldots, S$ of the random vector $(\mu_{jd}, \mu_{id}, \mu_{\ell d})$. The simulated expectation will be a function of the variogram parameters m', m'' and d and of σ^2. It is denoted $\phi_B(m, m', m'', d, \sigma^2)$ and estimated as follows:

$$
\phi_B(m', m'', d, \sigma^2) = \frac{1}{S} \sum_{s=1}^{S} |\bar{y}_{2s} - \bar{y}_{1s}| \bar{y}_{3s}.
$$

This element is constant over m' and m''. Hence, we use $\phi_B(m', m'', d, \sigma^2)$ as a simulated analog for $E[|\mu_{id}-\mu_{jd}|\mu_{\ell d}]$, so that the covariance term $\sum_\ell \frac{w_\ell}{w}\sum_i\sum_j \frac{w_i w_j}{w^2} E[|\mu_{id}-\mu_{jd}|\mu_{\ell d}]$ writes $\sum_\ell \frac{w_\ell}{w}\sum_i\sum_j \frac{w_i w_j}{w^2}\phi_B(m',m'',d,\sigma^2)$, or equivalently

$$\sum_i \frac{w_i}{w}\sum_{m'=1}^{B}\frac{\sum_{j\in d_{m'i}} w_j}{w}\sum_{m''=1}^{B}\frac{\sum_{\ell\in d_{m''i}} w_\ell}{w}\phi_B(m',m'',d,\sigma^2),$$

which is denoted $\sum_{m'=1}^{B}\sum_{m''=1}^{B}\omega(m',m'',d)\phi_B(m',m'',d,\sigma^2)$.

The second term of (22) is calculated as in (21). Overall, we are now allowed to write the covariance term as follows:

$$\begin{aligned} Cov[\Delta_{B\,d},\mu_d] &= \sum_{m'=1}^{B}\sum_{m''=1}^{B}\omega(m',m'',d)\phi_B(m',m'',d,\sigma^2) \\ &\quad -\sqrt{\frac{2}{\pi}}\mu\sum_{m'=1}^{B}\sum_i\sum_{j\in d_{mi}}\omega_{ij}(m,d)\sqrt{Var[|\mu_{id}-\mu_{jd}|]}, \end{aligned} \tag{23}$$

where

$$Var[|\mu_{id}-\mu_{jd}|] = \sum_{b=1}^{B_d}\sum_{b'=1}^{B_d} 2\omega_{ij}(b,b',d)\gamma(m-|b-b'|) - (\omega_i(b,b',d)+\omega_j(b,b',d))\gamma(b-b')$$

The weights have been already defined in (21). Plugging (13), (20), (21) and (23) into (18) we derive an estimator for the $GINI_B$ index SE. The last section discuss feasible estimators.

A.5 Implementation

Consider a sample of size n of income realizations y_i with $i=1,\ldots,n$. The income vector $\mathbf{y}=(y_1,\ldots,y_n)$ is a draw from the spatial random process $\{Y_s : s\in\mathcal{S}\}$, while for each location $s\in\mathcal{S}$ we assume to observe, at most, one income realization. Information about location of an observation i in the geographic space $\mathcal{S}$ under analysis is denoted by $s_i\in\mathcal{S}$, so that a location s identifies a precise point on a map. Information about latitude and longitude coordinates of s_i are given. In this way, distance measures between locations can be easily constructed. In applications involving geographic representations, the latitude and longitude coordinates of any pair of incomes y_i, y_j can be combined to obtain the geodesic distance among the locations of i and of j. Furthermore, observed incomes are associated with weights $w_i \geq 0$ and are indexed according to the sample units, with $w = \sum_i w_i$. It is often the case that the sample weights give the inverse probability of selection of an observation from the population.

The mean income within an individual neighborhood of range d, μ_{id}, is estimated by $\widehat{\mu}_{id} = \sum_{j=1}^{n} \hat{w}_j y_j$ where

$$\hat{w}_j := \frac{w_j \cdot \mathbf{1}(||s_i - s_j|| \leq d)}{\sum_j w_j \cdot \mathbf{1}(||s_i - s_j|| \leq d)}$$

so that $\sum_j \hat{w}_j = 1$, and $\mathbf{1}(.)$ is the indicator function. The estimator of the average neighborhood mean income is instead $\hat{\mu}_d = \sum_{i=1}^{n} \frac{w_i}{w} \widehat{\mu}_{id}$. The estimator of the $GINI_B$ index of spatial inequality, denoted $G\hat{I}NI_B(\mathbf{y}, d)$, is the Gini inequality index of the vector of estimated average incomes $(\hat{\mu}_{1d}, \ldots, \hat{\mu}_{nd})$, indexed by the size d of the individual neighborhood. It can be computed by mean of the plug-in estimators as in Binder and Kovacevic (1995) and Bhattacharya (2007). The estimator of the $GINI_W$ index of spatial inequality, denoted $G\hat{I}NI_W(\mathbf{y}, d)$, is the sample weighted average of the mean absolute deviation of the income realization in location s from the income realization in location s', with $||s - s'|| \leq d$. Formally

$$G\hat{I}NI_W(\mathbf{y}, d) = \sum_{i=1}^{n} \frac{w_i}{w} \frac{1}{2\hat{\mu}_{id}} \sum_{j=1}^{n} \hat{w}_j \, |y_i - y_j|,$$

where $\hat{w}_j$ is defined as above.

The estimation of the GINI indices is conditional on d, which is a parameter under control of the researcher. The distance d is conventionally reported in miles and is meant to capture a continuous measure of the extent of an individual neighborhood. In practice, however, one cannot produce estimates of spatial inequality for a continuum of neighborhoods, and so in applications the neighborhood size is parametrized by the product of the number and size of lags between observations. The GINI indices are estimated for a finite number of lags and for a given size of the lags. The maximum number of lags indicates the point at which distance between observations is large enough that the spatial GINI indices converge to their respective asymptotic values. For a given neighborhood of size d, we can then partition the distance interval $[0, d]$, defining the size of a neighborhood, into K intervals $d_0, d_1, \ldots, d_K$ of equal size, with $d_0 = 0$. We always use d_k to denote the distance between any pair of observations i and j located at distance $d_{k-1} < ||s_i - s_j|| \leq d_k$ one from the other. The pairs $(d_k, \hat{GINI}_B(\mathbf{y}, d_k))$ and $(d_k, \hat{GINI}_W(\mathbf{y}, d_k))$ for any $k = 1, \ldots, K$ can be hence plotted on a graph. The curves resulting by linearly interpolating these points are the empirical equivalent of the GINI spatial inequality curves.

A plug-in estimator for the asymptotic standard error of the GINI indices can be derived under the assumptions listed in the previous sections. The SE estimator crucially depend on four components: (i) the consistent estimator for the average $\tilde{\mu}$, denoted $\hat{\mu}$, which coincides with the sample average; (ii) the consistent estimator for variance σ^2, denoted $\hat{\sigma}^2$, which is given by the sample variance; (iii) the consistent estimator for the variogram; (iv) the estimator of the weighting schemes.

Empirical estimators $\hat{\mu}$ and $\hat{\sigma}^2$ are standard. The robust non-parametric estimator of the variogram proposed by Cressie and Hawkins (1980) can be used to assess the pattern of spatial dependency from spatial data on income realizations. The empirical variogram is defined for given spatial lags, meaning that it produces a measure of spatial dependence among observations that are located at a given distance lag one from the others. Under the assumption that data occur on the transect at equally spaced points, we use $b = 1, \ldots, B$ to partition the empirical spectrum of distances between observed locations into equally spaced lags, and we estimate the variogram on each of these lags. This means that $2\gamma(b)$ refers to the correlation between incomes placed at distance lags of exactly b distance units. It is understood that the size of the sample is large compared to B, in the sense that the sampling rate per unit area remains constant when the partition into lags becomes finer. This assumption allows to estimate a non-parametric version of the variogram at every distance lag. Following Cressie (1985), we use weighted least squares to fit a theoretical variogram model to the empirical variogram estimates. The theoretical model consists in a continuous parametric function mapping distance into the corresponding variogram level. In our empirical analysis of spatial inequality in the 50 largest U.S. metro areas, we choose the spherical variogram model for γ (see Cressie 1985). We also assume that $\gamma(0) \to 0$ and that $\gamma(a) = \sigma^2$, where a is the so-called range level: beyond distance a, the random variables Y_{s+h} and Y_s with $h > a$ are spatially uncorrelated. Under the assumption that data occur on a transect, we set the max number of lags B so that $B = 2a$. Parameters of the variogram are estimated by fitting via weighted least squares a parametric variogram model to the non-parametric variogram sample estimates at pre-determined distance cutoffs. The estimated parameters are then used to draw predictions for the estimator $2\hat{\gamma}$ of the variogram at each distance cutoff. The predictions are then plugged into the GINI indices SE estimators. Cressie (1985) has shown that this methodology leads to consistent estimates of the true variogram function under the stationarity assumptions mentioned above.

Finally, SE estimation requires to produce reliable estimators of the weights ω. These can be non-parametrically identified from the formulas provided above. In some cases, however, computation of the exact weights requires looping several times across observations. The overall computation time thus increases exponentially in the number of observations and the procedure becomes quickly unfeasible. We propose alternative, feasible estimator for these weights, denoted $\hat{\omega}$, that are expressed as linear averages. The computational time is, nevertheless, quadratic in the number of observations as it requires at least one loop across all observations.

We consider here only the weights that appear in the estimators $\hat{SE}_{W\,d}$ in (10) and $\hat{SE}_{B\,d}$ in (18) that cannot be directly inferred (i.e., are computationally unfeasible) from observed weights. For a given observation i, define $w(b,i) = \sum_{j \in d_{bi}} w_j$ for any gap $b = 1, \ldots, B_d, \ldots, B$ the weight associated with income realizations that are exactly located b lags away from i. Then, denote $w(d,i) = \sum_{j \in d_i} w_j = \sum_{b=1}^{B_d} w(b,i)$. We construct the following estimators for the weights appeasing in the $GINI_W$ SE estimator:

$$\text{For (14)} \quad : \quad \hat{\omega}(m,b,b',d) = \sum_i \frac{w_i}{w} \frac{w(b,i)}{w(d,i)} \frac{w(m,i)}{w} \frac{w(m+b',i)}{w(m+d,i)},$$

$$\text{For (16)} \quad : \quad \hat{\omega}(m,b',d) = \sum_i \frac{w_i}{w} \frac{w(m,i)}{w} \frac{w(b',i)}{w(d,i)},$$

To compute these weights, one has to loop over all observations twice, and assign to each observation i the total weight $w(b,i)$ of those observations $j \neq i$ that are located exactly at distance b from i. Then, $\hat{\omega}(m,b,b',d)$ and $\hat{\omega}(m,b',d)$ are obtained by averaging these weights across i's. The key feature of these estimators is that second-order loops across observations occurring at distance b' from an observation at distance m from i are estimated by averaging across all observations i the relative weight of observations at distance $m+b'$ from i.

For the computation of the $GINI_B$ index, one needs to construct the relative weights by taking as a reference the maximum distance achievable, and not the reference abscissa d for which the index is calculated. We hence assume that beyond the threshold $\overline{d}$, indicating half of the the maximum distance achievable in the sample, spatial correlation is negligible and weights can thus be set to zero. We implicitly maintain that $d \leq \overline{d}$. We then propose the following estimators:

$$
\begin{aligned}
\text{For (20)} &: \quad \hat{\omega}(m,m',m'',d) = \sum_i \frac{w_i}{w}\frac{w(m',i)}{w(\overline{d},i)}\frac{w(m,i)}{w(\overline{d},i)}\frac{w(m+m'',i)}{w(m+\overline{d},i)} \\
\text{For (21)} &: \quad \hat{\omega}_{ij}(b,b',d) = \frac{w(b,i)}{w(d,i)}\frac{w(m+b',i)}{w(m+d,i)} \\
\text{For (21)} &: \quad \hat{\omega}_{i}(b,b',d) = \frac{w(b,i)}{w(d,i)}\frac{w(b',i)}{w(d,i)} \\
\text{For (21)} &: \quad \hat{\omega}_{j}(b,b',d) = \frac{w(m+b,i)}{w(m+d,i)}\frac{w(m+b',i)}{w(m+d,i)} \\
\text{For (21)} &: \quad \sum_i \sum_{j\in d_{mi}} \hat{\omega}_{ij}(m,d) = \sum_i \frac{w_i}{w}\frac{w(m,i)}{w}
\end{aligned}
$$

By plugging these estimators into (19) we obtain the implementable estimator of the variance component $Var[\Delta_{B\,d}]$, defined as follows:

$$
\begin{aligned}
\widehat{Var}[\Delta_{B\,d}] \;=\; & \sum_{m=1}^{B}\sum_{m'}^{B}\sum_{m''=1}^{B} \hat{\omega}(m,m',m'',d)\theta_B(m,m',m'',d,\hat{\sigma}^2) - \\
& -\frac{2}{\pi}\left(\sum_{m'=1}^{B}\sum_i \frac{w_i}{w}\frac{w(m,i)}{w}\sqrt{\widehat{Var}[|\mu_{id}-\mu_{jd}|]}\right)^2 \qquad (24)
\end{aligned}
$$

where

$$\widehat{Var}[|\mu_{id} - \mu_{jd}|] = \sum_{b=1}^{B_d}\sum_{b'=1}^{B_d} 2\hat{\omega}_{ij}(b, b', d)\hat{\gamma}(m - |b - b'|) - (\hat{\omega}_i(b, b', d) + \hat{\omega}_j(b, b', d))\hat{\gamma}(b - b').$$

An equivalent procedure, based on analogous weighting scheme, has to be replicated to determine the empirical estimator for (23).

A.6 Testing hypotheses about spatial inequality

The empirical estimators of the GINI spatial inequality curves (presented in the Appendix) can be used to test hypotheses about the shape and dynamics of spatial inequality. (i) By contrasting the level of spatial inequality measured by the GINI curves at a given distance d with the overall level of inequality captured by the Gini index, it is possible to assess if, and to what extent, average income inequality experienced within a neighborhood of size d is different from the level of inequality in the city. (ii) Moreover, by contrasting the level of the GINI curves at d and at $d' > d$, it is possible to state if, by how much, and at which speed, local inequality converges with citywide inequality. (iii) Lastly, by comparing the levels of the GINI curves at distance d registered in different periods within the same city, it is possible to reach conclusions about the dynamics of spatial inequality.[40]

Estimators and their point-wise asymptotic distributions allow to use t-distributed statistics to assess spatial inequality at different distance abscissae.

[40] One is compelled to conclude in favor of spatial inequality only if there is strong evidence against the null hypothesis that the level of the GINI curve at d is the same as the Gini inequality index, and that the level of spatial inequality captured by the GINI curves does not change with d. When comparing two GINI (either between or within) curves, a strong increase or reduction in spatial inequality cannot be rejected if there is strong evidence against the null hypothesis that the two curves coincide *at every* d.

B Additional results

B.1 Inference results for spatial inequality curves, Chicago (IL)

Figure 8 shows that the gap in $GINI_W$ indices is small over time and never significant, not even at 90% confidence level. There is little statistical support to conclude that the GINI curves for within spatial inequality have changed across time at standard significance levels, a result which holds irrespectively of the extent of individual neighborhood. We draw a different conclusion for what concerns changes associated with the spatial inequality curves generated by $GINI_B$. Pairwise differences across these curves, along with their confidence intervals, are reported in Figure 9. The differences in inequality curves compared to the spatial inequality curve of the year 1980 (panels (a), (b) and (c) of the figure) are generally positive and significant at 95% confidence level. This indicates that spatial inequality between individual neighborhoods has increased compared to the initial period, roughly homogenously with respect to the individual neighborhood spatial extension. After that period, data display no statistical support for changes in inequality across the 1990' and 2000'. Spatial between inequality has slightly increased after 1990 (panels (d) and (e)), while it has remained stable after 2000 (panel (f)). In the latter case, the confidence bounds of the difference in spatial inequality curves of years 2010/2014 and 2000 always include the horizontal axis.

Estimates of the GINI standard errors allow to study the pattern of the spatial inequality curves. More specifically, differences in $GINI_W(d)$ or $GINI_B(d)$ indices are first computed at various abscissae d. Then, the standard errors of these differences are derived, and finally it is checked if these differences are significantly different than zero. In this way, we study how spatial inequality evolves with the size of the neighborhood. In particular, the sign of these differences predicts the direction of the change in spatial inequality. We refer to five distance thresholds referring to neighborhoods that are very small (0.1 and 0.2 miles), relatively large (0.6 and 2 miles), and inclusive neighborhoods (6 miles and 15 miles), which include most of the urban space under analysis. The resulting differences are reported in Table 4. The dip in the spatial inequality curve associated with

Index	Year	Differences across distance thresholds (miles)						
		0.2m vs 0.1m	0.6m vs 0.1m	2m vs 0.1m	15 vs 0.1m	6m vs 2m	15m vs 2m	15m vs 6m
$GINI_W$	1980	-0.004	-0.012	-0.006	0.015	0.013	0.025	0.012
		(0.019)	(0.020)	(0.020)	(0.021)	(0.021)	(0.023)	(0.023)
	1990	-0.006	-0.019	0.003	0.037*	0.036	0.051**	0.015
		(0.022)	(0.022)	(0.021)	(0.021)	(0.022)	(0.023)	(0.021)
	2000	-0.004	-0.016	-0.002	0.035*	0.034	0.050**	0.016
		(0.017)	(0.017)	(0.020)	(0.021)	(0.021)	(0.022)	(0.024)
	2010	-0.000	-0.004	0.001	0.033	0.019	0.036	0.017
		(0.017)	(0.018)	(0.019)	(0.021)	(0.021)	(0.023)	(0.024)
$GINI_B$	1980	-0.020**	-0.087**	-0.151**	-0.239**	-0.061**	-0.120**	-0.059**
		(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
	1990	-0.012**	-0.084**	-0.171**	-0.280**	-0.097**	-0.160**	-0.064**
		(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
	2000	-0.009**	-0.060**	-0.130**	-0.237**	-0.095**	-0.152**	-0.057**
		(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
	2010	-0.019**	-0.083**	-0.160**	-0.261**	-0.084**	-0.141**	-0.058**
		(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)

Table 4: Patterns of GINI indices across distance thresholds

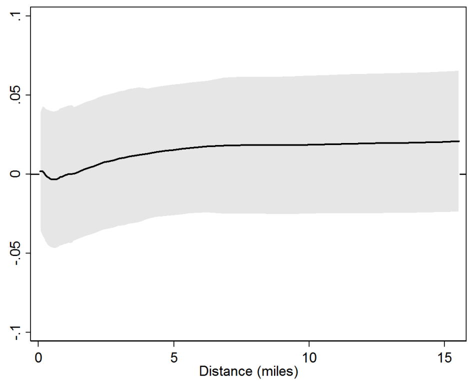
Note: Authors analysis of U.S. Census data. Each column report differences in GINI indices at various distance thresholds. Standard errors are reported in brackets. Significance levels: $* = 10\%$ and $** = 5\%$.

the $GINI_W$ is not statistically significant, since most of the changes in spatial inequality in very large neighborhoods is substantially equivalent to the spatial inequality observed for very small neighborhoods. For 1990 and 2000, we find a statistically significant increase in inequality when average size neighborhoods (1km of radius) are compared with very large concepts of neighborhoods. Overall, the $GINI_W$ index pattern is substantially flat when the distance increases beyond 10 miles. The pattern registered for the $GINI_B$ index is much more clear-cut: generally, the spatial inequality curve constructed from the index is decreasing in distance (differences in $GINI_B$ are always negative), and the patterns of changes are also significant at 5%, indicating strong reliability on the pattern of heterogeneity in average income distribution across neighborhoods.

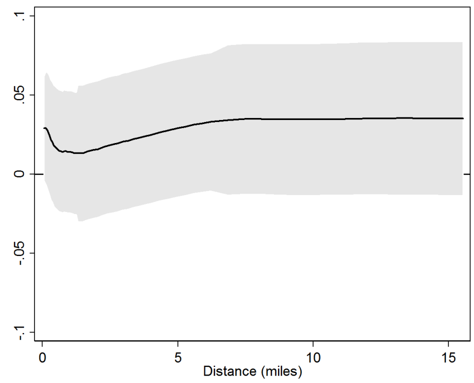
B.2 Spatial inequality in the largest U.S. metro areas

Figure 3 and Figure 4 in the main text report patterns of spatial inequality measured by GINI within and between indices for the 50 largest U.S. metro area (as of 2014). At any

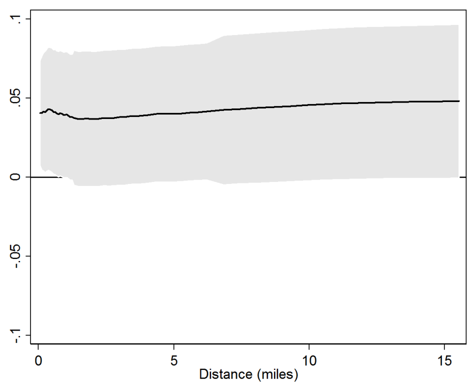
Figure 8: Differences in $GINI_W$ estimates over four decades, Chicago (IL)



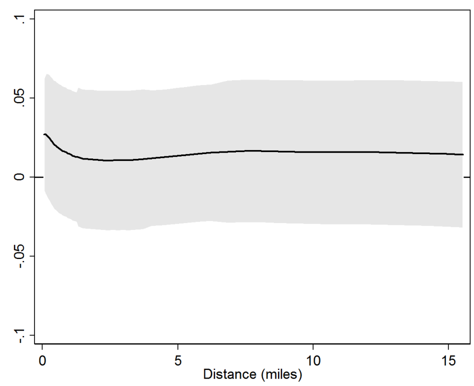
(a) $GINI_W$ 1990 - $GINI_W$ 1980



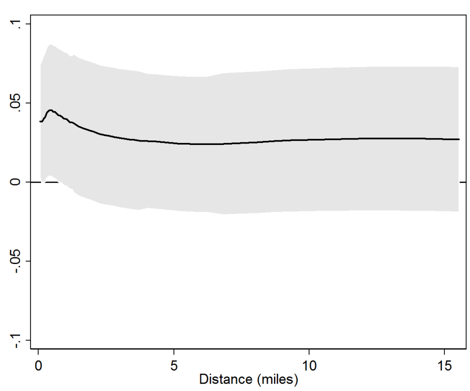
(b) $GINI_W$ 2000 - $GINI_W$ 1980



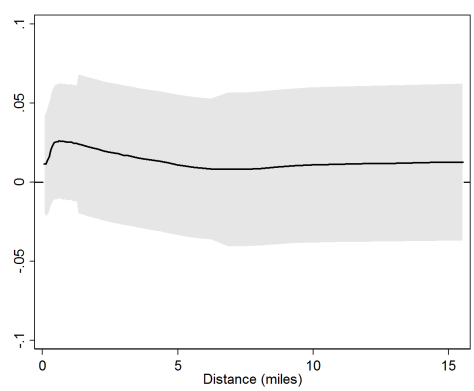
(c) $GINI_W$ 2014 - $GINI_W$ 1980



(d) $GINI_W$ 2000 - $GINI_W$ 1990



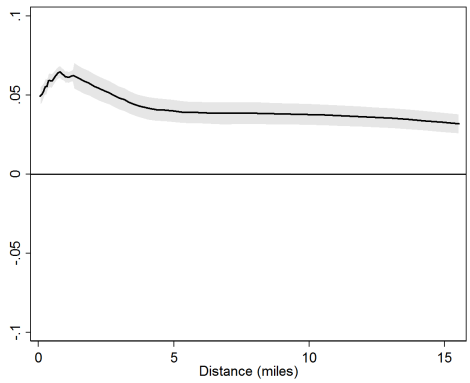
(e) $GINI_W$ 2014 - $GINI_W$ 1990



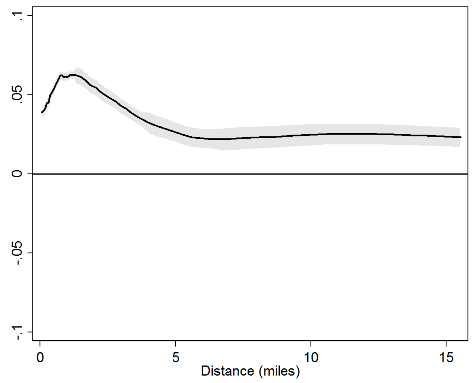
(f) $GINI_W$ 2014 - $GINI_W$ 2000

Note: Authors analysis of U.S. decennial Census data and 2010/14 CS data. The income concept is equivalent gross annual household income. Confidence bounds at 95% are based on standard error estimators discussed in the appendix A.

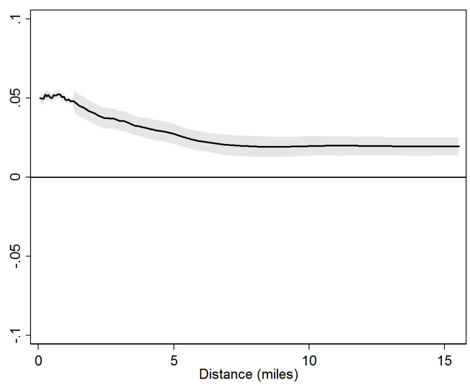
Figure 9: Differences in $GINI_B$ estimates over four decades, Chicago (IL)



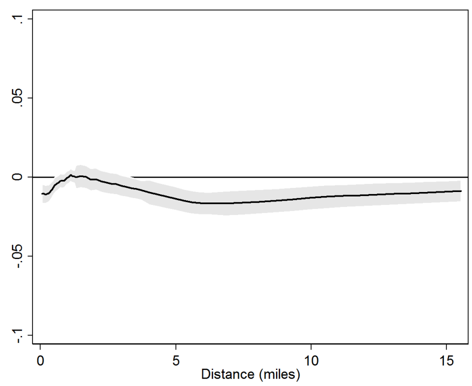
(a) $GINI_B$ 1990 - $GINI_B$ 1980



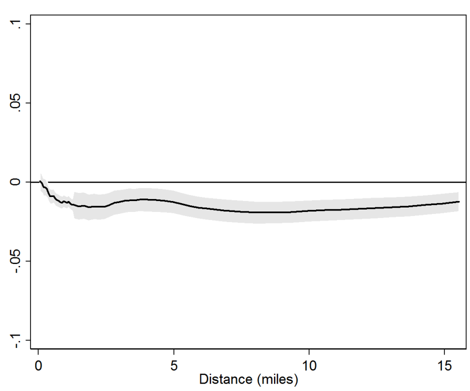
(b) $GINI_B$ 2000 - $GINI_B$ 1980



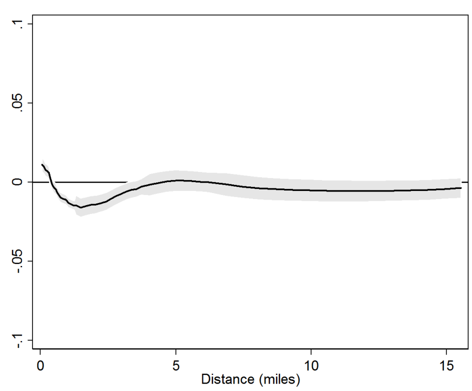
(c) $GINI_B$ 2014 - $GINI_B$ 1980



(d) $GINI_B$ 2000 - $GINI_B$ 1990



(e) $GINI_B$ 2014 - $GINI_B$ 1990



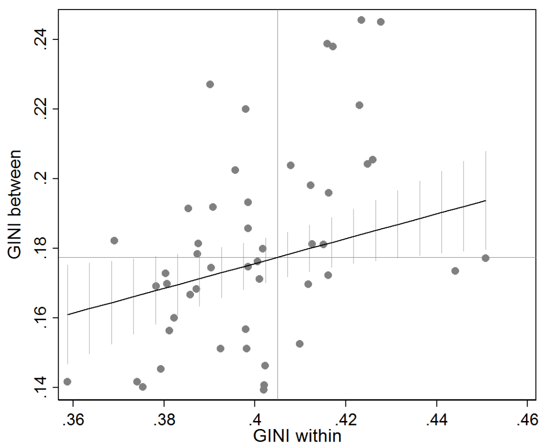
(f) $GINI_B$ 2014 - $GINI_B$ 2000

Note: Authors analysis of U.S. decennial Census data and 2010/14 CS data. The income concept is equivalent gross annual household income. Confidence bounds at 95% are based on standard error estimators discussed in the appendix A.

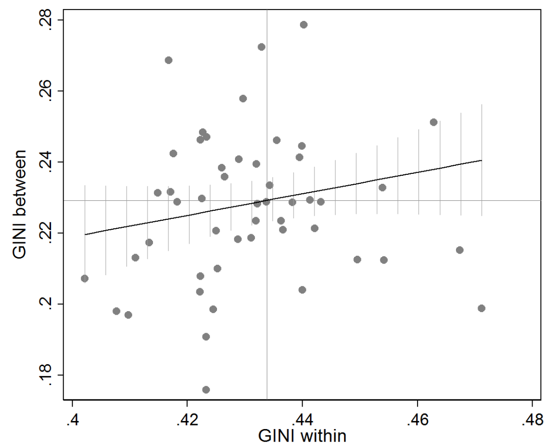
given distance abscissa, the graphs display substantial heterogeneity in measured spatial inequality across the metro areas. We correlate variability observed at a given distance threshold of two miles with characteristics of the citywide income distribution. We find that the GINI within and between indices capture dimensions of inequality that are not necessarily interconnected. Although both indices should converge to precise values when the neighborhood size is very small or very large, the in-between patterns capture different aspects of the joint distribution of incomes and locations. In panel (a) an (b) of Figure 10 we display the joint pattern of the two indices computed for the spatial distributions of incomes in the 50 largest U.S. cities. In this way, we capture substantial heterogeneity both in the geography and the inequality of urban income distributions. We compute both indices for individual neighborhoods of size less than two miles using 1980 Census data and 2010/14 ACS data. As the figure shows, the two dimensions of spatial inequality seem slightly positively correlated in 1980, although there is little statistical support for this claim. The 2010/14 ACS data do not reveal significance correlations of within and between GINI indices.

Figure 10.(c) displays the empirical relation between citywide inequality (measured by the Gini index) and spatial inequality. The degree of association is visualized by the slopes of the regression lines. We examine both within and between spatial inequality for the Census year 1980 and for ACS 2010/14 data, for an individual neighborhood of size two miles. As expected, the citywide Gini index and the GINI indices are positively correlated. Heterogeneity in $GINI_B$ around the regression lines is, however, substantially larger than heterogeneity in $GINI_W$, thus indicating less reliability in these latter correlations. In both cases, the degree of association between spatial and citywide inequality is slightly decreasing over time. Figure 10.(d) shows the association among GINI indices and city affluence (measured by the PPP average equivalized income in each city). Results are less clear-cut and we do not detect a remarkable association between city affluence and GINI spatial inequality, both in the within and the between form. This is somehow expected, as the GINI indices capture relative notions of inequality (thus improving comparability across cities that differ in affluence).

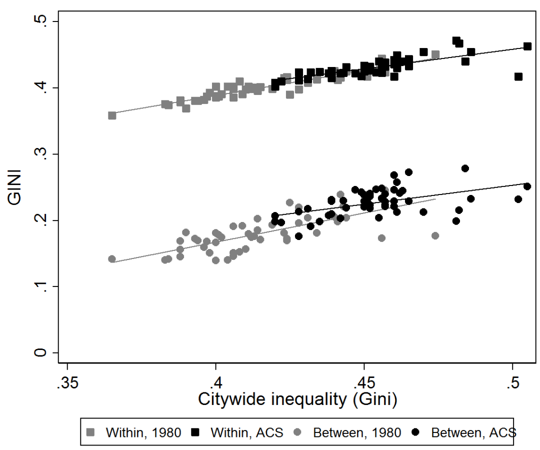
Figure 10: Spatial inequality, income inequality and average incomes across U.S. cities.



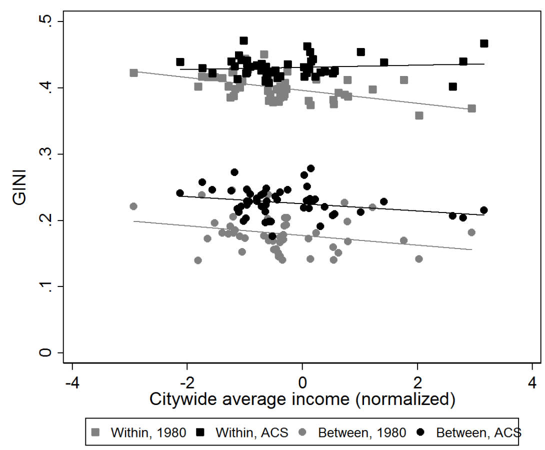
(a) Within and between GINI, 1980



(b) Within and between GINI, 2010/14



(c) Spatial and citywide inequality



(d) Spatial inequality and citywide income

Note: Authors analysis of U.S. Census and ACS data for 50 largest U.S. cities in 2014. Citywide income inequality and average incomes are based on block-group level household equivalent gross income estimates. Average income is normalized to have zero average and unit standard deviation over the weighted selected sample of 50 cities. Gray lines correspond to sample weighted averages of within and between GINI indices. Vertical spikes identify the 95% confidence bounds of regression predictions.

B.3 Regression analysis: data description and additional results

We construct regression models based on the full sample of Commuting Zones (CZ hereafter) in the U.S. for which estimates of the relevant outcomes (intergenerational mobility gains, rank mobility of long-term residents and average life expectancy at age 40 for males with income in the first quartile of the national income distribution) have been made available in Chetty and Hendren (2016) and Chetty, Stepner, Abraham, Lin, Scuderi, Turner, Bergeron and Cutler (2016). The full sample consists of 450 CZ covering the vast majority of the U.S. residents. The authors listed above make available alternative estimates of the effects of the neighborhood on individual outcomes at CZ level, made conditional on a large variety of attributes of the underlying population of interest. We focus on the preferred estimates of the authors for our analysis, and we refer to their paper for methodology, estimation issues and robustness checks.[41]

The *intergenerational mobility gains* are taken from Chetty and Hendren (2016) (variable *causal_p25_czkr26*). This variable measures the increase in a child's percentage income rank in adulthood if the parents of this child moved (while aged between 6 to 18) to a CZ of destination where the mean income rank of children of long-term residents is 1% larger than the mean income rank of children of long-term residents in the place of departure. We pick up intergenerational mobility by focusing on the effect for the group of children who are born in families from the bottom income quartile of the parents income distribution. In the overall sample, the intergenerational mobility gains vary between -0.927 to 1.67 percent points. More than half of the American CZ display negative estimates (the median being -0.02 and the mean -0.03 percent points) with positive effects clustered on the top quartiles.

The *rank mobility of long-term residents* is also taken from Chetty and Hendren (2016) (variable *per_res_p25_kr27*). It measures the average percent rank in the national household income distribution achieved by children who are long-term residents in a given CZ and have been raised from parents at the bottom income quartile of their respective income distribution. Across American CZ, rank mobility varies approximatively between

[41] Estimations are based on micro-data from the fiscal and medical authorities.

34% to 56%, where more than 90% of CZ display average mobility estimates smaller than 50%. The average mobility across CZ is 43.45%, which is far from 50%, the expected rank in the national income distribution in the absence of intergenerational transmission.

The *life expectancy at age 40 of poor male residents* is taken from Chetty, Stepner, Abraham, Lin, Scuderi, Turner, Bergeron and Cutler (2016) (variable *le_agg_q1_M*). It gives raw estimates of life expectancy taken from the administrative fiscal data. Life expectancy ranges between 73 and 81 years across CZ in the U.S. (average life expectancy if 77.12 years).

The treatment variable is spatial inequality measured by the $GINI_W$ index applied to 2000 Census data. Indices are computed for MSAs, defined on the basis of the 2015 Census Bureau geography. We focus on MSA level estimates for $GINI_W$ indices to focus on the residential area of urban agglomerates, which does not necessarily coincide with CZ, also including areas occupied by firms and non-urban residential areas.

We augment baseline regression models with controls for sorting within and between CZ. Summary statistics for controls used in our regression models are reported in Table 5. *Demographic controls (panel A)* are at the CZ level and include controls for agglomeration (log population density), racial composition (percentage of black residents and racial segregation measured by multi-group dissimilarity indices) and migration (stock and flow of foreign born residents) as of 2000. These data are estimated at the CZ level from the 2000 Census SFT-3A files tables.

Local finance controls (panel B) characterize the incidence of local taxation and the intensity of spending in the CZ. These controls include information on taxes collected locally (such as the average tax rate, the per capita fiscal revenues and the average EITC incidence for State where State-level EITC policies were implemented in 2000) as well as the per capita monetary expenditures. Data at CZ level are taken from Chetty and Hendren (2016).

Education controls (panel C) qualify the local public school system from the perspective of inputs as well as of performances, so that both dimensions can be jointly qualified in estimation. The input dimension is measured by estimates at the CZ level of schools

	MSA	Average	S.d.	Q5%	Q25%	Median	Q75%	Q95%
A) Pct black	450	0.114	0.087	0.008	0.054	0.082	0.188	0.275
A) Racial segregation	450	0.249	0.100	0.094	0.175	0.264	0.317	0.436
A) Pop density (log)	450	5.901	1.105	4.066	5.143	5.948	6.749	7.420
A) Pct foreign born	450	13.049	10.190	1.902	4.546	10.688	20.937	30.925
A) Migration flow	450	0.020	0.011	0.008	0.013	0.016	0.024	0.042
B) Avg tax rate	450	0.025	0.005	0.017	0.021	0.024	0.029	0.035
B) Fiscal revenues pc	450	0.938	0.301	0.473	0.720	0.899	1.152	1.439
B) Expenditure pc	450	2716.800	631.834	1675.292	2299.473	2738.578	3154.639	3609.343
B) Avg EITC exposure	450	1.160	3.046	0.000	0.000	0.000	0.476	6.905
C) Students/teachers (pub.)	429	19.256	3.004	15.021	16.871	18.657	21.044	24.805
C) Avg pub. school score	449	-4.758	7.574	-17.336	-8.394	-3.101	0.095	5.390
C) Avg dropout rate (pub.)	340	0.005	0.015	-0.016	-0.005	0.004	0.013	0.035
C) Pub. schoold pc	450	0.011	0.005	0.005	0.008	0.010	0.013	0.021
C) Avg tuition	446	6383.381	3294.186	1796.188	4312.804	5414.587	8685.150	10850.831
C) Kindergartens(pub.)	450	0.552	0.073	0.421	0.505	0.550	0.610	0.665
C) Students/teachers (priv.)	448	12.051	1.838	9.185	10.725	12.341	13.579	14.888
D)Sd of students/teachers (priv.)	413	2.376	1.921	0.801	1.389	1.949	2.981	4.787
D) Sd of students/teachers (pub.)	427	1.718	3.369	0.283	0.676	1.223	2.063	5.116
D) Pct black students (pub.)	445	0.133	0.114	0.012	0.050	0.107	0.177	0.335
D) Sd of pct black students (pub.)	422	0.102	0.073	0.008	0.047	0.085	0.151	0.241
D) Pct violent crime	420	0.002	0.001	0.001	0.002	0.002	0.003	0.004
D) Crimes pc	420	0.008	0.002	0.004	0.006	0.008	0.009	0.011
D) Median rent	450	637.751	129.277	442.792	532.895	638.199	729.821	848.695
D) Pct poors	450	0.118	0.038	0.075	0.089	0.108	0.143	0.174
D) Income segregation	450	0.096	0.028	0.043	0.077	0.104	0.121	0.130
D) Avg income	450	41382.611	7019.962	30119.068	36987.883	39706.934	45508.879	53705.695
D) Gini index	450	0.482	0.074	0.368	0.427	0.490	0.524	0.577
F) Pct current smokers, P25	448	0.258	0.046	0.198	0.217	0.259	0.292	0.326
F) Pct current smokers, P75	448	0.120	0.024	0.086	0.107	0.119	0.134	0.156
F) Pct obese, P25	448	0.279	0.036	0.218	0.247	0.274	0.308	0.336
F) Pct obese, P75	448	0.191	0.034	0.144	0.169	0.189	0.209	0.249
F) Pct practice exercises, P25	448	0.620	0.045	0.562	0.590	0.610	0.642	0.705
F) Pct practice exercises, P75	448	0.873	0.026	0.836	0.865	0.872	0.887	0.910
F) Pct w/o health insurance	450	16.938	5.570	9.990	12.917	15.881	21.464	25.399
IV: FMW	450	0.153	0.027	0.097	0.141	0.165	0.169	0.184
IV: RMW	450	-0.446	0.081	-0.504	-0.503	-0.438	-0.391	-0.348
IV: SI1990	436	0.402	0.021	0.370	0.390	0.401	0.415	0.437

Table 5: Summary statistics for control variables and instruments

Note: Based on authors' elaboration of data from U.S. Census, CCD, PSS, CPS March Supplement and from data discussed in Chetty and Hendren (2016) and Chetty, Stepner, Abraham, Lin, Scuderi, Turner, Bergeron and Cutler (2016). Controls are grouped by (A) Demographics, (B) Local finance, (C) Education, (D) Sorting and (F) Health indicators.

budget, of student/teacher rations available in the average class and the number of places in public primary and secondary education per resident. The average performance of schools in each CZ is measured by the average score reached by public schools in a given CZ compared to the national distribution (which measures achievements of students on the national scale), as well as the average dropout rate (which is instead informative of educational attainment). Achievement and attainment measures are informative of students career patterns and explain sorting behavior of parents. Data come from the *Common Core of Data (CCD) Public Elementary/Secondary School Universe Survey* for schooling year 2000/2001. The CCD is an inclusive survey of the universe of institutes providing publicly-financed educational services in the U.S. The survey is distributed by the National Center for Educational Statistics (NCES) and provides information about schools type, budget and inputs (teachers per class), students' performances, and ethnic composition at the level of the institute providing elementary to secondary educational programs. Information on accessory programs such as kindergarten and post-secondary education are also reported when available.

Pre-primary and tertiary education are not mandatory in the U.S.. Public financial support for pre- and post-formal education is hence limited and families generally resort to the private sector. CZ with larger availability of privately-supplied kindergarten are expected to charge smaller prices and thus grant larger access to pre-primary education of poor children. Lower tuition fees for colleges also increases human capital at the bottom of the distribution, thus fostering economic mobility prospects of the poor. We estimate CZ averages of pre-kindergarten attainment and local tuition for tertiary education using data from the *Private School Universe Survey (PSS)*. The survey covers private schools in the U.S. that meet the NCES definition (i.e., schools are not supported primarily by public funding, provide any of the K-12 teaching survey with activities in the classroom and has one or more teachers employed by the school). The PSS survey produces data that are similar to CCD, mostly consisting in summary table of students and teacher composition conditional on grade, diploma offered and other characteristics. We use the PSS 2003/2004 module of the survey, which provide detailed information of school composition as well as kindergarten services.

The Sorting (panel D) controls allow to partial out observable determinants of sorting of households within the CZ. There are two groups of controls. The first group of controls is associated with sorting on the basis of educational services offered locally. We use PSS and CCD to construct measures of variability of private and public schools characteristics (both in terms of inputs and students achievements) across catchment areas at the CZ level.[42] In this way, we capture variability in quality and performances of educational institutes (using standard deviations within the CZ for more relevant variables listed in panel C, both for public and private schools), which correlated with sorting within the city (while average characteristics of the school allow to control for sorting across cities). The second group of controls is associated with sorting within the CZ on the basis of quality of life offered across neighborhoods. We use information on the distribution of income

[42]In the surveys, schools addresses are reported so that each school can be associated with its reference catchment areas and the CZ where it is located (merging information at the County level).

in the city (average income and Gini index at the CZ level) and its segregation across neighborhoods, as well as median rent value in the city to proxy quality of life. Hedonic models make clear that, upon controlling for income, residential rents provide information on the implicit prices of amenities offered in the city and can be used to proxy quality of life therein. We also use information on crime events in the city. Data on the income distribution are estimated from the 2000 Census, using the same methodology described in Section 3. Data on rents and crime are from Chetty and Hendren (2016).

Finally, *Health (panel F)* controls are also introduced. The variables we use are CZ-specific averages of healthy lifestyles and attitude for males, estimated separately for males with income below the bottom quartile and above the upper quartile of the national income distribution. Microdata and quality of the data are discussed in Chetty, Stepner, Abraham, Lin, Scuderi, Turner, Bergeron and Cutler (2016).

The *Instruments FMW and RMW* are descried in the main text. We use the March Supplement of the Current Population Survey to compute industry employment and employment growth over 1980-2000. We use the 1980 and 2000 waves of the survey to obtain State-specific estimates of employment at major two-digits industry recode level (including agriculture and forestry, mining, manufacturing of durable and non-durable goods, transportation, wholesale, retail, finance, services to business, personal, entertainment, medical, hospital, educational and professional, as well as public administration). The 1980 CPS includes 87,218 employed workers, of which 78.3% report information on previous year earnings, weeks worked and estimated hours of work during the reference week of the survey. The 2000 CPS covers 68,318 employees, of which 93.4% are in the work force during the reference week when the survey has been run. Information on yearly earnings, weeks worked and hours worked during the typical week are also provided. Individual hourly wages are then estimated in both CPS modules. These estimates are compared to the minimum wage regulation provided by the U.S. Bureau of Labor Statistics. The federal minimum wage in 1980 was \$3.1 and in 2000 was \$5.15 in nominal prices. Based on this information, we estimate the share MW_{ij1980} of employed workers in a region and industry with a hourly wage smaller than the federal minimum wage in the base year. On average, 25.58% of employees receive a hourly pay less than the federal minimum wage in 1980, with values ranging from 16.8% in DC to 41.1% in South Dakota, and nationwide varies from less than 10% in mining sector (8.5%) and transportation (9.6%) to nearly 40% or above in services to business and medical.

We use the same data to determine the share of workers in a given region that are employed in industry i both in 1980 and 2000, and we compute $g_{j80/00}$ accordingly. From the data, we are able to estimate values of the predicted minimum wage coverage by State. We use crosswalk files to merge these estimates with Commuting-Zone level data.

Regression results that complement those in Section 3.3 are reported hereafter. Table 6 is an extended version of Table 2 in the main text. Table 7 reproduces estimates in models (1)-(8) in Table 6 while using as treatment the $GINI_W$ index in 2000 (normalized by the full sample standard deviation) computed on individual neighborhoods of distance range smaller than six miles. Overall, sign, size and significance of the coefficients in Table 7 are comparable to those reported in the main text. Tables 8 and Table 9 apply the same specifications of models (1)-(8) in Tables 6 and 7, respectively, to a new dependent variable, measuring intergenerational mobility (the percentage rank in the national income distribution occupied by a child during adulthood conditional on being born from parents with incomes in the bottom quartile of their respective national income distribution) of long term residents in the city. Differently form intergenerational mobility gains, intergenerational rank mobility estimates do not disentangle the implications of the place of residence from other sources of transmission of parental earnings, for instance via private investment, education choices, mechanical transmission of skills, and might well incorporate the implications of parental sorting. Our results suggest that spatial inequality has no causal implications for intergenerational rank mobility of long term residents after controlling for sorting. Lastly, Table 10 extends on Table 3.

	OLS					IV		
						SI1990	FMW	RMW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$GINI_W$ 2000	-0.039**	-0.036**	-0.029**	-0.045**	-0.032	-0.004	-0.194^{+}	-0.240^{+}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.13)	(0.16)
A) Pct black		-0.316**	-0.303**	-0.201	0.420	0.611	-0.240	-0.354
		(0.12)	(0.12)	(0.16)	(0.52)	(0.49)	(0.70)	(0.77)
A) Racial segregation		-0.224*	-0.280**	0.079	-0.438	-0.481^{+}	-0.505	-0.520
		(0.14)	(0.14)	(0.22)	(0.33)	(0.32)	(0.39)	(0.40)
A) Pop density (log)		0.009	-0.013	-0.055**	-0.048^{+}	-0.045	-0.041	-0.032
		(0.01)	(0.02)	(0.02)	(0.03)	(0.03)	(0.05)	(0.06)
A) Pct foreign born		-0.472**	-0.512**	0.119	-0.557	-0.438	-1.615	-2.005
		(0.10)	(0.14)	(0.22)	(0.56)	(0.55)	(1.23)	(1.44)
A) Migration flow		-1.727*	-2.111**	-4.615**	-0.393	0.352	-1.016	-1.299
		(0.90)	(0.93)	(1.31)	(2.63)	(2.50)	(2.95)	(3.09)
B) Avg tax rate			0.325	-0.191	-24.885**	-23.884**	-24.043**	-24.115*
			(3.73)	(5.12)	(12.04)	(11.33)	(11.90)	(12.38)
B) Fiscal revenues pc			0.115	0.129	0.947**	0.920**	1.127**	1.180**
			(0.08)	(0.12)	(0.36)	(0.34)	(0.39)	(0.42)
B) Expenditure pc			0.000	0.000	0.000	0.000	0.000	0.000
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
B) Avg EITC exposure			0.001	-0.003	-0.002	-0.002	-0.001	-0.002
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
C) Pub. school budget				0.003	0.016	0.006	-0.001	-0.004
				(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
C) Students/teachers (pub.)				0.003	0.015	0.021*	0.029*	0.027^{+}
				(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
C) Avg pub. school score				-0.001	0.000	-0.001	-0.003	-0.003
				(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
C) Avg dropout rate (pub.)				-2.486**	-0.980	-1.686^{+}	-0.177	-0.153
				(0.86)	(1.05)	(1.06)	(1.09)	(1.13)
C) Pub. schoold pc				6.146**	6.134**	6.465**	5.913*	5.967*
				(2.68)	(2.92)	(2.75)	(3.51)	(3.62)
C) Avg tuition				-0.000*	-0.000**	-0.000**	-0.000**	-0.000**
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
C) Kindergartens(pub.)				0.256	-0.004	-0.030	0.092	0.118
				(0.19)	(0.21)	(0.20)	(0.23)	(0.24)
C) Students/teachers (priv.)				0.007	0.015^{+}	0.017*	0.004	0.002
				(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
D)Sd of students/teachers (priv.)					-0.011	-0.013*	-0.008	-0.007
					(0.01)	(0.01)	(0.01)	(0.01)
D) Sd of students/teachers (pub.)					0.008	0.006	0.014	0.016^{+}
					(0.01)	(0.01)	(0.01)	(0.01)
D) Pct black students (pub.)					-0.891**	-1.066**	-0.684*	-0.643^{+}
					(0.32)	(0.32)	(0.38)	(0.41)
D) Sd of pct black students (pub.)					0.866**	0.856**	1.014**	0.999**
					(0.37)	(0.35)	(0.41)	(0.44)
D) Pct violent crime					25.001	45.449^{+}	54.980^{+}	64.874^{+}
					(26.23)	(28.48)	(35.92)	(40.76)
D) Crimes pc					-13.232^{+}	-16.964**	-18.677*	-20.679*
					(8.65)	(8.52)	(10.58)	(11.43)
D) Median rent					-0.001	-0.001	-0.001*	-0.001*
					(0.00)	(0.00)	(0.00)	(0.00)
D) Pct poors					1.235	0.840	3.880^{+}	4.705^{+}
					(1.01)	(1.00)	(2.56)	(3.02)
D) Income segregation					2.289**	2.376**	1.137	0.821
					(0.88)	(0.84)	(1.28)	(1.43)
D) Avg income					-0.000	-0.000	-0.000	-0.000
					(0.00)	(0.00)	(0.00)	(0.00)
D) Gini index					-0.520	-0.683*	0.120	0.314
					(0.39)	(0.38)	(0.64)	(0.74)
Constant	-0.038**	0.099*	0.119	-0.025	0.616	0.629	0.132	-0.011
	(0.01)	(0.06)	(0.09)	(0.22)	(0.51)	(0.48)	(0.64)	(0.70)
E) Regional fe	-	-	-	-	-	-	x	x
R-squared	0.033	0.128	0.146	0.224	0.342	0.347	0.235	0.150
MSA	450	450	450	319	263	262	245	245

Table 6: Spatial inequality within the neighborhood and intergenerational mobility gains (full list of estimates)

Note: Based on authors' elaboration of data from U.S. Census, CCD, PSS, CPS March Supplement and Chetty and Hendren (2016). The dependent variable is defined as in Figure 7. $GINI_W$ in 2000 normalized by the full-sample standard deviation. Individual neighborhoods based on less than two miles range. Significance levels: $^{+}$ = 15%, * = 10% and ** = 5%.

	OLS					IV		
						SI1990	FMW	RMW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$GINI_W$ 2000	-0.044**	-0.034**	-0.029**	-0.046**	-0.035*	-0.016	-0.216^{+}	-0.266^{+}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.14)	(0.17)
A) Pct black		-0.329**	-0.309**	-0.222	0.437	0.570	0.092	0.059
		(0.12)	(0.12)	(0.16)	(0.51)	(0.49)	(0.66)	(0.71)
A) Racial segregation		-0.196^{+}	-0.258*	0.141	-0.433	-0.478^{+}	-0.501	-0.510
		(0.14)	(0.14)	(0.22)	(0.34)	(0.32)	(0.40)	(0.42)
A) Pop density (log)		0.010	-0.013	-0.056**	-0.046	-0.041	-0.042	-0.035
		(0.01)	(0.02)	(0.02)	(0.03)	(0.03)	(0.05)	(0.06)
A) Pct foreign born		-0.442**	-0.473**	0.210	-0.550	-0.530	-1.565	-1.928
		(0.10)	(0.14)	(0.23)	(0.54)	(0.52)	(1.17)	(1.40)
A) Migration flow		-1.684*	-2.086**	-4.672**	-0.505	0.161	-1.053	-1.328
		(0.90)	(0.93)	(1.31)	(2.63)	(2.50)	(3.14)	(3.37)
B) Avg tax rate			0.705	-0.213	-24.531**	-23.834**	-22.559*	-22.189^{+}
			(3.73)	(5.09)	(12.02)	(11.31)	(12.74)	(13.57)
B) Fiscal revenues pc			0.113	0.135	0.953**	0.939**	1.128**	1.173**
			(0.08)	(0.12)	(0.36)	(0.34)	(0.43)	(0.48)
B) Expenditure pc			0.000	0.000	0.000	0.000	-0.000	-0.000
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
B) Avg EITC exposure			0.001	-0.002	-0.002	-0.001	0.001	0.001
			(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
C) Pub. school budget				0.000	0.014	0.005	0.004	0.001
				(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
C) Students/teachers (pub.)				0.004	0.017	0.022*	0.034**	0.034*
				(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
C) Avg pub. school score				-0.000	0.000	-0.001	-0.003	-0.003
				(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
C) Avg dropout rate (pub.)				-2.386**	-0.863	-1.576^{+}	0.453	0.615
				(0.86)	(1.05)	(1.06)	(1.19)	(1.30)
C) Pub. schoold pc				6.194**	6.228**	6.482**	6.235*	6.379*
				(2.67)	(2.92)	(2.74)	(3.63)	(3.77)
C) Avg tuition				-0.000**	-0.000**	-0.000**	-0.000**	-0.000**
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
C) Kindergartens(pub.)				0.238	-0.005	-0.021	0.065	0.082
				(0.19)	(0.21)	(0.20)	(0.24)	(0.26)
C) Students/teachers (priv.)				0.007	0.014^{+}	0.016*	0.002	-0.001
				(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
D)Sd of students/teachers (priv.)					-0.011	-0.013^{+}	-0.010	-0.009
					(0.01)	(0.01)	(0.01)	(0.01)
D) Sd of students/teachers (pub.)					0.008	0.006	0.015^{+}	0.017^{+}
					(0.01)	(0.01)	(0.01)	(0.01)
D) Pct black students (pub.)					-0.901**	-1.044**	-0.850**	-0.850**
					(0.32)	(0.31)	(0.37)	(0.40)
D) Sd of pct black students (pub.)					0.826**	0.837**	0.732^{+}	0.649
					(0.37)	(0.35)	(0.50)	(0.55)
D) Pct violent crime					26.216	46.526^{+}	59.749^{+}	70.474^{+}
					(26.12)	(28.35)	(37.60)	(43.65)
D) Crimes pc					-13.860^{+}	-17.386**	-21.131*	-23.621*
					(8.65)	(8.52)	(11.50)	(12.80)
D) Median rent					-0.001	-0.001	-0.001*	-0.001*
					(0.00)	(0.00)	(0.00)	(0.00)
D) Pct poors					1.202	1.022	3.489^{+}	4.210^{+}
					(0.97)	(0.94)	(2.27)	(2.73)
D) Income segregation					2.447**	2.379**	2.028*	1.921*
					(0.87)	(0.82)	(1.06)	(1.15)
D) Avg income					-0.000	-0.000	-0.000	-0.000
					(0.00)	(0.00)	(0.00)	(0.00)
D) Gini index					-0.473	-0.615^{+}	0.609	0.917
					(0.39)	(0.38)	(0.93)	(1.11)
Constant	-0.035**	0.085^{+}	0.108	-0.016	0.609	0.594	0.073	-0.086
	(0.01)	(0.06)	(0.09)	(0.22)	(0.51)	(0.48)	(0.69)	(0.77)
E) Regional fe	-	-	-	-	-	-	x	x
R-squared	0.048	0.128	0.148	0.227	0.345	0.350	0.159	0.029
MSA	449	449	449	318	262	261	244	244

Table 7: Spatial inequality within the neighborhood and intergenerational mobility gains (full list of estimates)

Note: Based on authors' elaboration of data from U.S. Census, CCD, PSS, CPS March Supplement and Chetty and Hendren (2016). The dependent variable is defined as in Figure 7. $GINI_W$ in 2000 normalized by the full-sample standard deviation. Individual neighborhoods based on less than six miles range. Significance levels: $^{+} = 15\%$, $^{*} = 10\%$ and $^{**} = 5\%$.

	OLS					IV		
						SI1990	FMW	RMW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$GINI_W$ 2000	-0.666**	-0.400**	-0.217**	-0.439**	-0.147	0.244	1.912	1.358
	(0.16)	(0.10)	(0.10)	(0.13)	(0.20)	(0.25)	(1.53)	(1.57)
A) Pct black		-17.737**	-16.524**	-13.860**	-24.095**	-22.000**	-16.485**	-17.863**
		(1.27)	(1.18)	(1.47)	(4.58)	(4.41)	(6.63)	(6.23)
A) Racial segregation		-11.470**	-10.477**	-6.544**	-3.533	-3.869	-2.477	-2.650
		(1.43)	(1.37)	(1.97)	(2.96)	(2.81)	(3.52)	(3.32)
A) Pop density (log)		0.464**	-0.386**	-1.024**	-1.263**	-1.268**	-2.440**	-2.332**
		(0.12)	(0.15)	(0.21)	(0.29)	(0.28)	(0.45)	(0.44)
A) Pct foreign born		4.401**	7.131**	10.692**	18.771**	21.384**	43.382**	38.680**
		(1.02)	(1.37)	(2.03)	(4.94)	(4.87)	(14.73)	(14.68)
A) Migration flow		-45.857**	-50.279**	-65.107**	-12.959	-6.833	-22.168	-25.571
		(9.58)	(9.10)	(11.86)	(23.29)	(22.28)	(37.81)	(35.81)
B) Avg tax rate			-143.127**	-91.740**	-362.759**	-356.644**	-244.328**	-245.188**
			(36.51)	(46.57)	(106.51)	(101.04)	(105.23)	(99.12)
B) Fiscal revenues pc			5.449**	4.270**	14.255**	13.835**	7.710*	8.345**
			(0.83)	(1.10)	(3.21)	(3.05)	(4.00)	(3.77)
B) Expenditure pc			-0.001**	-0.001**	-0.001*	-0.000$^+$	-0.000	-0.000
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
B) Avg EITC exposure			0.158**	0.044	0.054$^+$	0.060*	0.119**	0.115**
			(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)
C) Pub. school budget				0.093	0.026	-0.015	0.000	-0.044
				(0.16)	(0.20)	(0.20)	(0.33)	(0.31)
C) Students/teachers (pub.)				0.206**	0.393**	0.431**	0.803**	0.784**
				(0.08)	(0.11)	(0.11)	(0.17)	(0.16)
C) Avg pub. school score				0.039	0.019	0.014	0.021	0.018
				(0.03)	(0.04)	(0.04)	(0.05)	(0.05)
C) Avg dropout rate (pub.)				-28.133**	-12.144	-16.296*	2.475	2.768
				(7.83)	(9.26)	(9.44)	(12.57)	(11.72)
C) Pub. schoold pc				27.853	19.946	21.982	24.552	25.200
				(23.28)	(25.84)	(24.53)	(29.54)	(27.78)
C) Avg tuition				0.000	-0.000	-0.000	-0.000	-0.000
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
C) Kindergartens(pub.)				-1.398	-3.312*	-3.597**	-4.648**	-4.336**
				(1.75)	(1.88)	(1.78)	(2.23)	(2.14)
C) Students/teachers (priv.)				0.391**	0.278**	0.302**	0.442**	0.419**
				(0.06)	(0.08)	(0.08)	(0.12)	(0.11)
D)Sd of students/teachers (priv.)					0.131*	0.110$^+$	-0.003	0.010
					(0.07)	(0.07)	(0.08)	(0.08)
D) Sd of students/teachers (pub.)					-0.057	-0.077	-0.176*	-0.154$^+$
					(0.07)	(0.07)	(0.11)	(0.10)
D) Pct black students (pub.)					7.175**	5.726**	1.780	2.275
					(2.88)	(2.82)	(3.76)	(3.45)
D) Sd of pct black students (pub.)					2.378	2.458	4.429	4.248
					(3.28)	(3.11)	(3.45)	(3.03)
D) Pct violent crime					396.927*	471.970*	-50.766	68.623
					(232.04)	(254.03)	(421.62)	(422.17)
D) Crimes pc					-210.880**	-224.952**	-108.787	-132.947
					(76.49)	(76.04)	(116.43)	(115.46)
D) Median rent					-0.015**	-0.014**	-0.006	-0.007
					(0.01)	(0.00)	(0.01)	(0.01)
D) Pct poors					-12.253	-18.662**	-54.752*	-44.799$^+$
					(8.92)	(8.91)	(30.73)	(30.99)
D) Income segregation					19.072**	21.144**	34.288**	30.465**
					(7.82)	(7.49)	(14.29)	(14.22)
D) Avg income					-0.000*	-0.000*	-0.000	-0.000
					(0.00)	(0.00)	(0.00)	(0.00)
D) Gini index					-8.541**	-10.531**	-18.616**	-16.276**
					(3.44)	(3.35)	(7.53)	(7.46)
Constant	43.321**	45.851**	50.189**	44.524**	60.980**	61.930**	64.321**	62.597**
	(0.14)	(0.61)	(0.93)	(1.96)	(4.50)	(4.32)	(7.00)	(6.87)
E) Regional fe	-	-	-	-	-	-	x	x
R-squared	0.039	0.594	0.660	0.715	0.786	0.783	0.709	0.754
MSA	451	451	451	320	263	262	245	245

Table 8: Spatial inequality within the neighborhood and intergenerational mobility of long-term residents (full list of estimates)

Note: Based on authors' elaboration of data from U.S. Census, CCD, PSS, CPS March Supplement and Chetty and Hendren (2016). The dependent variable is the average percent-rank at age 27 in the national household income distribution for long term residents in the MSA born in families at the bottom quartile. $GINI_W$ in 2000 normalized by the full-sample standard deviation. Individual neighborhoods based on less than two miles range. Significance levels: $^+ = 15\%$, $^* = 10\%$ and $^{**} = 5\%$.

	OLS					IV		
						SI1990	FMW	RMW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$GINI_W$ 2000	-0.576**	-0.356**	-0.235**	-0.502**	-0.260$^+$	-0.045	2.096	1.530
	(0.14)	(0.10)	(0.09)	(0.12)	(0.18)	(0.23)	(1.73)	(1.74)
A) Pct black		-17.935**	-16.553**	-14.080**	-24.493**	-23.320**	-19.783**	-20.157**
		(1.27)	(1.17)	(1.44)	(4.53)	(4.33)	(5.72)	(5.17)
A) Racial segregation		-11.133**	-10.253**	-5.713**	-3.176	-3.552	-2.562	-2.659
		(1.44)	(1.37)	(1.97)	(2.96)	(2.80)	(3.83)	(3.53)
A) Pop density (log)		0.474**	-0.397**	-1.077**	-1.317**	-1.290**	-2.406**	-2.328**
		(0.12)	(0.15)	(0.21)	(0.30)	(0.28)	(0.46)	(0.43)
A) Pct foreign born		4.726**	7.552**	12.109**	18.419**	19.237**	42.630**	38.528**
		(1.03)	(1.40)	(2.08)	(4.78)	(4.63)	(14.88)	(14.49)
A) Migration flow		-44.760**	-49.751**	-64.235**	-13.626	-8.685	-22.047	-25.150
		(9.59)	(9.09)	(11.79)	(23.23)	(22.15)	(39.86)	(37.12)
B) Avg tax rate			-140.775**	-92.025**	-358.271**	-355.278**	-259.632**	-255.440**
			(36.56)	(45.93)	(106.26)	(100.34)	(116.96)	(107.30)
B) Fiscal revenues pc			5.450**	4.249**	14.201**	14.030**	7.785*	8.303**
			(0.82)	(1.08)	(3.20)	(3.02)	(4.35)	(3.95)
B) Expenditure pc			-0.001**	-0.001**	-0.001**	-0.001*	-0.000	-0.000
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
B) Avg EITC exposure			0.159**	0.047	0.057$^+$	0.058*	0.098**	0.100**
			(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)
C) Pub. school budget				0.110	0.036	-0.012	-0.045	-0.073
				(0.16)	(0.20)	(0.20)	(0.34)	(0.32)
C) Students/teachers (pub.)				0.207**	0.395**	0.423**	0.752**	0.745**
				(0.08)	(0.11)	(0.10)	(0.17)	(0.16)
C) Avg pub. school score				0.037	0.016	0.010	0.022	0.018
				(0.03)	(0.04)	(0.04)	(0.05)	(0.05)
C) Avg dropout rate (pub.)				-27.049**	-11.772	-16.367*	-3.572	-1.738
				(7.77)	(9.24)	(9.44)	(14.66)	(13.86)
C) Pub. schoold pc				27.912	20.735	22.025	21.301	22.936
				(23.07)	(25.77)	(24.36)	(31.68)	(29.57)
C) Avg tuition				0.000	-0.000	-0.000	-0.000	-0.000
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
C) Kindergartens(pub.)				-1.820	-3.401*	-3.525**	-4.355*	-4.161**
				(1.74)	(1.87)	(1.77)	(2.25)	(2.09)
C) Students/teachers (priv.)				0.390**	0.284**	0.299**	0.463**	0.439**
				(0.06)	(0.08)	(0.08)	(0.13)	(0.12)
D)Sd of students/teachers (priv.)					0.122$^+$	0.110$^+$	0.013	0.020
					(0.07)	(0.07)	(0.09)	(0.08)
D) Sd of students/teachers (pub.)					-0.053	-0.064	-0.177$^+$	-0.156$^+$
					(0.07)	(0.07)	(0.11)	(0.11)
D) Pct black students (pub.)					7.345**	6.322**	3.431	3.436
					(2.86)	(2.78)	(3.60)	(3.27)
D) Sd of pct black students (pub.)					1.787	2.070	7.186$^+$	6.249
					(3.29)	(3.12)	(4.80)	(4.34)
D) Pct violent crime					426.689*	528.295**	-91.381	29.948
					(230.81)	(251.56)	(463.09)	(455.96)
D) Crimes pc					-216.837**	-233.659**	-86.314	-114.484
					(76.40)	(75.56)	(135.20)	(132.49)
D) Median rent					-0.015**	-0.014**	-0.006	-0.007
					(0.01)	(0.00)	(0.01)	(0.01)
D) Pct poors					-11.050	-13.665$^+$	-50.559*	-42.398$^+$
					(8.55)	(8.37)	(28.80)	(28.45)
D) Income segregation					19.645**	19.402**	25.491**	24.280**
					(7.67)	(7.25)	(10.89)	(10.23)
D) Avg income					-0.000*	-0.000*	-0.000	-0.000
					(0.00)	(0.00)	(0.00)	(0.00)
D) Gini index					-7.522**	-8.976**	-23.311**	-19.830*
					(3.47)	(3.41)	(11.58)	(11.43)
Constant	43.391**	45.708**	50.175**	44.797**	60.323**	60.651**	64.865**	63.067**
	(0.14)	(0.61)	(0.93)	(1.94)	(4.48)	(4.29)	(7.92)	(7.64)
E) Regional fe	-	-	-	-	-	-	x	x
R-squared	0.034	0.592	0.661	0.720	0.788	0.787	0.651	0.718
MSA	450	450	450	319	262	261	244	244

Table 9: Spatial inequality within the neighborhood and intergenerational mobility of long-term residents (full list of estimates)

Note: Based on authors' elaboration of data from U.S. Census, CCD, PSS, CPS March Supplement and Chetty and Hendren (2016). The dependent variable is the average percent-rank at age 27 in the national household income distribution for long term residents in the MSA born in families at the bottom quartile. $GINI_W$ in 2000 normalized by the full-sample standard deviation. Individual neighborhoods based on less than six miles range. Significance levels: $^+ = 15\%$, $^* = 10\%$ and $^{**} = 5\%$.

	OLS							IV FMW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$GINI_W$ 2000	0.211*	0.092*	0.124**	0.192**	0.098**	-0.035	-0.022	-0.139
	(0.11)	(0.05)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(1.01)
F) Pct current smokers, P25		-29.644**	-13.347**	-9.235**	-12.445**	-12.049**	-7.864**	-7.364**
		(1.36)	(1.07)	(1.32)	(1.24)	(0.91)	(1.25)	(2.91)
F) Pct current smokers, P75		-7.918**	-1.823	-3.210*	-2.020	-1.916	-1.048	-1.321
		(2.53)	(1.57)	(1.74)	(1.78)	(1.41)	(1.75)	(2.07)
F) Pct obese, P25		-13.748**	0.635	2.799*	1.291	-1.605	-0.596	-0.965
		(1.91)	(1.31)	(1.56)	(1.41)	(1.17)	(1.51)	(4.75)
F) Pct obese, P75		-9.753**	-8.137**	-6.056**	-8.420**	-5.513**	-3.802**	-4.023**
		(1.99)	(1.40)	(1.58)	(1.54)	(1.23)	(1.43)	(1.53)
F) Pct practice exercises, P25		-0.291	-0.966	2.805**	-1.084	1.488*	4.875**	4.443**
		(1.62)	(0.98)	(1.38)	(1.07)	(0.90)	(1.28)	(1.55)
F) Pct practice exercises, P75		-3.768	-0.120	-0.556	0.252	4.144**	2.910*	2.257
		(2.70)	(1.70)	(1.72)	(1.84)	(1.52)	(1.66)	(4.18)
F) Pct w/o health insurance		0.025**	-0.018**	-0.028**	-0.021**	-0.048**	-0.044**	-0.036**
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
A) Pct black			-4.511**	-3.865**	-5.780**	-5.791**	-1.282	-0.300
			(0.44)	(0.53)	(1.04)	(0.43)	(1.11)	(2.24)
A) Racial segregation			-3.556**	-1.988**	-2.991**	-1.868**	0.876	0.383
			(0.46)	(0.67)	(0.59)	(0.46)	(0.75)	(0.84)
A) Pop density (log)			0.016	-0.097	0.023	0.038	-0.329**	-0.285*
			(0.05)	(0.07)	(0.06)	(0.05)	(0.08)	(0.16)
A) Pct foreign born			0.124**	0.151**	0.128**	0.091**	0.119**	0.116**
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.05)
A) Migration flow			-5.018^{+}	8.034*	-5.313^{+}	-2.124	-5.425	-4.336
			(3.40)	(4.73)	(3.64)	(3.71)	(5.85)	(11.67)
B) Avg tax rate			32.948**	14.314	36.180**	-74.484**	-17.595	-1.225
			(13.50)	(15.59)	(14.13)	(18.58)	(30.24)	(88.66)
B) Fiscal revenues pc			-0.263	0.160	-0.328	3.065**	0.465	0.040
			(0.31)	(0.37)	(0.33)	(0.48)	(0.88)	(1.92)
B) Expenditure pc			0.000**	0.000^{+}	0.000**	0.000*	0.000	0.000
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
B) Avg EITC exposure			0.016^{+}	0.008	0.016^{+}	0.009	0.007	0.008
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
C) Students/teachers (pub.)				0.003			-0.020	-0.041
				(0.02)			(0.03)	(0.08)
C) Avg pub. school score				0.006			0.018*	0.017*
				(0.01)			(0.01)	(0.01)
C) Avg dropout rate (pub.)				3.899^{+}			-0.253	0.608
				(2.62)			(2.40)	(2.48)
C) Pub. schoold pc				10.665			-7.179	-5.946
				(7.66)			(6.84)	(9.71)
C) Avg tuition				0.000			0.000**	0.000**
				(0.00)			(0.00)	(0.00)
C) Kindergartens(pub.)				-0.975*			-1.303**	-1.347*
				(0.56)			(0.48)	(0.73)
C) Students/teachers (priv.)				0.036*			0.020	0.019
				(0.02)			(0.02)	(0.03)
D)Sd of students/teachers (priv.)					0.010		0.032*	0.031
					(0.01)		(0.02)	(0.03)
D) Sd of students/teachers (pub.)					0.002		-0.008	-0.007
					(0.01)		(0.02)	(0.05)
D) Pct black students (pub.)					1.556**		-1.568**	-1.906
					(0.74)		(0.73)	(1.90)
D) Sd of pct black students (pub.)					-1.292^{+}		-2.438**	-2.294
					(0.83)		(0.87)	(1.69)
D) Pct violent crime						-41.598	50.627	54.895
						(39.60)	(58.65)	(125.54)
D) Crimes pc						32.943**	0.094	-8.861
						(14.22)	(19.51)	(45.28)
D) Median rent						0.001^{+}	0.005**	0.004**
						(0.00)	(0.00)	(0.00)
D) Pct poors						8.733**	14.484**	16.296
						(1.70)	(2.20)	(18.21)
D) Income segregation						-10.146**	-12.121**	-12.484**
						(1.69)	(1.98)	(5.55)
D) Avg income						-0.000**	0.000	0.000
						(0.00)	(0.00)	(0.00)
D) Gini index						5.352**	4.073**	4.270
						(0.78)	(0.94)	(4.27)
Constant	77.147**	94.474**	81.815**	77.851**	81.045**	75.572**	70.261**	70.695**
	(0.10)	(2.23)	(1.53)	(1.73)	(1.69)	(1.51)	(1.84)	(1.97)
E) Regional fe	-	-	-	-	-	-	-	x
R-squared	0.008	0.815	0.942	0.913	0.945	0.964	0.956	0.956
MSA	449	447	447	319	406	417	264	264

Table 10: Spatial inequality within the neighborhood and life expectancy of long-term resident (full list of estimates)

Note: Based on authors' elaboration of data from U.S. Census, CCD, PSS, CPS March Supplement and Chetty, Stepner, Abraham, Lin, Scuderi, Turner, Bergeron and Cutler (2016). The dependent variable is the average life expectancy in years at age 40 (at MSA level) for males in the bottom quartile of the national income distribution in 2000. $GINI_W$ in 2000 normalized by the full-sample standard deviation. Individual neighborhoods based on less than six miles range. Significance levels: $^{+} = 15\%$, $^{*} = 10\%$ and $^{**} = 5\%$.

C Statistics for selected U.S. cities

City	Year	# Blocks	Hh/block	Eq. scale	Equivalent household income				
					Mean	*20%*	*80%*	*Gini*	*90%/10%*
New York (NY)	1980	6319	1318	1.572	12289	4601	19034	0.474	11.247
	1990	6774	1664	2.058	22763	7799	35924	0.507	13.013
	2000	6618	1537	1.604	41061	12196	66542	0.549	25.913
	2010/14	7182	1140	1.566	56558	19749	92656	0.502	17.323
Los Angeles (CA)	1980	5059	1052	1.615	14697	6167	22248	0.441	10.735
	1990	5905	1585	2.012	26434	10509	41048	0.475	12.391
	2000	6103	1158	1.690	38844	13720	59767	0.509	19.256
	2010/14	6385	1107	1.649	55224	19056	90324	0.505	13.628
Chicago (IL)	1980	3756	1122	1.630	13794	5798	20602	0.434	11.351
	1990	4444	1217	2.029	21859	9132	32316	0.461	11.903
	2000	4691	1173	1.625	41193	16076	61667	0.473	11.533
	2010/14	4763	1060	1.575	55710	20022	89856	0.486	13.452
Houston (TX)	1980	1238	1253	1.624	15419	6900	22718	0.428	10.233
	1990	2531	1291	1.994	22827	10203	33287	0.462	11.771
	2000	2318	1418	1.667	39231	16619	57539	0.472	10.736
	2010/14	2781	2148	1.644	55841	22156	88033	0.484	12.394
Philadelphia (PA)	1980	3978	855	1.650	12651	5589	18557	0.410	10.245
	1990	3300	1384	2.001	21816	9601	31606	0.442	11.788
	2000	4212	982	1.602	38995	15788	57841	0.454	10.972
	2010/14	3819	1124	1.566	56205	21567	89602	0.465	13.174
Phoenix (AZ)	1980	697	1155	1.609	12854	5920	18741	0.401	8.972
	1990	1857	961	1.970	21233	9831	30732	0.439	9.803
	2000	1984	1222	1.622	37860	17098	54998	0.437	8.541
	2010/14	2494	1110	1.590	48194	20218	73509	0.456	10.906
San Antonio (TX)	1980	597	891	1.686	10501	4364	15399	0.451	10.206
	1990	1101	890	1.983	17350	7569	25243	0.455	9.903
	2000	1065	1189	1.651	31592	13726	45517	0.454	16.081
	2010/14	1220	1307	1.623	44773	19048	68074	0.454	11.225
San Diego (CA)	1980	908	1471	1.577	12759	5628	18338	0.412	8.893
	1990	1628	1473	1.961	24194	11007	35191	0.434	11.239
	2000	1678	1172	1.637	39537	16698	57219	0.451	9.644
	2010/14	1789	1546	1.615	55564	21947	88783	0.452	11.978

Table 12: Income and population distribution across block groups, U.S. 50 largest cities

Continued

City	Year	# Blocks	Hh/block	Eq. scale	Equivalent household income				
					Mean	*20%*	*80%*	*Gini*	*90%/10%*
Dallas (TX)	1980	1141	931	1.620	14614	6759	21494	0.425	9.522
	1990	2310	965	1.993	24074	11287	35141	0.454	11.691
	2000	2189	1251	1.633	43913	19306	65158	0.464	10.093
	2010/14	2696	1251	1.625	54729	23689	84291	0.460	11.163
San Jose (CA)	1980	571	1417	1.633	16762	8441	24258	0.365	7.215
	1990	1016	1400	1.954	32120	15598	47103	0.405	8.339
	2000	965	1169	1.689	59428	24663	91637	0.433	9.465
	2010/14	1071	1427	1.664	82154	30785	137435	0.455	14.295
Austin (TX)	1980	296	1084	1.517	11407	4867	17064	0.440	9.902
	1990	718	1345	2.019	18968	8497	27339	0.461	10.522
	2000	644	1416	1.569	38993	17418	55766	0.442	9.455
	2010/14	899	1662	1.576	55093	23478	85981	0.443	11.403
Jacksonville (FL)	1980	434	1000	1.622	10868	4602	15546	0.428	9.415
	1990	628	1509	1.973	19217	8365	27219	0.435	9.512
	2000	505	2358	1.590	34398	14528	49341	0.434	8.629
	2010/14	688	1757	1.550	46517	18370	71941	0.450	10.883
San Francisco (CA)	1980	1083	1166	1.514	16322	6927	24339	0.424	9.864
	1990	1226	1477	2.040	28783	11624	44191	0.467	13.379
	2000	1105	1316	1.549	60967	20961	97430	0.494	13.179
	2010/14	1210	1328	1.525	85755	28440	145763	0.482	16.858
Indianapolis (IN)	1980	730	1073	1.617	12550	5958	18183	0.388	9.032
	1990	1029	1395	1.985	20996	9806	29406	0.425	9.515
	2000	944	1395	1.573	37021	16392	52896	0.423	8.317
	2010/14	1030	1639	1.568	47262	19870	71036	0.450	10.624
Columbus (OH)	1980	758	1105	1.593	12427	5984	17840	0.394	8.874
	1990	1281	1128	1.988	19865	9262	28819	0.427	9.649
	2000	1140	986	1.553	35926	16152	51815	0.431	8.848
	2010/14	1269	1293	1.560	48270	21115	72778	0.439	11.633
Fort Worth (TX)	1980	640	650	1.615	12873	5870	18794	0.409	9.169
	1990	1203	956	1.972	21517	10428	30620	0.424	9.835
	2000	1101	1147	1.638	37074	17140	52607	0.429	8.719
	2010/14	1326	1294	1.625	50540	21830	75565	0.449	10.553
Charlotte (NC)	1980	346	1169	1.614	11411	5203	16277	0.400	8.864
	1990	930	1032	1.959	20366	8961	29519	0.424	9.445
	2000	856	1195	1.583	39683	16640	59188	0.451	9.145
	2010/14	1172	1299	1.579	47697	19231	74717	0.452	11.757
Detroit (MI)	1980	2184	764	1.638	12853	5587	19246	0.415	10.783
	1990	4531	974	1.990	22673	10194	33441	0.445	12.181
	2000	3954	963	1.603	40742	17362	59654	0.439	9.817
	2010/14	3798	986	1.560	46492	18592	71604	0.456	11.856
El Paso (TX)	1980	218	897	1.759	8525	3572	12373	0.443	9.182
	1990	425	1042	1.969	15009	6372	21601	0.456	8.963
	2000	418	960	1.750	23862	9095	33972	0.476	16.668
	2010/14	511	1142	1.694	33277	13049	51000	0.462	11.060

Continued

City	Year	# Blocks	Hh/block	Eq. scale	Equivalent household income				
					Mean	*20%*	*80%*	*Gini*	*90%/10%*
Seattle (WA)	1980	1405	885	1.540	14437	6481	21204	0.398	8.514
	1990	2255	1004	1.984	22563	10601	31905	0.416	10.514
	2000	2473	855	1.568	42386	18650	60276	0.427	8.448
	2010/14	2475	1087	1.555	59626	24442	92751	0.438	10.314
Denver (CO)	1980	1054	899	1.575	14283	6866	20352	0.396	8.081
	1990	1694	983	2.005	22072	10791	31410	0.432	11.069
	2000	1711	1038	1.578	43300	20142	62101	0.425	8.100
	2010/14	1908	1230	1.561	58203	24081	90216	0.450	10.751
Washington (DC)	1980	1580	1608	1.619	18273	9281	26315	0.390	8.361
	1990	2540	2193	1.968	32091	16818	45700	0.404	7.758
	2000	2642	1409	1.603	53263	24898	78715	0.425	8.968
	2010/14	3335	1360	1.600	80366	35929	124973	0.420	10.665
Memphis (TN)	1980	478	1021	1.639	11370	4852	16693	0.457	10.804
	1990	920	903	1.997	17888	8072	26052	0.471	10.945
	2000	783	1153	1.605	33086	13753	47853	0.471	18.640
	2010/14	764	1380	1.573	42700	17702	65757	0.465	11.492
Boston (MA)	1980	3662	809	1.622	12696	5417	18790	0.406	10.048
	1990	4497	1032	1.997	24633	10314	37112	0.436	12.226
	2000	3963	961	1.584	43840	16776	66109	0.458	11.004
	2010/14	4082	1058	1.566	64422	23196	105048	0.470	13.712
Nashville (TN)	1980	375	1043	1.605	12416	5382	18373	0.442	10.358
	1990	755	1260	1.979	19811	8712	28653	0.442	9.710
	2000	723	1374	1.555	36360	15118	52565	0.448	9.000
	2010/14	911	1535	1.568	49714	20024	76735	0.452	10.444
Baltimore (MD)	1980	1517	900	1.641	12751	5932	18442	0.400	10.075
	1990	1965	1269	1.972	23987	11302	34591	0.426	11.780
	2000	1780	1204	1.588	38615	16954	55517	0.431	9.565
	2010/14	1932	1182	1.567	59954	25171	93398	0.439	11.158
Oklahoma City (OK)	1980	709	720	1.573	12933	5777	18878	0.419	9.075
	1990	1034	854	1.993	17551	7499	26072	0.445	9.616
	2000	880	941	1.557	30578	12488	44422	0.447	15.739
	2010/14	1015	1021	1.562	45377	18504	68795	0.457	10.504
Portland (OR)	1980	696	1077	1.526	12819	5411	18704	0.404	9.155
	1990	1145	1131	1.991	19987	8840	28511	0.424	9.403
	2000	1141	1111	1.586	37618	16409	53854	0.417	8.385
	2010/14	1374	1211	1.567	49201	19927	74485	0.428	10.490
Las Vegas (NV)	1980	150	2018	1.554	12756	5568	17713	0.406	8.542
	1990	318	2570	1.976	20006	8888	27960	0.431	9.310
	2000	796	1396	1.620	36442	16095	51823	0.430	8.202
	2010/14	1284	1215	1.592	44657	18771	66044	0.442	9.525
Louisville (KY)	1980	582	873	1.592	11451	5036	17218	0.414	9.188
	1990	957	938	1.990	18323	7864	27067	0.445	9.771
	2000	742	1021	1.542	32264	13213	46595	0.444	15.196
	2010/14	840	1087	1.536	45220	17798	69576	0.451	10.739

Continued

City	Year	# Blocks	Hh/block	Eq. scale	Equivalent household income				
					Mean	*20%*	*80%*	*Gini*	*90%/10%*
Milwaukee (WI)	1980	1125	788	1.606	13629	6277	19823	0.384	8.008
	1990	1540	935	1.994	20192	9430	29189	0.420	9.621
	2000	1389	883	1.575	36437	15855	52408	0.426	8.692
	2010/14	1465	927	1.540	48088	19198	72556	0.452	10.903
Albuquerque (NM)	1980	278	957	1.629	11593	5209	16795	0.413	9.366
	1990	430	884	1.992	18125	8120	26181	0.444	9.886
	2000	404	941	1.558	33181	13980	47243	0.440	9.523
	2010/14	434	1176	1.533	43410	17042	66070	0.461	11.785
Tucson (AZ)	1980	306	810	1.578	10384	4601	15056	0.400	8.130
	1990	561	1029	2.000	16834	7279	24236	0.461	9.772
	2000	601	1045	1.551	30864	12504	44934	0.460	15.544
	2010/14	614	1423	1.534	42082	16637	64100	0.463	11.018
Fresno (CA)	1980	571	1417	1.633	16762	8441	24258	0.365	7.215
	1990	532	1044	1.989	18020	7467	26327	0.463	9.649
	2000	546	933	1.730	27064	10878	38272	0.471	16.750
	2010/14	587	1094	1.714	37117	15473	56226	0.461	11.747
Sacramento (CA)	1980	423	1148	1.529	11659	4941	17097	0.408	9.032
	1990	1031	1557	1.968	21357	9535	30607	0.421	10.800
	2000	1094	1199	1.616	36344	15452	52005	0.434	9.269
	2010/14	1369	1143	1.606	49000	20048	75343	0.435	11.883
Kansas City (MO-KS)	1980	1006	991	1.587	13577	6444	19645	0.393	9.056
	1990	1465	1043	1.991	20820	9844	29980	0.426	9.736
	2000	1352	1005	1.575	38395	17532	54896	0.426	8.529
	2010/14	1468	1111	1.562	50056	21337	76139	0.439	10.496
Atlanta (GA)	1980	840	1150	1.591	11821	4837	17433	0.457	10.792
	1990	1962	1650	1.959	24596	11684	35257	0.431	11.546
	2000	1639	1826	1.628	43435	19191	63050	0.438	9.395
	2010/14	2379	1631	1.598	51857	20271	80941	0.460	12.044
Norfolk (VA)	1980	541	1142	1.666	11265	5156	16109	0.411	9.453
	1990	903	1531	1.951	19181	9208	27018	0.405	9.323
	2000	892	1189	1.619	32543	15069	45638	0.412	7.757
	2010/14	1089	1135	1.572	48576	21406	72037	0.420	9.538
Omaha (NE-IA)	1980	399	814	1.616	12576	5952	17858	0.388	8.192
	1990	626	728	1.991	19465	9546	27285	0.424	9.462
	2000	650	626	1.584	35338	16484	49614	0.417	7.904
	2010/14	745	801	1.570	47979	21411	70100	0.428	9.776
Colorado Springs (CO)	1980	159	961	1.583	11320	5290	16547	0.406	8.194
	1990	308	1077	1.970	19034	9441	26299	0.408	9.125
	2000	303	1174	1.612	35946	18023	49660	0.391	7.238
	2010/14	362	1506	1.590	47967	21394	72013	0.422	9.581
Raleigh (NC)	1980	237	1331	1.563	12403	5620	18069	0.414	9.799
	1990	499	1623	1.981	21517	9825	30516	0.421	11.087
	2000	430	1545	1.553	40050	16738	57936	0.445	9.987
	2010/14	707	1679	1.567	54607	22647	84366	0.444	10.753

Continued

City	Year	# Blocks	Hh/block	Eq. scale	Equivalent household income				
					Mean	*20%*	*80%*	*Gini*	*90%/10%*
Miami (FL)	1980	1307	2022	1.559	12962	5246	18895	0.444	9.980
	1990	1549	3062	2.008	19659	7405	28802	0.477	10.503
	2000	638	1987	1.556	35599	14112	51177	0.451	9.572
	2010/14	936	1474	1.557	47343	18170	73153	0.457	11.349
Oakland (CA)	1980	1376	1007	1.589	14714	6930	21331	0.397	9.819
	1990	1636	1673	1.972	27737	13353	40200	0.428	11.701
	2000	1488	1277	1.631	47663	20554	71300	0.443	11.010
	2010/14	1676	1289	1.622	68482	27490	110290	0.457	13.566
Minneapolis (MN)	1980	1704	829	1.593	14300	6794	20511	0.383	7.374
	1990	2239	1096	1.986	23220	11170	33176	0.411	10.532
	2000	2105	1136	1.593	43427	20413	61659	0.408	7.339
	2010/14	2244	1231	1.570	57533	24116	88819	0.432	9.900
Tulsa (OK)	1980	340	823	1.546	12889	5475	19014	0.431	9.341
	1990	730	779	1.990	18258	7716	26596	0.455	9.883
	2000	541	980	1.566	33077	13504	48629	0.446	8.419
	2010/14	599	1154	1.566	44777	17354	68006	0.457	10.355
Cleveland (OH)	1980	1654	867	1.631	12466	5551	18359	0.402	9.899
	1990	2691	1052	2.005	19509	8388	28706	0.446	10.056
	2000	2272	1029	1.563	35221	14392	50973	0.443	9.109
	2010/14	2238	1085	1.519	44764	17146	68783	0.460	11.080
Wichita (KS)	1980	289	704	1.576	12717	5768	18455	0.388	8.499
	1990	451	896	1.989	19303	8801	27625	0.428	9.526
	2000	371	954	1.590	33430	15421	47101	0.414	7.812
	2010/14	411	1133	1.575	43162	18600	64259	0.431	9.672
New Orleans (LA)	1980	938	960	1.623	11743	4629	17279	0.456	11.116
	1990	1215	1113	2.015	15751	5944	23640	0.484	26.274
	2000	974	1009	1.597	29996	10495	43919	0.490	18.694
	2010/14	1053	924	1.532	44250	15342	69804	0.481	13.121
Bakersfield (CA)	1980	169	810	1.635	11081	4431	15901	0.423	9.342
	1990	374	1170	1.965	18526	8018	26588	0.433	9.347
	2000	353	1171	1.723	27908	11092	39953	0.459	16.969
	2010/14	450	1319	1.723	38846	16404	59346	0.447	11.251
Tampa (FL)	1980	903	1300	1.515	10663	4430	15388	0.424	8.280
	1990	1547	1620	1.980	17140	7176	24448	0.440	9.216
	2000	1448	1307	1.530	32815	13303	46343	0.448	8.451
	2010/14	2002	1131	1.506	43788	17047	66315	0.460	10.445

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